Machine Learning Applications in Physics at Rice

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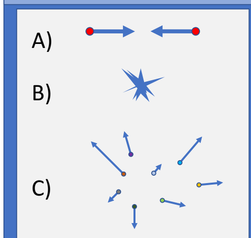
Rice University's Bonner Lab has been focused on applying machine learning techniques to physics data analysis and detector operation.

Particle Search



Background

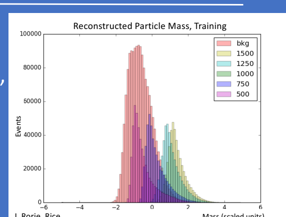
- Event
  - Initial particles are accelerated [A]
  - Collision [B]
  - Secondary, tertiary, etc. particles are created [C]
- New, undiscovered particles may be created
- Reconstruct event
- Look for new particles

Data and Tools

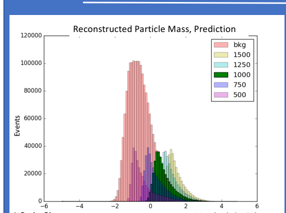
- UCI HEPMASS datasets [1]: 7x106 training, 3.5x106 test events
- Keras with TensorFlow (1.X) backend
- Features include: momenta of final state particles, particle types, missing momentum, b-tagging of jets, jet momentum, reconstructed masses of intermediate particles

Analysis Strategy

- Use new particle mass as parameter
- Train on dataset without "new particle"
- Validate with dataset sans new particle
- Run trained NN on dataset with new particle included
- Based on Ref [2]



Result of regression training a densely connected NN with 27 parameters including particle mass, 4 hidden layers, with one particle class removed



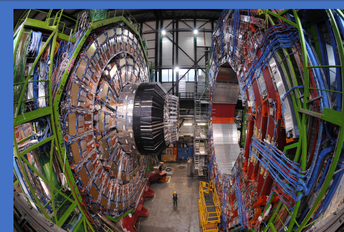
Prediction of trained model run on data with all particle classes present

Result and Conclusions

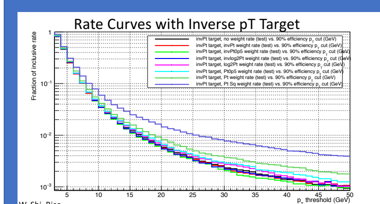
- Can find particles that were not present in training
- Can be used to "scan" mass range
- Next: apply in real data (CMS)
  - More complicated backgrounds
  - Rare particles = smaller signal

Compact Muon Solenoid Detector Triggering

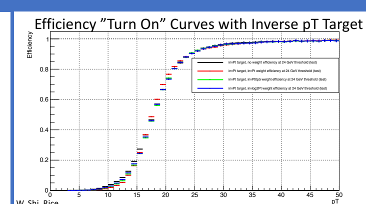
- Event rate reduction is critical
  - Approx. 1 MB/Event
  - Up to $40x10^6$ events/second (rate)
- Must retain interesting physics
  - One criterion: muon momentum transverse to beam axis (pT)
  - Event kept if pT above threshold
- Use ML to develop algorithms to determine pT from detector data



The CMS Detector at the CERN Large Hadron Collider. It is even more impressive in person.



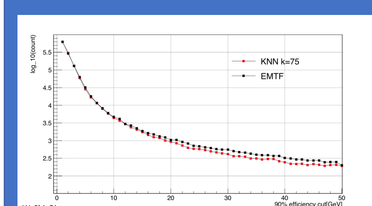
Curves showing the reduction of rate as threshold pT increases for various weighting functions used in the BDTs. The most effective weighting was studied further.



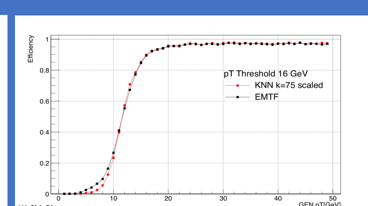
Muon acceptance efficiency as a function of muon pT for most effective BDT weighting. The Ideal curve is a Heaviside function at threshold pT.

Trigger Study

- Boosted Decision Trees
- 800K testing and training events
- Features like discrete ϕ, θ
- Select ~5-7 out of 30+ possible features
- Both CMS simulation and data used
- Run with TMVA [3] in Root [4]



KNN with 75 nearest neighbors compared to BDT trainied in 2016. KNN shown to have comparable perfomance at low pT, divergence at high pT .



KNN with 75 nearest neighbors compared to BDT trained in 2016. Better rejection at low range, poorer rejection just above threshold, comparable in plateau region.

Algorithm Comparisons

Looking beyond Boosted Decision trees to K Nearest Neighbor, MLP, Densely connected DNNs, and CNNs

Current projects include applying DNNs to characterization of experimental backgrounds due to the J/ψ particle, searches for new particles in CMS experiment data, improved trigger performance, and performing initial checks of raw experiment data quality.

Particle search study: Dr. J. Rorie with D. Williams, P. Menninger., R. Liu [Rice University]. Special thanks to A. Patel.

Trigger Study: Wei Shi [Rice University] in collaboration with Andrew Brinkerhoff [U Florida] et al. [HOW TO CREDIT?]

[1] https://archive.ics.uci.edu/ml/datasets/HEPMASS
[2] arXiv:1601.07913v1
[3] http://tmva.sourceforge.net/