

WWZ Analysis: BDT Summary

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Baseline (Cut-Based Analysis)

Which bins are the most sensitive?

No changes in selection since numbers were shared w/ Kelci

SR Bins	Summary			Composition of N_{total}				
	N_{total}	NonResonant WWZ	ZHWWZ	ZZ	ttZ	Higgs	WZ	Other
Bin1	1.33 ± 0.21	0.65 ± 0.01	3.05 ± 0.01	0.62 ± 0.02	0.32 ± 0.03	0.27 ± 0.19	0.11 ± 0.08	0.01 ± 0.01
Bin2	0.96 ± 0.11	0.74 ± 0.01	1.35 ± 0.01	0.62 ± 0.02	0.38 ± 0.03	-0.06 ± 0.10	0 ± 0	0.01 ± 0.01
Bin3	1.39 ± 0.22	1.48 ± 0.01	0.35 ± 0.01	0.39 ± 0.02	0.83 ± 0.05	-0.06 ± 0.16	0.18 ± 0.13	0.04 ± 0.04
Bin4	3.60 ± 0.23	5.14 ± 0.01	0.15 ± 0.01	0.50 ± 0.02	2.51 ± 0.09	0.45 ± 0.17	0.12 ± 0.12	0.02 ± 0.01

Table 19: Yields in $e\mu$ SR bins (as of September 1st, 2023)

SR Bins	Summary			Composition of N_{total}				
	N_{total}	NonResonant WWZ	ZHWWZ	ZZ	ttZ	Higgs	WZ	Other
Bin5	3.25 ± 0.22	2.33 ± 0.01	0.95 ± 0.01	1.32 ± 0.03	1.32 ± 0.06	0.61 ± 0.21	0 ± 0	0.01 ± 0.01
Bin6	6.18 ± 0.36	1.97 ± 0.01	1.52 ± 0.01	4.58 ± 0.05	1.12 ± 0.06	0.42 ± 0.35	0 ± 0	0.06 ± 0.04
Bin7	3.15 ± 0.18	0.57 ± 0.01	0.68 ± 0.01	2.78 ± 0.04	0.27 ± 0.03	0.10 ± 0.17	0 ± 0	0.01 ± 0.01

Table 20: Yields in $ee/\mu\mu$ SR bins (as of September 1st, 2023)

Training Region (TR) Selection

4-lepton analysis selection criteria	
Category	Cut
Preselection	
Triggers	Passes at least one dilepton ($ee/e\mu/\mu\mu$) trigger
Lepton ID	4 leptons (e/μ) passing "tight" requirements of TOP-UL-MVA ID
Lepton p_T	$p_T^{leading} > 25$ GeV, $p_T^{subleading} > 15$ GeV, $p_T^{3rd,4th} > 10$ GeV
Z-candidate leptons	same-flavor, opposite sign pair closest to m_Z
Z mass window	Z candidate leptons must satisfy $ m_{ll} - m_Z < 10$ GeV
Additional lepton requirements	Muons (Electrons) must satisfy $ IP_{3D}/\sigma_{IP_{3D}} < 4$ (and $I_{rel,03,all} < 0.2$)
QCD low mass resonance veto	Any opposite charge pair of leptons must have $m_{ll} > 12$ GeV
b-tagged jet veto	Require 0 b-tagged jets in event ($p_T > 20$ GeV, $ \eta < 2.4$, DeepCSV loose WP, loose Jet ID)
Same-Flavor Channel	W-candidate leptons are the same flavor
Off-Z peak requirement	W candidate leptons must have $ m_{\ell\ell} - m_Z > 10$ GeV
Signal Regions - Cut Based	
Bin A	$p_T^{miss} > 120$ GeV
Bin B	$70 \text{ GeV} < p_T^{miss} < 120 \text{ GeV}$, $40 \text{ GeV} < p_T^{4\ell} < 70 \text{ GeV}$
Bin C	$70 \text{ GeV} < p_T^{miss} < 120 \text{ GeV}$, $p_T^{4\ell} > 70 \text{ GeV}$
Opposite-Flavor Channel	W-candidate leptons are different flavor
Signal Regions - Cut Based	
Bin 1	$m_{T2} > 25$ GeV, $0 \text{ GeV} < m_{\ell\ell}^W \text{ cands} < 40$ GeV
Bin 2	$m_{T2} > 25$ GeV, $40 \text{ GeV} < m_{\ell\ell}^W \text{ cands} < 60$ GeV
Bin 3	$m_{T2} > 25$ GeV, $60 \text{ GeV} < m_{\ell\ell}^W \text{ cands} < 100$ GeV
Bin 4	$m_{\ell\ell}^W \text{ cands} > 100$ GeV

- Training region selection is a subset of the full cut-based selection
- Training region selection is shown in purple
 - Note: no additional cuts applied for opposite-flavor channel
- Cut-based SRs are a combination of purple and black
 - I.e. preselection + channel specific selection

Yields after TR selection

	Summary			Composition of N_{total}				
	N_{total}	NonResonant WWZ	ZHWWZ	ZZ	ttZ	Higgs	WZ	Other
Opp Flav Yield	27.3601 ± 0.5570	9.2928 ± 0.0169	7.933 ± 0.0202	20.487 ± 0.110	4.6626 ± 0.1180	1.5297 ± 0.4641	0.5747 ± 0.2592	0.1058 ± 0.0406
Opp Flav Entries	45517	386138	562626	39470	5743	146	6	152
Same Flav Yield	681.024 ± 1.117	8.5219 ± 0.0162	7.9725 ± 0.0202	671.271 ± 0.617	4.3152 ± 0.1136	5.2241 ± 0.9202	0.1066 ± 0.0755	0.1073 ± 0.0404
Same Flav Entries	1660574	354713	566117	1654879	5316	227	2	150

Table 24: Yields in training region for all processes.

- ZZ and ttZ are the only backgrounds used in training
 - Other backgrounds are limited by low statistics

Training+Testing samples

- 4 BDTs are trained using TMVA
 - W candidate leptons are same flavor ($ee/\mu\mu$) or opposite flavor ($e\mu$)
 - WWZ vs Backgrounds (ZZ + ttZ)
 - ZH→WWZ vs Backgrounds (ZZ + ttZ)
- Training+Testing samples obtained by splitting full MC samples in half
 - Alternate putting events into training+testing samples when looping over events
- Full list of samples shown below (includes full Run 2 MC)

Process	Sample Names (NanoAOD v9)
WWZ	WWZJetsTo4L2Nu_4F_TuneCP5_13TeV-amcatnlo-pythia8_RunII Summer20UL1(6/7/8)*
ZH→WWZ	GluGluZH_HToWWTo2L2Nu_M-125_TuneCP5_13TeV-powheg-pythia8_RunII Summer20UL1(6/7/8)* HZJ_HToWWTo2L2Nu_ZTo2L_M-125_TuneCP5_13TeV-powheg-jhugen727-pythia8_RunII Summer20UL1(6/7/8)*
Backgrounds	ZZTo4L_TuneCP5_13TeV_powheg_pythia8_RunII Summer20UL1(6/7/8)* ZZTo2Q2L_mllmin4p0_TuneCP5_13TeV-amcatnloFXFX-pythia8_RunII Summer20UL1(6/7/8)* ZZTo2L2Nu_TuneCP5_13TeV_powheg_pythia8_RunII Summer20UL1(6/7/8)* GluGluToContInToZZTo(2e2mu/2e2tau/2mu2tau/4e/4mu/4tau)_TuneCP5_13TeV-mcfm701-pythia8_RunII Summer20UL1(6/7/8)* TTZToLL_M-1to10_TuneCP5_13TeV-amcatnlo-pythia8_RunII Summer20UL1(6/7/8)* TTZToLLNuNu_M-10_TuneCP5_13TeV-amcatnlo-pythia8_RunII Summer20UL1(6/7/8)* TTZToQQ_TuneCP5_13TeV-amcatnlo-pythia8_RunII Summer20UL1(6/7/8)*

Splitting Cross Check

The table below shows the yields for the training and testing datasets

Sample	SF Training	SF Testing	Ratio (SF)	DF Training	DF Testing	Ratio (DF)
WWZ	4.25206 ± 0.011483	4.25563 ± 0.0114843	0.99916	4.63711 ± 0.011984	4.63956 ± 0.011984	0.99947
ZH	4.00546 ± 0.014288	7.30354 ± 0.018344	0.54843	3.98529 ± 0.014279	7.31073 ± 0.018378	0.54513
$\Sigma(\text{ZZ}, \text{ttZ})$	336.588 ± 0.445	336.658 ± 0.445	0.99979	12.54460 ± 0.11383	12.60440 ± 0.11382	0.99526

Note: ZH is not split 1/1 → Performed some checks, still unsure why this is happening (however this really doesn't matter too much for the interpretation of results)

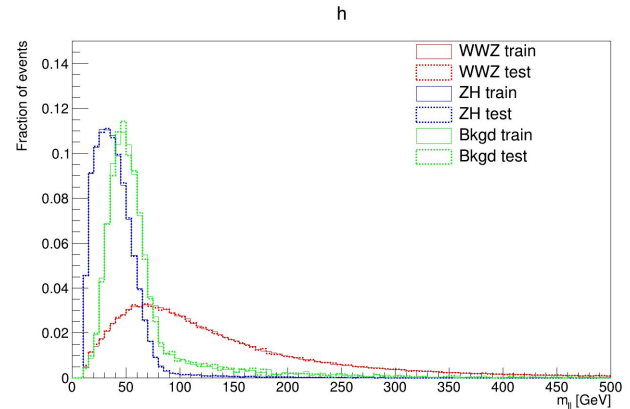
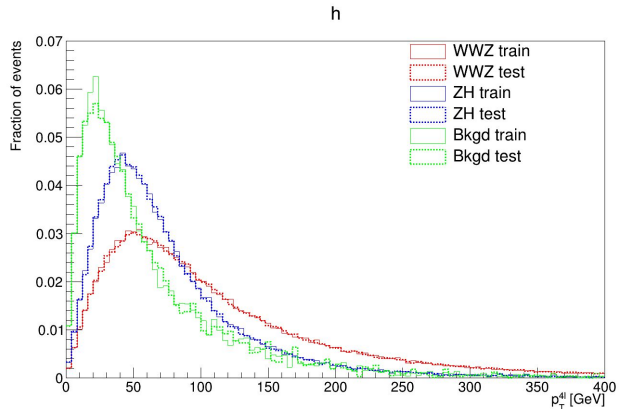
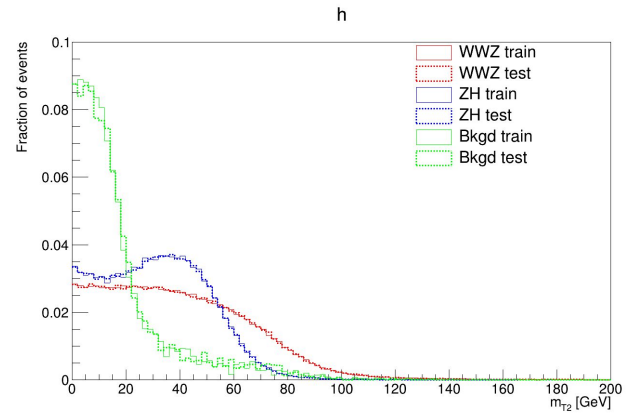
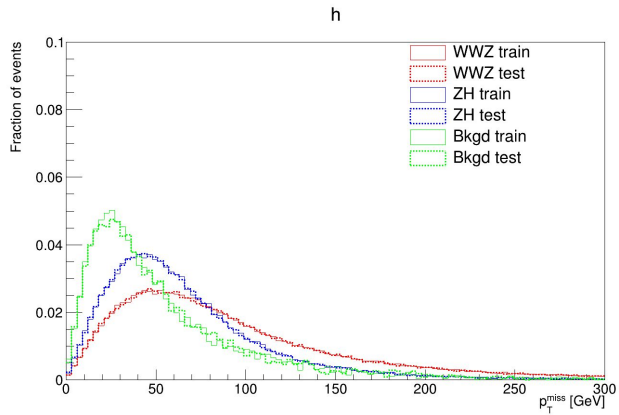
WWZ and Backgrounds have very similar statistics for training + testing datasets

BDT Input Variables

Input variables for 4-lepton MVA	
Variable	Brief Description
m_{ll}^{Wcands}	Invariant mass of the W-lepton candidates
M_{T2}	Analogue of m_T for two semi-invisibly decaying particles
p_T^{miss}	Missing Transverse Energy (PuppiMET)
p_T^{4l}	Transverse momentum of the 4-lepton system
p_T^{Z1}	p_T of leading Z-candidate lepton
p_T^{Z2}	p_T of subleading Z-candidate lepton
p_T^{W1}	p_T of leading W-candidate lepton
p_T^{W2}	p_T of subleading W-candidate lepton
$\sum_{lep, MET, jet} p_T$	Scalar sum of transverse energy in event
$\sum_{lep, MET} p_T$	Scalar sum of leptonic and missing transverse energy in event
$\Delta R(l^{Z1}, l^{Z2})$	Solid angle (in $\eta - \phi$ coordinates) difference between Z-candidate leptons
$\Delta R(l^{W1}, l^{W2})$	Solid angle (in $\eta - \phi$ coordinates) difference between W-candidate leptons
$\Delta R(WW, Z)$	Solid angle (in $\eta - \phi$ coordinates) difference between W candidate lepton system and Z boson
$\Delta\phi(WW, p_T^{miss})$	Angular separation between WW system and p_T^{miss}
$\Delta\phi(Z, p_T^{miss})$	Angular separation between Z boson and p_T^{miss}
$\Delta\phi(WWZ, p_T^{miss})$	Angular separation between the 4-lepton system and p_T^{miss}

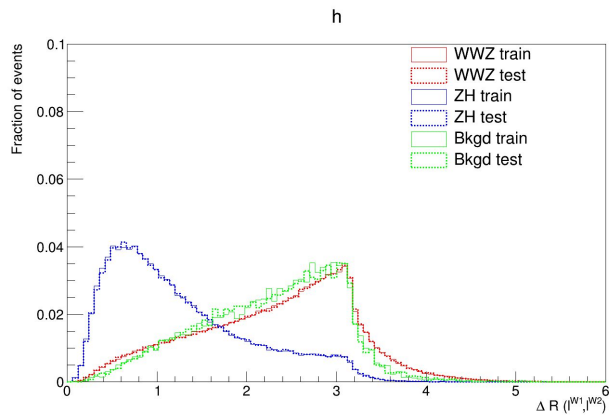
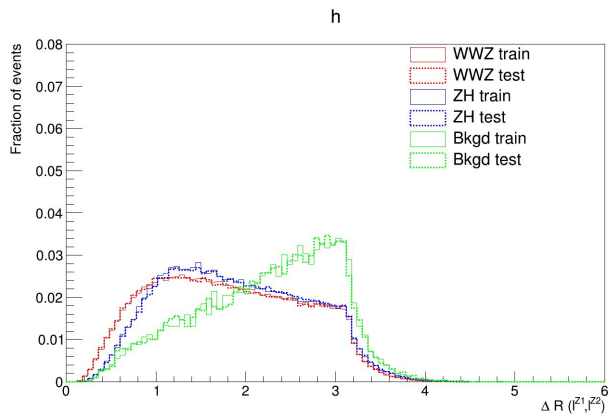
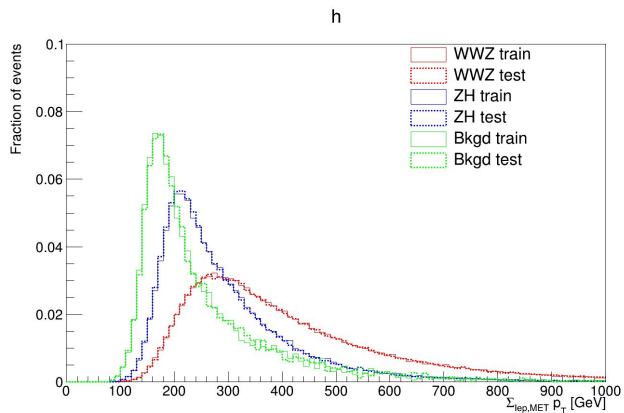
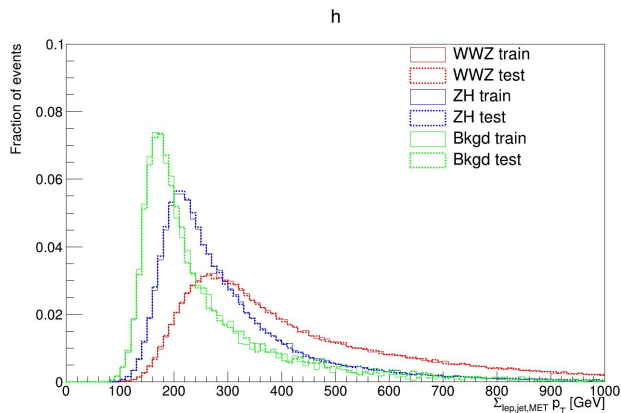
Table 15: Input variables for 4-lepton Boosted Decision Tree.

BDT Input Variables - Opposite Flavor



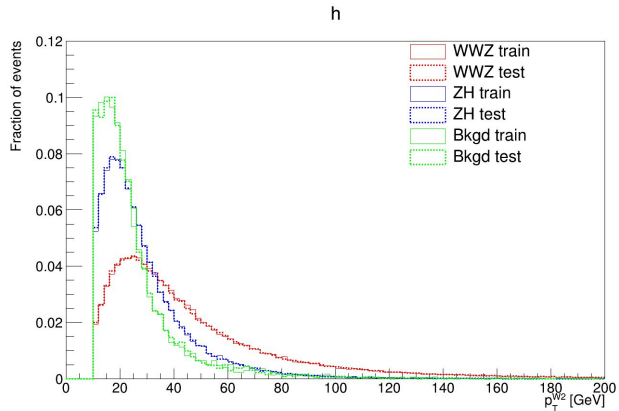
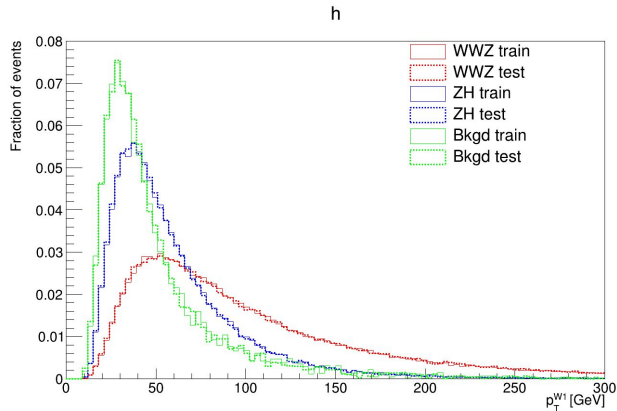
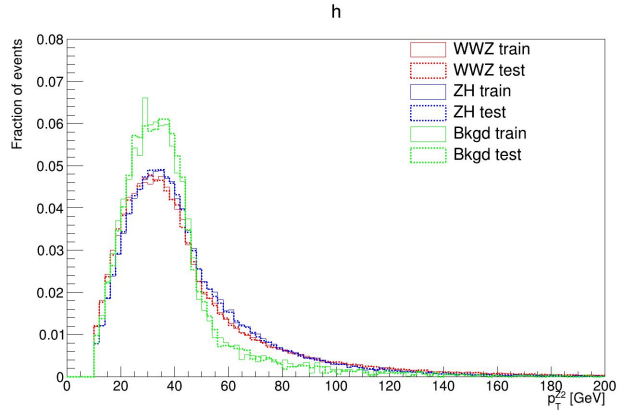
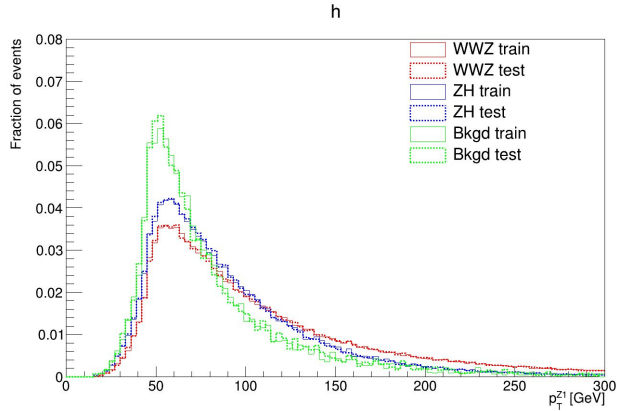
All distributions normalized to 1!

BDT Input Variables - Opposite Flavor (cont.)



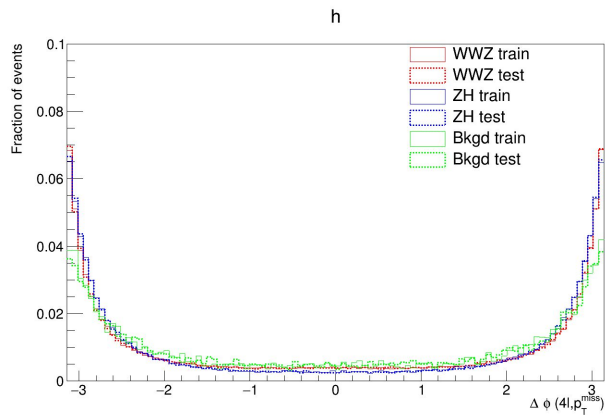
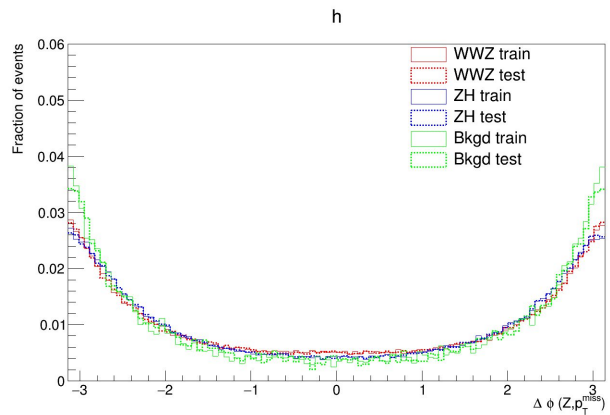
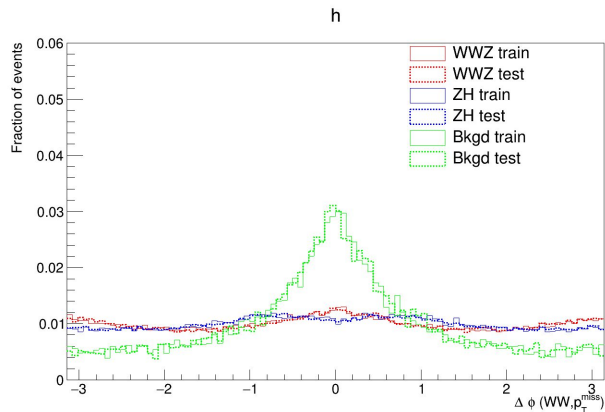
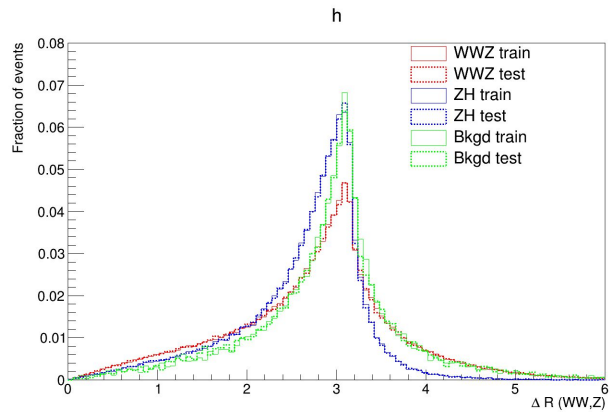
All distributions normalized to 1!

BDT Input Variables - Opposite Flavor (cont.)



All distributions normalized to 1!

BDT Input Variables - Opposite Flavor (cont.)

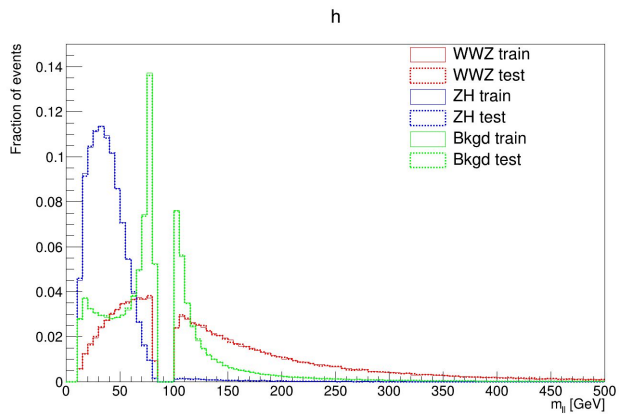
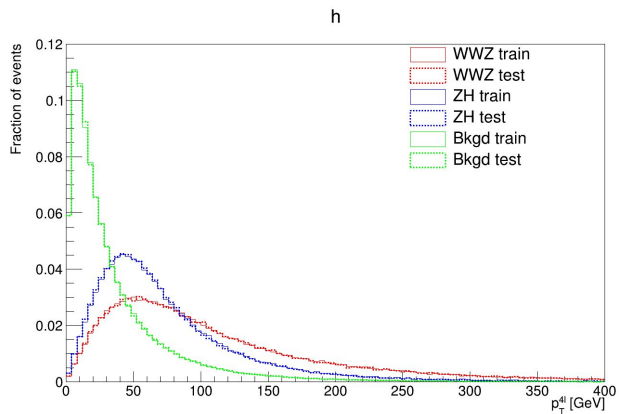
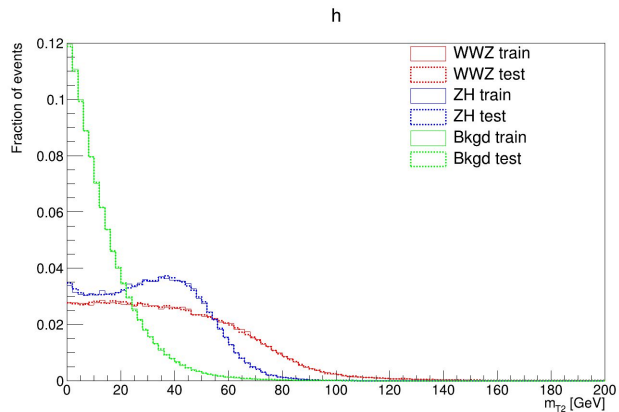
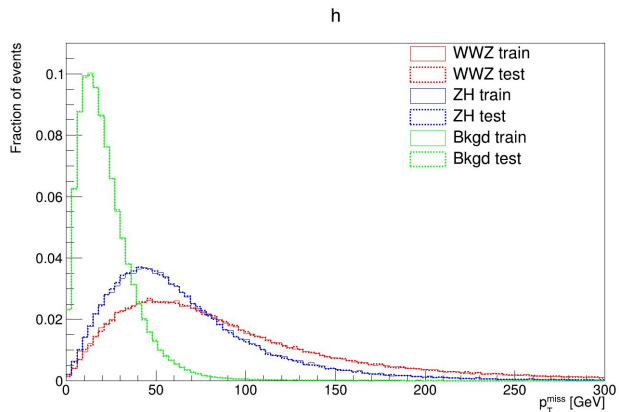


All distributions normalized to 1!

Variable Rankings - Opposite Flavor

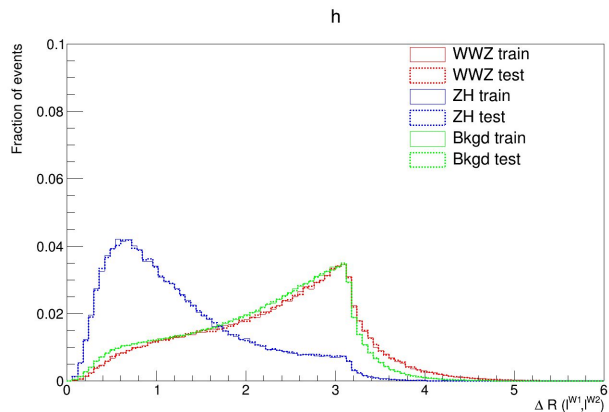
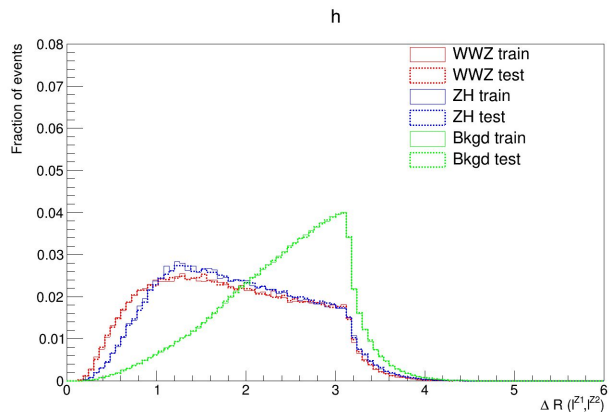
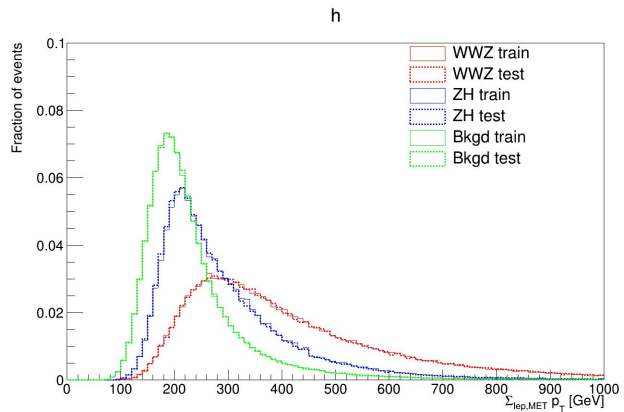
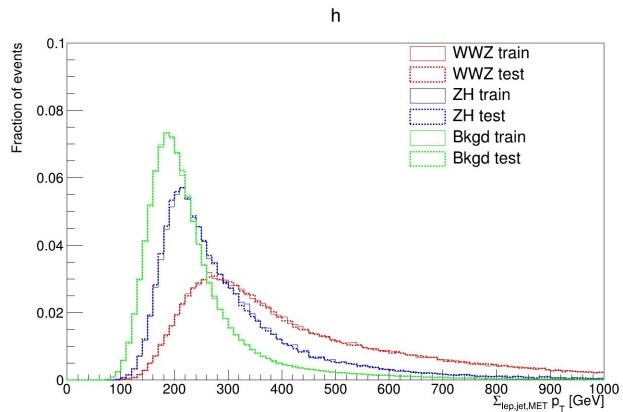
- Good variables
 - $m_{ll}, m_{T2}, dR(l^{W1}, l^{W2})$
- Minor variables → vars we may want to drop eventually
 - $\Delta\phi(4l, MET), \Delta\phi(Z, MET), STLepHad$ or $STLep$
- Bad variables → vars that may cause problems (i.e. bad data/MC)
 -

BDT Input Variables - Same Flavor



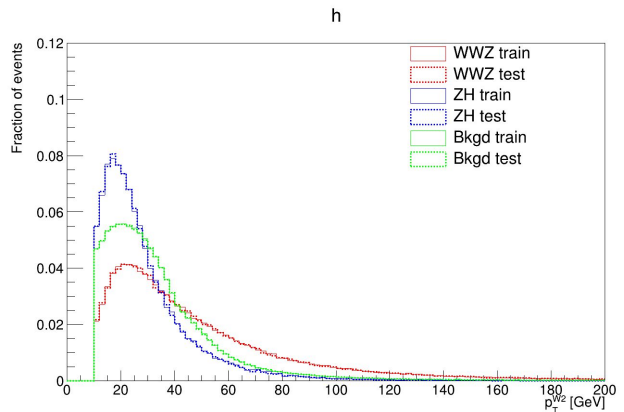
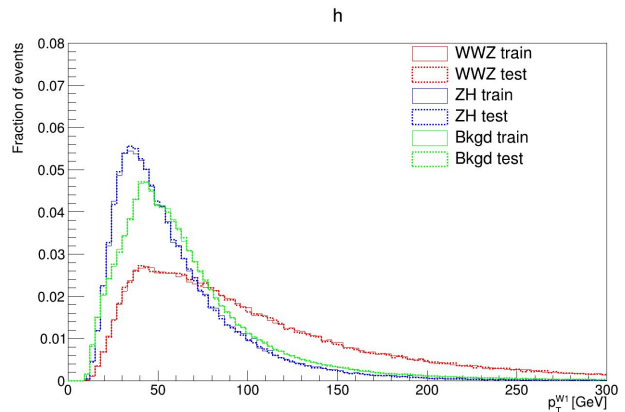
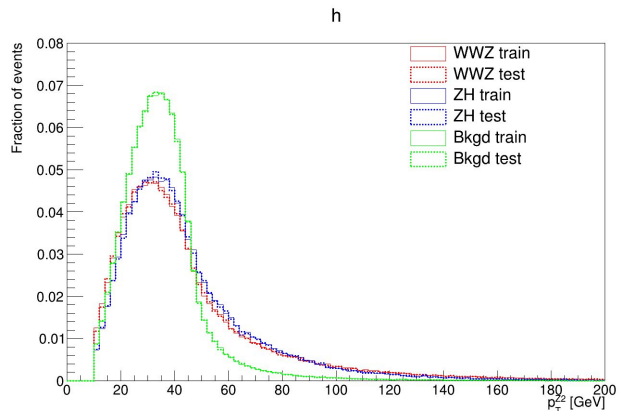
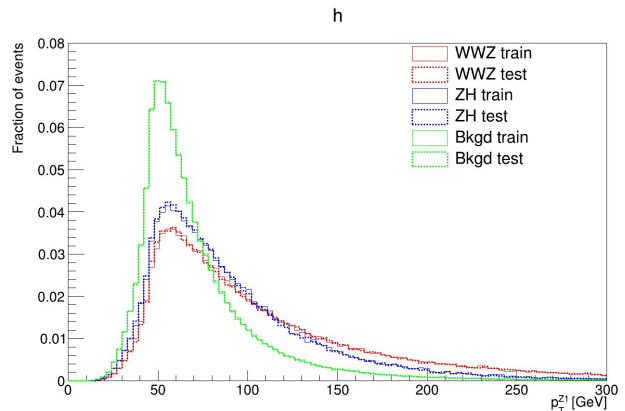
All distributions normalized to 1!

BDT Input Variables - Same Flavor (cont.)



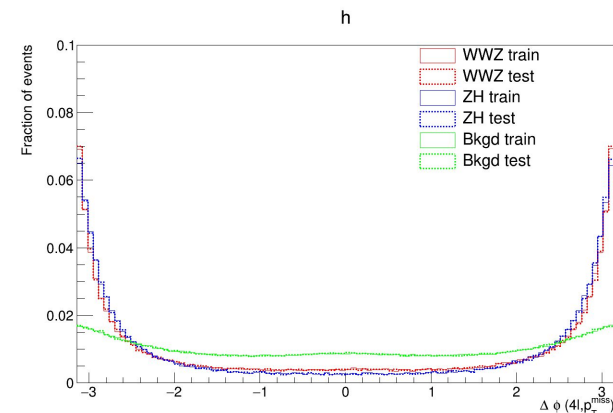
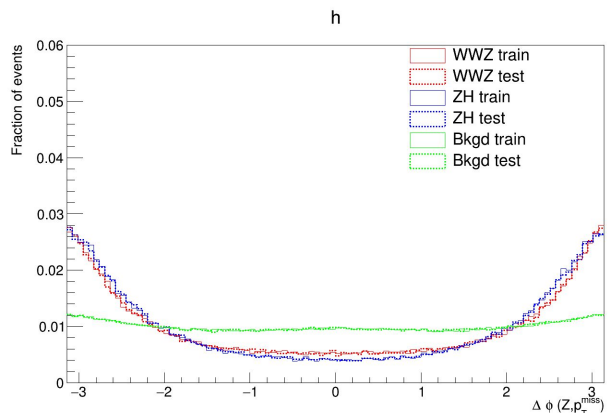
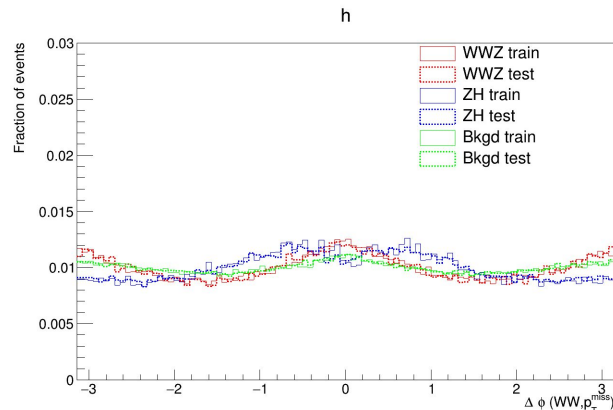
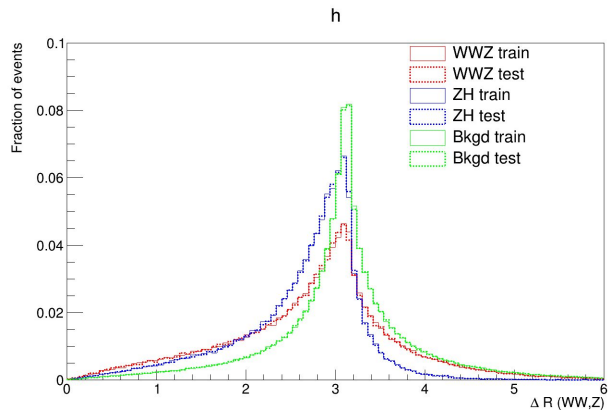
All distributions normalized to 1!

BDT Input Variables - Same Flavor (cont.)



All distributions normalized to 1!

BDT Input Variables - Same Flavor (cont.)



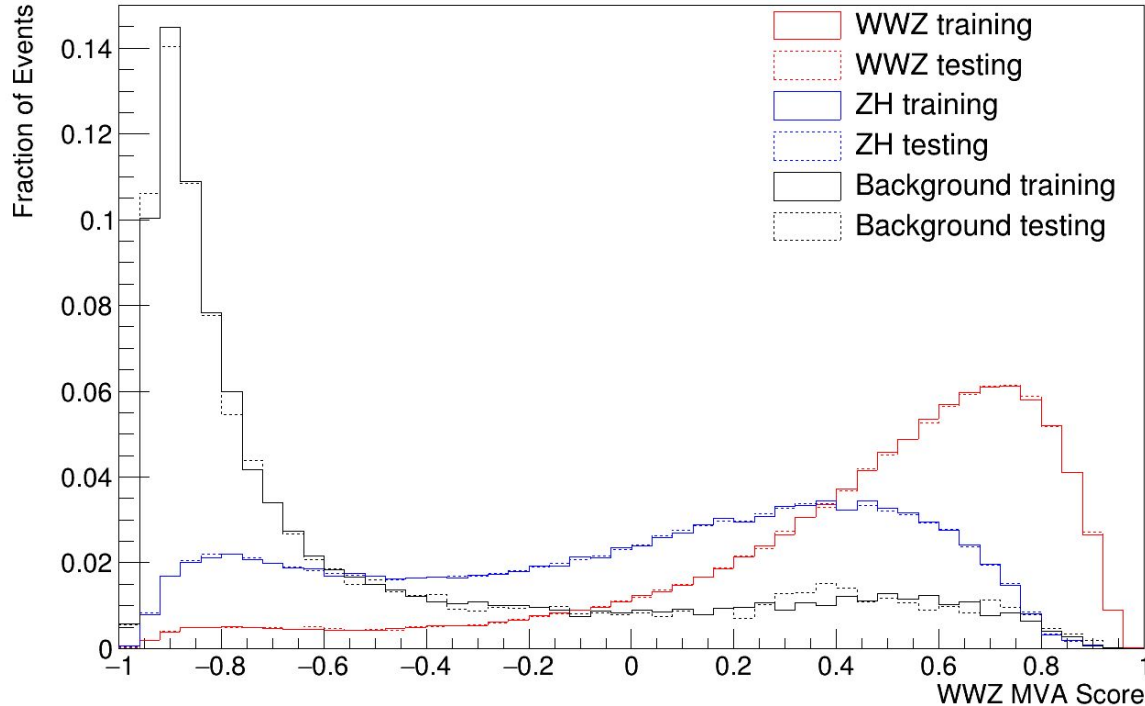
All distributions normalized to 1!

Variable Rankings - Same Flavor

- Good variables
 - MET, m_{T2} , p_T^{4l}
- Minor variables → may want to drop these eventually
 - $\Delta\phi(WW, MET)$, p_T^{leptons} , STLepHad or STLep
- Bad variables → prone to data/MC mismodelling
 - m_{ll}

Validation Check - Opposite Flavor

WWZ MVA Score

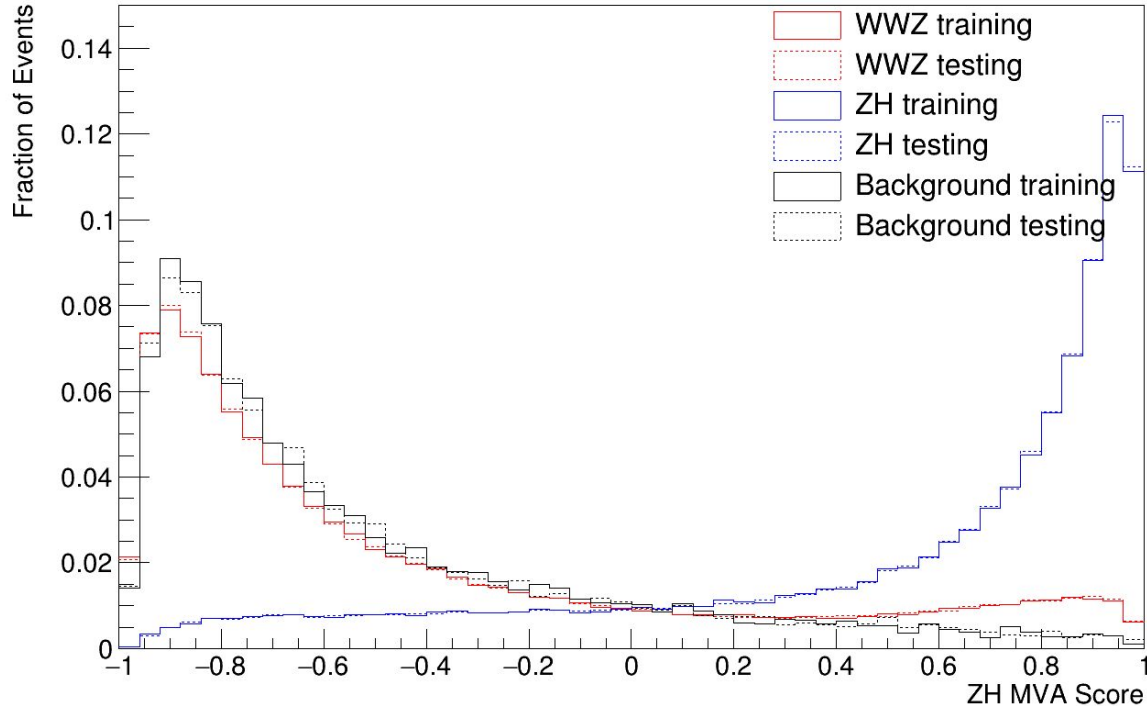


Good shape agreement
between training and
testing datasets

Note: Background
distribution has low
stats compared to
WWZ and ZH

Validation Check - Opposite Flavor (cont.)

ZH MVA Score

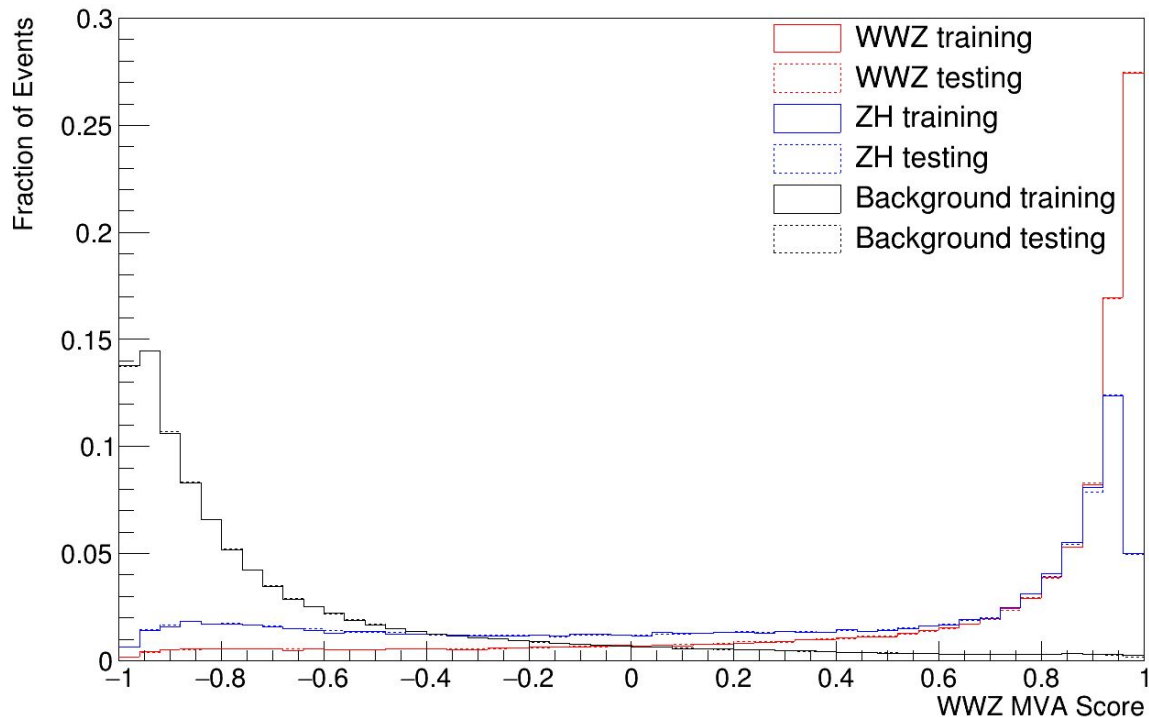


Good shape agreement
between training and
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Note: Background
distribution has low
stats compared to
WWZ and ZH

Validation Check - Same Flavor

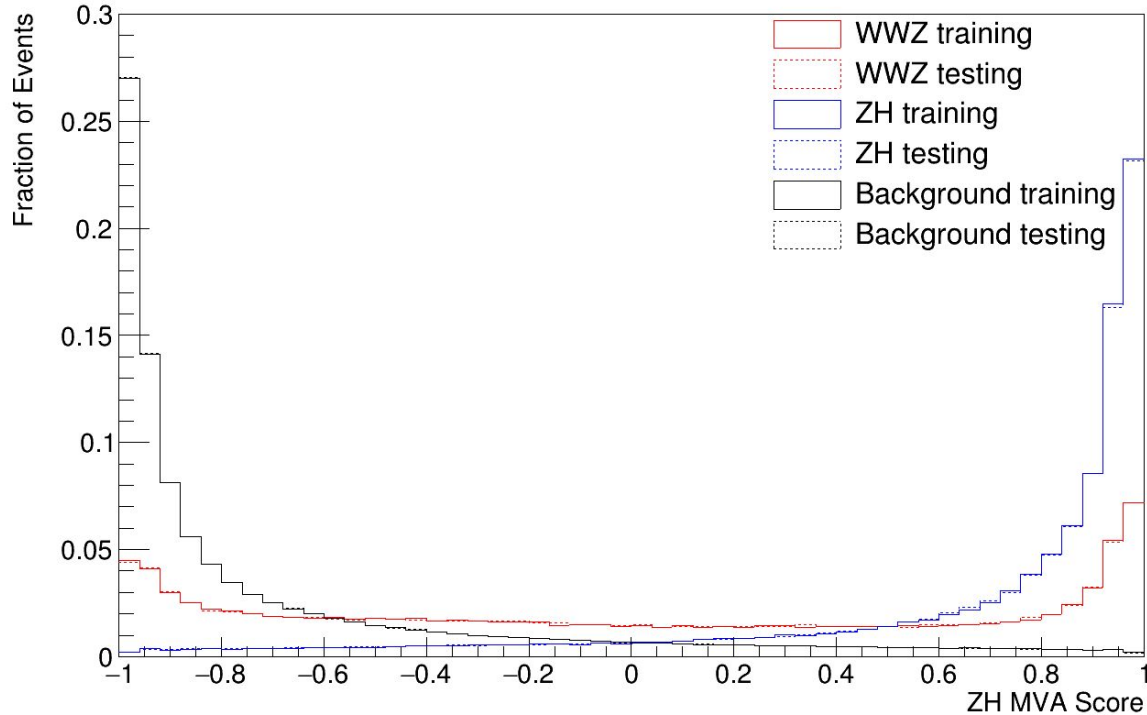
WWZ MVA Score



Good shape agreement
between training and
testing datasets

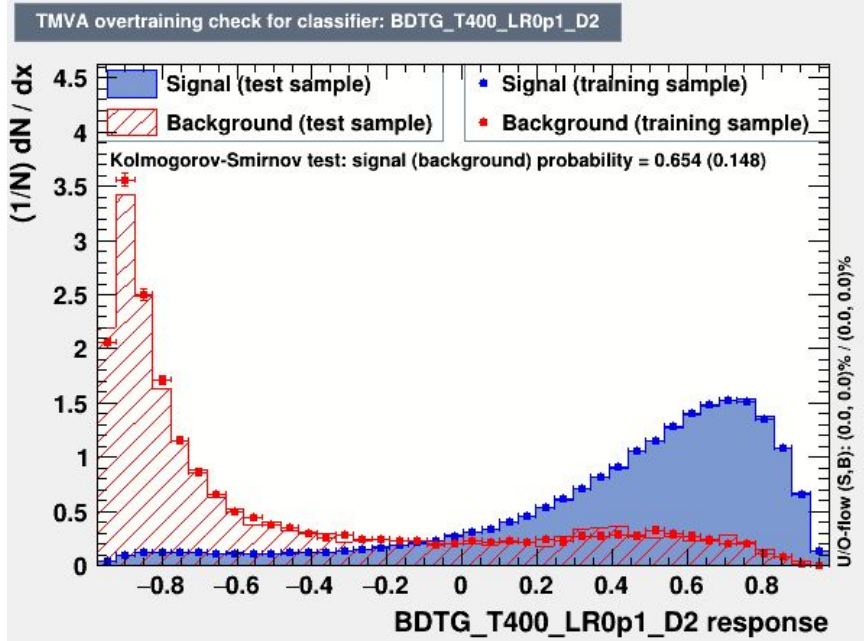
Validation Check - Same Flavor (cont.)

ZH MVA Score

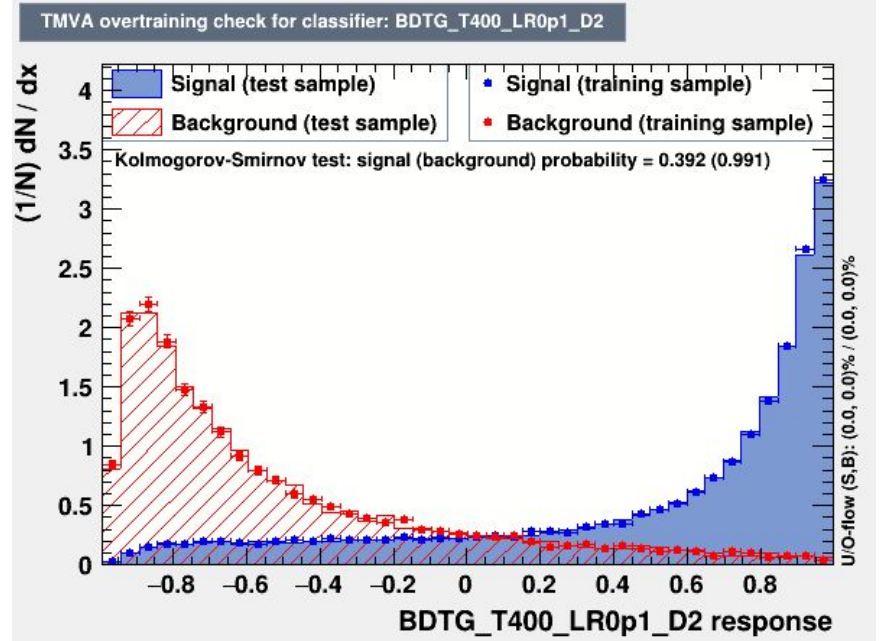


Good shape agreement
between training and
testing datasets

KS Test - Opposite Flavor



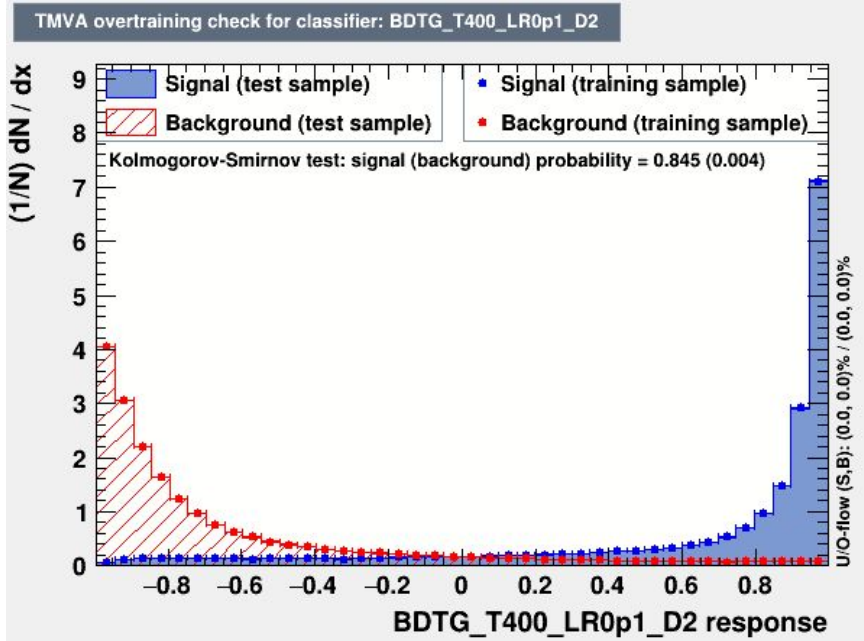
WWZ BDT



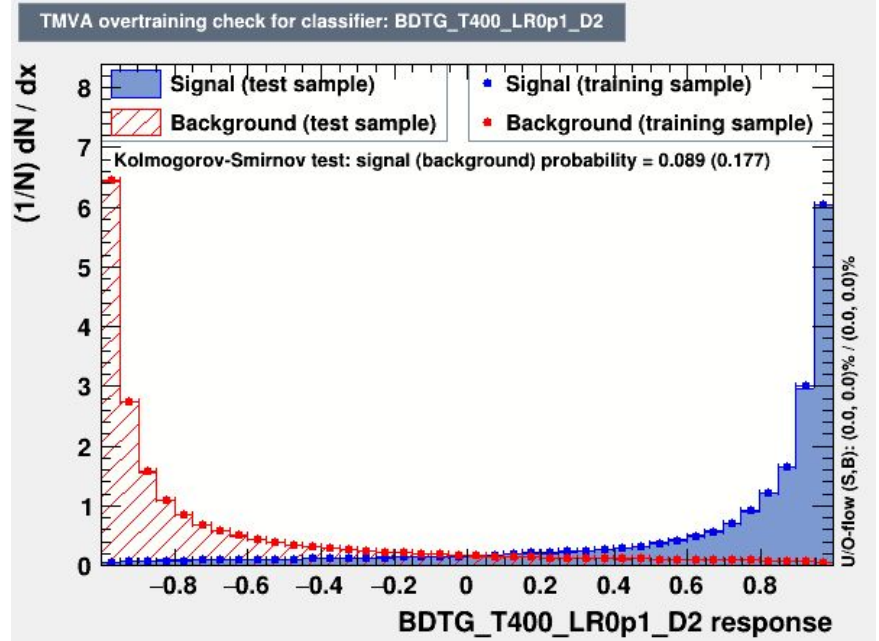
ZH BDT

→ Don't seem to have overtraining

KS Test - Same Flavor



WWZ BDT



ZH BDT

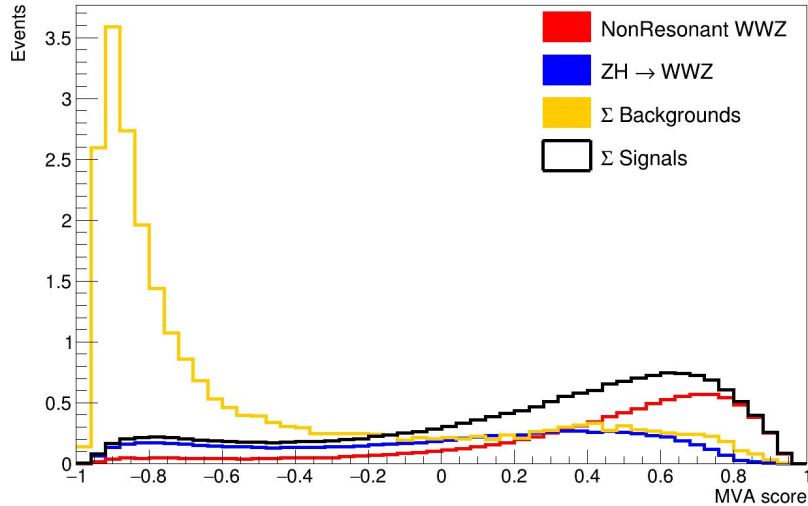
KS test seems to suggest overtraining → Not obvious visually

Merging of Testing+Training Events

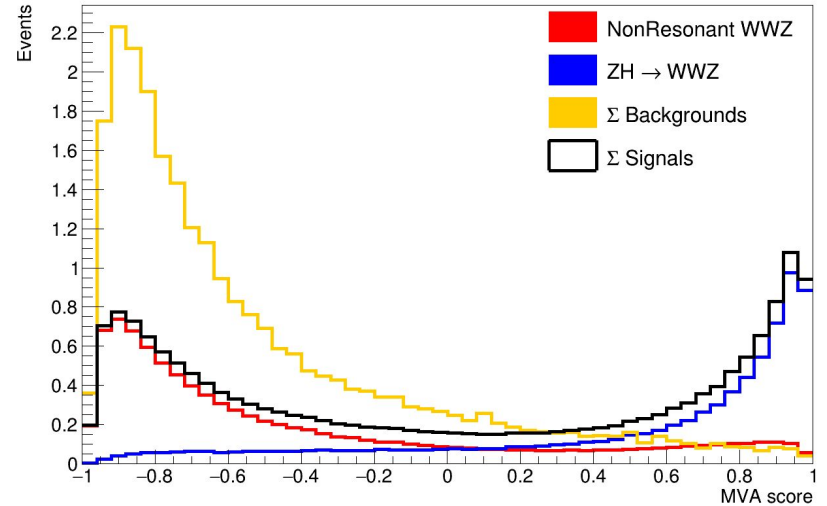
- Can we merge testing+training?
 - Without overtraining, we can evaluate the MVA score for all events
 - If there is no bias towards the training dataset, then re-using the training data during evaluation will not bias the results
- Since there is no obvious overtraining, I suggest evaluating all (training+testing) events rather than scaling the testing dataset

BDT MVA Distributions - Opposite Flavor

WWZ MVA score (Opposite Flavor Channel)



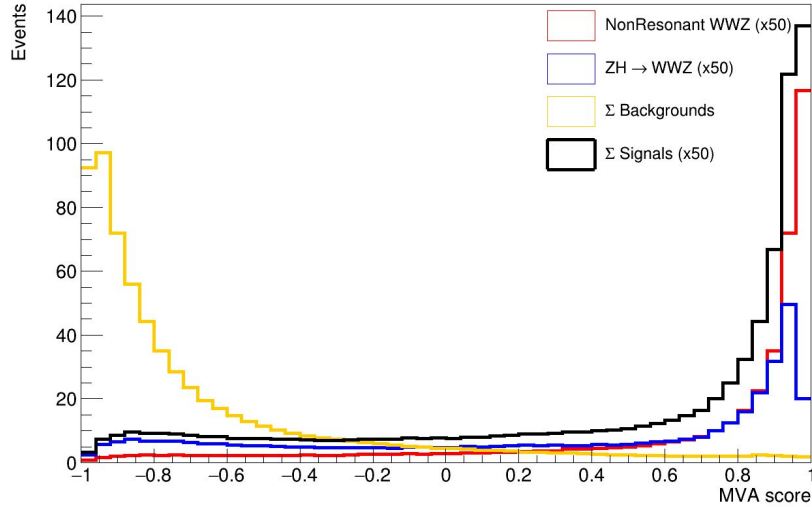
ZH MVA score (Opposite Flavor Channel)



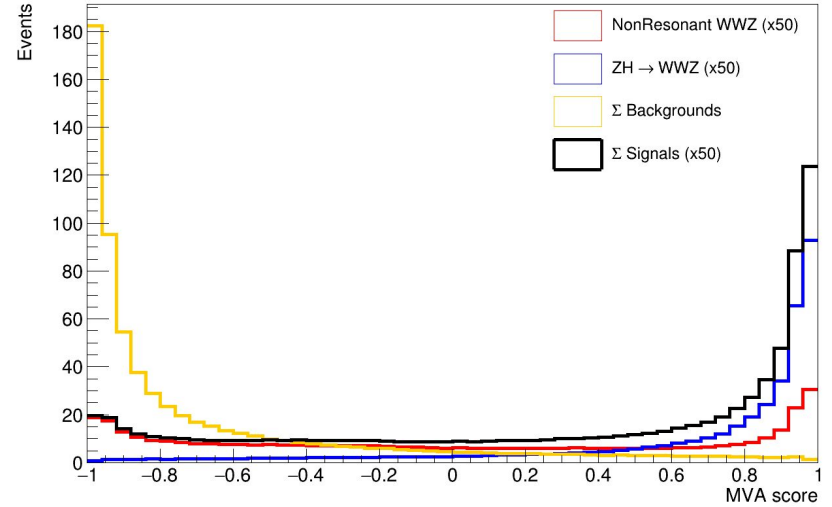
Comparing MVA distributions for signals and backgrounds
→ Looks reasonable

BDT MVA Distributions - Same Flavor

WWZ MVA score (Same Flavor Channel)

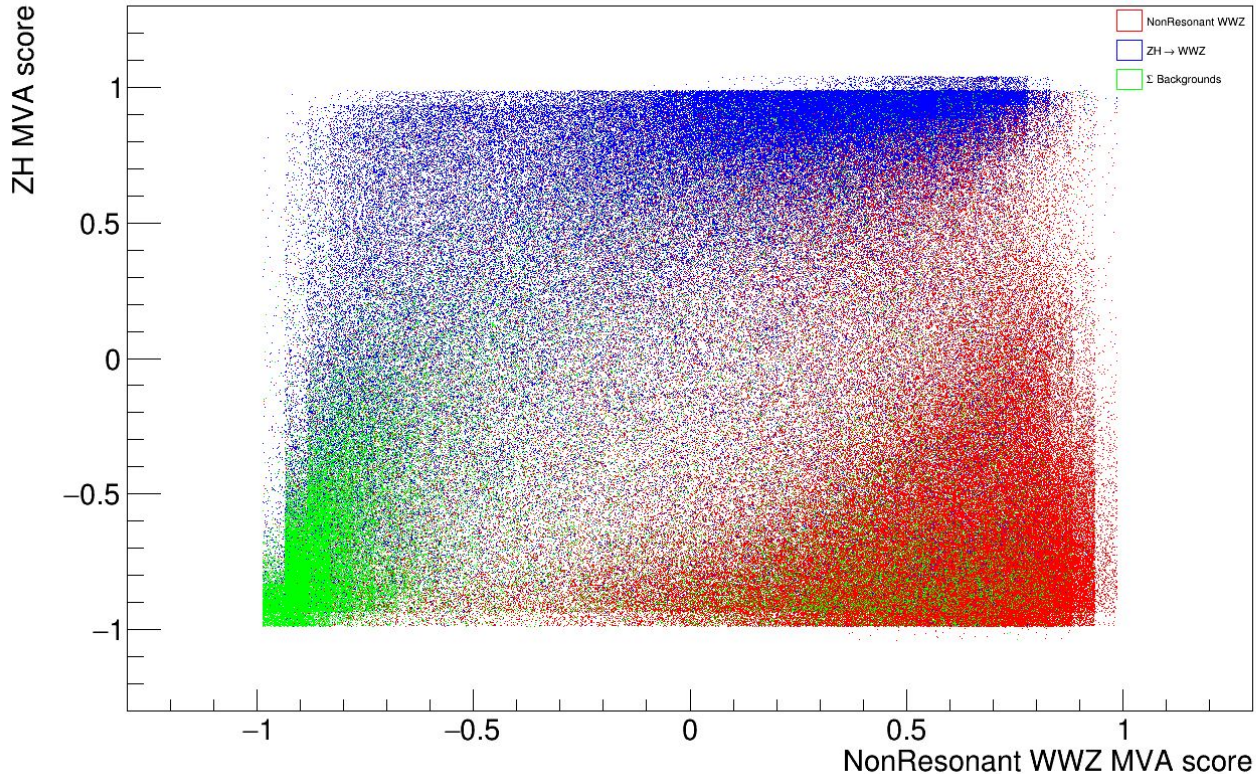


ZH MVA score (Same Flavor Channel)



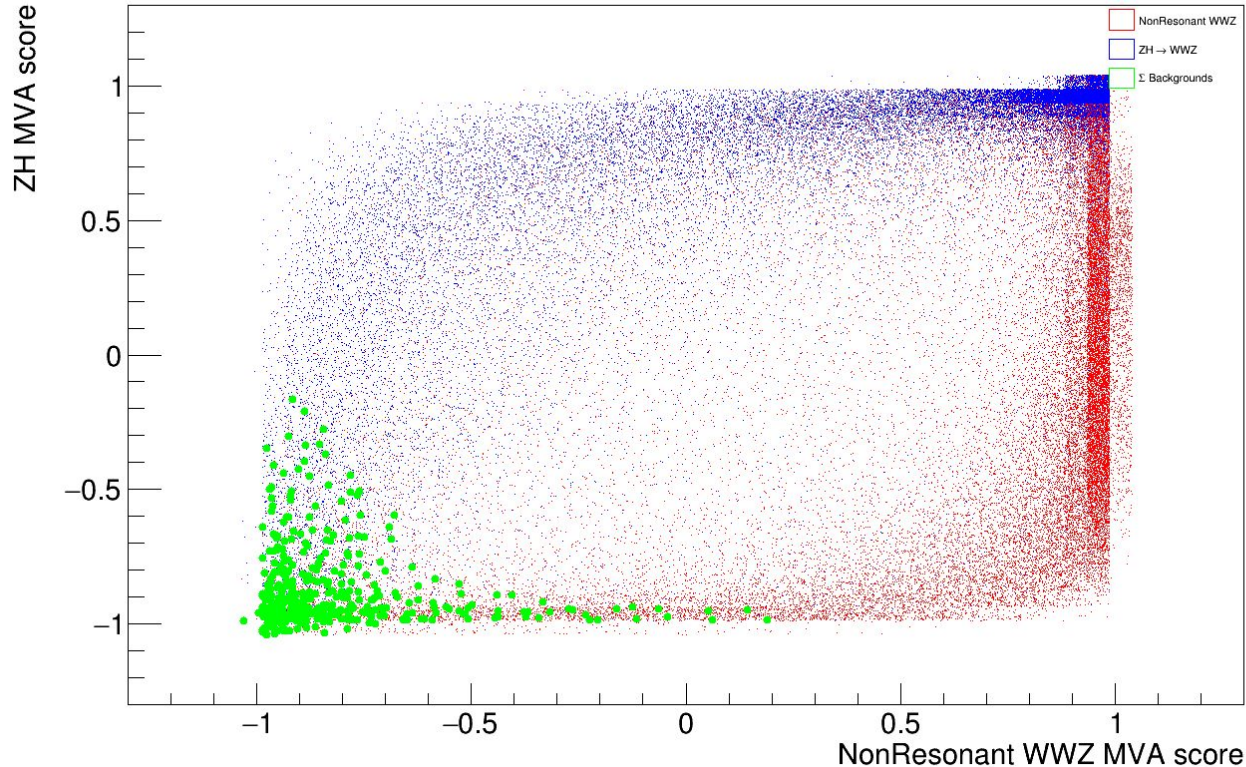
Again, this looks reasonable

BDT MVA outputs - 2D scatter plot (Opposite Flavor)



- Can identify regions that are “ZH-like” and “WWZ-like”
 - Top right: ZH-like
 - Bottom right: WWZ-like

BDT MVA outputs - 2D scatter plot (Same Flavor)



- Can identify 2 regions where signal tends to live
 - ZH: high ZH score and high WWZ score
 - WWZ: High WWZ score and (somewhat) uniform in ZH score

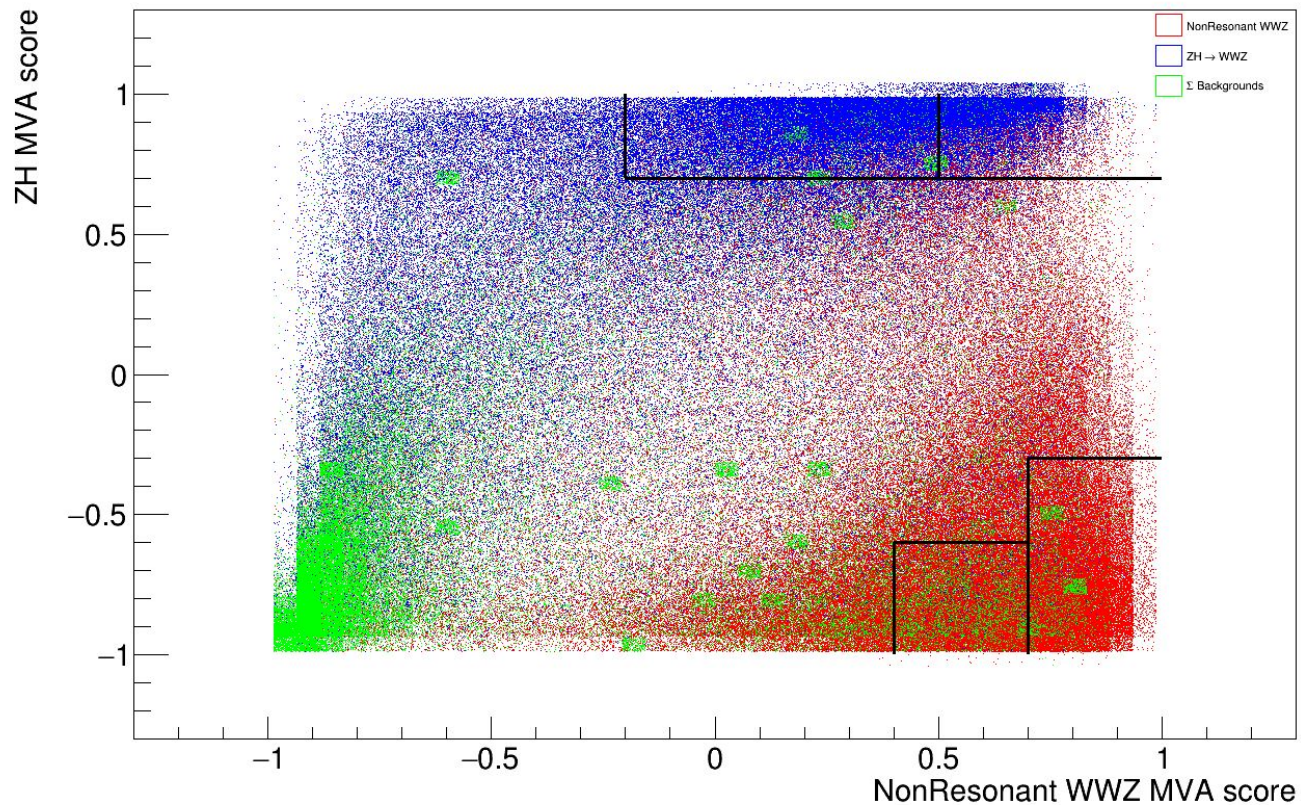
Binning for SRs

- Binning was done “by eye”
 - Idea: define regions that isolate the individual signals
 - Easier said than done → Considerable overlap between signals in 2D plots
- For each channel, define 2 SRs for each signal
 - 2 signals x 2 bins x 2 channels = 8 bins total
 - For each signal, 1 bin is “pure” in the signal while the other tends to be “mixed”

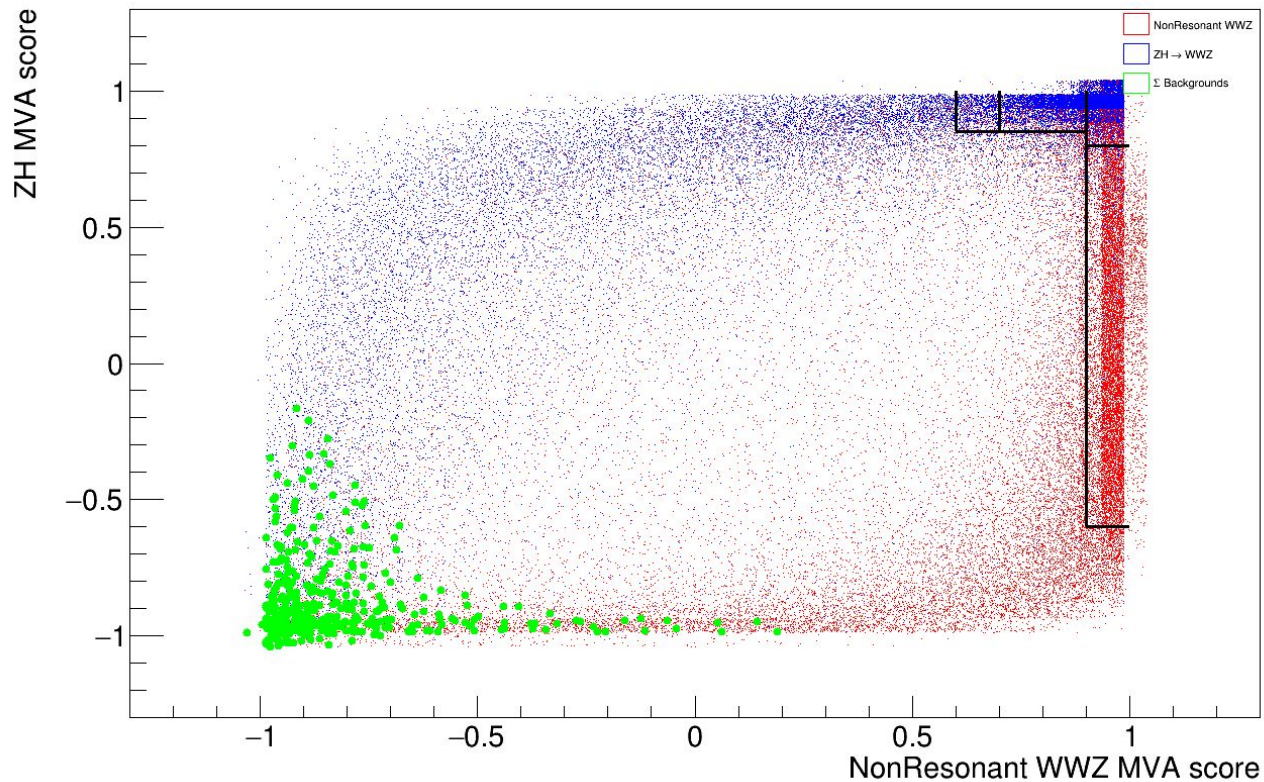
SR	SF SR 1	SF SR 2	SF SR 3	SF SR 4	OF SR 1	OF SR 2	OF SR 3	OF SR 4
WWZ Score	> 0.9	> 0.9	$\in (0.7,0.9)$	$\in (0.6,0.7)$	> 0.7	$\in (0.4,0.7)$	> 0.5	$\in (-0.2,0.5)$
ZH Score	> 0.8	$\in (-0.6,0.8)$	> 0.85	> 0.85	< -0.3	< -0.6	> 0.7	> 0.7

(Binning shown on 2D plots on next 2 slides)

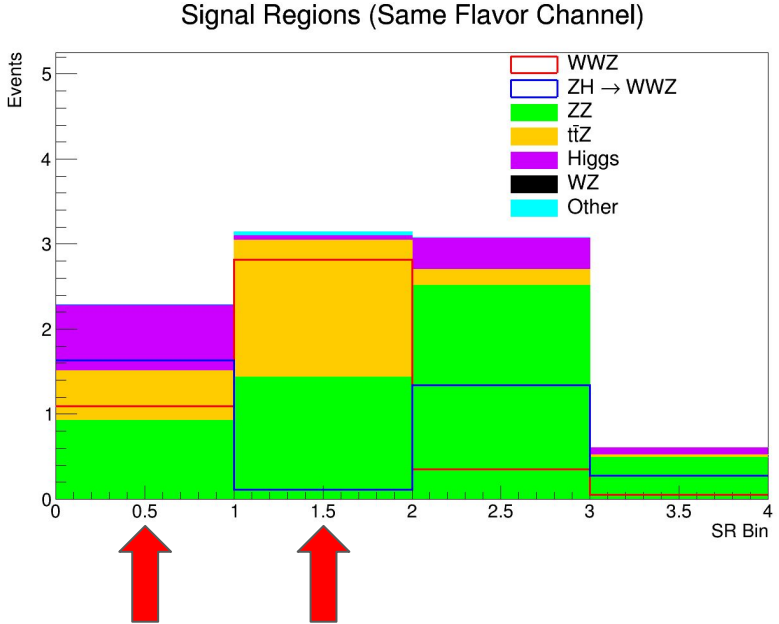
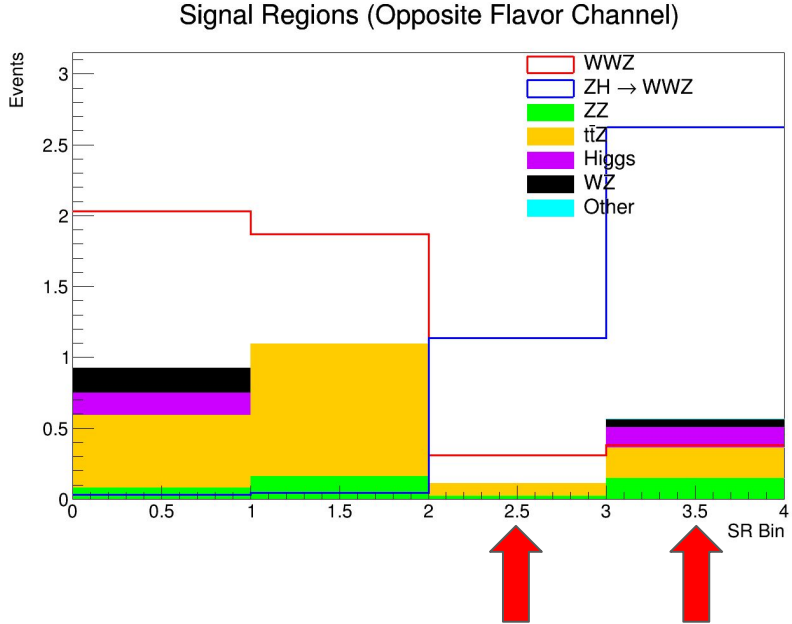
2D Signal Regions - Opposite Flavor



2D Signal Regions - Same Flavor



SR Yields - BDT Analysis



Arrows show 2 most sensitive bins in each channel

SR Yields - BDT Analysis (cont.)

SR	Summary					Composition of N_{total}				
	Bins	N_{total}	NonResonant WWZ	ZHWWZ	S/\sqrt{B}	ZZ	ttZ	Higgs	WZ	Other
Most sensitive bins (OF channel)	OF SR 1	0.93 ± 0.17	2.03 ± 0.01	0.032 ± 0.002	2.15	0.082 ± 0.007	0.51 ± 0.04	0.16 ± 0.10	0.18 ± 0.13	0.0001 ± 0.004
	OF SR 2	1.06 ± 0.12	1.87 ± 0.01	0.044 ± 0.002	1.86	0.16 ± 0.01	0.94 ± 0.06	-0.046 ± 0.101	0 ± 0	0.011 ± 0.005
	OF SR 3	0.11 ± 0.02	0.312 ± 0.003	1.135 ± 0.007	4.34	0.022 ± 0.004	0.090 ± 0.015	-0.002 ± 0.018	0 ± 0	0.001 ± 0.001
	OF SR 4	0.56 ± 0.12	0.380 ± 0.004	2.62 ± 0.01	4.00	0.147 ± 0.009	0.215 ± 0.023	0.145 ± 0.099	0.056 ± 0.056	0.001 ± 0.005
Most sensitive bins (SF channel)	SF SR 1	2.29 ± 0.27	1.09 ± 0.01	1.63 ± 0.01	1.80	0.93 ± 0.02	0.58 ± 0.04	0.78 ± 0.26	0 ± 0	0.009 ± 0.007
	SF SR 2	3.15 ± 0.09	2.82 ± 0.01	0.114 ± 0.003	1.65	1.44 ± 0.03	1.61 ± 0.07	0.055 ± 0.037	0 ± 0	0.043 ± 0.037
	SF SR 3	3.08 ± 0.26	0.354 ± 0.003	1.34 ± 0.01	0.97	2.52 ± 0.04	0.19 ± 0.02	0.37 ± 0.25	0 ± 0	0.003 ± 0.006
	SF SR 4	0.61 ± 0.09	0.049 ± 0.001	0.274 ± 0.004	0.41	0.49 ± 0.02	0.032 ± 0.008	0.079 ± 0.087	0 ± 0	0.000 ± 0.002

Table 23: Yields in BDT signal regions

SR	Summary					Composition of N_{total}				
	Bins	N_{total}	NonResonant WWZ	ZHWWZ	S/\sqrt{B}	ZZ	ttZ	Higgs	WZ	Other
Most sensitive bins (OF channel)	OF Bin 1	1.33 ± 0.21	0.65 ± 0.01	3.05 ± 0.01	3.21	0.62 ± 0.02	0.32 ± 0.03	0.27 ± 0.19	0.11 ± 0.08	0.01 ± 0.01
	OF Bin 2	0.96 ± 0.11	0.74 ± 0.01	1.35 ± 0.01	2.13	0.62 ± 0.02	0.38 ± 0.03	-0.06 ± 0.10	0 ± 0	0.01 ± 0.01
	OF Bin 3	1.39 ± 0.22	1.48 ± 0.01	0.35 ± 0.01	1.55	0.39 ± 0.02	0.83 ± 0.05	-0.06 ± 0.16	0.18 ± 0.13	0.04 ± 0.04
	OF Bin 4	3.60 ± 0.23	5.14 ± 0.01	0.15 ± 0.01	2.79	0.50 ± 0.02	2.51 ± 0.09	0.45 ± 0.17	0.12 ± 0.12	0.02 ± 0.01
Most sensitive bins (SF channel)	SF Bin 1	3.25 ± 0.22	2.33 ± 0.01	0.95 ± 0.01	1.82	1.32 ± 0.03	1.32 ± 0.06	0.61 ± 0.21	0 ± 0	0.01 ± 0.01
	SF Bin 2	6.18 ± 0.36	1.97 ± 0.01	1.52 ± 0.01	1.40	4.58 ± 0.05	1.12 ± 0.06	0.42 ± 0.35	0 ± 0	0.06 ± 0.04
	SF Bin 3	3.15 ± 0.18	0.57 ± 0.01	0.68 ± 0.01	0.70	2.78 ± 0.04	0.27 ± 0.03	0.10 ± 0.17	0 ± 0	0.01 ± 0.01

Table 25: Yields in Cut-Based SR bins (as of September 1st, 2023)

Based on S/\sqrt{B} considerations (purple), MVA bins are more sensitive!

Combine Result - MVA vs Cut-Based

- Take the MC-based yields from the previous slide
 - Use these to calculate the significance (Z) for the **MVA** and **cut-based** analyses

$$Z_{\text{MVA}} = 4.81 \sigma$$

$$Z_{\text{cut-based}} = 4.56 \sigma$$

→ **MVA outperforms cut-based analysis** (as expected)

This was achieved without “optimal” binning

BDT hyperparameters were also not “fully-optimized”

Thus.... **there is room for improvement on this result**

Improvements for the BDT

- Replace some “bad” training variables with variables that provide better discrimination
 - Also, figure out what these “better” variables are
- Tweak the BDT hyperparameters to find a combination that strikes a balance between (lack of) overtraining and discrimination power
- Figure out how to improve the 2D binning for the MVA SRs

To do

- Samples to add:
 - VVV (WWW, WZZ, ZZZ)
 - tWZ
- Reduce skim size
 - What progress has been made?
- Implement lepton SFs
- Background Estimation
 - ZZ, ttZ, WZ → 3 lepton + 1 fake

Backup

BDT Hyperparameters (TMVA)

- $N_{\text{trees}} = 400$
 - Number of trees in the forest
- $\text{MinNodeSize} = 5\%$
 - Minimum fraction of the training data used to construct individual nodes
- **Boost Type: Gradient Boost**
 - Algorithm used for boosting
- $\text{Shrinkage} = 0.1$
 - Learning rate for the Gradient Boost Algorithm
- $\text{MaxDepth} = 2$
 - Maximum depth of decision tree
- **SeparationType = SDivSqrtSPlusB**
 - Node splitting is done by computing $s/\sqrt{s+b}$ and comparing to the nominal value for “signal” or “background”
- **Ignore Negative Weights in Training**