Classifying Jets with Graphical NeuralNet and Boosted Particle Flow

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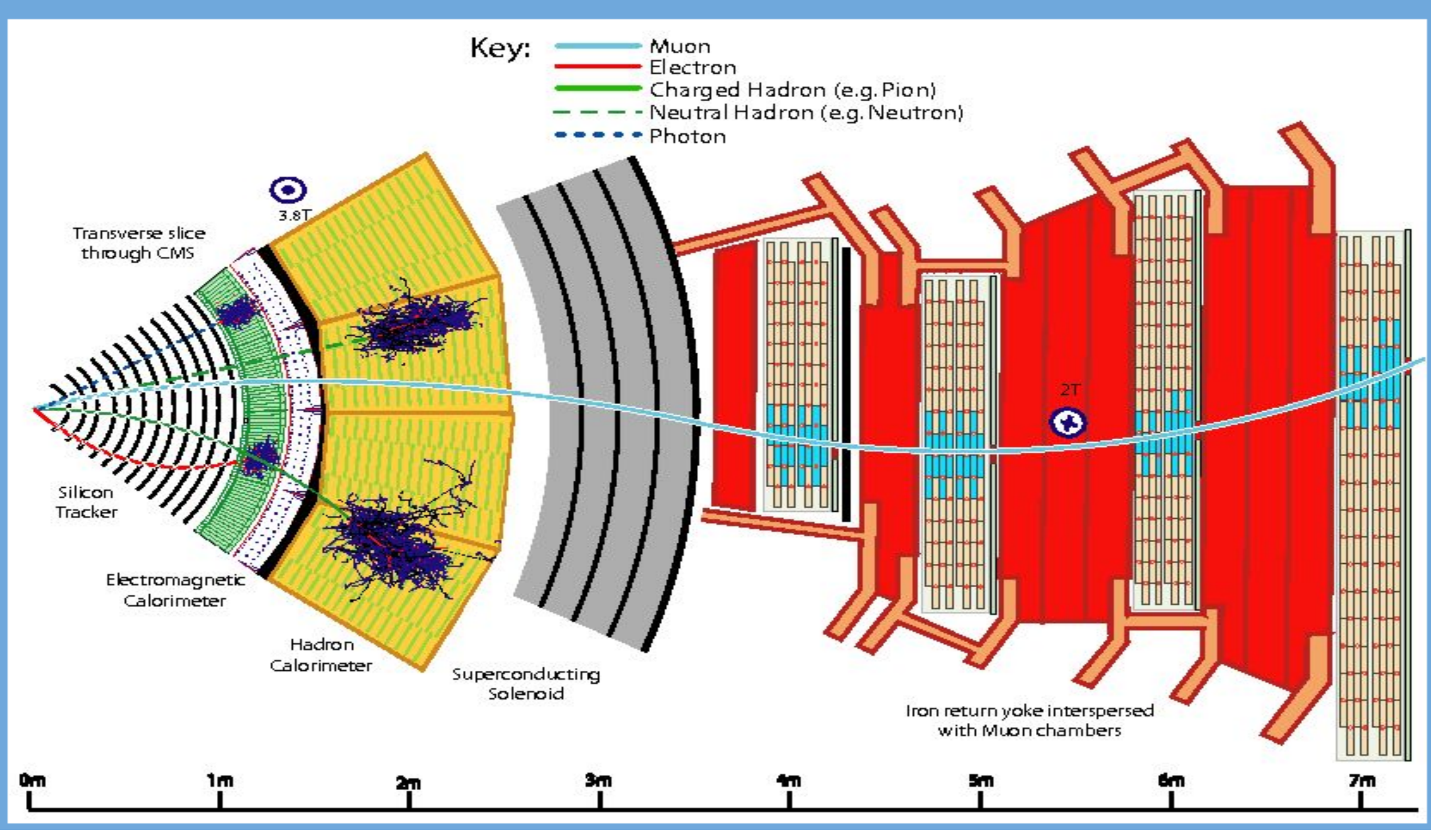
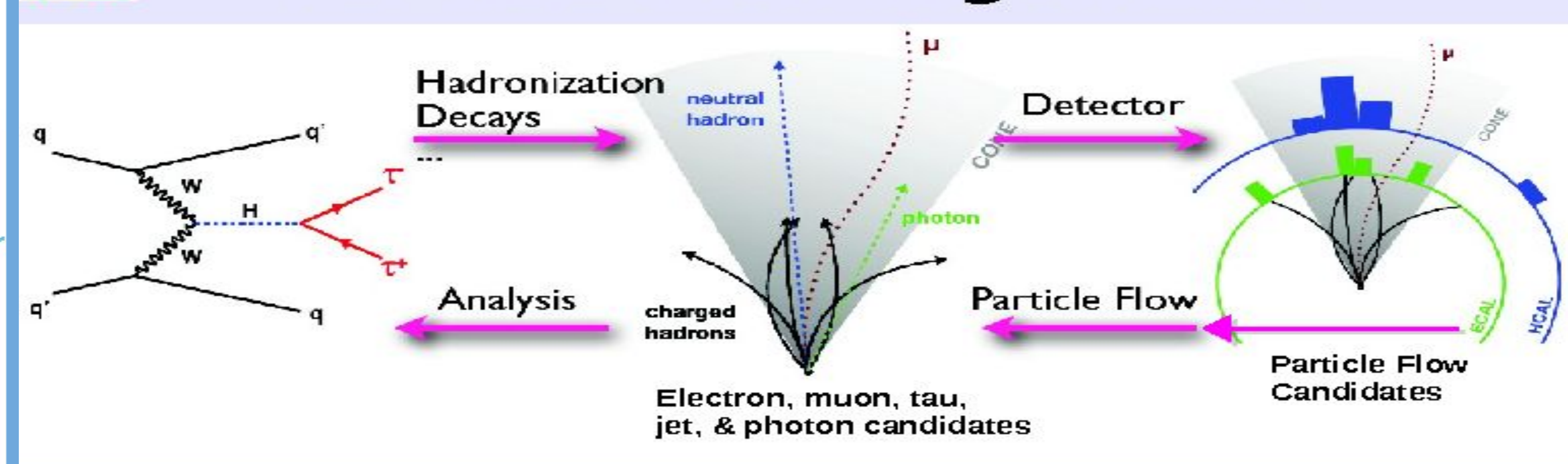
Abstract - The Higgs mass hierarchy is one of the major theoretical issues not addressed in the Standard Model of particle physics. Vector like quarks(VLQ) arise in many BSM(Beyond Standard Model) scenarios which attempt to address the Higgs mass hierarchy problem. We search for the gluon-mediated pair production process of VLQs at LHC in the all-hadronic channel. The events of the all-hadronic channels are expected to manifest themselves at the CMS detector with 4 highly boosted jets and a reasonably accurate jet classifier(which can classify a jet to be of one of the 6 categories - Higgs/top/W/Z/bottom/QCD) is an essential tool for the search. For this we are developing a dynamic graphical neural network based jet tagger that utilizes the boosted event shape features, among others, to classify a fat jet reconstructed at the CMS detector to be of one of the six mentioned categories.

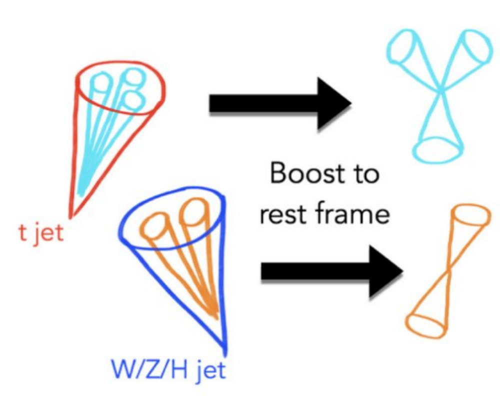


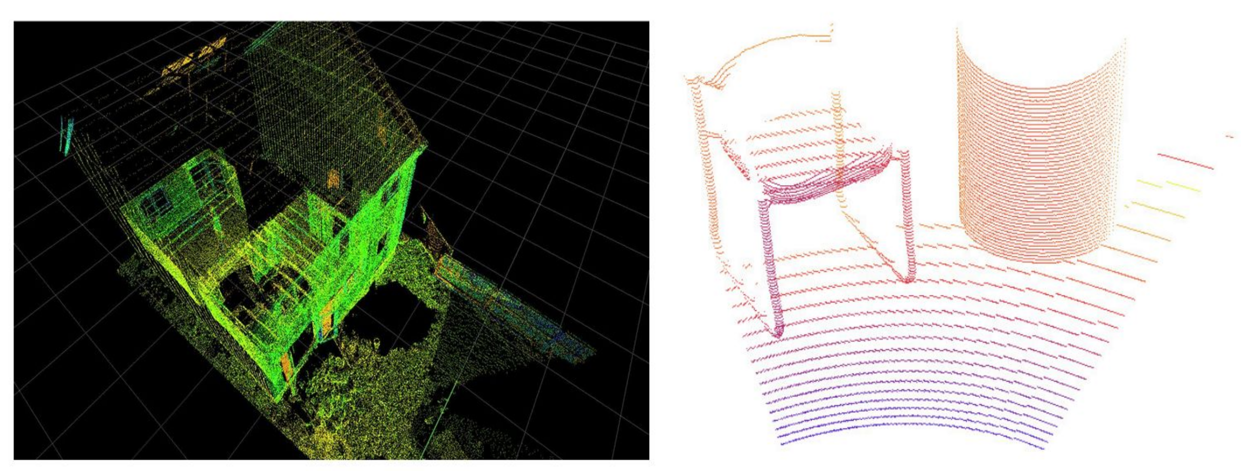
Particle Flow Algorithm



- Jets from the decay products of a heavy particle are often highly boosted and the constituents are merged together.
- Applying pattern recognition algorithms to identify jet substructures and regions of energy deposition inside a fat jet becomes difficult.
- PF constituents of a fat jet are boosted to 4 hypothesis rest frames based on t/W/Z/H mass to obtain more spherical and disentangled substructure.

The underlying expectation is that if we have boosted to the correct frame corresponding to the true origin of the fat jet, the overall momenta of the boosted constituents will be close to zero, either in terms of total momentum or momentum along the boost direction.





Point-Cloud representation of real-life objects.

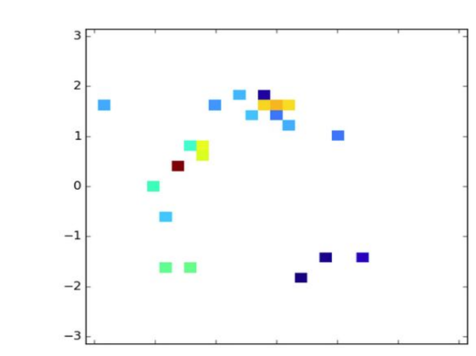
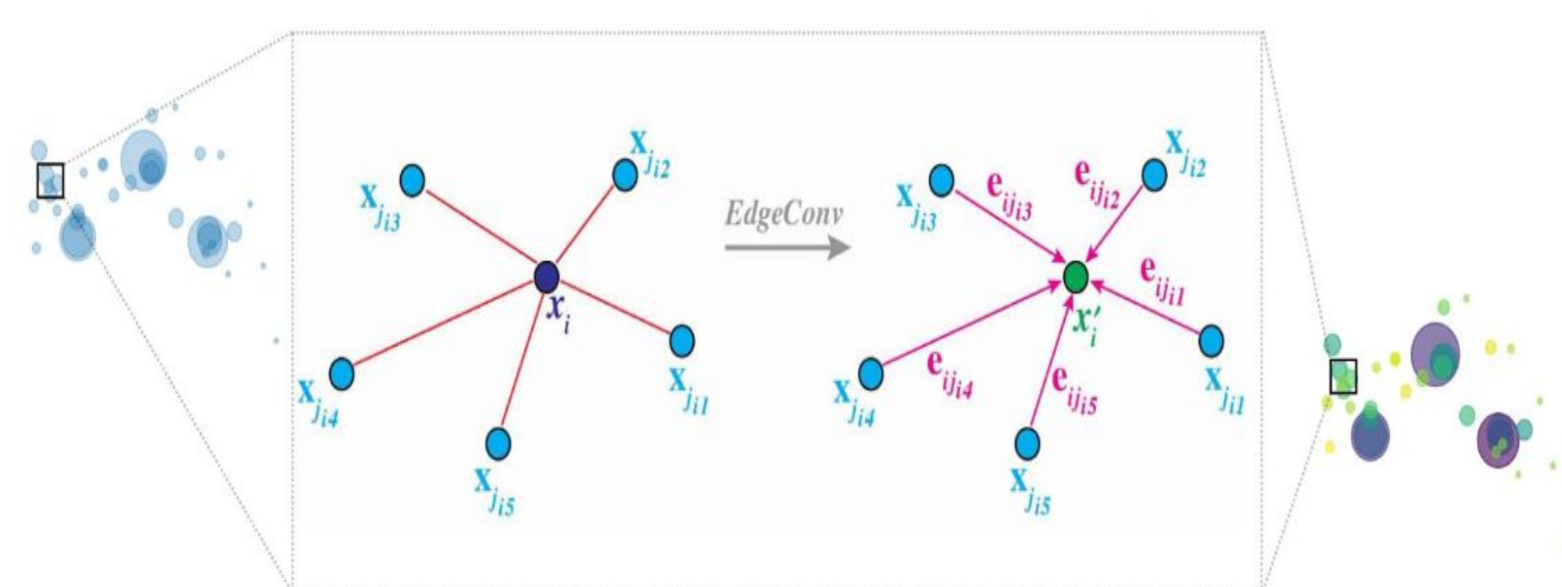


Image Representation of Detector Hits inside a Single Jet in θ, ϕ space



- How to go beyond sequences?
- Point cloud Transformers applied to Collider Physics, based on PCT: Point cloud Transformer
- Break the overall network into 2 major steps:
  - Feature extractor
  - Self-attention layers
- Define the Key, Query, and Value matrices using **convolutional layers** without biases
- Output attention is taken as an offset of the inputs

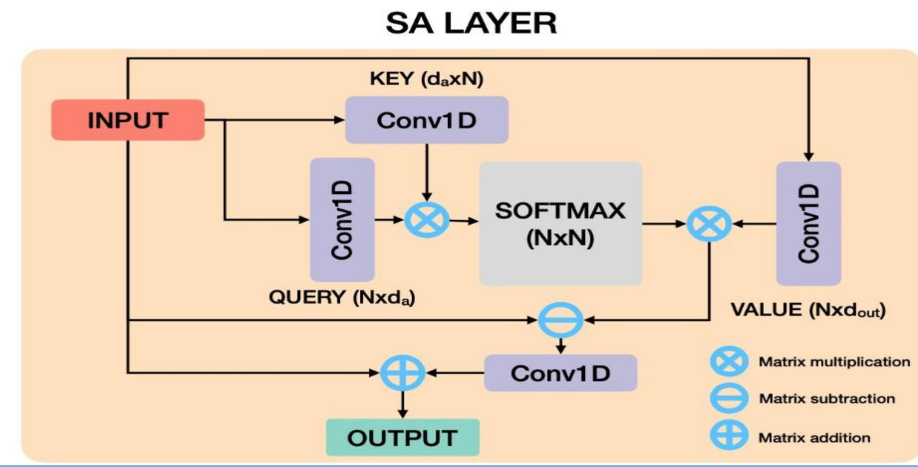
$$\mathrm{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = Z$$

$$Q, K, V = F_e \cdot (W_q, W_k, W_v)$$

$$Q, K \in \mathbb{R}^{N \times d_a}, V \in \mathbb{R}^{N \times d_{out}}$$

$$A = Q.K^T, A \in \mathbb{R}^{N \times N}$$

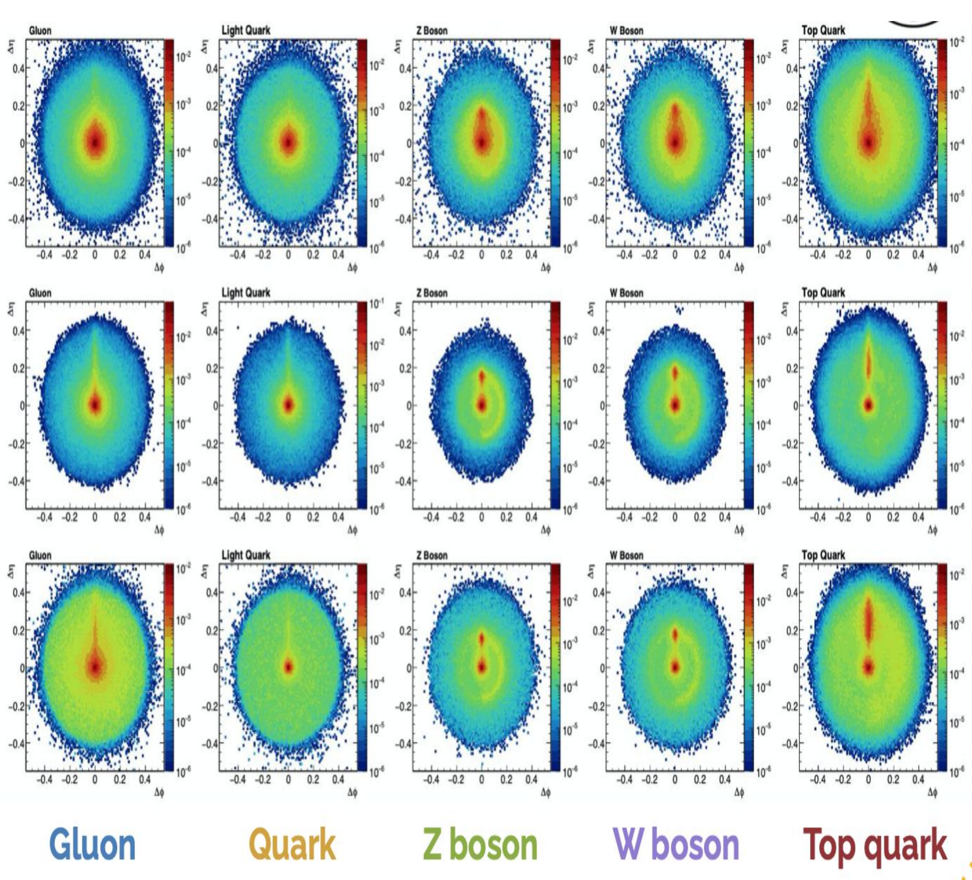
SA LAYER

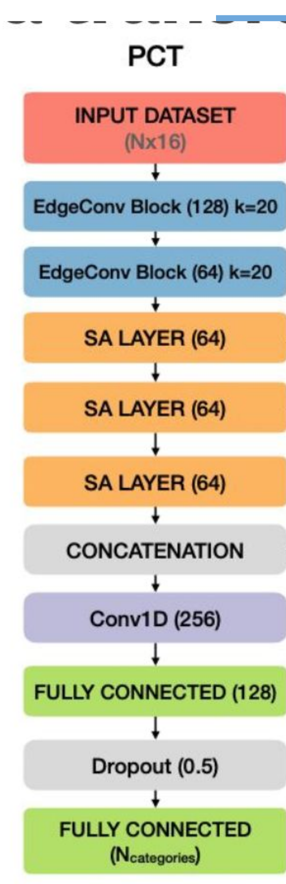


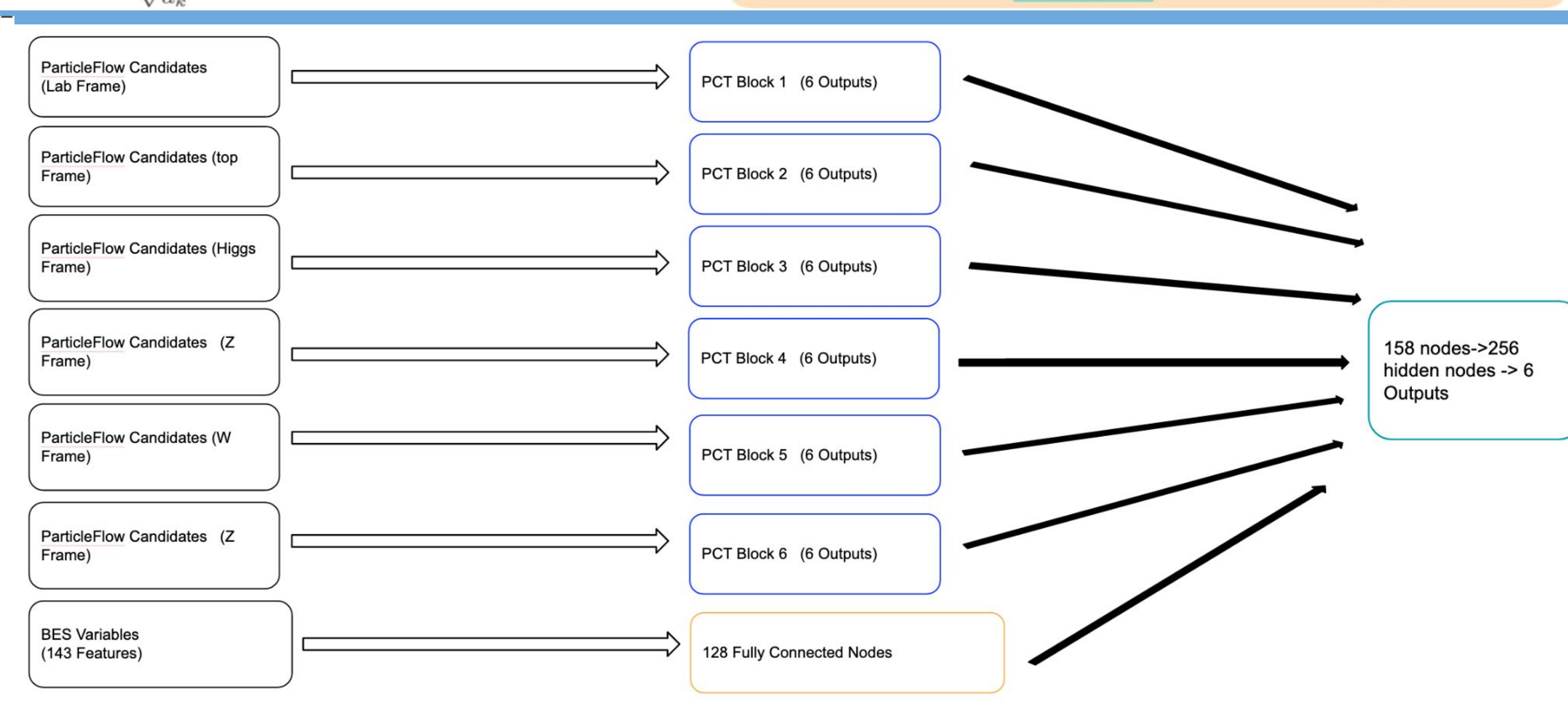
- Particle relationship
- Plot the **average histogram** for **10k jets**
- **z-axis** represent the **SA coefficient** between each particle and the most energetic

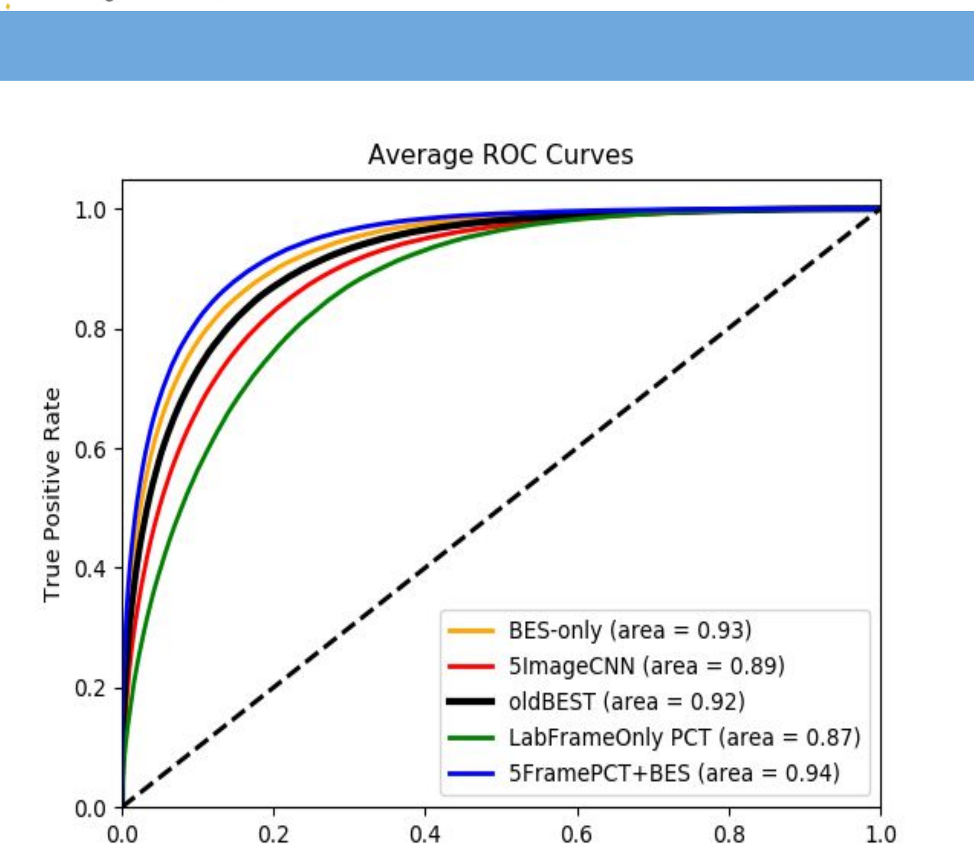
Aligning the images

- **Translate the jet image**, making most energetic particle be at (0,0)
- **Rotate the jet image**, making the second most energetic particle aligned with the y-axis
- **Flip the jet image** if the third most energetic particle is in the negative x-axis









Conclusion - **Point Cloud Transformers** combine self-attention layers to learn the **relationship between particles** and performs better compared to CNN-based tagger on average across all categories of jets.

References-

1. **Dynamic Graph CNN for Learning on Point Clouds(arXiv:1801.07829)**
2. **Point Cloud Transformers applied to Collider Physics(arXiv:2102.05073)**
3. **J.S. COnway et. al. Identification of High-Momentum Top Quarks, Higgs Bosons, and W and Z bosons using Boosted Event Shapes.**