Regression and BDTs in TMVA

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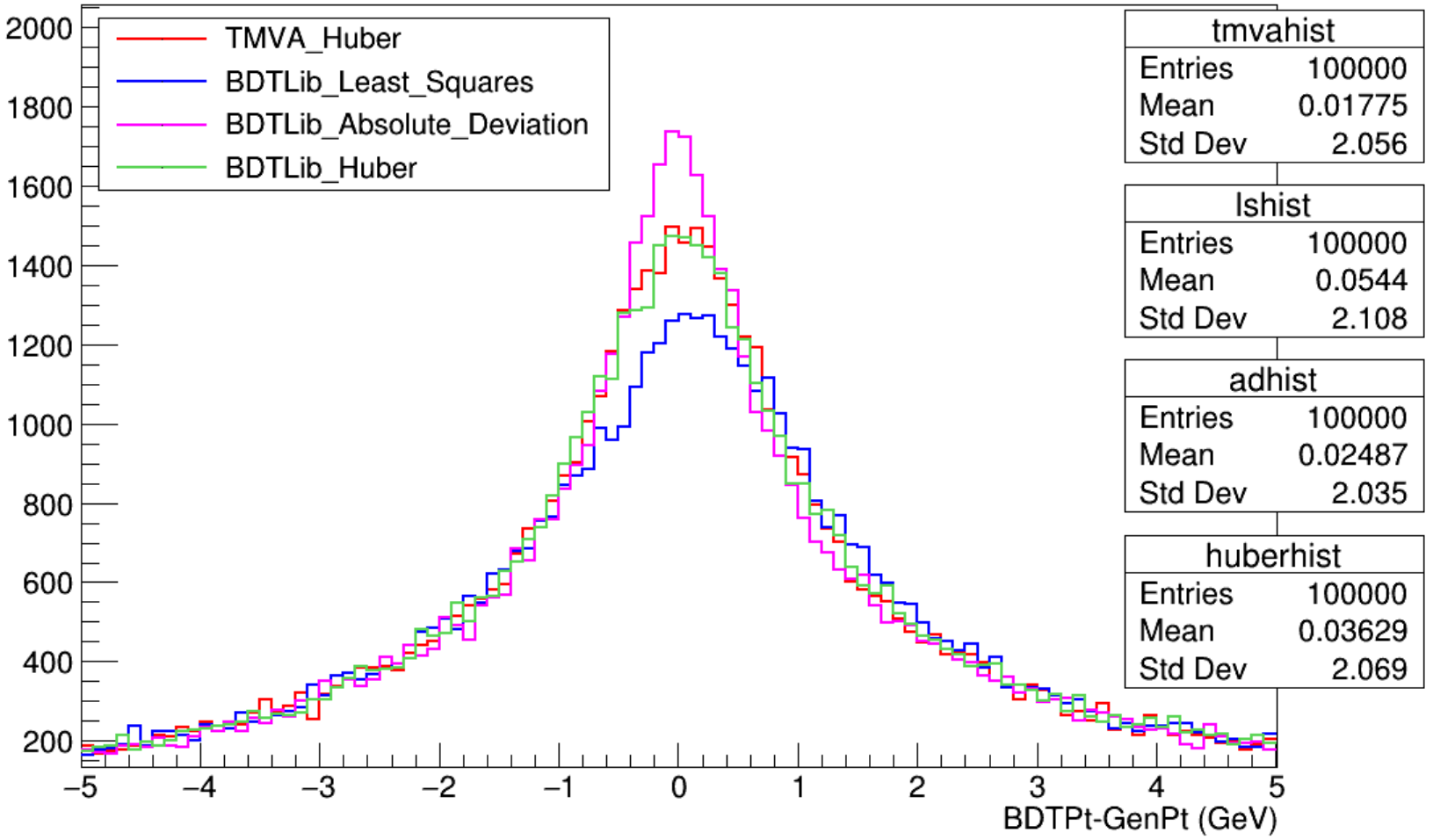
Intro

- Wrote a Boosted Decision Tree (BDT) package, BDTLib https://github.com/acarnes/bdt
    - Multiple loss functions
    - Consensus to integrate this functionality into TMVA
- Would also like to parallelize the BDTs
- Beginning to implement these additions
- Status
    - Began benchmarking
    - Outlining code structure
    - Familiarizing further with TMVAs BDT implementation

Benchmarking on CSC Pt Assignment

- Comparing some loss functions from BDTLib to TMVA's Huber Loss function in the context of regression
- Here we look at momentum assignment in the L1 Trigger's Cathode Strip Chambers using Monte Carlo
- We see an obvious difference in the predictions given different loss functions as expected



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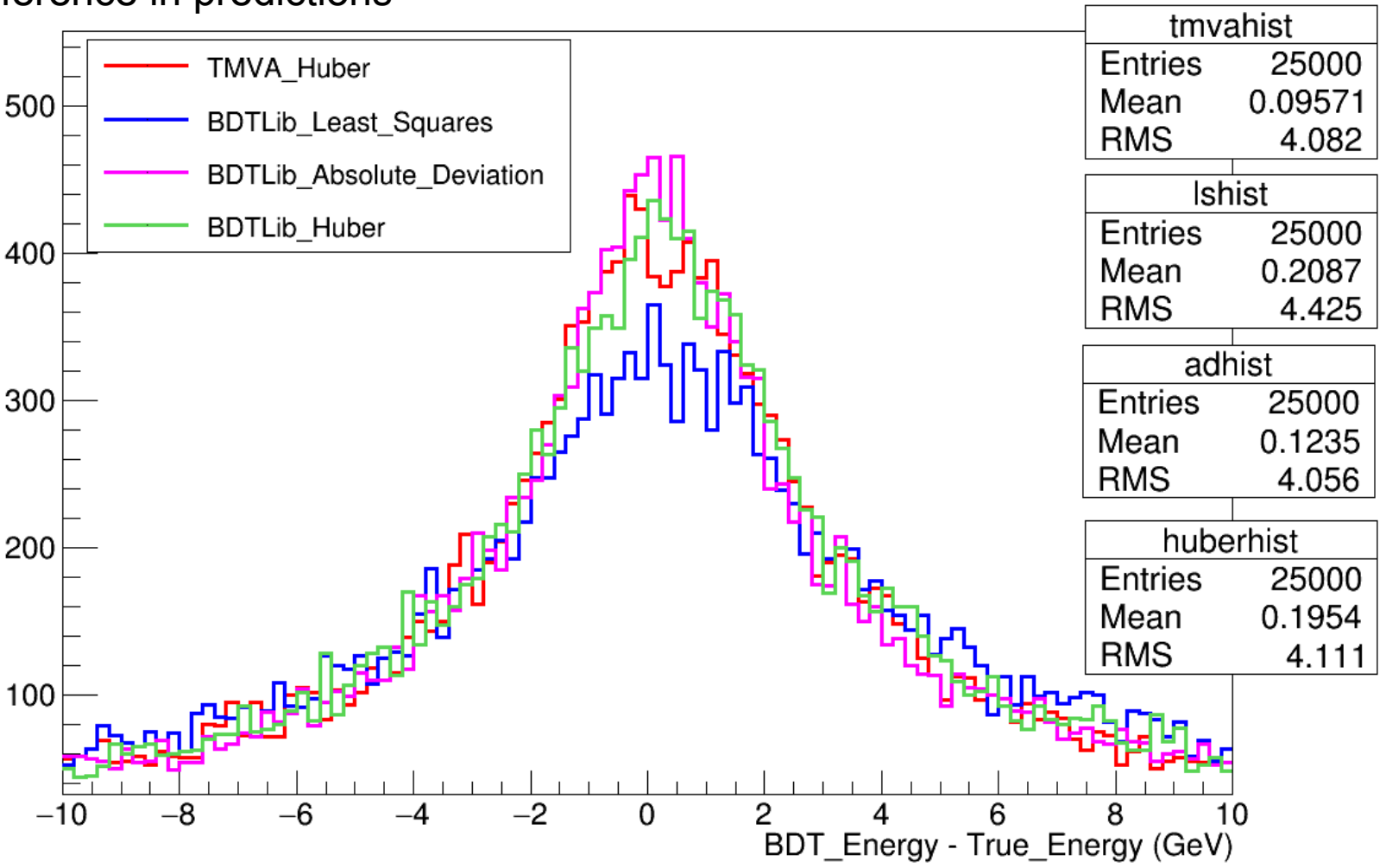
Benchmarking on Toy Calorimeter

- Again comparing some loss functions from BDTLib to TMVA's Huber Loss function in the context of regression
- Here we look at predicting the energy deposition in a toy calorimeter
  - Uses the sample from the page below
  - https://www.hep1.physik.uni-bonn.de/people/homepages/tmva/tmvatutorial
- Again we see a difference in predictions



Future Plans

- Benchmarks now available for comparison with future improvements
- Beginning to implement multiple loss functions into TMVA
    - Outlining code at the moment
    - Figuring out how the new class structure will fit into TMVA
- There are also plans to parallelize the BDTs in TMVA
    - Can search for the best cuts along each feature in parallel
    - Can reduce the BDT training time by a factor of the number of features
    - Can also parallelize the evaluation since the contribution from each tree doesn't depend on any of the others

Backup Slides

- BDT Algorithm Overview
- References

Brief BDT Algorithm Overview

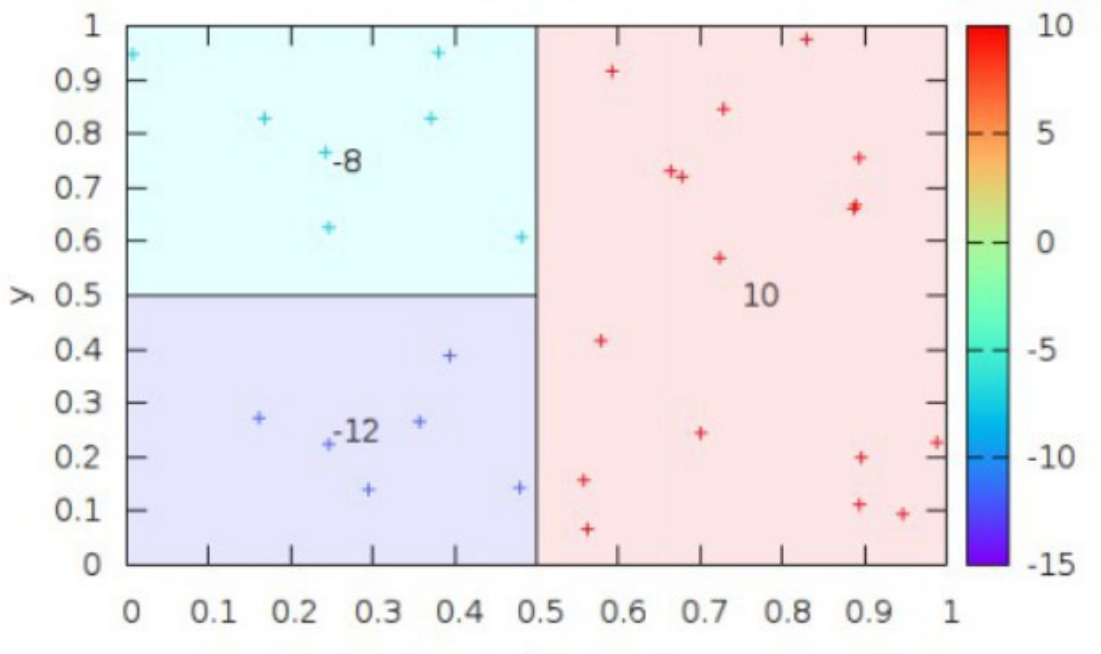


Fig 1. A decision tree with 3 terminal nodes

A Single Decision Tree

- Breaks up feature space into discrete regions using hyperplanes
- Fits a constant to each region
- The regions are greedily chosen to minimize a given Loss Function (a differentiable measure of the error)
- May be viewed as a series of decisions (shown below)

Boosting

- Make one tree, add another tree that corrects the predictions of the first
- Add another tree that corrects the net prediction of the first and second
- Continue the process
- End up with a collection of trees (Forest) and a net prediction
- $F(x) = T_0(x) + T_1(x) + T_2(x) + \ldots + T_N(x)$

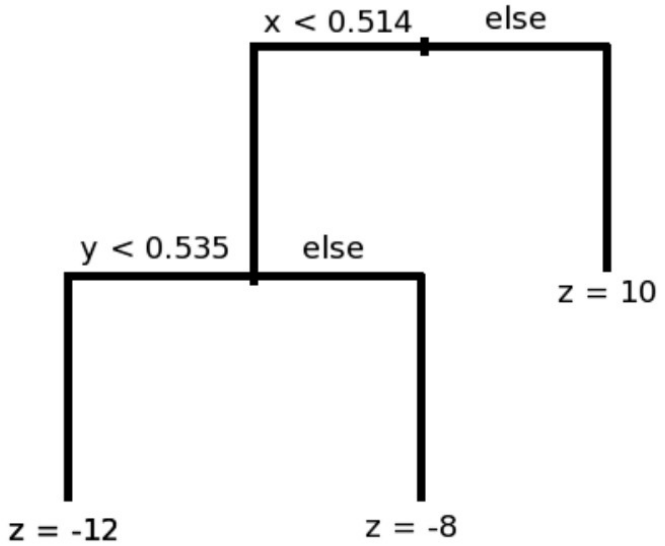


Fig 2. The same tree represented as a series of decisions

References

- Friedman, Jerome H. "Greedy function approximation: a gradient boosting machine." Annals of statistics (2001): 1189-1232.