

# Spectral Analysis of Jet Substructure with Neural Network: Boosted Higgs Case

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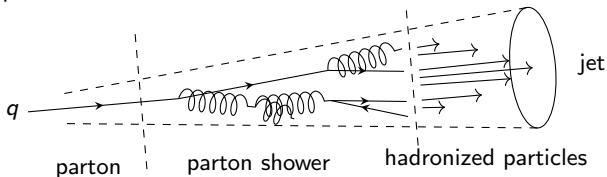


Supplementary materials for BOOST 2018, Paris, France

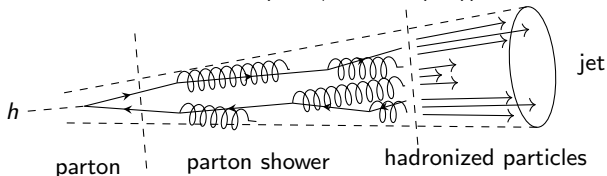
Jul. 2018

## Jets and Boosted Particles

- A jet is a collimated cluster of particles. It is often produced from a colored parton.



- As LHC stacking up multi  $TeV$  center-of-mass energy events, boosted heavy particles can be produced and form a single collimated cluster of particles similar to the QCD jet. ( $m_{EW}/\sqrt{\hat{s}} = \mathcal{O}(0.1)$ )



- We have to differentiate these non-QCD jets from QCD jets to maximize sensitivity of channels involving boosted particles.
- We use substructure observables on this purpose.

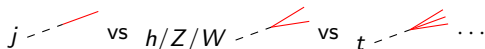
## Conventional observables of jet substructures

There are lots of observables of jet substructures, which are focussing on a particular substructure. A few examples are:

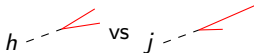
- mass of the mother particle:  $m_{\text{jet}}$ , trimmed  $m_{\text{jet}}$ , ...



- $n$ -prong jet:  $n$ -subjettiness ratio,  $D_2$ , ...



- subjet  $p_T$  asymmetry: mass drop tagger, ...



- color charge: jet girth (a kind of width), ...



- color substructures: jet pull between subjets, ...

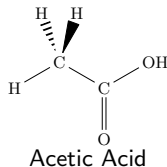
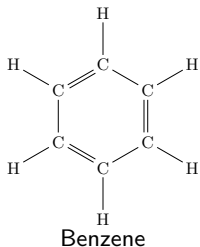
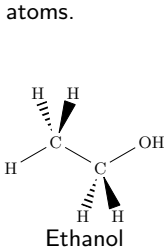


Q: is there any generic framework that unifies these variables?

- I want to introduce an analogy from Organic Chemistry.

# Organic Molecules

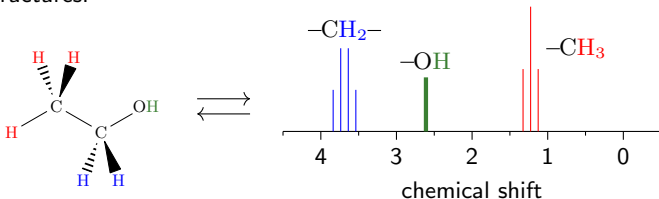
- Organic molecules are complex molecules contains carbon, hydrogen, and other atoms.



- How chemists identified these complex substructures?  
Proton Nuclear Magnetic Resonance (<sup>1</sup>H-NMR) Spectroscopy

# Analogy of Jet Substructures and Organic Molecules

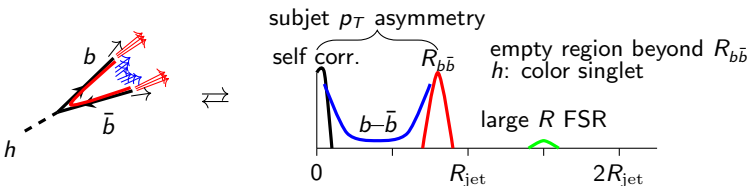
- $^1\text{H-NMR}$  is a successful example of spectral analysis of molecular substructures.



- The perturbative description of jets is analogous to organic molecules.

Spectral analysis	$^1\text{H-NMR}$ spectroscopy	$\rightarrow$	??
Primary geometry	Carbon skeleton	$\rightarrow$	partons from the decay
Observables	Hydrogen	$\rightarrow$	hadronized particles

- Can we build a similar analysis framework of jet substructures?



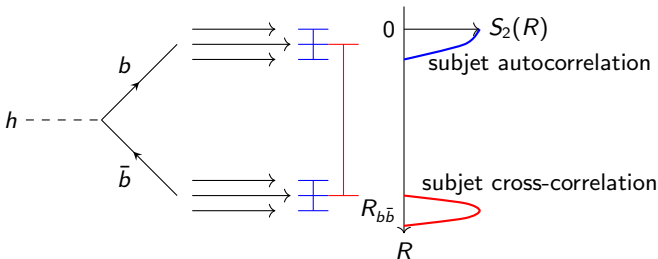
- We will introduce a spectral analysis of jet substructure.

## A spectral function of jet substructure

- We define a binned spectral function of transverse momenta of all particle pairs  $i$  and  $j$ ,  $p_{T,i}$  and  $p_{T,j}$ , and their angular distance  $R_{ij} = \sqrt{\eta_{ij}^2 + \phi_{ij}^2}$ ,

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

- This spectral function observes two-point correlations in a jet.



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

- Hence, this spectral function contains non-local correlation in jets. The correlations can be used for detailed jet substructure studies.

Physical Interpretation of  $S_2(R)$ 

$$\int_0^\infty dR S_2(R) = \left( \sum_{i \in \text{jet}} p_{T,i} \right)^2 \approx p_{T,\text{jet}}^2, \quad (2)$$

$$\int_0^\infty dR R^2 S_2(R) = \sum_{i,j \in \text{jet}} p_{T,i} p_{T,j} R_{ij}^2 \approx 2m_{\text{jet}}^2. \quad (3)$$

# IRC safety of $S_2(R)$

- The  $S_2(R)$  spectrum is better to be infrared and collinear (IRC) safe, namely invariant under soft and collinear radiations.
  - Soft radiation: the parton radiates a  $p_T = 0$  parton.

$$p_T \longrightarrow \begin{array}{c} \longrightarrow \\ \searrow \\ \swarrow \end{array} \quad \begin{array}{l} p_T \\ p_T = 0 \end{array}$$

- Collinear radiation: the parton splits in same direction  $\vec{R}$ .

$$p_T \longrightarrow \begin{array}{c} \longrightarrow \\ \longrightarrow \end{array} \quad \begin{array}{l} zp_T \\ (1-z)p_T \end{array}$$

- Otherwise, the virtual and real corrections in higher order perturbation theory do not sum up, and such a IRC unsafe observables are hard to be estimated from perturbative QCD calculations. (KNL theorem)

$$\text{Virtual} + \text{Real (top)} + \text{Real (bottom)} = \text{finite} \quad (4)$$

- $S_2(R)$  is IRC safe because soft or collinear radiation does not introduce any new angular scale  $R$ .

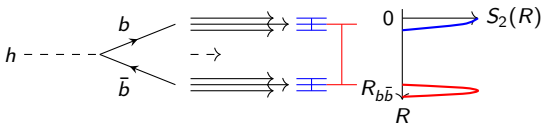


IRC safety of  $S_2(R)$ 

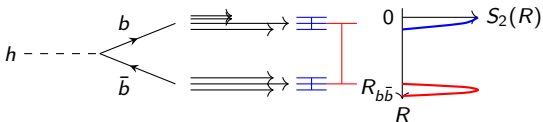
- The  $S_2(R)$  spectrum is IRC safe.

$$S_2(R; \Delta R) = \frac{1}{\Delta R} \sum_{\substack{i,j \in \text{jet} \\ R_{ij} \in [R, R+\Delta R)}} p_{T,i} p_{T,j}, \quad (5)$$

- Soft radiation is ignored safely because  $p_{T,i} p_{T,j} = 0$  if  $i$  or  $j$  is a soft radiation.

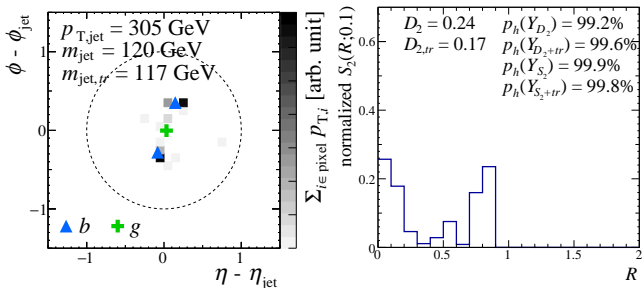
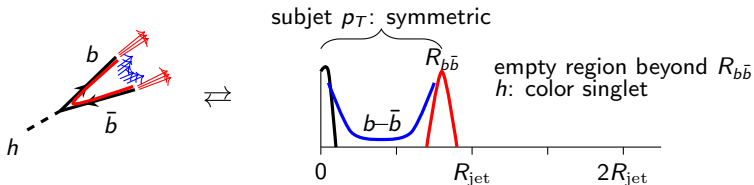


- Collinear radiation is okay because  $\vec{R}$  does not change and the radiation products always sum up.



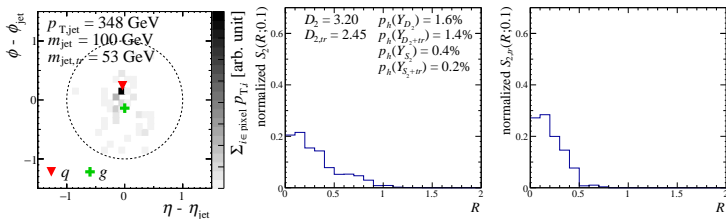
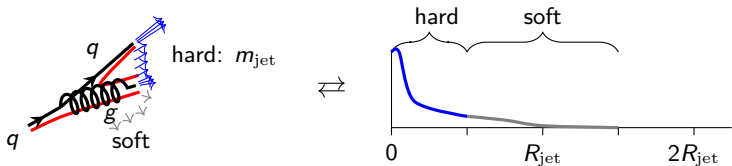
- Now, let's check how  $S_2(R)$  behaves with more realistic events at the detector level.

## A typical Higgs jet



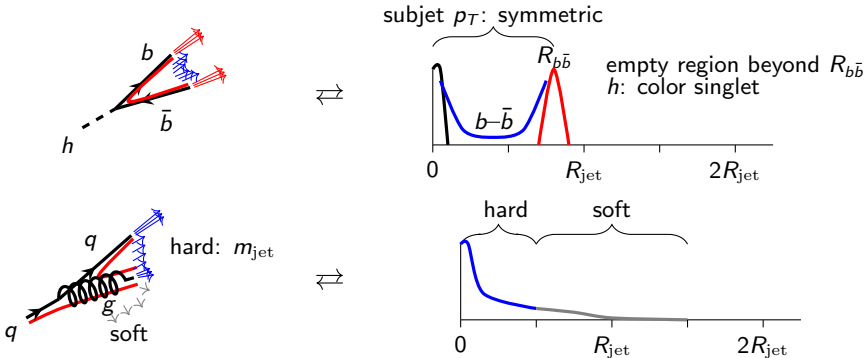
$$S_2(R) = \left( p_{T,b}^2 + p_{T,\bar{b}}^2 \right) \cdot \delta(R) + 2p_{T,b}p_{T,\bar{b}} \cdot \delta(R - R_{b\bar{b}}).$$

## A typical QCD jet and jet trimming



- Jet trimming removes soft subjets in the jet.
- Jet trimming helps differentiating hard and soft jet substructures.

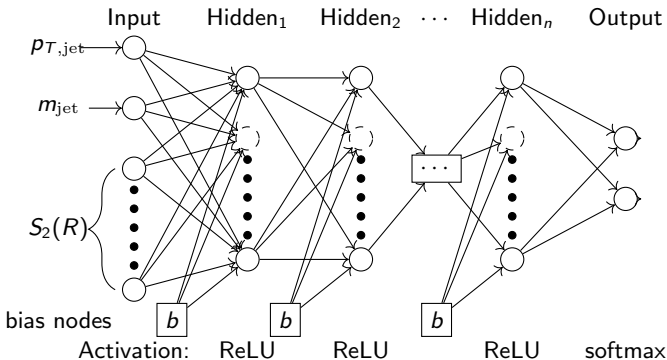
# Differentiating Higgs jets and QCD jets



- $S_2(R)$  contains various information on jet substructures. But how can we quantify it for classification?

## Deep Learning

# Artificial Neural Network



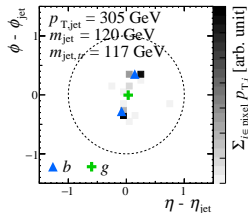
- The artificial neural network is a mathematical model of functions motivated from a biological neural network.
- To make a long story short, the neural network is a function maps inputs to outputs having lots of internal parameters needed to be optimized.

$$ANN(\{x_i\}) = f^{(n)}(W^{(n)} \dots f^{(2)}(W_{jk}^{(2)} f^{(1)}(W_{ij}^{(1)} x_i + b_j^{(1)}) + b_k^{(2)}) \dots + b^{(n)})$$

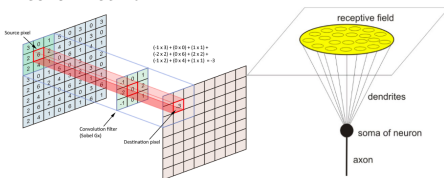
- The network setup for jet substructure analysis depends on how you interpret jets.

# Jet as an Image

- We may interpret the calorimeter energy deposit as an image, and apply image recongnition techniques.



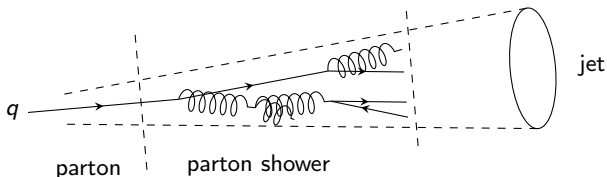
- Convolutional neural network



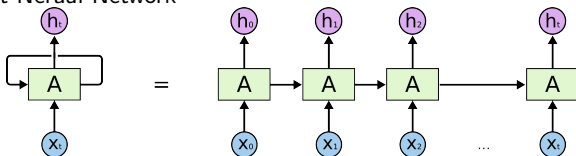
- This ANN mimicks human eye and can be used for image recongnition.
- It focuses on local spatial correlations
- References: 1407.5675, 1511.05190

# Jet as a sequential data

- The parton shower description of jets can be interpreted as a sequential data.

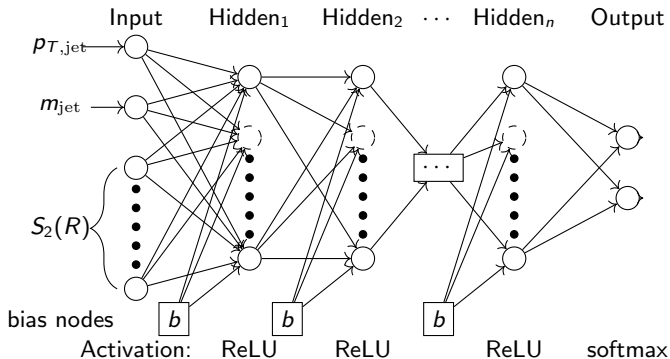


- We may recluster the jet to get a parton shower history and feed this to ANN.
- Recurrent Neural Network



- The ANN understand data in sequence and find out correlations by reading data sequentially.
- Focussing on local temporal correlations
- References: 1607.08633, 1702.00748

## Our ANN setup



- We used a simple shallow fully-connected neural network.
- Inputs for  $S_2(R)$  analysis
  - $\mathcal{N}_{S_2} : \{x_i\}_{S_2} = \{p_{T,jet}, m_{jet}, S_2(0; 0.1), \dots, S_2(1.9; 0.1)\}$
  - $\mathcal{N}_{S_2+tr} : \{x_i\}_{S_2+tr} = \{x_i\}_{S_2} \cup \{p_{T,jet,tr}, m_{jet,tr}, S_{2,tr}(0; 0.1), \dots, S_{2,tr}(1.9; 0.1)\}$



## Comparison to another variable

- For comparison, we prepare an ANN analysis with  $D_2$  variable (1409.6298)

$$e_2^\beta = \frac{1}{p_{T,\text{jet}}^2} \sum_{\substack{i,j \in \text{jet} \\ i < j}} p_{T,i} p_{T,j} R_{ij}^\beta, \quad (6)$$

$$e_3^\beta = \frac{1}{p_{T,\text{jet}}^3} \sum_{\substack{i,j,k \in \text{jet} \\ i < j < k}} p_{T,i} p_{T,j} p_{T,k} R_{ij}^\beta R_{jk}^\beta R_{ki}^\beta, \quad (7)$$

$$D_2^\beta = \frac{e_3^\beta}{(e_2^\beta)^3} \sim \frac{\Delta}{(-)^3}, \quad (8)$$

- For Higgs jets,  $D_2$  is small because three-point energy correlation have to count soft or collinear radiation.

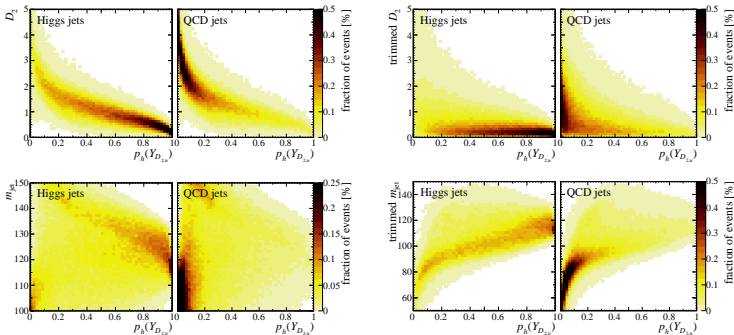
$$D_2^\beta \approx \frac{\text{triangle}}{(-)^3} \approx \frac{-}{-} \ll 1$$

- Inputs for ANN with  $D_2$

- $\mathcal{N}_{D_2} : \{x_i\}_{D_2} = \{p_{T,\text{jet}}, m_{\text{jet}}, D_2^{\beta=2}\}$
- $\mathcal{N}_{D_2+tr} : \{x_i\}_{D_2+tr} = \{x_i\}_{D_2} \cup \{p_{T,\text{jet},tr}, m_{\text{jet},tr}, D_{2,tr}^{\beta=2}\}$

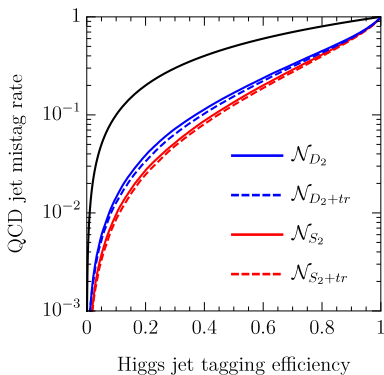
## Performance check of ANN with $D_2$

- We first check that the performance of  $\mathcal{N}_{D_2+tr}$  with The distributions of Higgs jets and QCD jets in the Higgs-like probability  $p_h(Y_{D_2+tr})$  and inputs in  $\{X_i\}_{D_2+tr}$ .



- $\mathcal{N}_{D_2+tr}$  has a tendency to classify jets with small  $D_2$  and  $m_{jet} \approx 125$  GeV as a Higgs jet. This behavior is similar to the conventional cut-based analysis.
- Now it looks working well, so let us compare it with  $\mathcal{N}_{S_2+tr}$ .

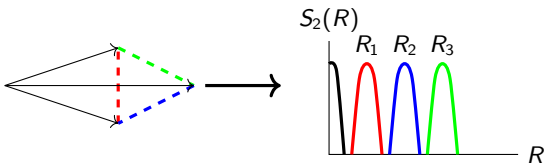
## ROC curve



- Event preselection:
  - $m_{\text{jet}} \in [100, 150]$  GeV.
  - $p_{T,\text{jet}} \in [300, 400]$  GeV.
  - Then  $R_{b\bar{b}} \gtrsim 0.6$  and anti- $k_T$  algorithm with  $R_j = 1$  finds the collimated cluster well.
  - For Higgs jets, at least one  $b$  parton should be found in the jet.
- At the Higgs tagging efficiency 0.4 (0.2), QCD jet mistag rate of  $\mathcal{N}_{S_2+tr}$  is reduced by 21.6% (26.7%) compared to that of  $\mathcal{N}_{D_2+tr}$ .
- Why  $S_2(R)$  is doing better than  $D_2$ ?

$S_2(R)$  and  $D_2$ 

- $S_2(R)$  includes  $D_2$  partially. Let's consider a three-prong jet.



- Two-point correlation function.

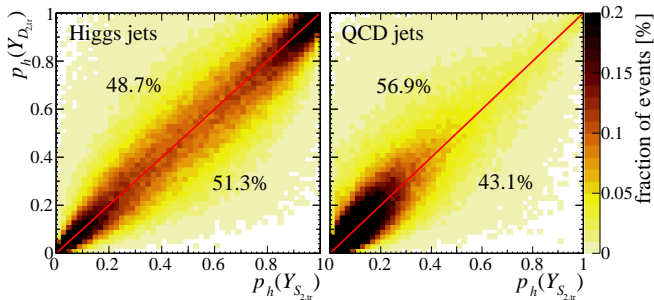
$$\int_0^{\infty} dR R^{\beta} S_2(R) = 2p_{T,\text{jet}}^2 e_2^{\beta} \quad (9)$$

- Three-point correlation function.

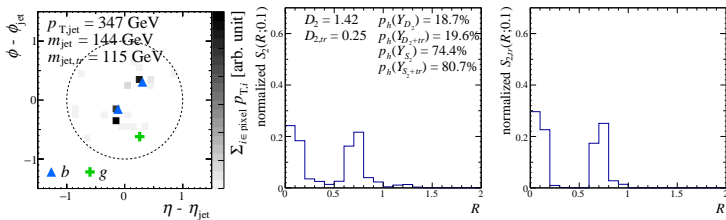
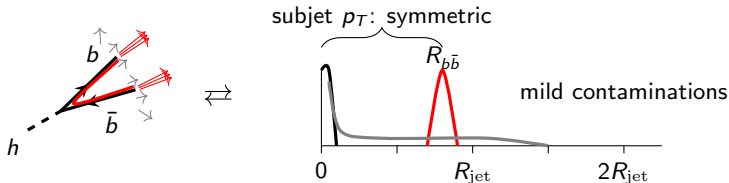
$$e_3^{\beta} \approx p_{T,\text{jet}}^{-1} \cdot \sqrt{(\Delta R)^3 S_2(R_1; \Delta R) S_2(R_2; \Delta R) S_2(R_3; \Delta R) R_1^{\beta} R_2^{\beta} R_3^{\beta}} \quad (10)$$

- Therefore, we may build  $D_2$  from  $S_2(R)$  if it is required.
- How the classifier  $\mathcal{N}_{S_2+tr}$  is correlated to  $\mathcal{N}_{D_2+tr}$  and why  $\mathcal{N}_{S_2+tr}$  is doing better job?

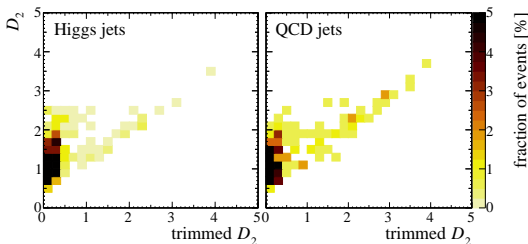
# Correlation between taggers



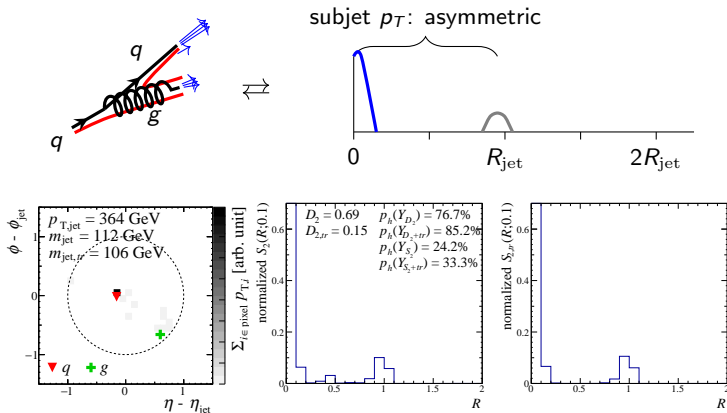
- For Higgs jets, the lower triangular region contains more events compared with the upper triangular region, 51.3% of the total events.
- For QCD jets, the lower triangular region contains less events, 43.1%.
- Hence,  $\mathcal{N}_{S_{2+tr}}$  improves signal and background ratio  $S/B$  from  $\mathcal{N}_{D_{2+tr}}$ .
- Let's check what kinds of jets are located in the off-diagonal region.

A jet tagged in  $S_2$  analysis only

- This jet looks like a Higgs jet but why  $\mathcal{N}_{D_2+tr}$  classify it as a QCD jet?

A jet tagged in  $S_2$  analysis only

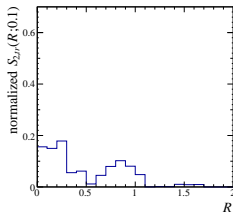
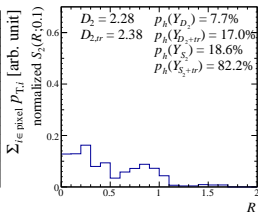
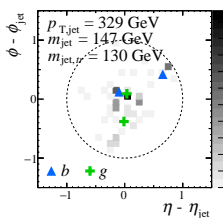
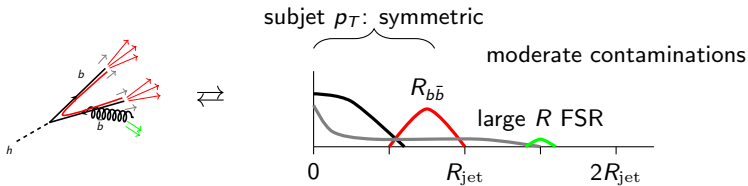
- Event selection:  $p_h(Y_{D_{2,tr}}) < 30\%$  and  $p_h(Y_{S_{2,tr}}) > 70\%$ .
- ANN tries to utilize every information in the inputs.
- As a result, large  $D_2$  and small trimmed  $D_2$  are signs of large angle soft activity which is a QCD jet's feature compared to a Higgs jet. Hence  $\mathcal{N}_{D_{2+tr}}$  classifies these jets as a QCD jets.

A jet tagged in  $D_2$  analysis only

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

- $p_T$  asymmetric subjects are often occur in QCD jets.
- Even though this jet is two-prong, it's better to avoid this jet to enhance S/B ratio as mass drop tagger does.



A jet tagged in  $S_2$  analysis with trimming only

- This jet has two-prong substructure, but the subjets are wide and contaminated by other QCD activities.
- Jet trimming helps differentiating hard and soft substructure, and  $\mathcal{N}_{S_2+tr}$  classify this jet as a Higgs jet.

## Conclusion

- $\mathcal{N}_{S_2}$  and  $\mathcal{N}_{S_2+tr}$  learned non-local correlations in jets from the spectrum.
- $\mathcal{N}_{S_2}$  discriminates between boosted Higgs jets and QCD jets with better performance compared to  $\mathcal{N}_{D_2}$ .
- Introducing trimming to  $S_2(R)$  helps separating hard and soft substructures, and the ANN with trimmed observable outperforms the ANN without trimming.
- The  $S_2(R)$  has information on multi-point correlations and is easily applicable to other jet substructures.