TAGGING LOW p_T B-JETS

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WHY A LOW p_T B-TAGGER?

- Certain SUSY stop production models have a compressed mass scenario
 - mass difference between the stop and LSP is small
 - b quarks can be produced in intermediate steps of these stop decays, with a relatively low p_T
 - Want a tagger optimized for finding these b-jets
- Current taggers are supported for p_T ranges 20-1000 GeV
 - These are not optimized for a specific p_T range





JETS AND B HADRONS

| | tracks | b jet |
|---|--|---------------------|
| ets • narrow cone of particles produced by hadronization of quarks and gluons | b hadron impact parameter | |
| o-quarks hadronize into B- adrons → forms jets | and the second sec | secondary vertex |
| -jet identifiers Displaced tracks Large impact parameter Displaced vertices (secondary vertex) Sizable lifetime (1.5 ps) | light jet - prim | nary vertex |

CSV ALGORITHM

- Combined Secondary Vertex (CSV):
 - Tagger that makes use of SV and track-based lifetime information
 - Iterations:
 - CSV (likelihood)
 - CSVv2 (Artificial NN)
 - DeepCSV (DNN)

- Discriminating power for different situations
 - No vertex
 - Pseudo Vertex
 - Vertex



DEEPCSV – PREPROCESSING

- Data used is official CMS MC
 - QCD Multijets Pythia8
 - $t\bar{t}$ MadgraphMLM, Pythia8
- Data preparation
 - Original Samples converted to flat ROOT ntuples (DeepNTuples framework)
 - C
 - ROOT files converted to numpy arrays with pre-processing applied
 - Python, some compiled C modules
- Data pre-processing
 - Mean normalization
 - Zero-padding
 - p_T/η flattening of classes



DEEPCSV - INPUTS

• 28 variables

12 jet / jet-track associated variables

- p_T , η , n_{SV} , vertex category, $\sum (E_T^{tracks})/E_T^{jet}$, $\Delta R(p_{tracks}^{\mu}, jet)$, 1st track IP significance/value above Charm, $n_{selected\ tracks}$, n_{tracks} , w/η_{rel}
- 7 track variables, keeping up to 6 tracks per jet
 - p_T^{rel} , min track-jet distance, $\Delta R(track, jet)$, p_T/E_T , IP sig/val, decay length
- 1 associated track variable, keeping up to 4 entries per jet
 - η^{rel}
- 8 secondary vertex variables, keeping up to 1 vertex per jet
 - mass, n_{tracks} , E_T^{sv}/E_T^{Total} , $\Delta R(sv, jet)$, flight distance sig/val
- Grand total of 66 inputs

DEEPCSV - DNN

- DNN Characteristics
 - 66 inputs (x)
 - 4 truth categories (classes) (y) \rightarrow isB, isBB, isC, isUDSG
 - Fully connected
 - 7 layers
 - 5 hidden layers \rightarrow 100 nodes each
 - Dropout rate: 0.1
 - Activation: ReLU on hidden layers, softmax on last layer
 - Loss: categorical x-entropy
 - $CE = -\sum_{i=1}^{C} t_i \log(f(s)_i)$ $f(s)_i = \frac{e^{s_i}}{\sum_{i=1}^{C} e^{s_j}}$
 - Learning rate: 0.003
 - Batch size: 5000
 - Epochs: 50

DEEPJET FRAMEWORK

- Training and testing is done using the DeepJet Framework
 - <u>https://github.com/DL4Jets</u>
 - Specifically made for jet tagging
- Pure Keras + Tensorflow for training/testing
 - Includes some compiled C modules for data processing
- Class structure for modifying data structures
 - Start with a basic structure consisting of truth inputs, basic jet variables
 - 12 usable truth classes (flavors of jets)
 - b, bb, gbb, lepb, lepb_c, c, cc, gcc, ud, s, g, undefined
 - Create new data class that inherits basic structure, and add to it
- Set of base models for training supplied as python pseudomodules, and can be further adjusted
- Plotting macros for ROC curves, performance plots

ACTION ITEMS FOR PROJECT

- Reproduce training results for base DeepCSV structure/model as found in the DeepJet framework
 - Try to determine how this can be optimized for low p_T jets
- Look at correlation between inputs and jet p_T
 - look for new inputs (see what is available)
 - Determine collection sizes
 - Remain at 6 tracks per jet, or change?
 - Look at number of tracks against p_T
 - Will most likely be on the smaller size
 - Adjusting input weights
- Adjusting layers/NN
 - Currently using all dense layers
 - Can explore different types of NN
 - Ex) introduce convolutional layers
 - Introduce p_T related regression target on top of classification?

PLACES OF INTEREST

- Lectures from the 2018 CoDaS summer school
 - <u>https://indico.cern.ch/event/707498/timetable/</u>
- What I started with (documentation on DeepCSV):
 - <u>https://indico.cern.ch/event/595059/contributions/2497371/attach</u> ments/1430948/2198064/IML_2017.pdf
- ML at CERN: the IML Working Group
 - Public meetings
 - <u>https://indico.cern.ch/category/8009/</u>
 - EP-IT Data Science Seminars (also public)
 - <u>https://indico.cern.ch/category/9320/</u>
 - Forum (requires lightweight CERN account)
 - <u>https://account.cern.ch/account/externals/</u>
 - Anyone should be able to make one
 - <u>https://iml.web.cern.ch/</u>