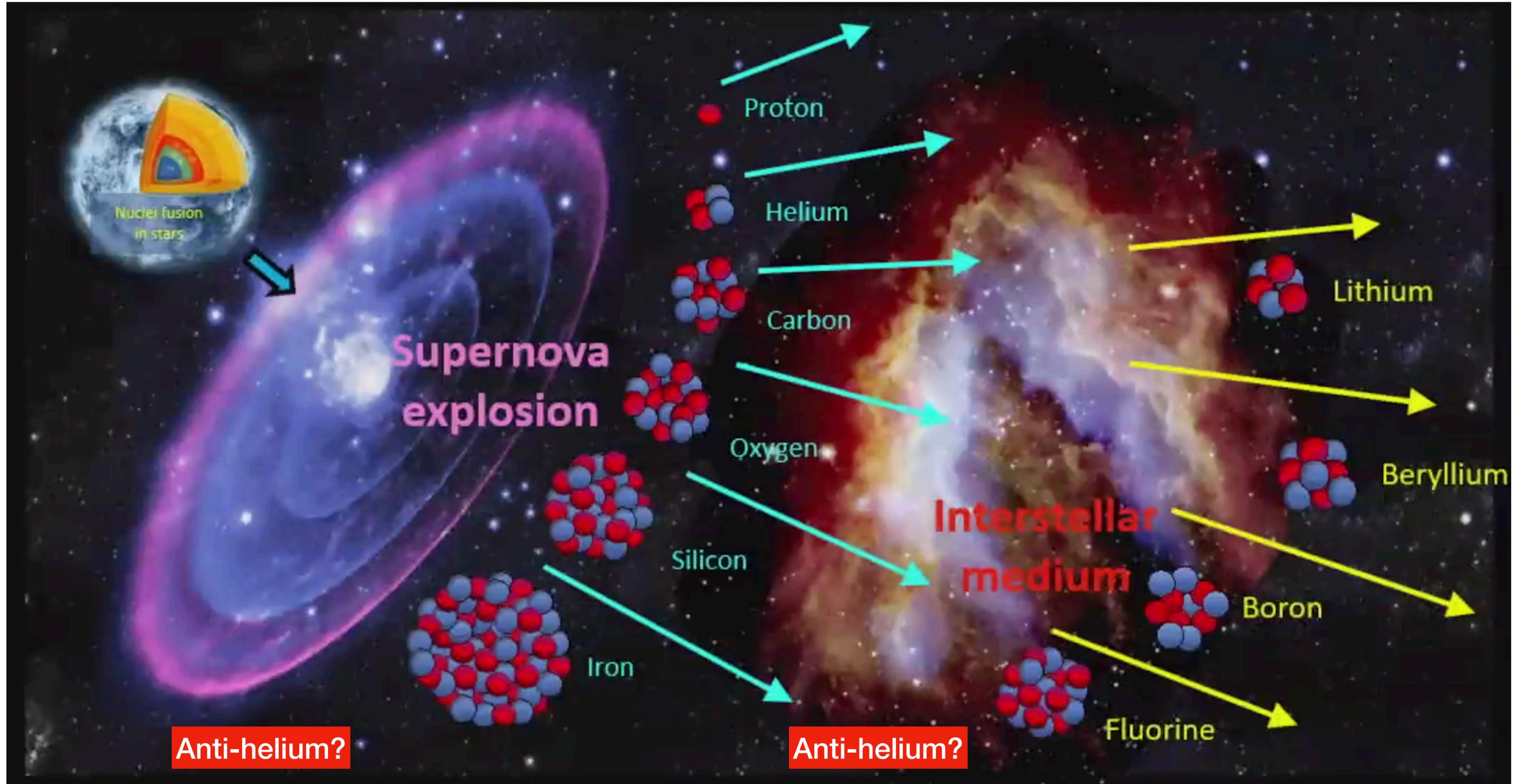


Progress on anti-helium search with ROOT TMVA

**AMS Italy Trento
2023-11-30**

Jian Tian / Roma 2

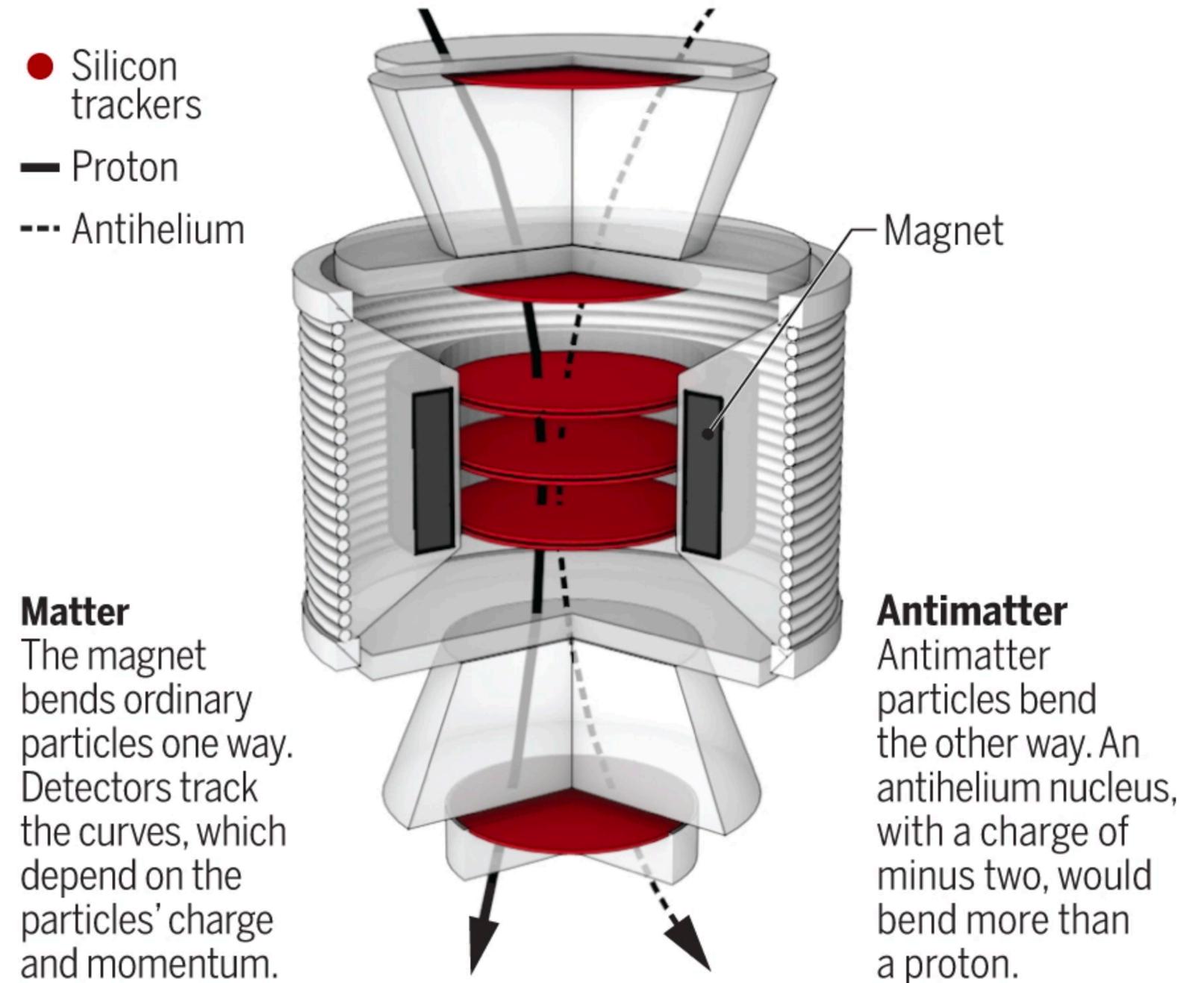
Cosmic rays' production and propagation



The aim of this analysis is search for anti-helium in cosmic rays

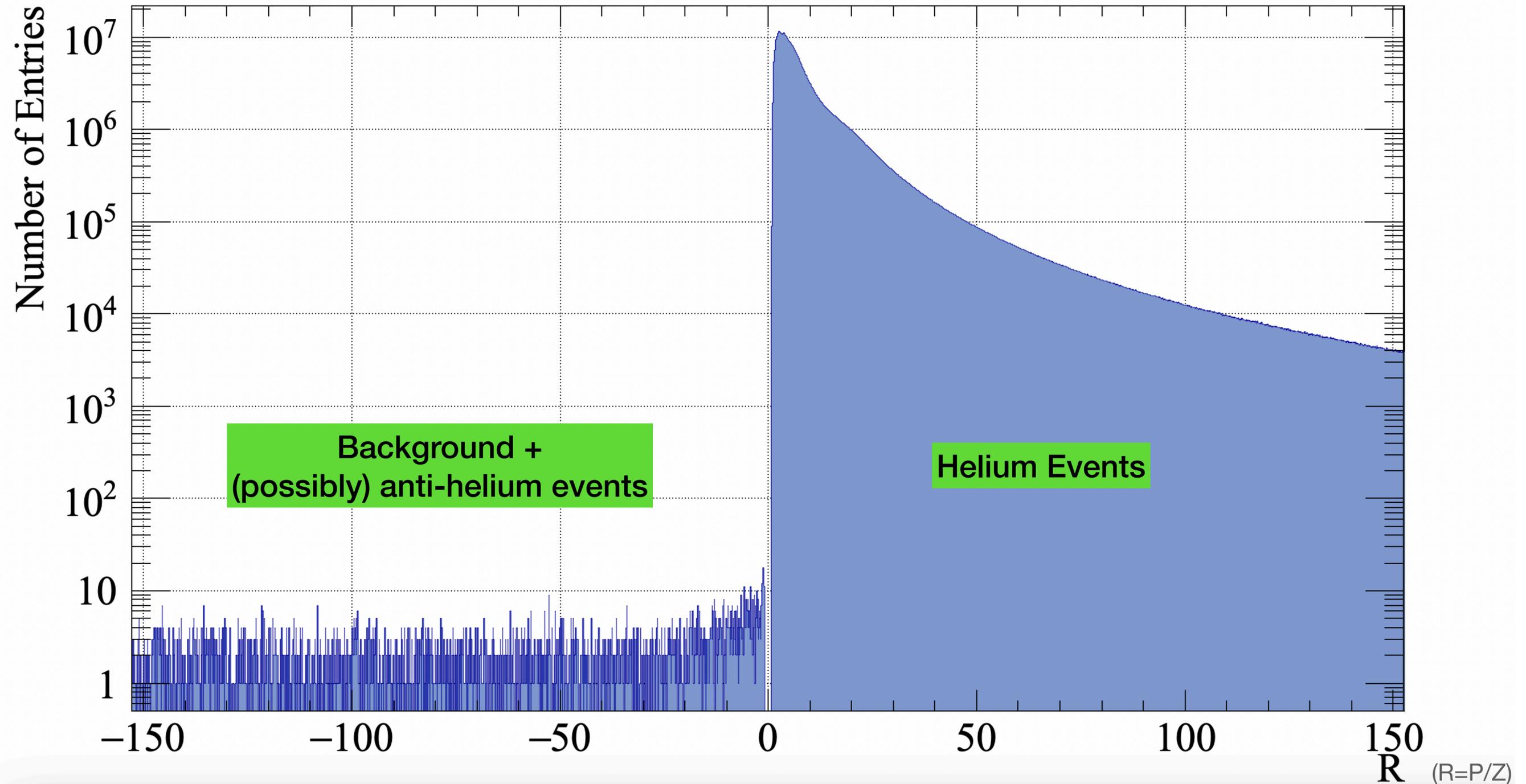
Antimatter particles in cosmic rays are unique messengers for the search of dark matter annihilation signals in the Galaxy, or the presents of large domains of antimatter in the universe.

AMS collaboration has publish the results of the positrons, anti-protons. Now we are searching for heavier antimatters in the cosmic rays. Anti-helium is interesting since till now we have no clear evidence that we have anti-helium in cosmic rays.



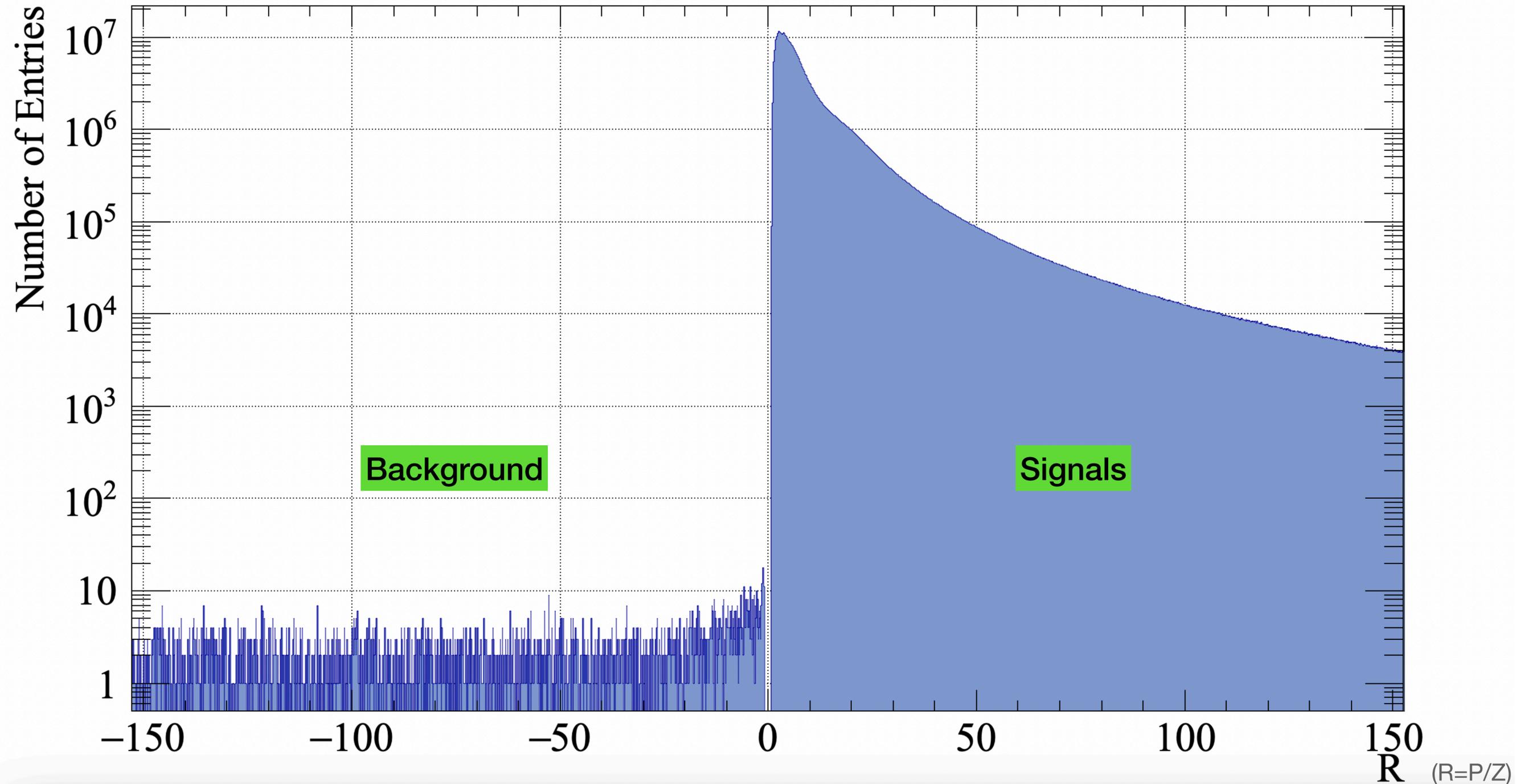
From the propagation theory of the cosmic ray, anti-helium is unlikely to be produced in the cosmic rays, that means, even there are some, should be very small amount. That make the most of the events with charge = -2 reconstructed in AMS are backgrounds.

Cosmic ray events with fabs(charge) ~ 2

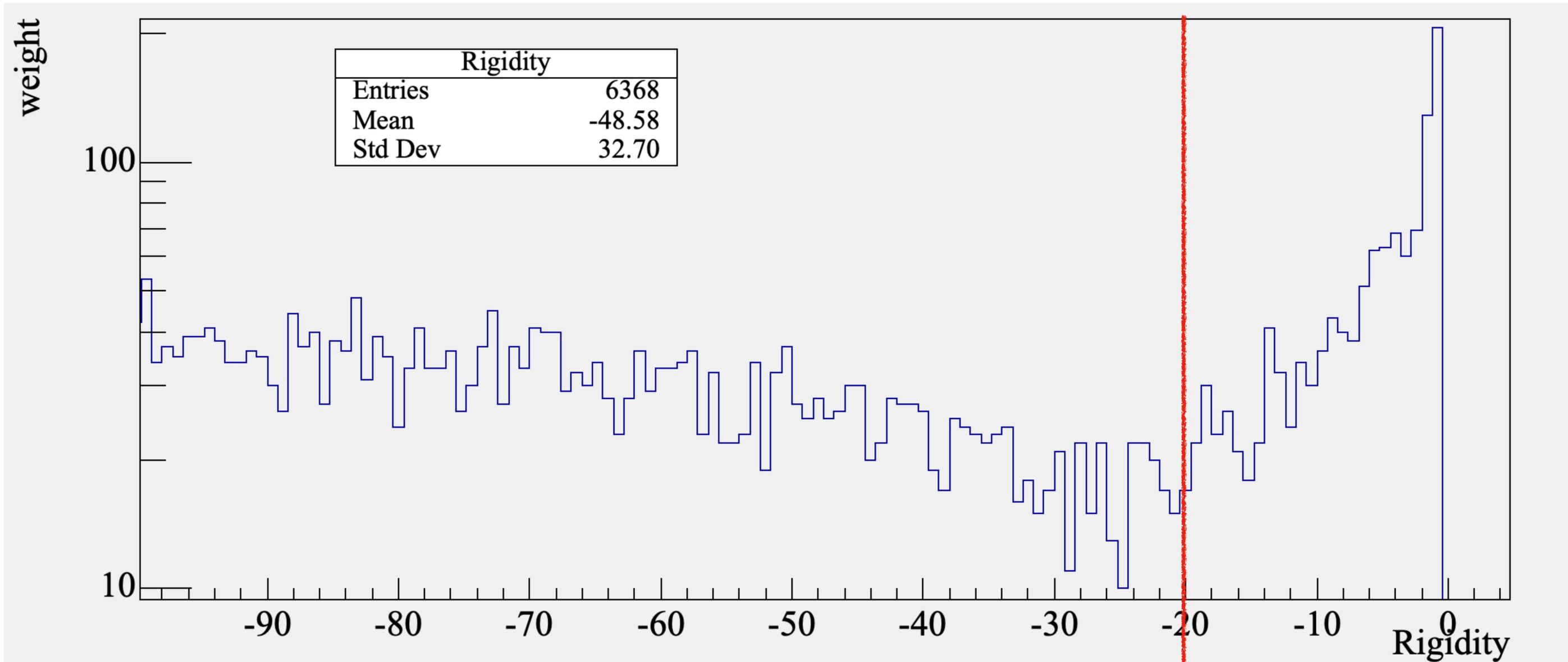


For most variables of the performance in the detector, Anti-helium should share the similar distribution as helium. So first, we need to find the variables that can be used to discriminate signals from backgrounds, both in Monte Carlo (MC) and the experimental data.

Cosmic ray events with fabs(charge) ~ 2



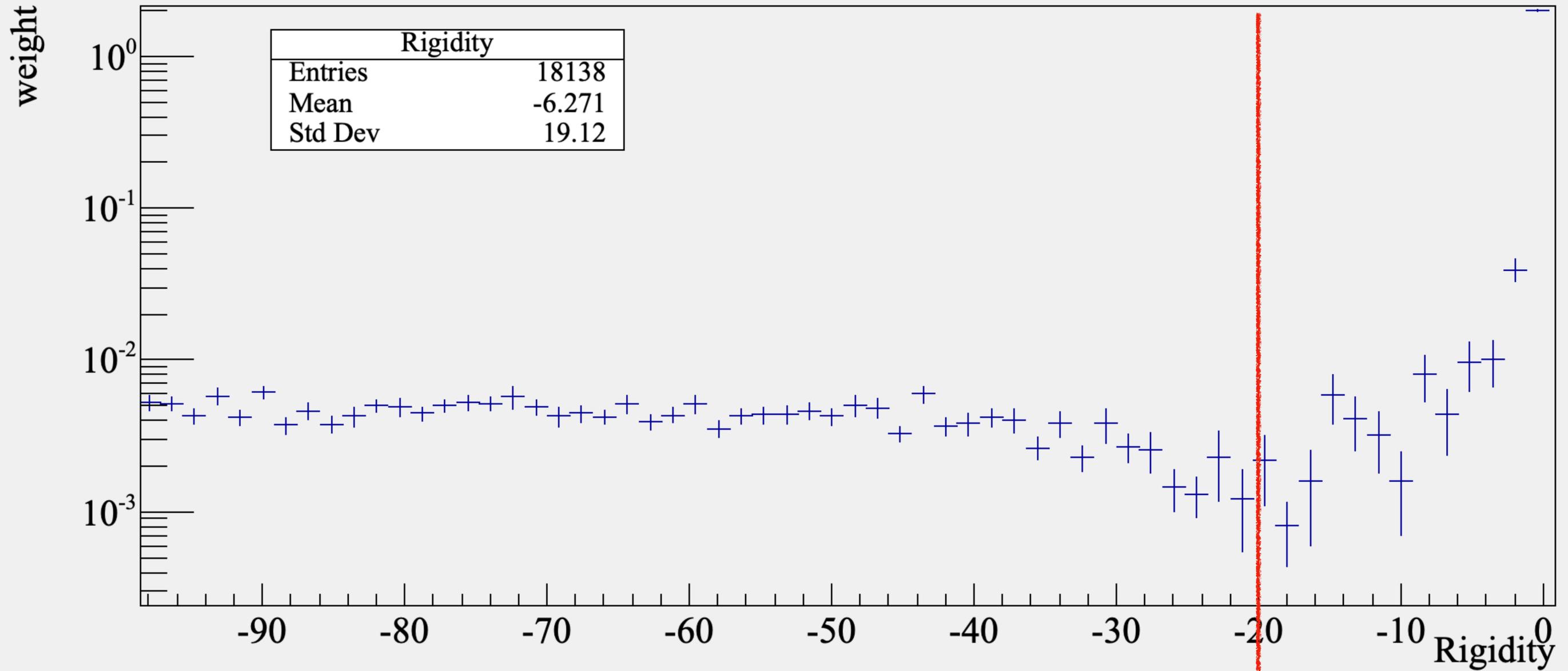
Data



At high energy, the background is mostly from the finite resolution of the detector, that some helium events are reconstructed with negative charge.

At low energy, the background is mostly from the particle scattering in the detector. Due to the scattering, some of the helium events are reconstructed with negative charge.

MC

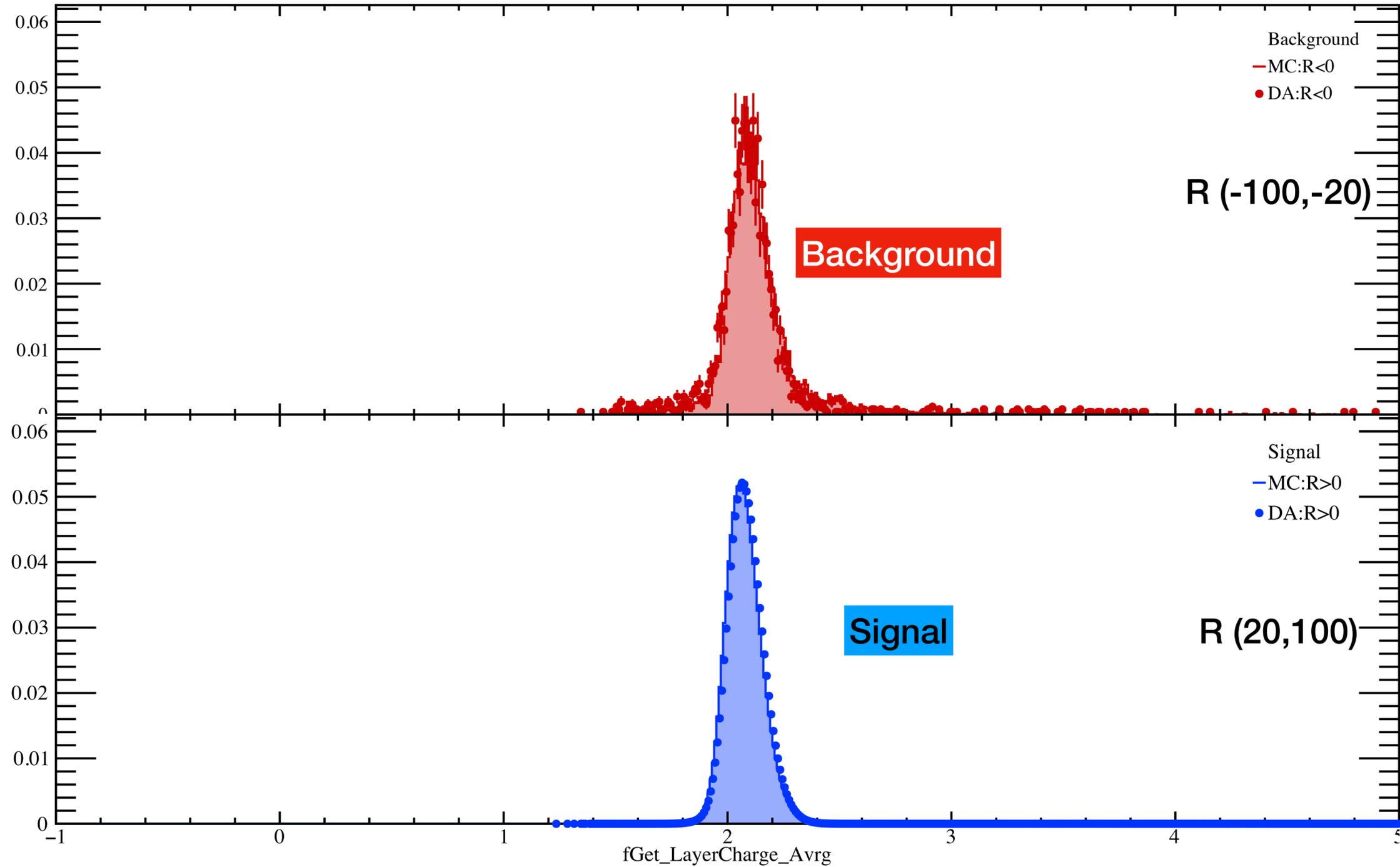


High Rigidity: $fabs(R) \geq 20$

Low Rigidity: $fabs(R) < 20$.

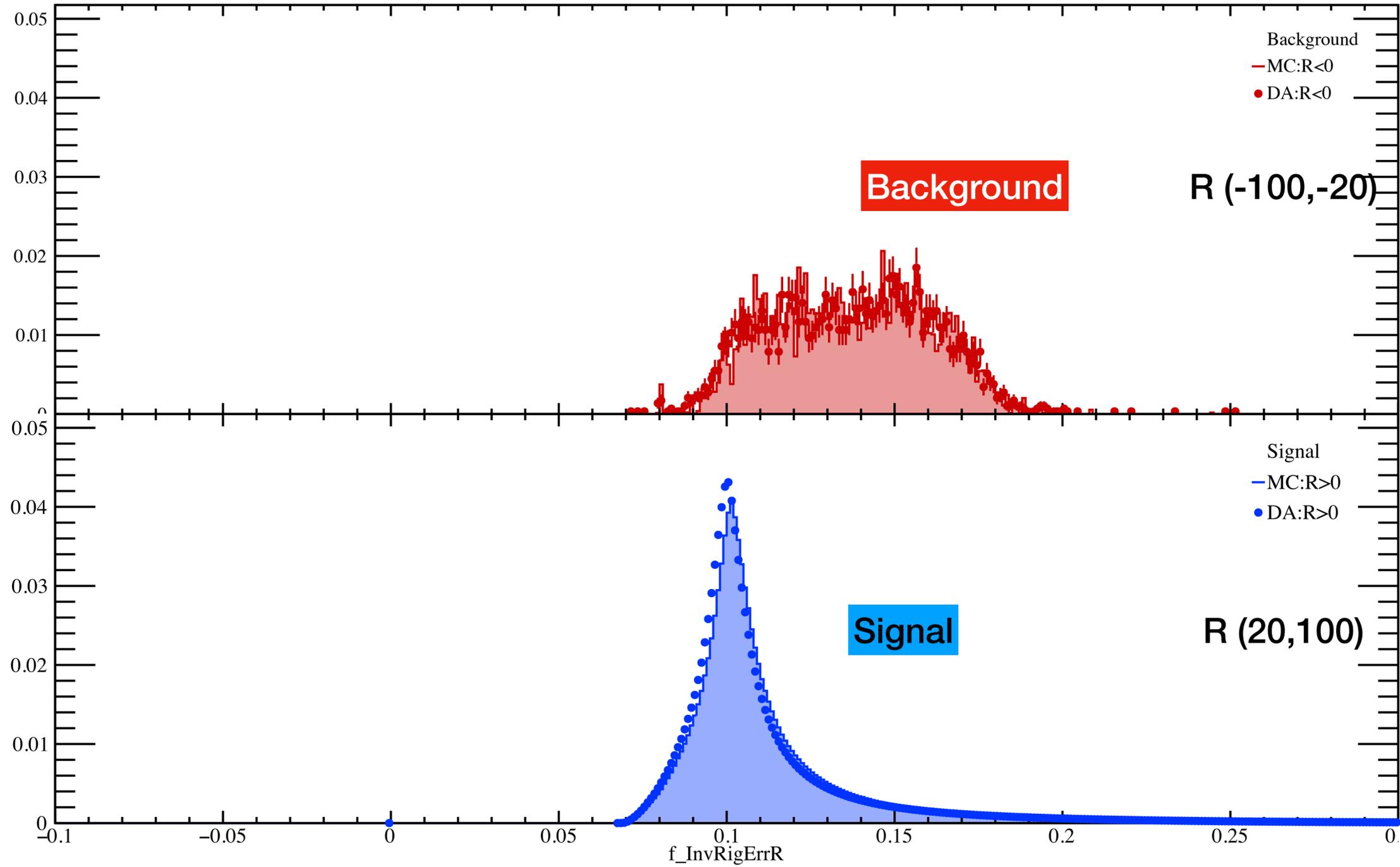
High Rigidity: $\text{fabs}(R) \geq 20$

looking for variables could discriminate signals from backgrounds.

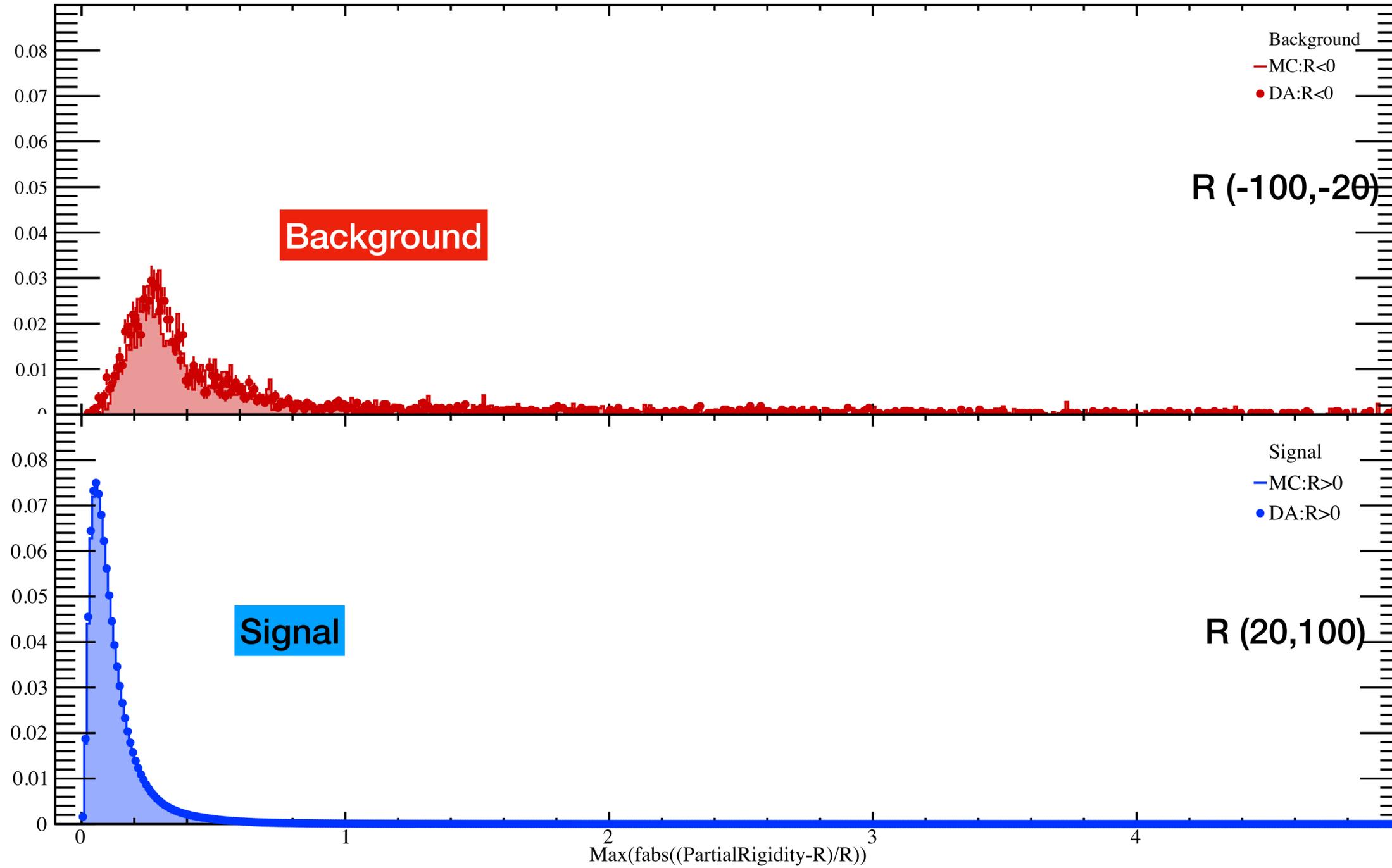


Average charge of the 7 layers in the inner tracker

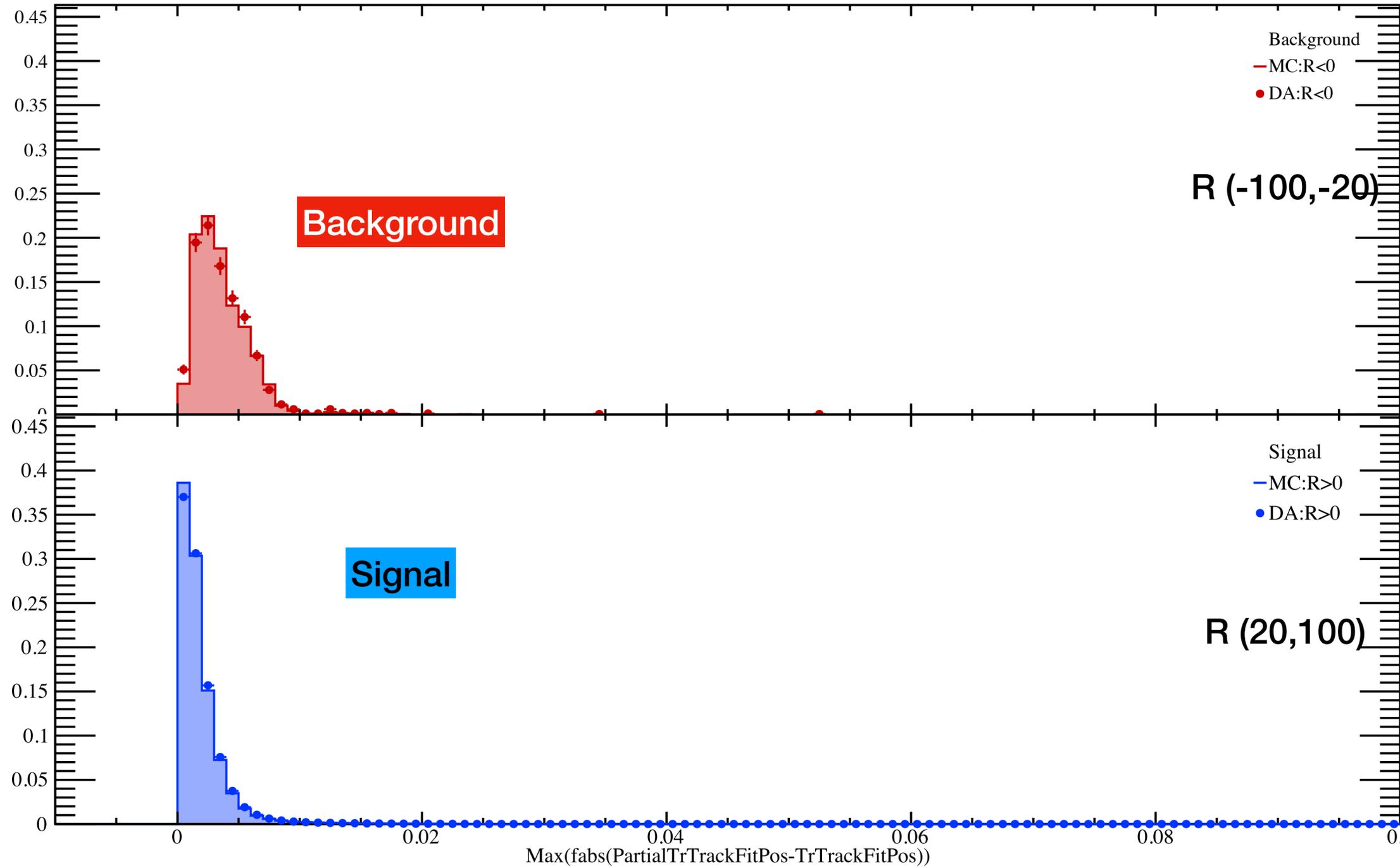
looking for variables could discriminate signals from backgrounds.



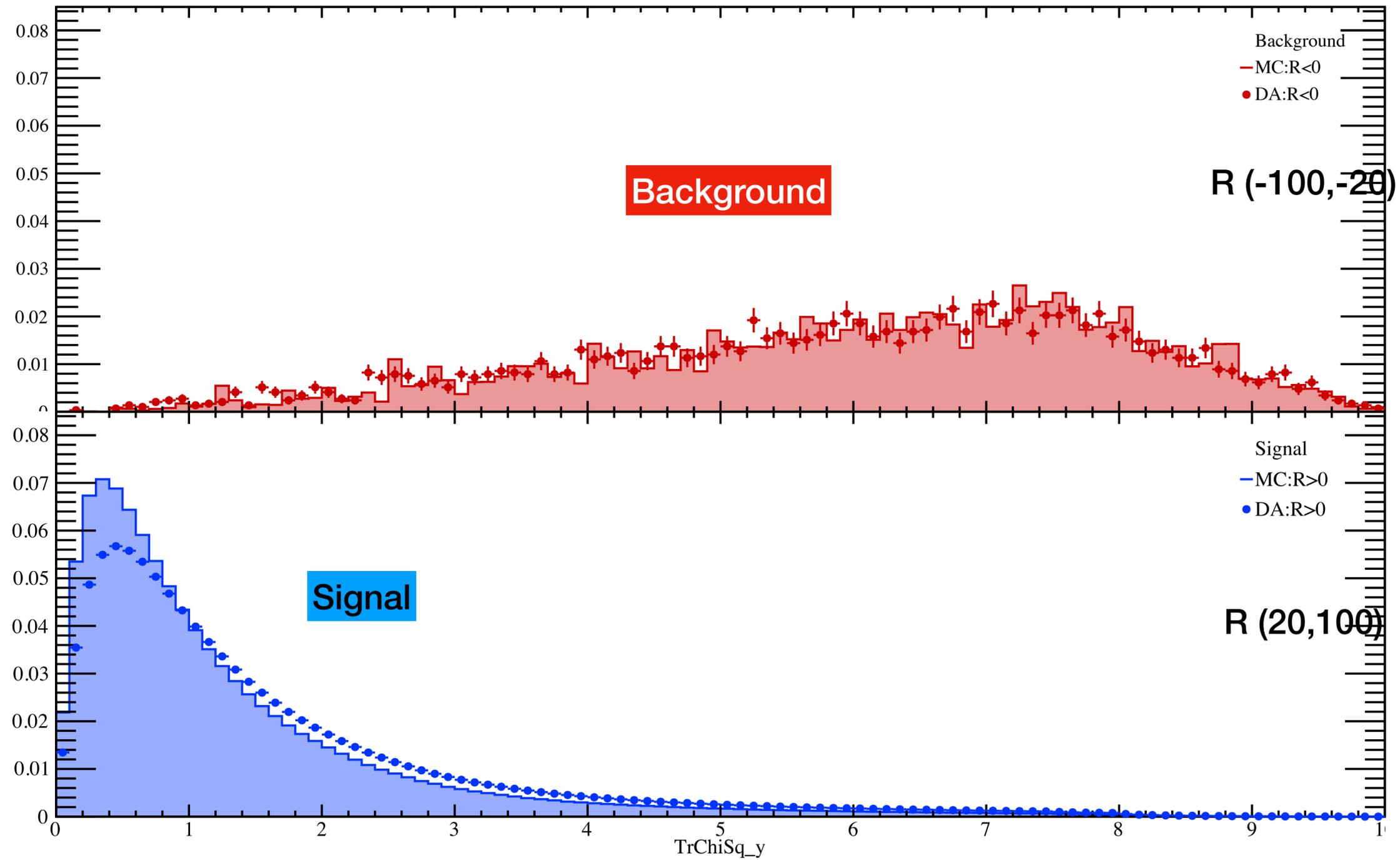
looking for variables could discriminate signals from backgrounds.



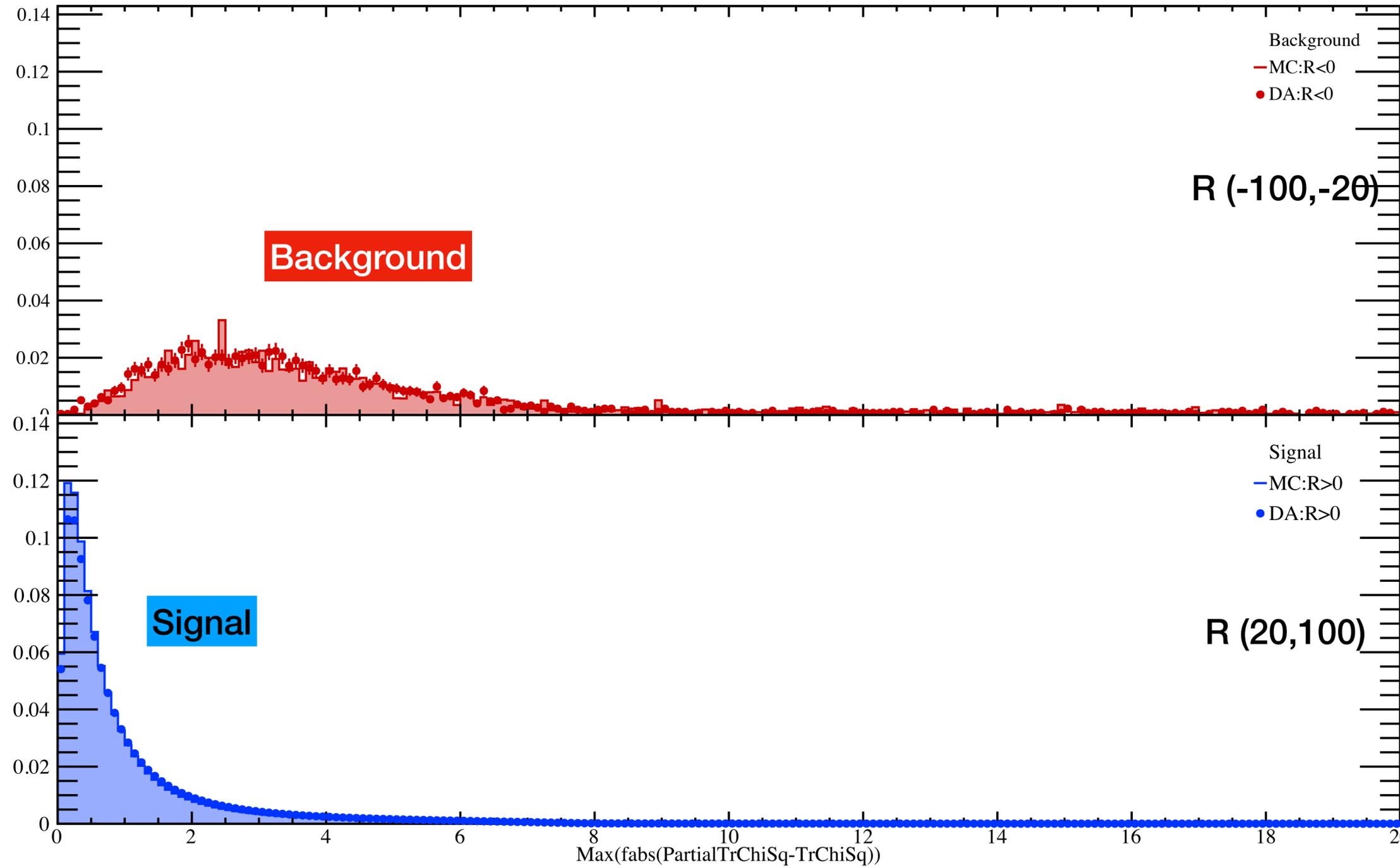
looking for variables could discriminate signals from backgrounds.



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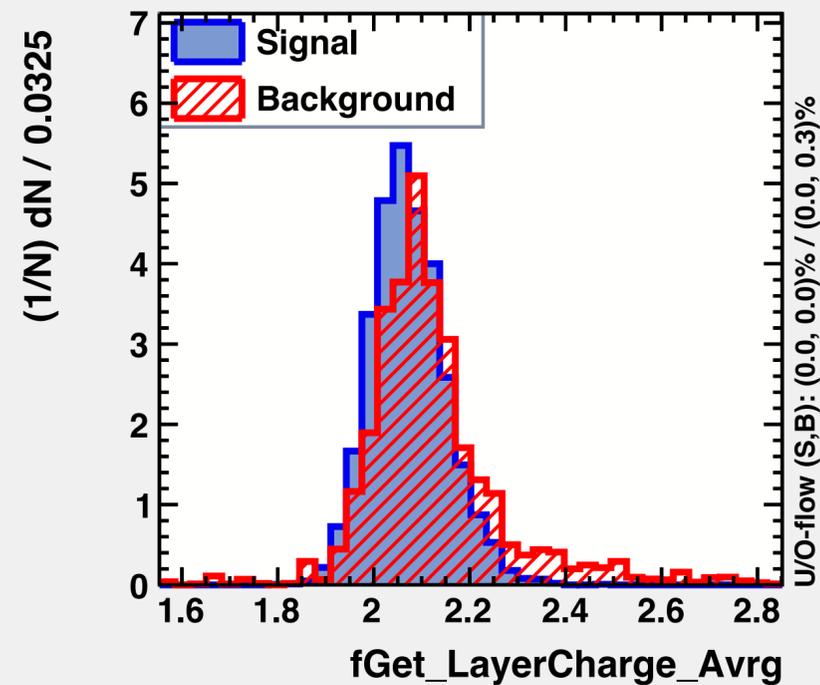


looking for variables could discriminate signals from backgrounds.

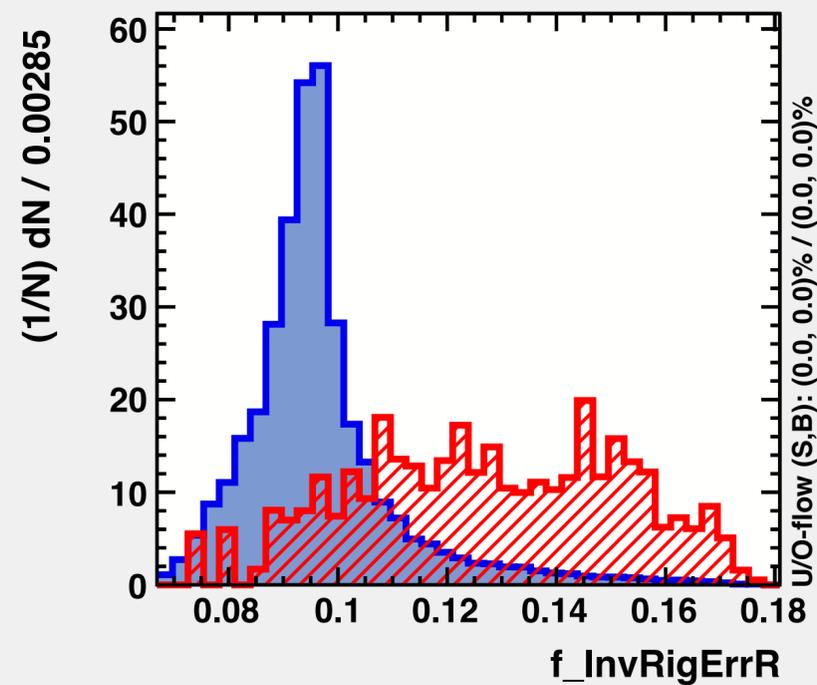


High Rigidity: fabs(R)>=20

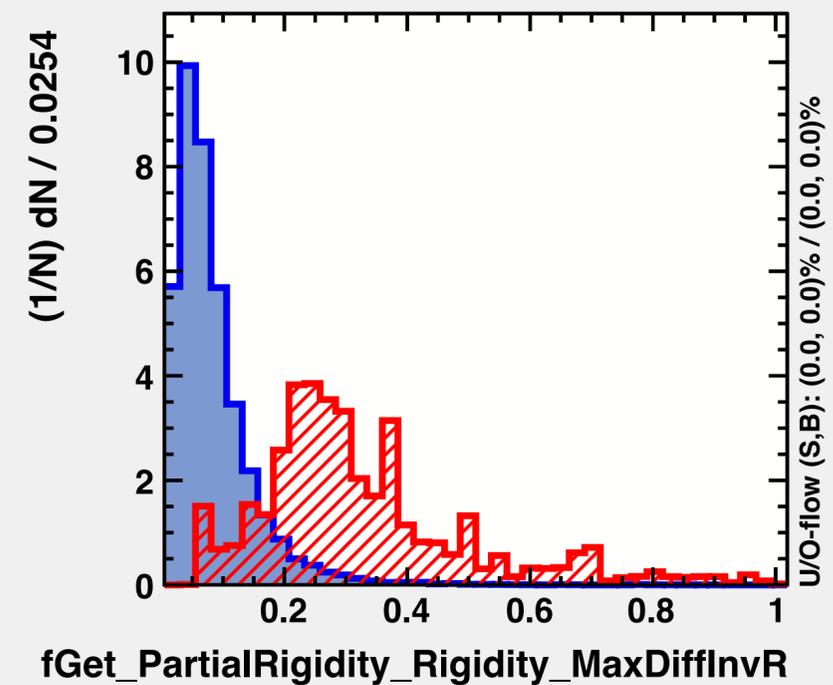
Input variable: fGet_LayerCharge_Avrg



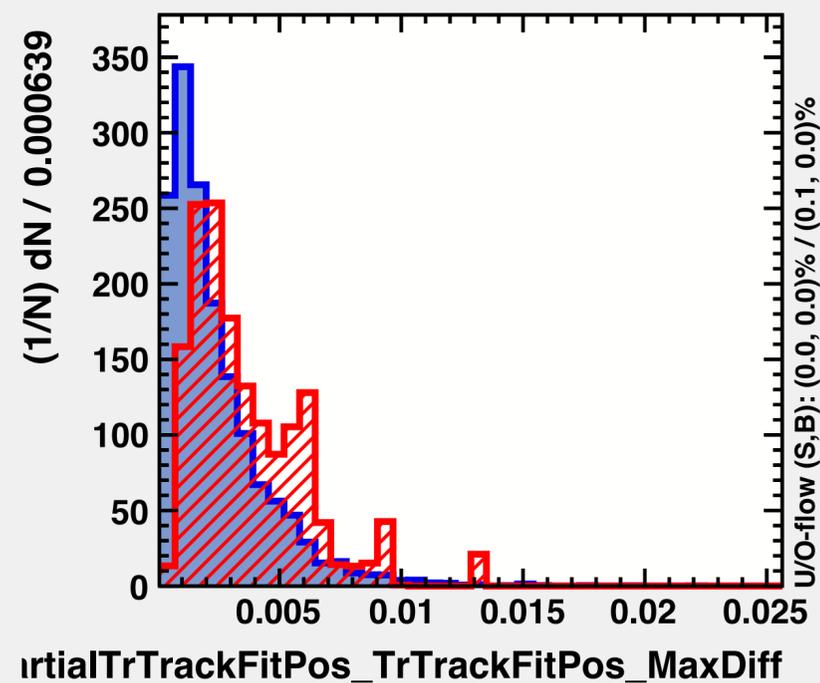
Input variable: f_InvRigErrR



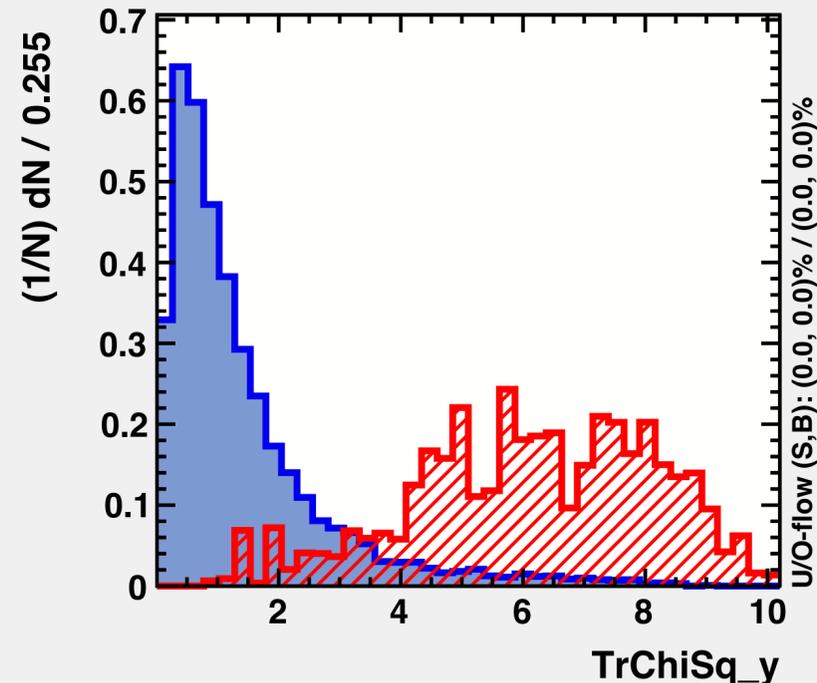
Input variable: fGet_PartialRigidity_Rigidity_MaxDiffInvR



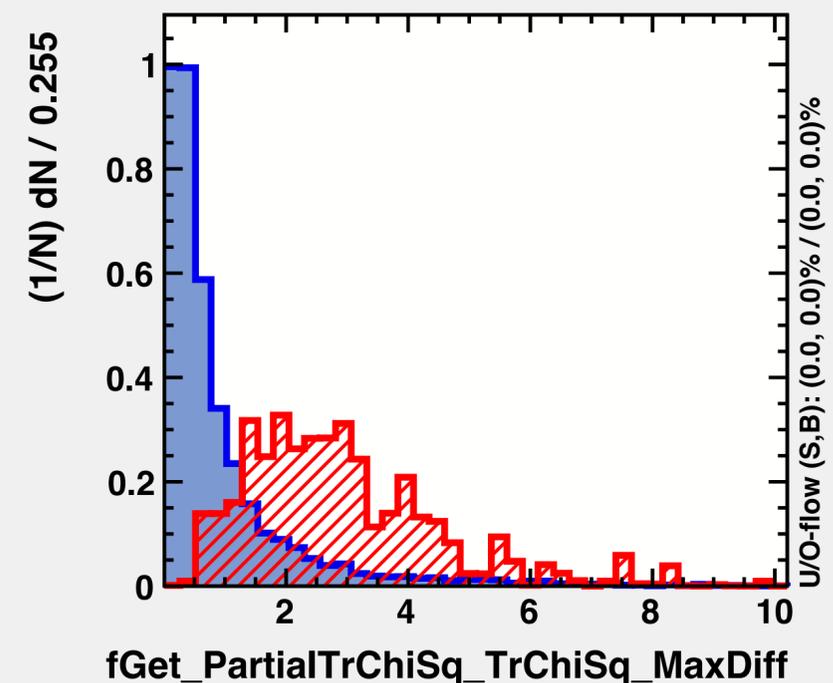
Input variable: fGet_PartialTrTrackFitPos_TrTrackFitPos_MaxDiff



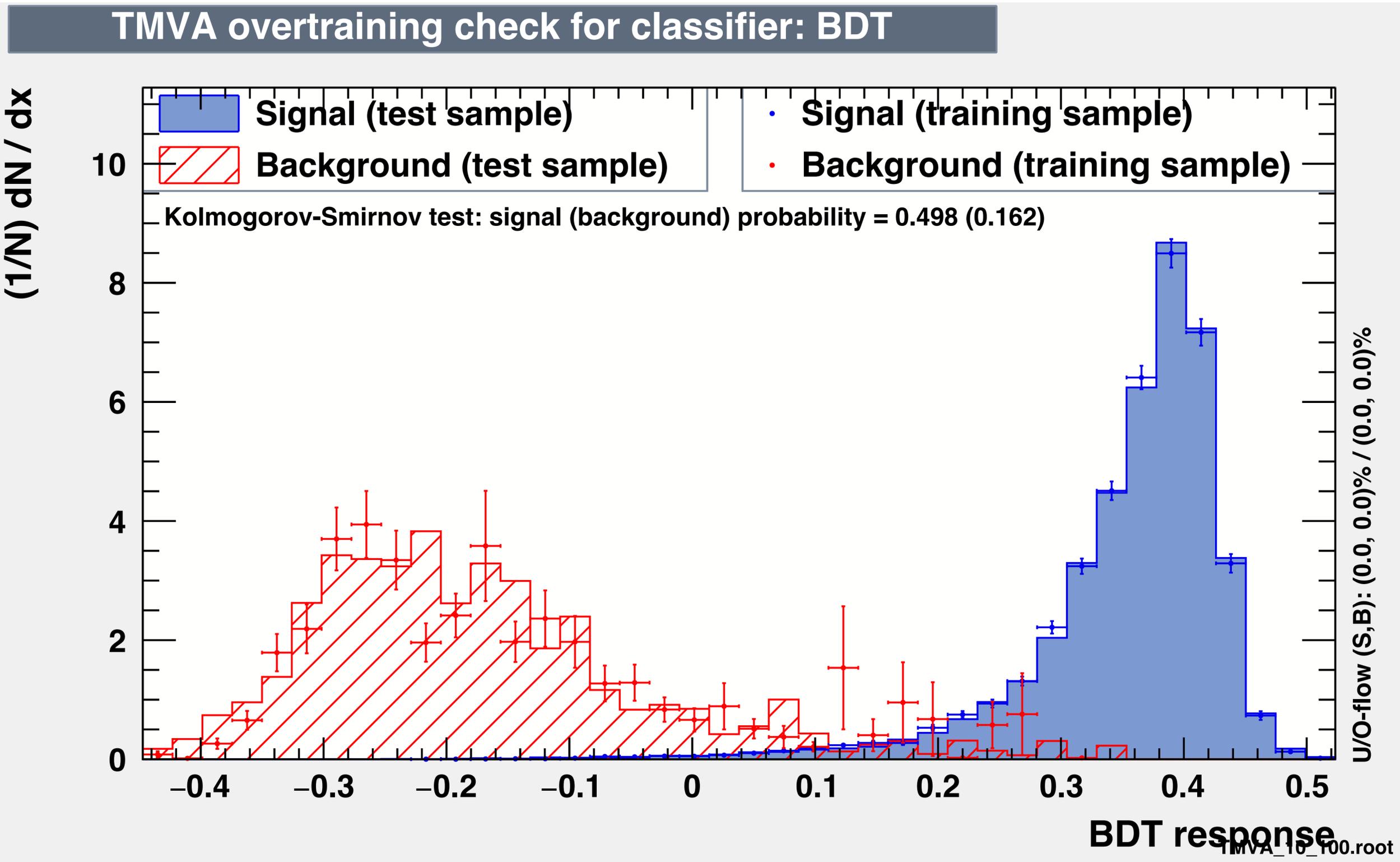
Input variable: TrChiSq_y



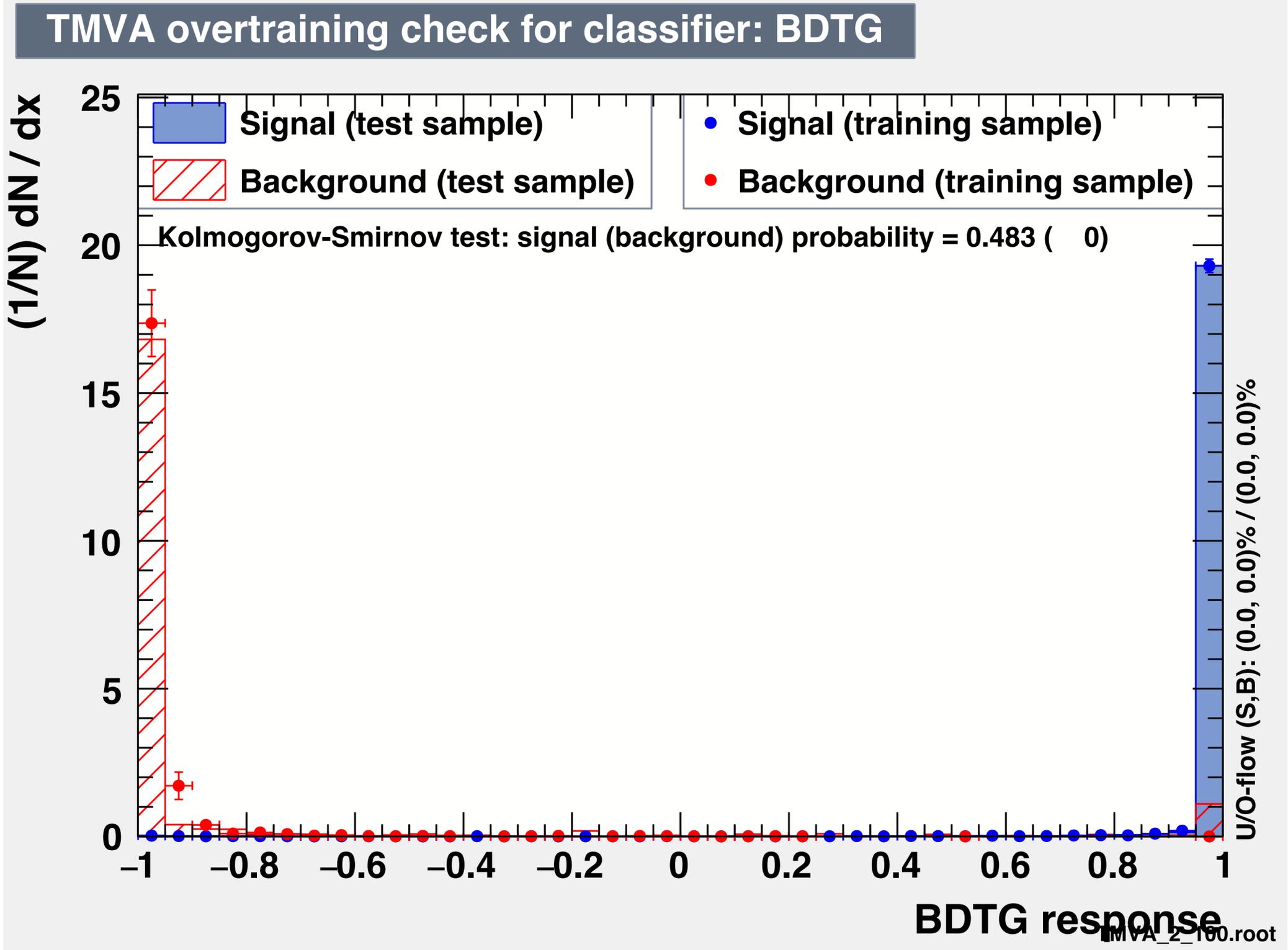
Input variable: fGet_PartialTrChiSq_TrChiSq_MaxDiff



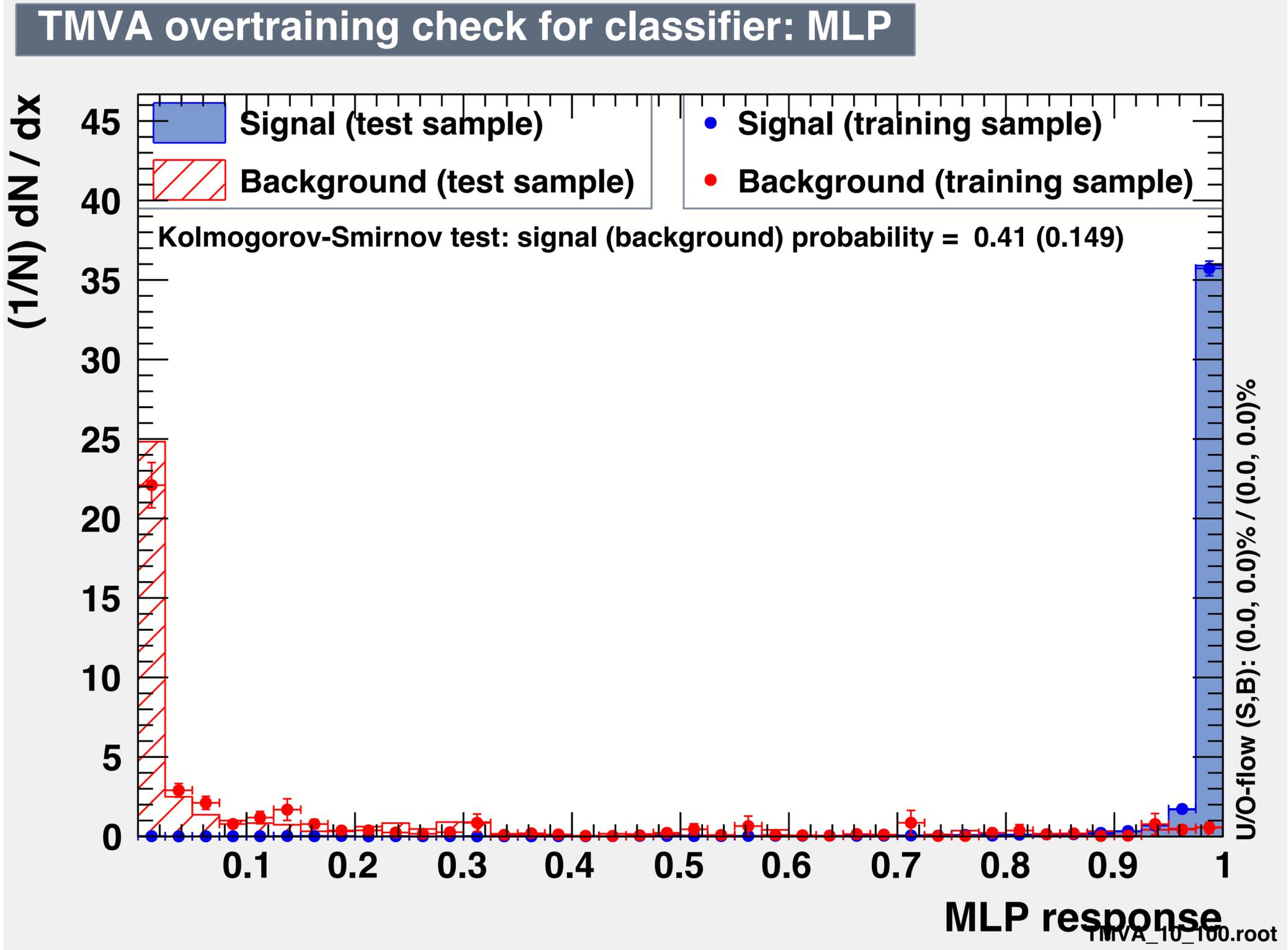
Employ the variables found before, perform machine learning with TMVA integrated in ROOT.
Train the MC data to get the classifier



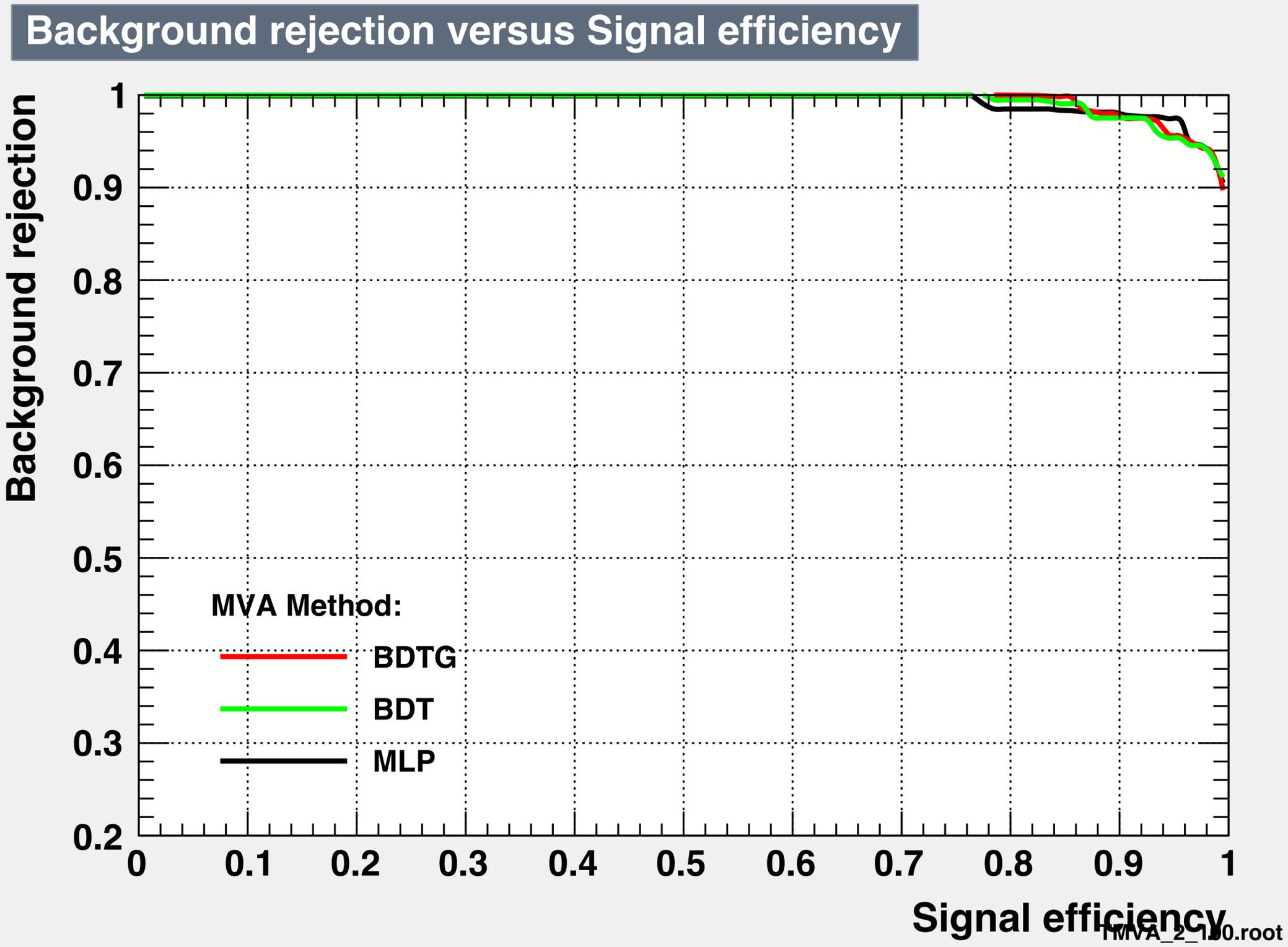
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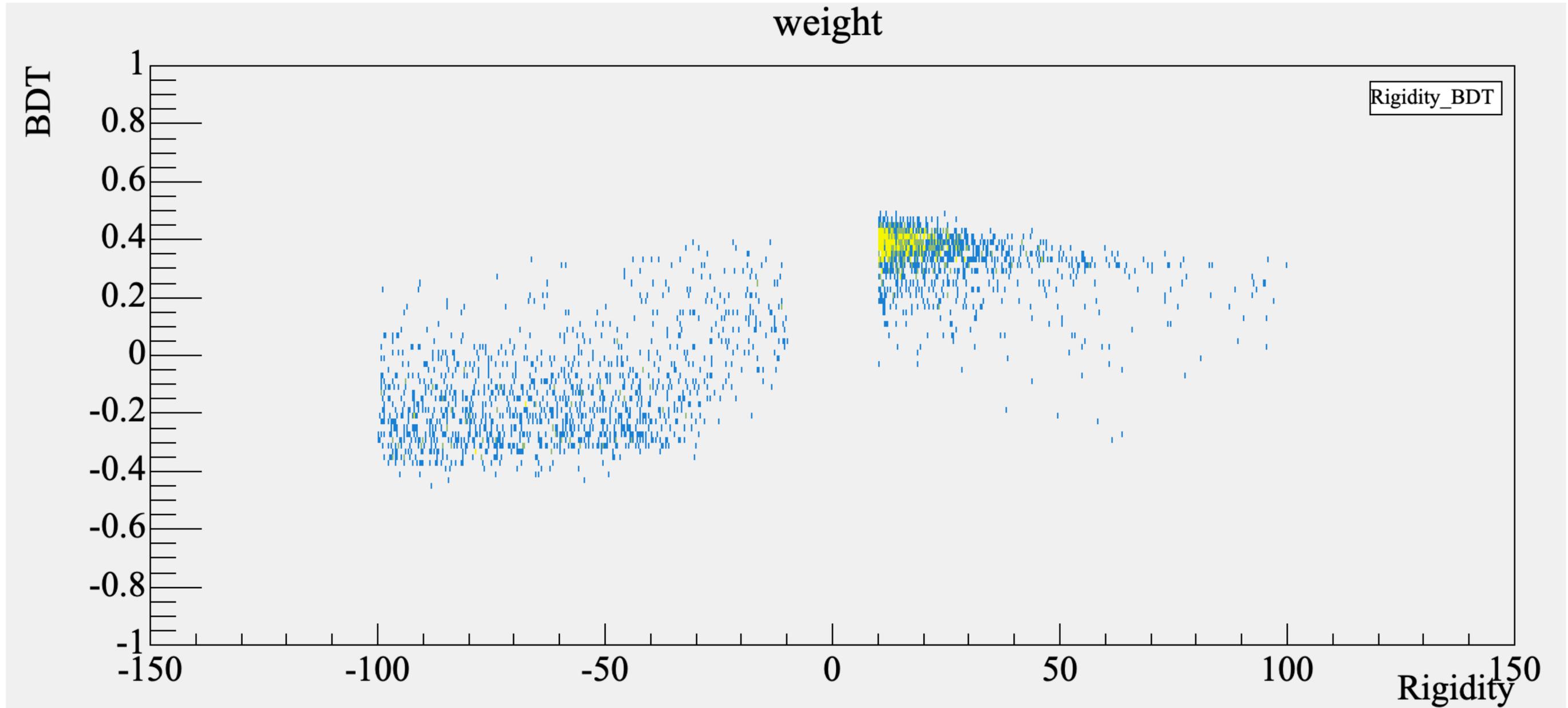
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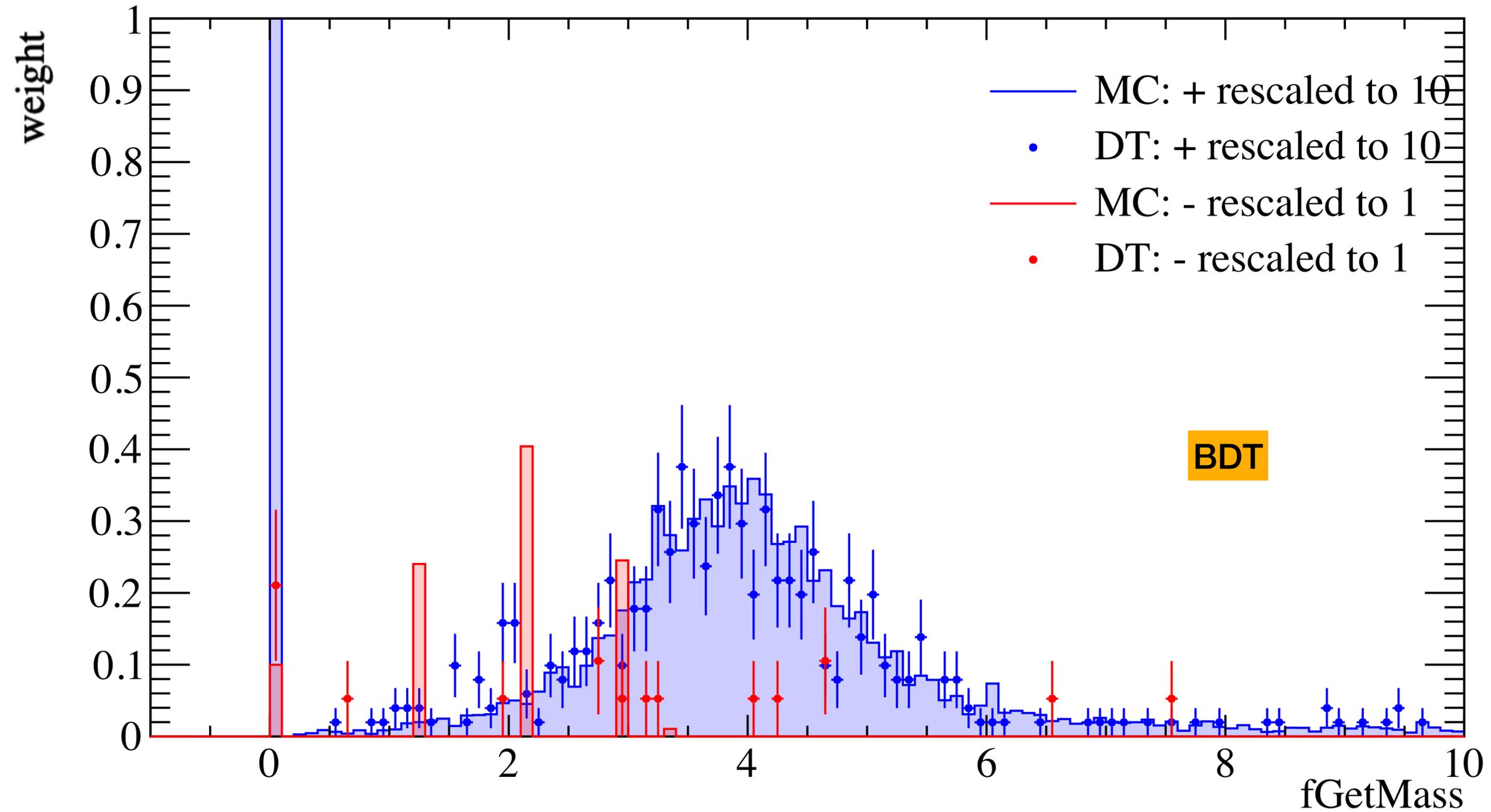


Apply the classifier to data



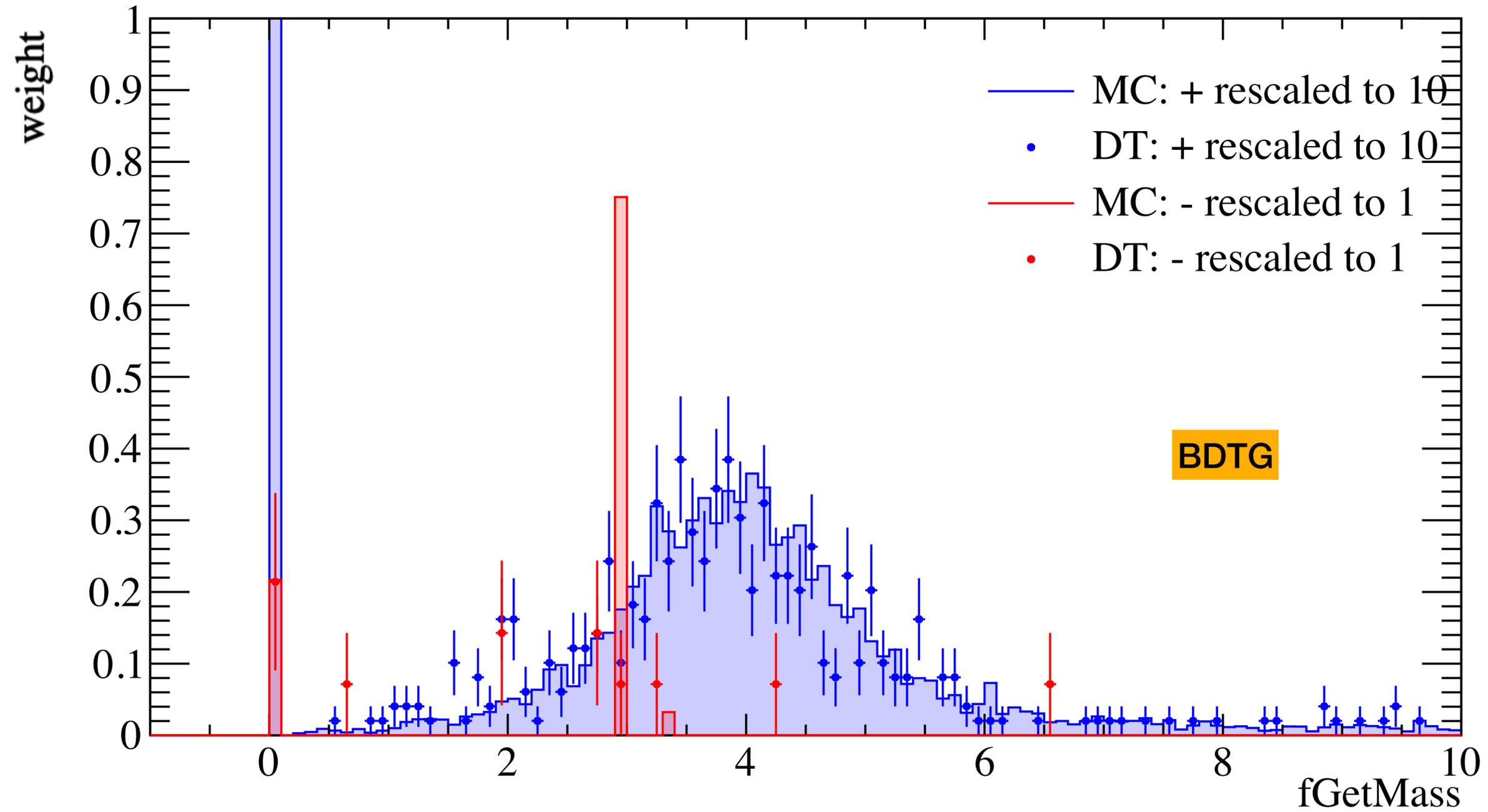
Apply the classifier to the experimental data

High Rigidity: $f_{abs}(R) \geq 20$



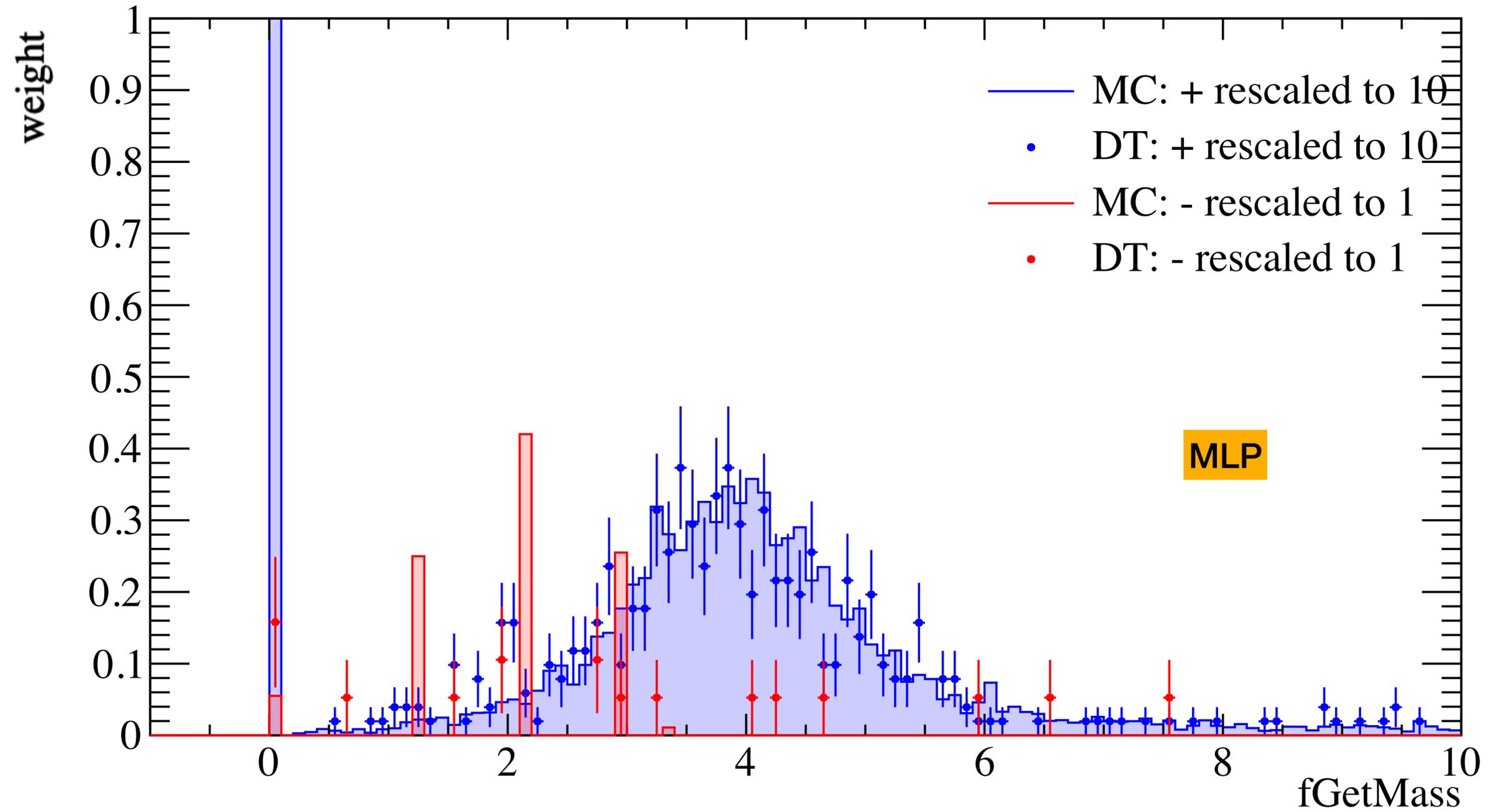
Apply the classifier to the experimental data

High Rigidity: $f_{abs}(R) \geq 20$



Apply the classifier to the experimental data

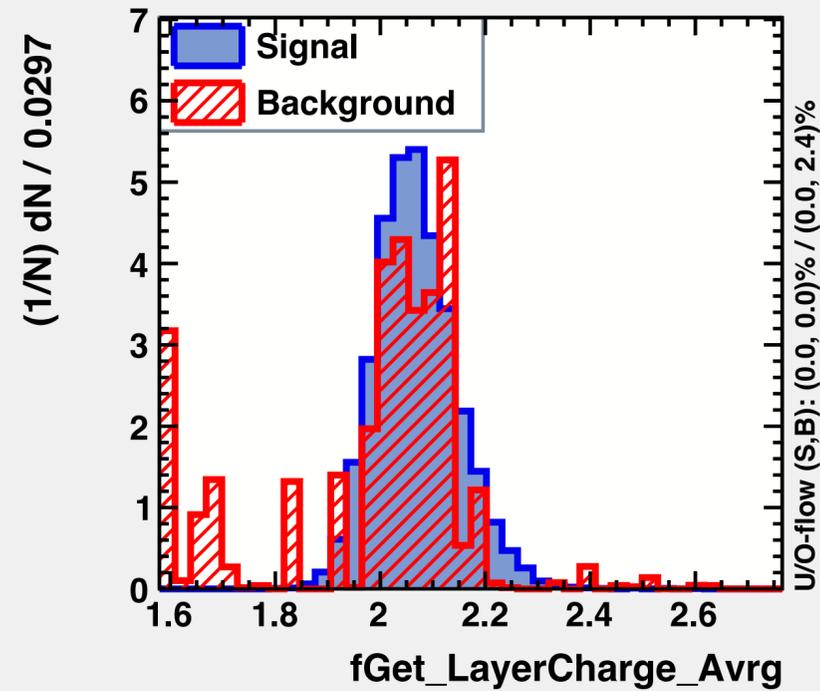
High Rigidity: fabs(R) \geq 20



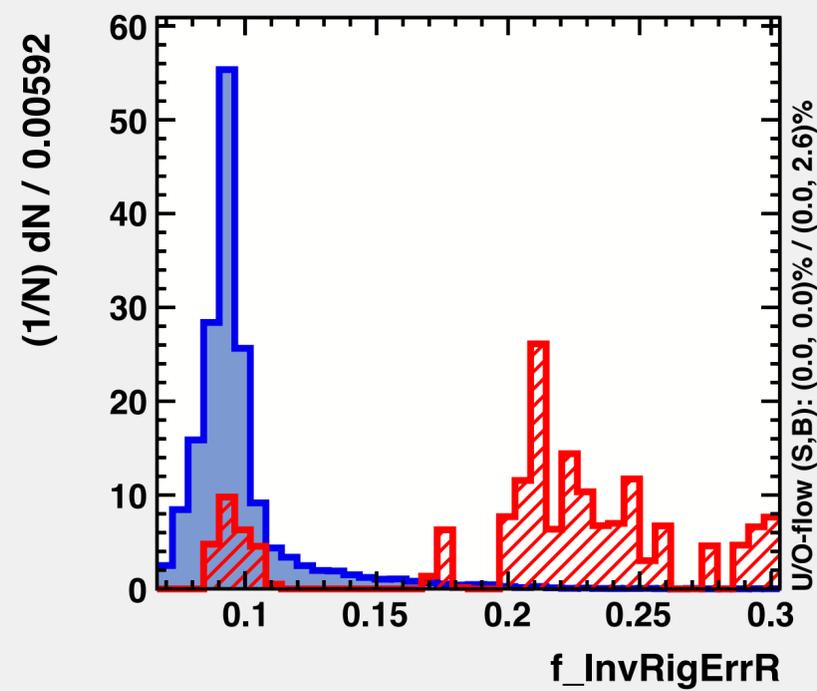
Low Rigidity: $\text{fabs}(R) < 20$

Low Rigidity: fabs(R)<20

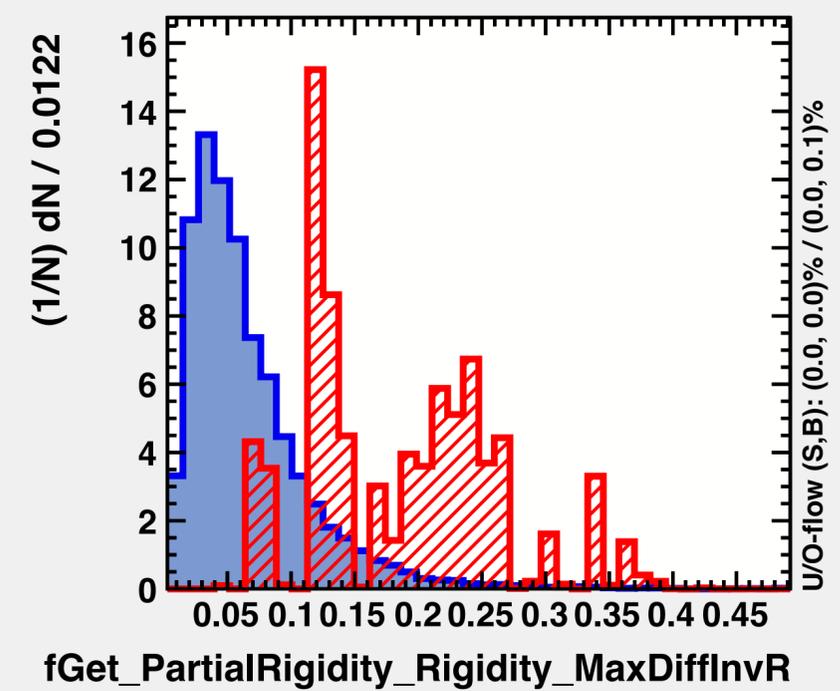
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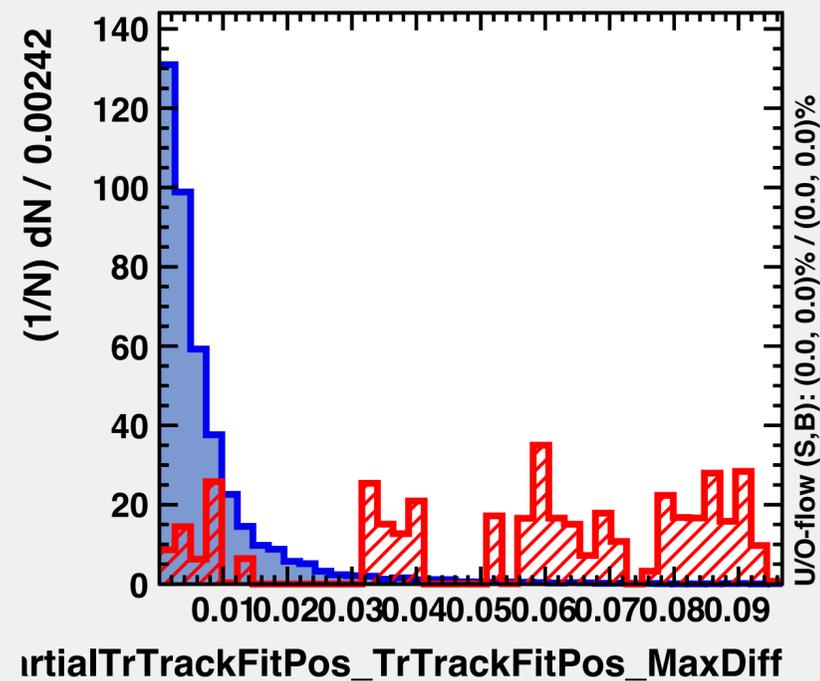
Input variable: f_InvRigErrR



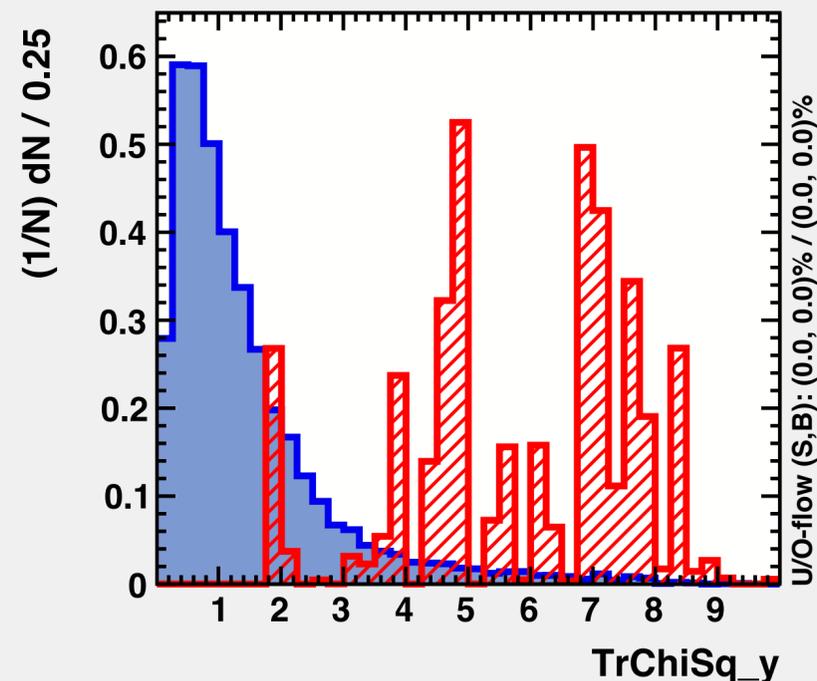
Input variable: fGet_PartialRigidity_Rigidity_MaxDiffInvR



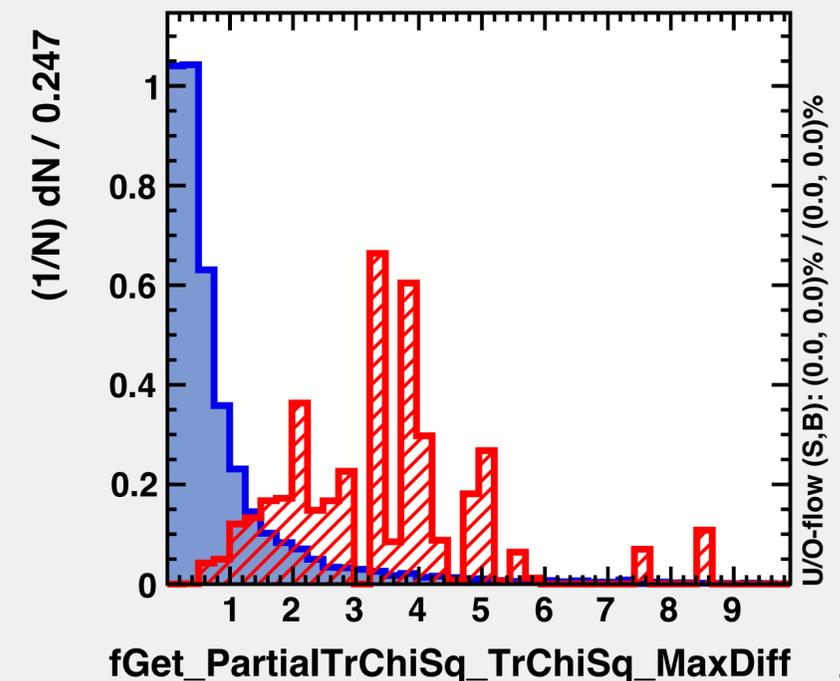
Input variable: fGet_PartialTrTrackFitPos_TrTrackFitPos_MaxDiff



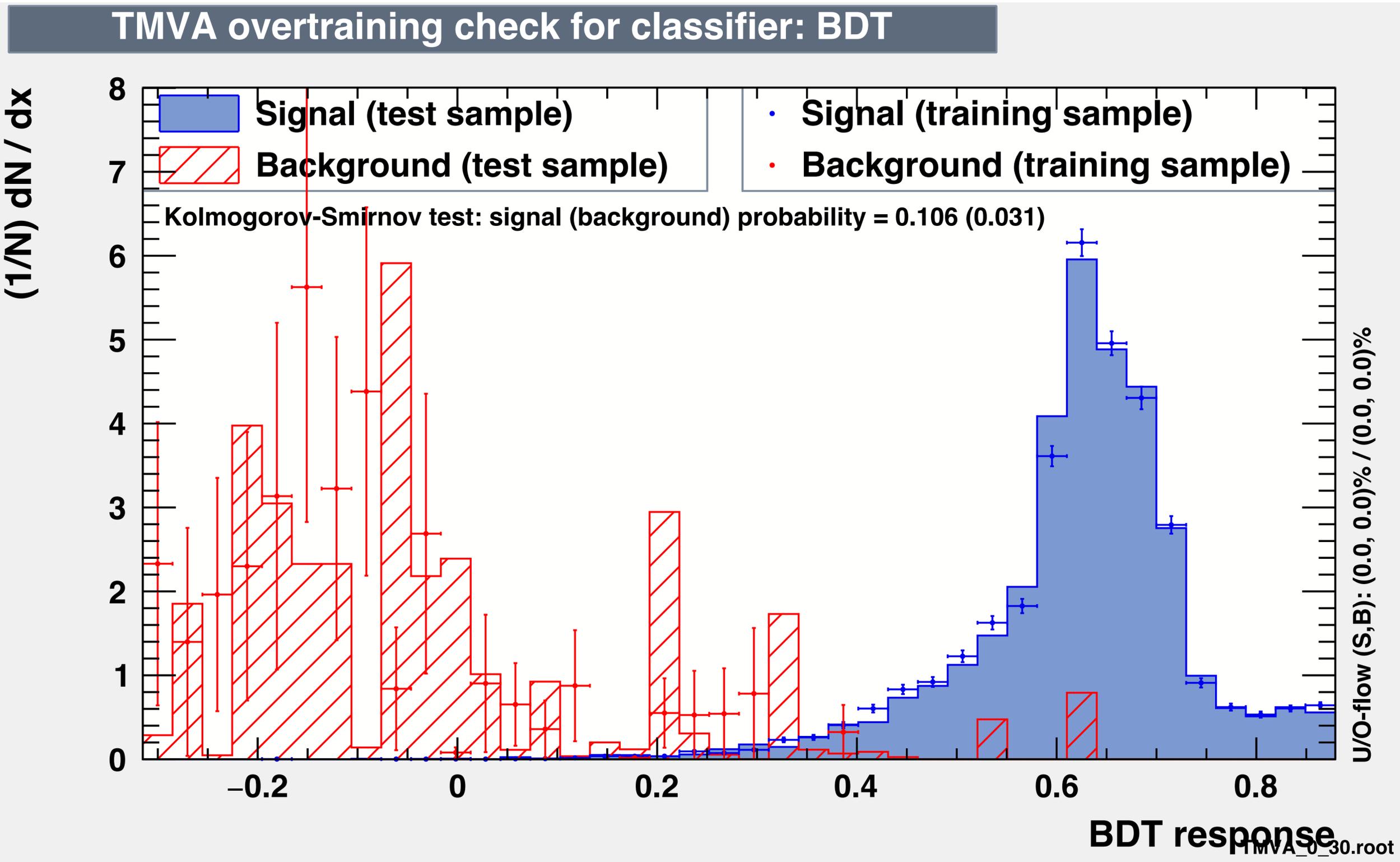
Input variable: TrChiSq_y



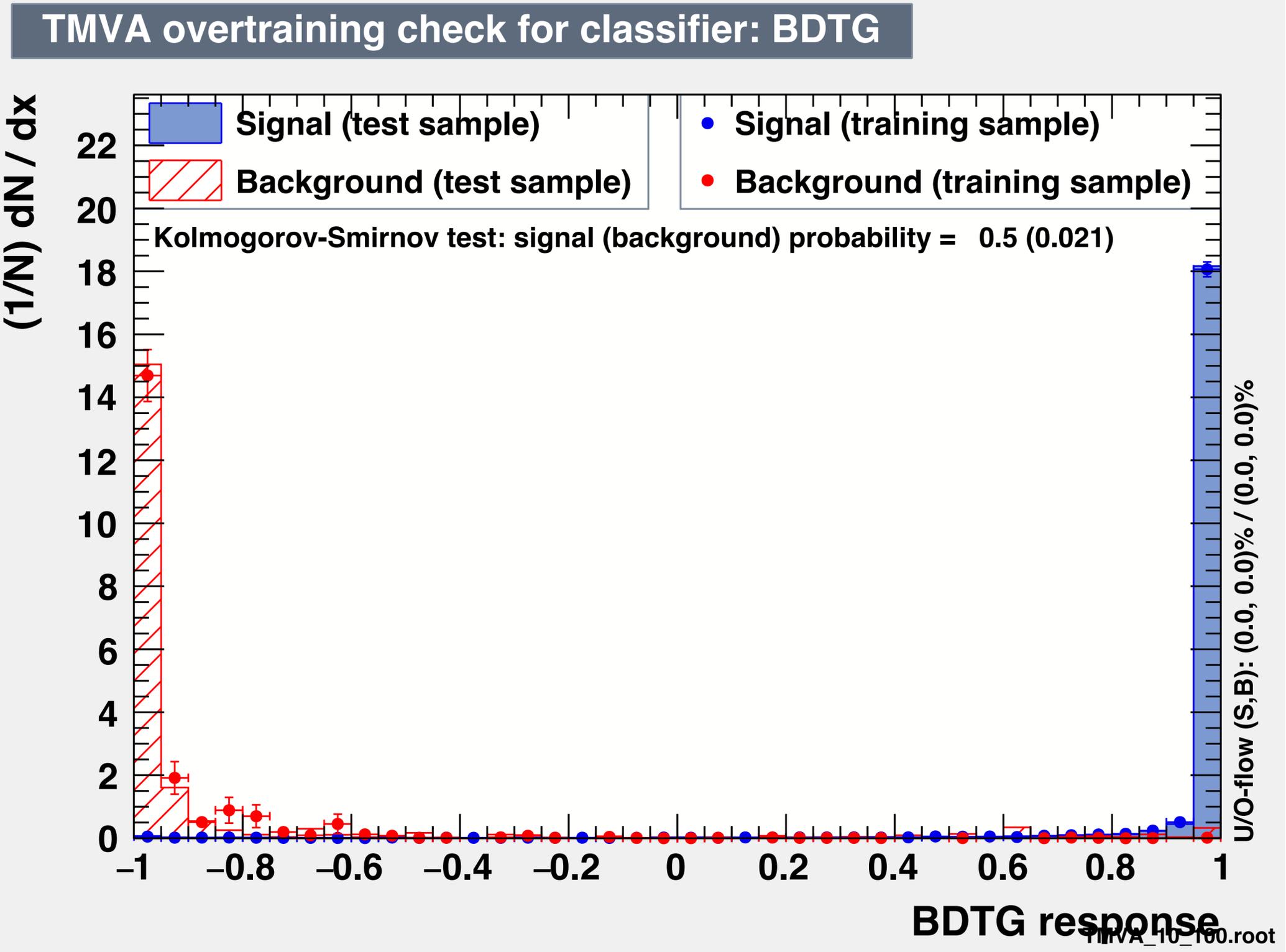
Input variable: fGet_PartialTrChiSq_TrChiSq_MaxDiff



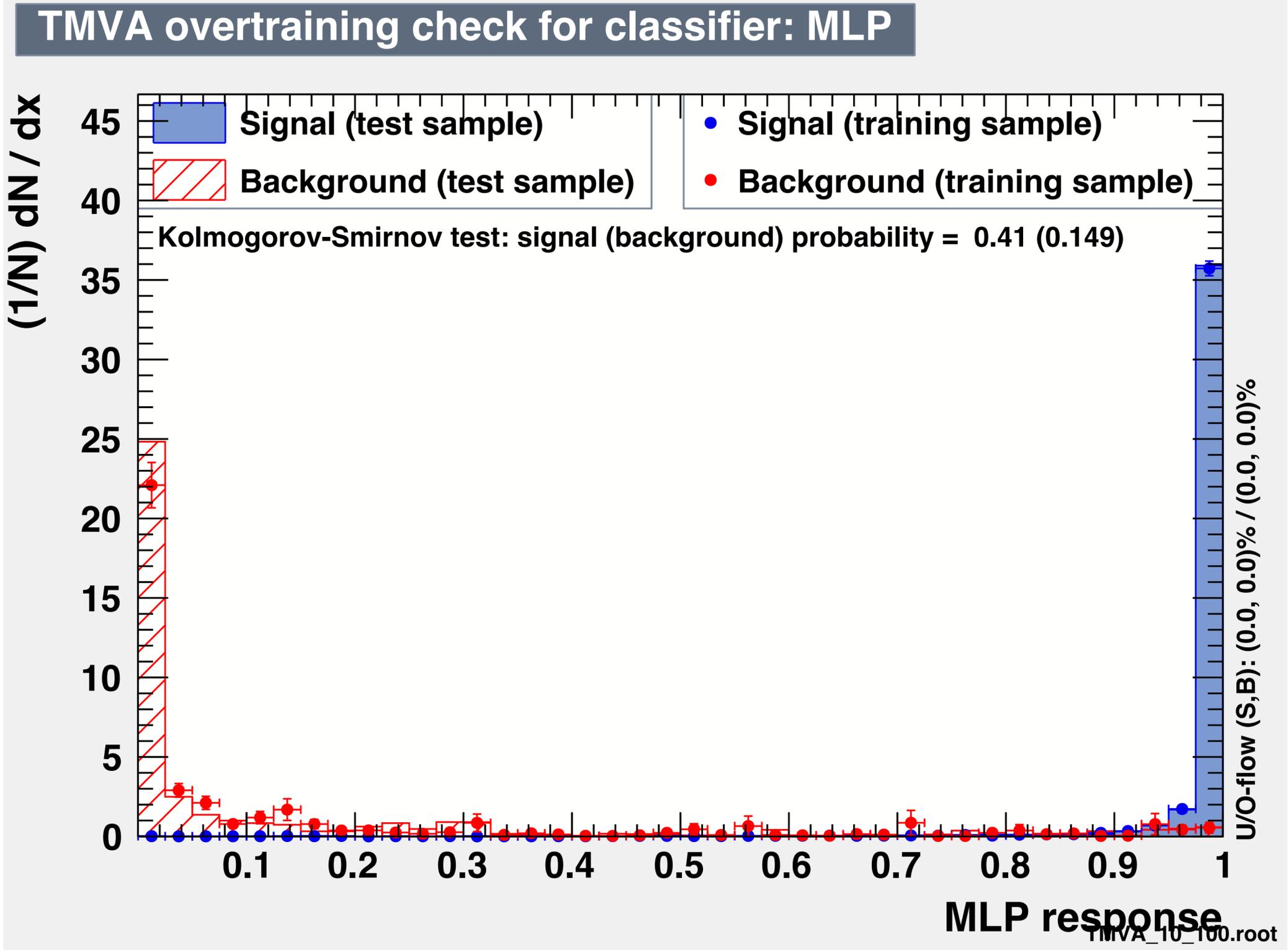
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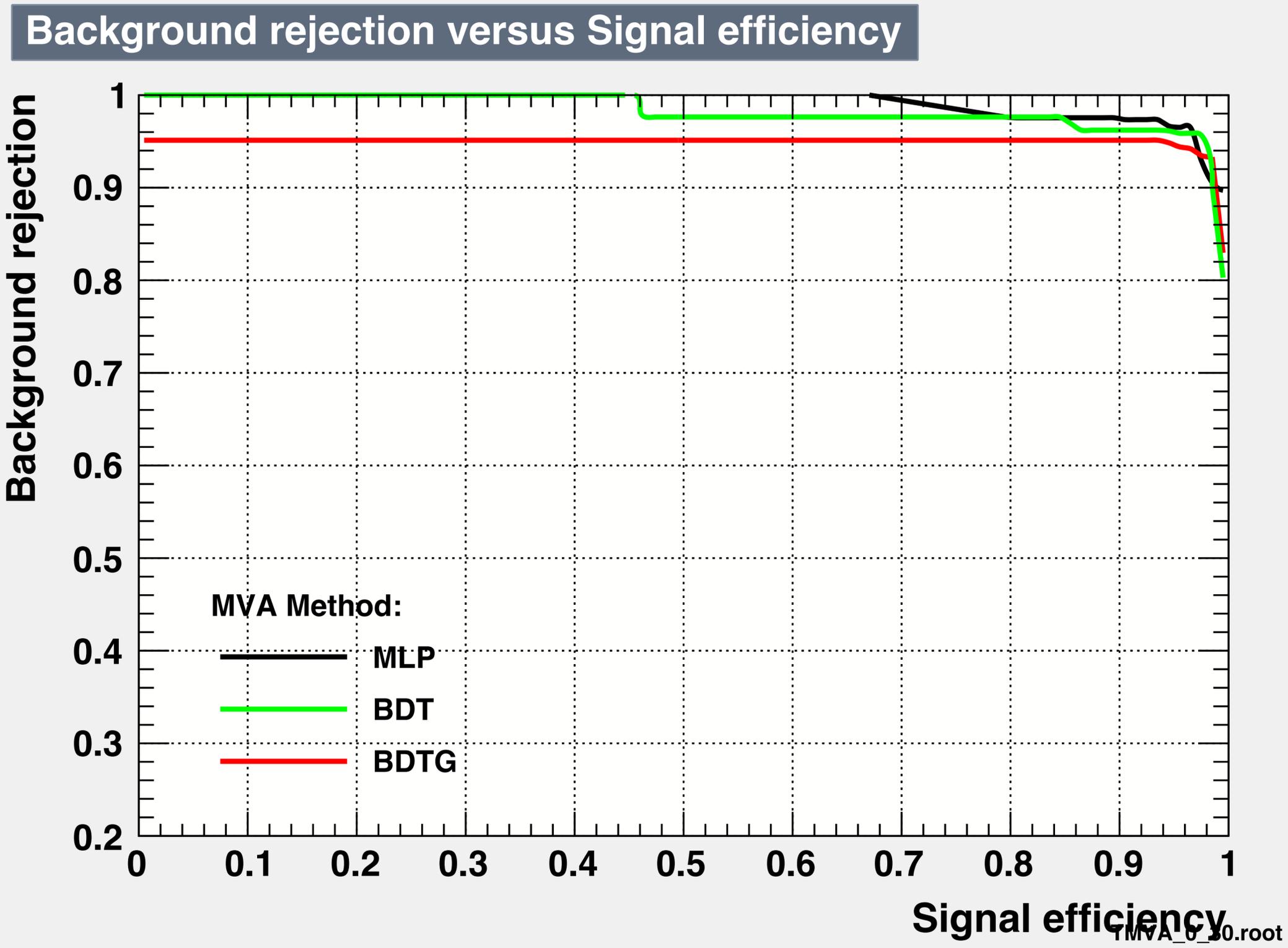
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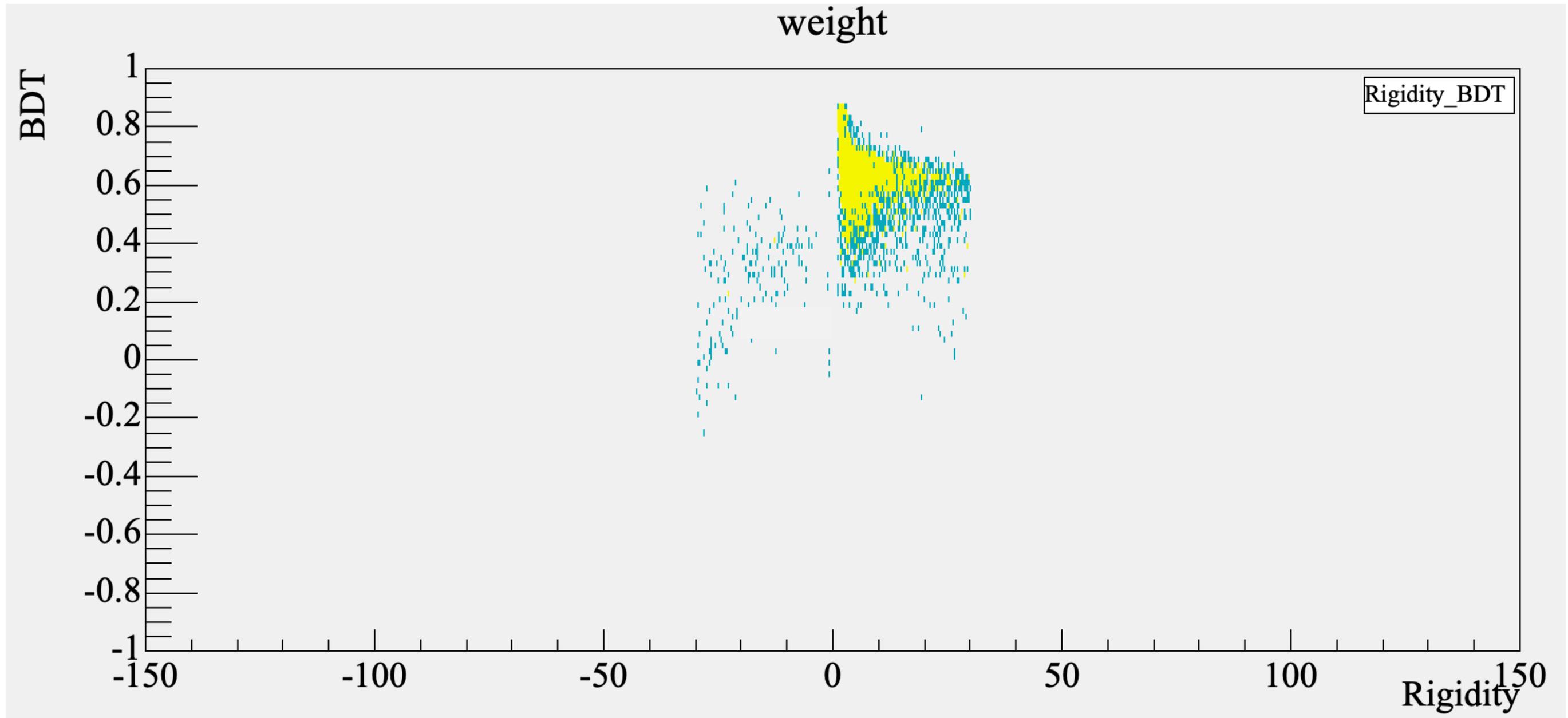
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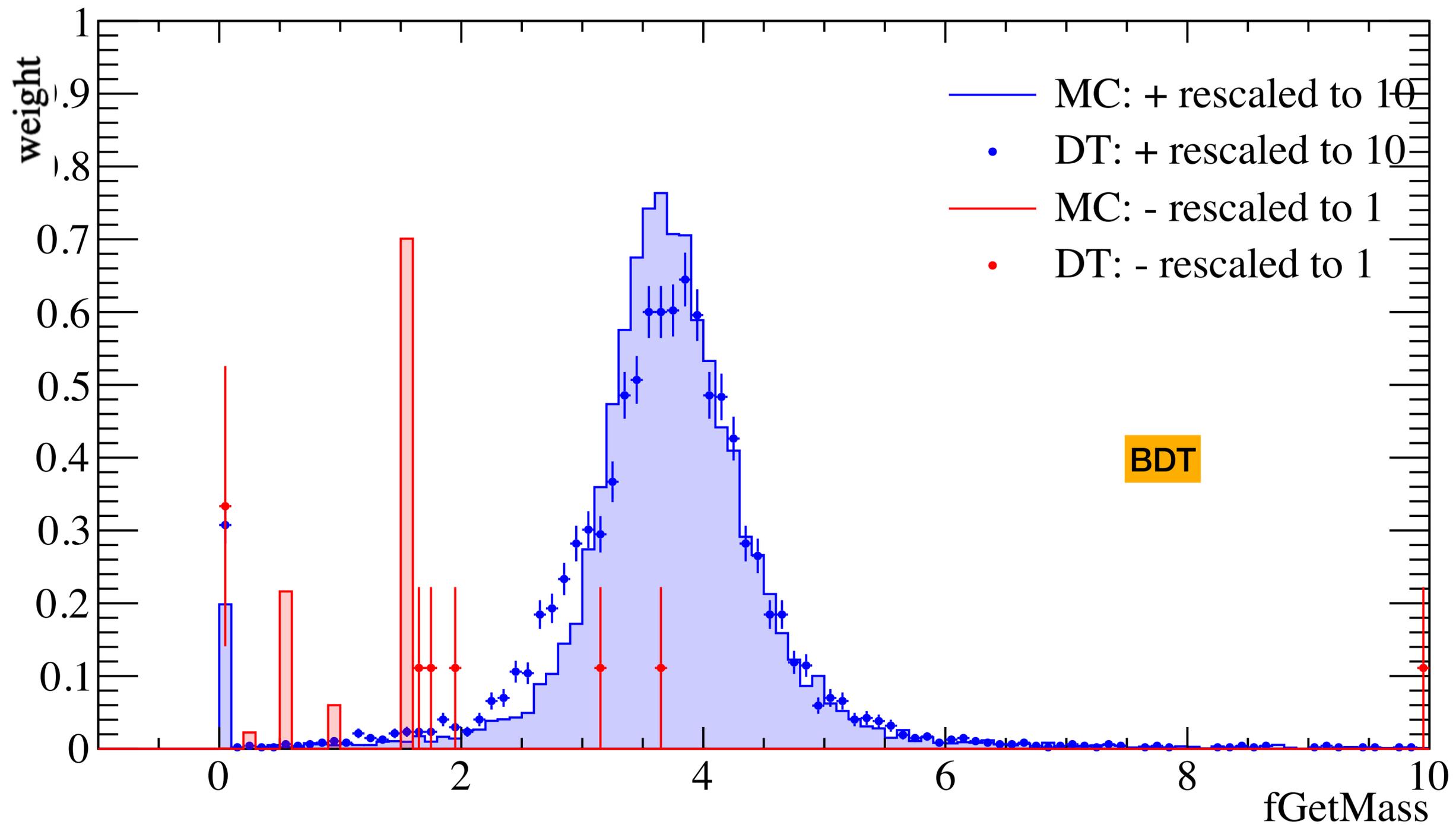


Apply the classifier to data



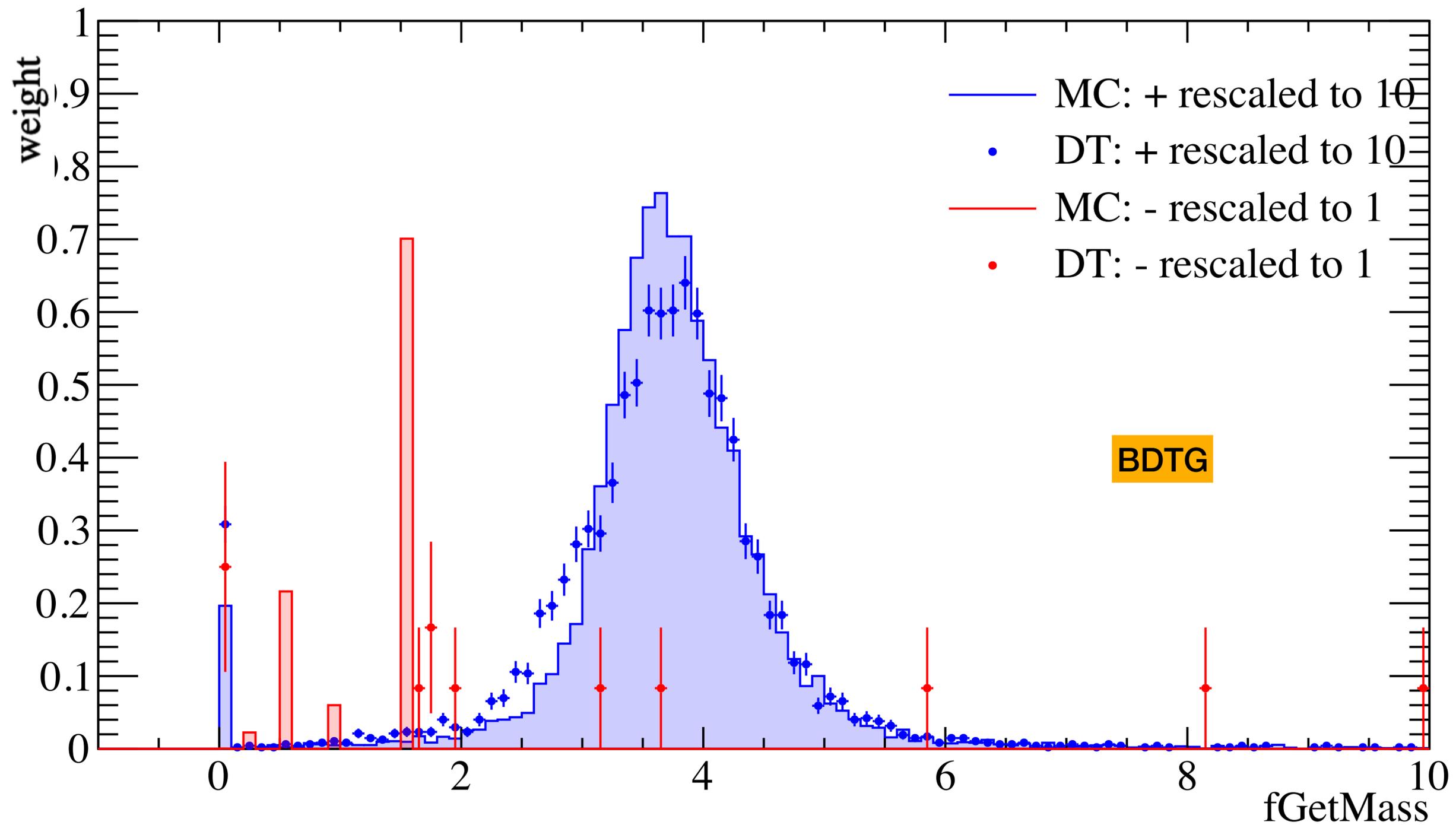
Apply the classifier to the experimental data

Low Rigidity: $f_{abs}(R) < 20$



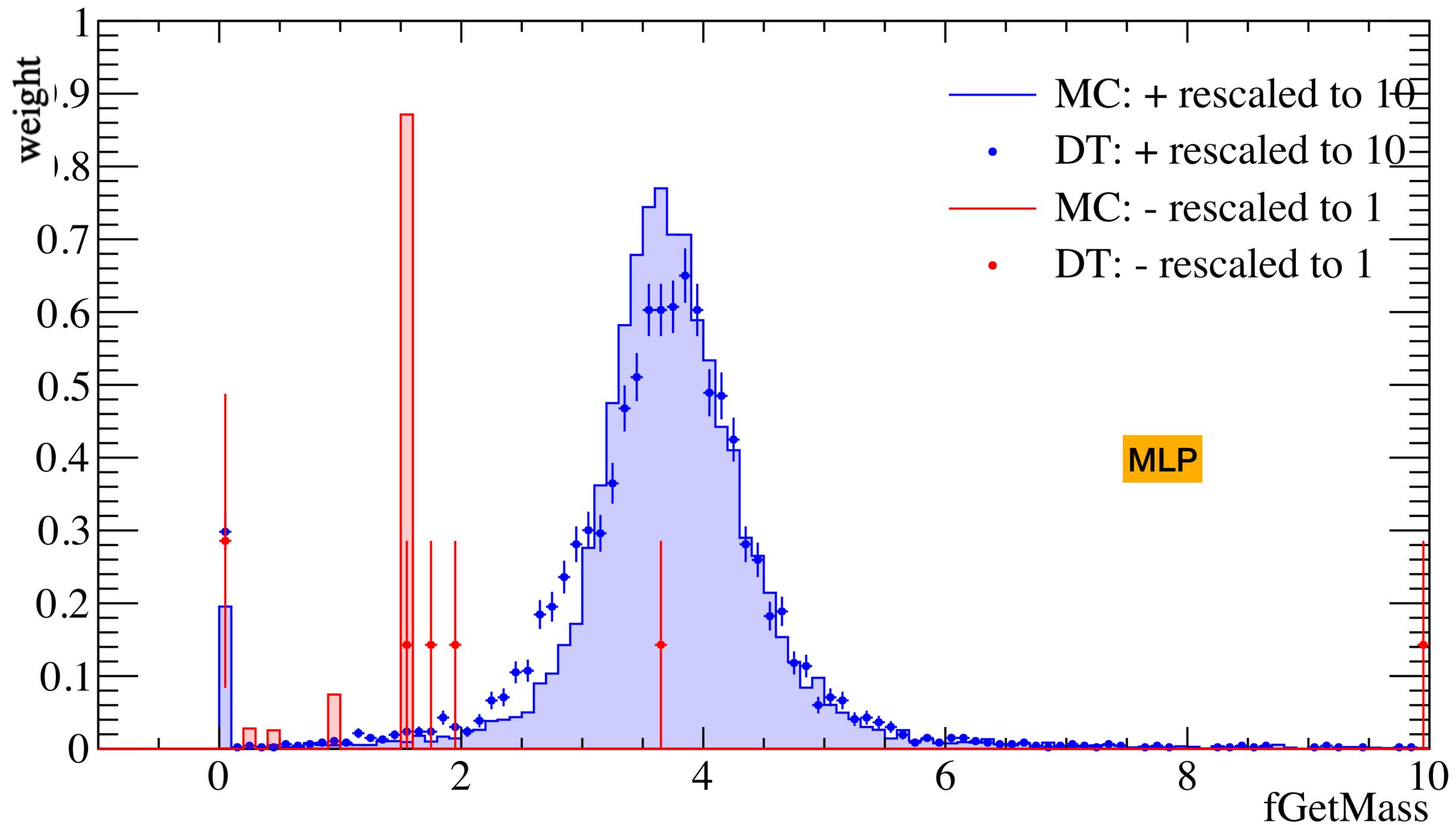
Apply the classifier to the experimental data

Low Rigidity: $f_{abs}(R) < 20$



Apply the classifier to the experimental data

Low Rigidity: fabs(R)<20



Conclusion:

Three TMVA Classifiers (BDT,BDTG,MLP) are studied in high rigidity and low rigidity region respectively.

NEXT: check the mass measurement.

