

Performance of BDTs for Electron Identification

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Motivation

- Lepton (e , μ , τ) Identification with high efficiency is crucial for new physics discoveries at the LHC
- Great efforts in ATLAS to develop the algorithms for electron identification:
 - Cut-based algorithm: IsEM
 - Multivariate algorithms: Likelihood and BDT
- Further improvement could be achieved with better treatment of the multivariate training using the Boosted Decision Trees technique

Electron ID Studies with BDT

Select electrons in two steps

- 1) Pre-selection: an EM cluster matching a track
- 2) Apply electron ID based on pre-selected samples with different e-ID algorithms (IsEM, Likelihood ratio, AdaBoost and **EBoost**).

New BDT e-ID development at U. Michigan (Rel. v12)

- H. Yang's talk at US-ATLAS Jamboree on Sept. 10, 2008

<http://indico.cern.ch/conferenceDisplay.py?confId=38991>

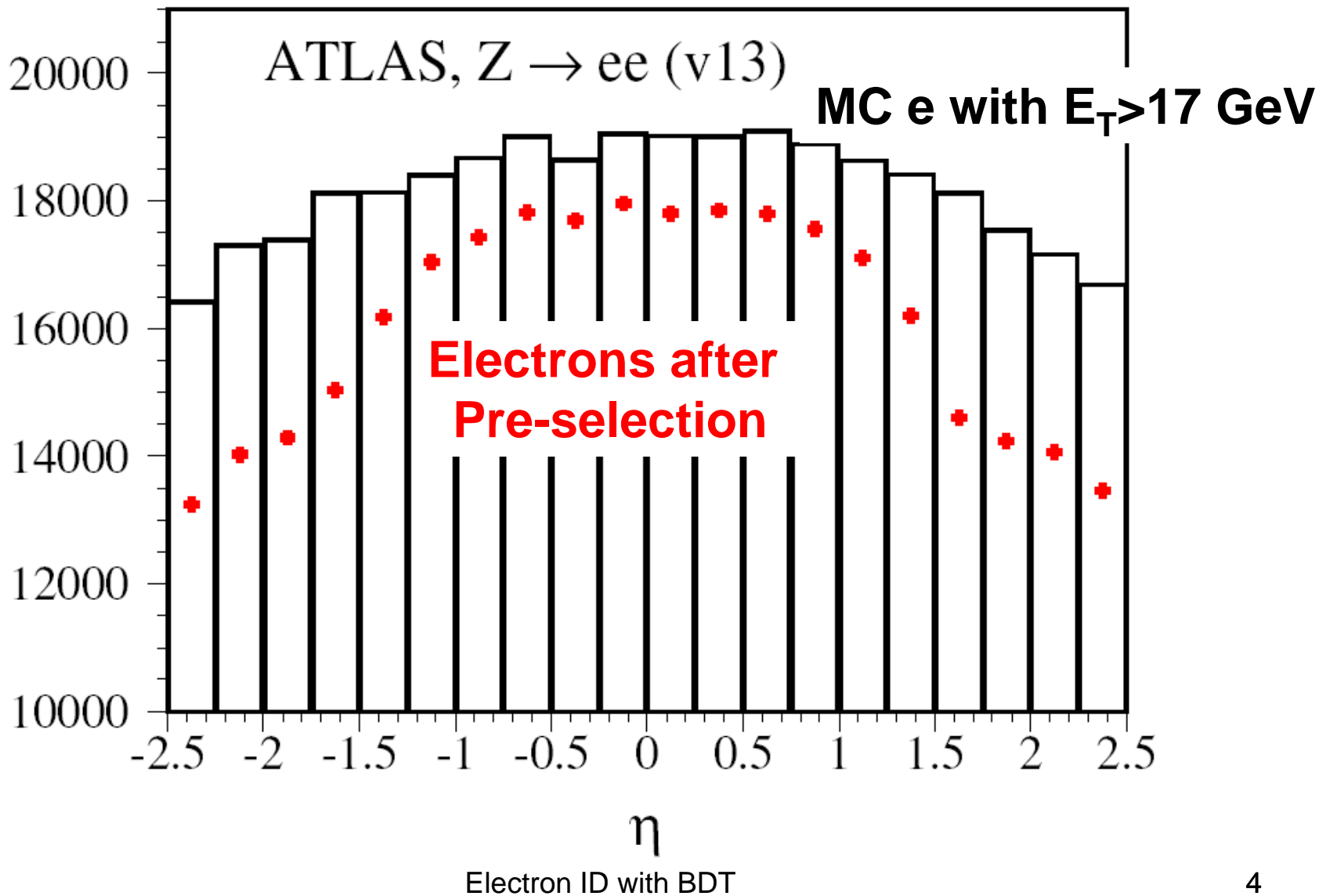
New BDT e-ID (**EBoost**) based on Rel. v13

- H. Yang's talk at ATLAS performance and physics workshop at CERN on Oct. 2, 2008

<http://indico.cern.ch/conferenceDisplay.py?confId=39296>

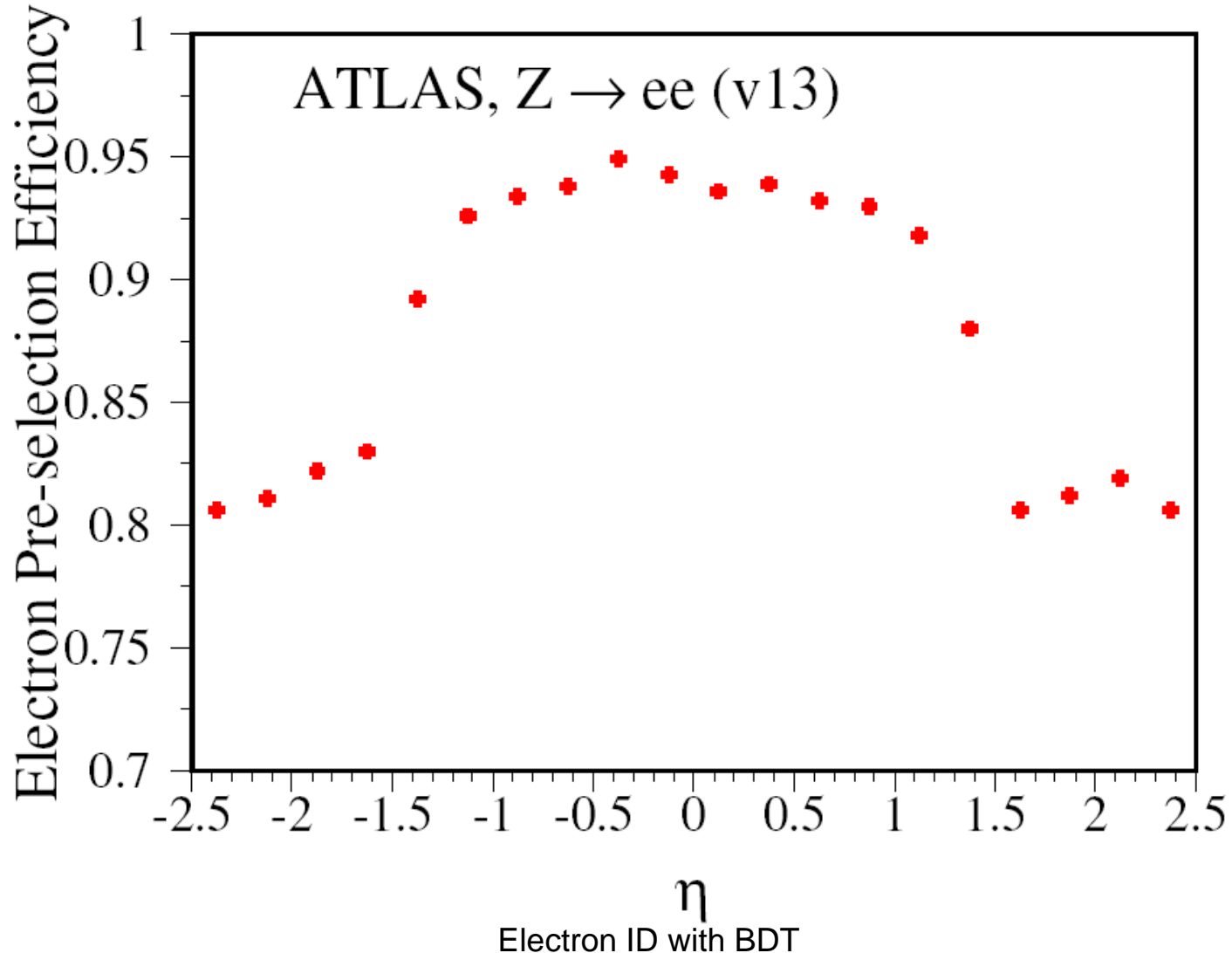
Implementation of **EBoost** in EgammaRec (Rel. v14)

Electrons



Electron Pre-selection Efficiency

The inefficiency mainly due to track matching



BDT e-ID (EBoost) Training

- BDT multivariate pattern recognition technique:
 - [H. Yang et. al., NIM A555 (2005) 370-385]
- BDT e-ID training signal and backgrounds (jet faked e)
 - $W \rightarrow e\nu$ as electron signal (DS 5104, v13)
 - JF17 (DS 5802, v13)
- Using the same e-ID variables as IsEM for training (see variable list in next page)
- BDT e-ID training procedure
 - Apply additional cuts on the training samples to select hardly identified jet faked electron as background for BDT training to make the BDT training more effective.
 - Apply event weight to high P_T backgrounds to effectively reduce the jet fake rate at high P_T region. Event weight training technique reference, [H. Yang et. al., JINST 3 P04004 (2008)]

Variables Used for BDT e-ID (EBoost)

The same variables for IsEM are used

▶ `egammaPID::ClusterHadronicLeakage`

fraction of transverse energy in TileCal 1st sampling

▶ `egammaPID::ClusterMiddleSampling`

Ratio of energies in 3*7 & 7*7 window

Ratio of energies in 3*3 & 7*7 window

Shower width in LAr 2nd sampling

Energy in LAr 2nd sampling

▶ `egammaPID::ClusterFirstSampling`

Fraction of energy deposited in 1st sampling

Delta E_{max2} in LAr 1st sampling

E_{max2}-E_{min} in LAr 1st sampling

Total shower width in LAr 1st sampling

Shower width in LAr 1st sampling

F_{side} in LAr 1st sampling

▶ `egammaPID::TrackHitsA0`

B-layer hits, Pixel-layer hits, Precision hits

Transverse impact parameter

▶ `egammaPID::TrackTRT`

Ratio of high threshold and all TRT hits

▶ `egammaPID::TrackMatchAndEoP`

Delta eta between Track and egamma

Delta phi between Track and egamma

E/P – egamma energy and Track momentum ratio

▶ `Track Eta and EM Eta`

▶ `Electron isolation variables:`

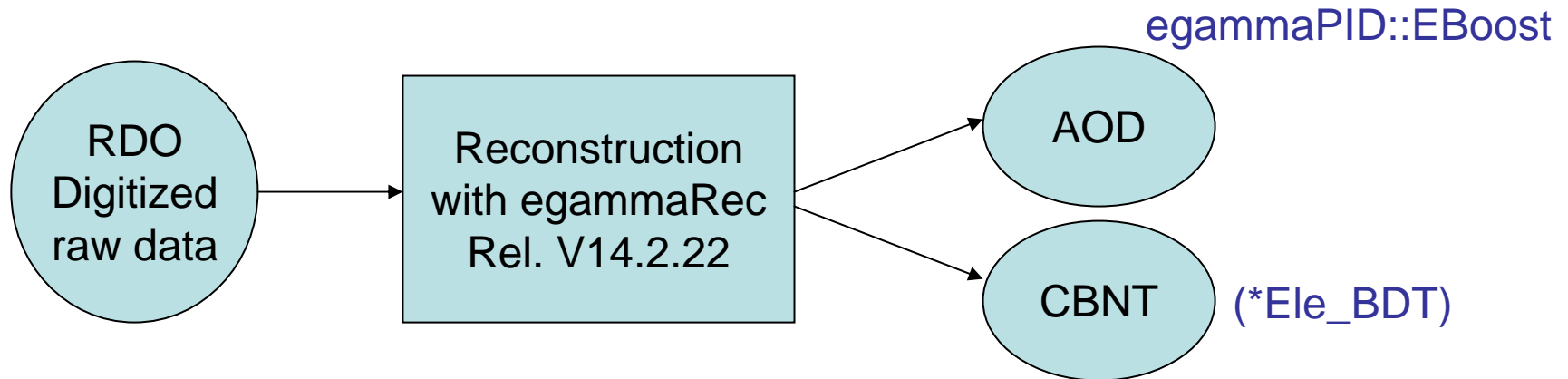
Number of tracks ($\Delta R=0.3$)

Sum of track momentum ($\Delta R=0.3$)

Ratio of energy in EtCone45 / E_T

Implementation of BDT Trees in EgammaRec Package and Test

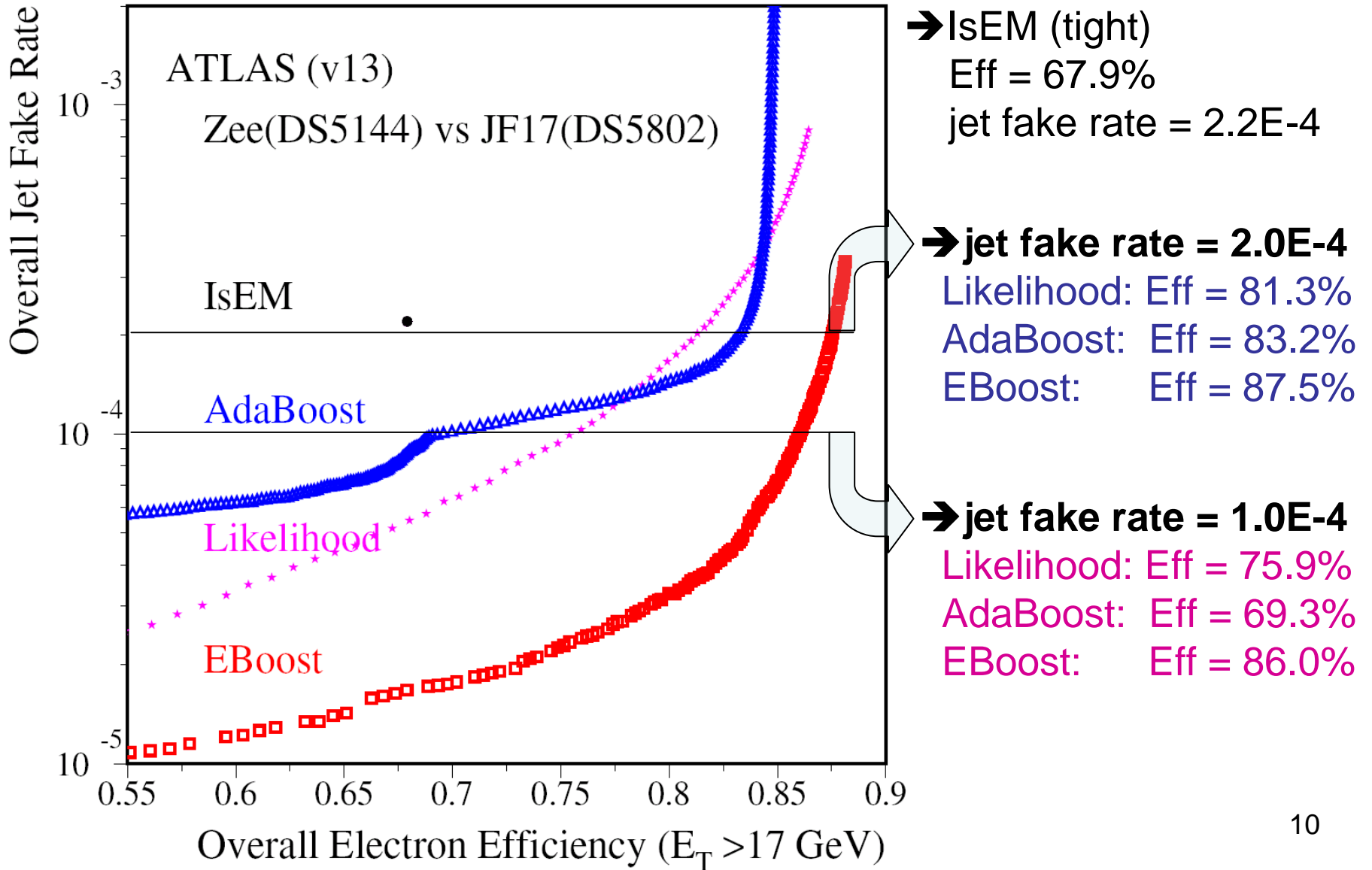
- E-ID based on BDT has been implemented into egammaRec (04-02-98) package (private).
- We run through the whole reconstruction package based on v14.2.22 to test the BDT e-ID.



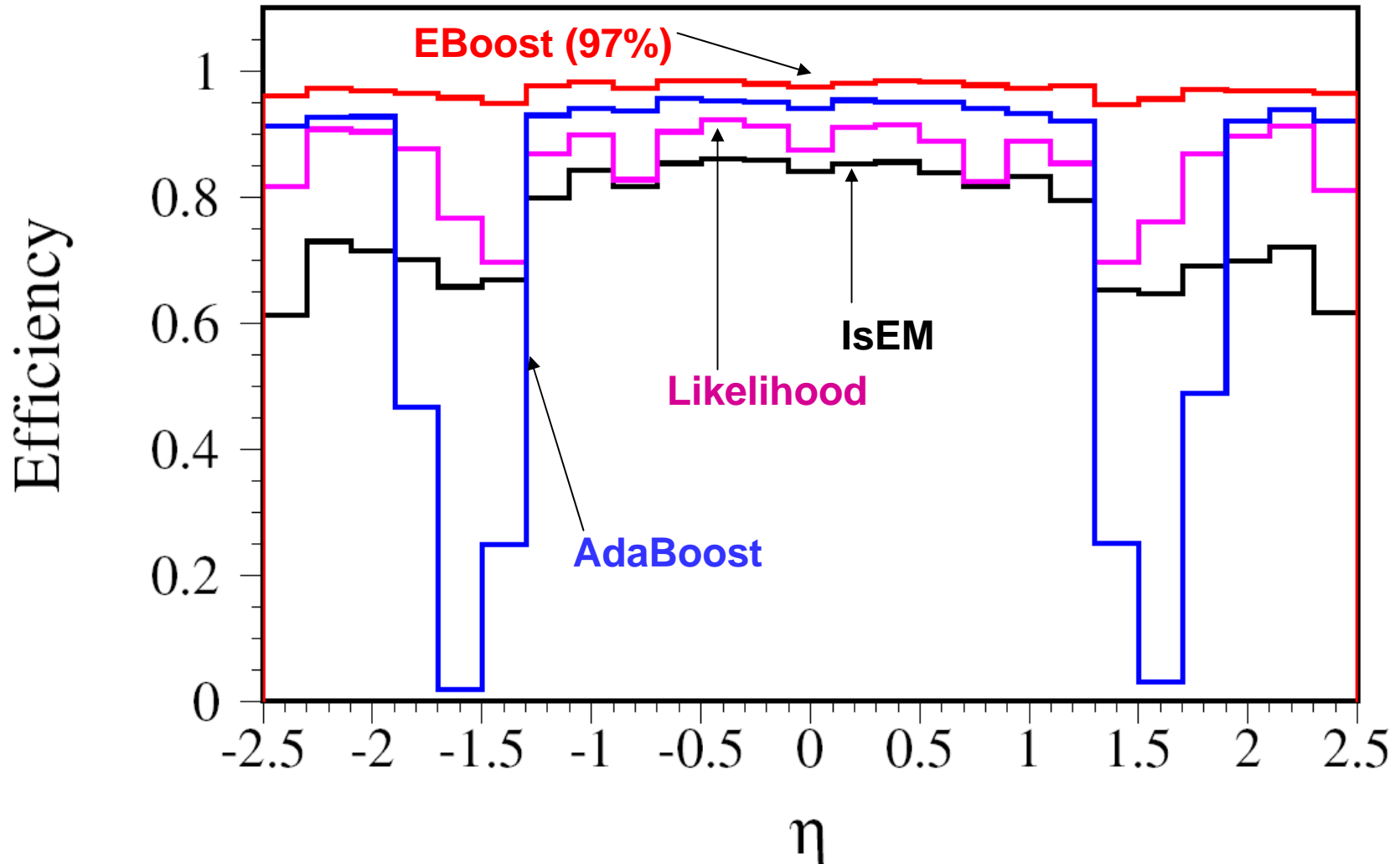
E-ID Testing Samples Produced at $\sqrt{s} = 14 \text{ TeV}$ (v13)

- Wenu: DS5104 (Eff_precuts = 88.6%)
 - 42020 electrons with $E_t > 17 \text{ GeV}$, $|\eta| < 2.5$
 - 37230 electrons after pre-selection cuts
- Zee: DS5144 (Eff_precuts = 88.6%)
 - 181281 electron with $E_t > 17 \text{ GeV}$, $|\eta| < 2.5$
 - 160615 electrons after pre-selection cuts
- JF17: DS5802 (Eff_precuts = 2.4%)
 - 1946968 events, 7280046 reconstructed jets
 - 176727 jets after pre-selection

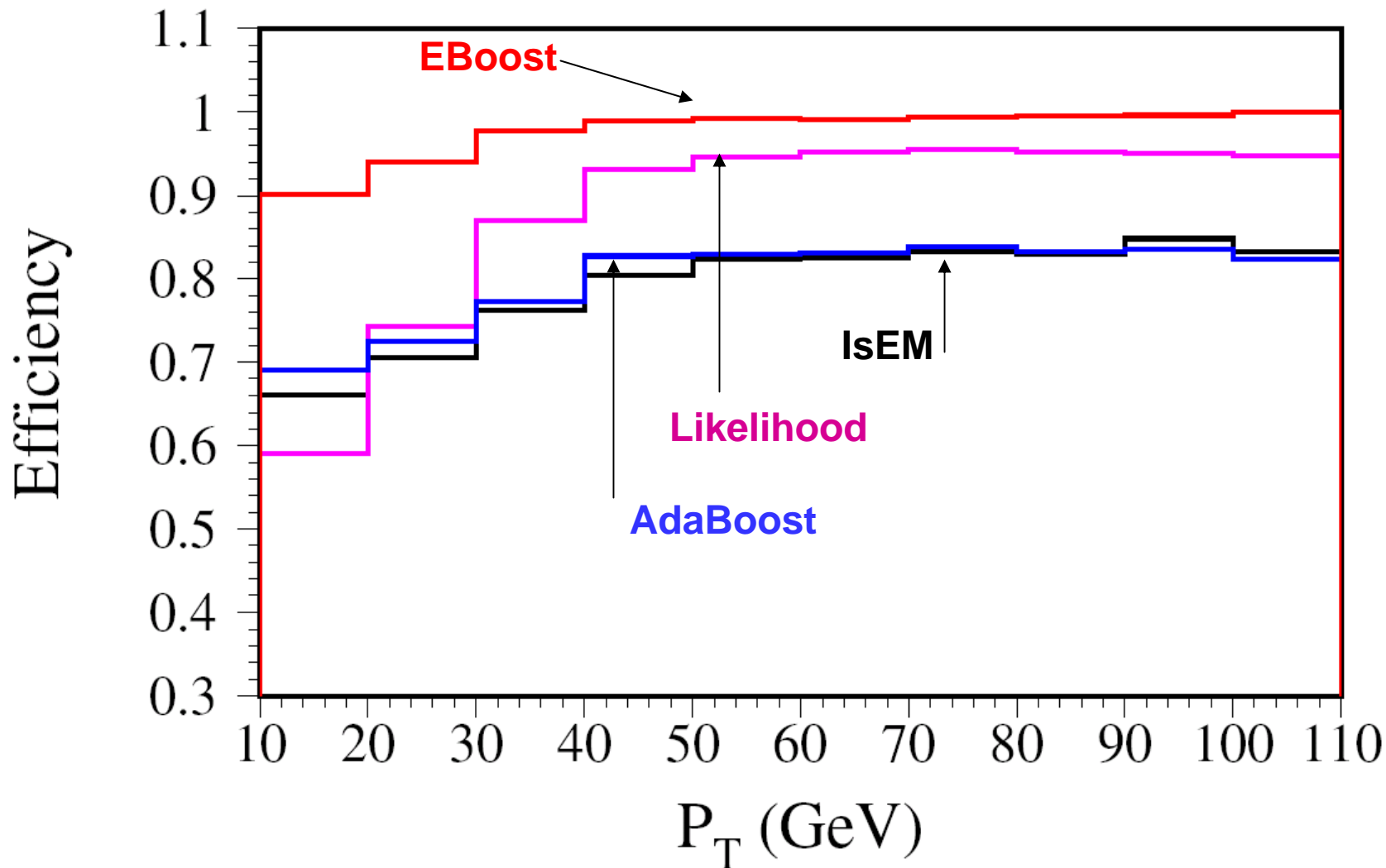
Comparison of e-ID Algorithms (v13)



E-ID Efficiency after pre-selection vs η (v13, jet fake rate=1.0E-4)



E-ID Efficiency after pre-selection vs Pt (v13, jet fake rate=1.0E-4)



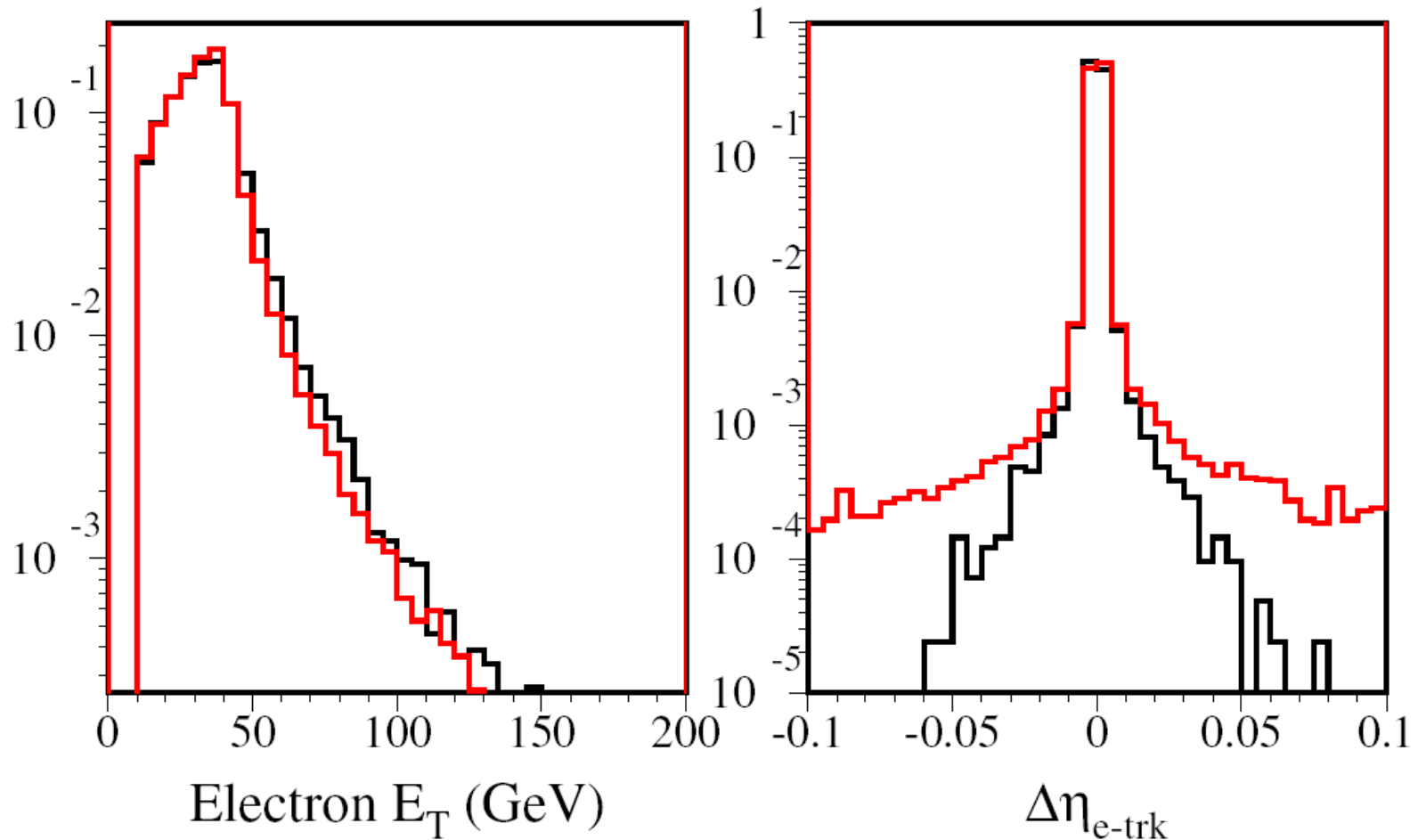
E-ID Testing Samples Produced at $\sqrt{s} = 10 \text{ TeV}$ (v14)

- Wenu: DS106020 (Eff_precuts = 86.7%)
 - 58954 electrons with $E_t > 17 \text{ GeV}$, $|\eta| < 2.5$
 - 51100 electrons after pre-selection cuts
- Zee: DS106050 (Eff_precuts = 86.7%)
 - 108550 electrons with $E_t > 17 \text{ GeV}$, $|\eta| < 2.5$
 - 94153 electrons after pre-selection cuts
- JF17: DS105802 (Eff_precuts = 2.34%)
 - 237950 events, 896818 reconstructed jets
 - 20994 jets after pre-selection cuts

Variable distribution Comparison

14 TeV vs 10 TeV

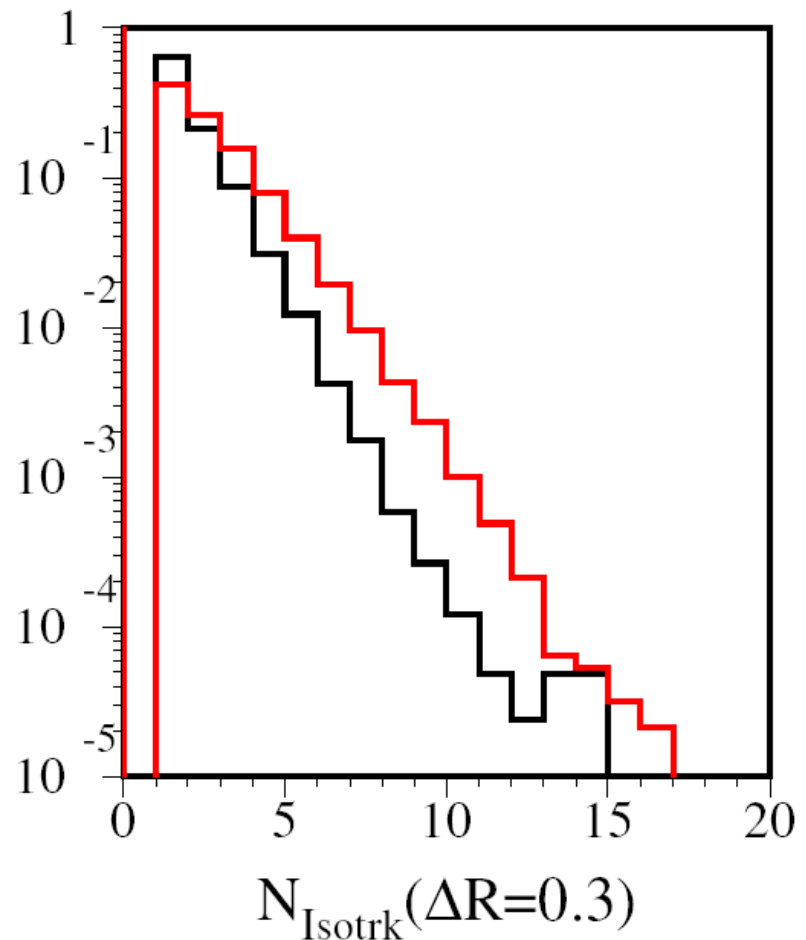
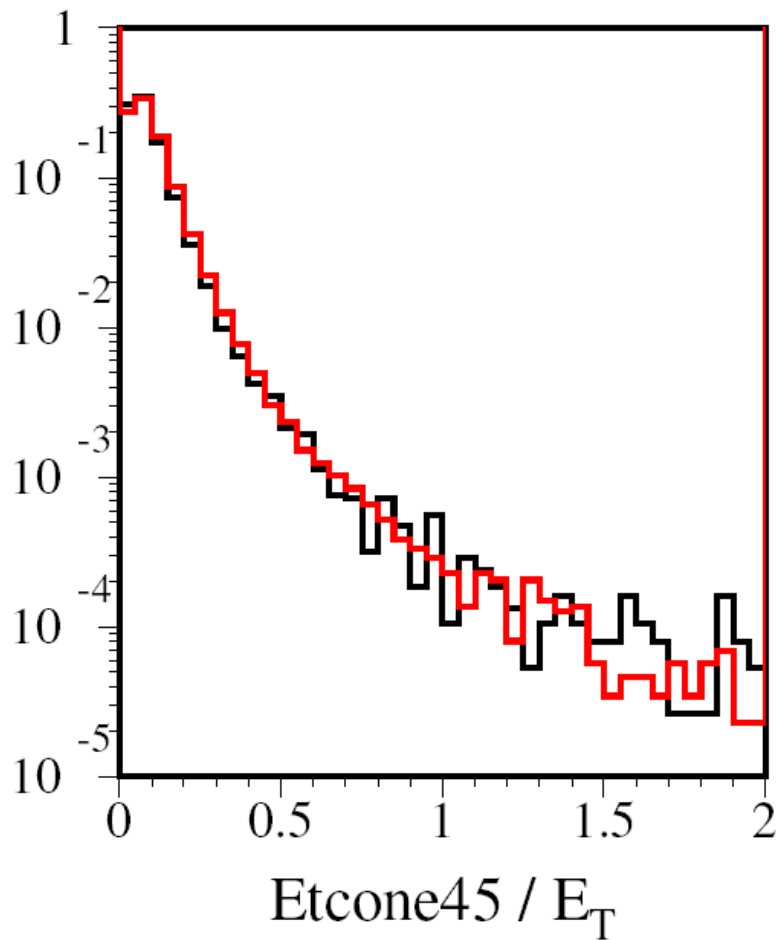
$W \rightarrow e\nu$, DS5104(14TeV,black) vs DS106020(10TeV,red)



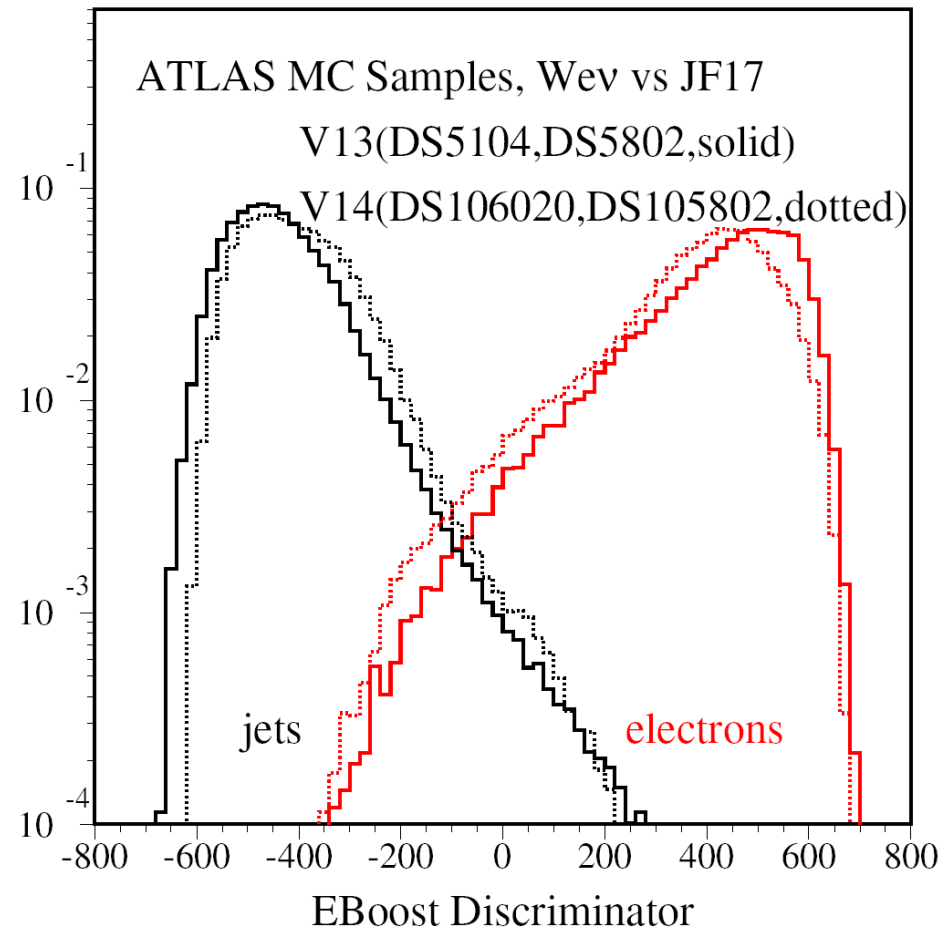
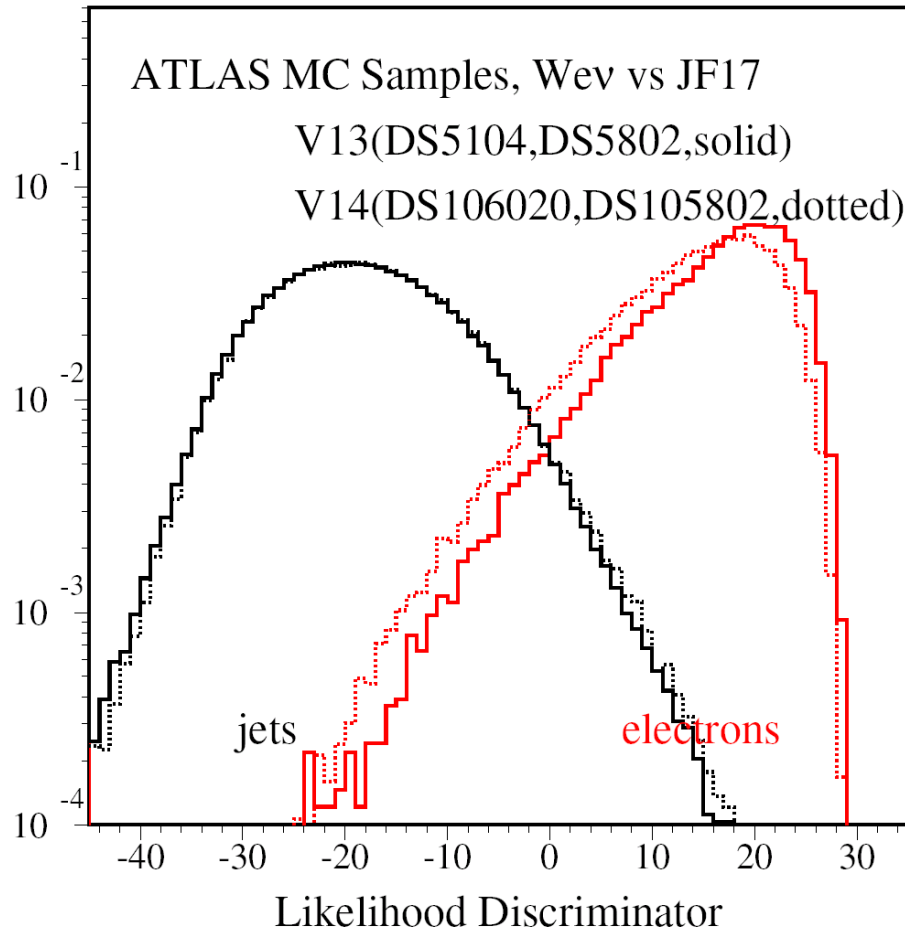
Variable distribution Comparison

14 TeV vs 10 TeV

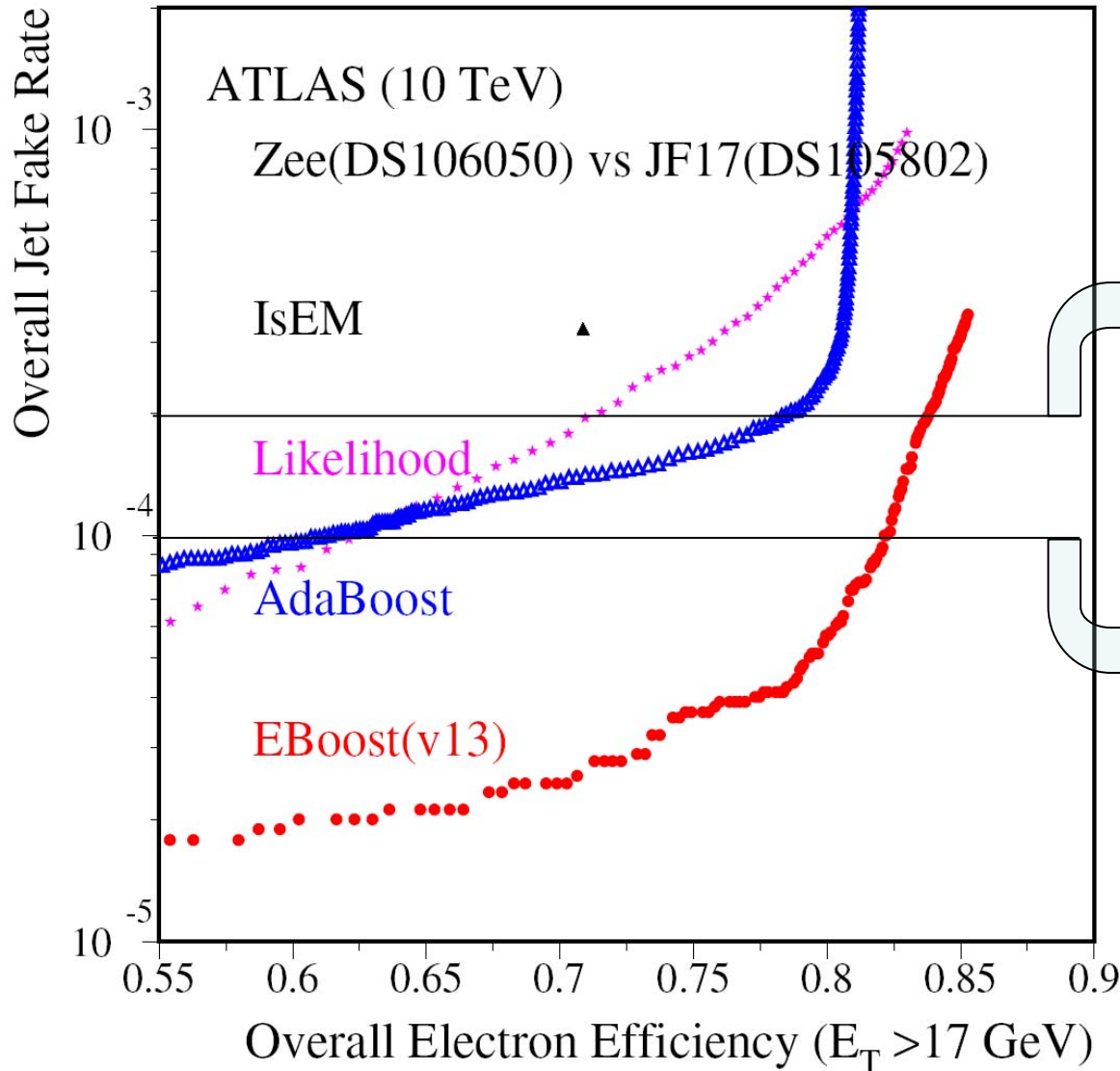
$W \rightarrow e\nu$, DS5104(14TeV,black) vs DS106020(10TeV,red)



E-ID Discriminators with no retraining for 10 TeV MC Samples



Comparison of e-ID Algorithms (v14)



→ IsEM (tight)
Eff = 70.9%
jet fake rate = $3.2E-4$

→ jet fake rate = $2.0E-4$
Likelihood: Eff = 71.6%
AdaBoost: Eff = 78.5%
EBoost: Eff = 83.9%

→ jet fake rate = $1.0E-4$
Likelihood: Eff = 62.9%
AdaBoost: Eff = 61.2%
EBoost: Eff = 82.2%

Robustness of Multivariate e-ID

($\sqrt{s} = 14$ TeV vs. 10 TeV without retraining)

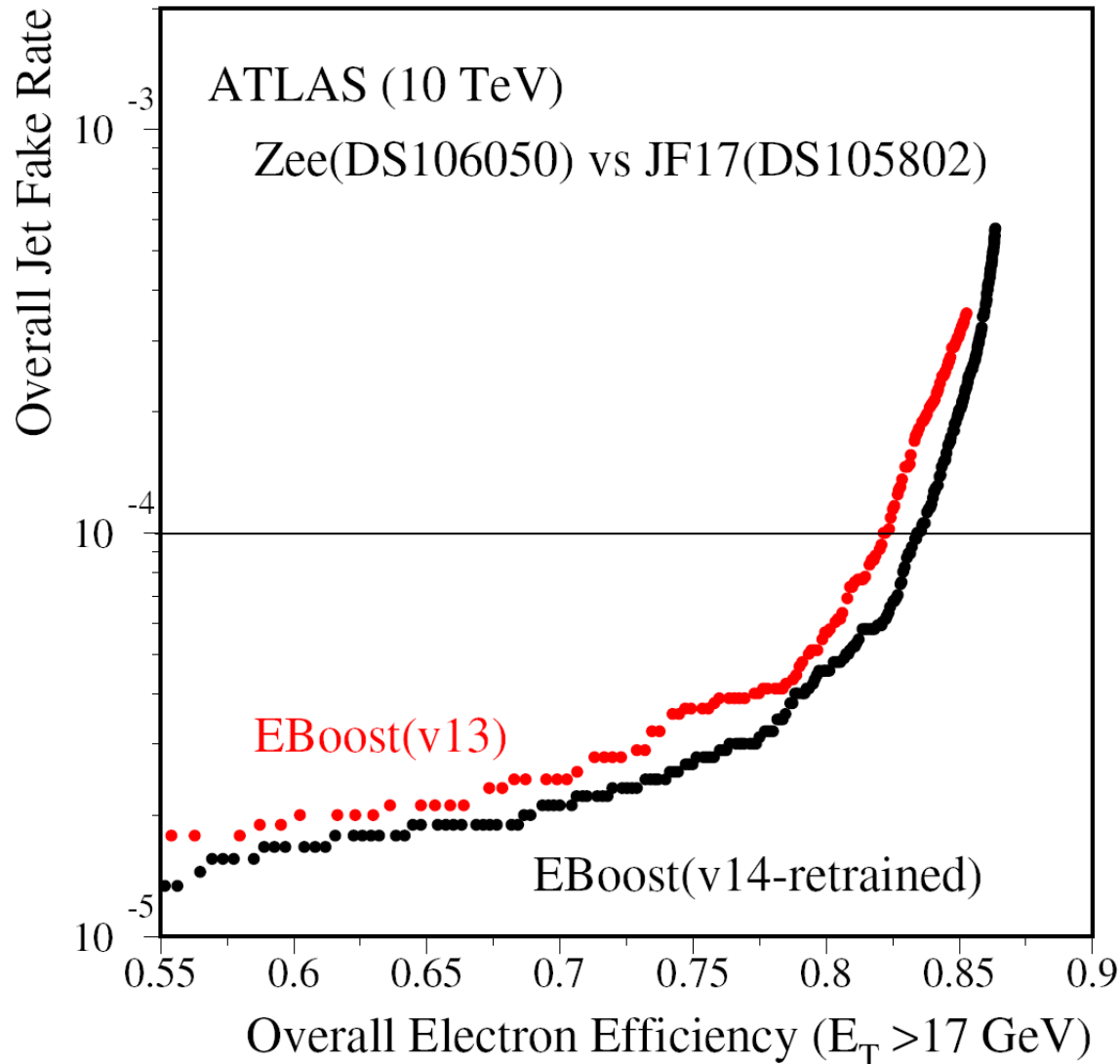
| Test MC | Precuts | Likelihood | AdaBoost | EBoost |
|---|---------|------------|----------|--------|
| Z \rightarrow ee (v13) $\sqrt{s} = 14$ TeV | 88.6% | 75.9% | 69.3% | 86.0% |
| Z \rightarrow ee (v14) $\sqrt{s} = 10$ TeV | 86.7% | 62.9% | 61.2% | 82.2% |
| Eff. Change after pre-sel | -1.9% | -13.0% | -8.1% | -3.8% |
| | | -11.1% | -6.2% | -1.9% |
| JF17 (v13) $\sqrt{s} = 14$ TeV | 2.4E-2 | 1.0E-4 | 1.0E-4 | 1.0E-4 |
| JF17 (v14) $\sqrt{s} = 10$ TeV | 2.3E-2 | 1.0E-4 | 1.0E-4 | 1.0E-4 |

Robustness of Multivariate e-ID

($\sqrt{s} = 14$ vs 10 TeV without retraining)

| Test MC | Precuts | Likelihood | AdaBoost | EBoost |
|---|---------|------------|----------|--------|
| Z \rightarrow ee (v13) $\sqrt{s} = 14$ TeV | 88.6% | 81.3% | 83.2% | 87.5% |
| Z \rightarrow ee (v14) $\sqrt{s} = 10$ TeV | 86.7% | 71.6% | 78.5% | 83.9% |
| Eff. Change after pre-sel | -1.9% | -9.7% | -4.7% | -3.6% |
| | | -7.8% | -2.8% | -1.7% |
| JF17 (v13) $\sqrt{s} = 14$ TeV | 2.4E-2 | 2.0E-4 | 2.0E-4 | 2.0E-4 |
| JF17 (v14) $\sqrt{s} = 10$ TeV | 2.3E-2 | 2.0E-4 | 2.0E-4 | 2.0E-4 |

Improvement with EBoost Re-training using $\sqrt{s} = 10$ TeV MC Samples

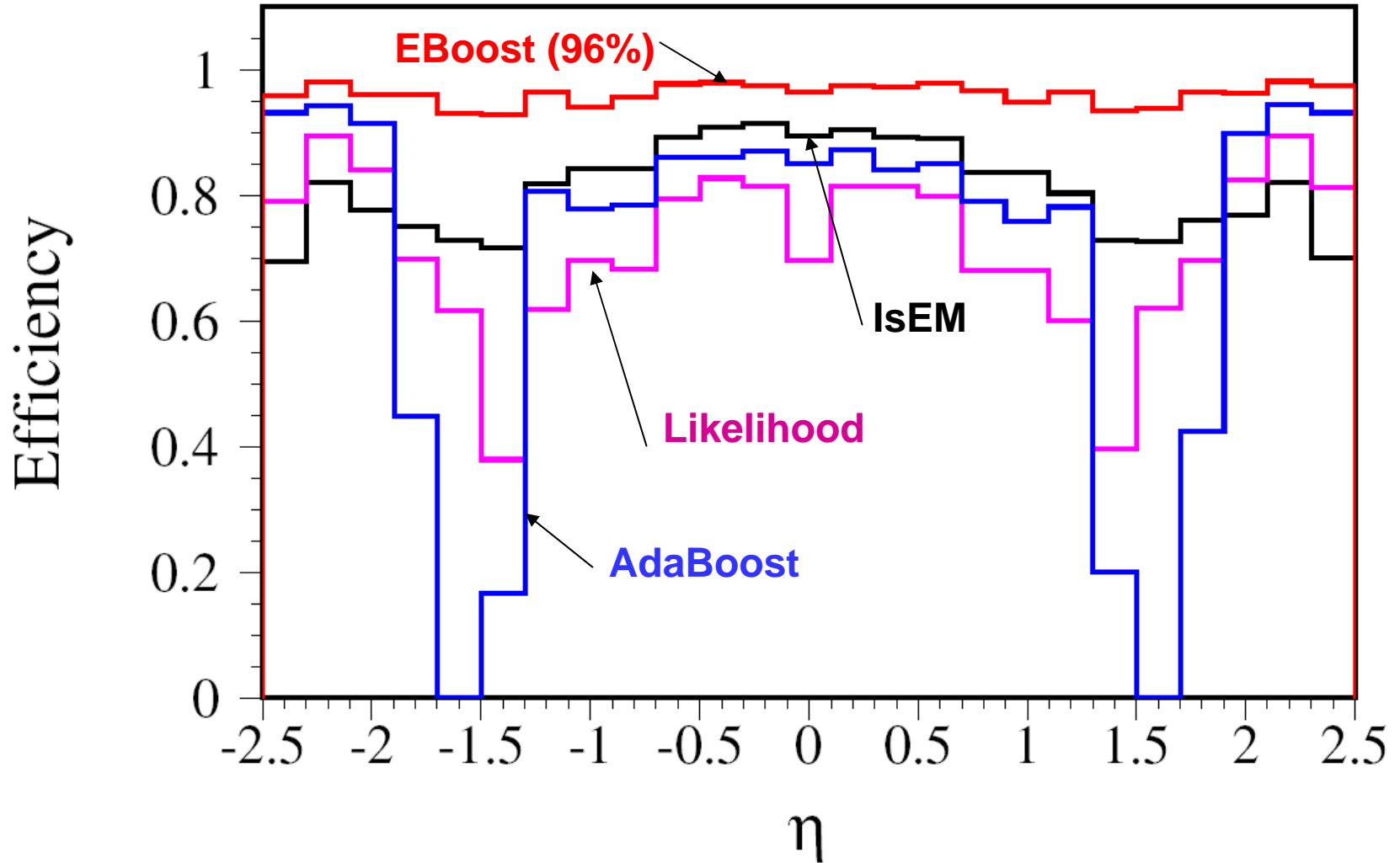


→ EBoost (retrained)
Eff = 82.2 → 83.4%
jet fake rate = 1.0E-4

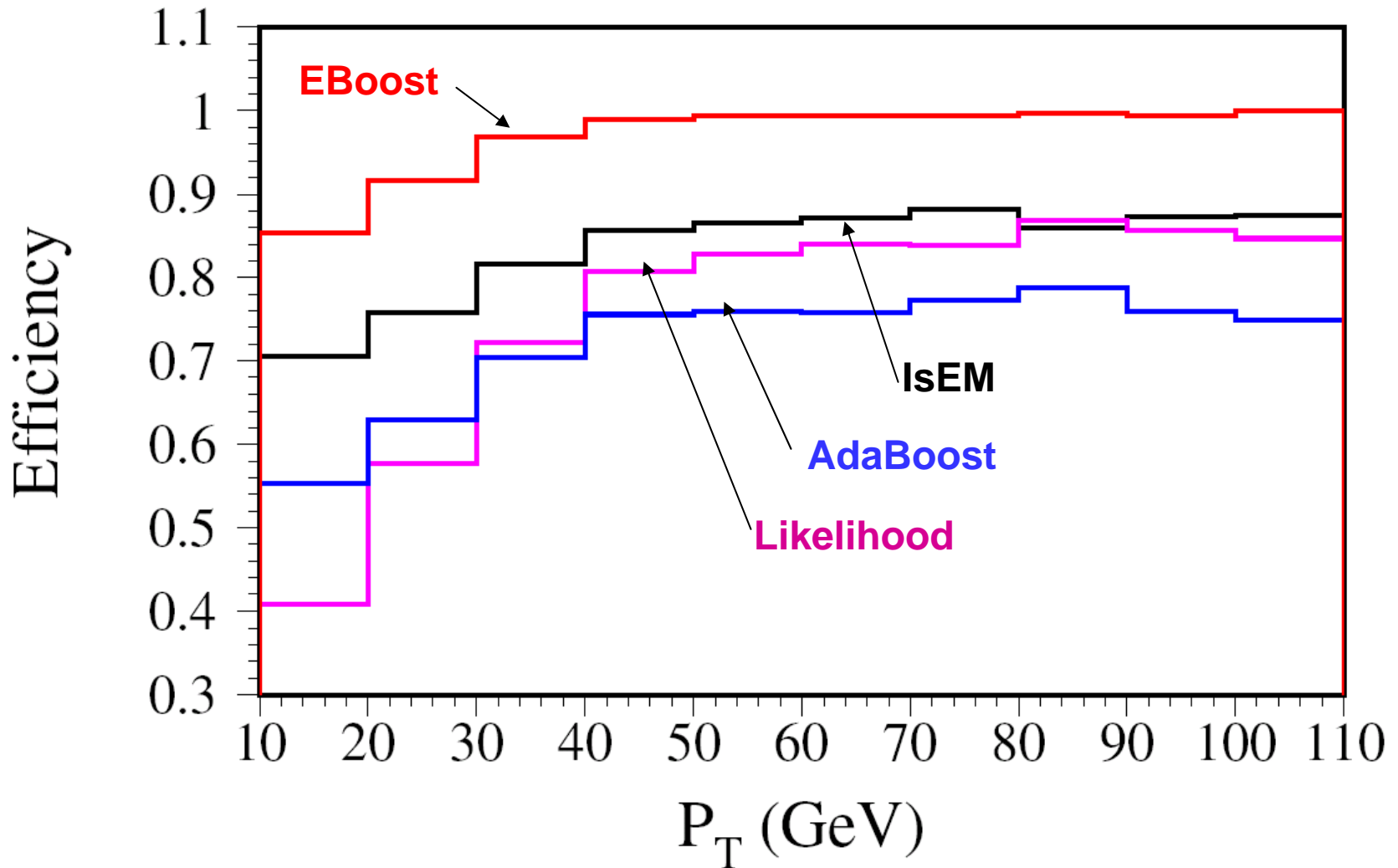
→ For each major release multivariate e-ID should be retrained to obtain optimal performance

→ All multivariate e-ID should be retrained using real data

E-ID Efficiency after pre-selection vs η (v14, jet fake rate=1.0E-4)



E-ID Efficiency after pre-selection vs Pt (v14, jet fake rate=1.0E-4)

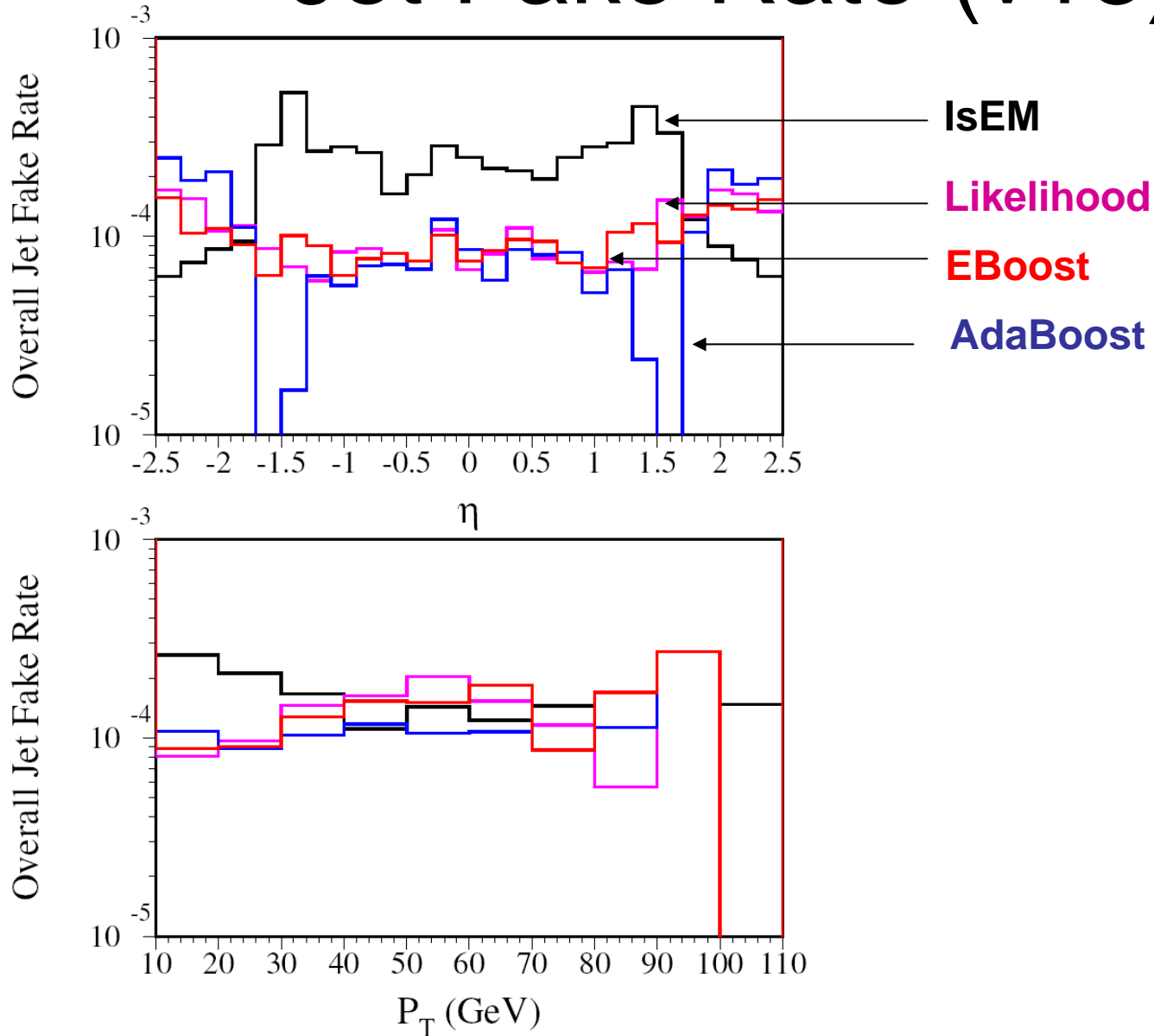


Future Plan

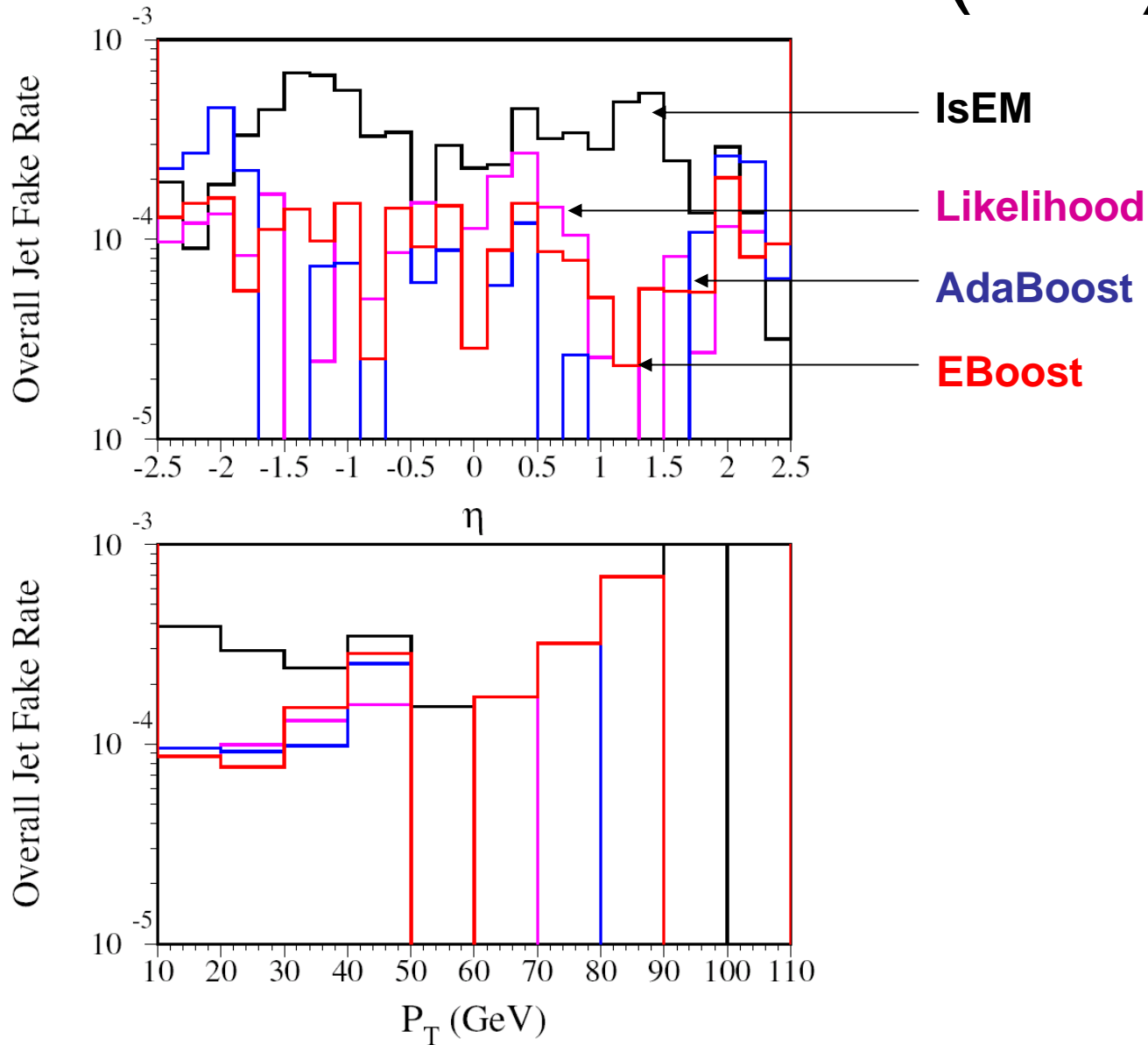
- We have requested to add the EBoost in ATLAS official egammaRec package and make EBoost discriminator variable available for more test and for physics analysis.
- We have proposed to provide EBoost trees to ATLAS egammaRec for each major software release
- We will explore new variables to further improve e-ID by suppressing γ converted electron etc.

Backup Slides

Jet Fake Rate (v13)



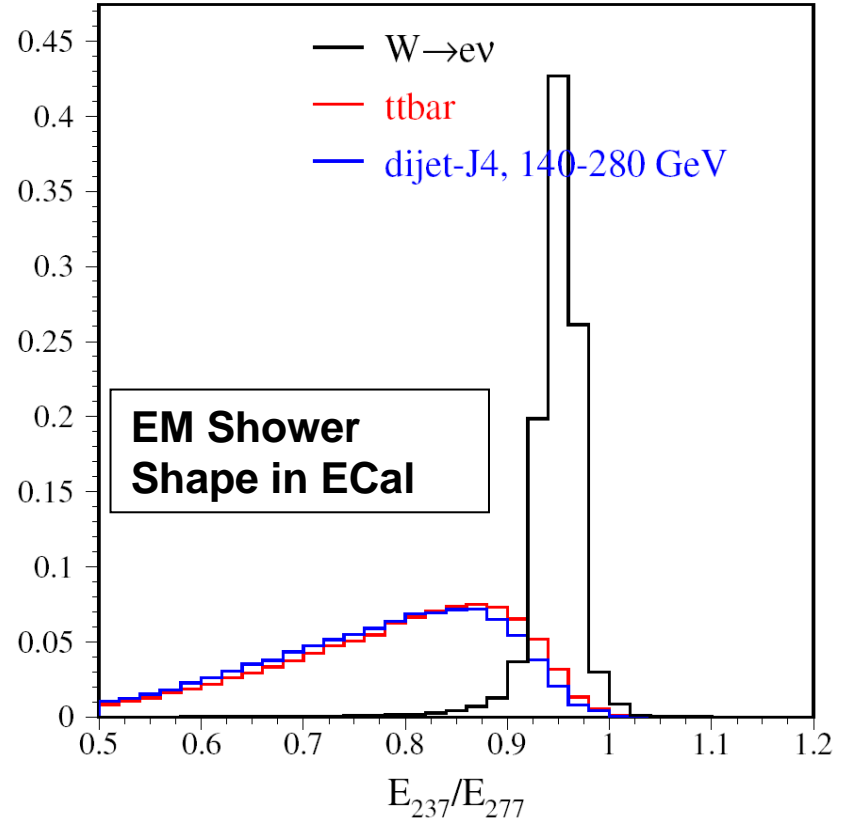
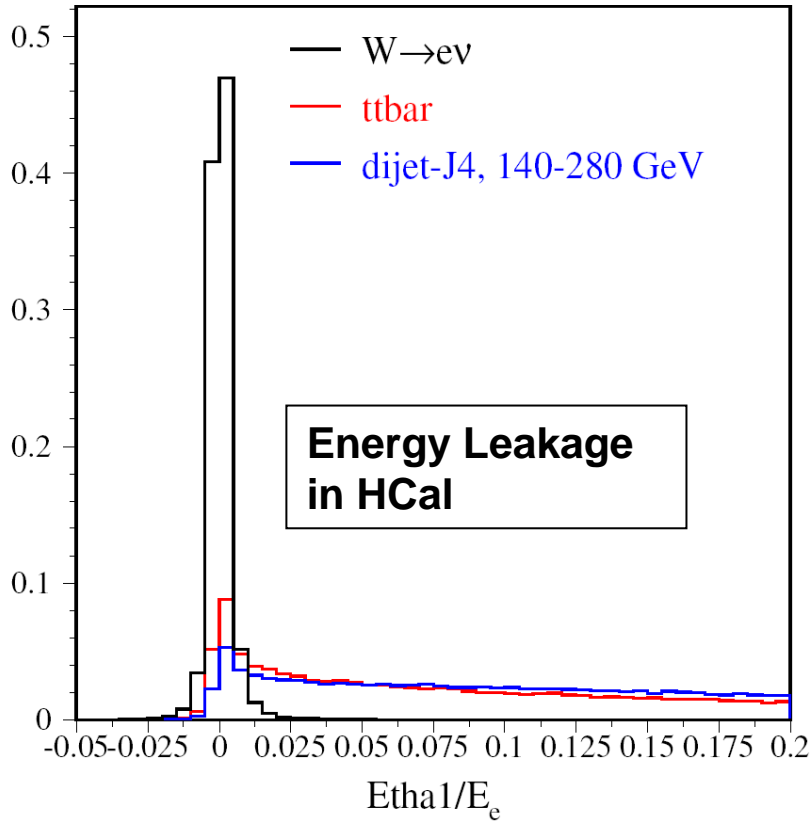
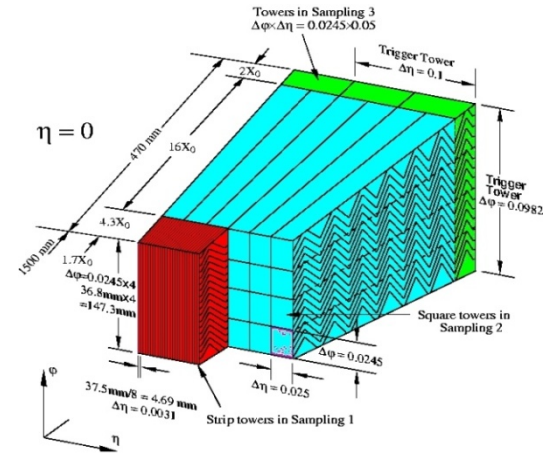
Jet Fake Rate (v14)



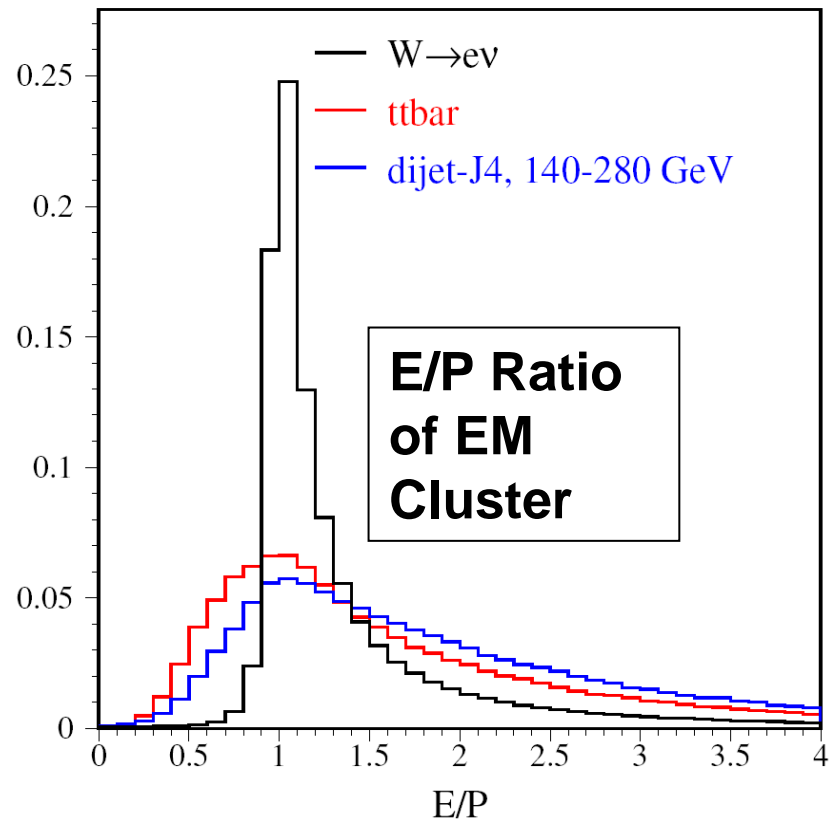
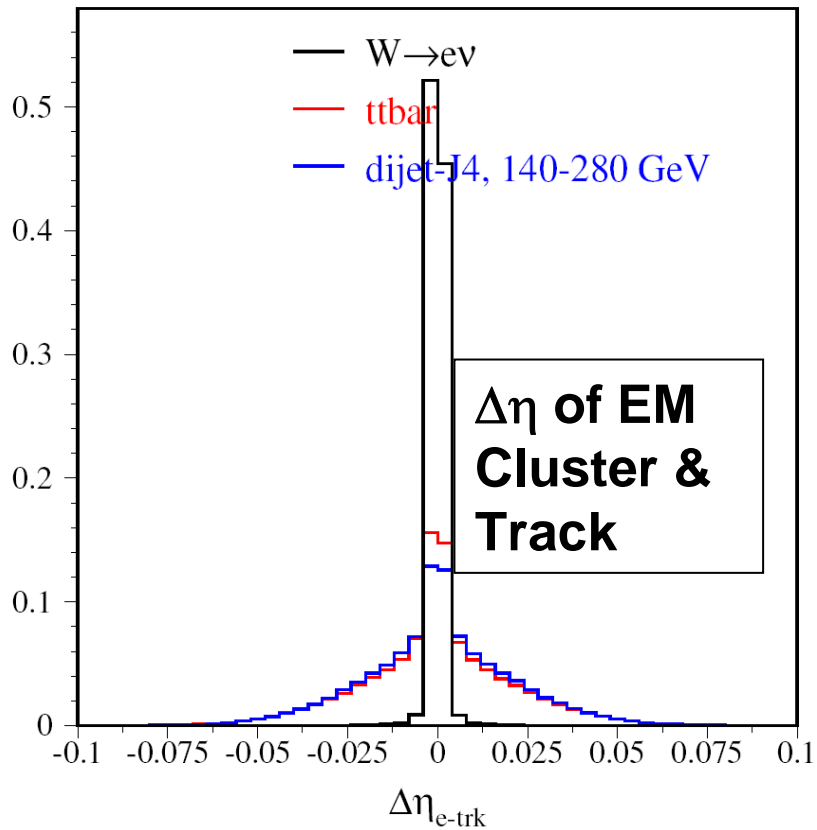
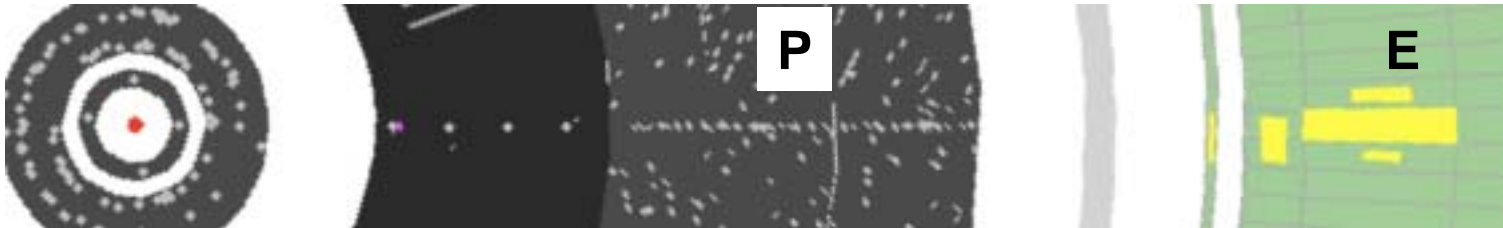
List of Variables for BDT

1. Ratio of $E_t(\Delta R=0.2-0.45) / E_t(\Delta R=0.2)$
2. Number of tracks in $\Delta R=0.3$ cone
3. Energy leakage to hadronic calorimeter
4. EM shower shape E_{237} / E_{277}
5. $\Delta\eta$ between inner track and EM cluster
6. Ratio of high threshold and all TRT hits
7. Number of pixel hits and SCT hits
8. $\Delta\phi$ between track and EM cluster
9. $E_{\max 2} - E_{\min}$ in LAr 1st sampling
10. Number of B layer hits
11. Number of TRT hits
12. $E_{\max 2}$ in LAr 1st sampling
13. E_{overP} – ratio of EM energy and track momentum
14. Number of pixel hits
15. Fraction of energy deposited in LAr 1st sampling
16. E_t in LAr 2nd sampling
17. η of EM cluster
18. D_0 – transverse impact parameter
19. EM shower shape E_{233} / E_{277}
20. Shower width in LAr 2nd sampling
21. Frac_{s1} – ratio of $(E_{7\text{strips}} - E_{3\text{strips}}) / E_{7\text{strips}}$ in LAr 1st sampling
22. Sum of track P_t in $\Delta R=0.3$ cone
23. Total shower width in LAr 1st sampling
24. Shower width in LAr 1st sampling

EM Shower shape distributions of discriminating Variables (signal vs. background)

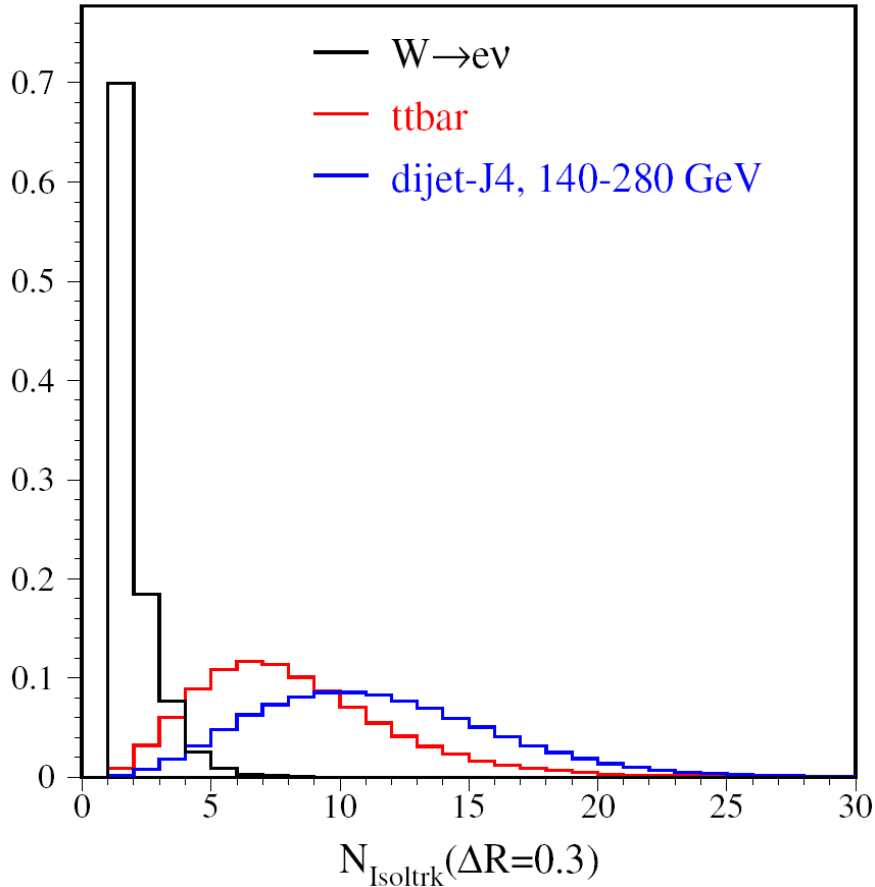


ECal and Inner Track Match

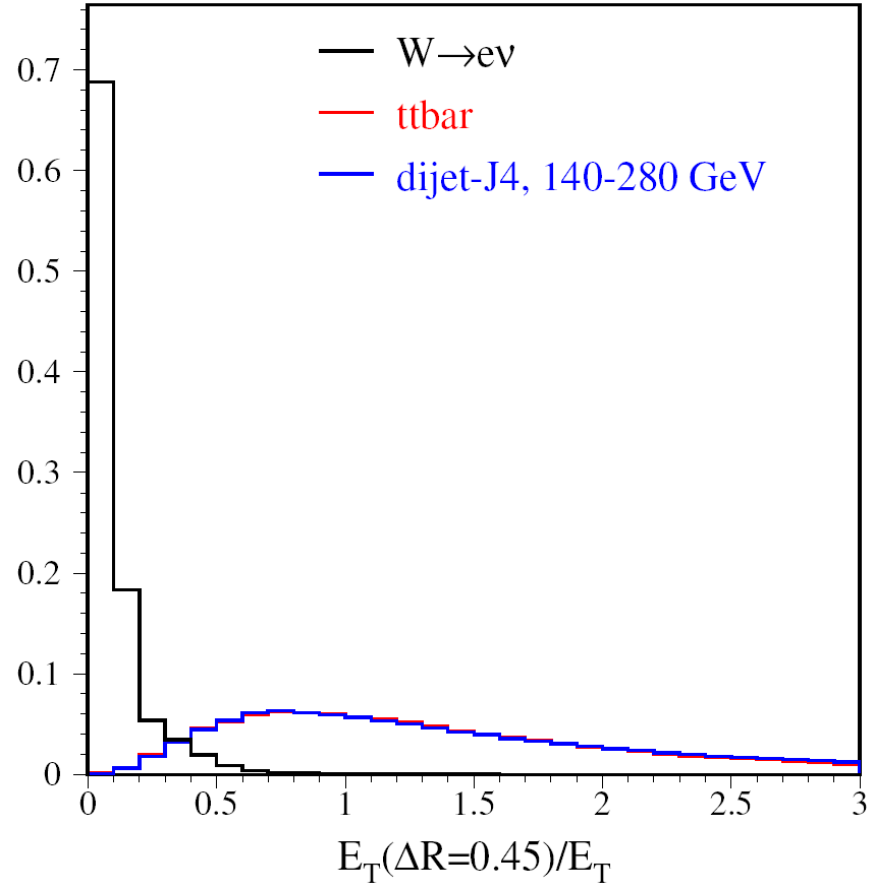


Electron Isolation Variables

N_{trk} around Electron Track



$E_T(\Delta R=0.2-0.45)/E_T$ of EM



Signal Pre-selection: MC electrons

- MC True electron from $W \rightarrow e\nu$ by requiring
 - $|\eta_e| < 2.5$ and $E_T^{\text{true}} > 17 \text{ GeV}$ (N_e)
- Match MC e/ γ to EM cluster:
 - $\Delta R < 0.2$ and $0.5 < E_T^{\text{rec}} / E_T^{\text{true}} < 1.5$ (N_{EM})
- Match EM cluster with an inner track:
 - $\text{eg_trkmatchnt} > -1$ ($N_{\text{EM/track}}$)
- **Pre-selection Efficiency = $N_{\text{EM/Track}} / N_e$**

Pre-selection of Jet Faked Electrons

- Count number of reconstructed jets with
 - $|\eta_{\text{jet}}| < 2.5$ (N_{jet})
- Loop over all EM clusters; each cluster matches with a jet
 - $E_{\text{T}}^{\text{EM}} > 17 \text{ GeV}$ (N_{EM})
- Match EM cluster with an inner track:
 - $\text{eg_trkmatchnt} > -1$ ($N_{\text{EM/track}}$)
- **Pre-selection Acceptance = $N_{\text{EM/Track}} / N_{\text{jet}}$**