Machine Learning in Jet Physics

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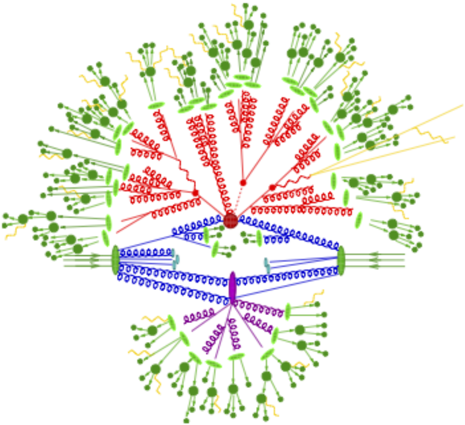
January 8, 2019

What is a Jet?

What happens in proton-proton collisions?



- Hard Scattering

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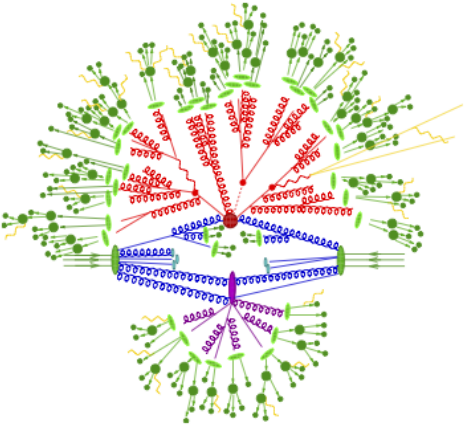

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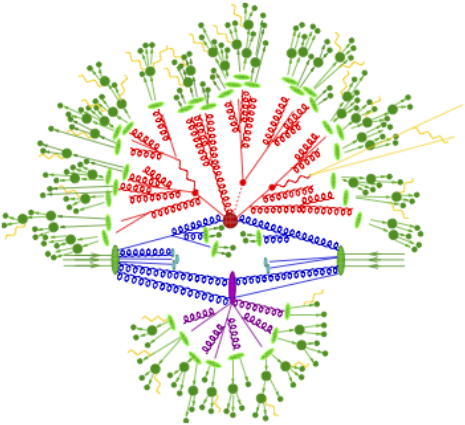

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- Initial state radiation

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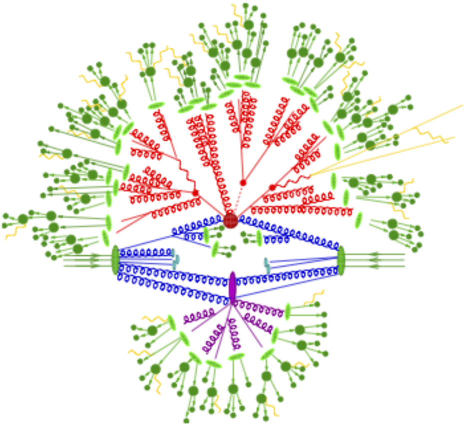

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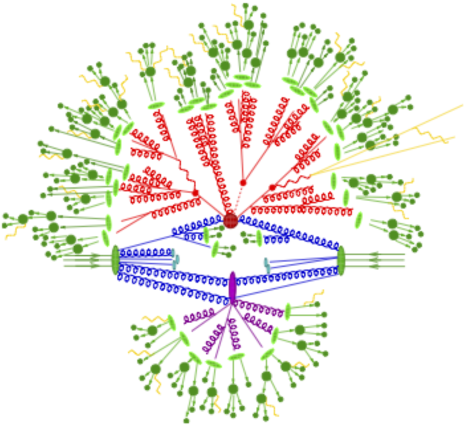

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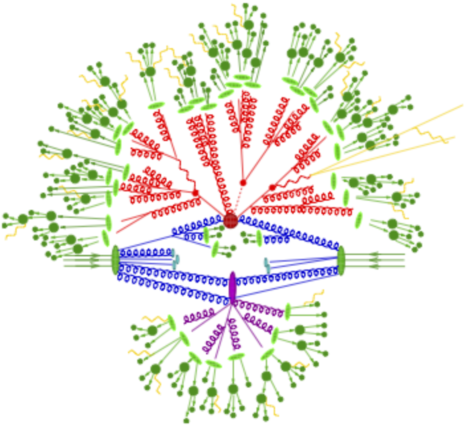

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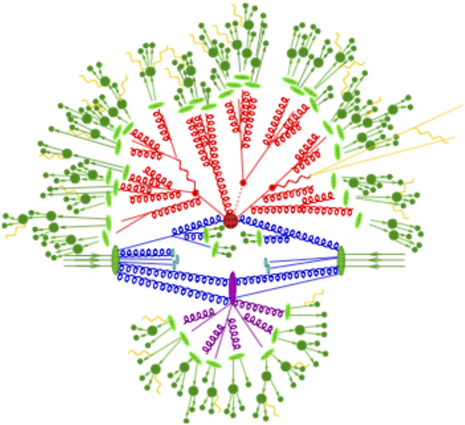

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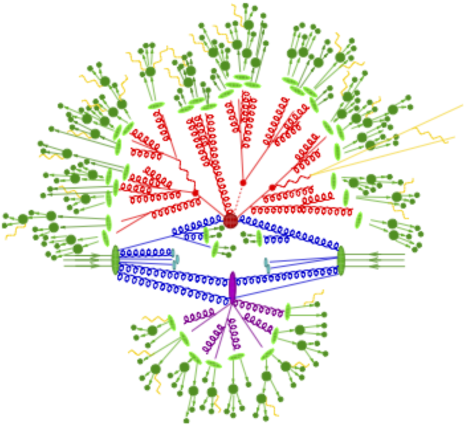

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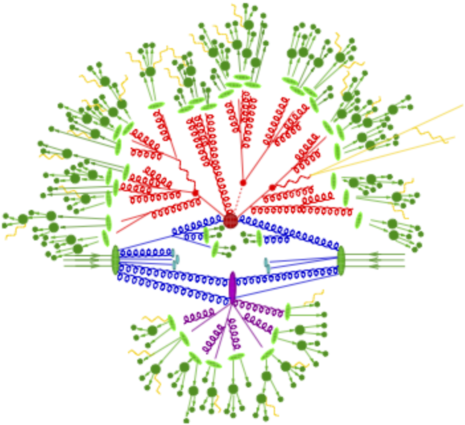

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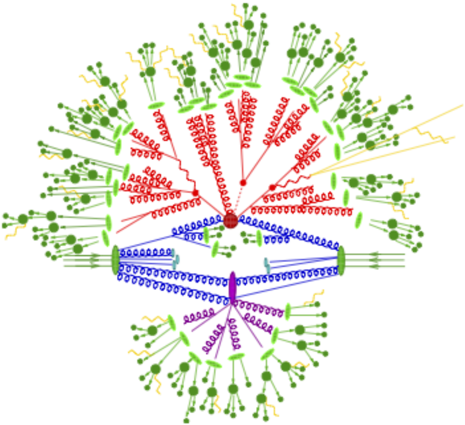

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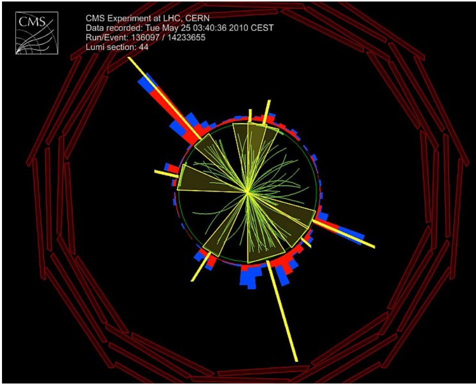
- Initial state radiation : Emissions from incoming partons before hard scattering.
- Showering : Showering of radiation from QCD decay.
- Hadronization : Formation of hadrons from partons.
- Multi-parton interactions(MPI) : Interactions of what is left of the protons after hard scattering.

Jets - Definition

- Jets are collimated stream of particles produced by particle collisions.
- Jets are used to interpret complex hadronic activities.



Measuring Jets

- Jet has a four-momentum. $E = \sum_i E_i \quad \overrightarrow{p} = \sum_i \overrightarrow{p}_i$
- Transverse momentum of a jet:

$$p_T^{JET} = \sqrt{p_x^2 + p_y^2}$$

- The radius of the jet (R) is given by,

$$R^2 = (\eta_i - \eta^{JET})^2 + (\phi_i - \phi^{JET})^2$$

- Position in the collider in two coordinates:
  - Pseudorapidity of the jet (η):

$$\eta^{JET} = -ln(tan\frac{\theta}{2})$$

where θ is the polar angle and $cos\theta = \frac{\sqrt{p_x^2 + p_y^2}}{p_z}$

  - Azimuthal angle of the jet (ϕ):

$$\phi^{JET} = tan^{-1}(\frac{p_y}{p_x})$$

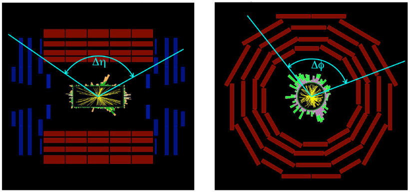


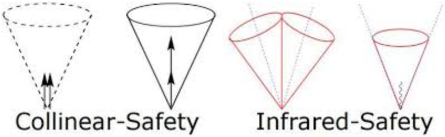
Figure 1: Coordinates

Jet Clustering

- The final state particles from the collisions are clustered using jet algorithms.
- Jet algorithms have different types:
  - Cone Algorithms
  - Clustering Algorithms

Sequential clustering algorithms

- Sequential clustering algorithms are the most commonly used algorithms today.
    - Combines particles according to the distance between them.
    - Infrared and collinear (IRC) safe.
        - Infrared safety: The outcome is not affected by the emission of a low energy (soft) gluon.
        - Collinear safety: The outcome is not affected when the gluons are emitted in a very close angle to the parton in the event.



R. Ellis, W. Stirling, and B. Webber, QCD and Collider Physics, ser. Cambridge Monographson Particle Physics, Nuclear Physics and Cosmology. Cambridge University Press, 2003.

Sequential clustering algorithms

- Cluster particles which have smallest distance between them in the momentum space.

$$d_{ij} = min(p_{ti}^a, p_{tj}^a) \times \frac{R_{ij}^2}{R}$$

where R is the radius of the cone and R_{ij} is the distance between particles in (η, ϕ) space.

$$R_{ij}^2 = (\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2$$

$$d_{iB} = p_{ti}^a$$

R. Atkin, Review of jet reconstruction algorithms, Journal of Physics: Conference Series, vol.645, no. 1, p. 012008, 2015. [Online]. Available:http://stacks.iop.org/1742-6596/645/i=1/a=012008

K_t

K_t:

- a =2.

$$d_{ij} = min(p_{ti}^2, p_{tj}^2) \times \frac{R_{ij}^2}{R}$$

  and $d_{iB} = p_{ti}^2$

- Clusters soft particles first.
- Good at resolving subjets.

R. Atkin, Review of jet reconstruction algorithms, Journal of Physics: Conference Series, vol.645, no. 1, p. 012008, 2015. [Online]. Available:http://stacks.iop.org/1742-6596/645/i=1/a=012008

Anti-K_t

Anti-K_t:

- a =-2.

$$d_{ij} = min(1/p_{ti}^2, 1/p_{tj}^2) \times \frac{R_{ij}^2}{R}$$

  and $d_{iB} = 1/p_{ti}^2$
- Clusters hard particles first.
- Good resolving power.

R. Atkin, Review of jet reconstruction algorithms, Journal of Physics: Conference Series, vol.645, no. 1, p. 012008, 2015. [Online]. Available:http://stacks.iop.org/1742-6596/645/i=1/a=012008

Cambridge/Aachen

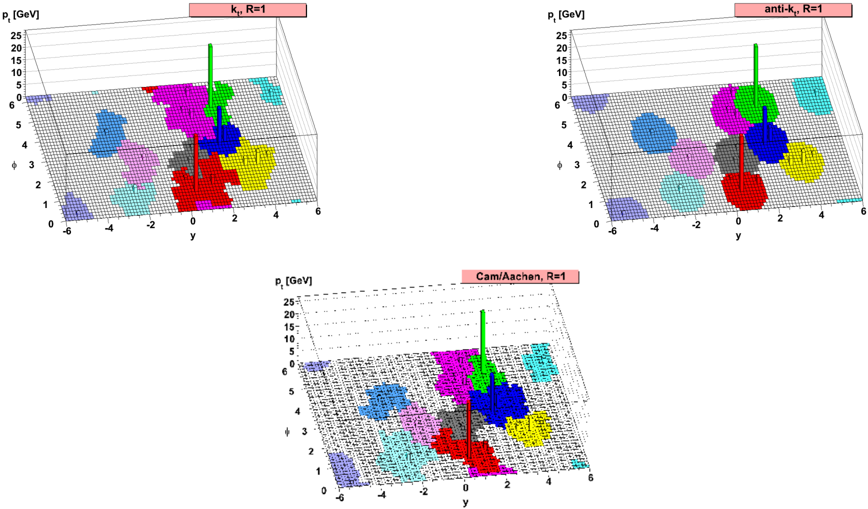
Cambridge/Aachen:

- a =0.

$$d_{ij} = \frac{R_{ij}^2}{R}$$

  and $d_{iB} = 1$
- Both variables are independent of momentum.
- Best suited for studying the substructure.

R. Atkin, Review of jet reconstruction algorithms, Journal of Physics: Conference Series, vol.645, no. 1, p. 012008, 2015. [Online]. Available:http://stacks.iop.org/1742-6596/645/i=1/a=012008



Matteo Cacciari, Gavin P. Salam, Gregory Soyez, The anti-kt jet clustering algorithm, arXiv: arXiv:0802.1189 [hep-ph]

Ok, now we know what a jet is!
Why do we need it?

- We get information of regions of the detector by clustering the particles into jets.
- Jets show properties of the initial hard-process and are used to classify quark-initiated jets from gluon initiated jets.
- Jets are an efficient tool in the classification of the hadronic decay of heavy particles and hadronic activity of a QCD processes in the final state.

How do we classify these jets?

By studying the jet-substructure!

Jet-Substructure

- Jet substructure techniques exploit the internal structure of a jet.
- Two classes of jet- substructure techniques are:
  - Jet grooming

Deepak Kar, Jet substructure: a discovery tool, Available:

http://events.saip.org.za/getFile.py/access?resId=30materialId=6confId=53

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- Two classes of jet- substructure techniques are:
  - Jet grooming : Eliminate extra energy deposits in the jet coming from pile-up, ISR and the uderlying event.
  - Jet tagging : Defining observables and distributions to classify signal and background jets.

Deepak Kar, Jet substructure: a discovery tool, Available: http://events.saip.org.za/getFile.py/access?resId=30materialId=6confId=53

N- Subjettiness

- N-subjettiness is a jet shape used for tagging boosted objects.
- Variables quantifying the amount of radiation contained within a jet (event) is aligned along different (sub)jet axes.

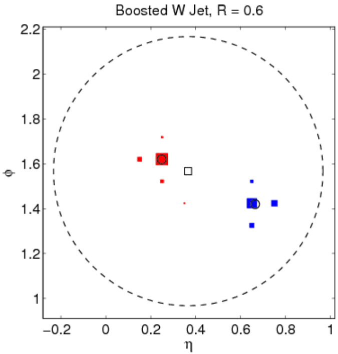
$$\tau_N^{(\beta)} = \frac{1}{p_{T,J}} \sum_{i \in J} p_{T,i} \min \left\{ R_{1i}^{\beta}, R_{2i}^{\beta}, \ldots, R_{Ni}^{\beta} \right\}$$

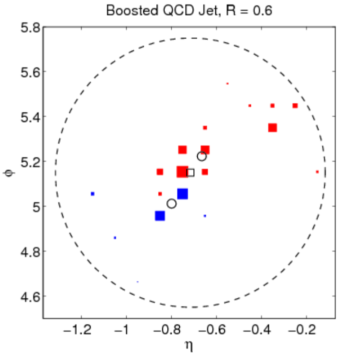
where,

- R_{Ni} is the distance in the $\eta - \phi$ plane of the jet constituent i to the axis N.
- p_T is the transverse momentum.
- β is an angular exponent.

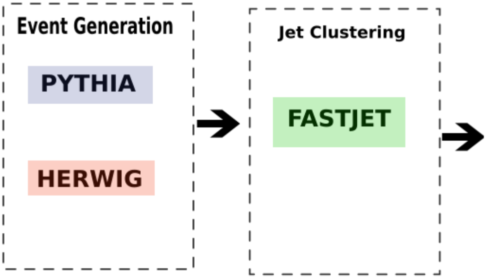
Kaustuv Datta, Andrew Larkoski, How Much Information is in a Jet?, arXiv:1704.08249 [hep-ph]

- τ_{21}=τ_2/τ_1 is a n-subjettiness variable for 2-pronged jets.





Jesse Thaler, Ken Van Tilburg , Identifying Boosted Objects with N-subjettiness, arXiv: arXiv:1011.2268 [hep-ph]



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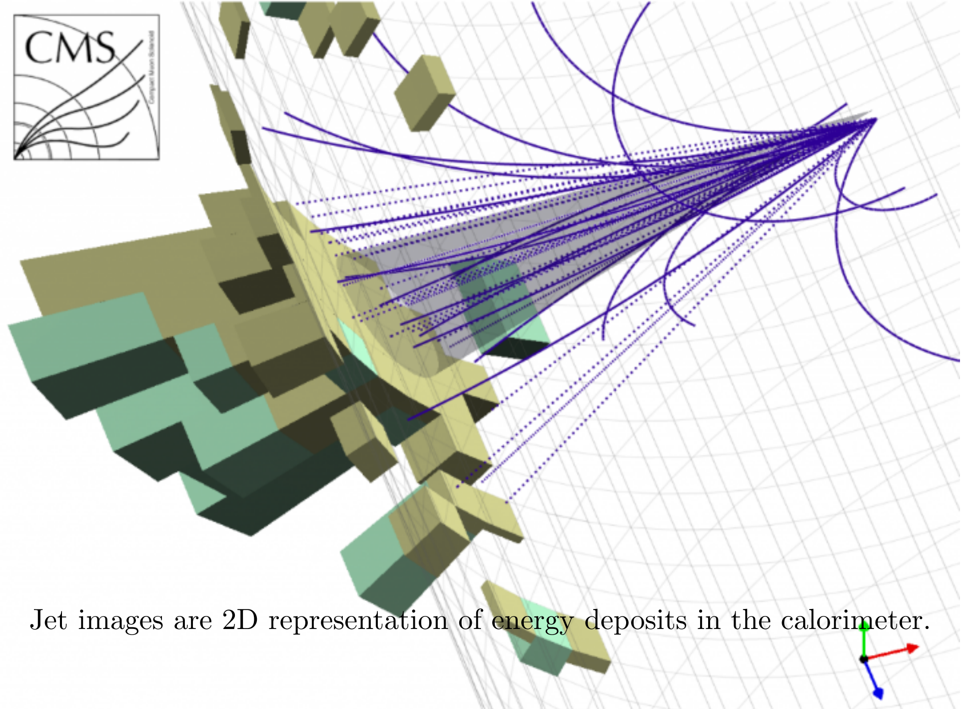
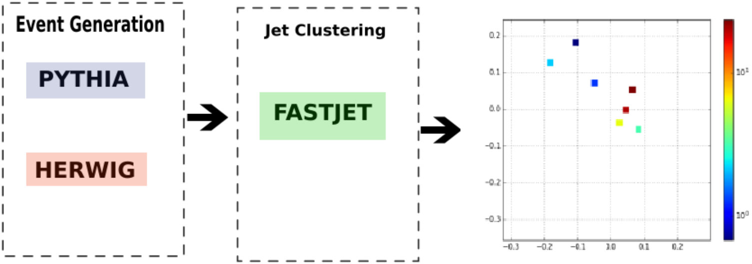


Jet images are 2D representation of energy deposits in the calorimeter.

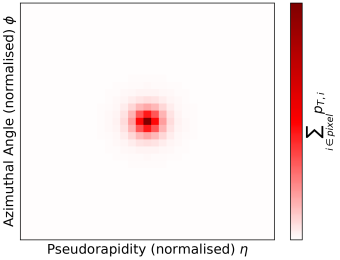
Jet-Images

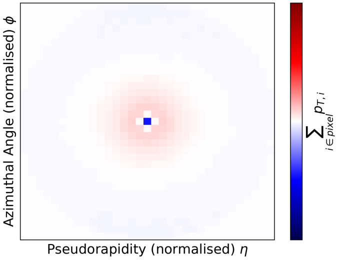


Preproccessing

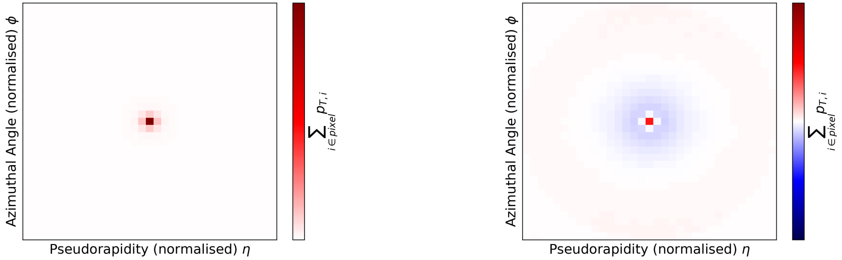
1. Centering: The jet is rotated and boosted so that the central pixel is at $(0, 0)$.
2. Crop: Crop the image with $(\eta, \phi) \epsilon (-R, R)$.
3. Normalize: Total pixel intensity of the image is $\sum I_{ij} = 1$.
4. Zero-center: $I_{ij} \rightarrow I_{ij} - \mu_{ij}$, where μ_{ij} is the average of the training set.
5. Standardize: $I_{ij} \rightarrow I_{ij}/(\sigma_{ij} + r)$ where σ_{ij} is the standard deviation of the training set and $r = 10^{-5}$.

P. T. Komiske, E. M. Metodiev, M. D. Schwartz, Deep learning in color: towards automated quark/gluon jet discrimination, arXiv:1612.01551 [hep-ph]





Average ZZ (signal: $pp \to Z_1 Z_2$, $Z_1 \to jj$, $Z_2 \to \nu\bar{\nu}$) image after normalization on the left and after pixel standardization on the right.



Average Zj (background: $pp \to Zj$, $Z \to \nu\bar{\nu}$) image after normalization on the left and after pixel standardization on the right.

Machine Learning

Figure 2: My PhD!

Why Machine Learning?

- Powerful tool to extract information from the input dataset.
- Widely used in HEP (Well, in every field!).
- ML is mainly used for jet tagging and classification (like quark/gluon) purposes.

- The most important part of machine learning is to build a model that can predict the results correctly.
- A hypothesis function is defined over the input variables to predict the output variable ($h : x \rightarrow y$).
- Cost function measures the accuracy of this hypothesis.
- With large number of variables, a linear hypothesis function fails to predict the results.

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That's why we use Neural Networks!

Neural Networks

- Neural Networks(NN) have a non-linear hypothesis function.
- NN consists of an input layer, multiple hidden layers and an output layer.
- NN with many hidden layers is called a Deep Neural Network (DNN).

The hypothesis function of a neural network can be written as,

$$h_\theta(x) = a^{(j+1)} = g(\Theta^{(j)} a^{(j)})$$

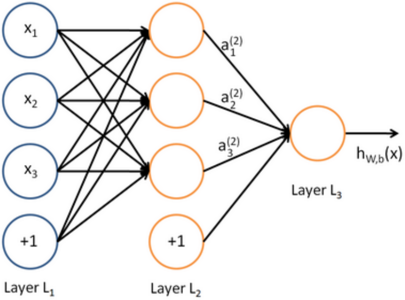


Figure 3: Neural Network architecture

Convolutional Neural Network

- Convolutional Neural Network (CNN) are neural networks for image recognition and image classification.
- CNN scans over the two dimensional pixel intensities of an RGB image.

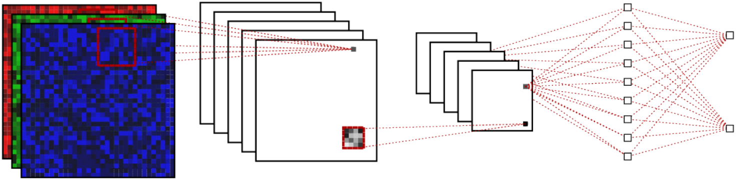


Figure 4: Convolutional Neural Network

P. T. Komiske, E. M. Metodiev, M. D. Schwartz, *Deep learning in color: towards automated quark/gluon jet discrimination*, arXiv:1612.01551 [hep-ph]

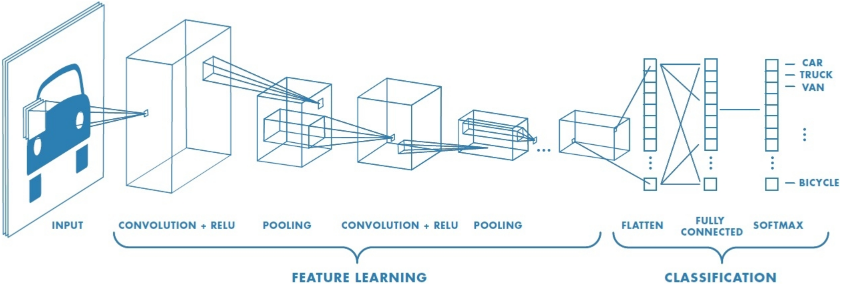
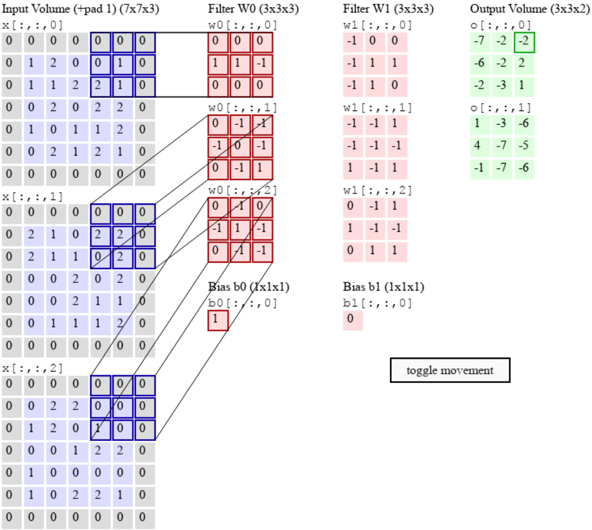


Figure 5: Components of a CNN



Convolutional Neural Networks for Visual Recognition, Available: http://cs231n.github.io/neural-networks-3/anneal

Our Work: 1807.04769

We compare the results of two machine learning techniques used to classify Z/top jets with QCD jets:

Convolutional Neural Network on Jet Images

- Image recognition techniques to classify signal and background.

Deep Neural Network on N-subjettiness variables

- Physics motivated variable learned using DNN.

Processes

Z boson tagging

- Signal: $pp \to Z_1 Z_2$, $Z_1 \to jj$, $Z_2 \to \nu\bar{\nu}$
- Background: $pp \to Zj$, $Z \to \nu\bar{\nu}$
- p_T ranges:$p_T(Z/j) \geq 500\text{GeV}$

Top quark tagging

- Signal : $pp \to W_1^- t$, $t \to W_2^+ b$, $W_2^+ \to jj$, $W_1^- \to e^- \bar{\nu}_e$
- Background : $pp \to W^- j, W \to e^- \bar{\nu}_e$
- p_T ranges: $[350, 400]$ GeV, $[500, 550]$ GeV and $[1300, 1400]$ GeV

Parameters

Z boson tagging

- Radius $= 0.8$
- Pseudorapidity $|\eta| < 5.0$

Top quark tagging

- Radius $= 0.8$ ($[1300, 1400]$ GeV), 1.5
- Pseudorapidity $|\eta| < 2.5$ ($[1300, 1400]$ GeV) and $|\eta| < 1.0$

Machine Learning on N-subjettiness variables

The input variables for the Deep Neural Network are,

$$\left\{\tau_1^{(0.5)}, \tau_1^{(1)}, \tau_1^{(2)}, \tau_2^{(0.5)}, \tau_2^{(1)}, \tau_2^{(2)}, \ldots, \tau_{M-2}^{(0.5)}, \tau_{M-2}^{(1)}, \tau_{M-2}^{(2)}, \tau_{M-1}^{(1)}, \tau_{M-1}^{(2)}\right\}$$

- This covers M-body phase space with 3M−4 observables.
- Jet mass is also included as an input to the neural network.

Kaustuv Datta, Andrew Larkoski, How Much Information is in a Jet?, arXiv:1704.08249 [hep-ph]

The network consists of,

- Four fully connected hidden layers
- First two with 300 nodes and a dropout regularisation of 0.2
- Last two with 100 nodes and a dropout regularisation of 0.1
- Activation: ReLU

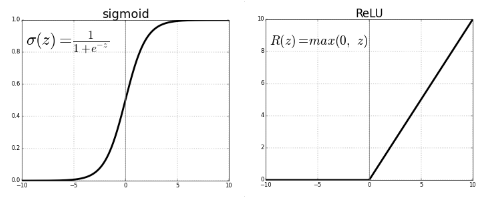


Figure 6: ReLU and Sigmoid activations

- Optimizer: Adam
- Learning rate $\alpha = 0.001$

Machine Learning on Jet-Images

- Jet images of size 33×33.
- 3 convolutional layer and 2 fully connected layer.
- ReLU activation.
- Filters of size 8×8, $4 \times 4$and 4×4 are used.
- Maxpooling layers 2×2 is also applied to the CNN with a stride length of 2.
- The fully connected layer consists of 128 units.

- Convolutional Neural Network is trained on Tensorflow using NVIDIA GeForce 1080Ti GPU on Cuda 9.0 platform.
- The network is trained over 50 epochs with a learning rate α of 0.001.
- Additional network with mass is trained for 500 epochs with same parameters as n-subjettiness network.
- 2M jet images are used for training, 100k images for validation and 200k images are used for testing.

ROC-Curves

- Receiver operating characteristic (ROC) is used to visulaize the performance of a binary classifier.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 7: Confusion Matix

ROC-Curves

- Plot the true positive rates (TPR) and false positive rates (FPR) for every possible classification threshold to obtain a ROC curve.

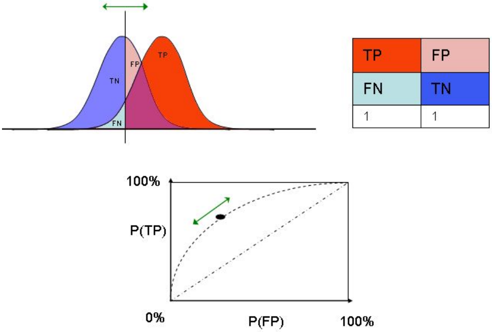
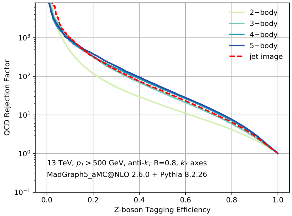
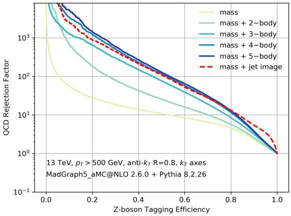


Figure 8: ROC-curve

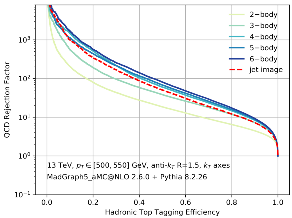
Conclusions

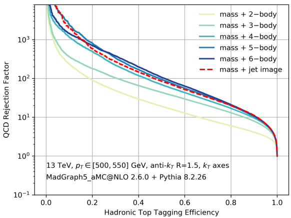
- Mass as an additional information improves the performance of the network.
- As the ROC curves are matching, we can conclude that the information learned from both methods are the same.





ROC curves for Z boson tagging without mass on the left and with mass on the right for $p_T > 500$ GeV.





ROC curves for top quark tagging without mass on the left and with mass on the right, for $p_T \in [500, 550]$ GeV.

Future Works

🤔

- What happens when this method is applied to real data?
- Is there any bias between various event generators? Will we get the same results if we use different event generators?
- What exactly is a convolutional neural network learning from these images?

Thank you!

Domain Adversarial Neural Netwrok (DANN)

- Domain adversarial neural network is a new learning approach for data trained and tested on similar but different distributions.

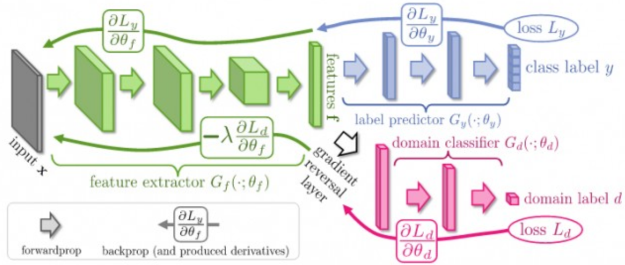


Figure 9: DANN architecture

Y. Ganin et al. , Domain-Adversarial Training of Neural Networks, arXiv:1505.07818 [stat]

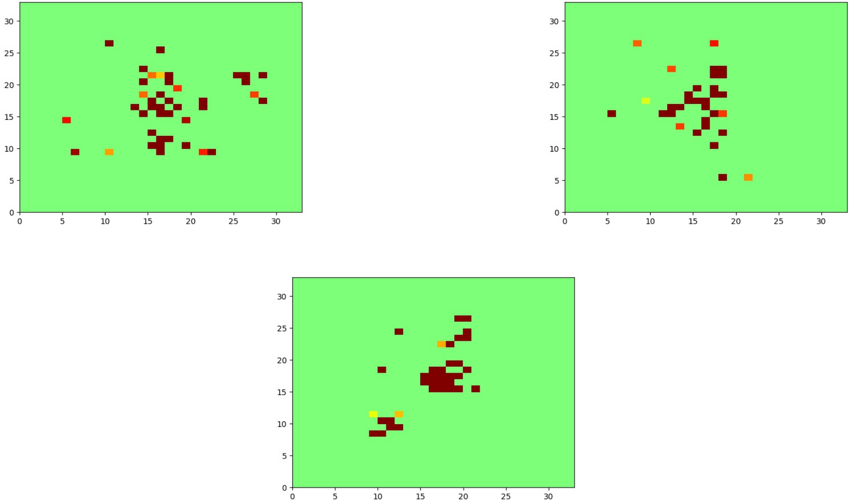


Figure 10: Sample top images