CNN for Jet Tagging

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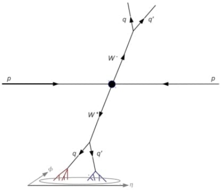
November 22, 2021

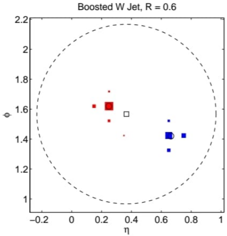
Outline

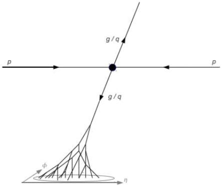
Definitions [5]

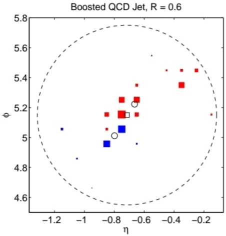
a. Jets are collimated spray of particles which are produced due to high energy(GeV or TeV) beam particles.
b. QCD Jet is that one whose vertex is high-energy light parton(quarks or gluons) and dynamics involves Strong Force.
c. Boosted Jet is that one whose vertex is high-energy heavy parton or heavy particle and dynamics involves Electro-Weak Force .
d. $\eta - \phi$ are the coordinate of the particles detected in calorimeter tower. p_T transverse momentum of the particles. ΔR is euclidean distance in eta-phi space.

A look at some jet pictures









N-subjettiness [4]

N-subjettienss, a inclusive jet shape denoted by τ_N is calculated by

$$\tau_N = \frac{1}{d_0}\Sigma_k[p_{T,k} min\{\Delta R_{1,k}, \Delta R_{2,k}, ...\Delta R_{N,k}\}]$$

where,
k runs over all constituents in the jet,
$p_{T,k}$ is transverse momentum of the kth constituent,
$\Delta R_{j,k}$ is the distance of kth constituent from jth candidate subjet and
d_0 is the Normalization factor taken as

$$d_0 = \Sigma_k[p_{T,k} R_0]$$

where,
R_0 is the characteristic jet radius.

Data Generation

Here simulated data is obtained using three software...

1. Delphes: runs configuration file with in Pythia to mimic detector specifications
2. Pythia: simulate data using laws of physics model applied on.
3. Fastjet: runs Anti-K_T or K_T clustering algorithms [1].

Aim and methodology

Aim is to classify these two jets. Older method used discriminant method(N-subjettiness or Fisher discriminant [2] etc) to classify these jet. Neural Network method is new to this field.

- N-subjettiness discriminant: τ_{21} is the ratio of τ_2 and τ_1. Logically τ_{21} should be lowest for two prong decay.
- CNN method: Using different sets of convolution layers, non-linearity and Max pooling with input as direct jet images, classification can be done with some accuracy.

Architecture of the used CNN Model

```
def Model():
    model=Sequential()
    model.add(Conv2D(10,kernel_size=2,activation='relu',input_shape=(25,25,1)))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Conv2D(5,kernel_size=2,activation='relu'))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Flatten())
    #model.add(Dense(10, activation='softmax'))
    model.add(Dense(2, activation='softmax'))
    #model.add(Dense(2, activation='sigmoid'))
    model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
    return model
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 24, 24, 10)        50
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 12, 12, 10)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 11, 11, 5)         205
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 5, 5, 5)           0
_________________________________________________________________
flatten (Flatten)            (None, 125)               0
_________________________________________________________________
dense (Dense)                (None, 2)                 252
=================================================================
Total params: 507
Trainable params: 507
Non-trainable params: 0
```

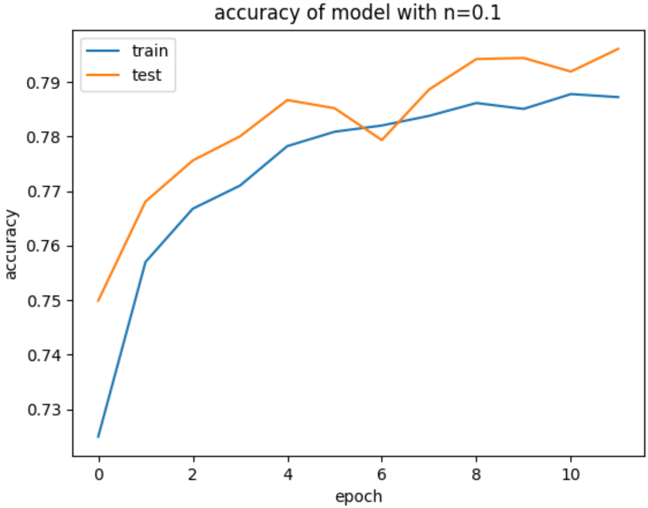
Data set used [3]

A publicly available dataset produced by B. Nachman, L. de Oliveira, and M. Paganini. The data were simulated with Pythia8 (v. 8.219) using a center of mass energy of $\sqrt{s} = 14$ TeV.

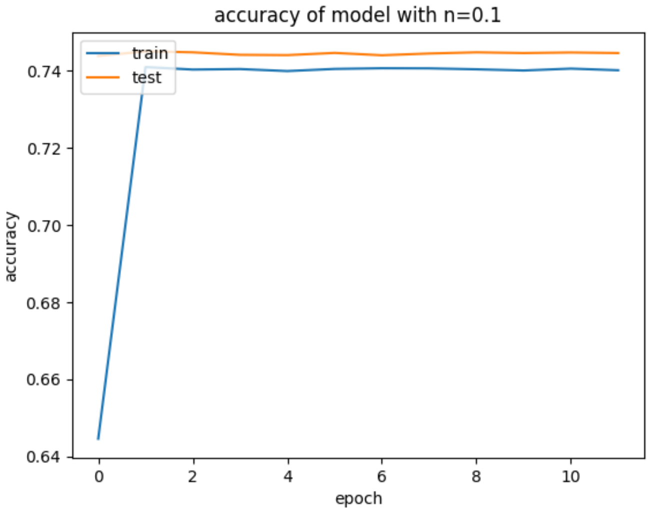
During event generation, the FastJet (v. 3.0.3) algorithm applies cuts (i.e., only consider jet candidates with $250 < p_T < 300$ GeV, a jet mass of $60 < m < 100$ GeV, only consider candidates with opening angle of the parton shower is $\Delta R = 0.6$, etc.) and then further classification of the leading jets to distinguish the subjets within the main jet.

Total number of instances 872666. Where each image is 25x25 on $\eta - \phi$ grid. Labels are available with key name signal(1 for W jet and 0 for QCD jet).

Result from CNN



Result from N-subjettiness discriminant



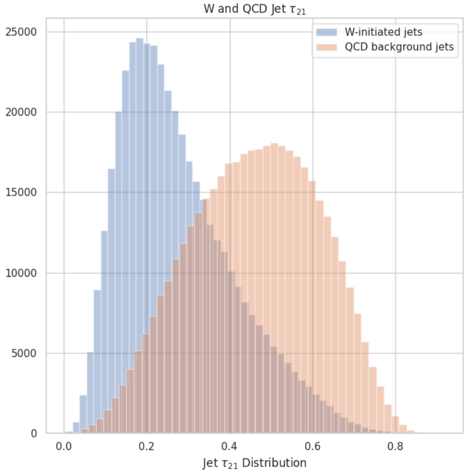
Comparison I

For same size data set with equal epochs CNN is giving better accuracy than N-subjettiness. Reason may be follows..

a. QCD jet can also be two prong if it is not a gluonic jet. Due to this reason there will be high overlap of τ_{21} between QCD and Boosted-W jets.
b. Another reason may be that N-subjettiness is obatained after clustering algorithm performed on calorimeter data. While for the case of CNN model we are directly using calorimeter data as jet images.

Comparison II

Let us see the distribution over τ_{21}.



References I

Matteo Cacciari, Gavin P Salam, and Gregory Soyez.
The anti-ktjet clustering algorithm.
Journal of High Energy Physics, 2008(04):063–063, Apr 2008.

Josh Cogan, Michael Kagan, Emanuel Strauss, and Ariel Schwartzman.
Jet-images: computer vision inspired techniques for jet tagging.
Journal of High Energy Physics, 2015(2), Feb 2015.

Benjamin Nachman, Luke de Oliveira, and Michela Paganini.
Pythia Generated Jet Images for Location Aware Generative Adversarial Network Training, February 2017.
Generation and analysis code available at https://github.com/lukedeo/adversarial-jets To reproduce this dataset: - follow instructions available at https://github.com/lukedeo/adversarial-jets/tree/master/generation - docker image available

References II

(from Docker Hub) under lukedeo/ji:latest - tested on MacOS Sierra, Ubuntu16.04 - depends on Pythia, ROOT, FastJet and modern Python installation (only tested on 2.7, but should work on 3.4+).

Jesse Thaler and Ken Van Tilburg.
Identifying boosted objects with n-subjettiness.
Journal of High Energy Physics, 2011(3), Mar 2011.

Cheuk-Yin Wong.
Introduction to High-Energy Heavy-Ion Collisions.
WORLD SCIENTIFIC, 1994.