Machine Learning for Jet Physics

Sung Hak Lim
Theory Center, KEK

KAIST-KAIX Workshop for Future Particle Accelerators
July 2019

S. H. Lim, M. M. Nojiri, arXiv:1807.03312, JHEP10(2018)181.
A. Chakraborty, **S. H. Lim**, M. M. Nojiri, arXiv:1904.02092, accepted in JHEP.
A. Chakraborty, **S. H. Lim**, M. M. Nojiri, M. Takeuchi, in preparation.

Interpretable Machine Learning for Jet Physics

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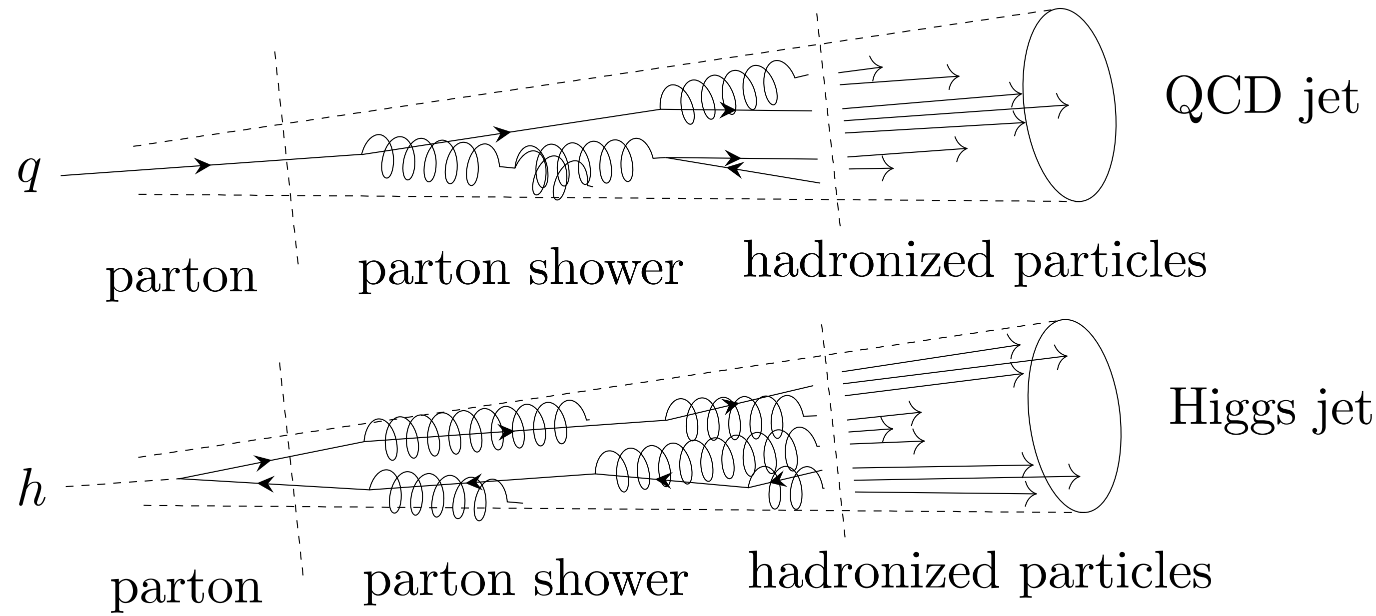
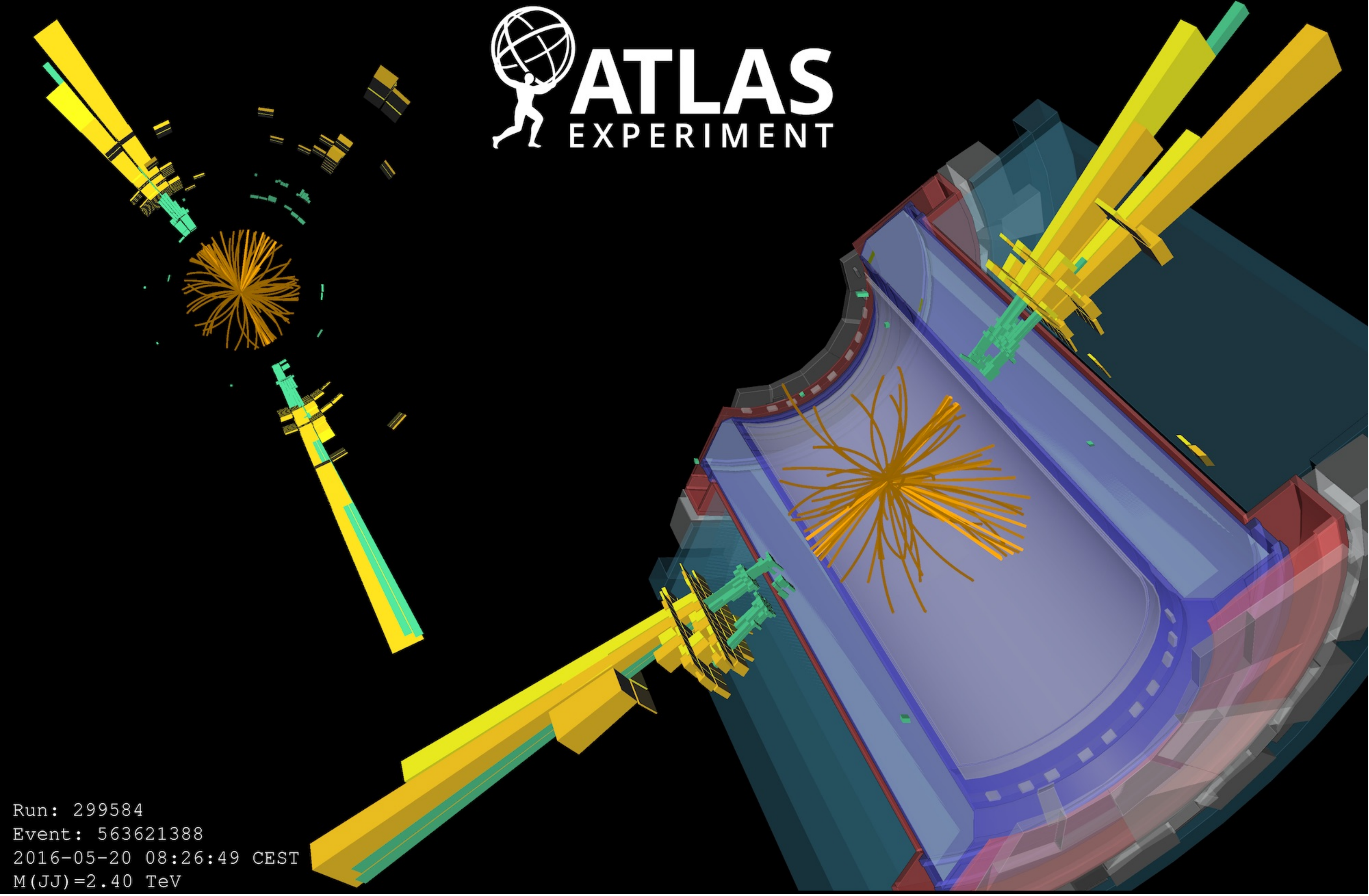
Boosted Jets:
Jets have substructure!

- As LHC stacking up multi TeV center-of-mass energy events, boosted heavy particles is produced and forms a single collimated cluster of particles similar to the QCD jets. ($m_{\mathrm{EW}}/\sqrt{\hat{s}} \approx \mathcal{O}[0.1]$)



- We will see more and more these boosted jets!

<u>**LHC**</u>		<u>**HE-LHC**</u>		<u>**FCC**</u>
14 TeV	→	27 TeV	→	100 TeV



https://atlas.cern/updates/physics-briefing/hunting-new-physics-boosted-bosons

Classification of Jets

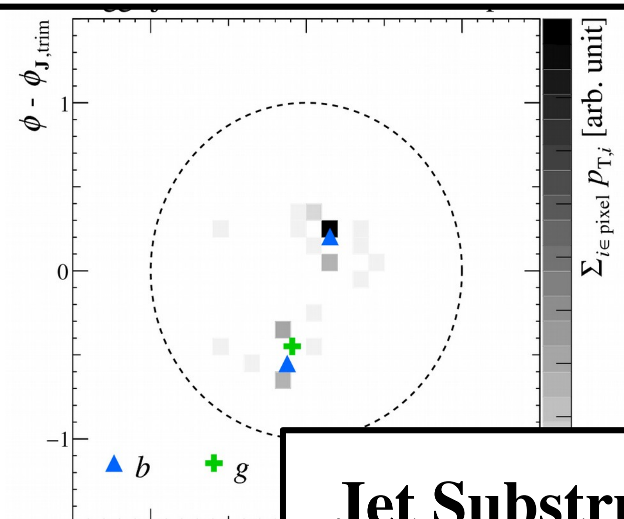
- We want a quick and reliable method for classifying those jets.
- Thanks to the development in physics and computer science…

Theoretical Understanding of QCD

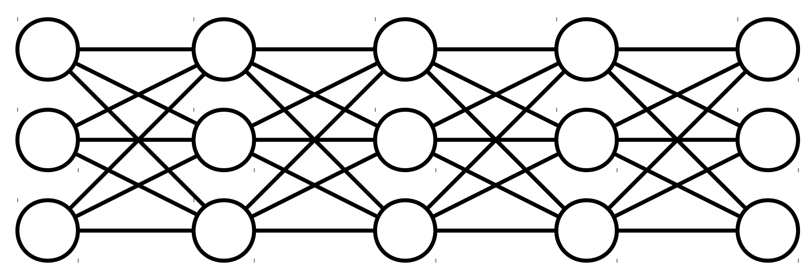
Development of Machine Learning

Huge Experimental Data

More Computational Power



<u>Jet Substructure</u>



<u>Deep Learning</u>

Classification Problem with Images

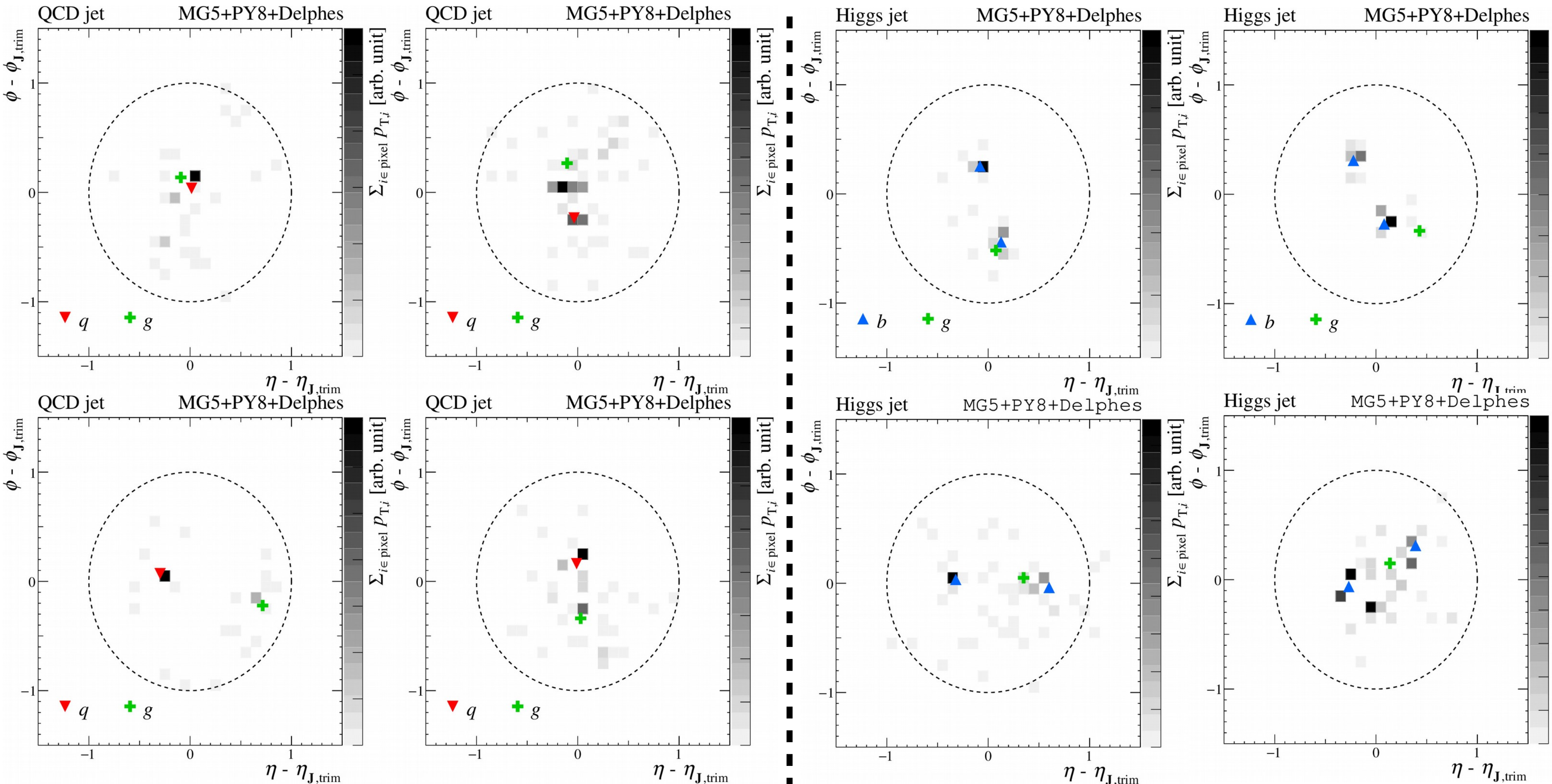
Can you distinguish cats and dogs from **pictures**?

Cats (?)

Dogs (?)

Classification Problem with Jet Images

Can you distinguish <u>QCD jets</u> and <u>Higgs jets</u> from **reconstructed particles**?

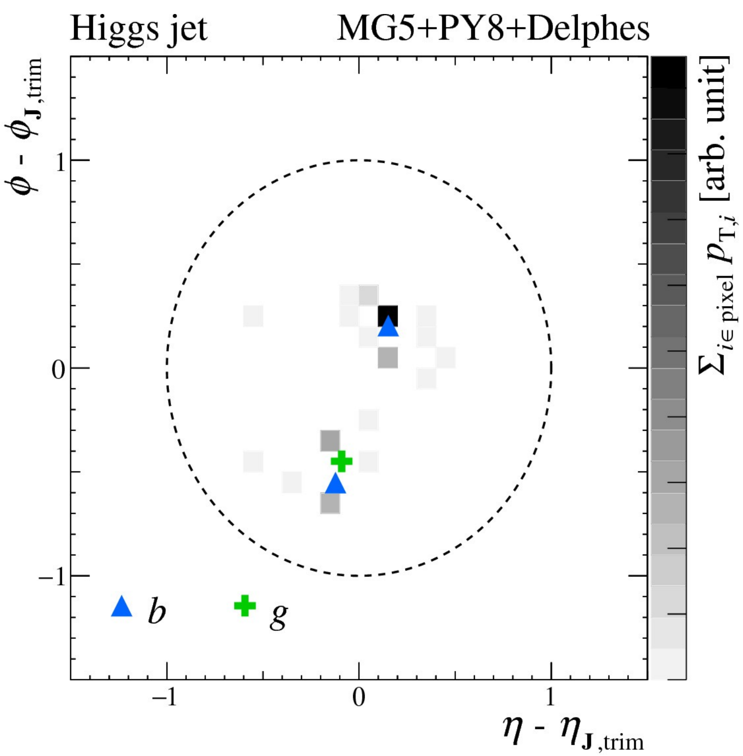


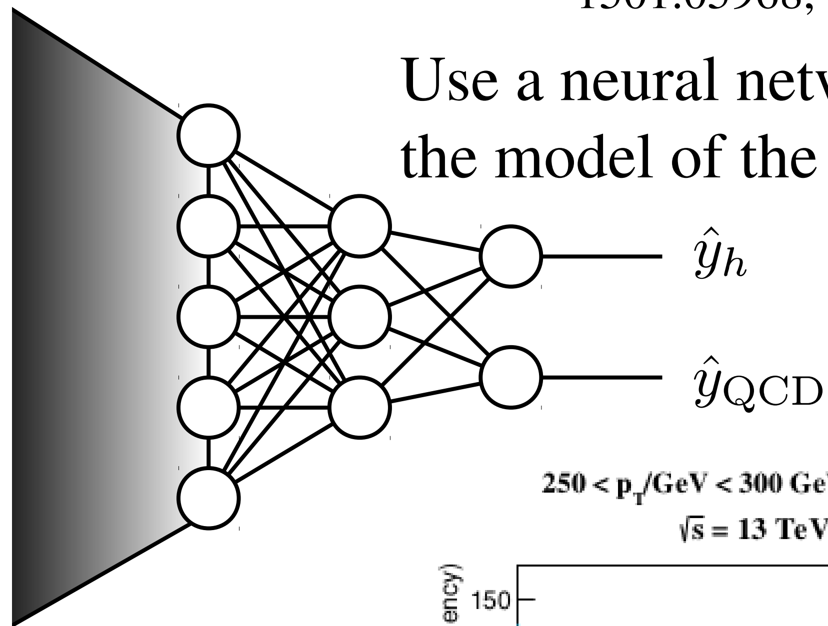
QCD jets

Higgs jets

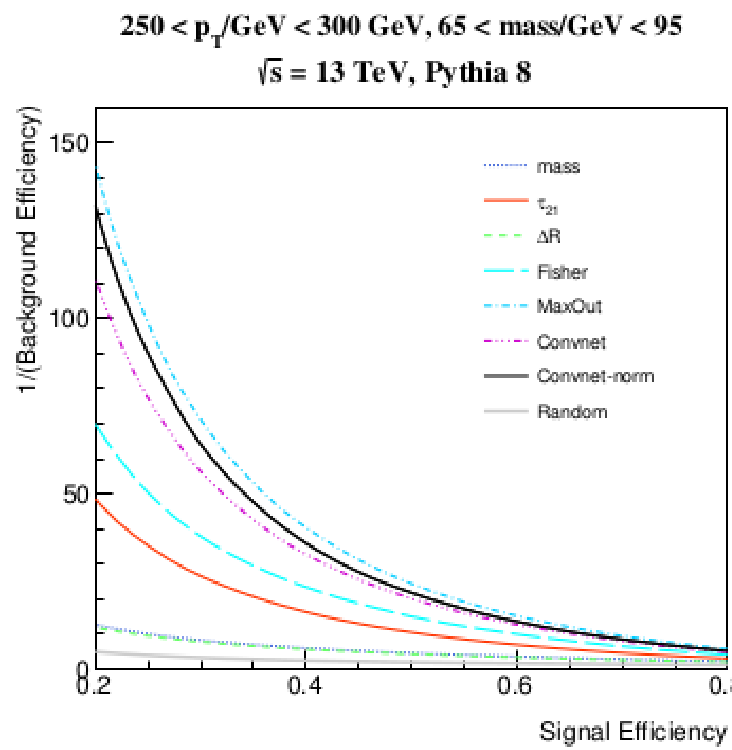
Classification with Jet Images

1501.05968, 1511.05190





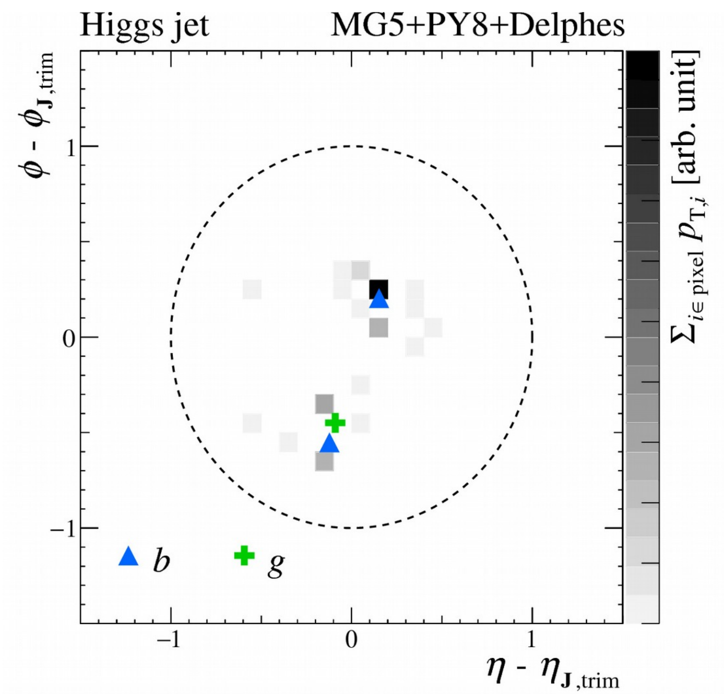
Use a neural network as the model of the classifier

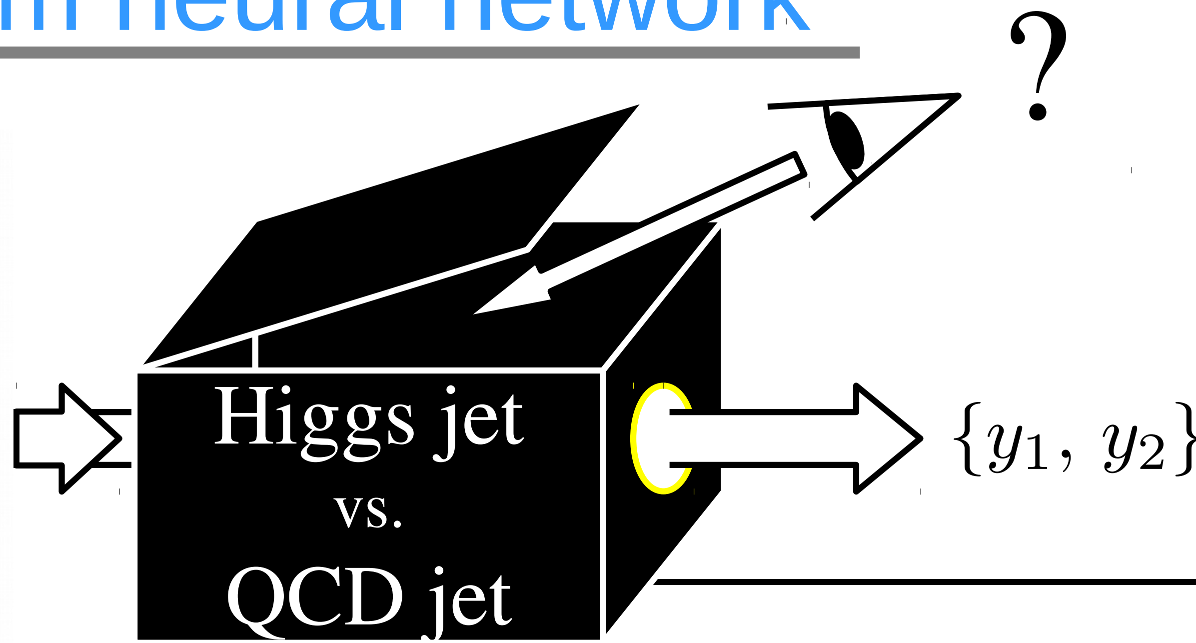


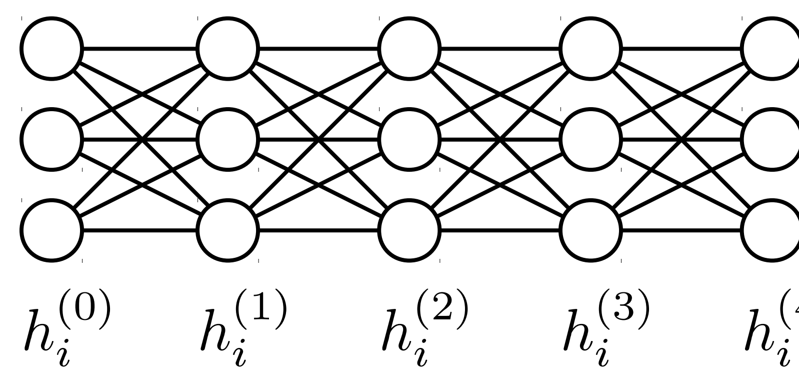
Deep learning is more powerful than a few physics motivated classifiers!

Disclaimer: physics motivated classifiers use particular features only.

Difficulties on understanding the results from neural network

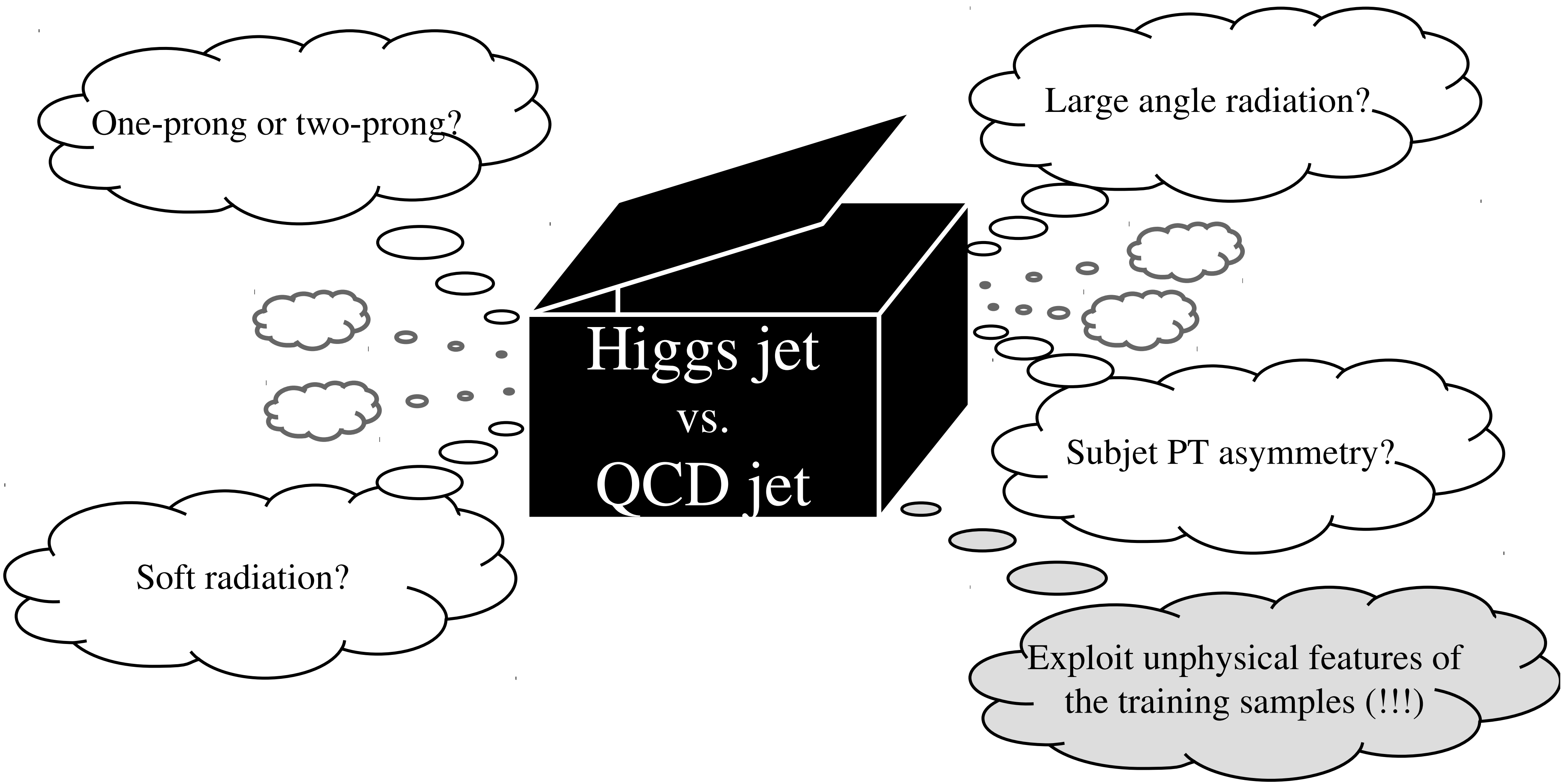






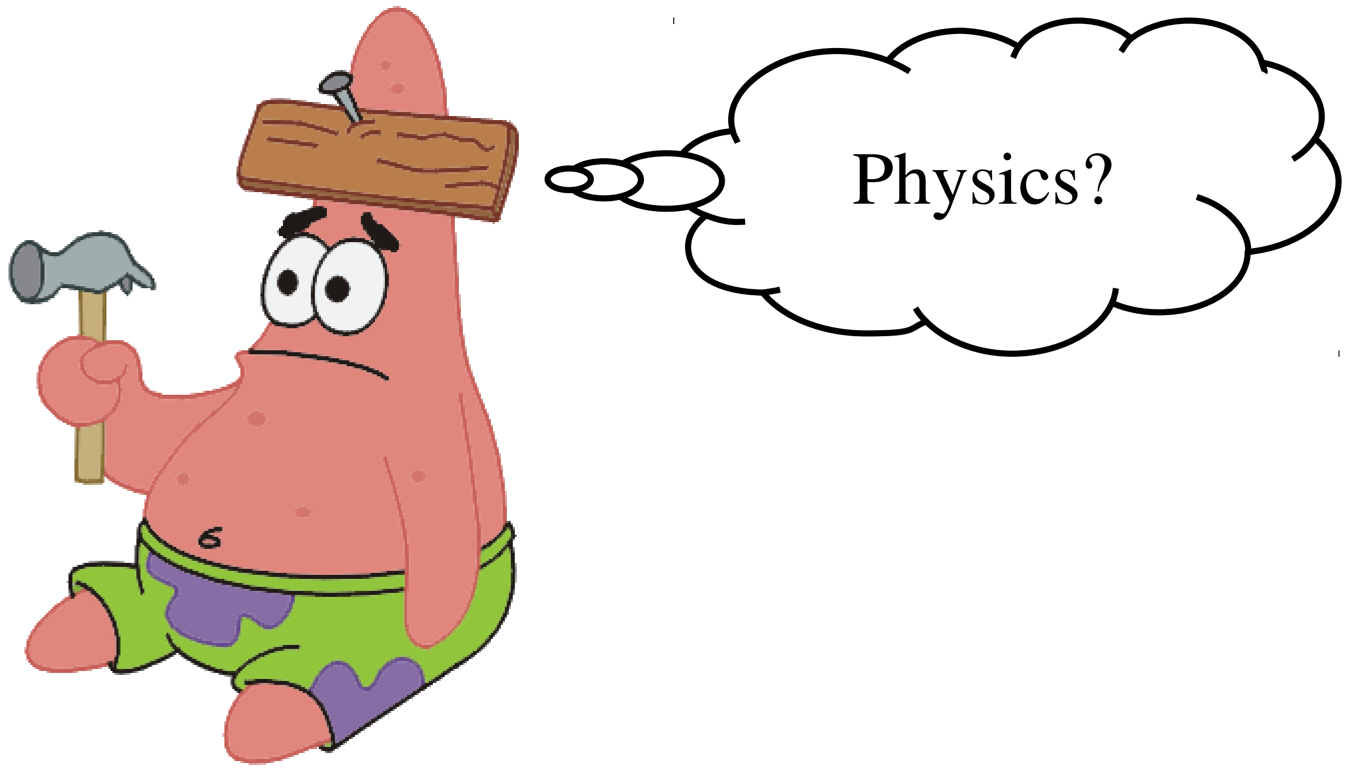
$$h_i^{(n)} = \varphi(w_{ij}^{(n)} h_j^{(n-1)} + b_i^{(n)})$$

Neural network is often considered as a **<u>black box</u>** because studying its internal information barely gives you an insight about the decision...



We also want to know how the deep learning reached the outputs!

Computers are dumb!

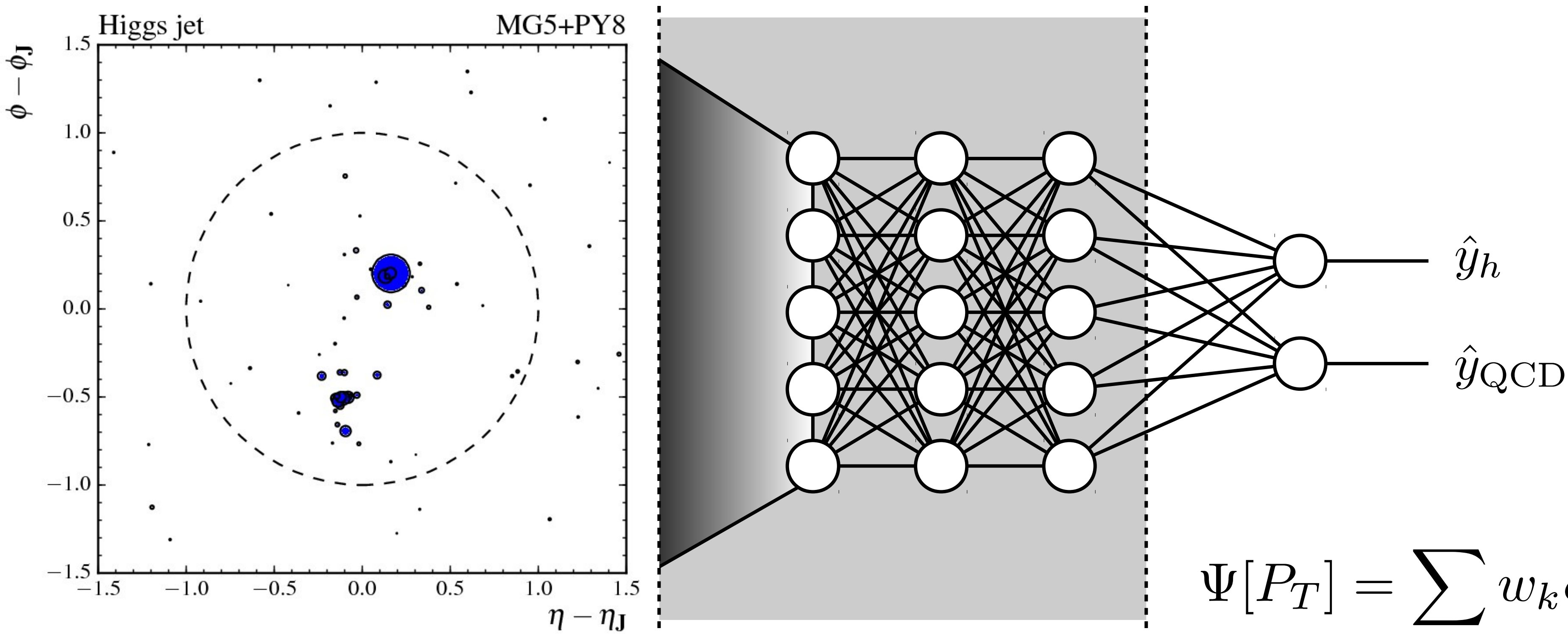


Computers will not give you any outputs
that you did not ask them **explicitly**!

What we asked: classification of Higgs jets and QCD jets.

What we did not ask: physical interpretation of the results.

Structure of a Neural Network Classifier



$$\Psi[P_T] = \sum_k w_k \phi_k[P_T]$$

$$P_T(\vec{R}) = \sum_{i \in \mathbf{J}} p_{T,i}\, \delta(\vec{R} - \vec{R}_i)$$

$$\phi_k = \Phi_k[P_T]$$

$$\hat{y}_h = \varphi_{\mathrm{sigmoid}}(\Psi[P_T])$$

Inputs | Feature map | Logistic regression

Building an interpretable model for the feature map will reveal the black box.

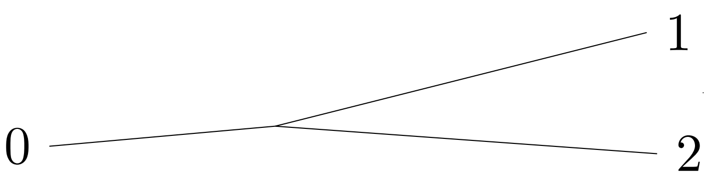
What could be a good feature for two-prong jet classification?

Kinematics inside Jet

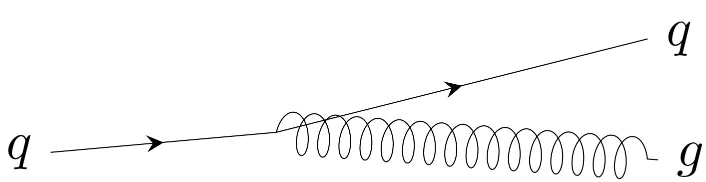
The parameter set $(p_{T,0}, z, R)$ determines the kinematics of parton evolution.

$$p_{T,1} = p_{T,0}z \qquad p_{T,2} = p_{T,0}(1-z)$$

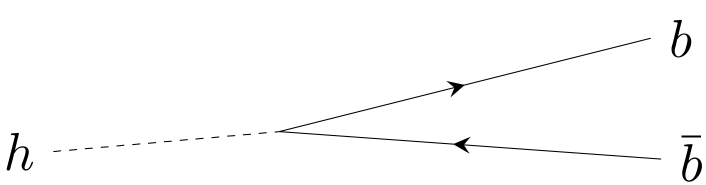
$$R^2 = (y_1 - y_2)^2 + (\phi_1 - \phi_2)^2$$



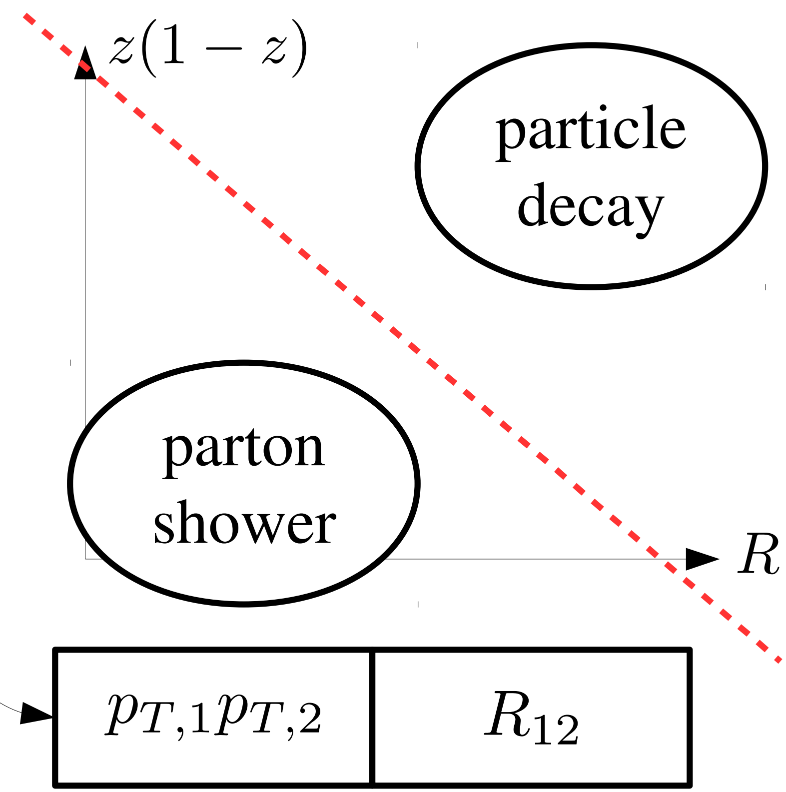
- parton shower



  - Collinear: small R
  - Soft: z ~ 0 or 1
- particle decay



  - Transverse decay:
    R ~ 2m/pt and z ~ 0.5



Let's make variables that encodes the profile of these two quantities.

Two-Point Correlation Spectrum

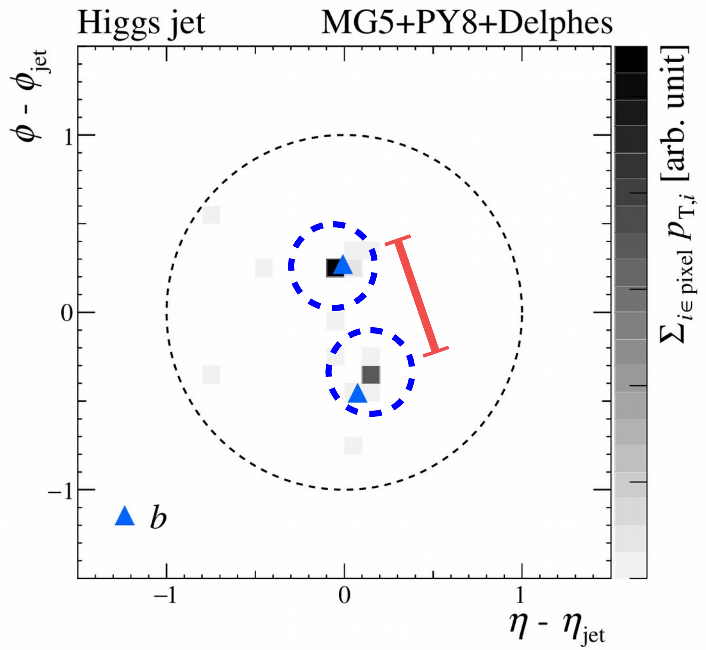
We introduce a two-point correlation spectrum:

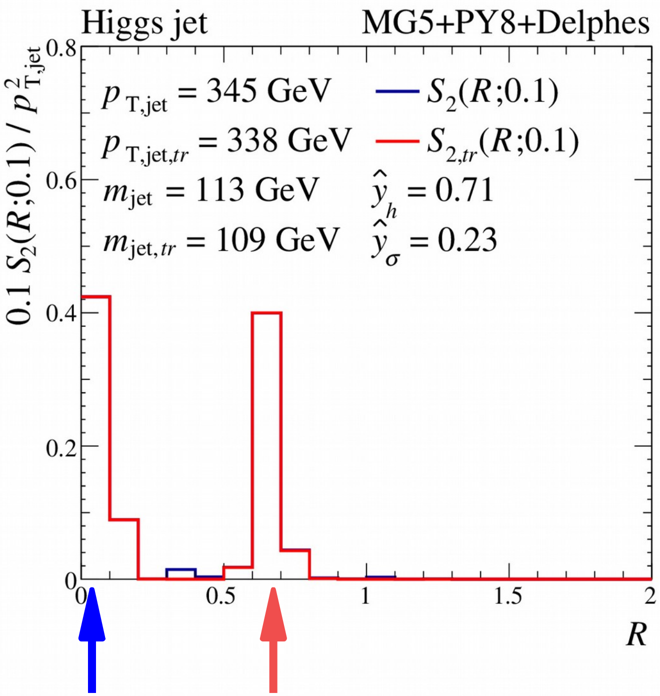
$$S_2(R;\Delta R) = \frac{1}{\Delta R} \sum_{\substack{i,j\in\text{jet} \\ R_{ij}\in[R,R+\Delta R]}} p_{T,i}\,p_{T,j}$$

Example: spectrum of a two-prong jet with two constituents

$$S_2(R) = (p_{T,b}^2 + p_{T,\bar{b}}^2)\cdot\delta(R) + 2p_{T,b}p_{T,\bar{b}}\cdot\delta(R - R_{b\bar{b}})$$

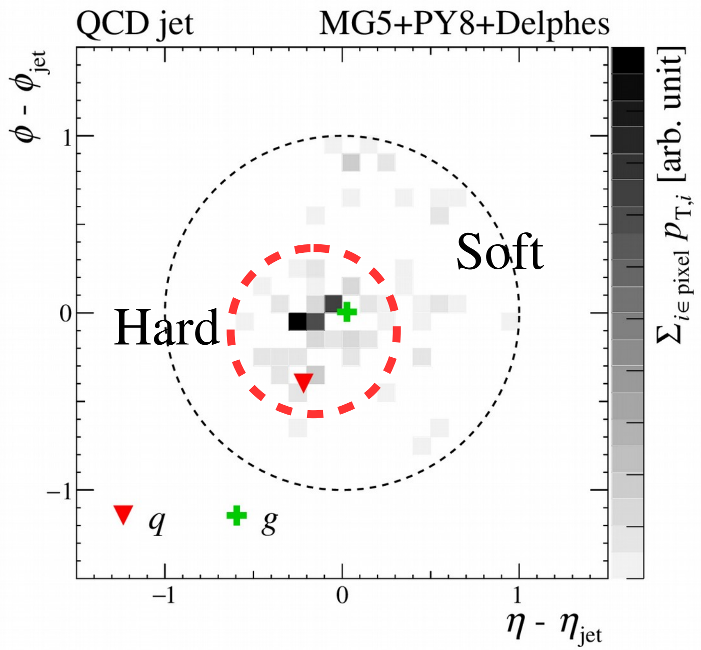
Autocorrelation Cross-Correlation

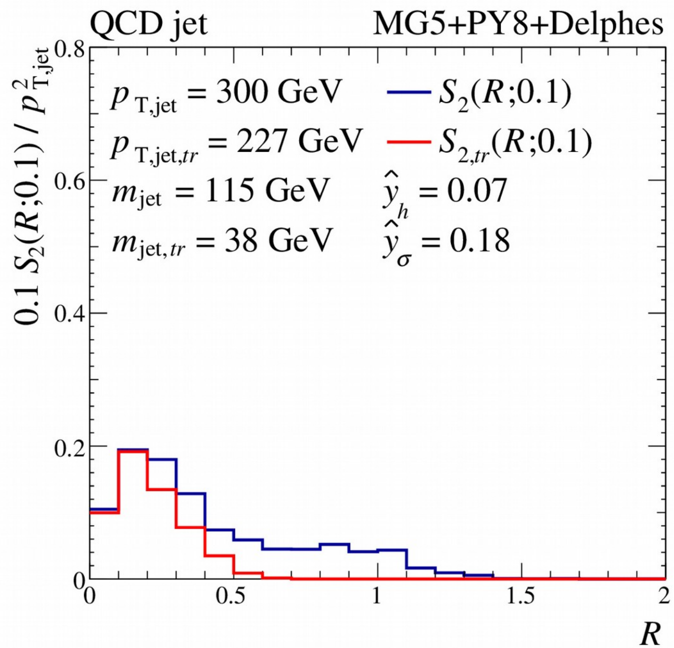




Two-Point Correlation Spectrum

- QCD jets are mostly one-prong jets
  with surrounding soft particles.
- Its spectrum has a smoothly falling behavior.





- This spectrum is not suddenly introduced
  but derived from the image classifier as follows...

Functional Taylor Expansion

Let us consider the functional Taylor expansion of the classifier.

$$\Phi[P_T] = w^{(0)} + \int d\vec{R}\, P_T(\vec{R}) w^{(1)}(\vec{R}) + \boxed{\frac{1}{2!}\int d\vec{R}_1 d\vec{R}_2\, P_T(\vec{R}_1) P_T(\vec{R}_2) w^{(2)}(\vec{R}_1, \vec{R}_2)} + \cdots$$

Since $\Phi[P_T]$ is a scalar and doesn't have any additional parameters, the first nontrivial term is

$$\Phi[P_T] = \int dR\, S_2(R) w^{(2)}(R) + \cdots$$

$$S_2(R) = \int d\vec{R}_1\, d\vec{R}_2\, P_T(\vec{R}_1) P_T(\vec{R}_2) \delta(R - R_{12})$$

$$P_T(\vec{R}) = \sum_{i \in \mathbf{J}} p_{T,i}\, \delta(\vec{R} - \vec{R}_i)$$

Two-level setup

The logistic classifier works well, but not enough.

$$\hat{R}_{b\bar{b}} = \frac{2m_h}{p_{T,h}}$$

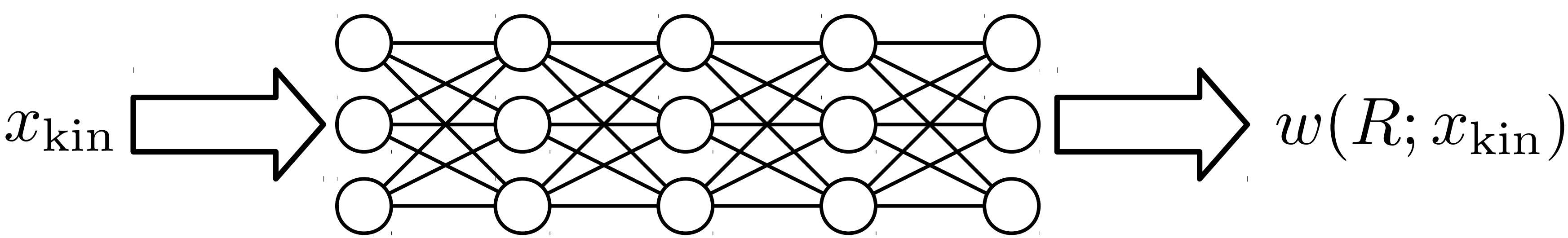
$$\Phi[P_T] = \int dR\, S_2(R) w(R)$$

The weights should learn the change of phase space!

$$\Phi[P_T; x_{\rm kin}] = \int dR\, S_2(R) w(R; x_{\rm kin})$$

$$x_{\rm kin} = \{p_{T,\rm jet}, m_{\rm jet}\}$$

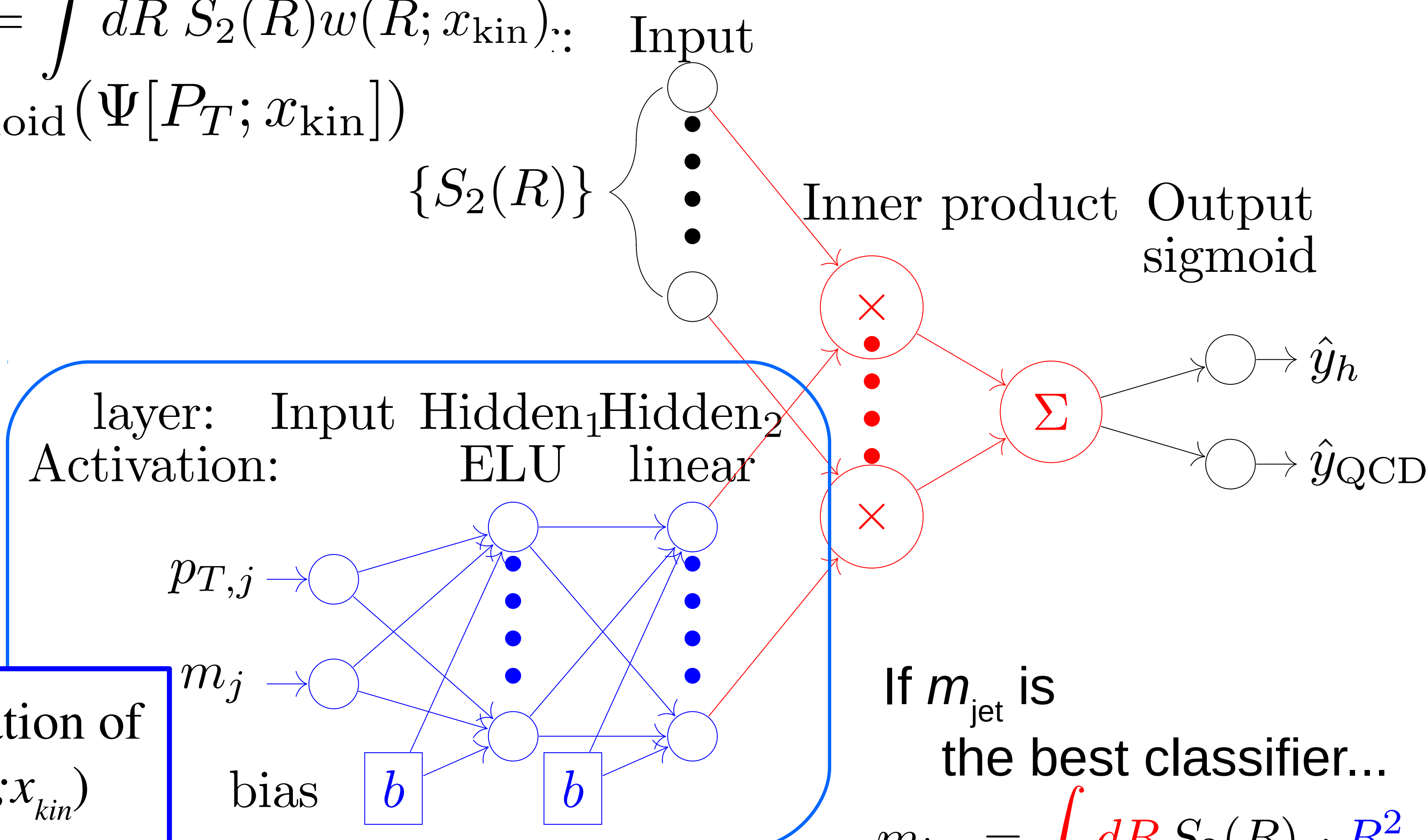
Use neural network to approximate the weight function.



Concrete realization of the neural network architecture

$$\Psi[P_T; x_{\rm kin}] = \int dR\, S_2(R) w(R; x_{\rm kin}),$$

$$y_h = \varphi_{\rm sigmoid}(\Psi[P_T; x_{\rm kin}])$$

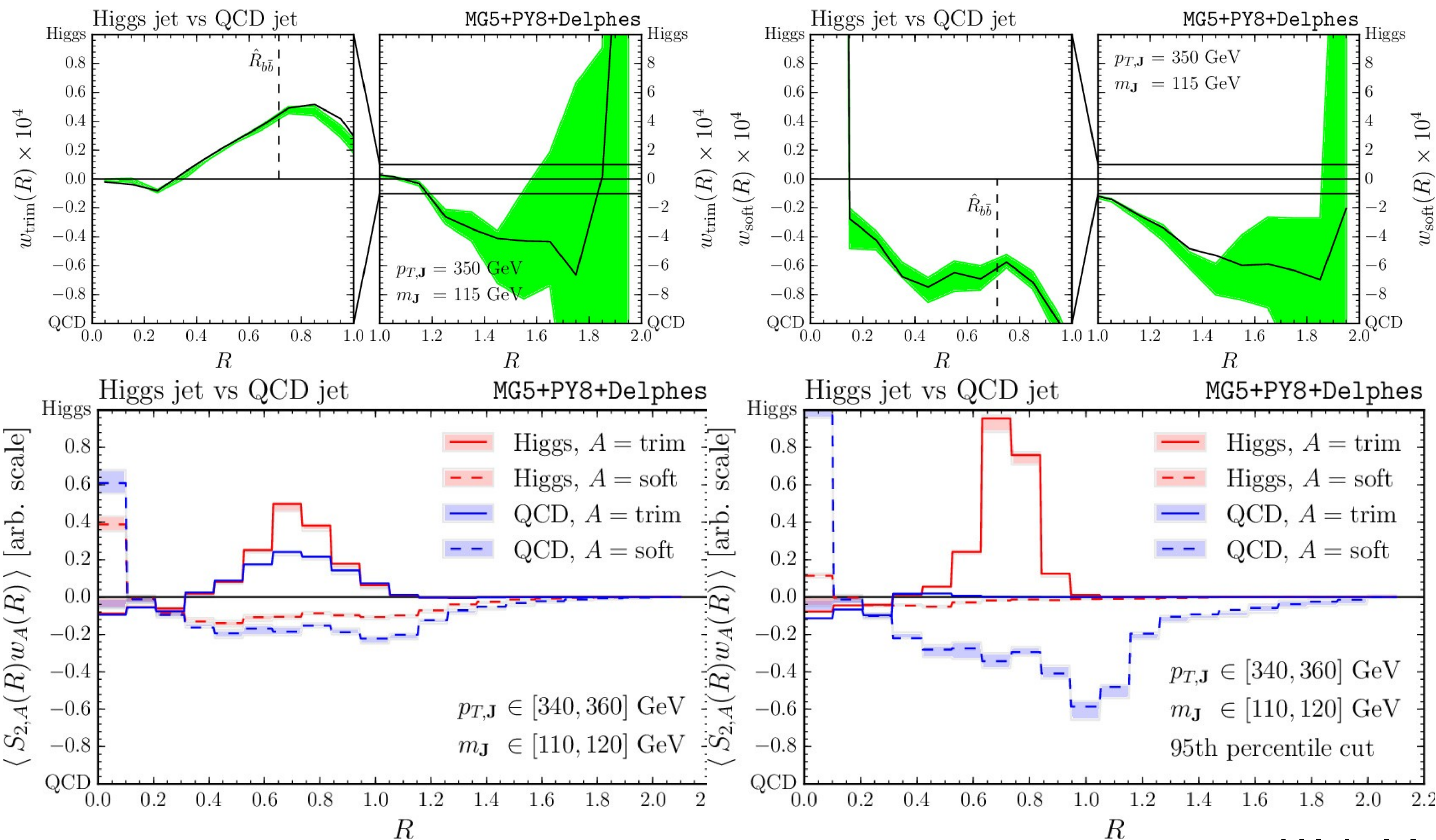


NN representation of kernel $w(R;x_{kin})$
→ **interpretable**

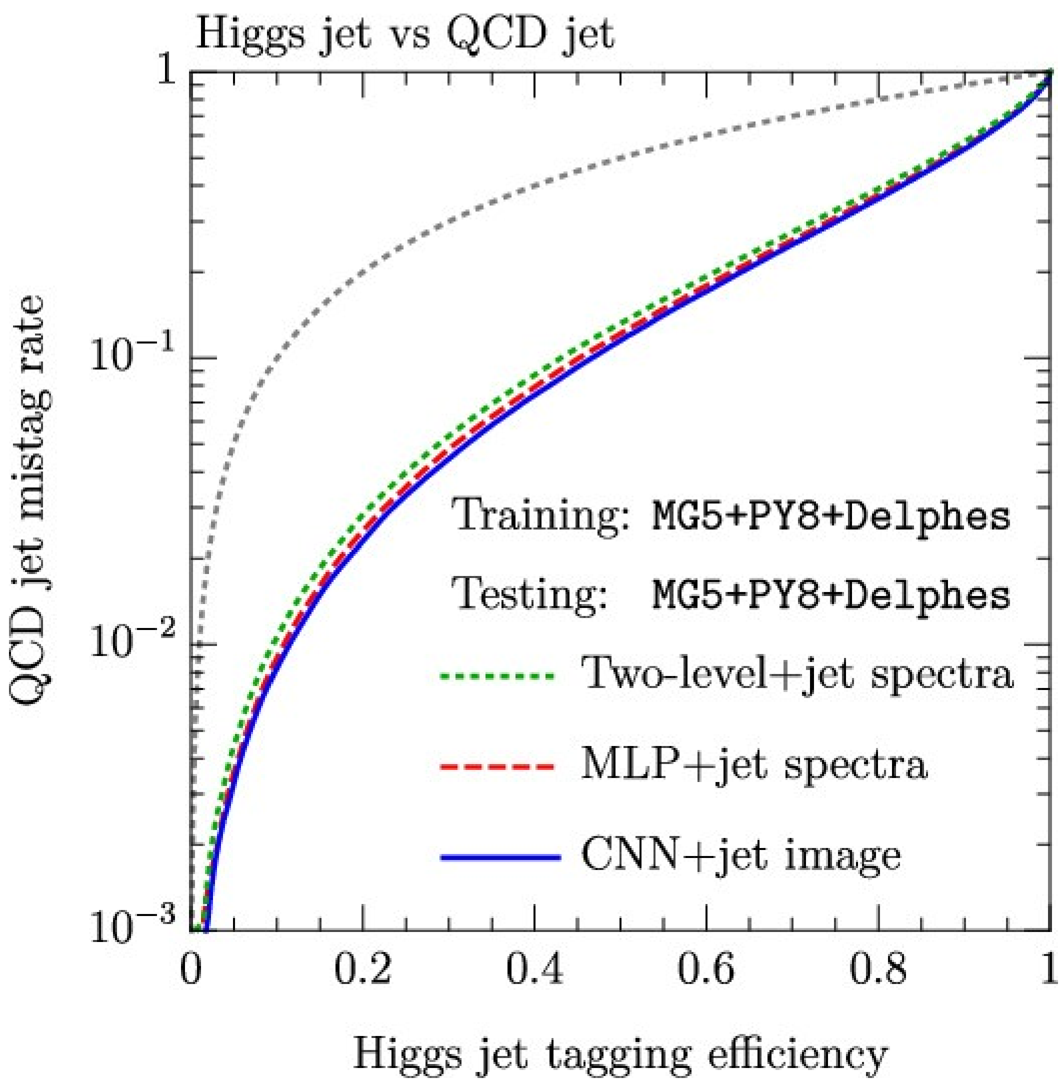
If $m_{\rm jet}$ is the best classifier...

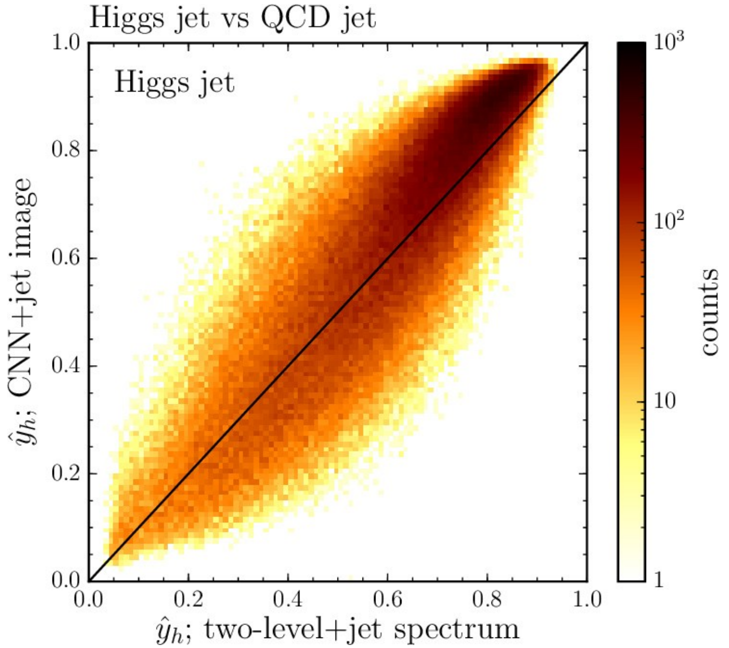
$$m_{\rm jet} = \int dR\, S_2(R) \cdot R^2$$

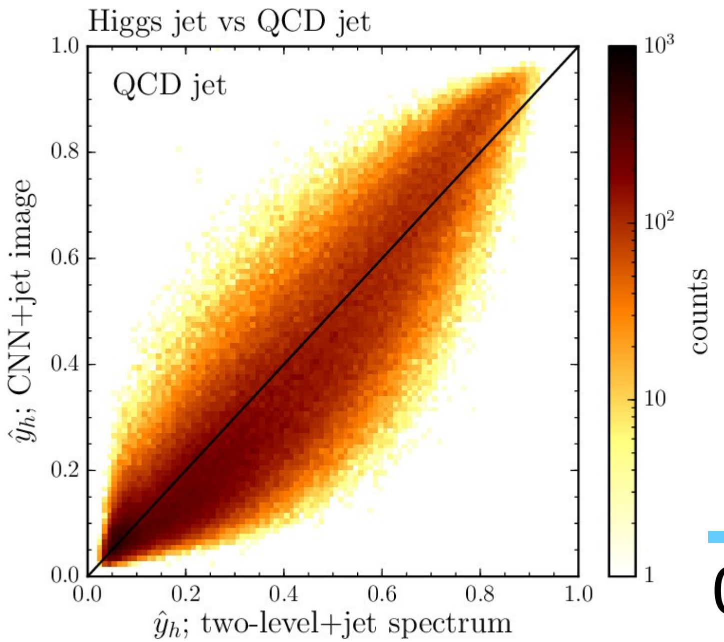
Results: Two-level Setup



Comparison with CNN



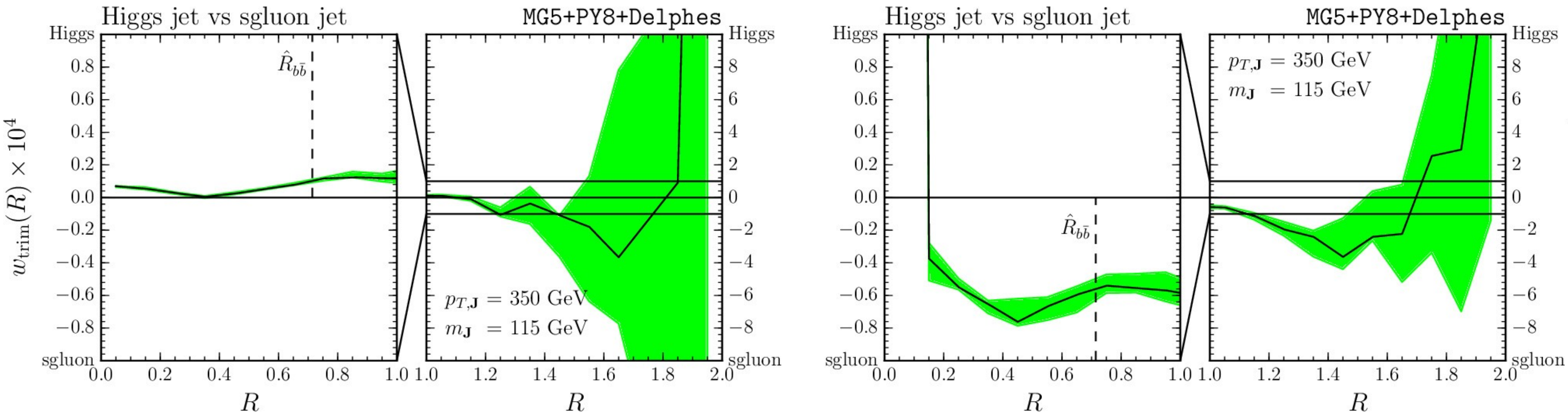




Other physics results

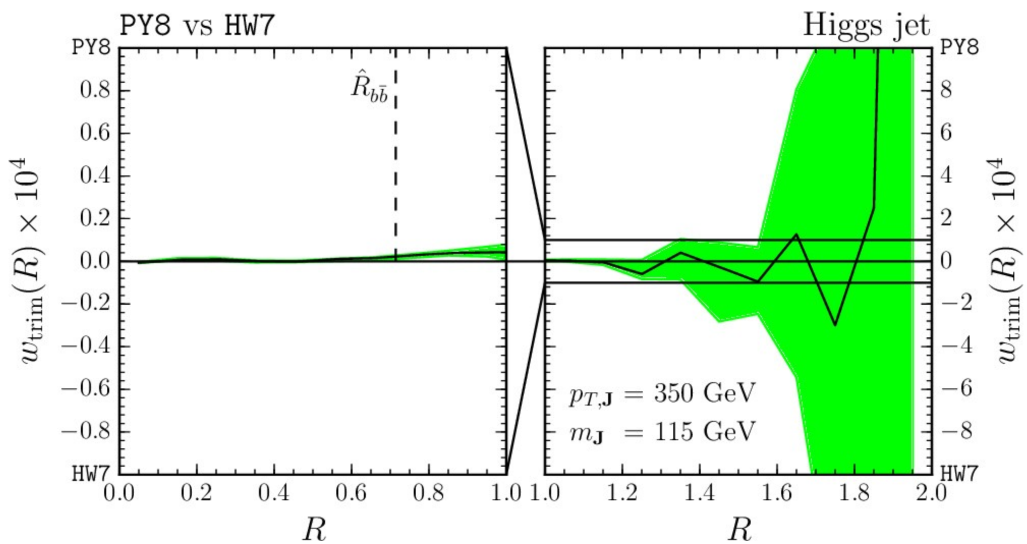
- During this talk, I have focused on explaining the results based on parton description, but the two-point correlation encodes other physical difference between Higgs jet and QCD jet.
- This architecture can be also used for distinguishing other objects:

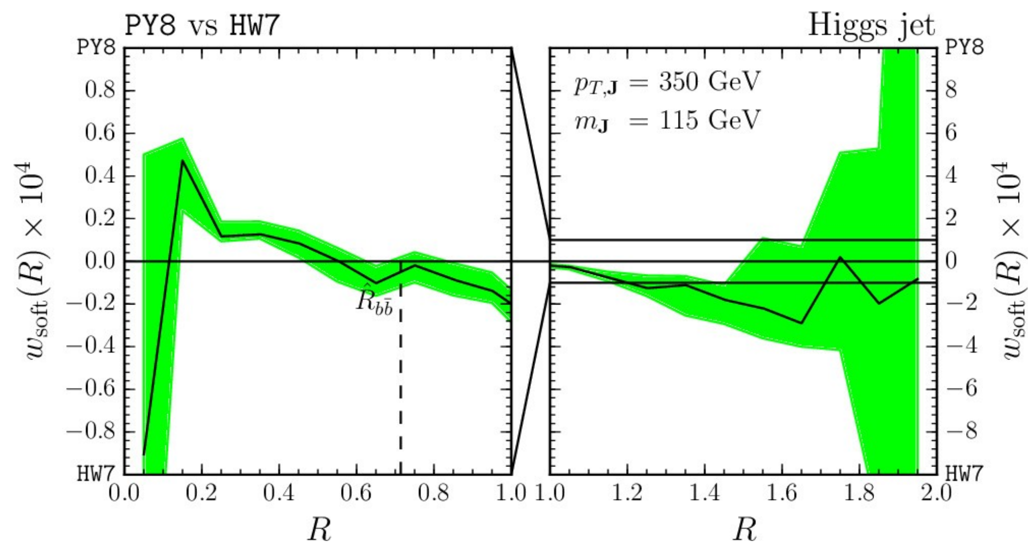
Identification of color of originating parton: **1** vs **8**



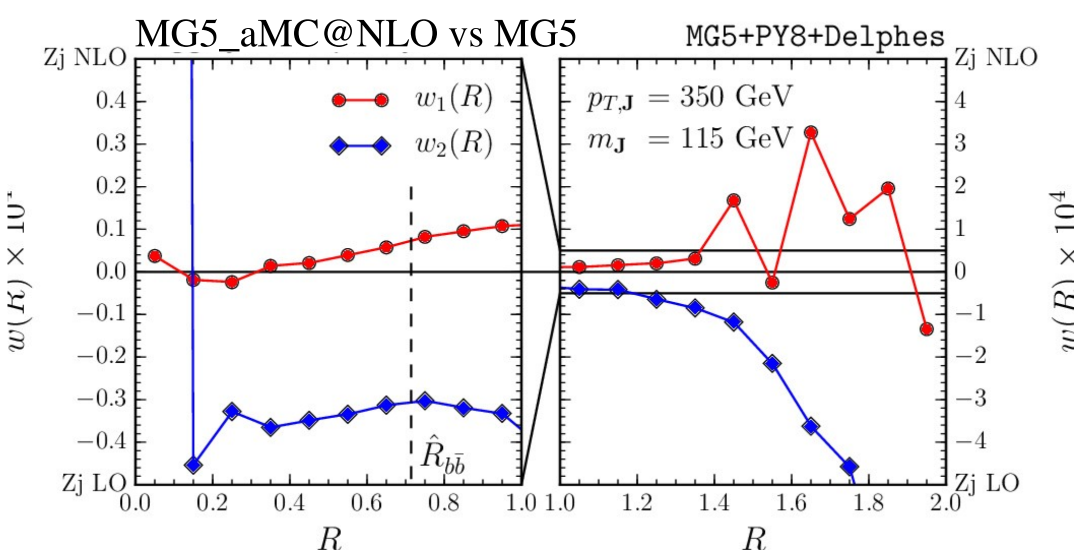
Other physics results

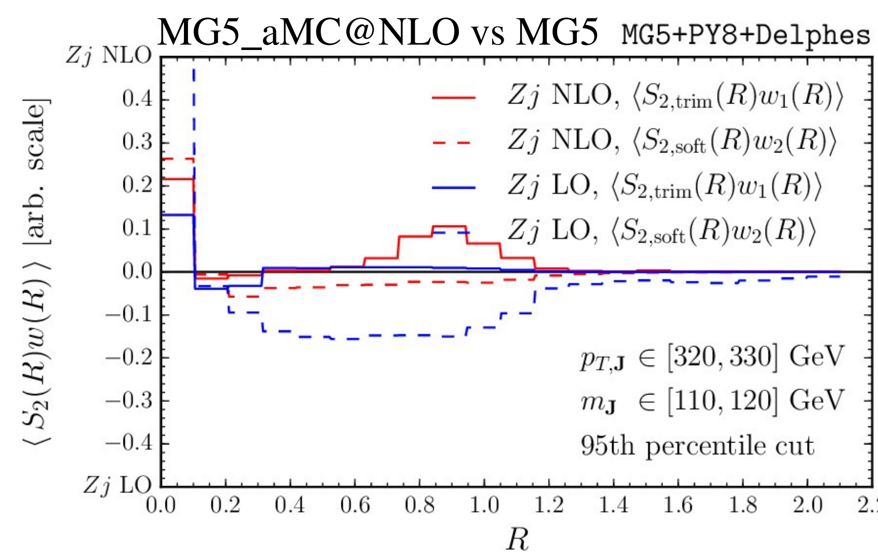
Comparison between parton shower monte carlo simulators:





Comparison between parton simulators:





Summary

- For the next run of LHC and future colliders, we need a quick and reliable jet substructure analysis framework.
- We developed a machine learning framework using **two-point correlation spectrum** for analyzing jet substructures.
- The spectrum is derived from the jet image analysis and the corresponding two-level model is physically **interpretable**.
- Its application is not limited to the two-prong jet identification, but we may extend this idea to various other problems.

Please stay tuned!