Jet-Flavour Tagging at Future e^+e^- Colliders

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with contributions from
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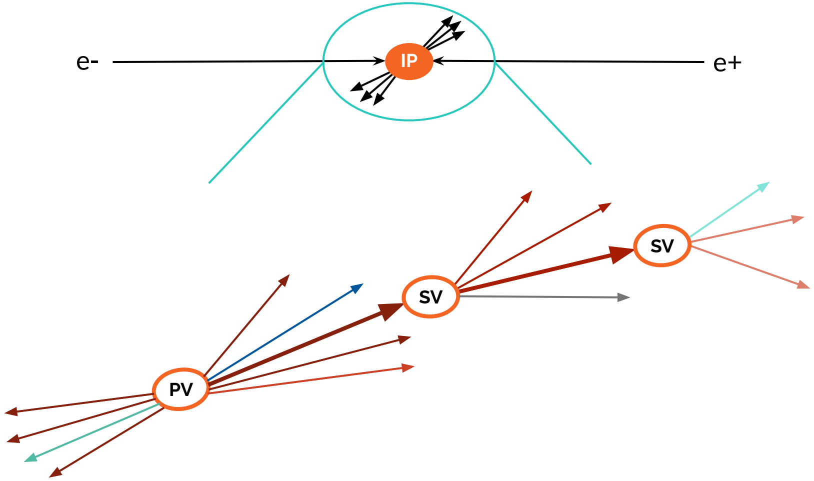
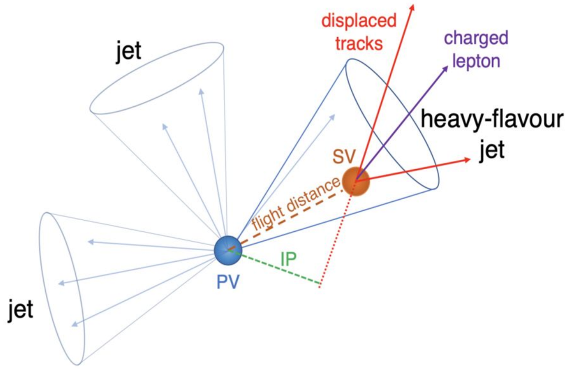
Motivation

- Jet-flavour tagging is a very important tool for studies with hadronic final states (e.g. Higgs couplings).
- Many well-performing jet-flavour tagging algorithms have been employed at the LHC experiments.
- Expect to do better at the future e+e- colliders (due to a cleaner environment etc.)
- Flavour tagging is a good tool to set detector requirements and to test detector performance.
- Improvement in tagging efficiency and accuracy with the use of advanced ML based algorithms.



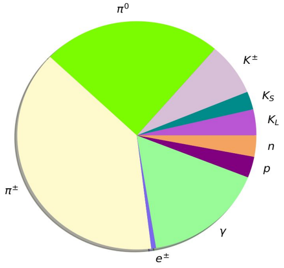
Basics of Jet Flavour Identification

bottom/charm-tagging

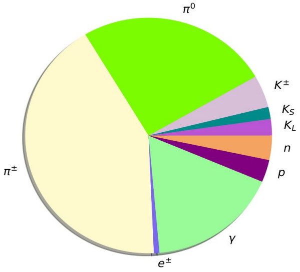


Important Variables:
- Significant lifetimes
- Displaced vertices/tracks
- Large track multiplicities
- Non-isolated e/μ

strange-tagging



Strange jets



Down jets

Important Variables:
- Different Kaon and pion multiplicities
  - K/π separation
  - V^0 reconstruction

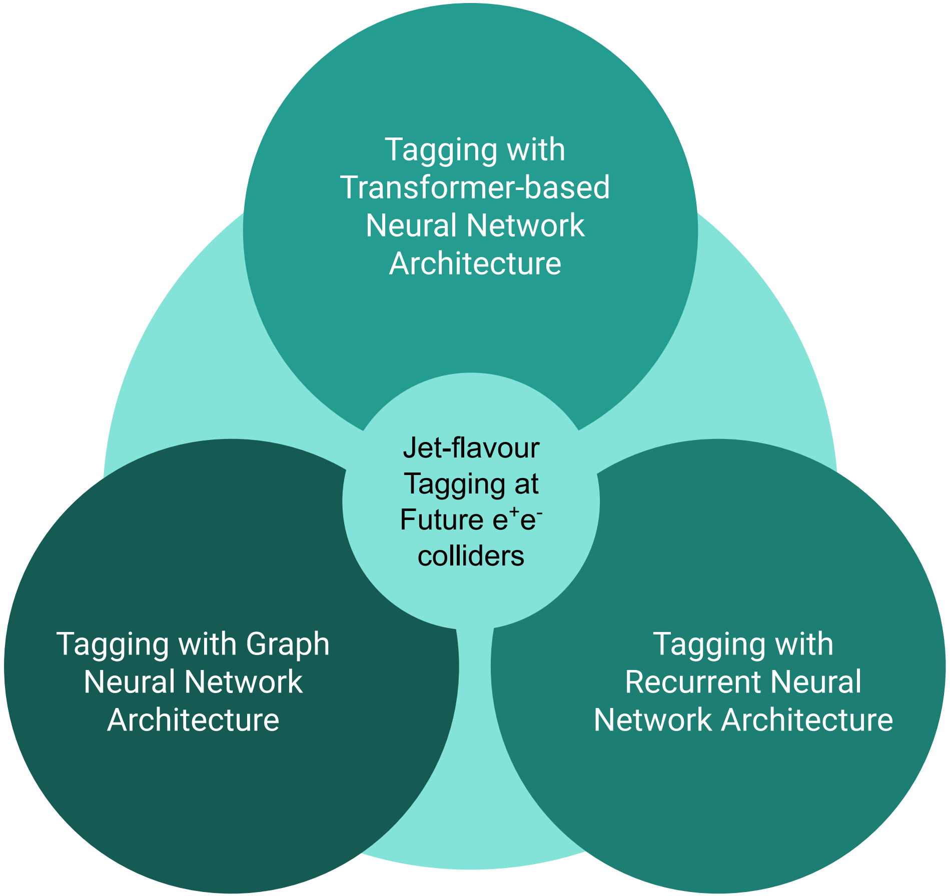
Detector Requirements:

Vertex/Tracking detectors
- Spatial resolution
- Precise Track alignment

PID detectors
- Timing capabilities
- Energy loss or cluster counting

Three Taggers

- Presented in this talk are three jet-flavour tagging algorithms that use different neural networks to tackle the problem of identifying the flavour of jets.
- All of them exploit sets of properties described before in order to differentiate between jet-flavours.
- One tagger trained on $Z \rightarrow qq$ samples, other two on $H \rightarrow qq/gg$



F. Blekman, F. Canelli, A. De Moor,
K. Gautam, A. Ilg, A. Macchiolo, E. Plörer

Tagging with Transformer-based Neural Network

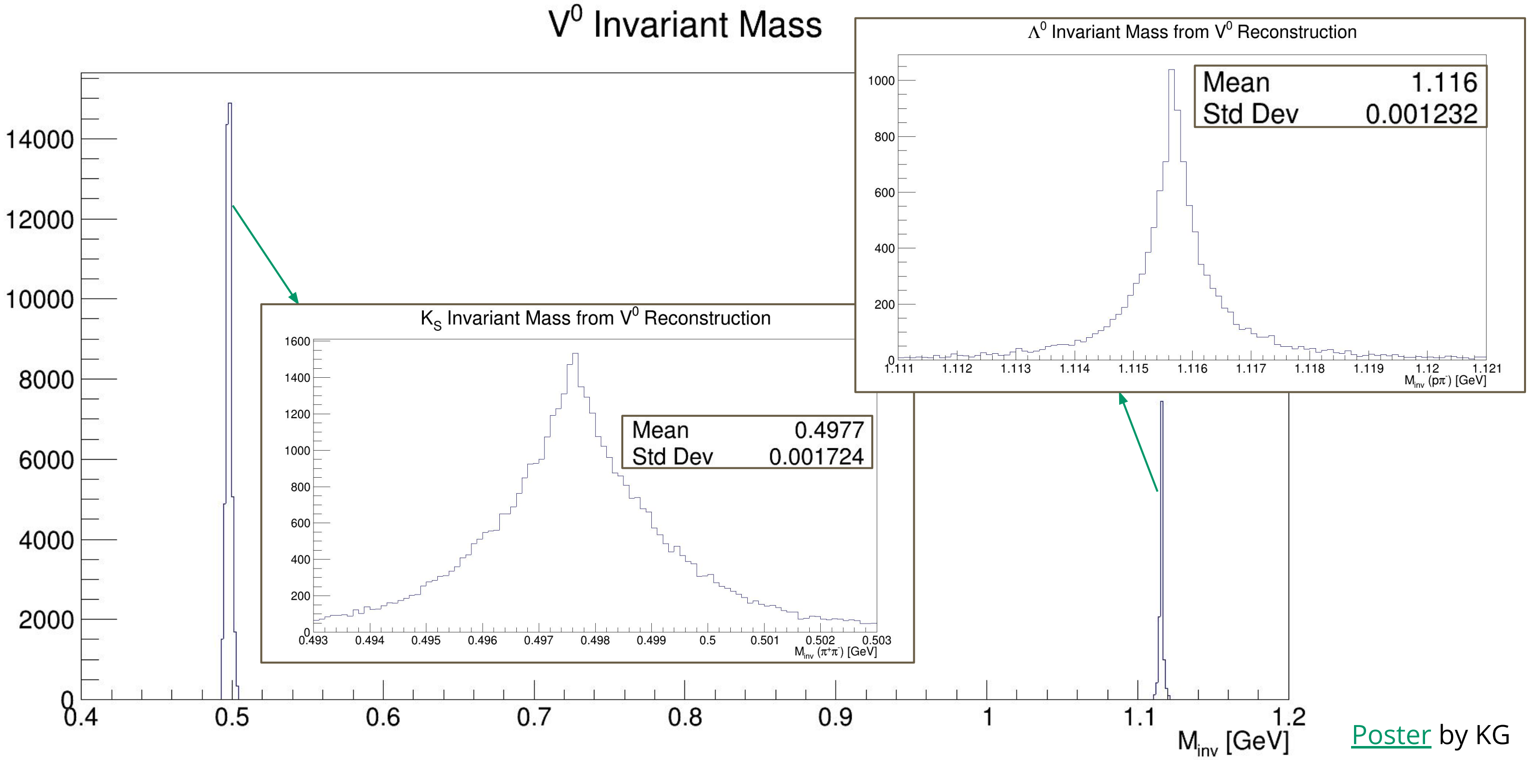
Multi-class tagger for FCCee

V^0 Reconstruction

Based on our studies presented in FCC Physics Workshop'22, it was concluded that V^0 (K_S & Λ^0) reconstruction and PID improve s-tagging performance.

100K dijet $Z \rightarrow uds$ samples [E_{CM}=91.2GeV] (Spring2021IDEA)

LCFIPlus: [1506.08371]



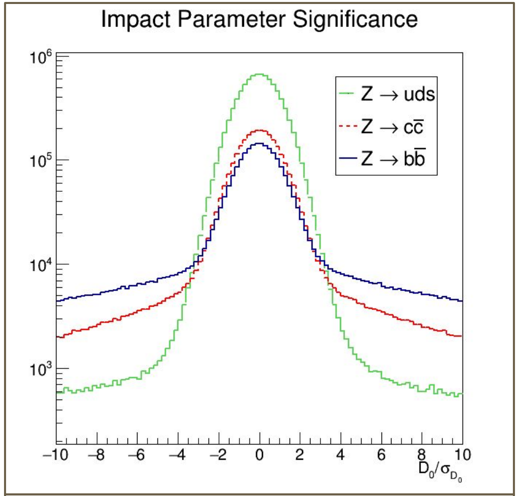
Poster by KG

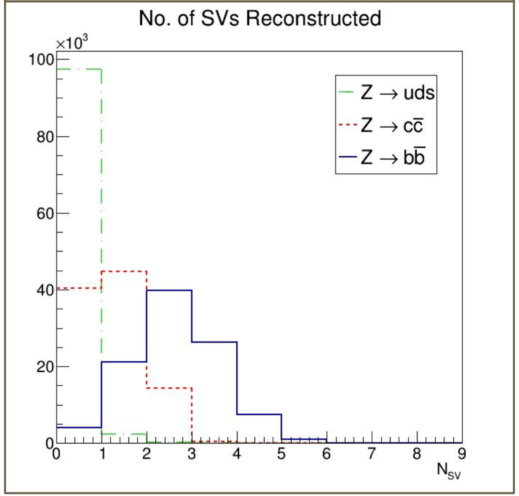
Input Features

Trained on Z → qq samples - centrally generated FCCee samples (Spring2021) with IDEA fast-simulation using FCCAnalyses

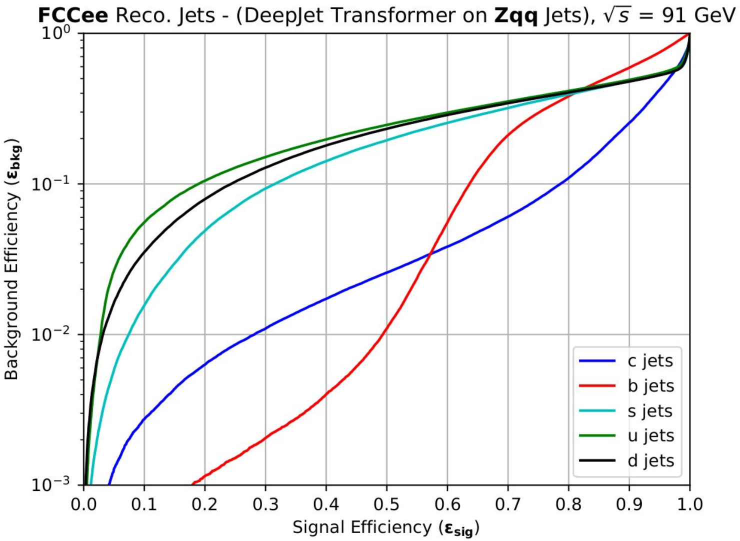
- Jet-level variables
- PF Variables
  - Charged
  - Neutral
- Secondary vertex variables
  - SVs reconstructed using the implementation of the vertexing module of LCFIPlus
- V^0 variables
  - Reconstructed

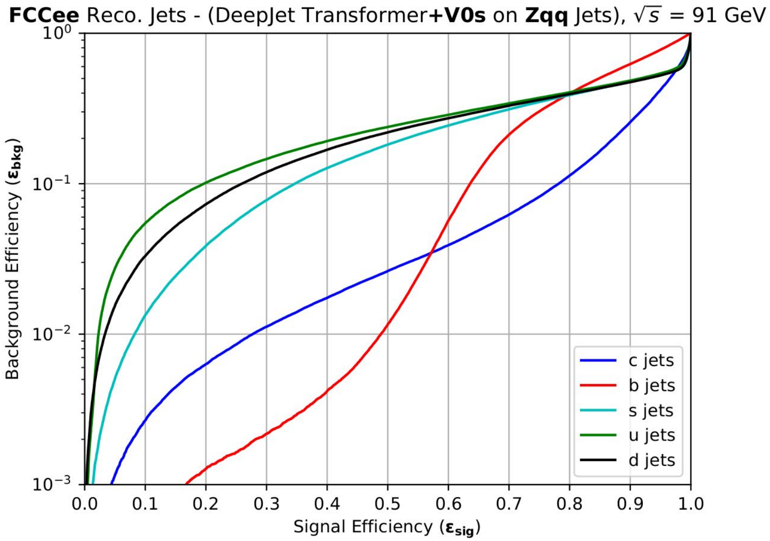
Flavour association done using particles in the decay chain: for details refer to talk at FCC Physics Performance meeting





Performance



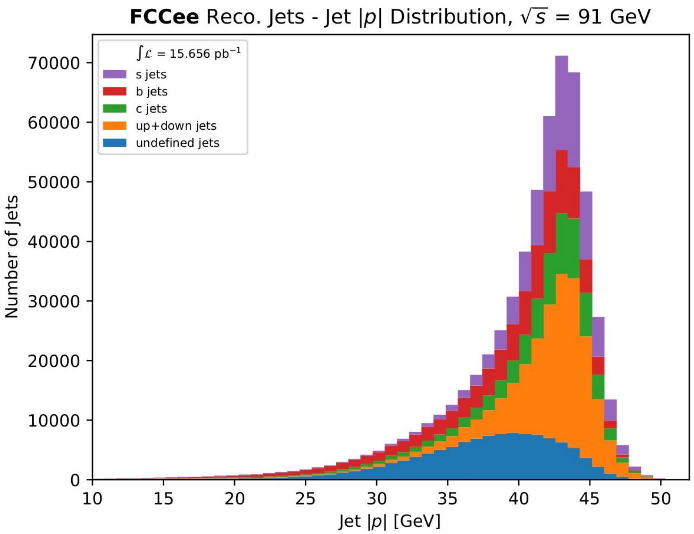


- The background for each jet flavour consists of every other flavour combined.
- Samples do not contain V^0s.

- **Few percent improvement** in s-tagging after adding **V^0s**, as was expected from our previous studies.

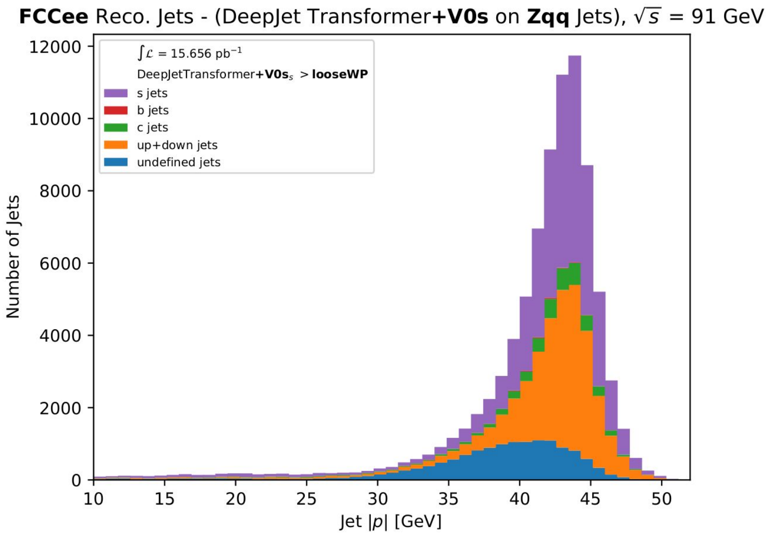
Performance

Preliminary Results



apply tagger at the s-tagging node

with 10% background efficiency



- For **s-tagging**, **ud-jets** consist the majority of the **background**.
- **PID** variables are **required** for further improvement in **ud-jet rejection**.

Poster by E.Plörer

Franco Bedeschi, Loukas Gouskos, Michele Selvaggi
[2202.03285]

Tagging with Graph Neural Network

ParticleNetIDEA
Multi-class tagger for e^+e^- colliders

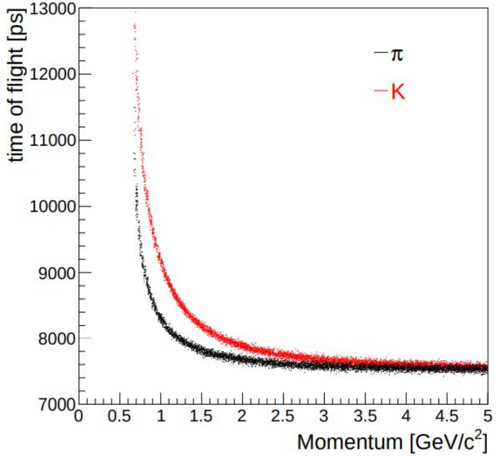
Particle Identification

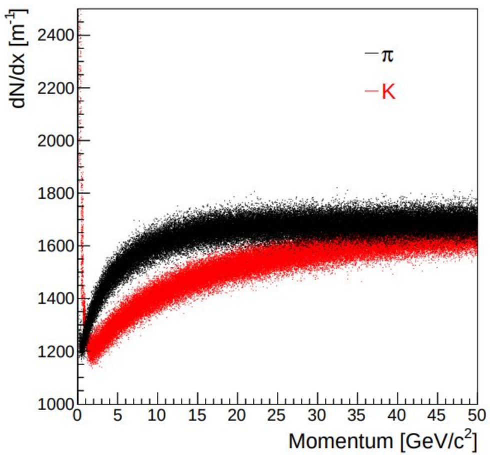
Time of Flight

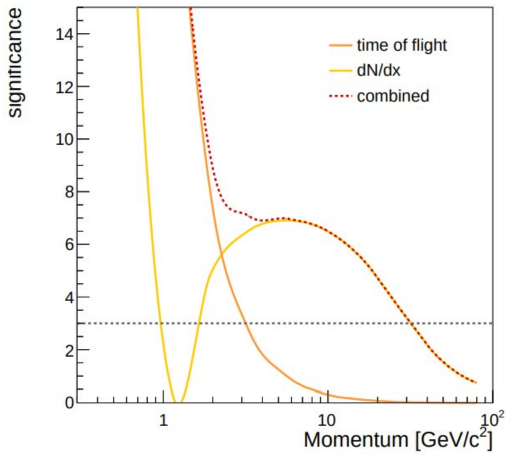
- Good K/π separation at low momenta

Cluster Counting

- Count number of primary ionization clusters along track path





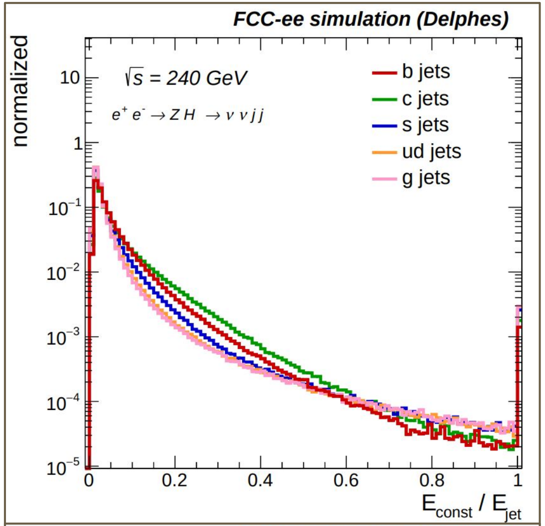


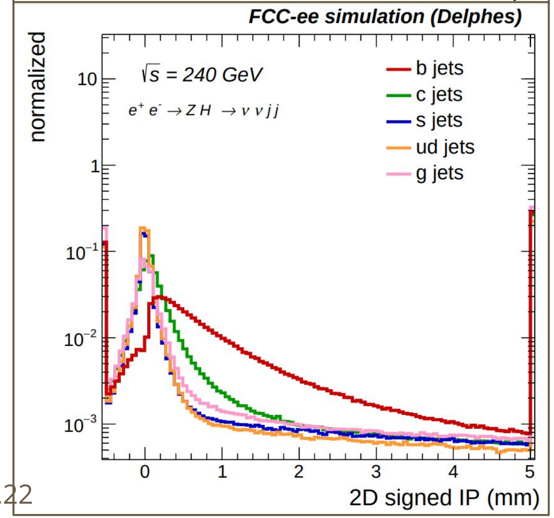
3-sigma separation for tracks with **p < 30GeV**

Input Features

Trained on (Z → inv)(H → qq/gg) samples with IDEA fast-simulation, where jets are represented as unordered set of particles

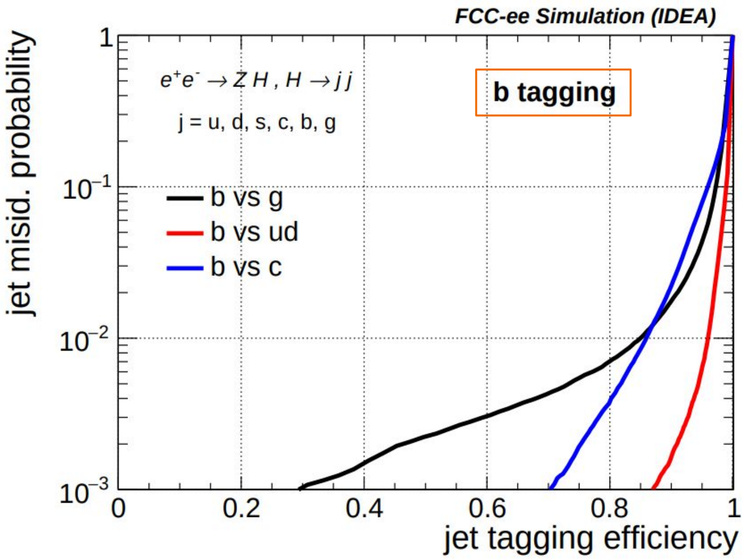
- Kinematic Variables
  - Features derived from the momentum of each jet-constituent
- Displacement Variables
  - Observables related to the longitudinal and transverse displacement of the jet-constituents
  - More **relevant** to identify **b & c jets**
- Identification Variables
  - Nature of each particle using the PF reconstruction and PID using ToF & dN/dx
  - **PID** important to identify **s jets**



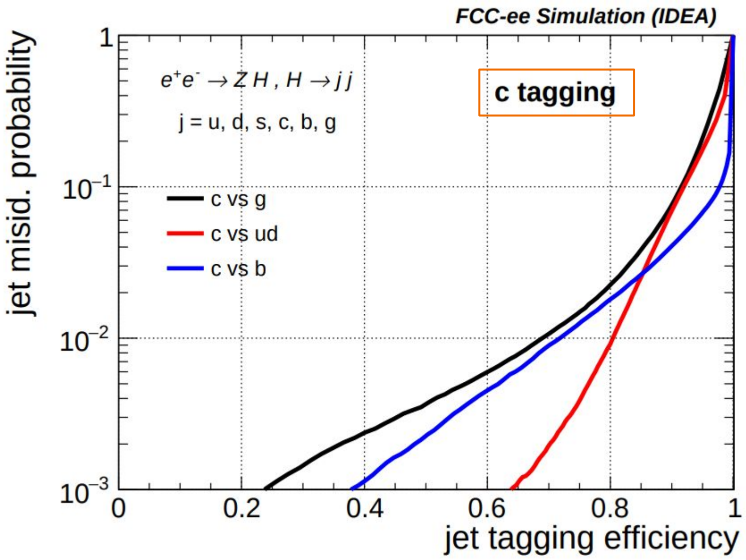


Performance

3 pixel layers
PID: dN/dx + ToF (30ps)



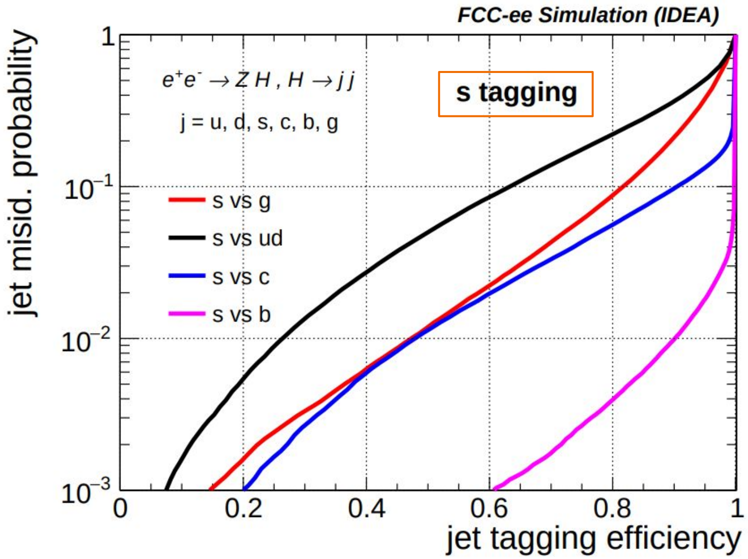
For **high-purity** region, **gluon jet rejection** is **worse** than c-jet rejection due a significant probability of **gluon splitting**



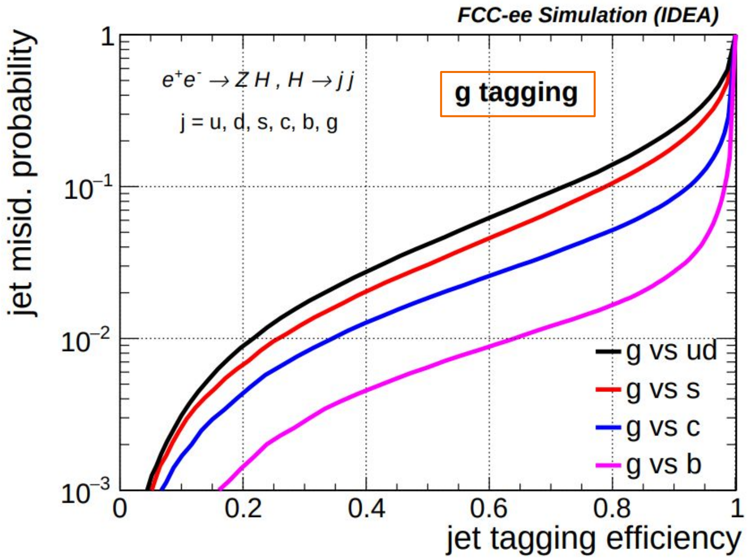
For **high-efficiency** region, b-jet discrimination is the **most effective** due to **difference in lifetimes** of B and D mesons.

Performance

3 pixel layers
PID: dN/dx + ToF (30ps)

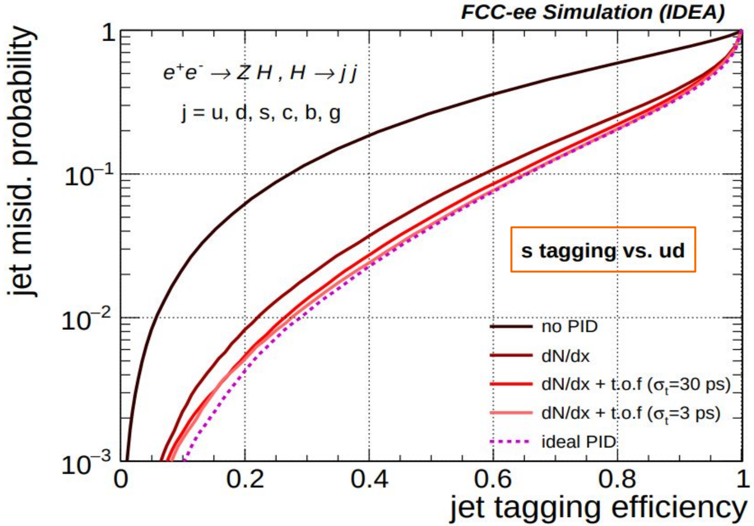


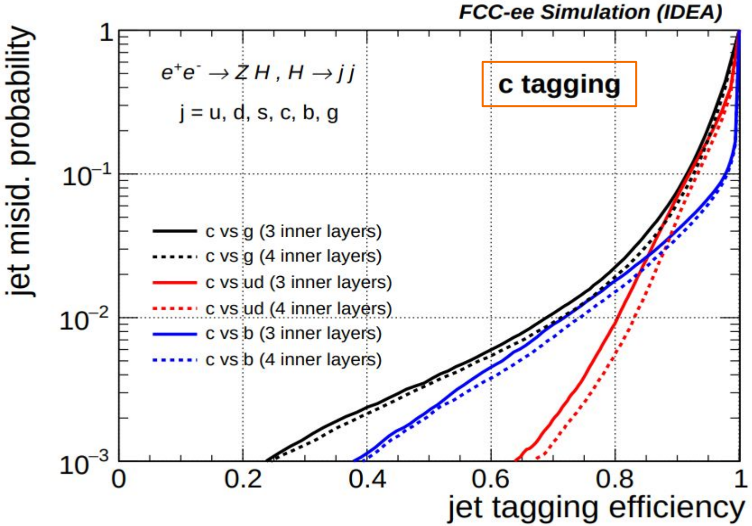
Discrimination against **ud-jets** is the most **challenging** since the algorithm mainly relies only on **PID-related variables**.



Rejection of **ud-jets** is the most **challenging** due to **similar particle displacements** and nature.

Performance with Different Detector Design





Impact of PID on s-tagging performance:

- **dN/dx** brings **most** of the **gain**
- Additional gain with ToF
- Performance **with dN/dx + ToF (30 ps)** is very **close to perfect PID**

Impact of inner tracking geometry on c-tagging performance:

- **2x** improved background rejection with an **additional pixel layer**
- marginal/no improvement in b-tagging

Matthew J. Basso, Valentina M. M. Cairo et al.
Snowmass : [2202.03285]

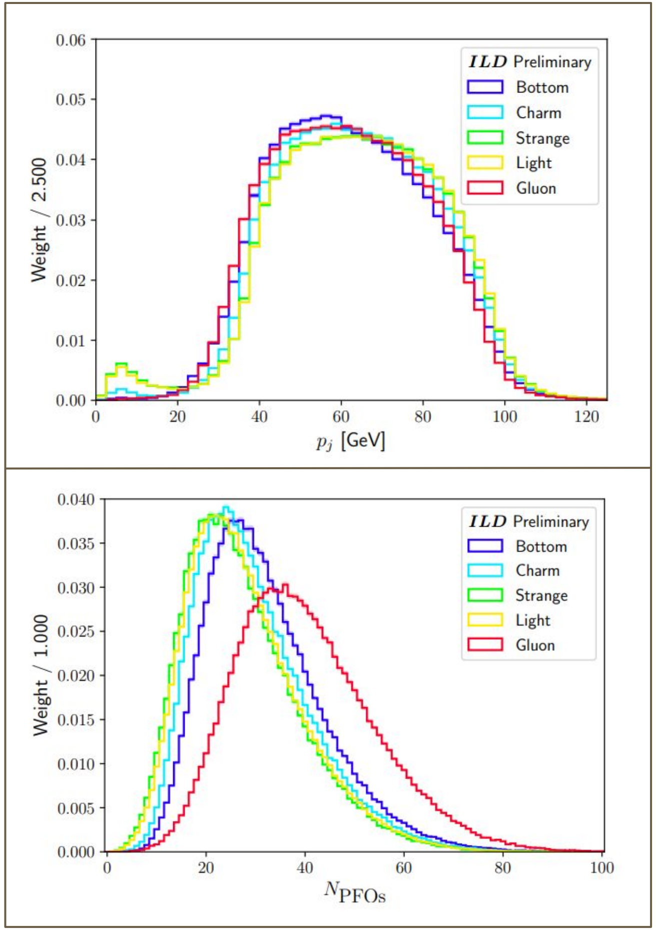
Tagging with Recurrent Neural Network

Multi-class tagger for ILC

Input Features

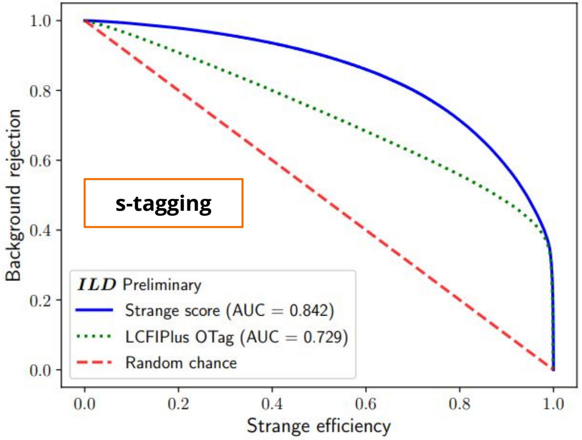
Trained on (Z → inv)(H → qq/gg) samples with ILD full-simulation

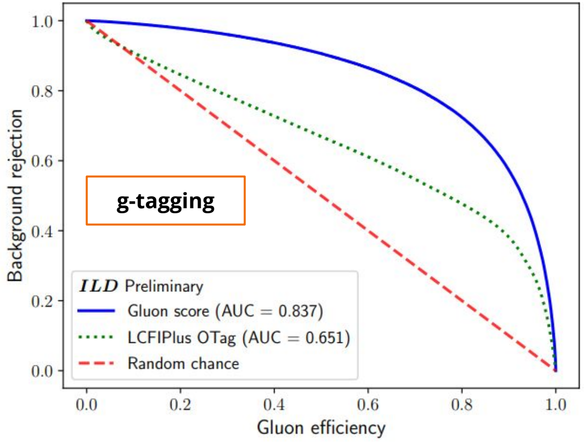
- Jet-level Variables
  - Kinematics
  - LCFIPlus tagger results
  - PFO multiplicities
- Variables for 10 leading particles in jets
  - Kinematics
  - Charge
  - PID truth likelihoods (representing the best-case scenario)

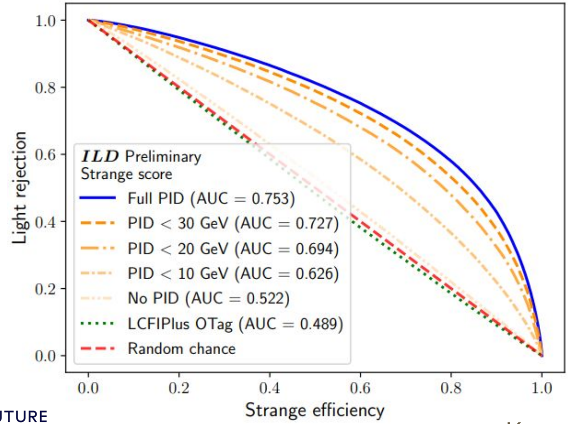


Performance

Significant improvement in strange and gluon tagging over ILC baseline tagger LCFIPlus







- No PID to **PID < 10 GeV** at fixed mistag rate: efficiency **increases** by almost **20%**
- No PID to **PID < 30 GeV** at fixed mistag rate: efficiency **doubles**

Proposed a **compact RICH detector** for **PID**

Summary

- Efficient jet-flavour tagging algorithms are essential for future e^+e^- colliders.
- Flavour tagging algorithms from LHC experiments are inspiring tagging efforts being conducted for future colliders like FCCee.
- Improved performance with the use of advanced ML models and additional properties:
  - V^0 reconstruction (K_S & Λ^0)
  - PID capabilities (cluster counting, ToF, compact RICH, etc)

Outlook

- Vertexing and PID improve performance of individual taggers, should work on common ntuples with all available variables (?)
- Testing all taggers at the same baseline process

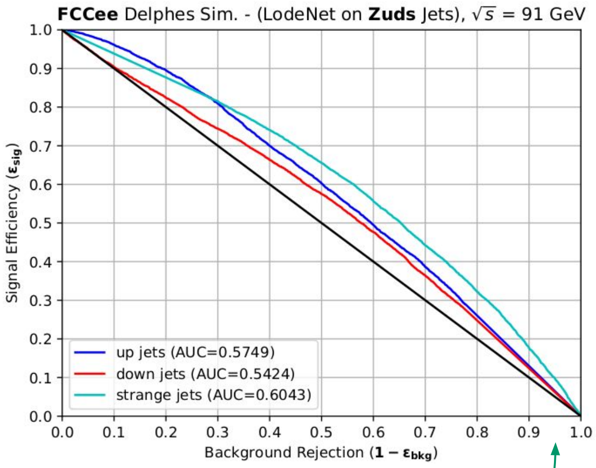
So long,

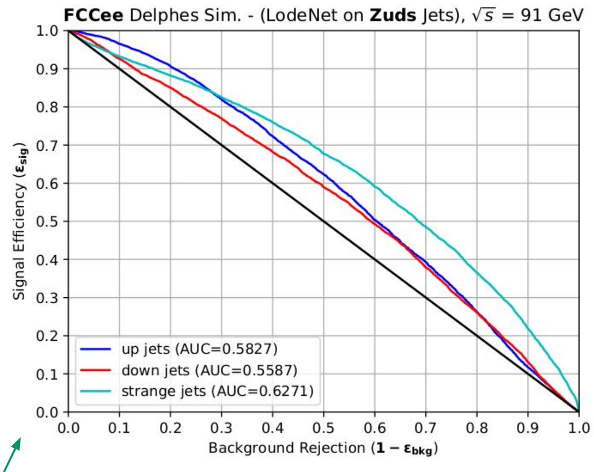
and **thanks** for all the fish

Back-up

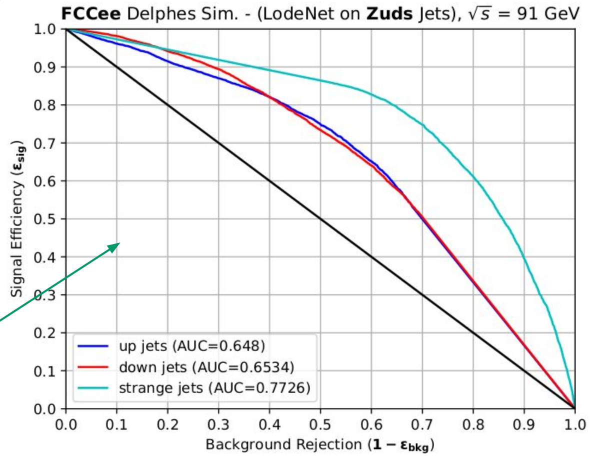
Performance(CNN)

Three working points defined at fake rates of **10%**, **5%**, and **1%**, respectively



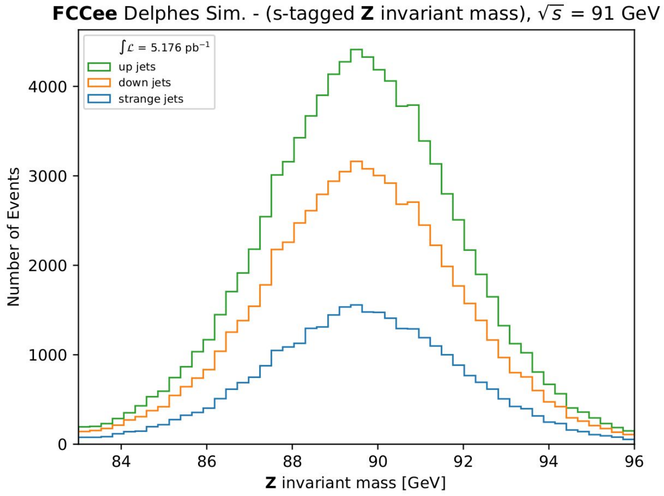


Signal Efficiency	10% fake rate	5% fake rate	1% fake rate
Generator	47.2%	27.7%	7.5%
PF only	17.7%	9.7%	2.0%
PF + K_S	21.9%	12.9%	4.4%
PF + K_S + $K^\pm$	39.5%	24.8%	7.0%



Z Peak Reconstruction(CNN)

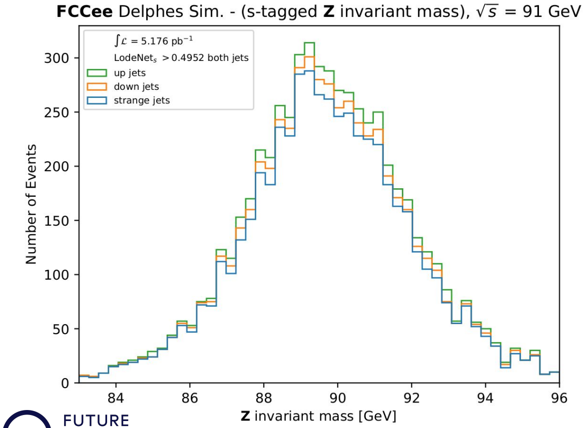
- Z peak before tagging vs after tagging both jets
- Ignored background and b/c quark decays (for now)

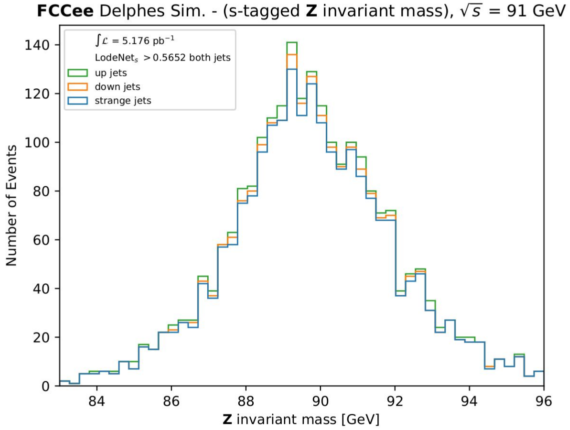


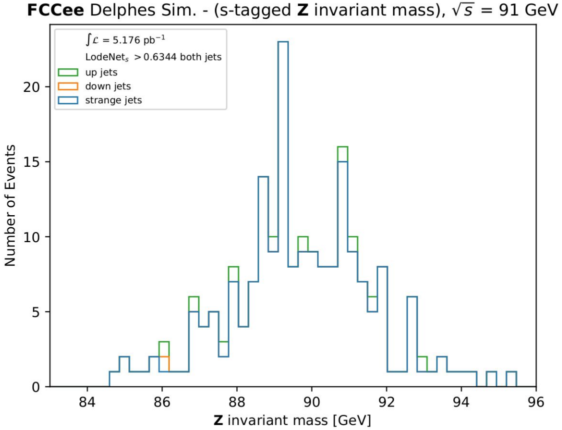
10%

5%

1%







Transformer-based NN

Network architecture

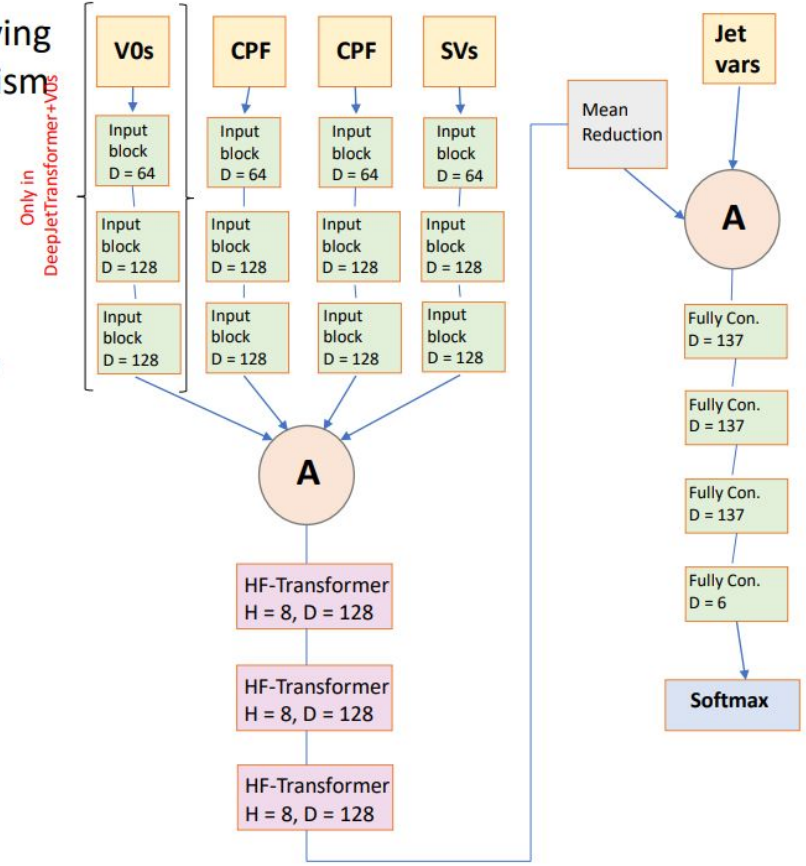
DeepJetTransformer(+V0s)

Neural Network (NN) relying on "attention[1]" mechanism dubbed HF-Transformer

Trained for n epochs and optimized with ranger optimizer[2]

Loss computed with categorical cross-entropy

$$\text{Loss} = -\sum_{i=0}^{n} truth_i \times \ln(pred_i)$$



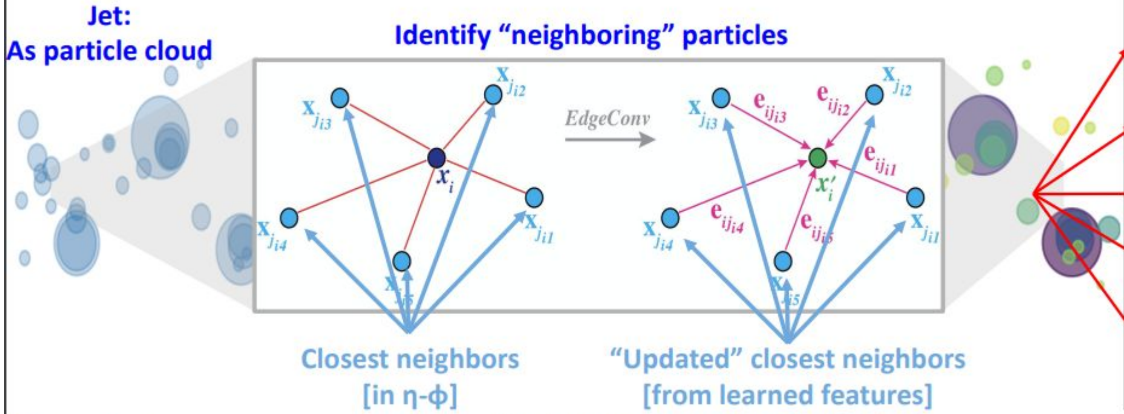
Poster by E. Plörer

ParticleNet

Pushing the limits in jet tagging

- **ParticleNet**: Novel algorithm w/ improved **jet representation** & **network arch.**
  - Jet represented as a "particle cloud"
  - Architecture: Graph Neural Networks
  - **Inputs:** PFcands & SV, **Output:** multi-class
- Follow a hierarchical learning approach
  - **First:** Learn "local" structures; **Then:** move to more "global" features
  - Treat the particle cloud as a graph
    - Particles are the vertices of the graph
      Relationships between the particles are the **edges** of the graph

PRD 101 (2020) 5, 056019
CMS-DP-2020-002



Category	Label
Top	bcq bqq bq cq
Higgs	bb cc VV*→qqqq
Z	bb cc qq
W	cq qq
QCD	g→bb g→cc b c others

RNN Architecture (ILD)

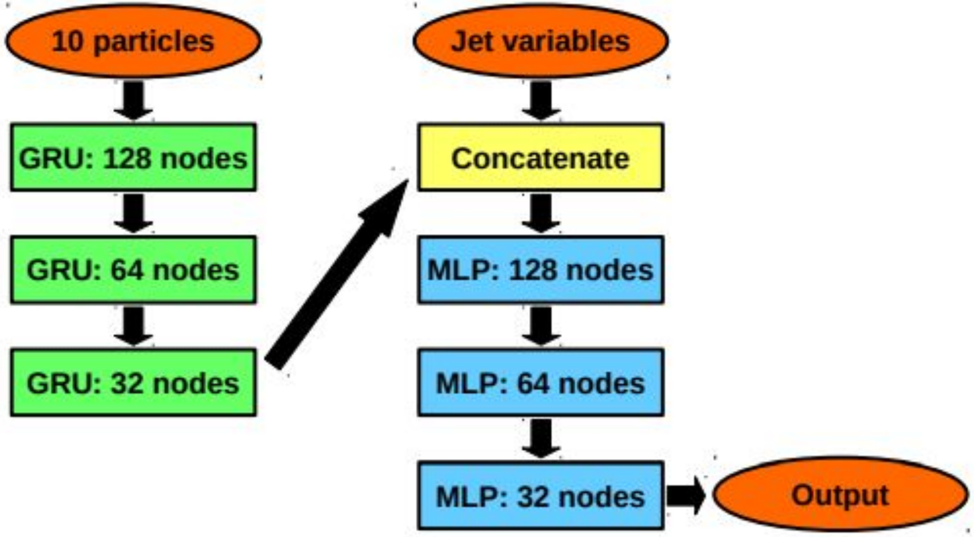


Figure 3: A cartoon of the network architecture used for the jet flavour tagger ANN. The arrows denote the flow of vectors through the network.

Performance (ILD)