BEYOND KINEMATICS FOR OPTIMAL HADRONIC TOP QUARK POLARIMETRY II

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BASED ON ARXIV:2405.XXXXX IN COLLABORATION WITH

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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:

$$\frac{1}{\Gamma}\frac{d\Gamma}{d\cos\theta_a} = \frac{1}{2}(1 + p\beta_a \cos\theta_a) \qquad \beta = \begin{cases} +1.0 & \text{for } \ell^+ \text{ or } \bar{d} \\ -0.31 & \text{for } \nu \text{ or } u \\ -0.41 & \text{for } b \end{cases}$$

Brandenburg, Si, Uwer 2002

- The original optimal direction is constructed as follows:

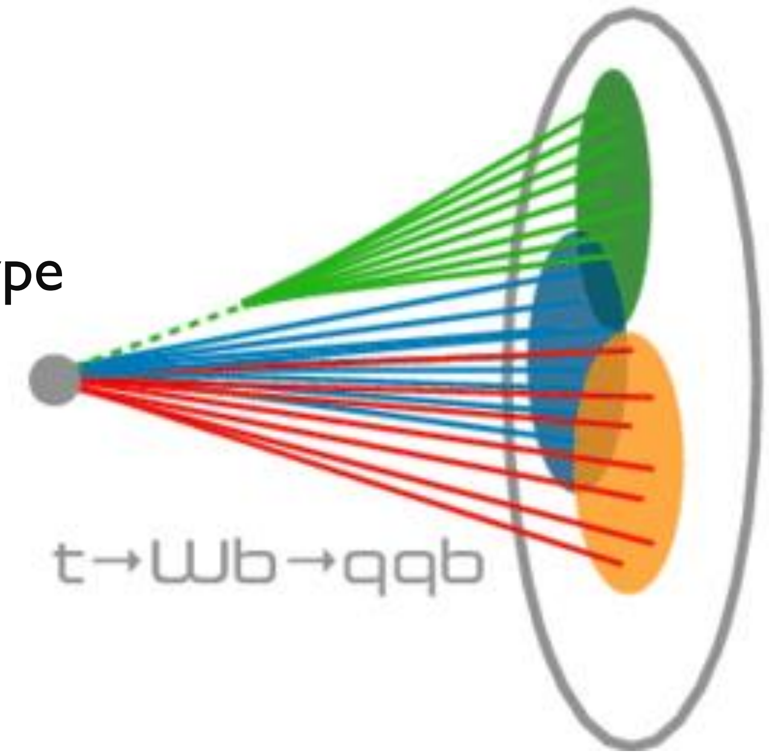
$$q_{\text{opt}} \equiv p(d \to q_{\text{soft}})\hat{q}_{\text{soft}} + p(d \to q_{\text{hard}})\hat{q}_{\text{hard}}$$

Tweedie 2014

- We will replace the probability with neural network output scores and apply on both left hand and right hand polarized top jet samples and check the corresponding cosine distributions.
- We will also check the vector length $|\vec{q}_{opt}|$of the NN constructed direction.
- Using soft quark direction gives equivalent $\beta = 0.5$

MACHINE LEARNING STRATEGY

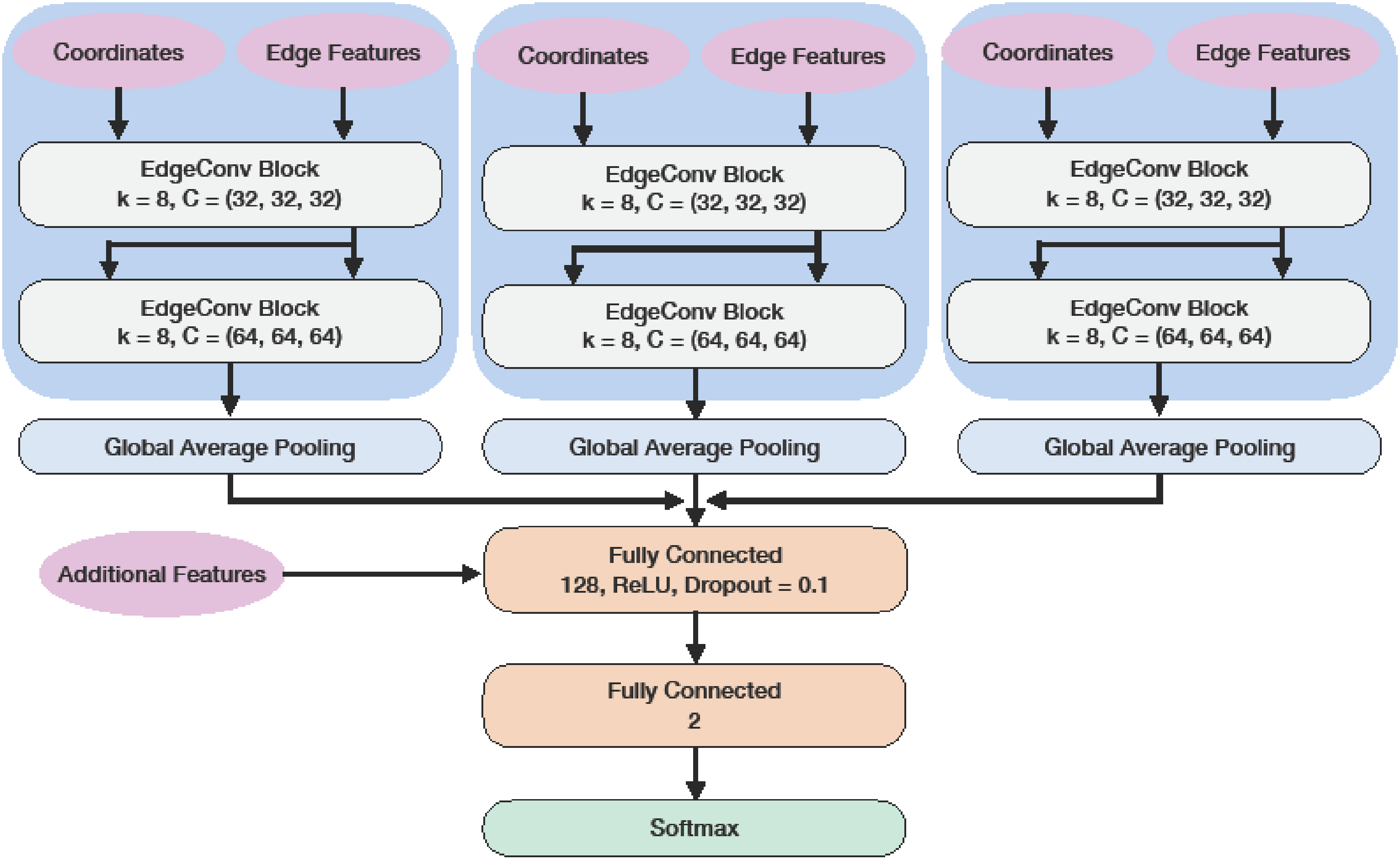
- Light jet flavor identification within top jet cone
- Input the jet constituent momenta and charge information for each of the subjets.
- Train the neural network to identify the down-type jet.
- Interpret the neural network score as the probability of each jet being down-type.



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 ΔR 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

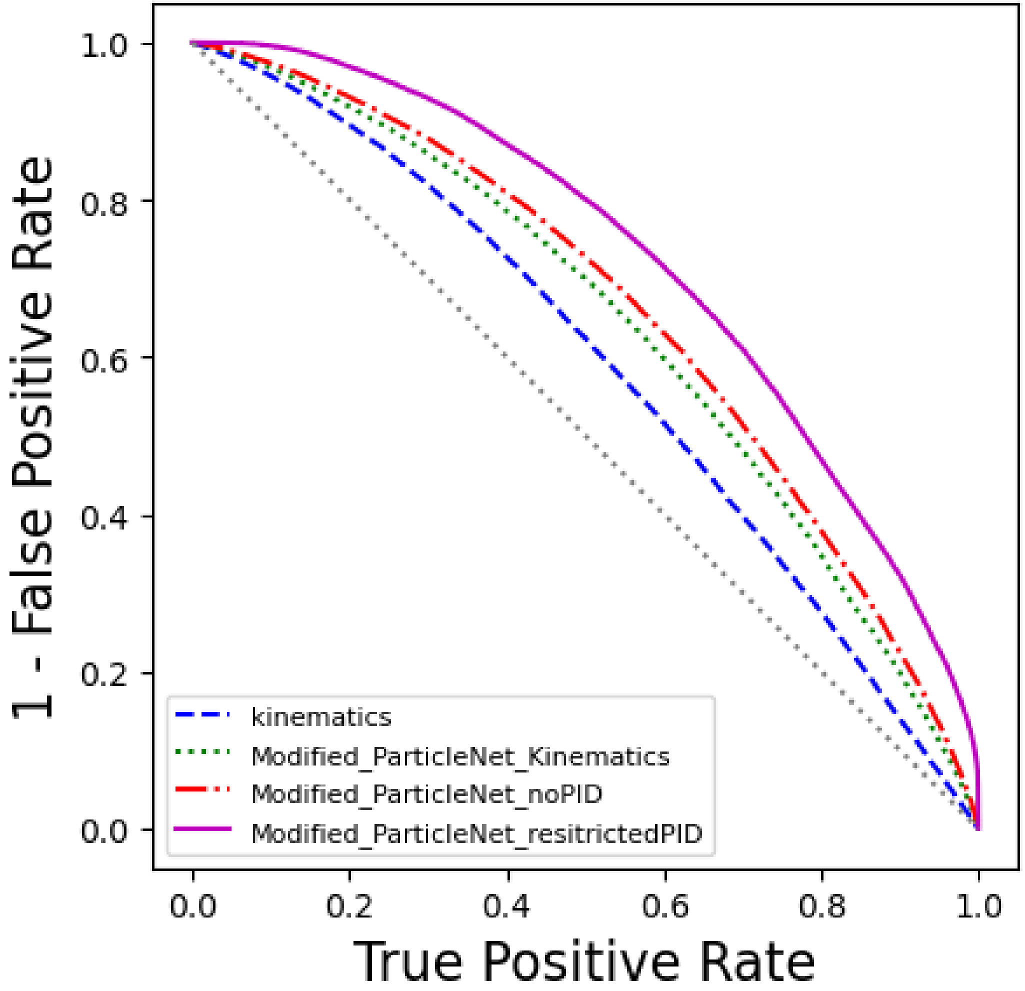
- The three graphs are then pooled and concatenated.
- Additional features for the overall top jet can also be fed into the linear layers.

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

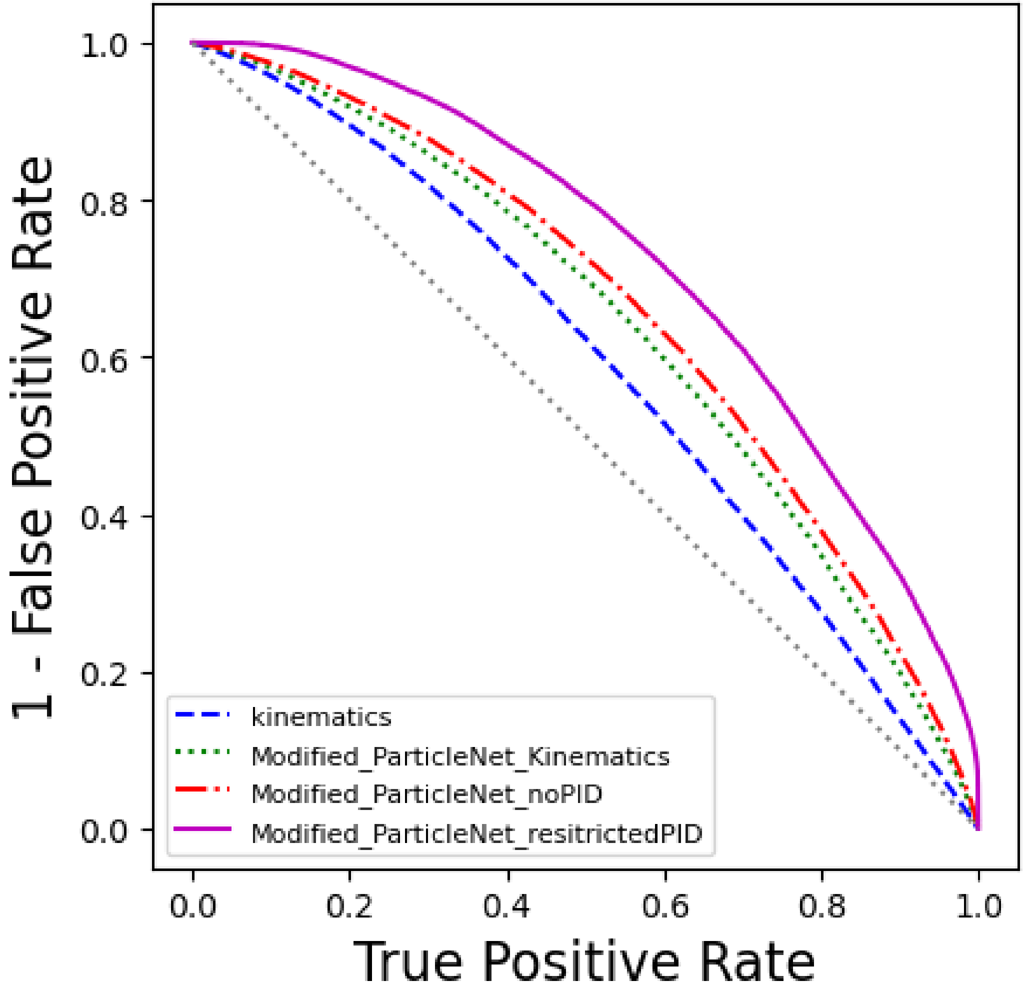
- Each particles within the jets will be associated with two sets of coordinates: the η and ϕ with respect to the top jet axis, or with respect to the individual subjet axis.
- The log-normalized energy and transverse momentum of each particles.
- Basic particle identification information.
- One could 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.

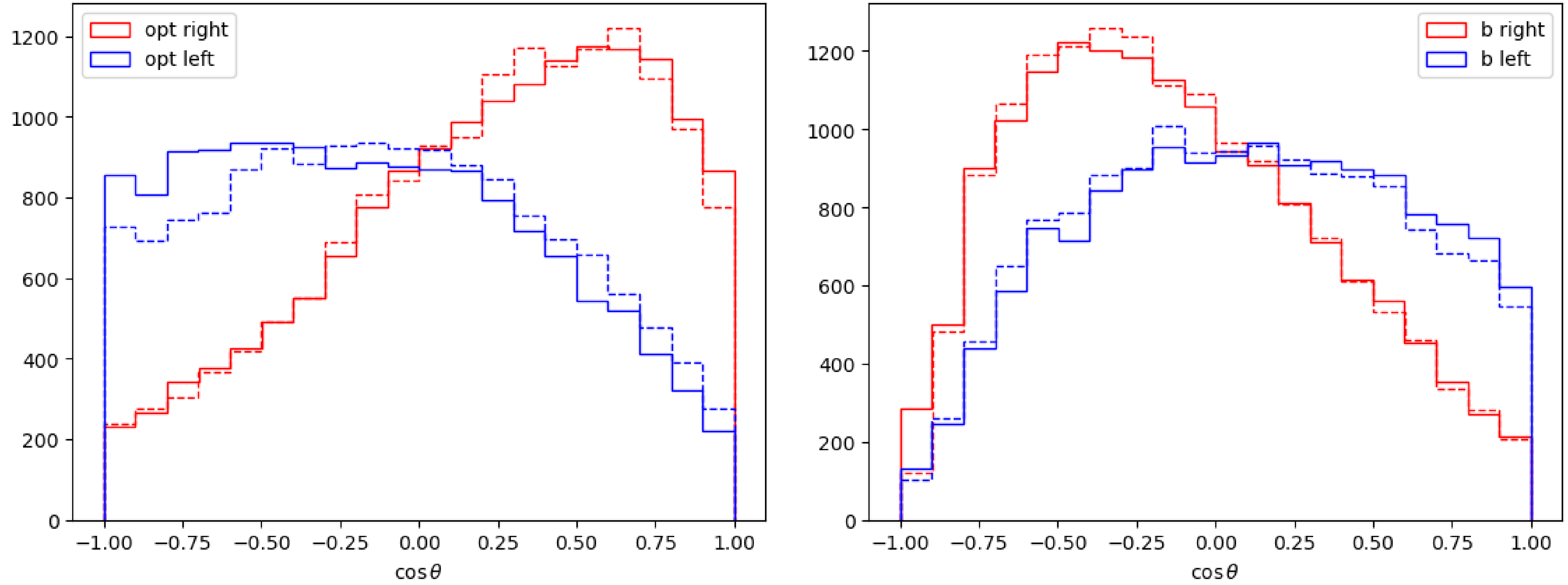
PERFORMANCE ON JET FLAVOR IDENTIFICATION



- 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)

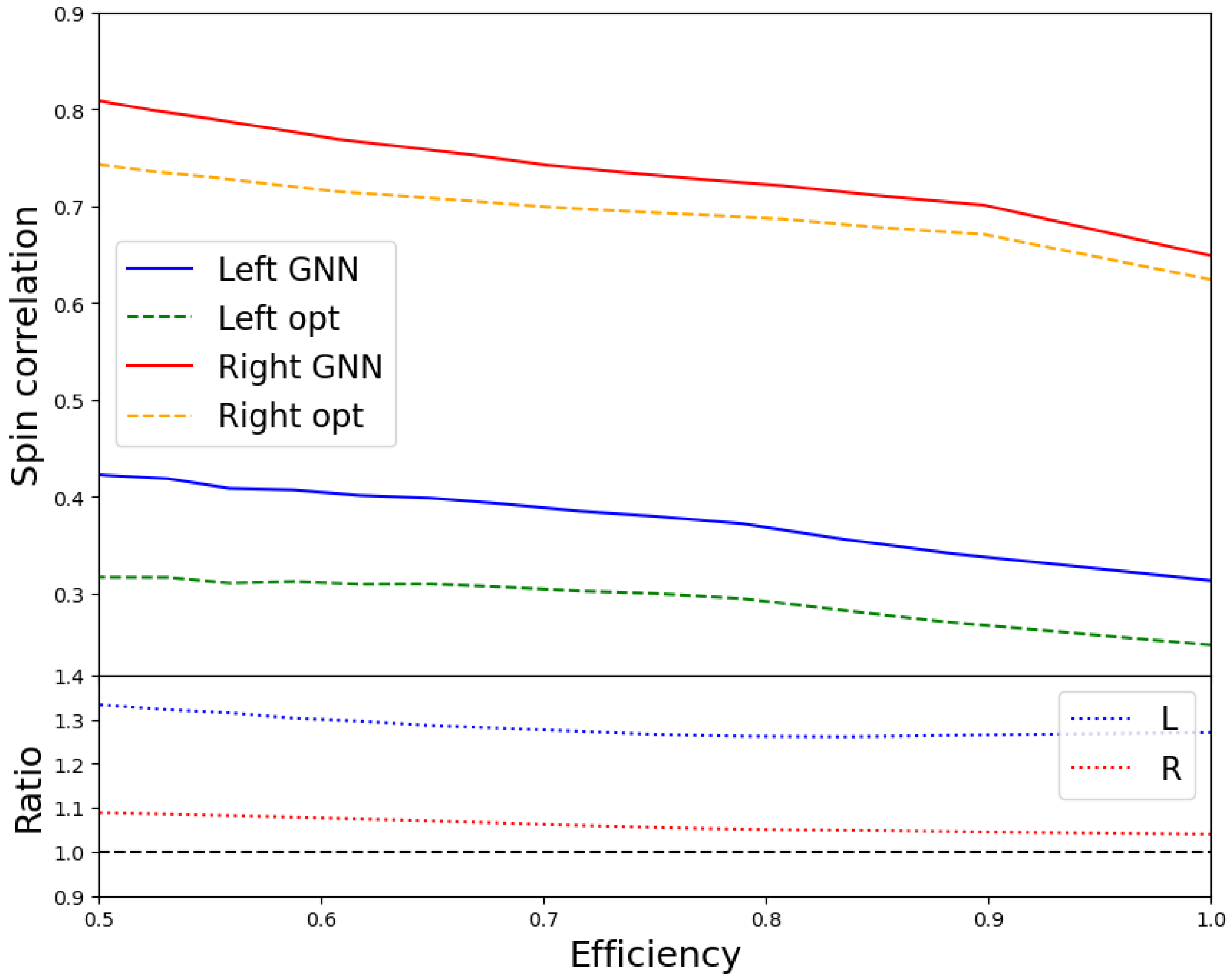


COMPARISON BETWEEN METHODS

	β_k	Left hand	Right hand
Matched Hadron	β_b	-0.214	-0.371
	β_{soft}	0.194	0.530
	β_{opt}	0.247	0.624
	$\lvert\vec{q}_{opt}\rvert$	0.636	0.638
DNN	β_{DNN}	0.253	0.618
	$\lvert\vec{q}_{DNN}\rvert$	0.622	0.625
GNN	β_{GNN}	0.313	0.648
	$\lvert\vec{q}_{GNN}\rvert$	0.678	0.685
Matched Parton	β_b	-0.295	-0.392
	β_{soft}	0.300	0.589
	β_{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 (β) BASED ON CUTS

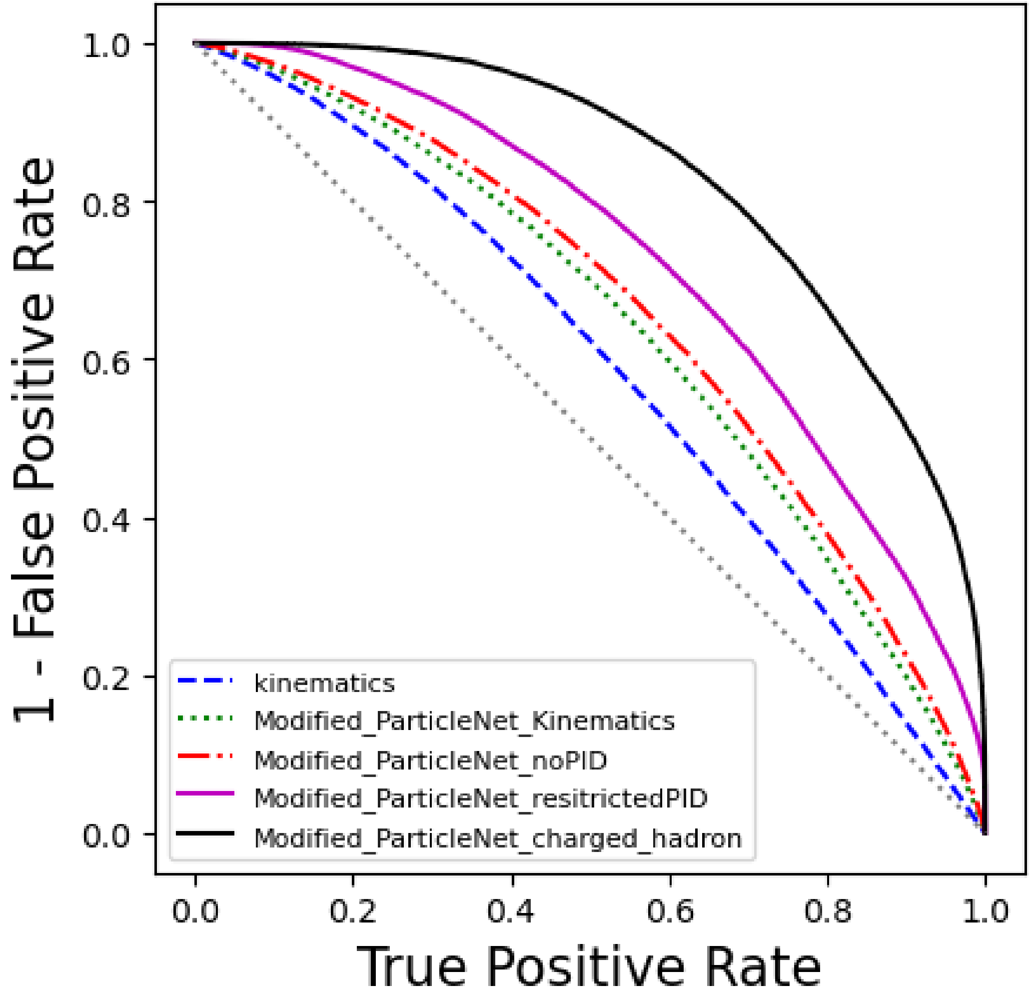


- Furthermore, we can put cuts on the neural network scores to significantly improve the spin correlation.
- We can apply large cuts on the events as long as we still have a larger cross section than dileptonic $t\bar{t}$.
- With the same cuts, not only the does the spin correlation of the NN constructed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

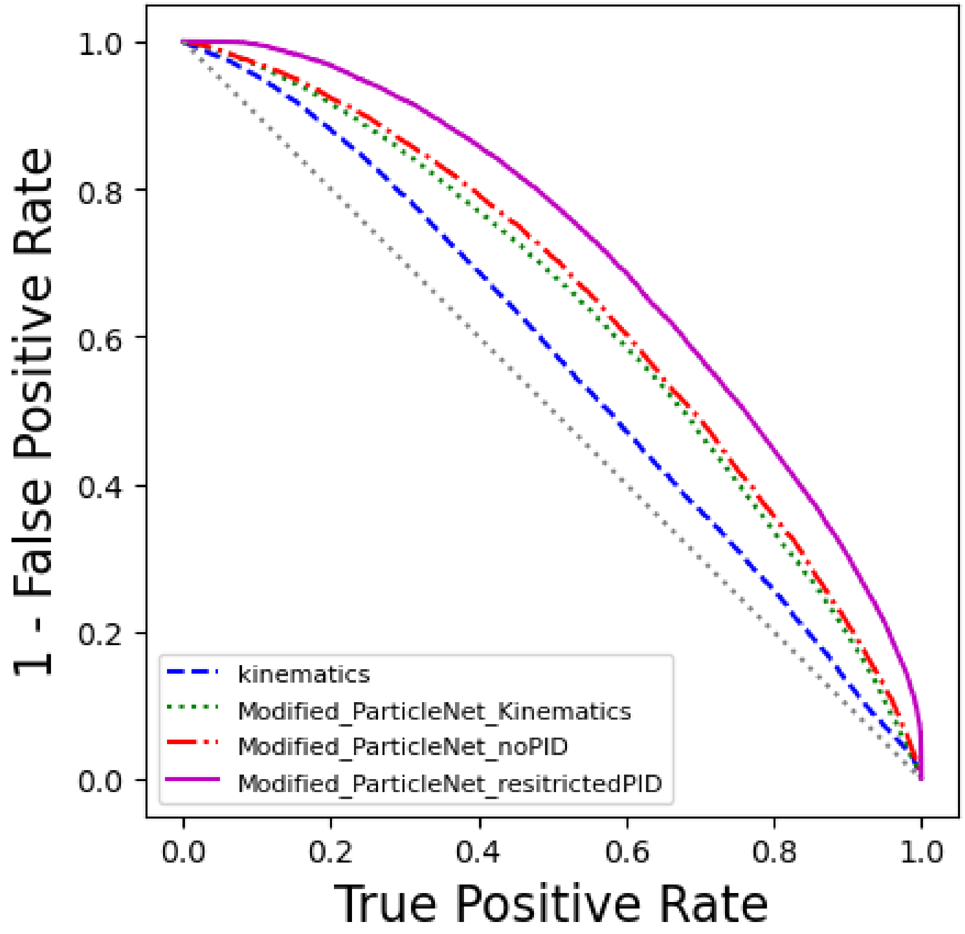
RESULTS USING ALL PARTICLE ID INFORMATION



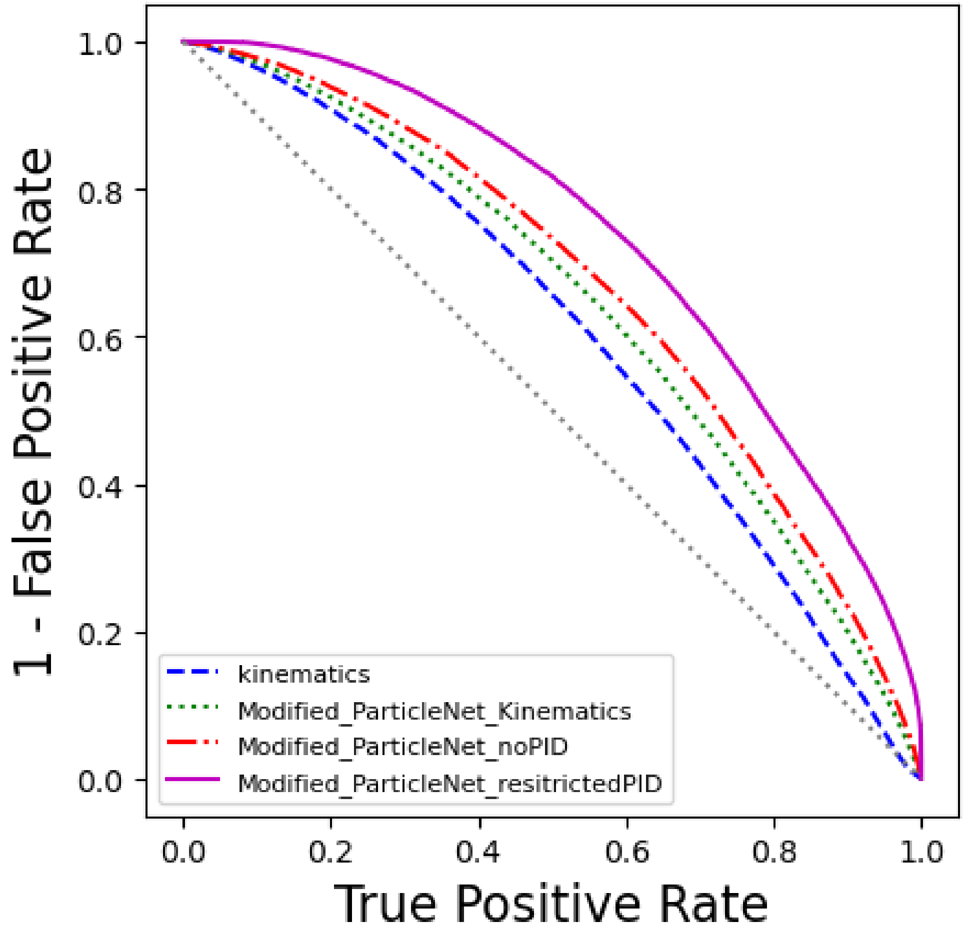
- Possible improvements with precise charged hadron identification. (Pion, Kaon, Proton)

ROC CURVE ON POLARIZED TOP SAMPLES

Left-handed top

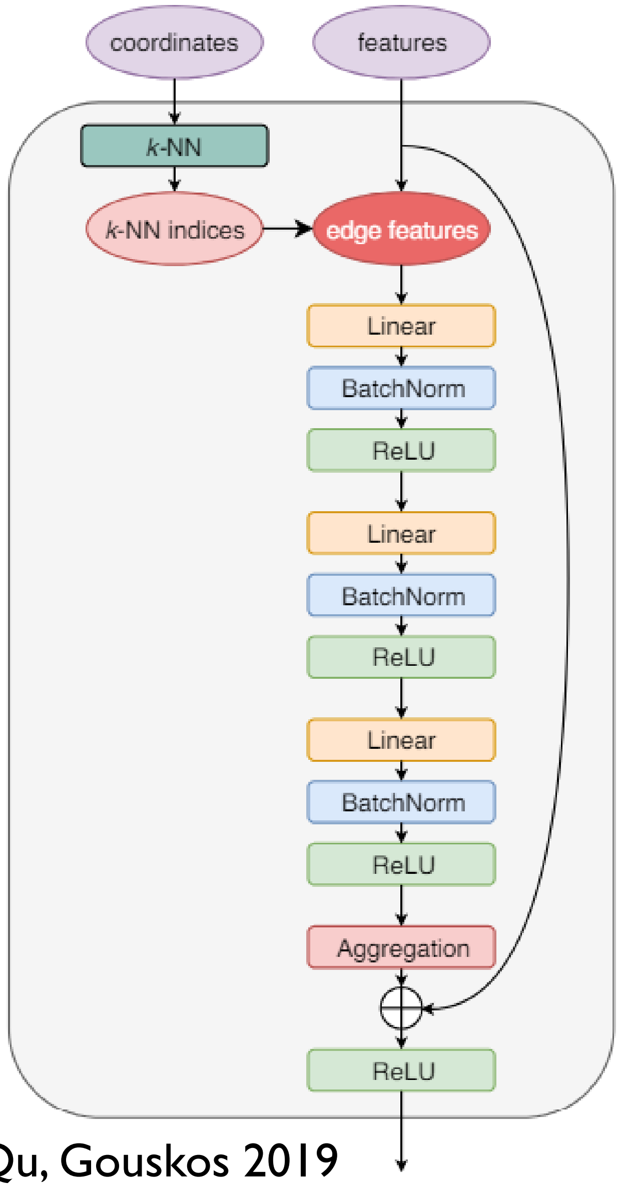


Right-handed top



GRAPH CONVOLUTION

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



Qu, Gouskos 2019