BDT Study in 1tau1l(2016)

Search for Four Top in Tau Final States

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Outline

1. Introduction
2. Results
3. Validation of BDT Variables
4. Summary

Section 1

Introduction

MVA optimization method

- Correlation removal method
  - To achieve best performance while keeping the number of input variables smallest
- Process
  - Start training from 50 most powerful(highest seperation power) variables
  - Remove one variable from the 50 variables list, the removal based on which pair has the largest correction, remove the less powerful variable from the pair. This forms a 49 variables list
  - Train BDT using the 49 variable list. Remove one variable using the same principle as above and we get 48 variable list
  - Repeat the above 2 steps until only one variable left
  - For each training, do the application and then feed the output BDT histgram to combine. Get the expected significance and expected limit
  - Plotting the number of training variables as a function of expected significance and limit

Various ways of determining the quality of training

- AUC
- Scanning the maximum significance
- Expected significance from combine
- Expected limit from combine

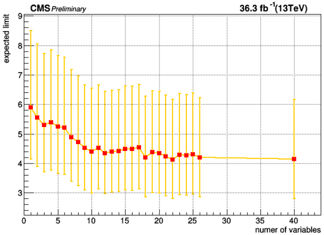
Training setup

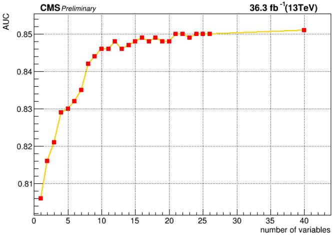
- BDT adaptive boost
- NormMode: None, NumEvents, EqualNumEvents???
  - Using EqualNumEvents
  - To adjust to only care for shape of signal and background. To investigate more
- Treating of negative gen weight events
  - Decision trees can correctly incorporate events with negative weights
  - In cases where a method does not properly treat events with negative weights, it is advisable to ignore such events for the training - but to include them in the performance evaluation to not bias the results
- 60% training, 40% testing
- MC correction: PUweight * EVENT_prefireWeight * EVENT_genWeight

Section 2

Results

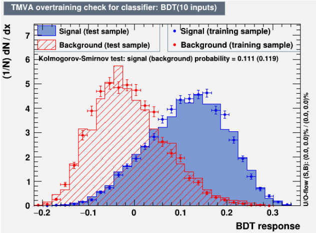
Expected limit Vs number of input variables

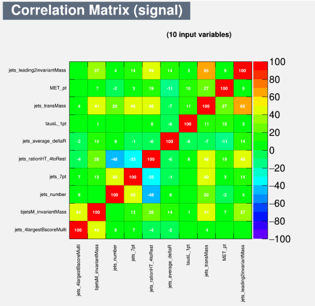




- Reach the plateau at 10 input variables.
- Expected significance 0.6
- We might need to think of some more powerful variables for training as the slope is a bit flat
- The variable list corresponds to the number of variables in the x axis in backup. Correlation matrix for these variables in back up too
- Interpretation of uncertainty of expected limit
  - Expected limit is actually medium limit
  - Expected limit means compare data model with $\mu S + B$ model, test until $f(model, \mu)$ the medium of $f(model, data)$ is 95%
  - Uncertainty: Vary the medium of $f(model, data)$ by up and down 34% and do the test to see for 95% CL the corresponding μ

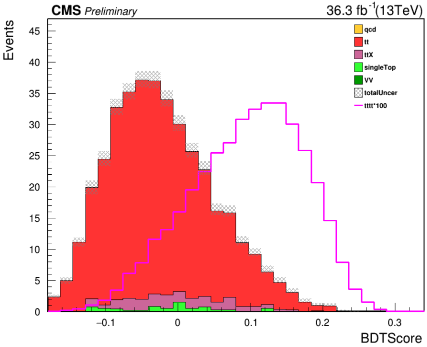
Training performance for 10 input variables





- Why for BDT the score range is [-0.2, 0.4] rather than [-1, 1]?
- Plots for other number of input variables in back up
- ROC to add

Templates for combine for 10 input variables



- For other variable list the template distribution in backup

Datacard to combine 10 variables

```
imax *
jmax *
kmax *
--------------------------------------------------------------------------------
shapes * *  /publicfs/cms/user/huahuil/tauOfTTTT_NanoAOD/TMVAoutput/2016/v3extra1tau1lCut_v41addVertexSelection/1tau1l_v0/AppResults_30bins/TMVApp_1tau1l_10var_f
bin          SR_1tau1l
observation  -1
--------------------------------------------------------------------------------
bin       SR_1tau1l         SR_1tau1l         SR_1tau1l         SR_1tau1l         SR_1tau1l
process   tttt              tt                ttX               VV                singleTop
process   0                 1                 2                 3                 4
rate      -1                -1                -1                -1                -1
--------------------------------------------------------------------------------
SR_1tau1l   autoMCStats  10
```

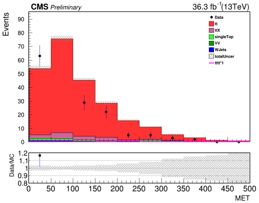
- Combine commands
  - text2workspace.py datacard.txt workspace.root
  - combine -M AsymptoticLimits workspace.root –run blind –name name
  - combine -M Significance workspace.root -t -1 –expectSignal=1 –name name
  - combine not working in CMSSW_12_2_4
- When feed histgrams to combine, should we sum bg samples or not?
  - To me, it doesn't matter. We group for better undertanding for the reading of the datacard

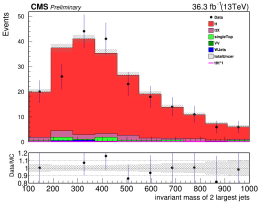
Section 3

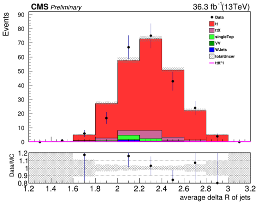
Validation of BDT Variables

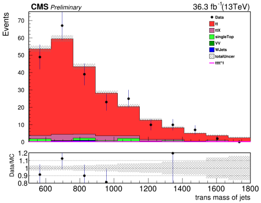
List of final input variables(10)

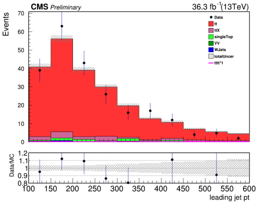
Input variables in tt control region(CR0)

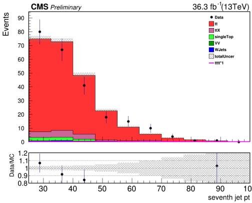






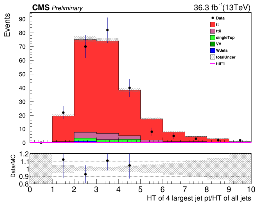


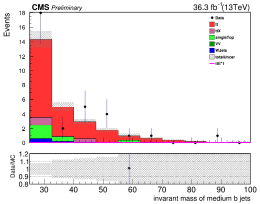


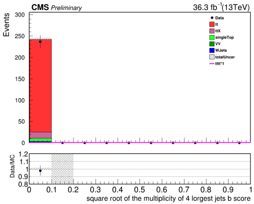


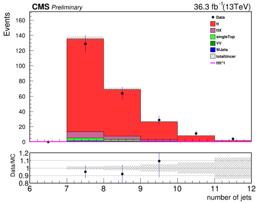
- Only statistic uncertainty included
- MC correction: prefiring reweighting, pileup reweighting
- MET correctionneeded

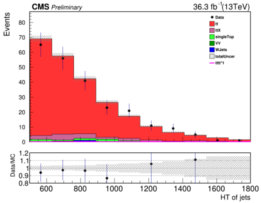
Input variables in tt control region(CR0)

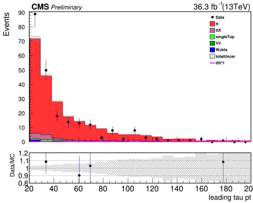






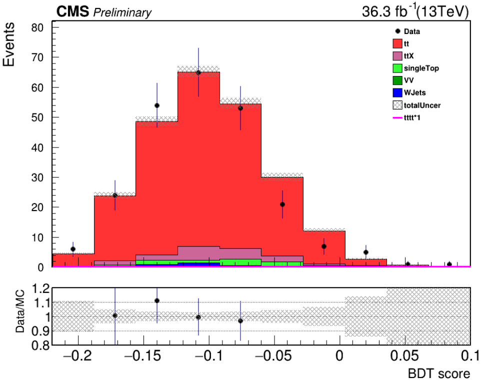






- We need to implement b tag corrections to see if agreement of the b jet related variables improves
- Variables in CR2 and control region definition in back up

BDT discriminant in CR0



- Agreement could improve after apply MET and b tag correction and re train

Section 4

Summary

Summary

- Summary
  - BDT training achived good results for 1tau1l
  - Seems we need to add b tag and MET correction in improve MC modeling of b tag and MET variables
- Next step
  - Add b tag and MET correction
  - Hypeparameter optimization for BDT
  - Repeat for 2017 and 2018

Section 5

Back up

V5 selection

- V5 added good vertex selection compared to v4
- Event yield for v5

1tau1l control region definition

	N_τ	N_l	N_{jets}	N_b
SR	1	1	>=7	>=2
CR0	1	1	>=7	1
CR1	1	1	>=7	0
CR2	1	1	6	>=2
CR3	1	1	6	<2

Table 1: 1tau1l

Total variable list and their meaning

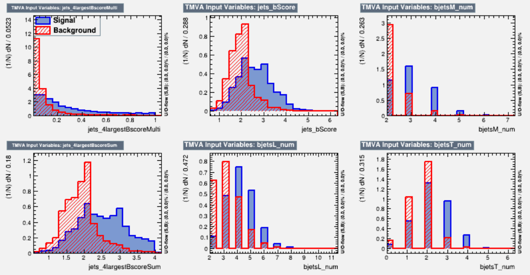
Hyperparameter optimization

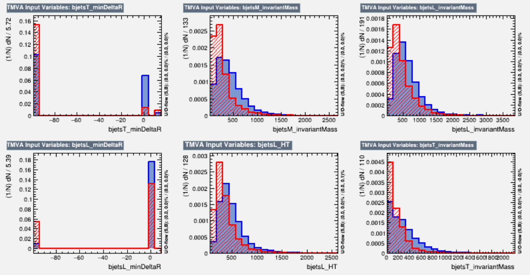
- Hypeparameters for BDT

Questions for my self

- How the BDT works much better compared to traditional cut based methods? How to understand this?

BDT input variable shape





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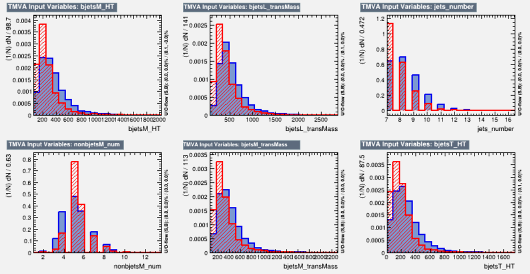
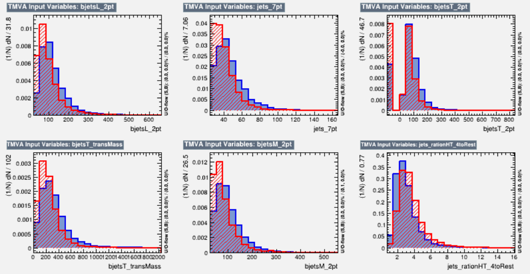
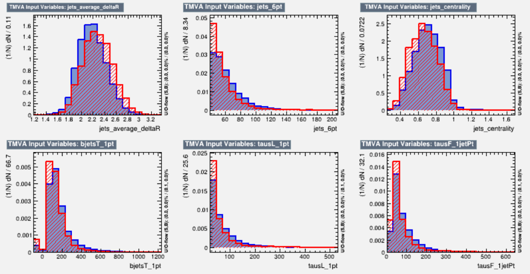
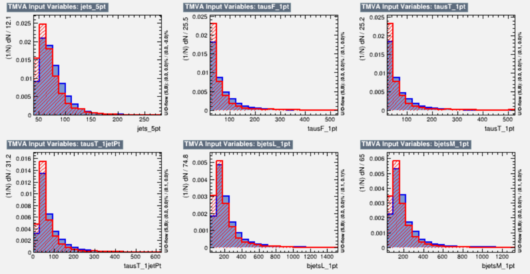




BDT input variable shape





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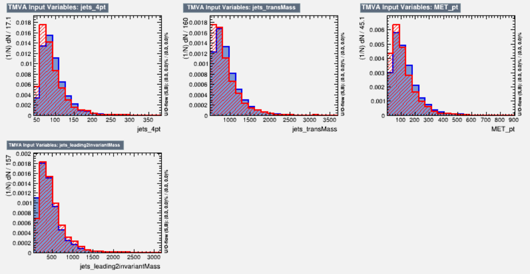
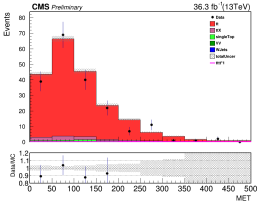
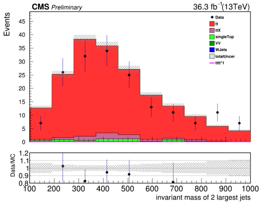
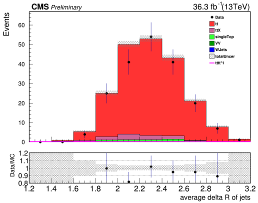
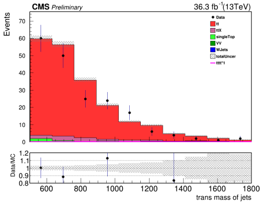


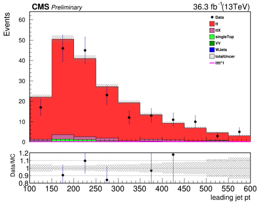
Input variables in tt control region(CR2)











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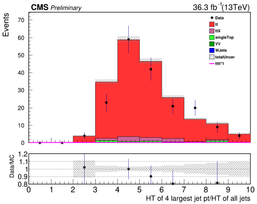

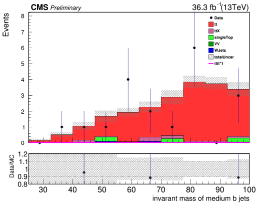

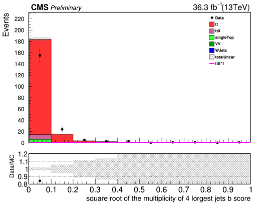

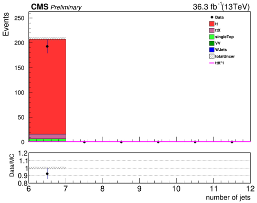

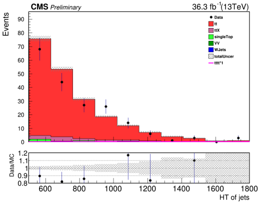

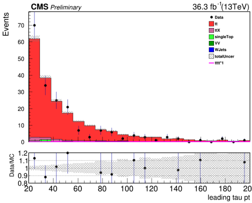

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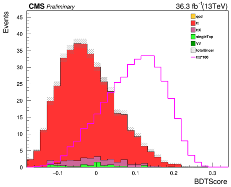
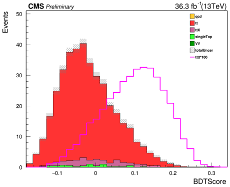
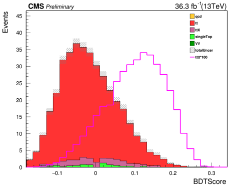
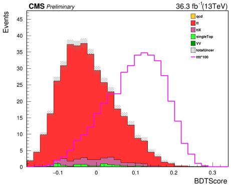
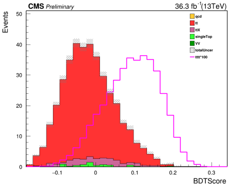
Templates for combine

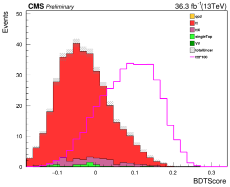






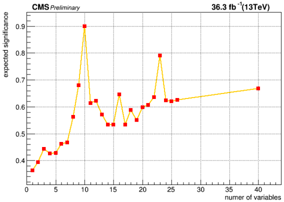






- 10, 11, 12
- 14, 23, 24

Expected limit and significance Vs number of input variables



- Why this fluctuation of expected significance? Intrensic quality of expected significance or something wrong with input templtaes or something wrong with training?
- Why compared to expected significance, expected limit seems more steady?
- How to take into account the uncertainty assioated with expected significance and limit?
- What it expected limit so sensitive to?