# BEYOND KINEMATICS FOR OPTIMAL HADRONIC TOP QUARK POLARIMETRY


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BASED ON ARXIV:2405.XXXXX IN COLLABORATION WITH

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MITCHELL CONFERENCE 23RD MAY 2024

# TWO TALKS FROM LAST YEAR

## Entanglement and Bell's Inequalities with boosted top quark pairs

May 17, 2023, 3:20 PM
25m
Hawking Auditorium (Texas A&M University)

Collider

### Speaker

Dorival Gonçalves (Oklahoma State University)

### Description

The Large Hadron Collider provides a unique environment to study quantum entanglement and violation of Bell's inequalities at the highest energy available today. In this talk, we will discuss the possible observation of these quantum correlations with top quark pair production, which represents a system of two-qubits. Our study focus on the semi-leptonic top pair channel. They indicate that the observation of entanglement is possible with the current dataset and the violation of Bell's inequalities can be probed at 3-$\sigma$ level at the HL-LHC.

- Discusses measure entanglement in top-pair production with semi-leptonic decay.
- Uses a combination of soft jet directions to probe the hadronic top quark polarimetry.

# TWO TALKS FROM LAST YEAR

## Understanding Jet Charge

May 17, 2023, 4:40 PM
25m
Hawking Auditorium (Texas A&M University)

Collider

### Speaker

Andrew Larkoski (UCLA)

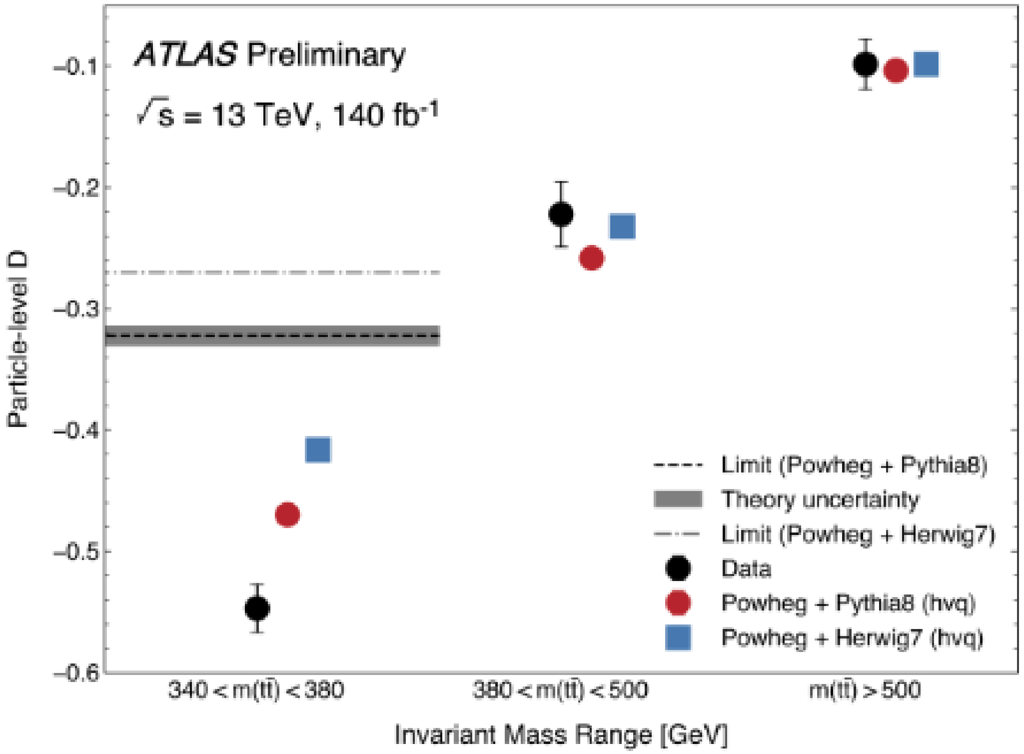
### Description

The jet charge is an old observable that has proven uniquely useful for discrimination of jets initiated by different flavors of light quarks, for example. In this talk, I propose an approach to understanding the jet charge by establishing simple, robust assumptions that hold to good approximation non-perturbatively, such as isospin conservation and large particle multiplicity in the jets, forgoing any attempt at a perturbative analysis. From these assumptions, the jet charge distribution with fixed particle multiplicity takes the form of a Gaussian by the central limit theorem and whose mean and variance are related to fractional-power moments of single particle energy distributions. These results make several concrete predictions for the scaling of the jet charge with the multiplicity, explaining many of the results already in the literature, and new results we validate in Monte Carlo simulation.

- An analytical approach to understand the jet charge variable based on simple assumptions.
- Demonstrates the potential of using jet charge to differentiate quark jet flavors.

# ENTANGLEMENT IN DILEPTON CHANNEL

- Top quark polarization allows us to measure spin correlations in top-pair production
- Recently, spin correlations in top-pair production have been recently used to measure entanglement at the LHC.
- Measure violation of Bell's inequality would require the boosted regime and more statistics.




ATLAS 2023

See also CMS 2024

# SPIN ANALYZING POWER FROM ANGULAR DISTRIBUTION

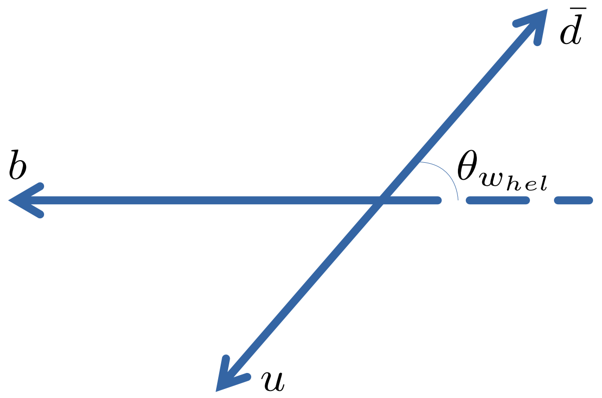
- The spin correlation between the top decay products and top propagation direction in the top rest frame is as follows:

$$\frac{1}{\Gamma}\frac{d\Gamma}{d\cos\xi_k} = \frac{1}{2}\left(1+\beta_k p\cos\xi_k\right) \qquad \beta_k = \begin{cases} +1, & \text{for } l^+ \text{ or } \bar{d}\text{-quark.} \\ -0.31, & \text{for } \bar{\nu} \text{ or } u\text{-quark.} \\ -0.41, & \text{for } b\text{-quark.} \end{cases}$$

Brandenburg, Si, Uwer 2002

- Down-type quark identification is challenging.
- The original optimal direction is constructed as follows:

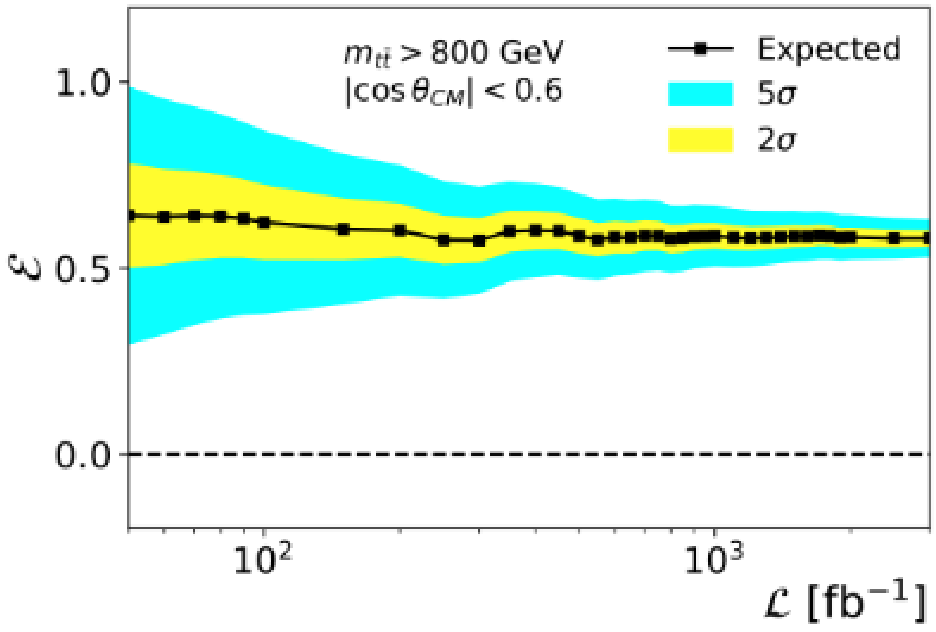
$$q_{\text{opt}} \equiv p(d \to q_{\text{soft}})\hat{q}_{\text{soft}} + p(d \to q_{\text{hard}})\hat{q}_{\text{hard}}$$

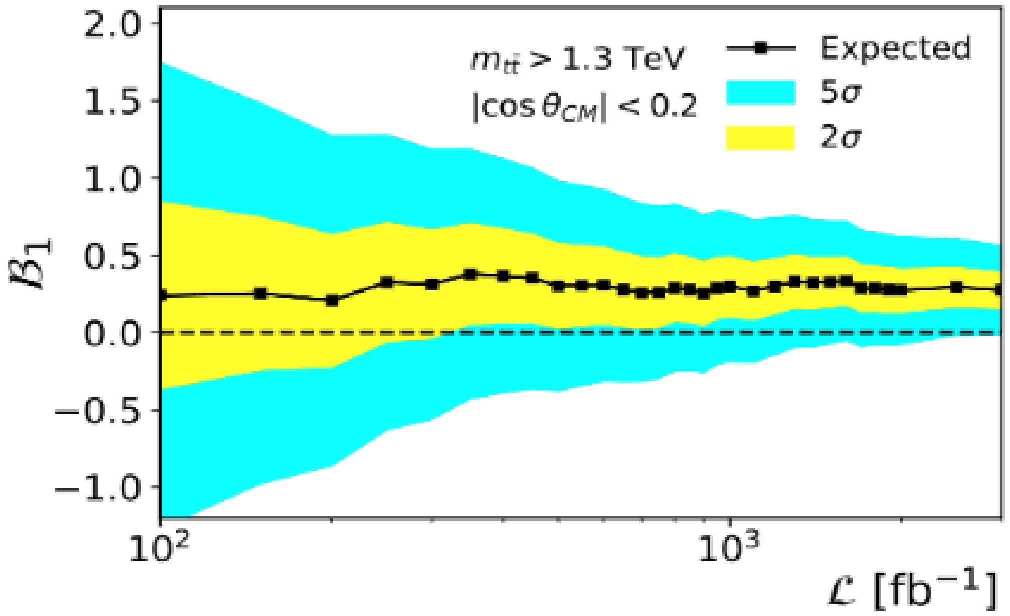



Tweedie 2014

# APPLICATION

- Use the optimal direction to address entanglement and violation of Bell's inequality in semi-leptonic decay



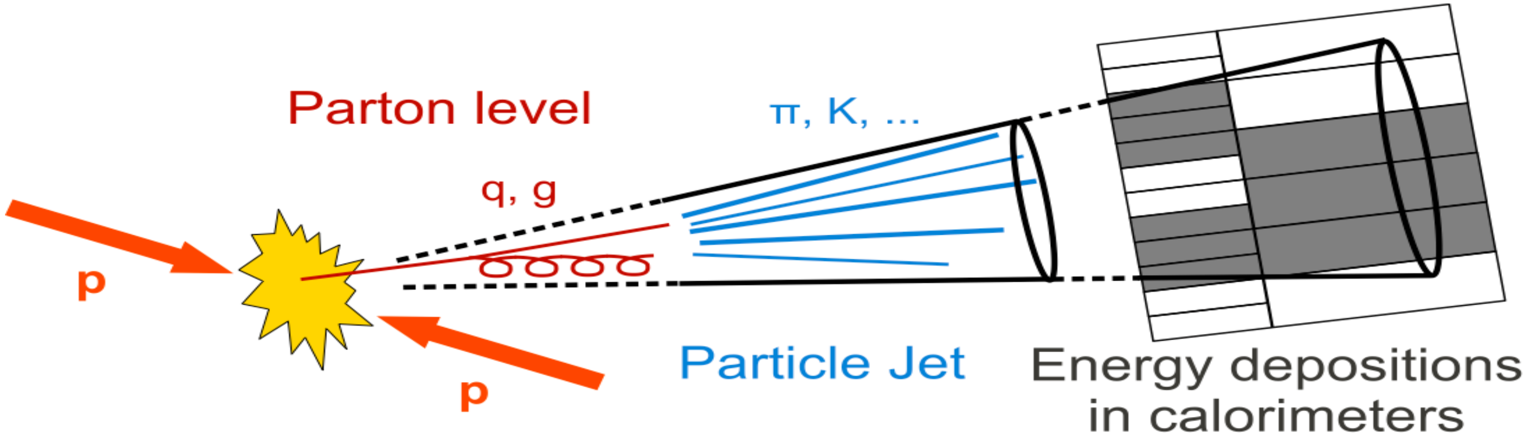




Dong, Gonçalves, Kong, Navarro 2023

See also Han, Low, Wu 2023

# BEYOND KINEMATIC INFORMATION

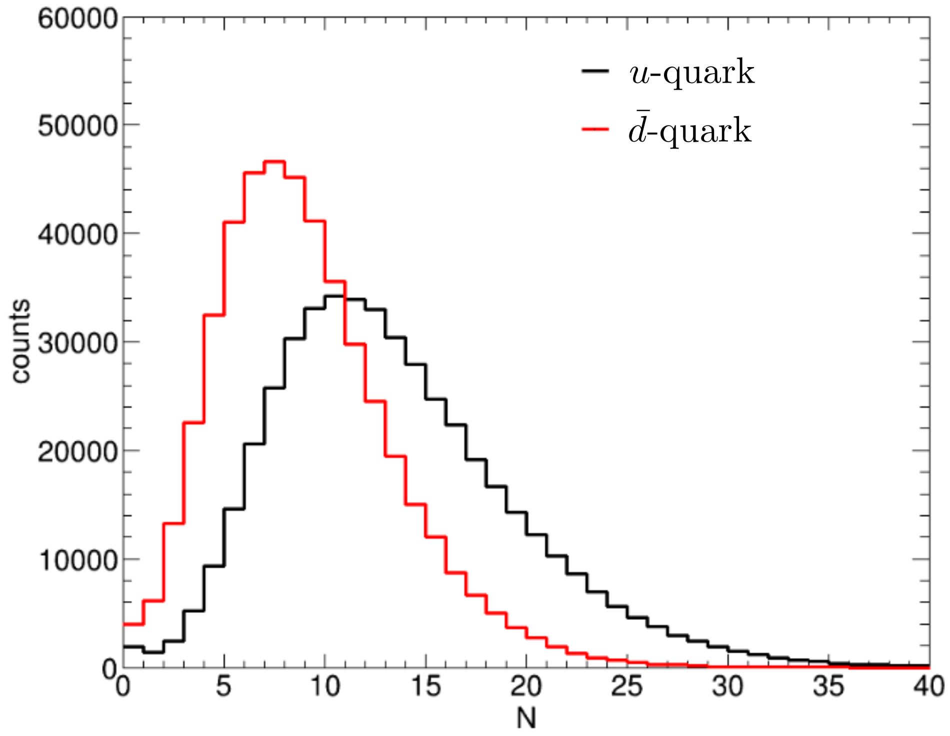
- The optimal hadronic direction uses all the kinematic information (momentum) of the top decay products. At particle-level, jets contain more information than just momentum.




- Other observables such as jet charge and particle multiplicity can be measured.

# PARTICLE MULTIPLICITY

- Particle (hadron) multiplicity can also give information about the up and down quark jets.
- Down-quark jet multiplicity distribution peaks at lower multiplicity than up jet.



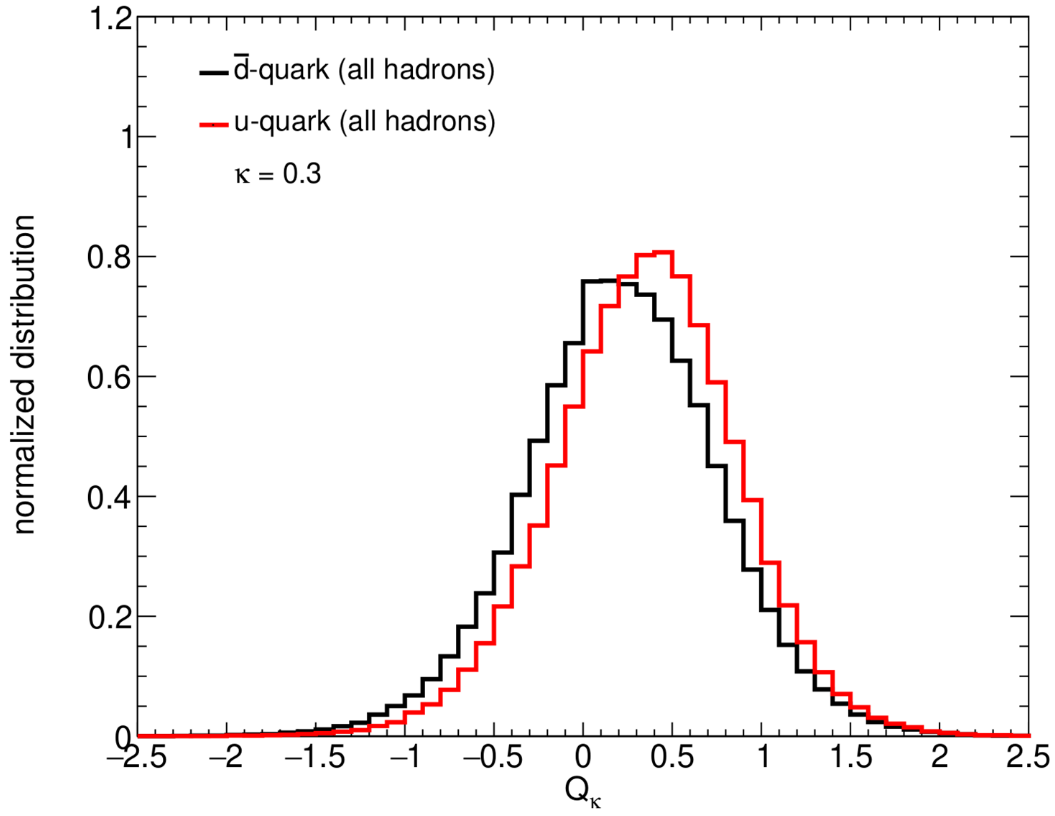
# JET CHARGE

- A definition of jet charge is

$$Q_\kappa = \sum_i Q_i \, z_i^\kappa = \sum_i Q_i \left(\frac{E_i}{E}\right)^\kappa$$

Field, Feynman 1978

- The jet charge distributions for up and down-type quarks are approximately Gaussian with means centered around the quark charges.



# JET CHARGE

- Under a few assumptions, the probability distribution of the jet charge conditioned on the multiplicity may be approximated as Gaussian with mean and variance

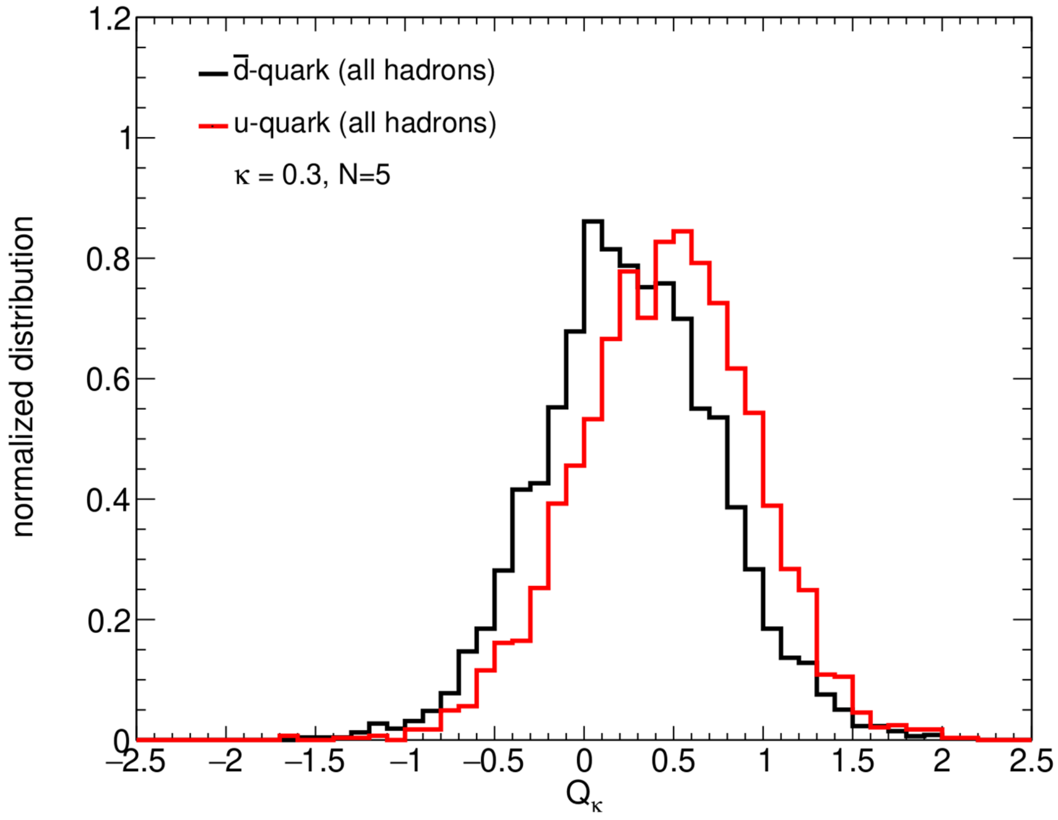
$$\langle Q_\kappa \rangle_u = \frac{2}{3}\langle z^\kappa \rangle\,, \quad \langle Q_\kappa \rangle_{\bar{d}} = \frac{1}{3}\langle z^\kappa \rangle\,, \quad \sigma_\kappa^2 = \frac{2}{3} N \langle z^{2\kappa} \rangle$$

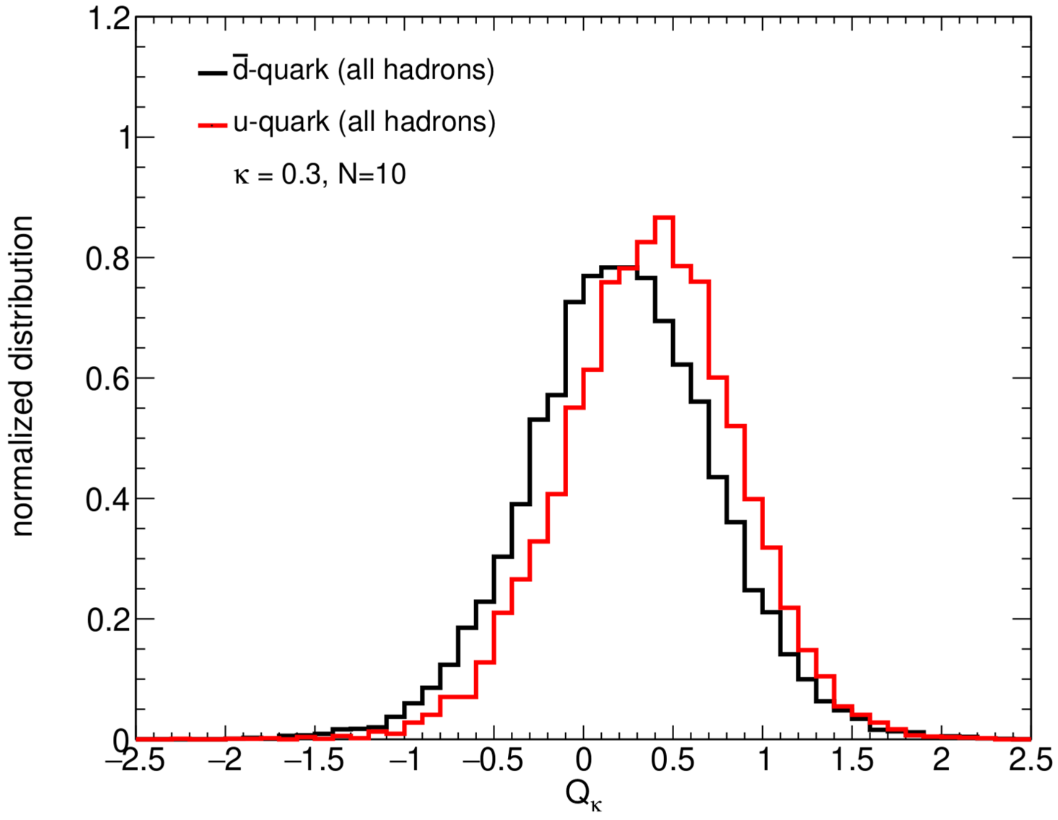
- One can define the discrimination power

Kang, Larkoski, Yang 2023

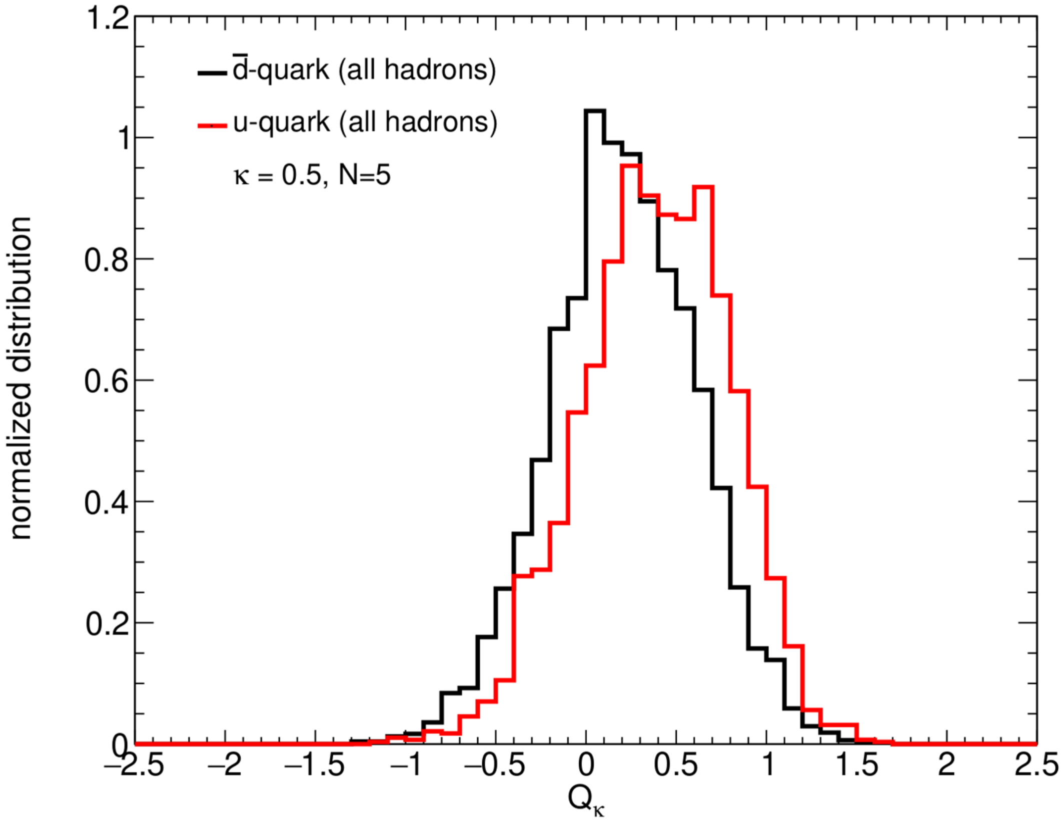
$$\eta = \frac{(\langle Q_\kappa \rangle_u - \langle Q_\kappa \rangle_{\bar{d}})^2}{\sigma_\kappa^2} \sim \frac{1}{N}\left(1 - \kappa^2 \sigma_z^2 N^2 ... + \right)$$

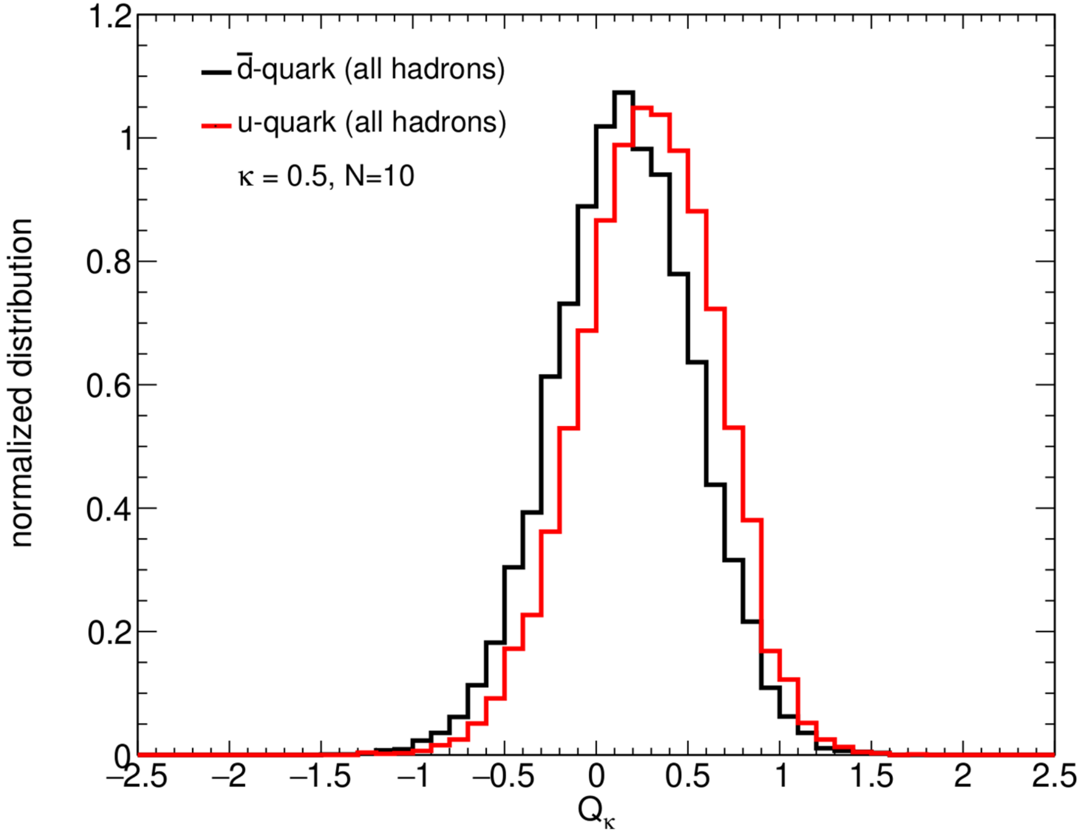
# JET CHARGE AND MULTIPLICITY



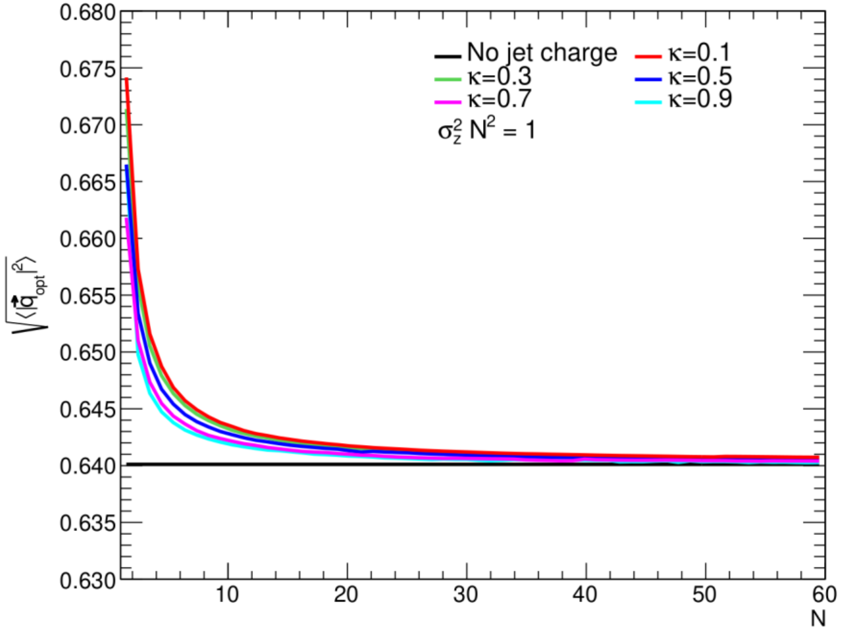
# JET CHARGE AND MULTIPLICITY

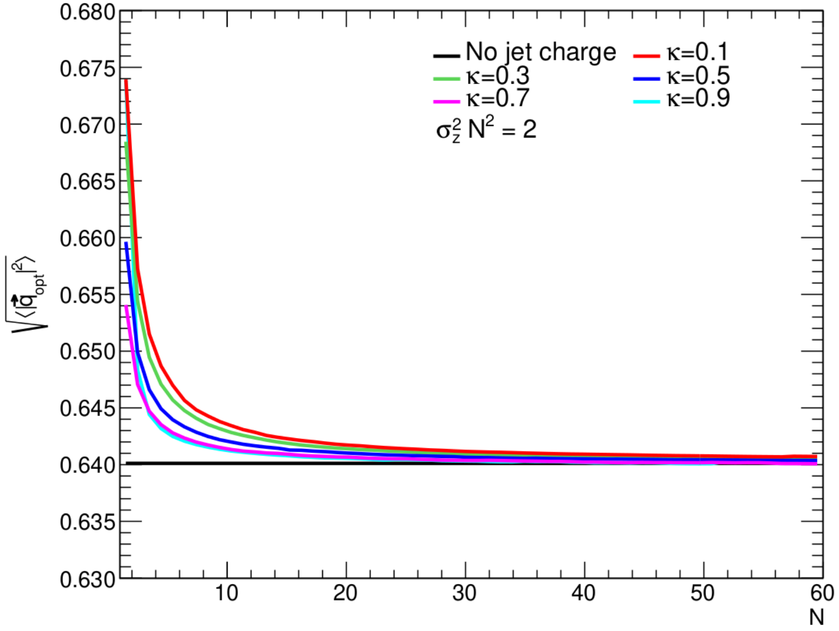


# JET CHARGE AND SPIN ANALYZING POWER

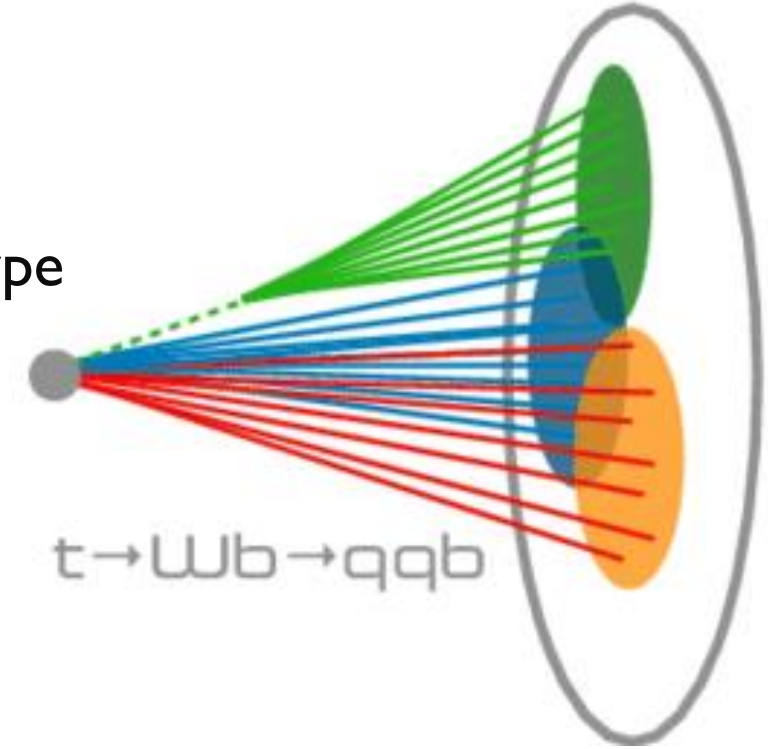
$$p(d \to q_{\rm hard}|c_W, Q_{\kappa,h}, N_h, Q_{\kappa,s}, N_s) = \frac{p(Q_{\kappa,h}|d \to q_{\rm hard}, N_h)}{p(Q_{\kappa,h}|d \to q_{\rm hard}, N_h)p(d \to q_{\rm hard}|c_W) + p(Q_{\kappa,h}|\bar{u} \to q_{\rm hard}, N_h)p(\bar{u} \to q_{\rm hard}|c_W)}$$
$$\times \frac{p(Q_{\kappa,s}|\bar{u} \to q_{\rm soft}, N_s)}{p(Q_{\kappa,s}|d \to q_{\rm soft}, N_s)p(d \to q_{\rm soft}|c_W) + p(Q_{\kappa,s}|\bar{u} \to q_{\rm soft}, N_s)p(\bar{u} \to q_{\rm soft}|c_W)}$$
$$\times\, p(d \to q_{\rm hard}|c_W)\,.$$



# MACHINE LEARNING STRATEGY

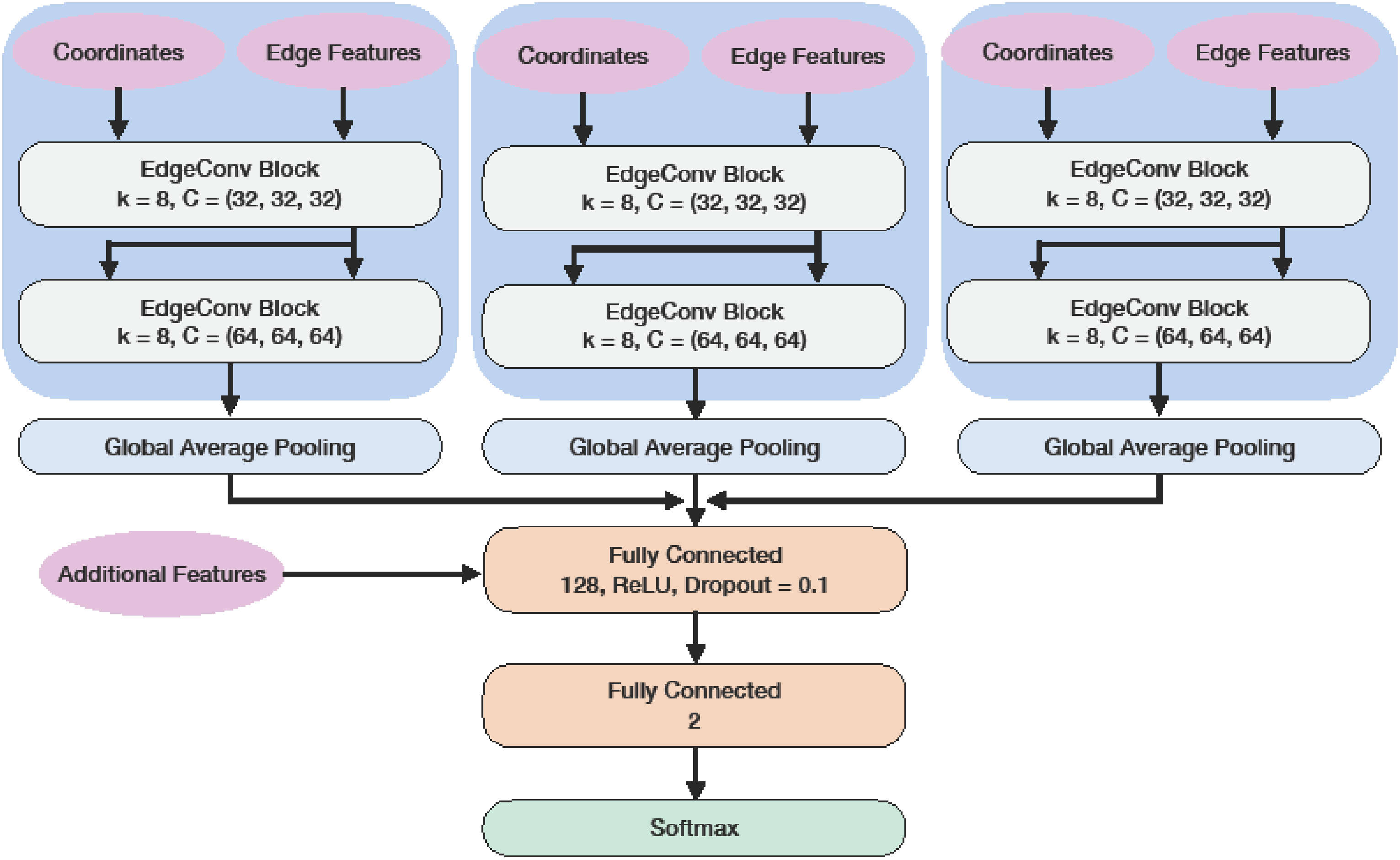
- Light jet flavor identification within top jet cone
- Input the jet constituent momenta and charge information for each of the subjets.
- Train the neural network to identify the down-type jet.
- Interpret the neural network score as the probability of each jet being down-type.



# DATA PREPARATION

- We generate 14TeV $pp \to t\bar{t} \to \ell^- \nu 2b2j$ events using MG5, with no cuts except for $p_{Tt} > 200$ GeV.
- Three sets of samples where the top quark is unpolarized, left hand polarized and right hand polarized in the $t\bar{t}$ rest frame.
- Parton shower and hadronization are done with PYTHIA8 without MPI.
- Identify the top jet using CA algorithm with $R = 1.5$, and $p_T > 250$ GeV. And decluster following the algorithm to find the subjets. Tweedie 2014
- We match the hadron level jets with true parton level momenta, by using the smallest $\Delta R$ between the two.

# NETWORK ARCHITECTURE




- We modified based on the ParticleNet architecture by utilizing three separate graph convolutions instead of one, corresponding to each of the jet inputs.

Qu, Gouskos 2019

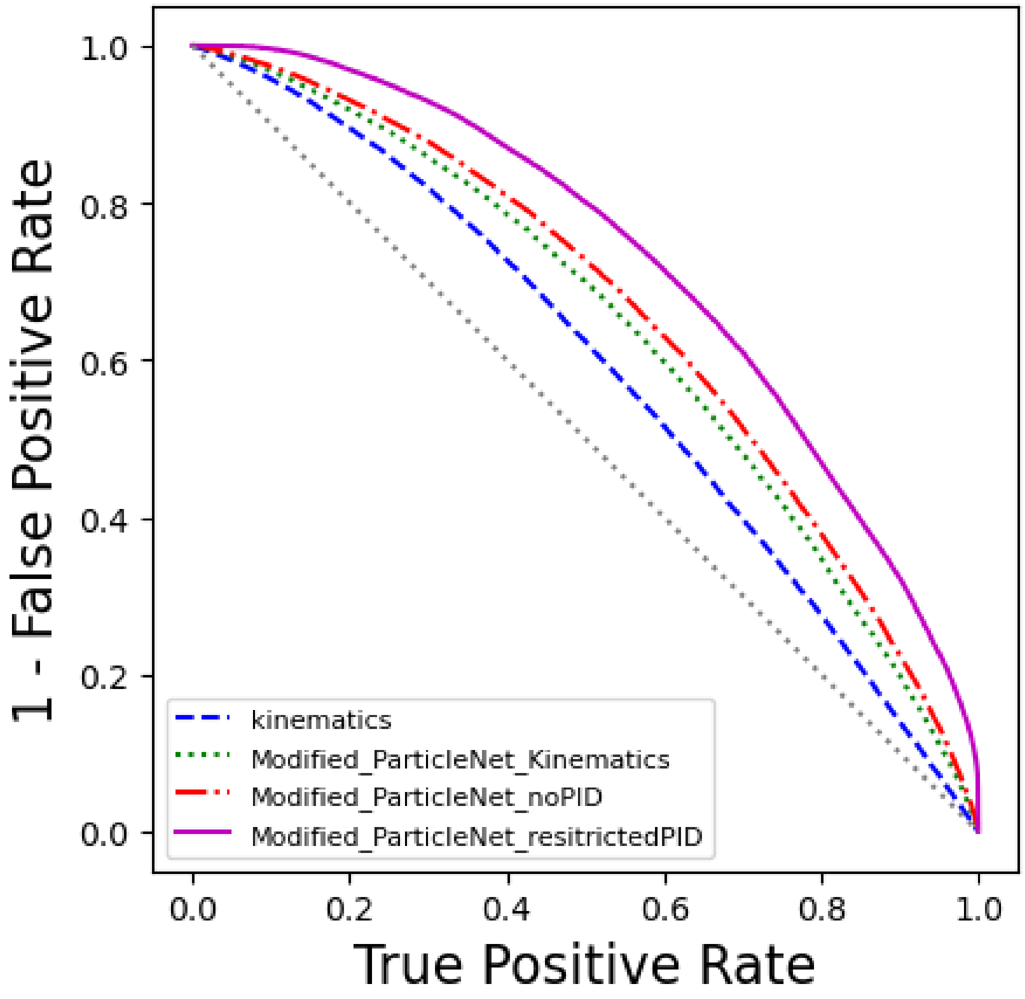
- The three graphs are then pooled and concatenated.
- Additional features for the overall top jet can also be fed into the linear layers.

# INPUT FEATURES

| Variable | Definition |
|---|---|
| $\Delta\eta_t$ | difference in pseudorapidity between the particle and the top jet axis |
| $\Delta\phi_t$ | difference in azimuthal angle between the particle and the top jet axis |
| $\Delta\eta_j$ | difference in pseudorapidity between the particle and the subjet axis |
| $\Delta\phi_j$ | difference in azimuthal angle between the particle and the subjet axis |
| $\log\ p_T$ | logarithm of the particle's $p_T$ |
| $\log\ E$ | logarithm of the particle's Energy |
| $q$ | electric charge of the particle |
| isElectron | if the particle is an electron |
| isMuon | if the particle is a muon |
| isPhoton | if the particle is a photon |
| isChargedHadron | if the particle is a charged hadron |
| isNeutralHadron | if the particle is a neutral hadron |

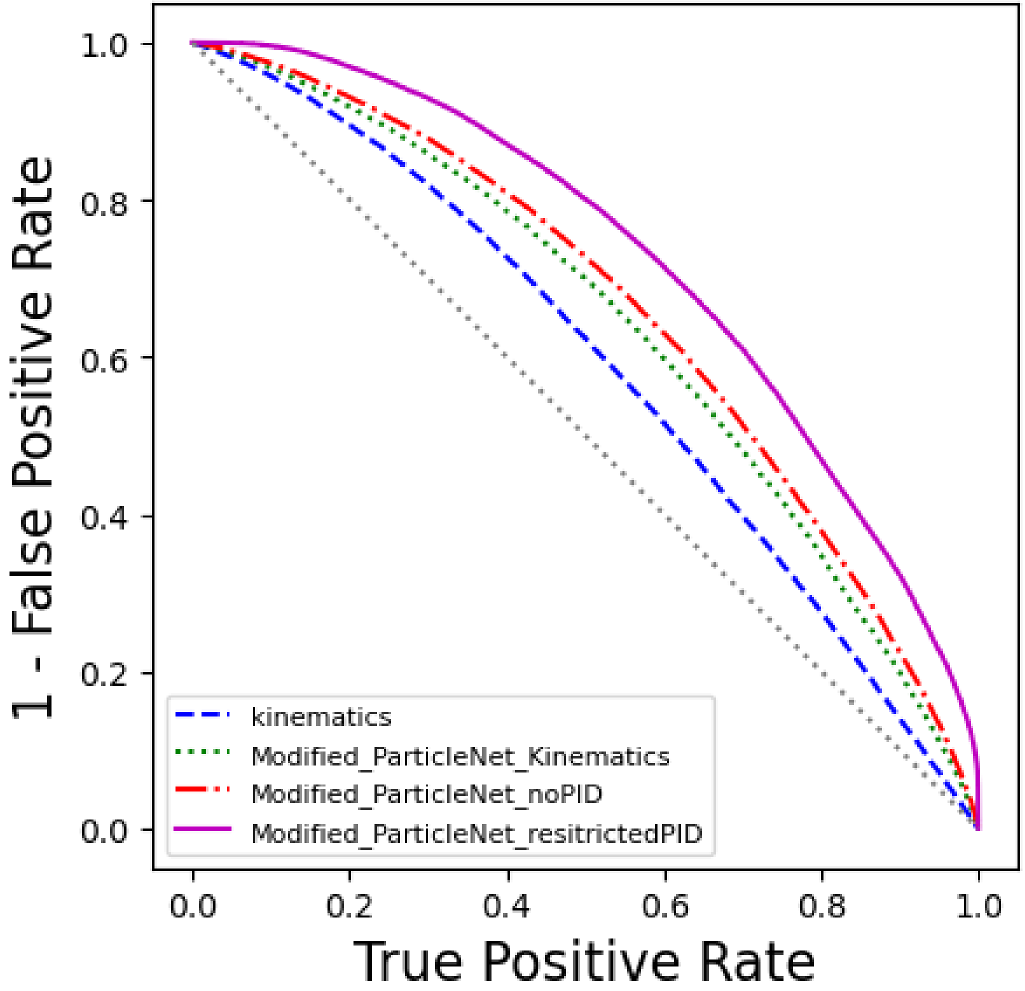
- Each particles within the jets will be associated with two sets of coordinates: the $\eta$ and $\phi$ with respect to the top jet axis, or with respect to the individual subjet axis.
- The log-normalized energy and transverse momentum of each particles.
- Basic particle identification information.
- One could try to include more precise PID, separating the charged hadrons.

# PERFORMANCE ON JET FLAVOR IDENTIFICATION




- The ROC curve of the network trained and tested on the unpolarized top data.
- "kinematics" curve is the baseline constructed using a fully connected DNN with jet momenta input.

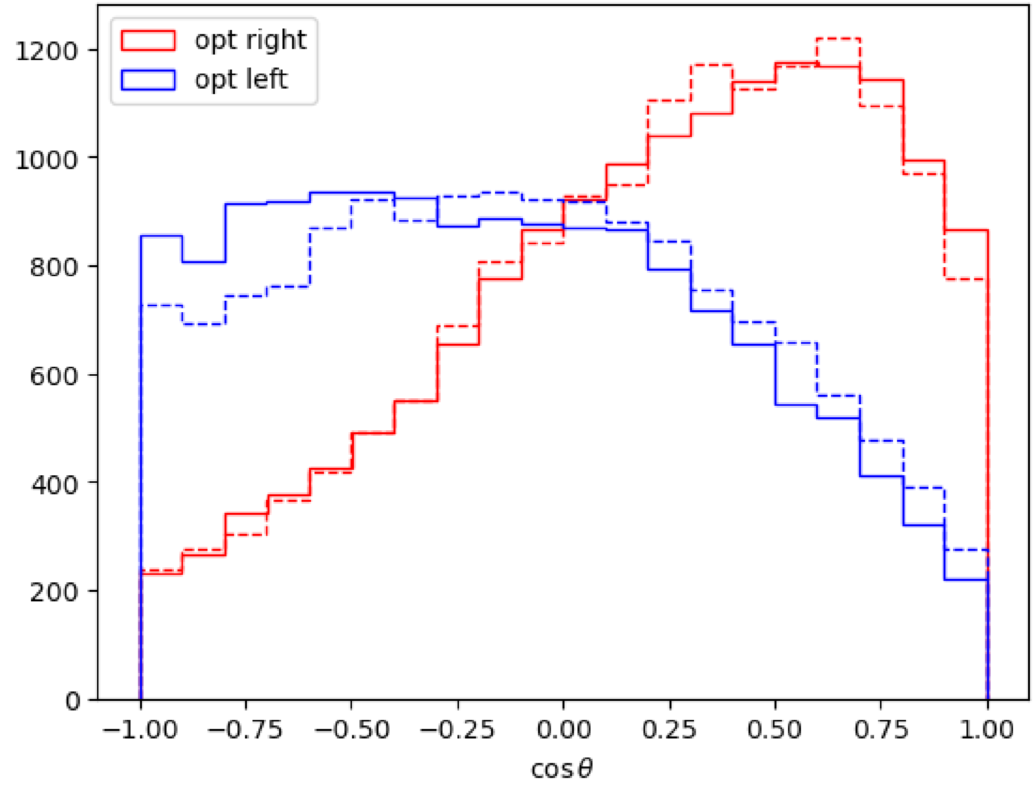
# PERFORMANCE ON JET FLAVOR IDENTIFICATION

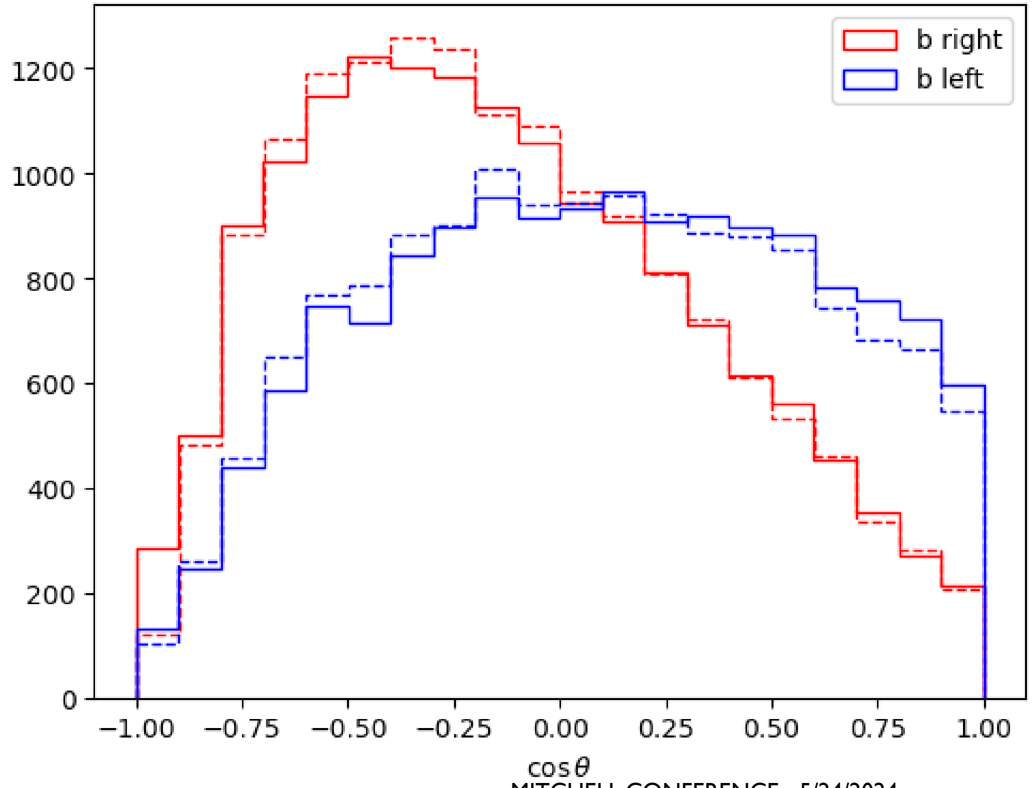



- With graph architecture tested on inputs:
- Kinematics of the constituents
- Kinematics + charge
- Kinematics + charge+ basic ID

# DEPENDENCE ON TOP POLARIZATION

- Parton (solid line) vs. reconstructed (dashed line)



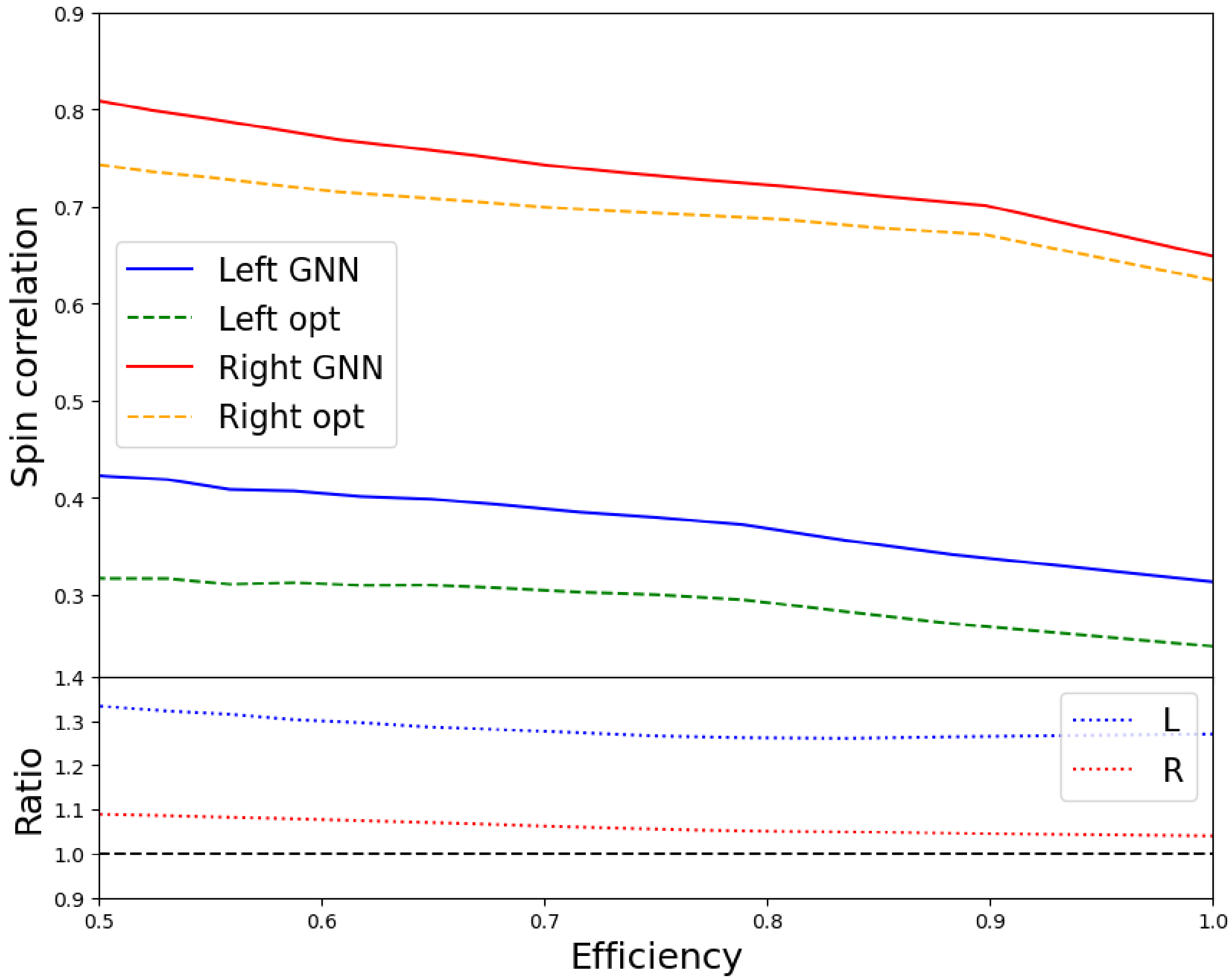



# COMPARISON BETWEEN METHODS

| | $\beta_k$ | Left hand | Right hand |
|---|---|---|---|
| Matched Hadron | $\beta_b$ | -0.214 | -0.371 |
| | $\beta_{soft}$ | 0.194 | 0.530 |
| | $\beta_{opt}$ | 0.247 | 0.624 |
| | $\lvert\vec{q}_{opt}\rvert$ | 0.636 | 0.638 |
| DNN | $\beta_{DNN}$ | 0.253 | 0.618 |
| | $\lvert\vec{q}_{DNN}\rvert$ | 0.622 | 0.625 |
| GNN | $\beta_{GNN}$ | 0.313 | 0.648 |
| | $\lvert\vec{q}_{GNN}\rvert$ | 0.678 | 0.685 |
| Matched Parton | $\beta_b$ | -0.295 | -0.392 |
| | $\beta_{soft}$ | 0.300 | 0.589 |
| | $\beta_{opt}$ | 0.407 | 0.659 |
| | $\lvert\vec{q}_{opt}\rvert$ | 0.634 | 0.634 |

- In general, neural network constructed directions outperforms the original optimal direction at the hadron level in terms of spin correlation.
- Compared to the same events at parton level, the spin correlation is in between soft direction and the original optimal direction.
- The length of the vector is not a good indicator of spin correlation after selections.

# SPIN CORRELATION ($\beta$) BASED ON CUTS



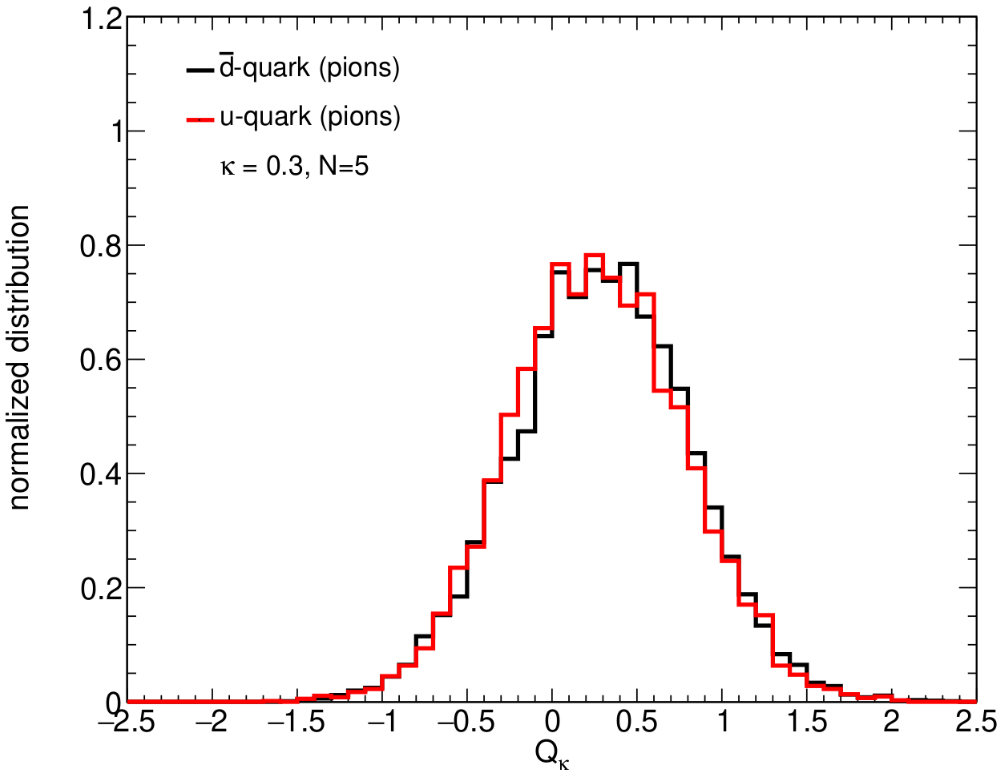

- Furthermore, we can put cuts on the neural network scores to significantly improve the spin correlation.
- We can apply large cuts on the events as long as we still have a larger cross section than dileptonic $t\bar{t}$.
- With the same cuts, not only the does the spin correlation of the NN constructed direction improves, but so does the original optimal direction.

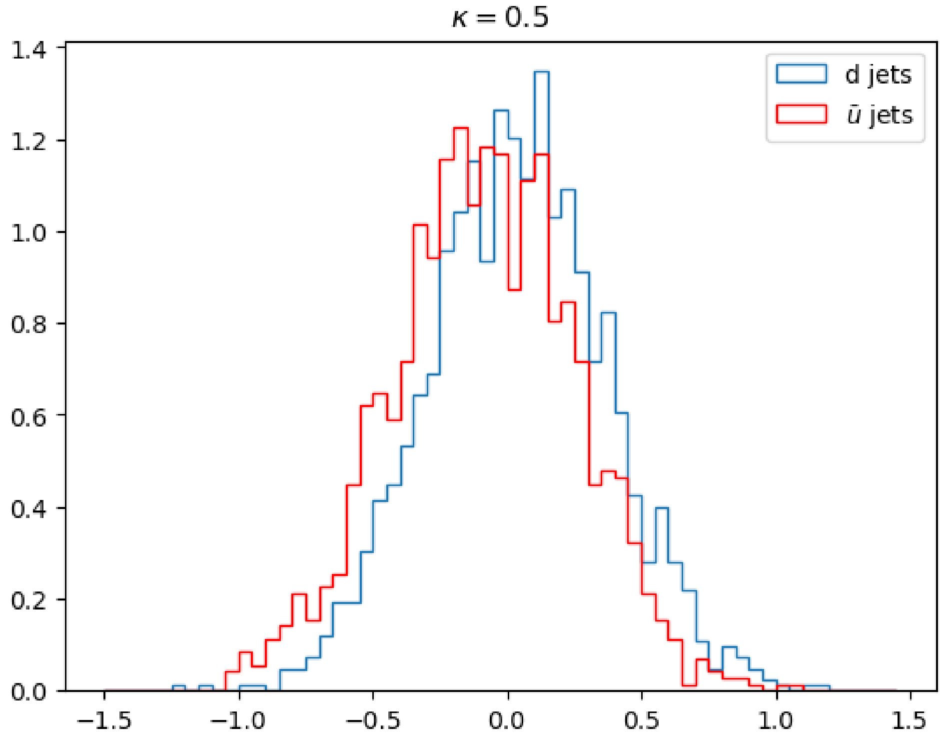
# SUMMARY AND DISCUSSION

- We can train a machine learning model on identifying the light jet flavor within the top jet and use it to improve the spin analyzing power of the hadronic top.
- $u$ - $\bar{d}$ discrimination is challenging in general but can be improved in tagged top jet.
- With the inclusion of variables beyond kinematic information in the input, we can improve the spin analyzing power compared to the direction constructed using only kinematics.
- The neural networks also provides a way to make selections on the events to improve the spin analyzing power, which means better top spin measurements.

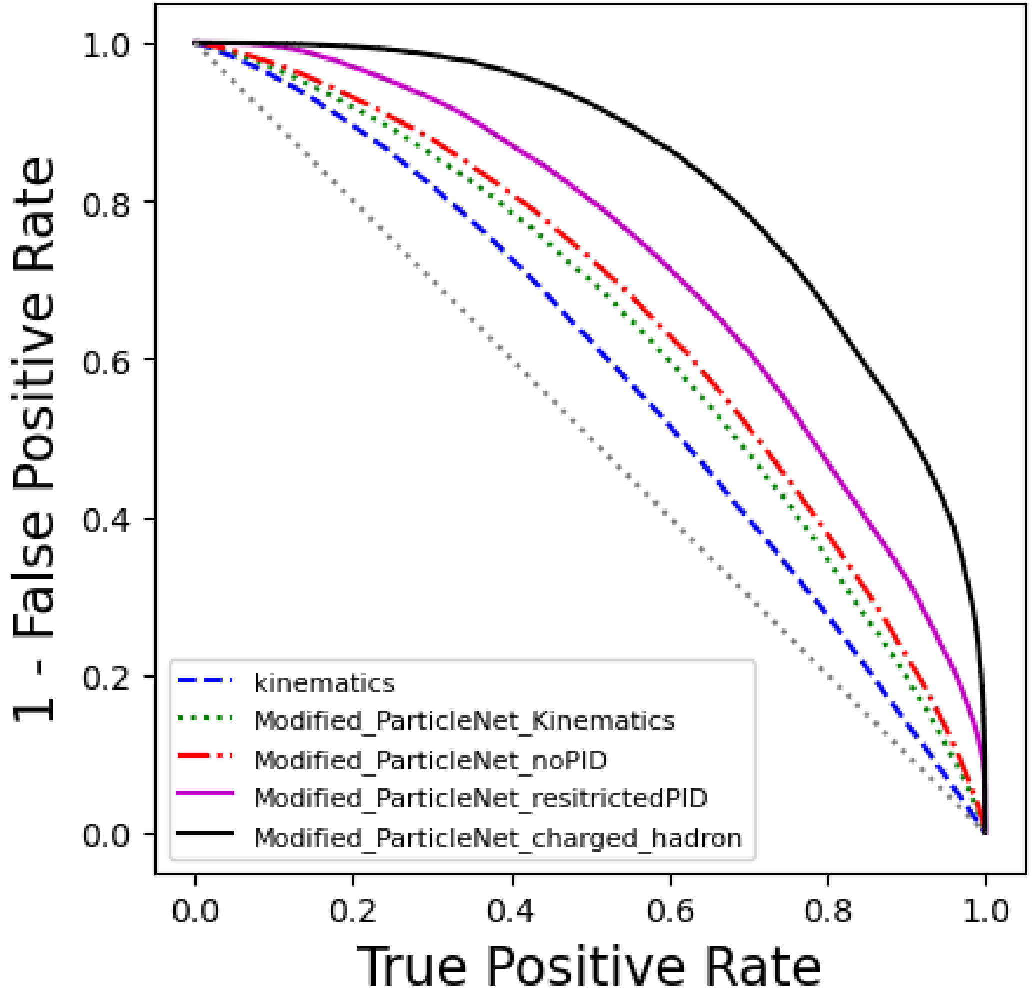
# SEPARATING MULTIPLICITIES

- Discrimination depends on the types of charged hadrons considered.



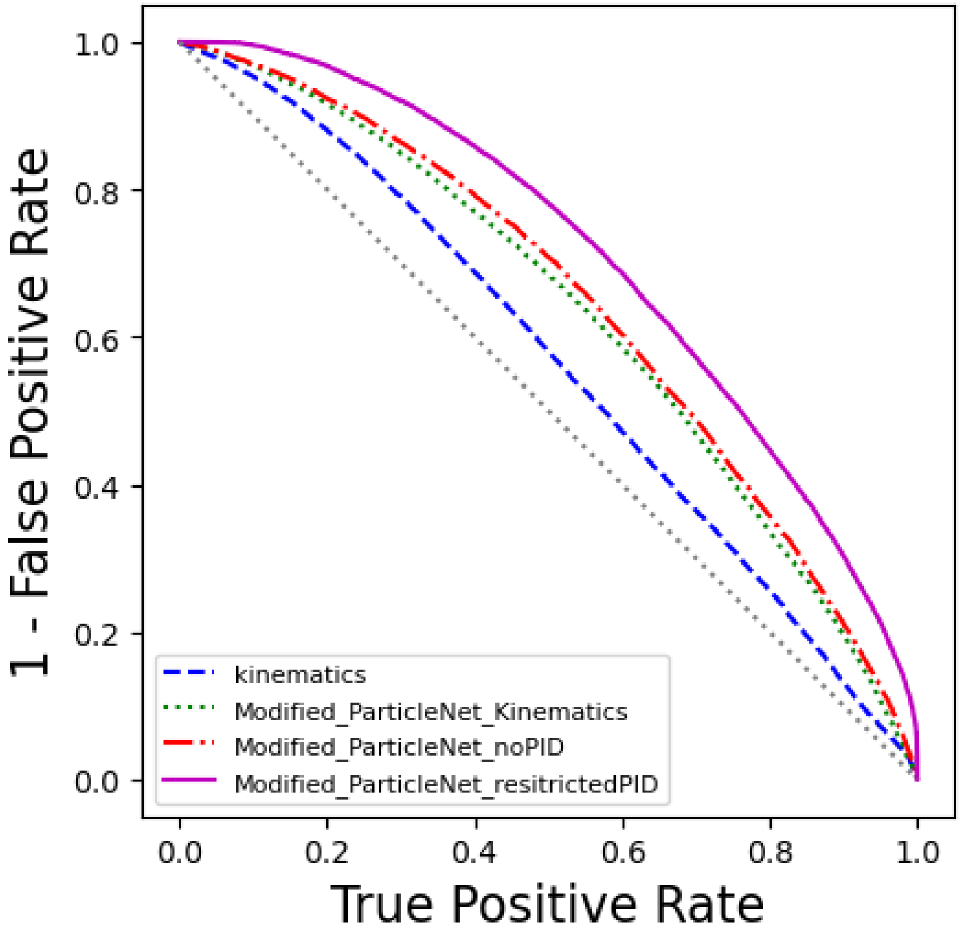
# RESULTS USING ALL PARTICLE ID INFORMATION



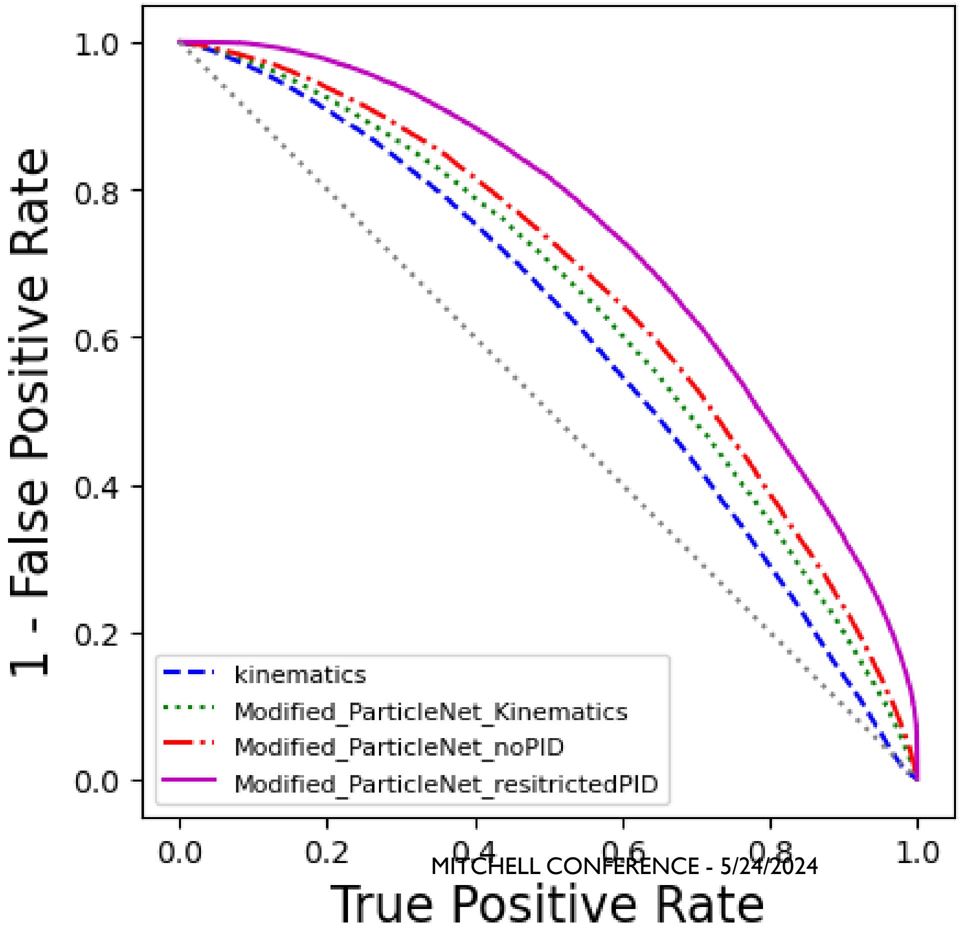

- Possible improvements with precise charged hadron identification. (Pion, Kaon, Proton)

# ROC CURVE ON POLARIZED TOP SAMPLES

Left-handed top

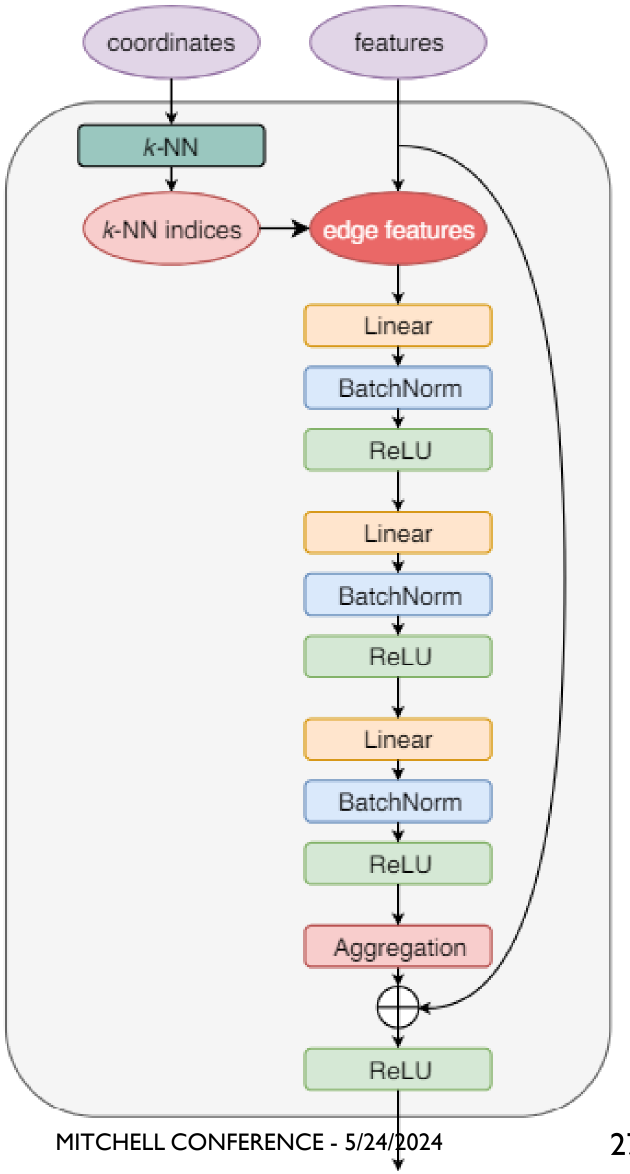



Right-handed top



# GRAPH CONVOLUTION

- Data represented as point cloud
- Convolutions on edges of the graph




Qu, Gouskos 2019