Hadronic Top Quark Polarimetry with ParticleNet

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Top quark spin

- Top quark decays before it hadronizes or spin flips

$$\tau_{top} \approx 5 \times 10^{-25} s$$

$$\tau_{had} \sim 1/\Lambda_{QCD} \sim 10^{-24} s$$

$$\tau_{flip} \sim m_t/\Lambda^2_{QCD} \sim 10^{-21} s$$

Mahlon, Parke 2010

- Top polarization can be observed from the angular distribution of its decay products, which provides us an opportunity for non-resonant new physics searches.

$$\frac{1}{\Gamma}\frac{d\Gamma}{d\cos\xi_k} = \frac{1}{2}(1 + \beta_k \cos\xi_k)$$

$$\beta_k = \begin{cases} +1, & \text{for } l^+ \text{ or } \bar{d}\text{-quark.} \\ -0.31, & \text{for } \bar{\nu} \text{ or } u\text{-quark.} \\ -0.41, & \text{for } b\text{-quark.} \end{cases}$$

Spin analyzing power

Brandenburg, Si, Uwer 2002

Entanglement and Bell Inequalities with Top Quarks

- The LHC provides a unique environment to study entanglement and Bell's inequality at high energy
- Top quark pair production is an optimal candidate for these studies

Afik, Nova 2020
Fabbrichesi, Floreanini, Panizzo 2021
Severi, Boschi, Maltoni, Sioli 2021
Saavedra, Casas 2022
Severi, Vryonidou 2022
ZD, Gonçalves, Kong, Navarro 2023
Han, Low, Wu 2023
ATLAS Nature vol 633, 542–547 (2024)
CMS 2406.03976
CMS 2409.11067
ZD, Gonçalves, Kong, Larkoski, Navarro 2024
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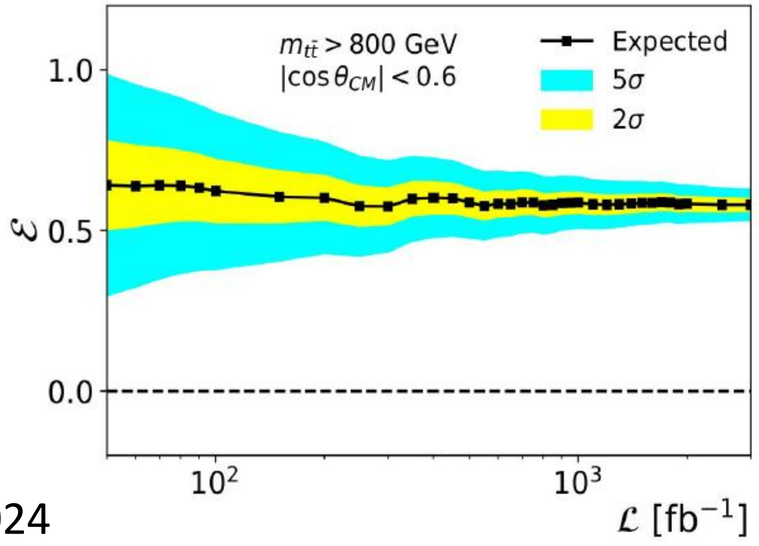
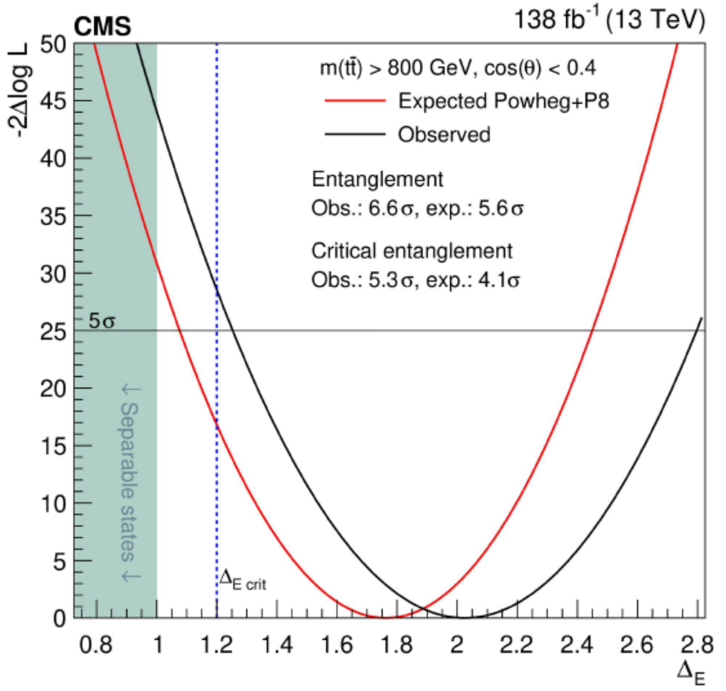


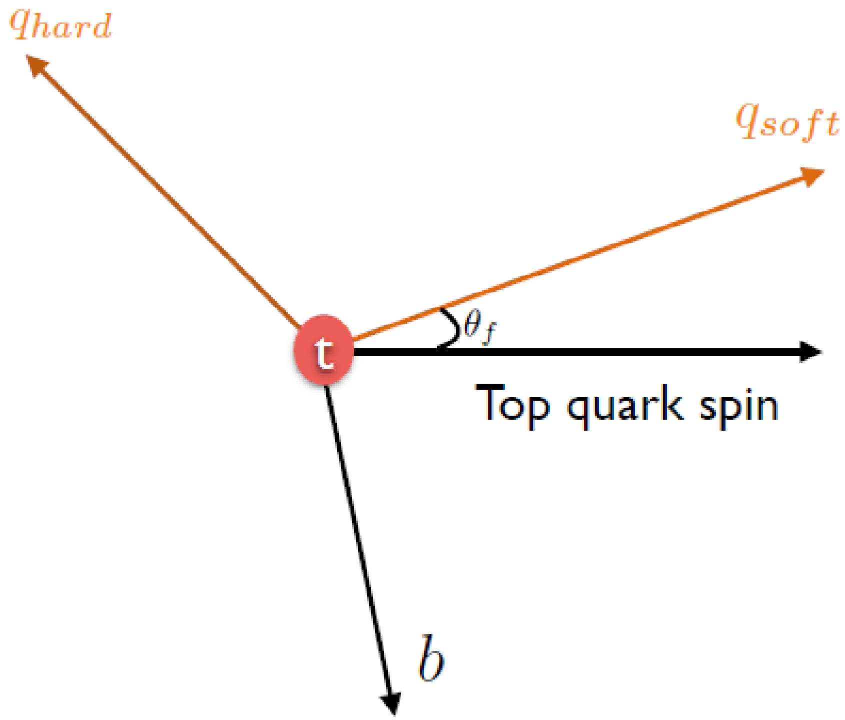


Hadronic top polarimetry

- Semi-leptonic and hadronic channel has much higher event rate than dileptonic channel
- down-type quark is best polarimeter, but tagging it in a collider environment is challenging
- We can use a proxy direction for down-quark

$$\frac{1}{\Gamma_f}\frac{d\Gamma_f}{d\cos\theta_f} = \frac{1}{2}(1 + \mathbf{0.5}\,\cos\theta_f)$$

Jezabek 1994



Optimal hadronic direction

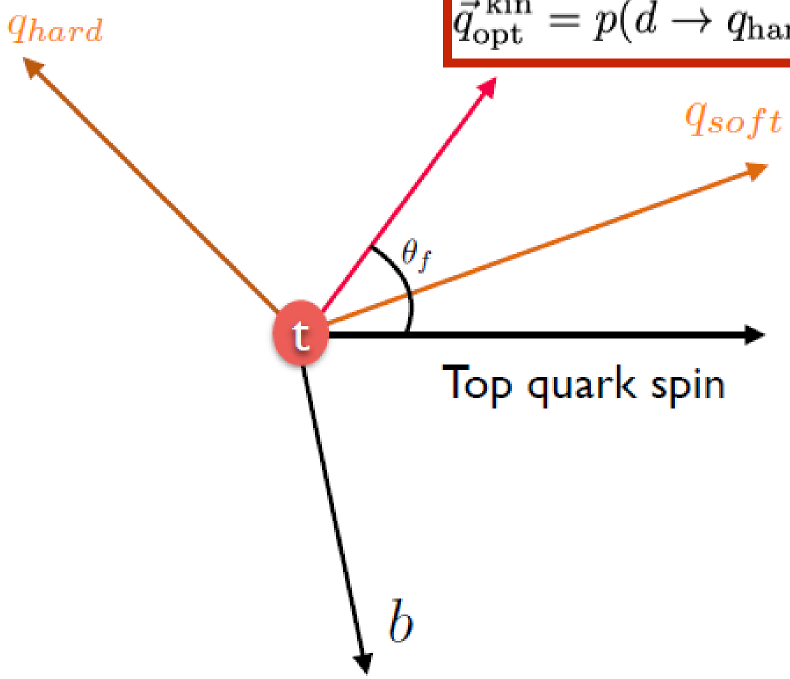
$$\rho\left(c_{W\mathrm{hel}}\right) \equiv \frac{3}{8} f_R \left(1 + c_{W\mathrm{hel}}\right)^2 + \frac{3}{4} f_0 \left(1 - c_{W\mathrm{hel}}^2\right) + \frac{3}{8} f_L \left(1 - c_{W\mathrm{hel}}\right)^2$$

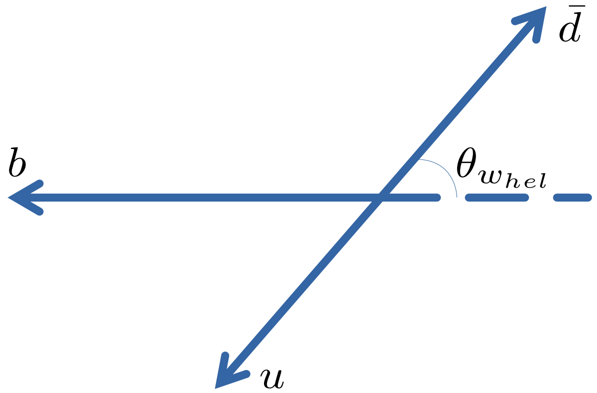
$$p(d \to q_{\mathrm{soft}}) = \frac{\rho\left(-|c_{W\mathrm{hel}}|\right)}{\rho\left(|c_{W\mathrm{hel}}|\right) + \rho\left(-|c_{W\mathrm{hel}}|\right)}$$

$$p(d \to q_{\mathrm{hard}}) = \frac{\rho\left(|c_{W\mathrm{hel}}|\right)}{\rho\left(|c_{W\mathrm{hel}}|\right) + \rho\left(-|c_{W\mathrm{hel}}|\right)}$$

- Using a linear combination of soft jet directions as the proxy

$$\boxed{\vec{q}^{\,\mathrm{kin}}_{\mathrm{opt}} = p(d \to q_{\mathrm{hard}}|c_W)\hat{q}_{\mathrm{hard}} + p(d \to q_{\mathrm{soft}}|c_W)\hat{q}_{\mathrm{soft}}}$$



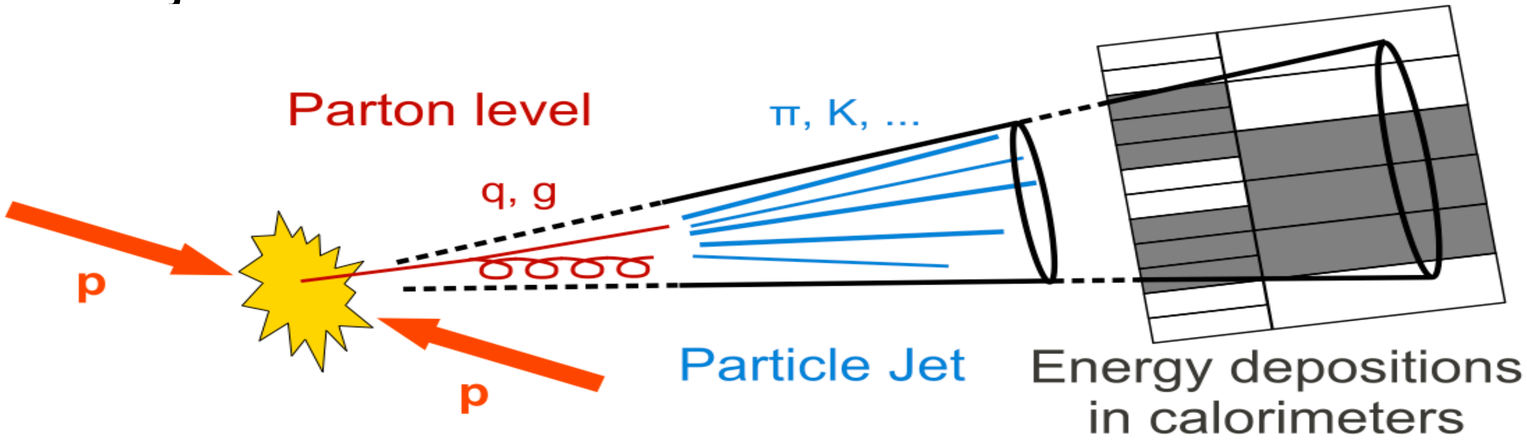


$$\frac{1}{\Gamma_f}\frac{d\Gamma_f}{d\cos\theta_f} = \frac{1}{2}\left(1 + \mathbf{0.64}\cos\theta_f\right)$$

Tweedie 2014

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.



$$\vec{q}_{\rm opt} = p(d \to q_{\rm hard} | c_W, \{\mathcal{O}\})\, \hat{q}_{\rm hard} + p(d \to q_{\rm soft} | c_W, \{\mathcal{O}\})\, \hat{q}_{\rm soft}$$

ZD, Gonçalves, Kong, Larkoski, Navarro 2024

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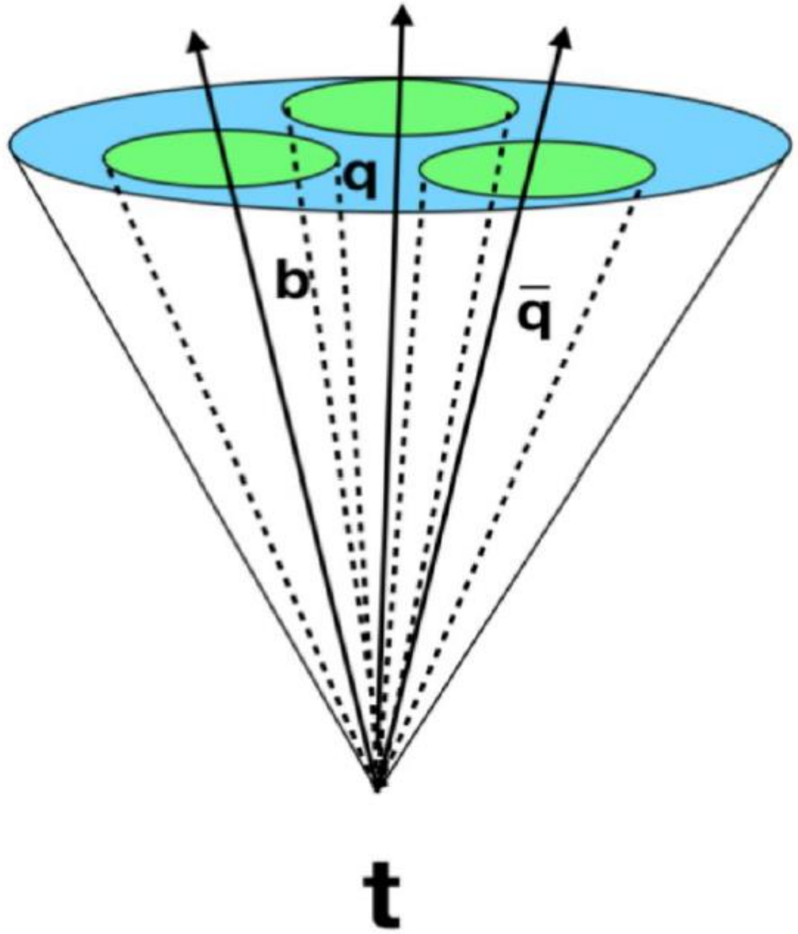
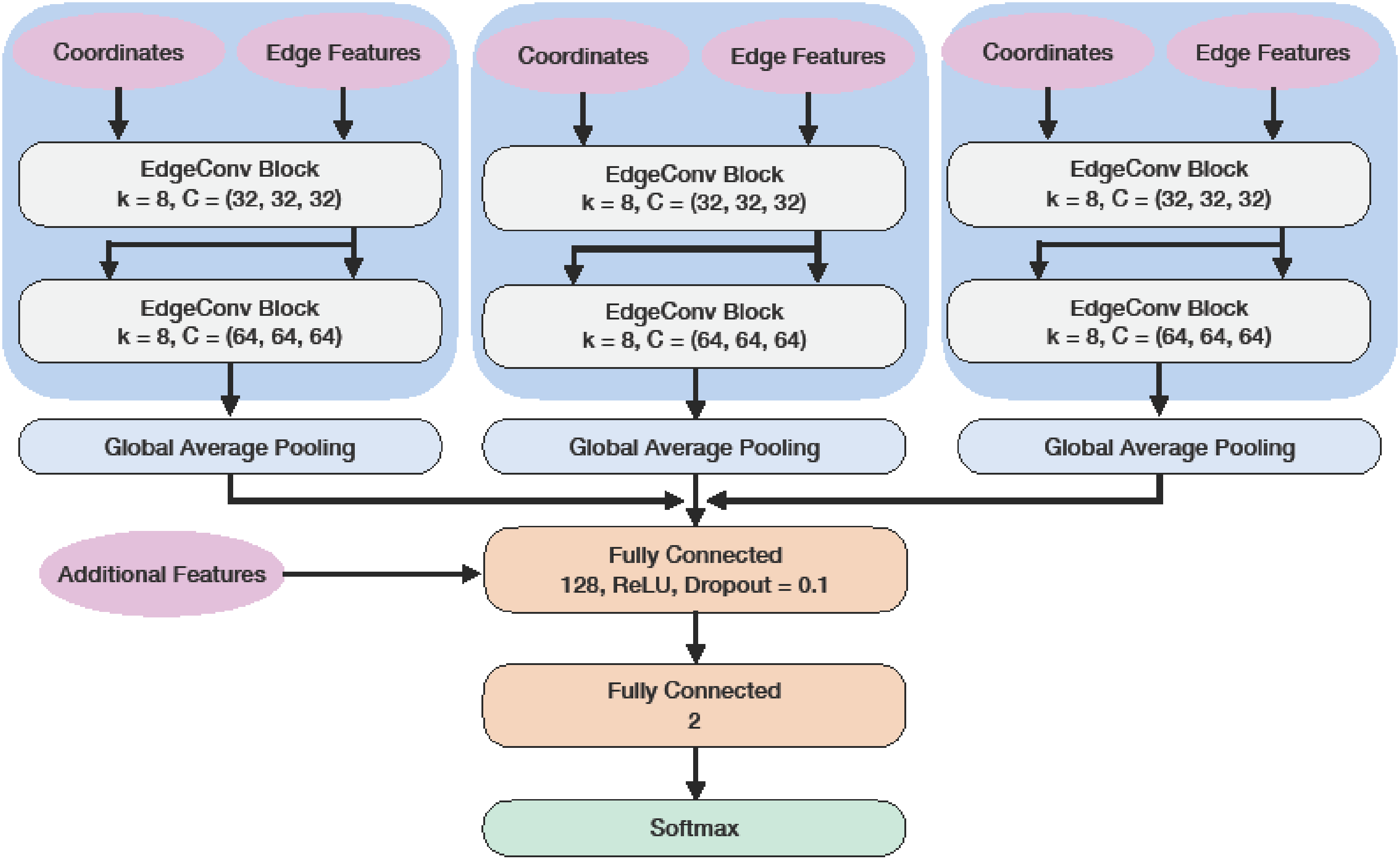
Machine Learning Strategy

- 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 theconditional probability of each jet being down-type and form a new proxy direction



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

Qu, Gouskos 2019

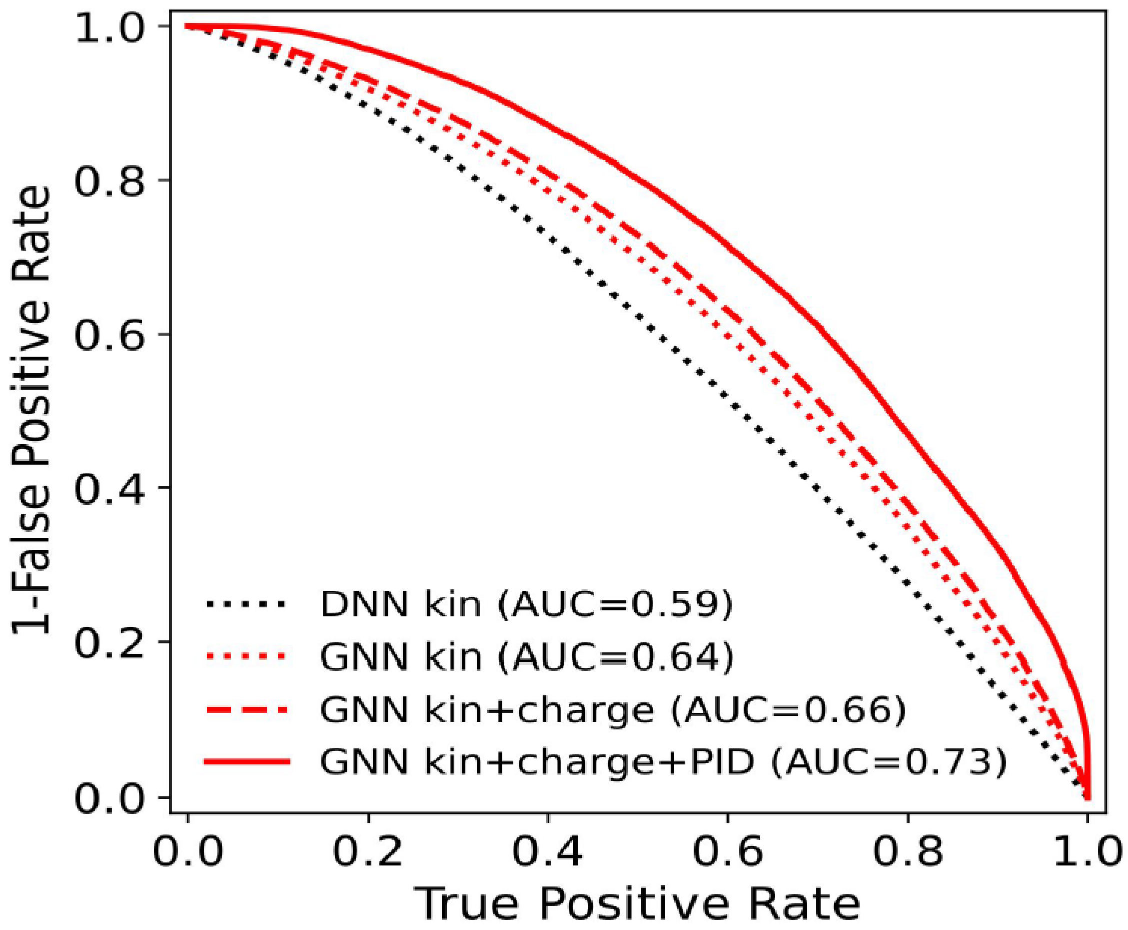
See also: Gong et al. 2022
Bogatskiy, Hoffman, Miller, Offermann 2022

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.

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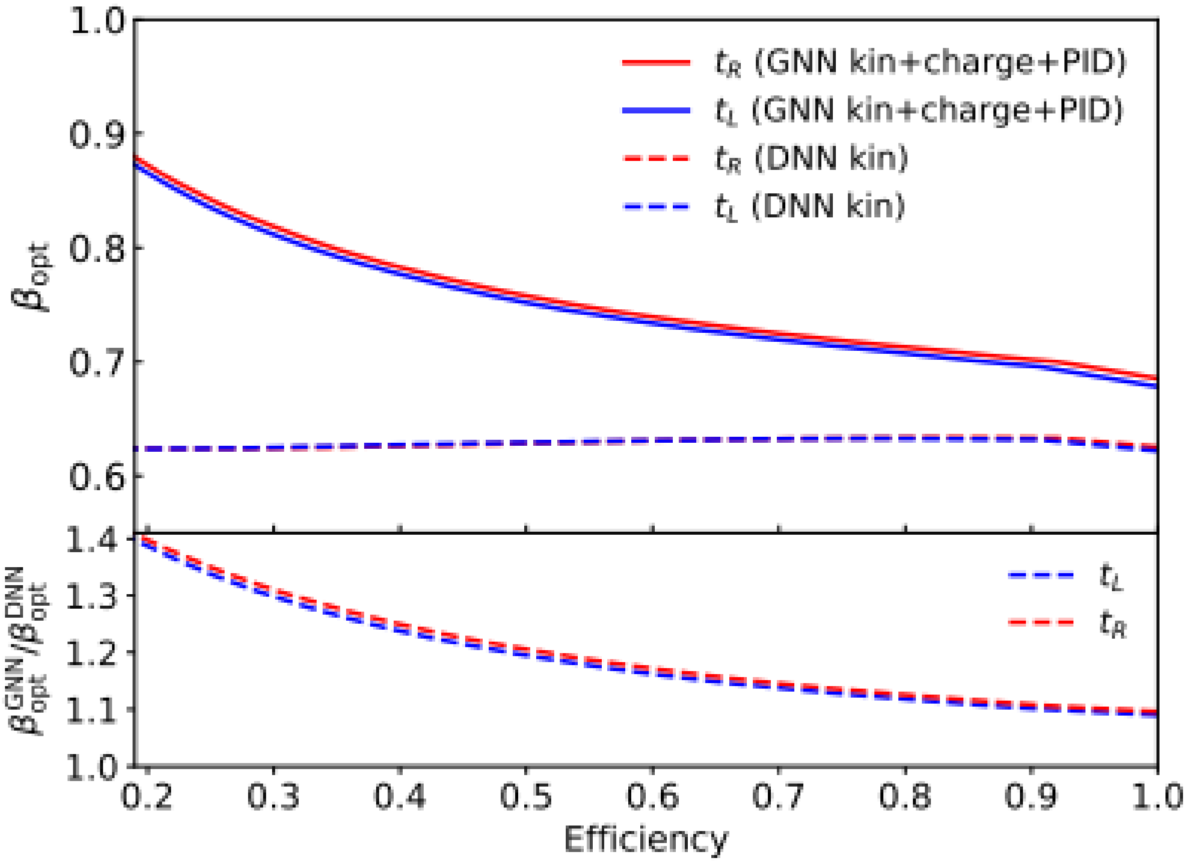
Spin correlation (β) based on cuts



	$\beta_{\rm opt}^{t_L}$	$\beta_{\rm opt}^{t_R}$
$\rm DNN_{Eff=100\%}$	0.622	0.625
$\rm GNN_{Eff=100\%}$	0.678	0.685
$\rm GNN_{Eff=50\%}$	0.751	0.758
$\rm GNN_{Eff=20\%}$	0.863	0.869

- 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 $t\bar{t}$.

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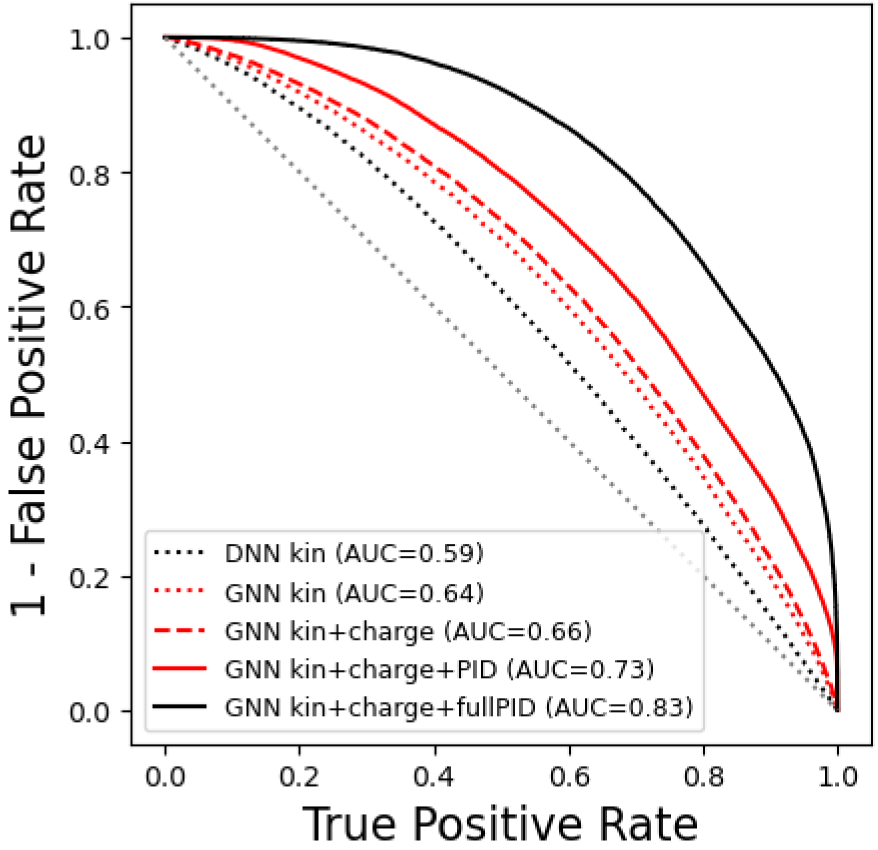
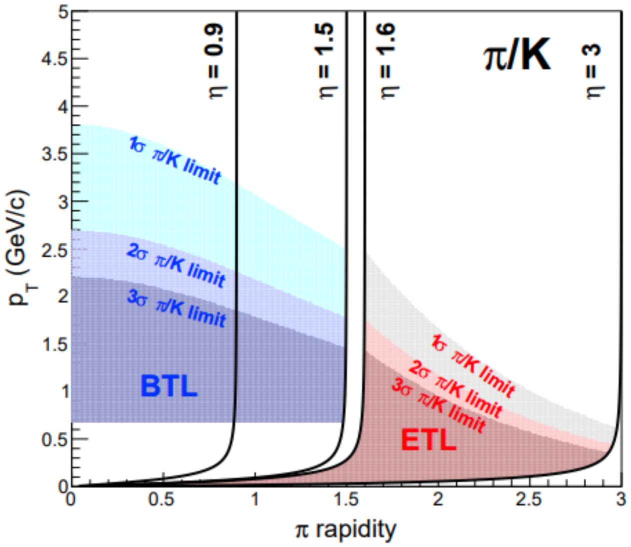
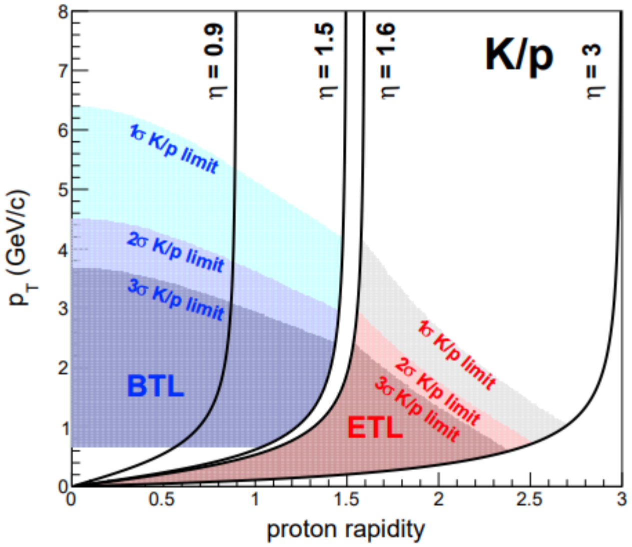
Kaon/Pion discrimination

- Performance can be further improved significantly with Kaon/Pion discrimination
- They are not well distinguished at the LHC, but can be improved with future timing detector
- In principle, we can consider imperfect Kaon/Pion label
- Theoretical challenge of handling non perturbative effects of hadronization



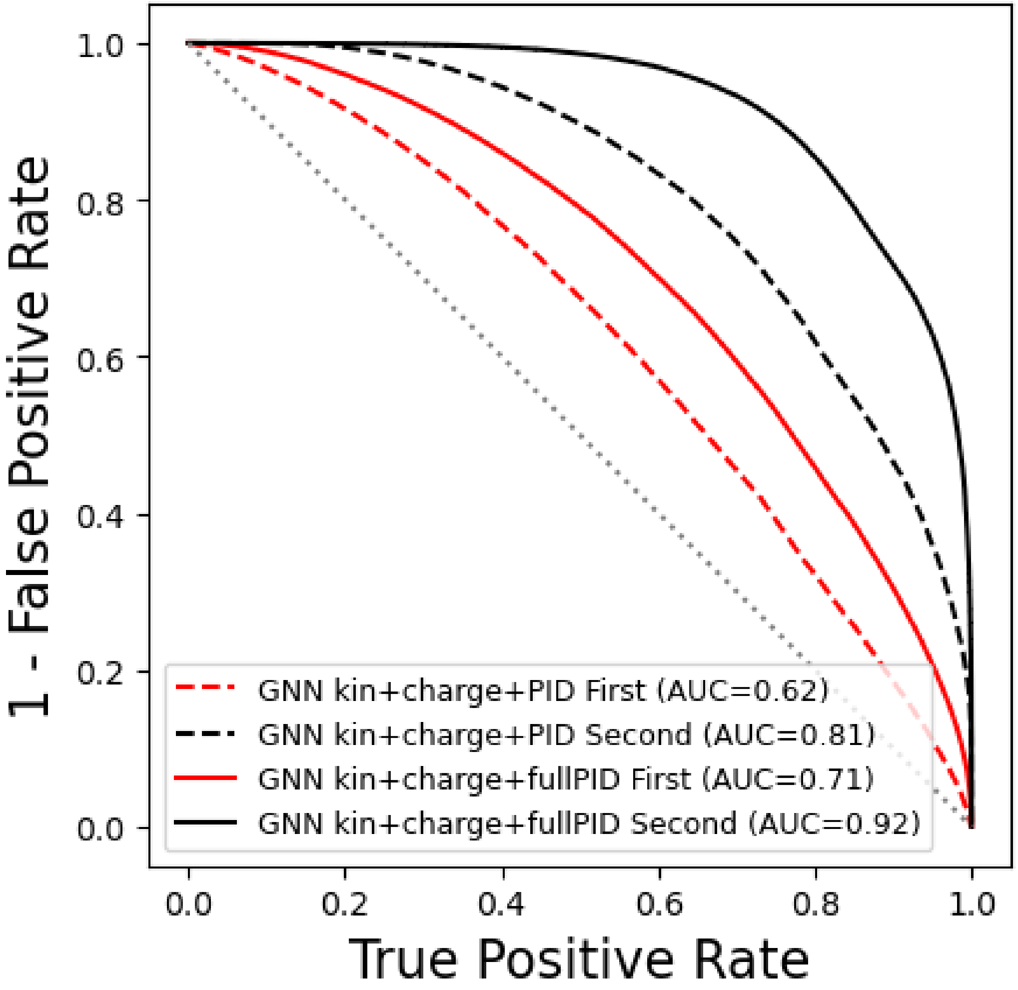




CMS-TDR-020

Beyond polarimetry

- Doing light quark jet tagging within the top jet can help us understand more about the light quarks themselves, not just about top quarks
- The model's performance depends on the generation of quarks
- We could also include additional information such as charm tagging
- A well tuned model may enable us to do a direct measurement on Cabbibo angle.



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.

Back up

Data preparation

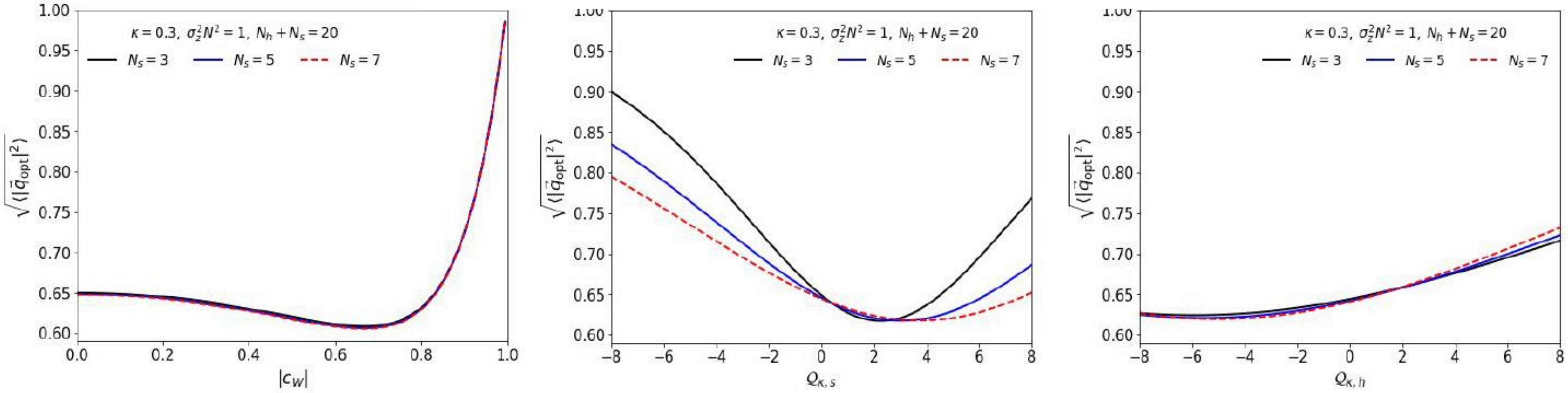
- We generate 14TeV $pp \to t\bar{t} \to \ell^- \nu 2b2j$ events using MG5, with no cuts except for $p_{Tt} > 200$ GeV.
- Three sets of samples where the top quark is unpolarized, left hand polarized and right hand polarized in the $t\bar{t}$ rest frame.
- Parton shower and hadronization are done with 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.
- We match the hadron level jets with true parton level momenta, by using the smallest ΔR between the two.

Analytical results

$$p(\bar{d} \to q_{\text{hard}}|c_W, \mathcal{Q}_{\kappa,h}, N_h, \mathcal{Q}_{\kappa,s}, N_s) = \frac{1}{p(\bar{d} \to q_{\text{hard}}|c_W) + \frac{p(\mathcal{Q}_{\kappa,h}|u \to q_{\text{hard}}, N_h)}{p(\mathcal{Q}_{\kappa,h}|\bar{d} \to q_{\text{hard}}, N_h)} p(u \to q_{\text{hard}}|c_W)}$$

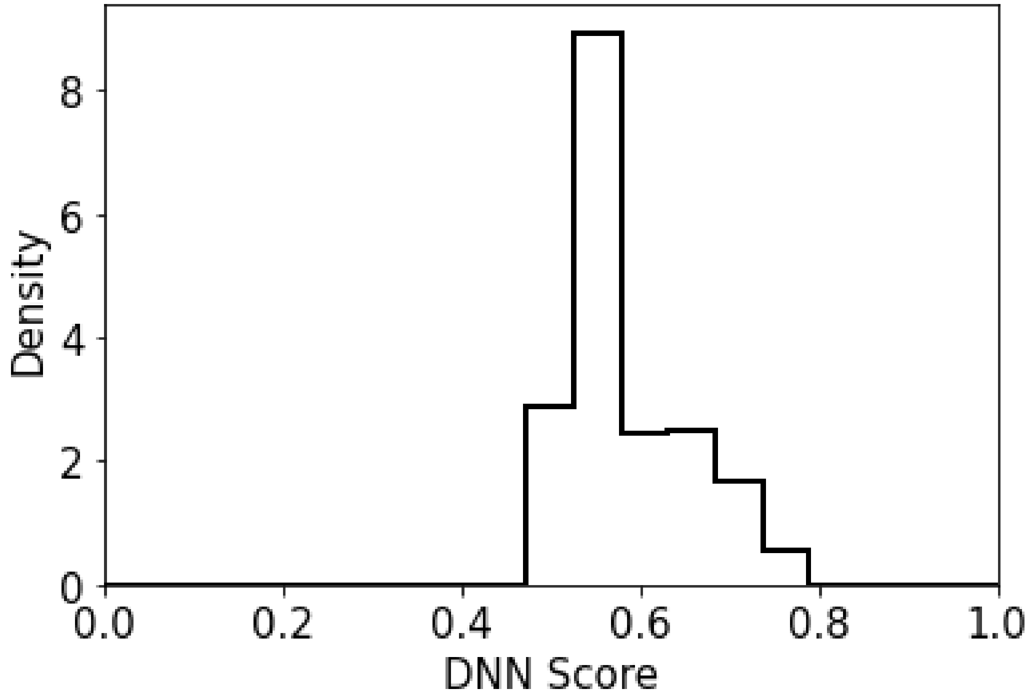
$$\times \frac{1}{\frac{p(\mathcal{Q}_{\kappa,s}|\bar{d} \to q_{\text{soft}}, N_s)}{p(\mathcal{Q}_{\kappa,s}|u \to q_{\text{soft}}, N_s)} p(\bar{d} \to q_{\text{soft}}|c_W) + p(u \to q_{\text{soft}}|c_W)}$$

$$\times\, p(\bar{d} \to q_{\text{hard}}|c_W)\,.$$



DNN

- Using Jets momenta as input
- Total of 20k trainable parameters
- Trained on 200k unpolarized samples
- Tested on 50k right-hand and left-hand polarized samples.



GNN

- Total of 77k trainable parameters
- Trained on 200k unpolarized samples
- Tested on 50k right-hand and left-hand polarized samples.