Identifying Heavy-Flavor Jets Using Vectors of Locally Aggregated Descriptors

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Based on **JINST 16 (2021) 03, P03017**

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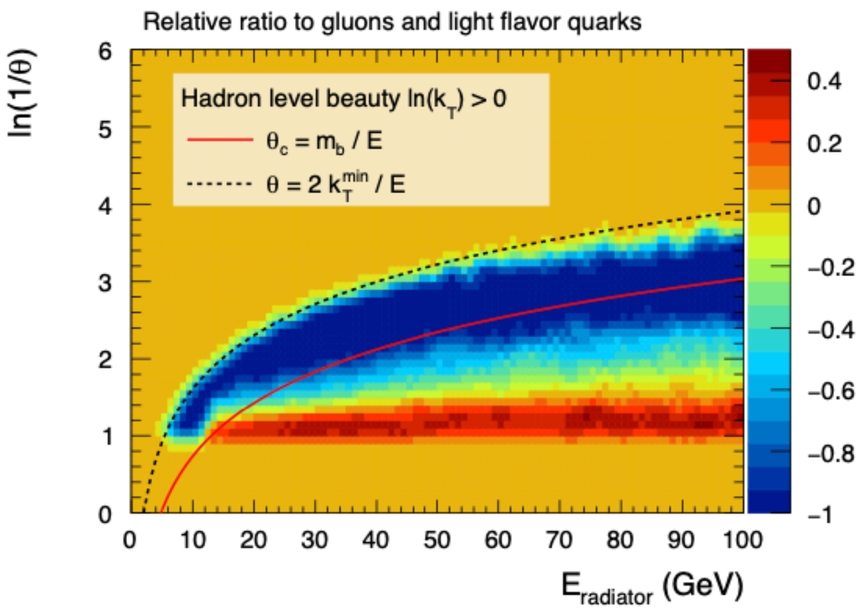
Why Heavy-Flavor Jets?

Generally, heavy-flavor jets are an important class of observables in itself

Measuring jet substructure of low-p_T heavy-flavor jets is an exciting measurement in physics, since it can answer

- Change in radiation patterns of heavy-quarks (so-called dead-cone effect)
- Mass dependence of QCD splitting functions
- Mass dependence of jet energy loss in nuclear medium



L. Cunqueiro, M. Płoskoń, Phys.Rev.D 99 (2019) 7, 074027

Rethinking Heavy-Flavor Jet Tagging

What is a jet?

- Event – a set of particle **state vectors**

$$\mathcal{E} = \{\mathbf{r}_i | i \in \{1, \dots, n\}, \mathbf{r}_i = (p_i^\mu, v_x, v_y, v_z, \dots)\}$$

- Jet – a subset of event identified by the jet clustering algorithm
- Without assuming jet substructure, jet is a **set of tracks**
- And we wish to take a **set of tracks** as an input to the tagging algorithm
- In Computer Vision there is an approach that might help us – **NetVLAD**
  - **For each set it generates a fixed-size vector** that characterizes it

NetVLAD: CNN architecture for weakly supervised place recognition

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Place Localization

Place of interest

(a) Mobile phone query (b) Retrieved image of same place

Variable number of other objects

Rethinking Jet Tagging Paradigm

Why is NetVLAD good solution?

- It operates on so-called descriptors (high-level feature vectors coming from the last layer of CNN)
- It is resistant to noise (due to variable number of objects in place localization)

Thus we introduce particle descriptors

- In jet physics all measured variables are high level and we do not need feature extractor (i.e. CNN)
- Hence, we can assume that our state vectors are descriptors

Dataset Generation

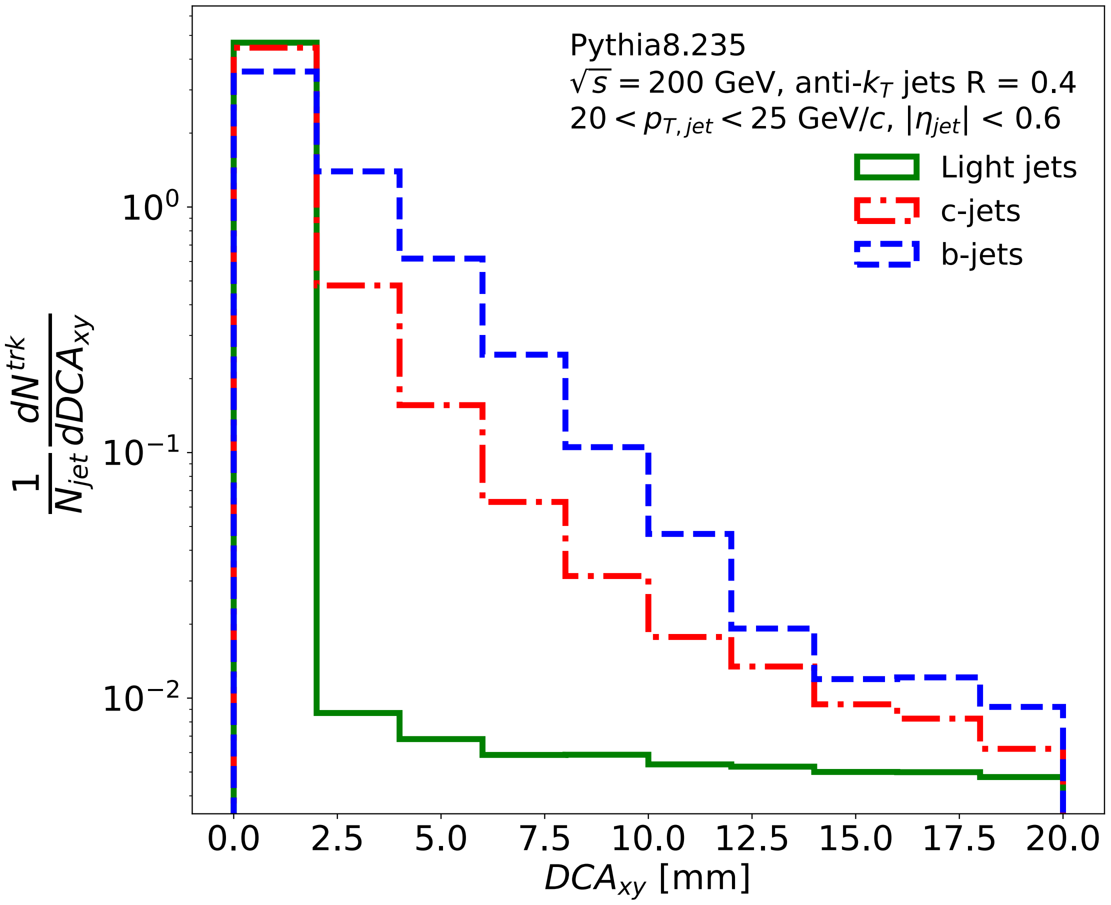
Pythia8.235 was used to generate data

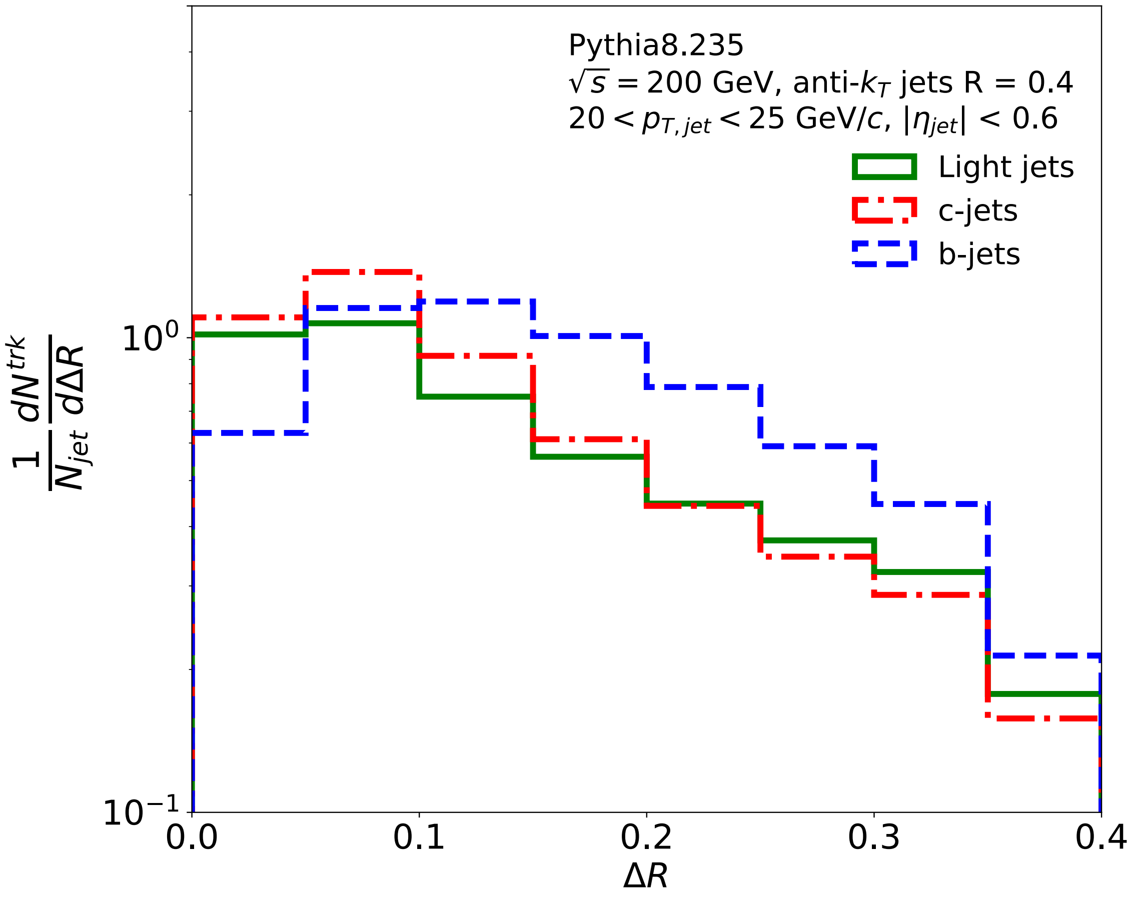
- 2 datasets are generated:
    - Weighted - that respects realistic jet flavor ratio
    - Balanced – 50% udsg-jet, 25% c-jet and 25% b-jet
- We separate datasets into two classes – udsg vs HF jets – which is better suited for RHIC physics
- The fast-sim approach is used to simulate finite resolutions:
    - Gaussian smearing of p_T is used in order to account for finite TPC resolution
    - Resolution of the STAR HFT is used to smear vertex information

Input Features

Type	Inputs	Definition
Tracking	p_T	Transverse momentum in the $x - y$ plane
	η	pseudorapidity
	ϕ	azimuthal angle
Fragmentation	z	momentum fraction $\frac{p_T^{track}}{p_T^{jet}}$
	ΔR	distance between track and jet axis $\sqrt{\Delta\phi^2 + \Delta\eta^2}$
	$z\Delta R^2$	higher level feature
Secondary Vertex	DCA_{xy}	Distance of closest approach in $x - y$/
	DCA_z	Distance between primary and secondary vertex in the z axis

Input Feature Distributions for 20-25 GeV/c Jets





Model Architecture

Symbolically the whole model can be described as

$$\mathrm{JetVLAD} = \mathrm{NetVLAD}(N_C) \rightarrow D \times [\mathrm{ResidualBlock}] \rightarrow \mathrm{SoftMax}$$

- Whole network has only two free hyperparameters – number of NetVLAD clusters N_c and depth D
- We use fully-connected ResNet-style blocks, since they lead to faster optimization
- 50% drop-out is also applied to increase model generalization

We optimize model by SGD with cosine-annealed learning rate

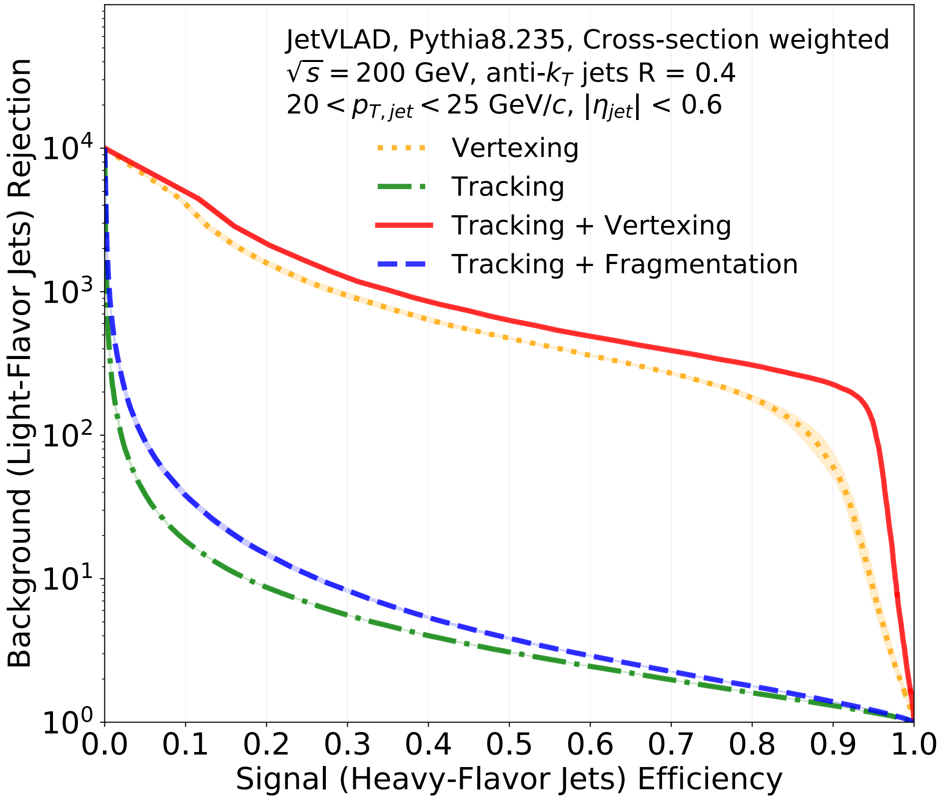
Performance Metrics

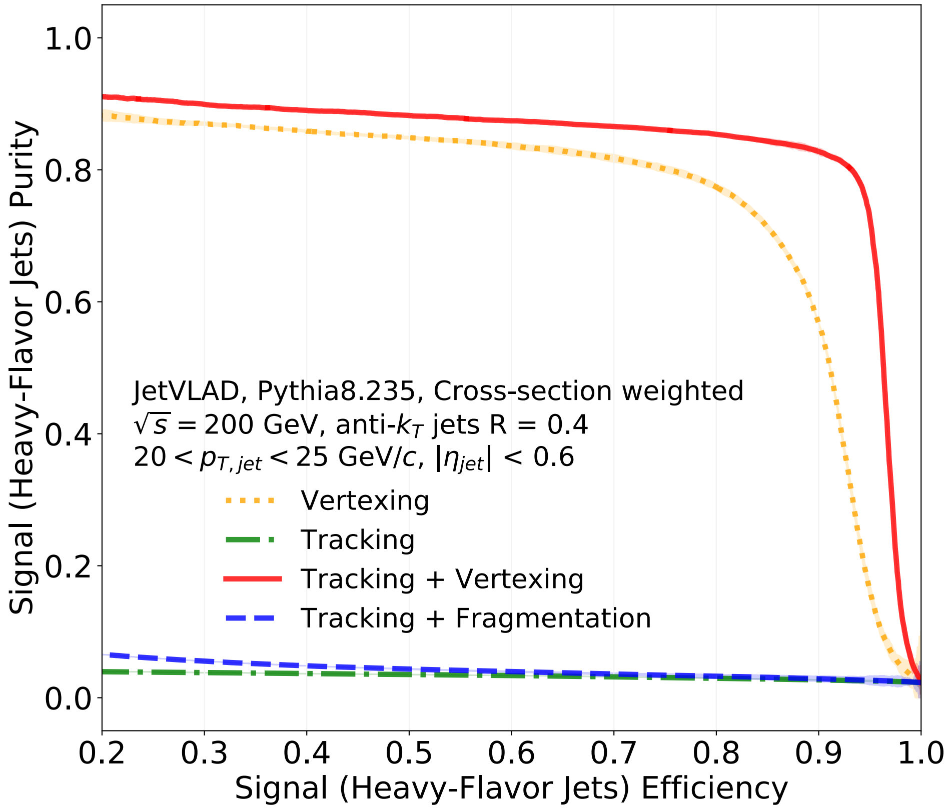
Physics	Machine Learning	Definition
Tagging Efficiency	True Positive Rate (TPR)/Recall	$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{P}}$
Misidentification Prob.	False Positive Rate (FPR)	$\mathrm{FPR} = \frac{FP}{N}$
Background Rejection		$\mathrm{REJ} = \frac{1}{\mathrm{FPR}}$
Signal Purity	Precision	$\mathrm{PREC} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$

Finding Optimal Input Variables

The following tagger versions are constructed:

- Vertexing - $\left(\mathrm{DCA_z}, \mathrm{DCA_{xy}}\right)$
- Tracking - (p_T, η, φ)
- Tracking + Fragmentation - $(p_T, \eta, \varphi, z, \Delta R, z(\Delta R)^2)$
- **Tracking + Vertexing - $\left(\boldsymbol{p_T}, \boldsymbol{\eta}, \boldsymbol{\varphi}, \mathbf{DCA_z}, \mathbf{DCA_{xy}}\right)$ - the optimal choice**

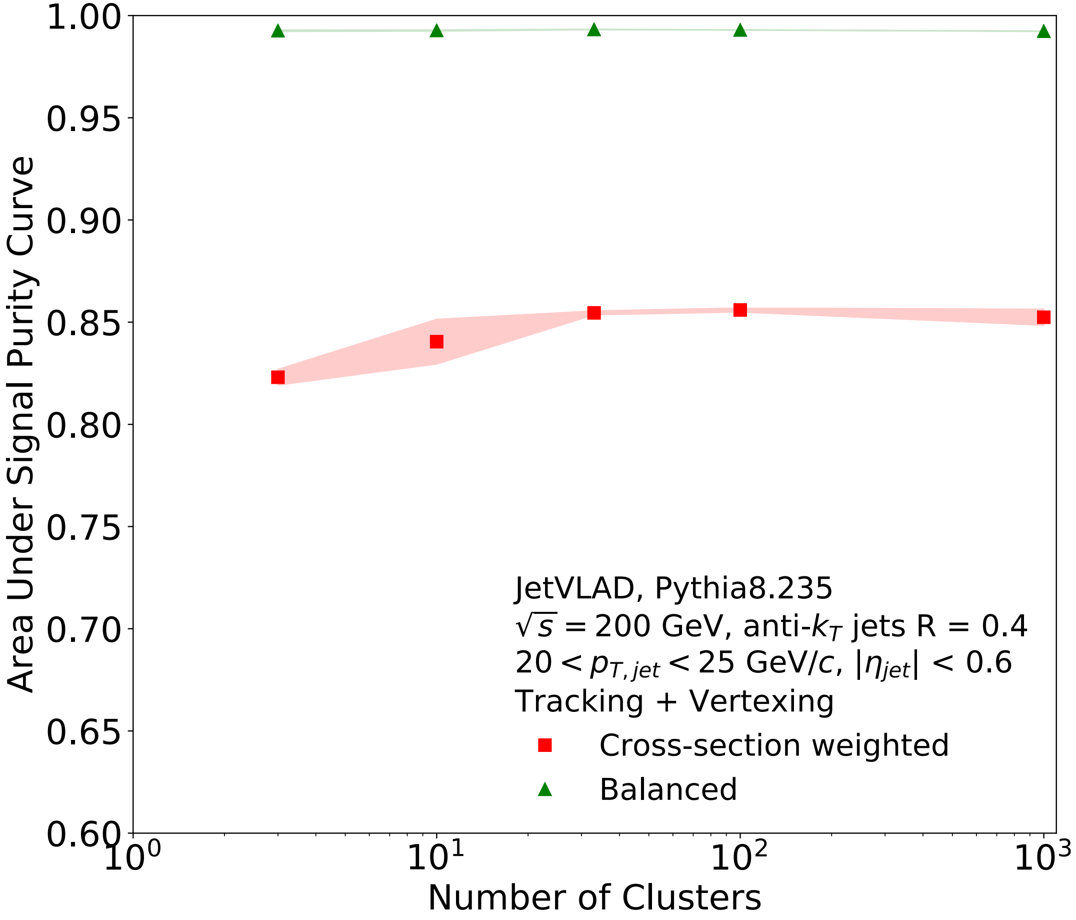


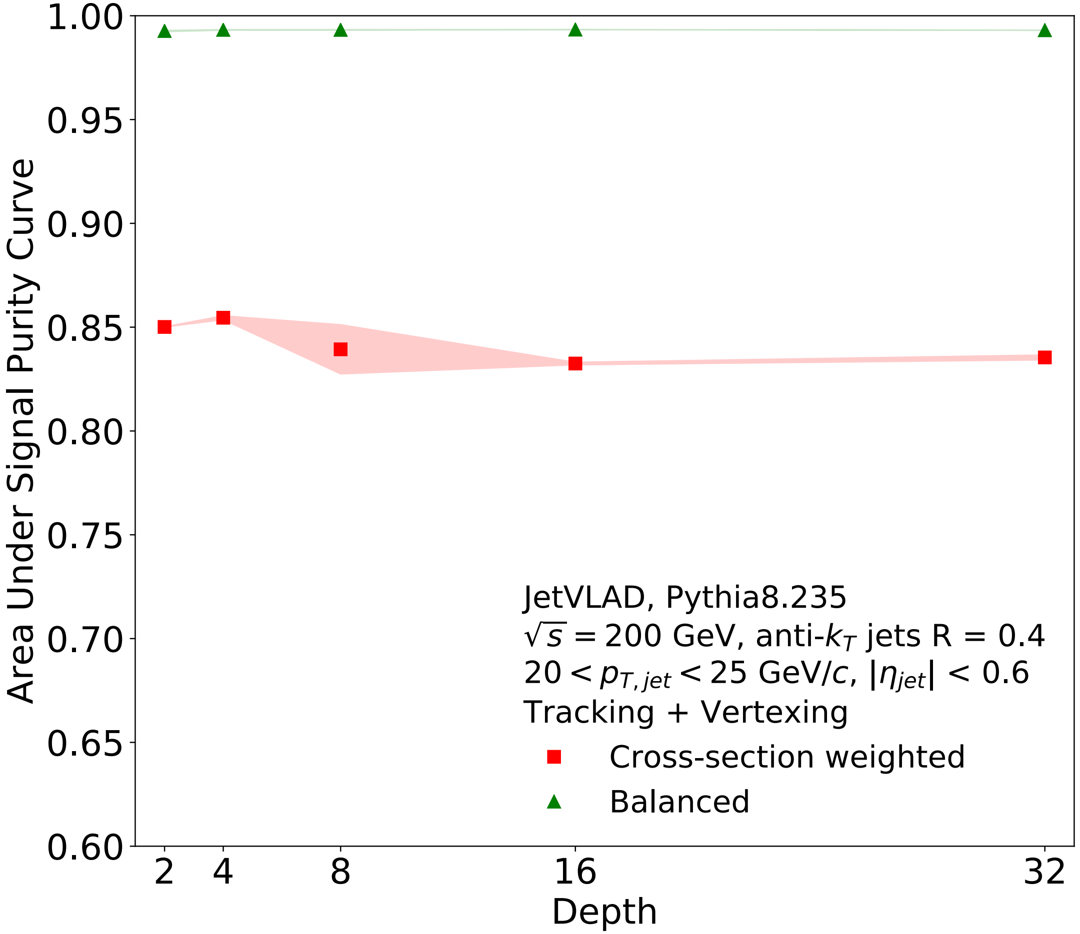


Finding Optimal Hyperparameters

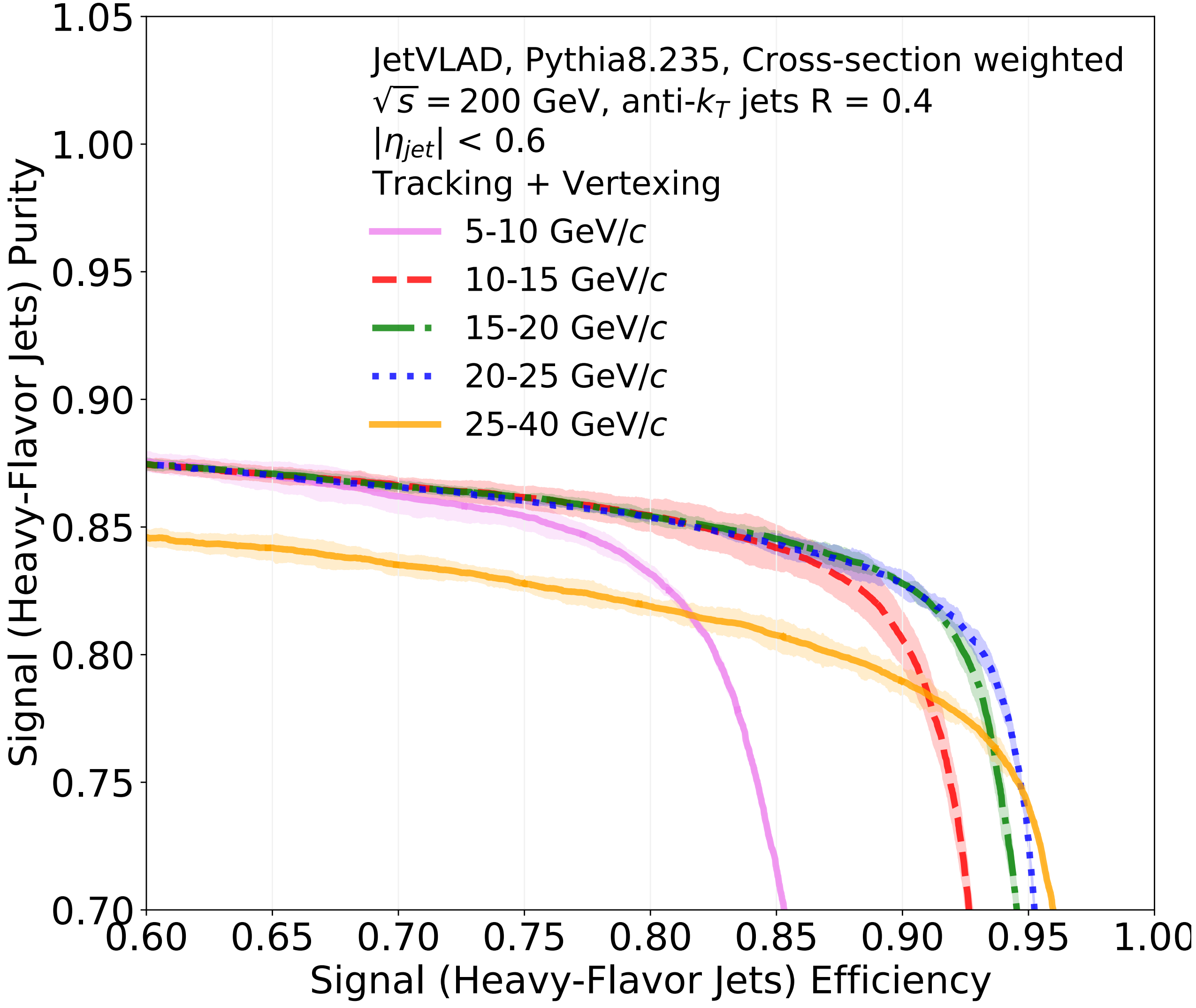
The optimal hyperparameters were found by running random grid search on depth D and number of clusters N_c and we obtain $N_c = 33$ and $D = 4$

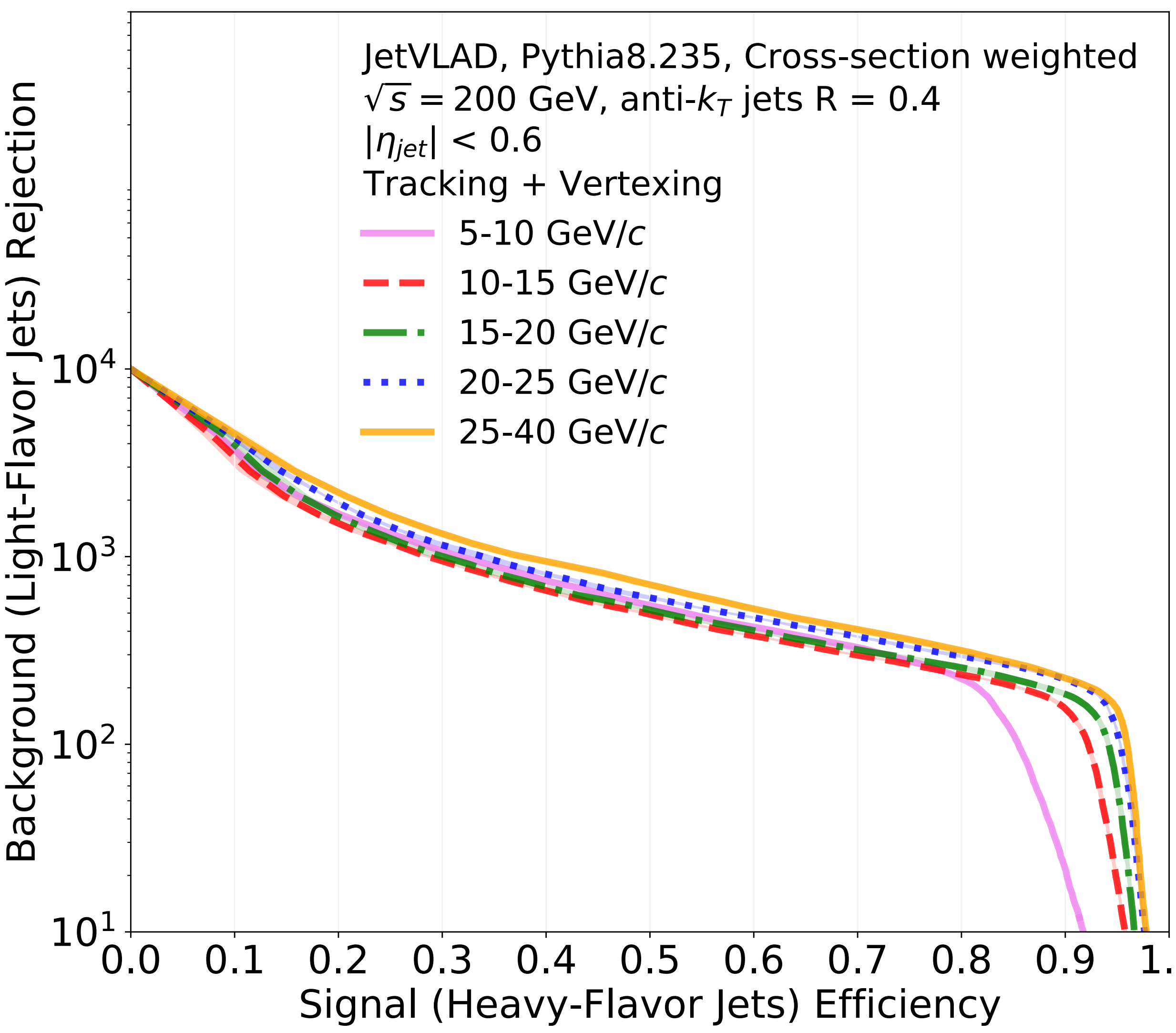
- It is important then to estimate sensitivity of hyperparameters with respect to model performance
- We do so by running hyperparameter sensitivity scan – fixing one and varying another





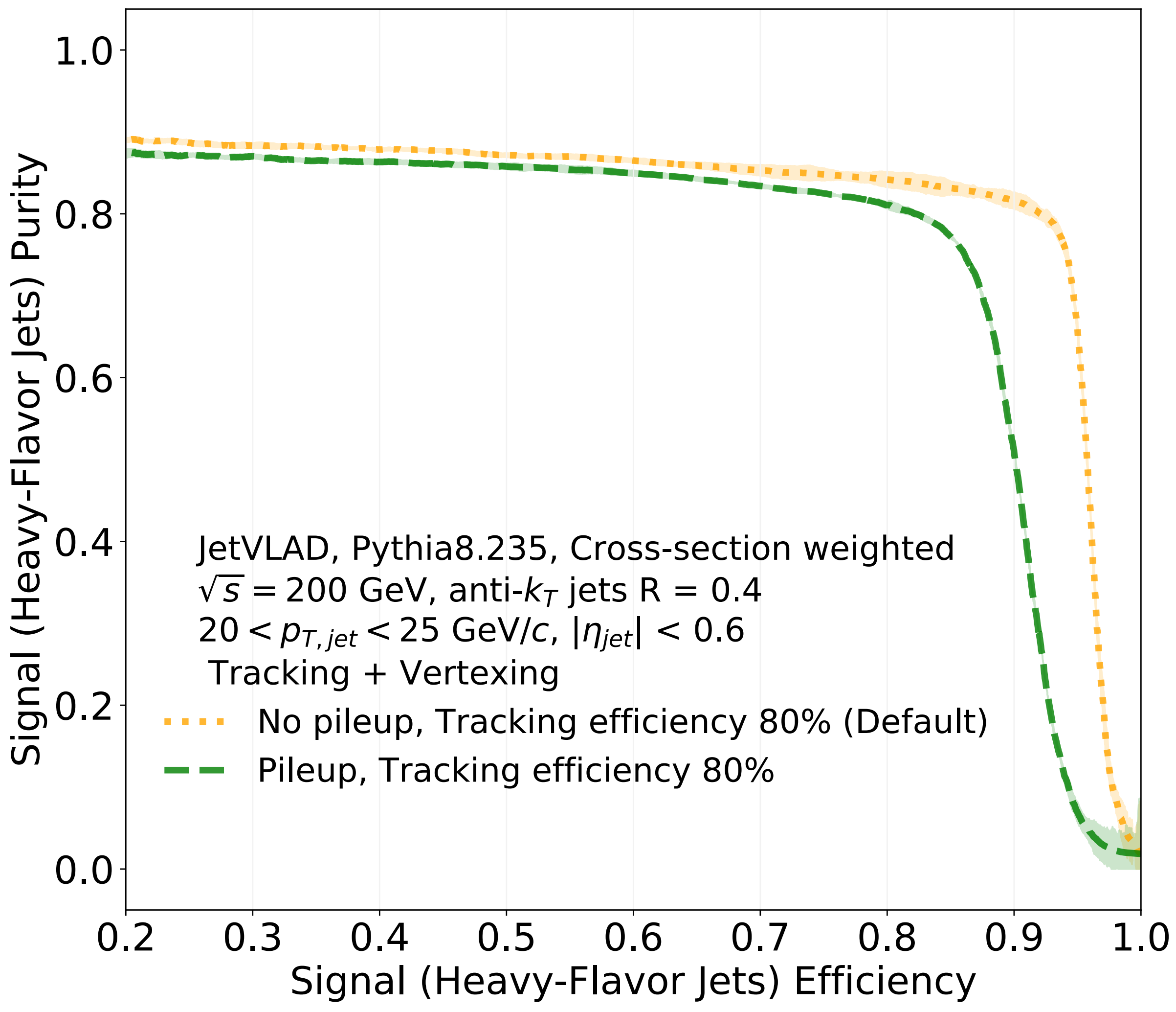
Jet p_T Dependent Rejection and Purity Graphs

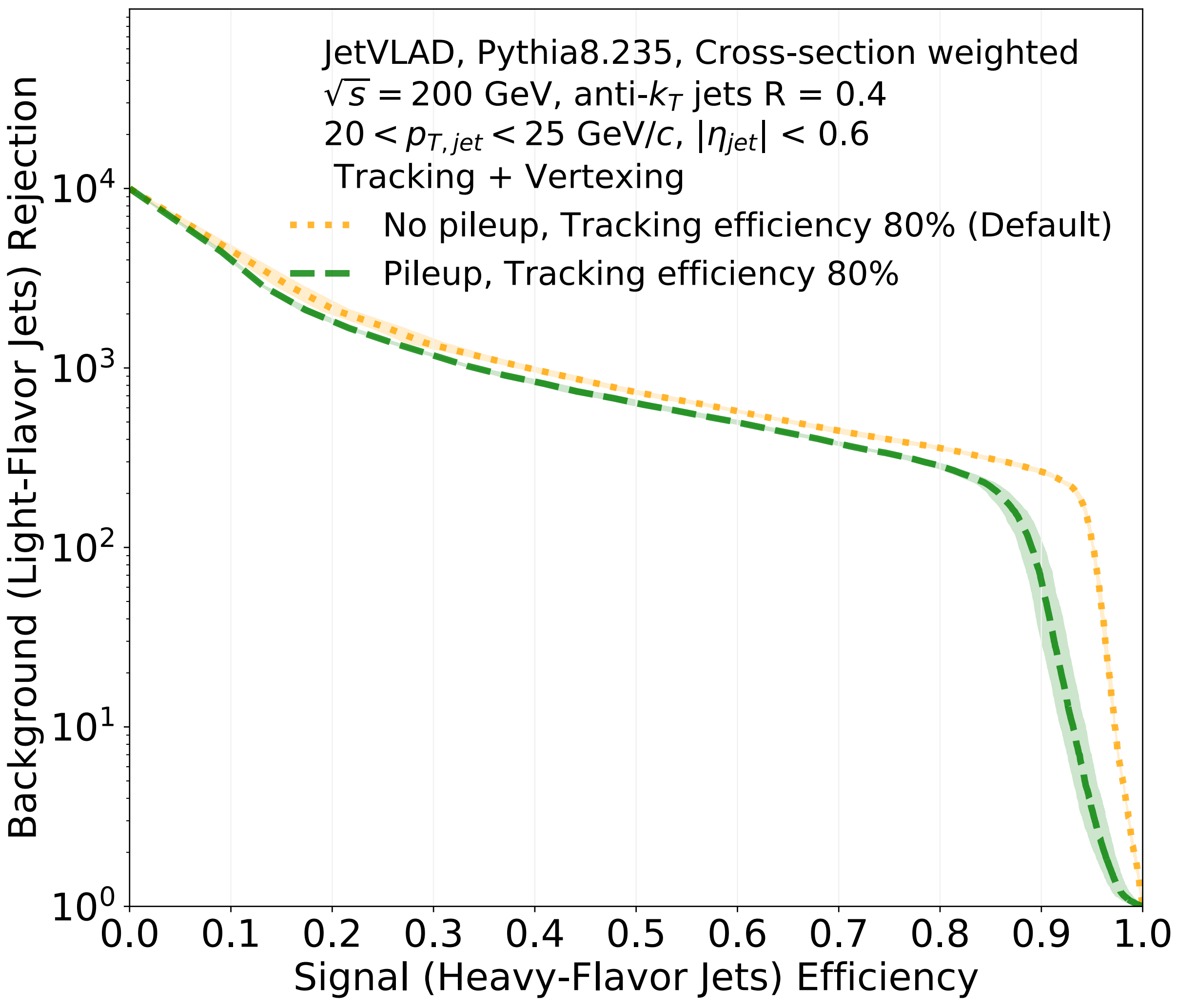




Our architecture achieves good performance across different p_T ranges

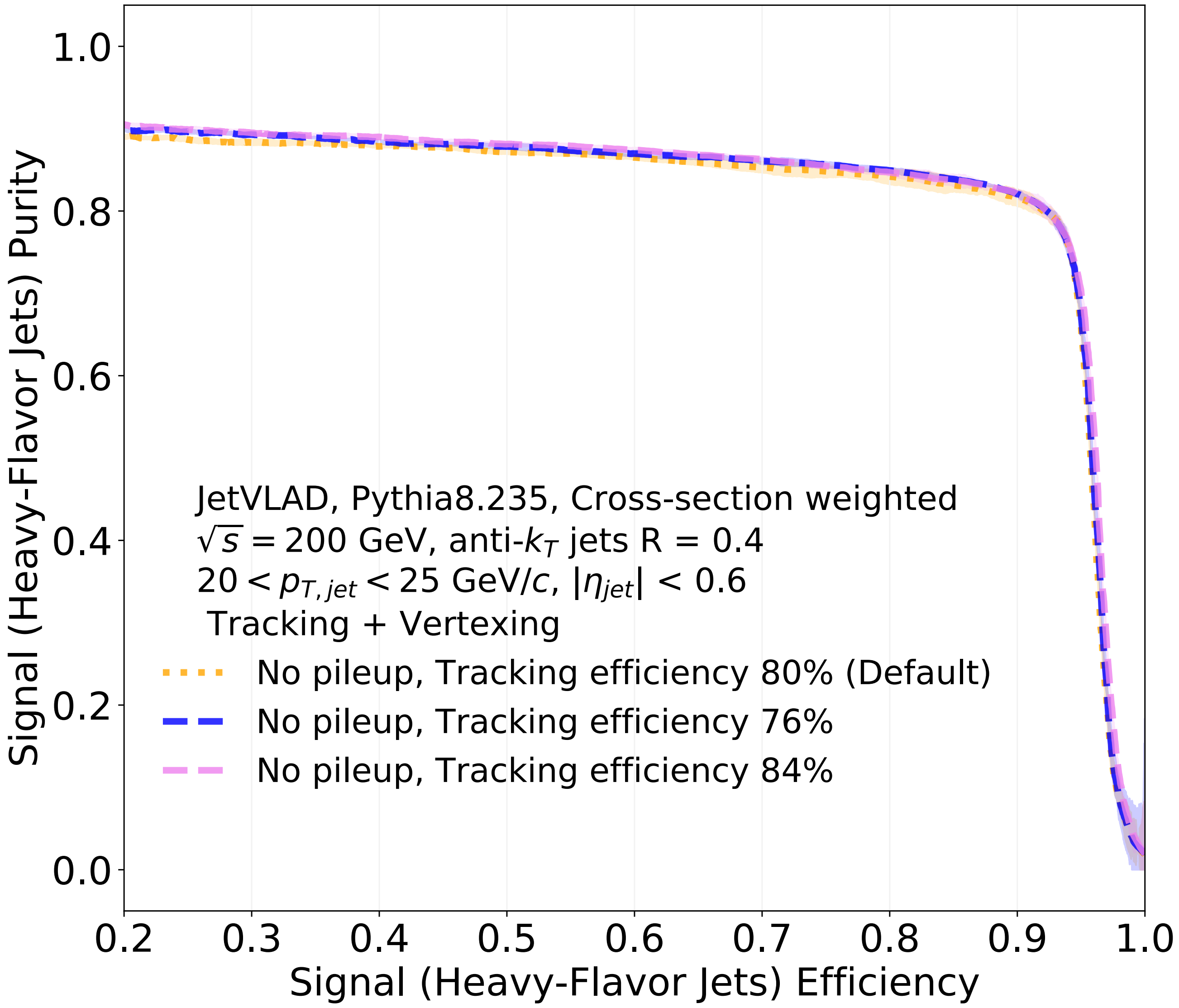
How is Pileup Influencing the Model?

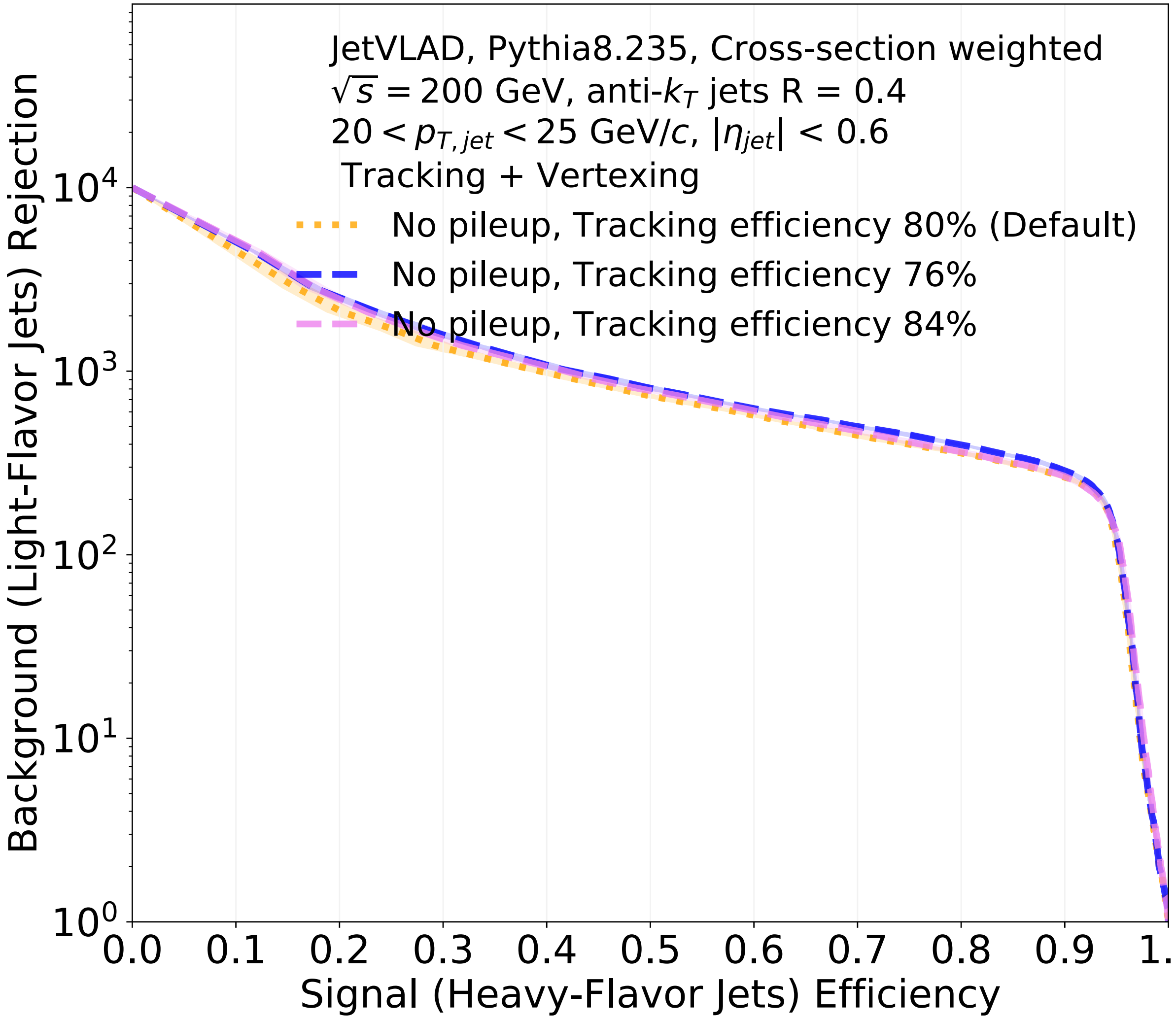




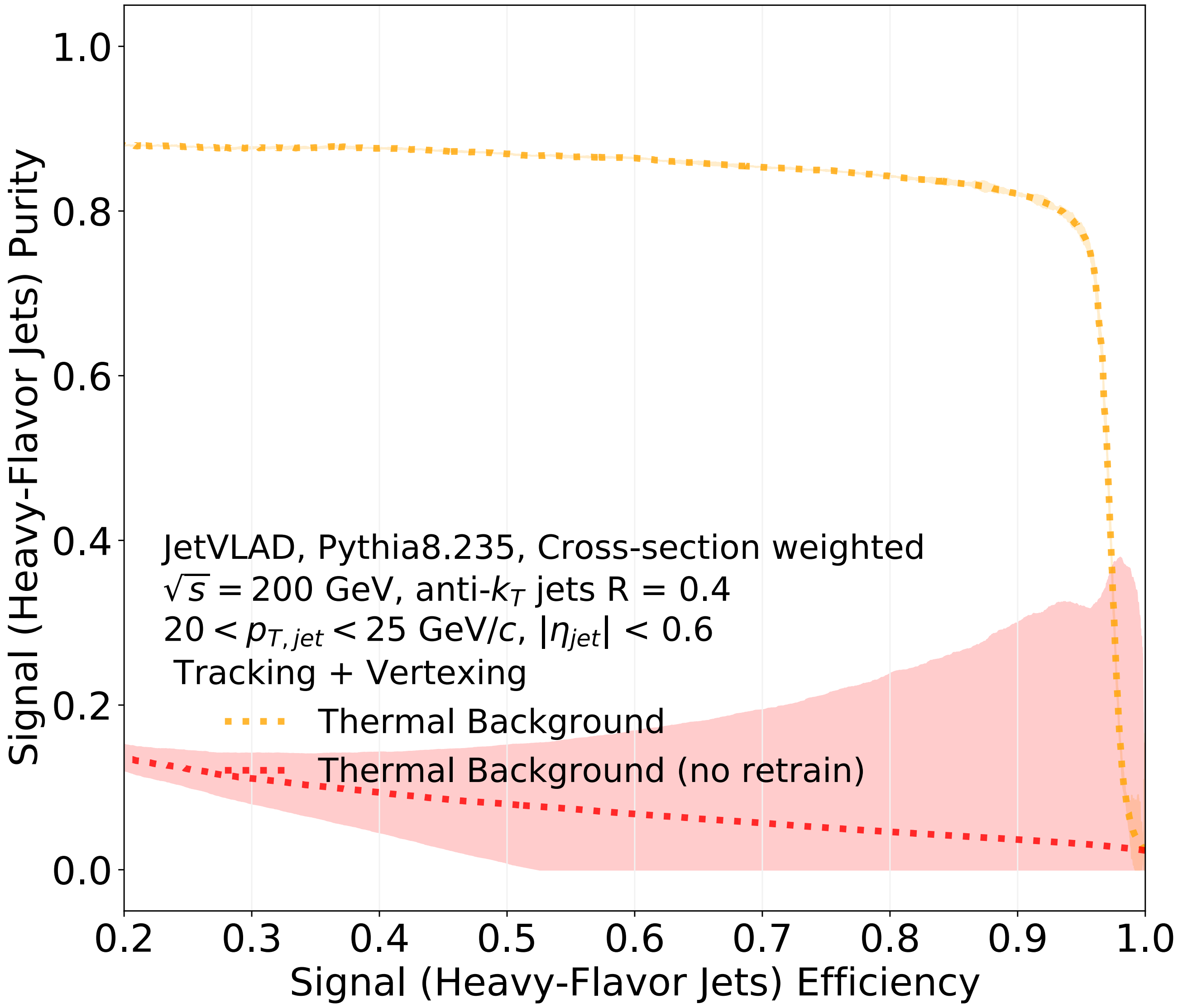
Add random min-bias event at random z position

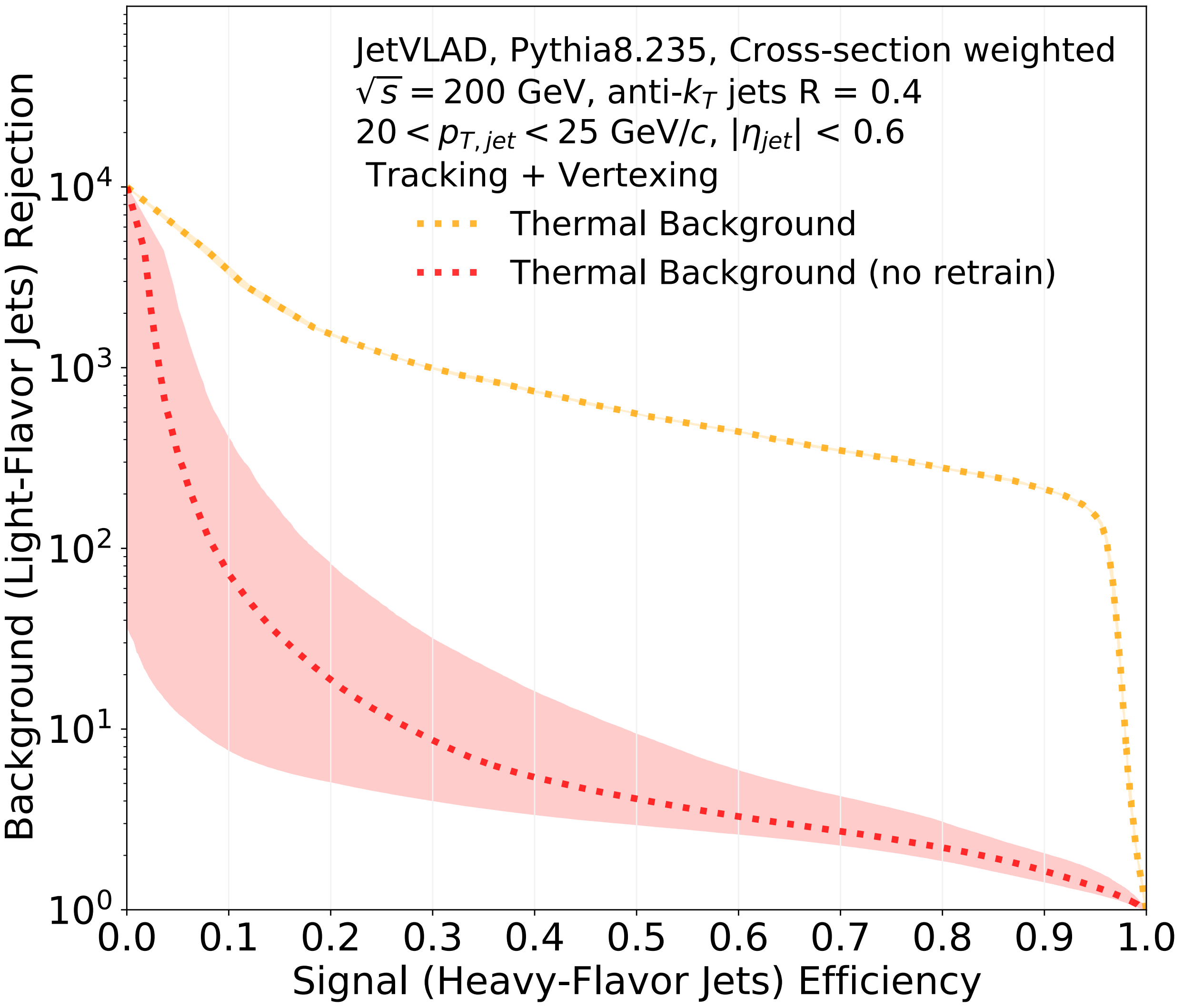
How is Tracking Efficiency Influencing the Model?





How is Thermal Backgrdoun Influencing the Model?





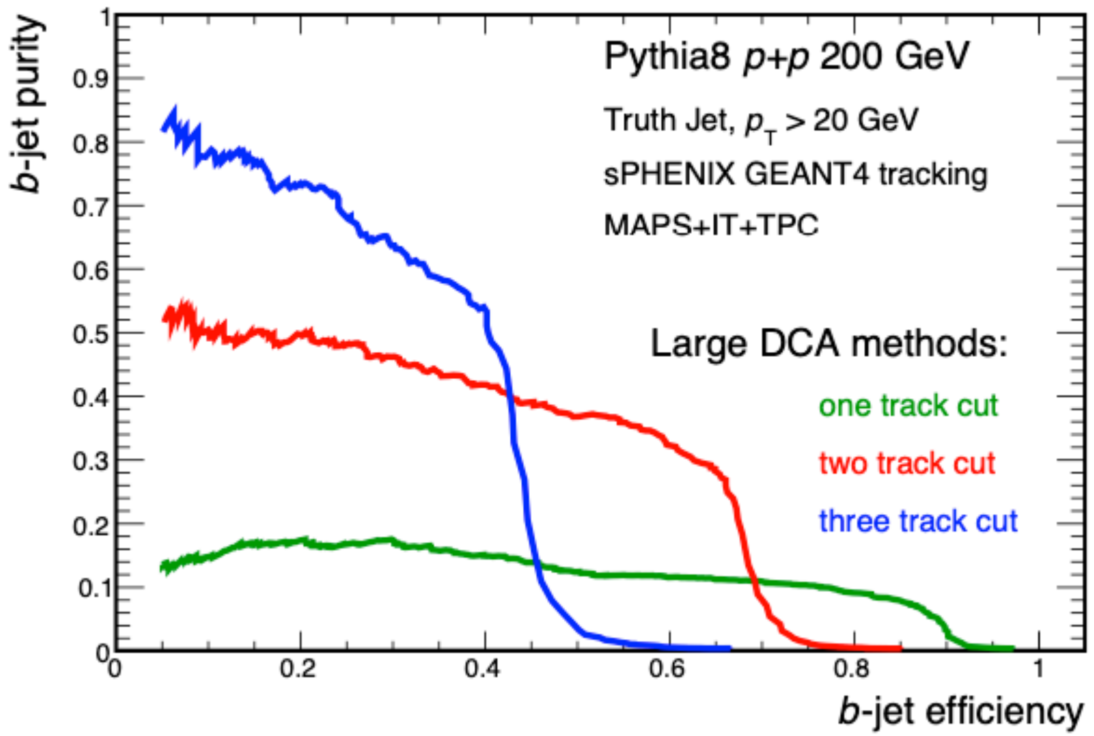
Conclusions

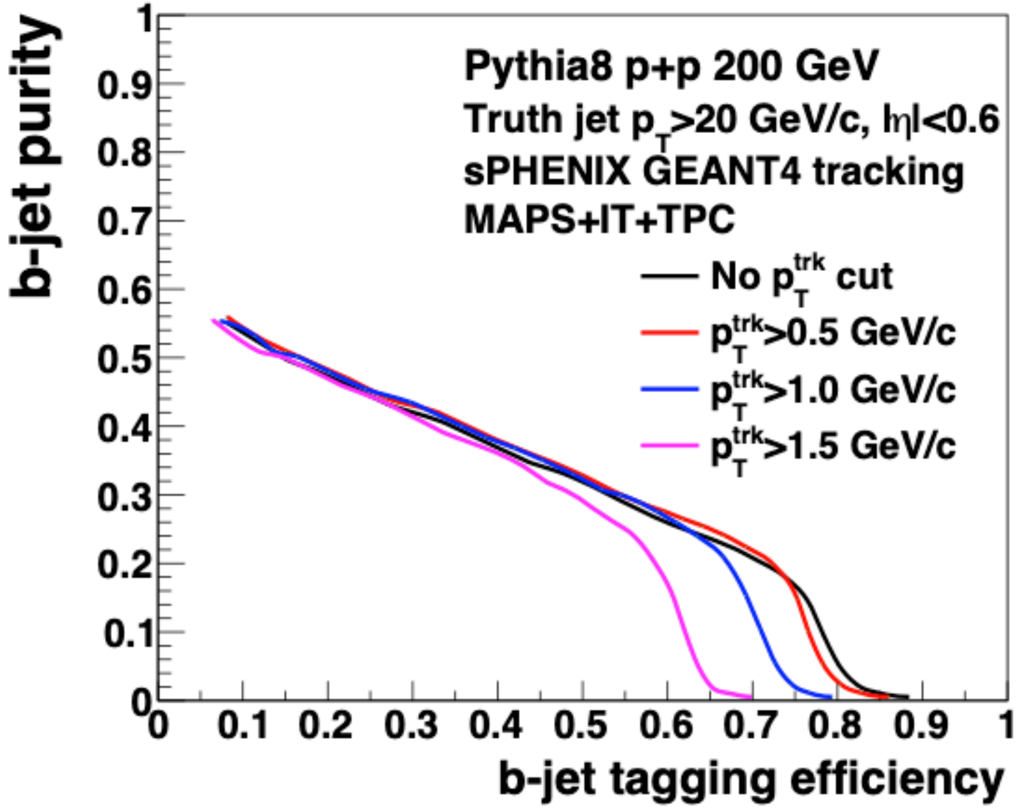
- We propose a novel set-based tagging method based on the NetVLAD layer
- The model allows to identify heavy-flavor jets down to the low-p_T at RHIC energies
  - Purity of $\sim 80\%$, Efficiency of $\sim 80\%$ and rejection factor of ~ 200 is achievable for low-p_T jet
  - This enables searches for signatures of heavy-flavor jet radiation patterns
- The NetVLAD layer is a general aggregation layer with many possible applications such as:
  - Jet similarity search
  - γ/π^0 discrimination
- We are investigating self-supervised and unsupervised learning applications of JetVLAD
  - Consistency cycles
  - Contrastive learning
  - Goal – to build multimodal jet-event feature space for fast similarity search of events/jets

https://github.com/ponimatkin/NetVLAD-tagger-pytorch

Thank you for your attention!

Backup: Performance of Classical Methods



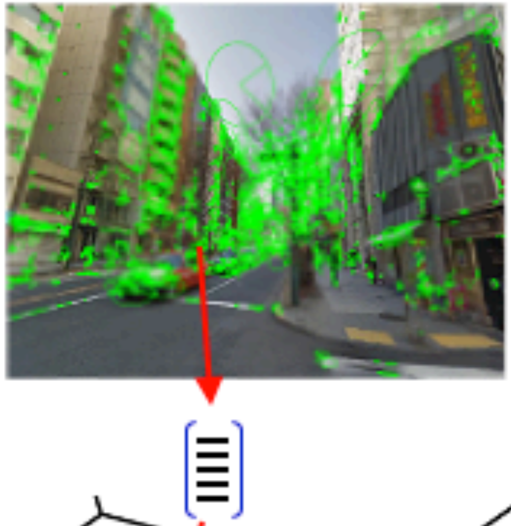


Taken from: “A monolithic active pixel sensor detector for the sPHENIX experiment”

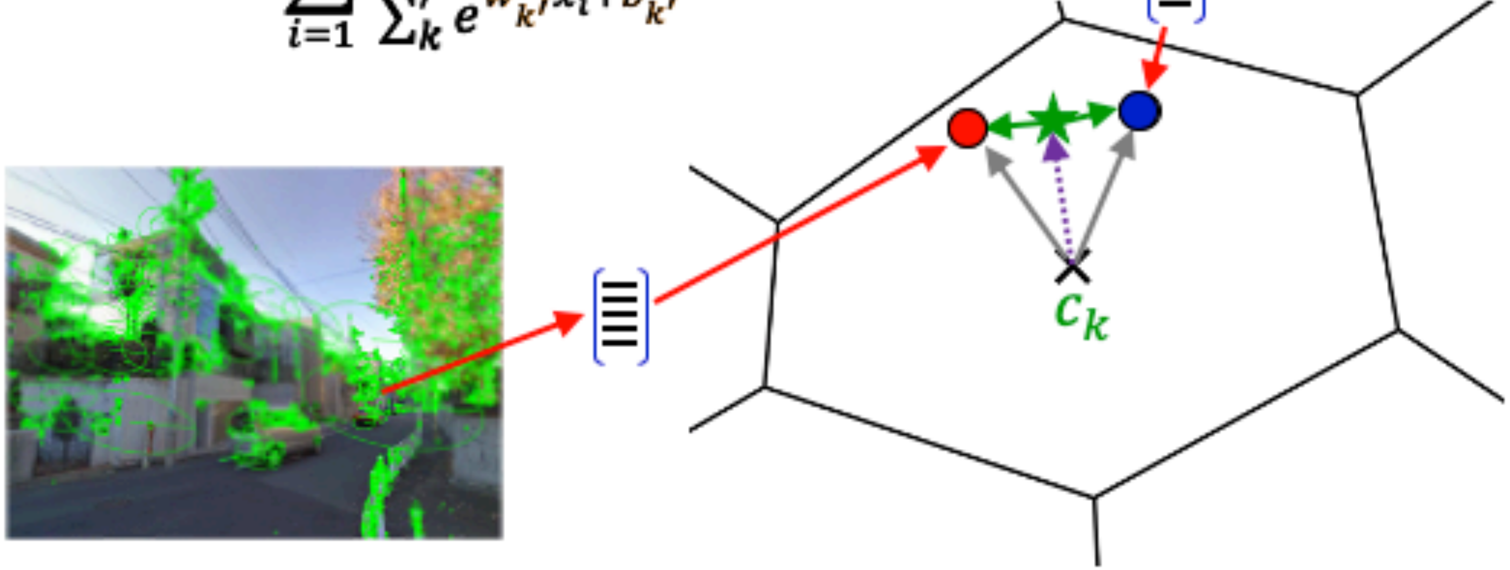
Backup: NetVLAD Principle

NetVLAD: Trainable pooling layer

Decouple assignment (w_k b_k) from anchor point c_k



$$V(:,k) = \sum_{i=1}^{N} \frac{e^{w_k^T x_i + b_k}}{\sum_{k'} e^{w_{k'}^T x_i + b_{k'}}} (x_i - c_k)$$



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