# ML for Polarized VBS

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# Starting data and cuts

In this analysis we focused on SSWW VBS and we studied the polarization of the W vector bosons; in particular, we applied the following cuts to the observed features

- $m_{jj} > 500$ GeV
- $m_{ll} > 20$ GeV
- $p_T^{MET} > 30$ GeV
- $d\eta_{jj} > 2.5$
- $p_T^{j1} > 50$ GeV
- $p_T^{j2} > 50$ GeV
- $p_T^{l1} > 25$ GeV
- $p_T^{l2} > 20$ GeV

The data we are working on are labeled with the polarization states of the W bosons in the LAB reference frame, with either an L for longitudinal polarization and T for transverse

- $W_L^{\pm}W_L^{\pm}$
- $W_T^{\pm}W_L^{\pm}$
- $W_T^{\pm}W_T^{\pm}$

Our goal is to build a ML model that can separate LL events from TX (i.e. TL or TT)

# Features

Of the various physical quantities available we focus on the subset that we consider relevant in characterizing the events (still not a small set – we train the model and then, in the case of useless variables, we can drop them):

- Leptons data:
  - transverse momenta $p_{l1}$ $p_{l2}$
  - pseudorapidities $\eta_{l1}$ $\eta_{l2}$
  - azimuthal angles $\phi_{l1}$ $\phi_{l2}$
- VBS Jets data (Jet data comes from anti-kt algorithm with radius=0.4; we call VBS Jets the first two jets in order of transverse momentum):
  - $p_{j1}$ $p_{j2}$, $\eta_{j1}$ $\eta_{j2}$, $\phi_{j1}$ $\phi_{j2}$
  - invariant masses $M_{j1}$ $M_{j2}$
- non-VBS Jets data (the following two jets, if any):
  - $p^{\nparallel}_{j1}$ $p^{\nparallel}_{j2}$, $\eta^{\nparallel}_{j1}$ $\eta^{\nparallel}_{j2}$, $\phi^{\nparallel}_{j1}$ $\phi^{\nparallel}_{j2}$, $M^{\nparallel}_{j1}$ $M^{\nparallel}_{j2}$
- Other data:
  - $m_{jj}$ $d\eta_{jj}$ of the VBS jets
  - missing transverse energy $p_T^{MET}$ $\phi^{MET}$
- Neutrino data (from GEN level):
  - $p_{j1}$ $p_{j2}$, $\eta_{j1}$ $\eta_{j2}$, $\phi_{j1}$ $\phi_{j2}$

For a total of 6+8+8+4+6=32 features

# New features

We decided to include other variables that could help in extracting even more information from the event data:

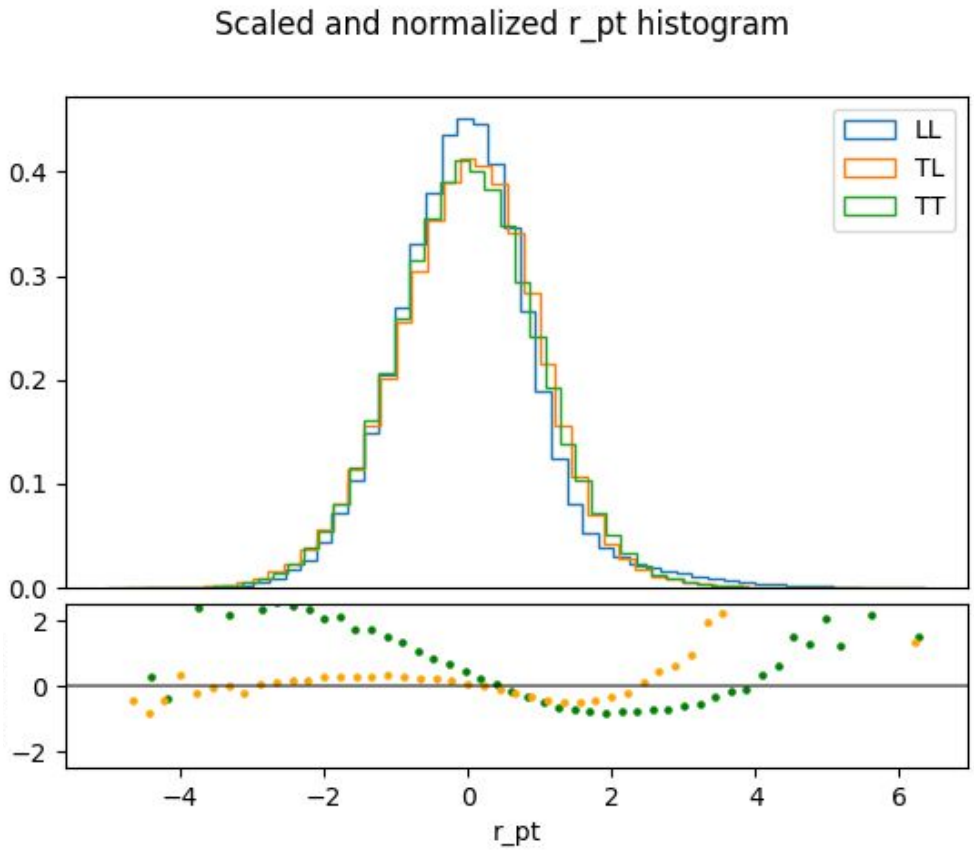
- $\cos\theta^*$ – the lepton decay angle in the W frame (the axis are rotated before applying the boost), one per lepton (Pelliccioli 1710.09339)
- $\cos\theta_{CS}$ – Collins-Soper frame angle (1605.05450)
- $\cos\theta_{2D}$ – transverse helicity angle, one per lepton (1203.2165)
- $R_{pT}$ – ratio of leptons and highest-$p_T$-jets transverse momenta (1201.2768)

So 2+1+2+1=6 new features.

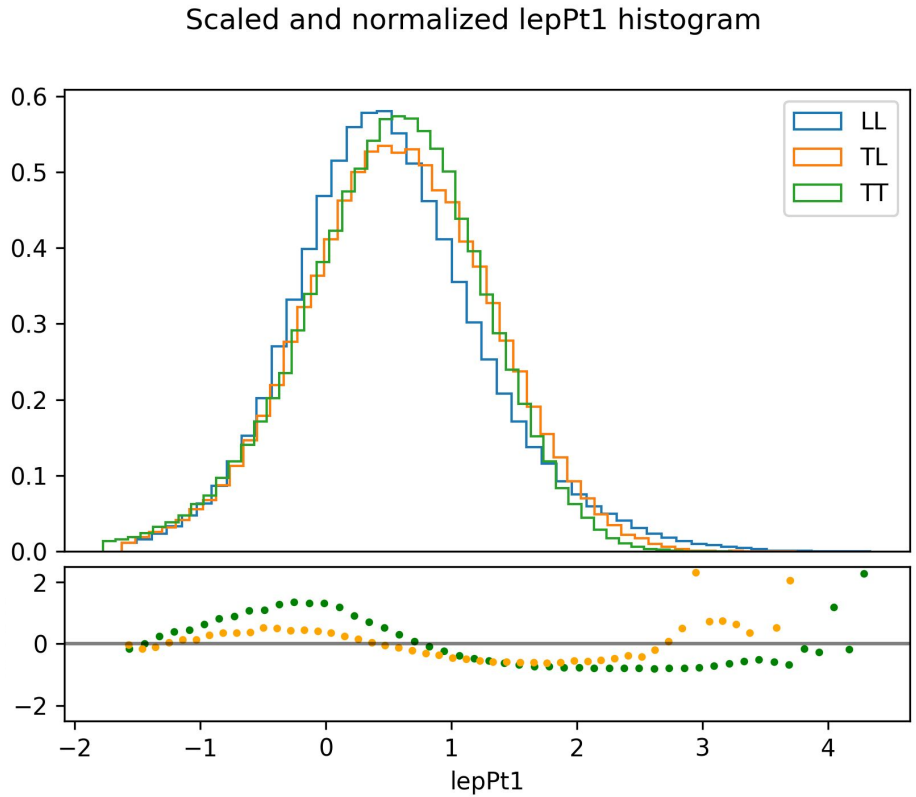
Each feature is scaled if (and as) needed and then normalized, so that the ML models can fruitfully understand the distributions

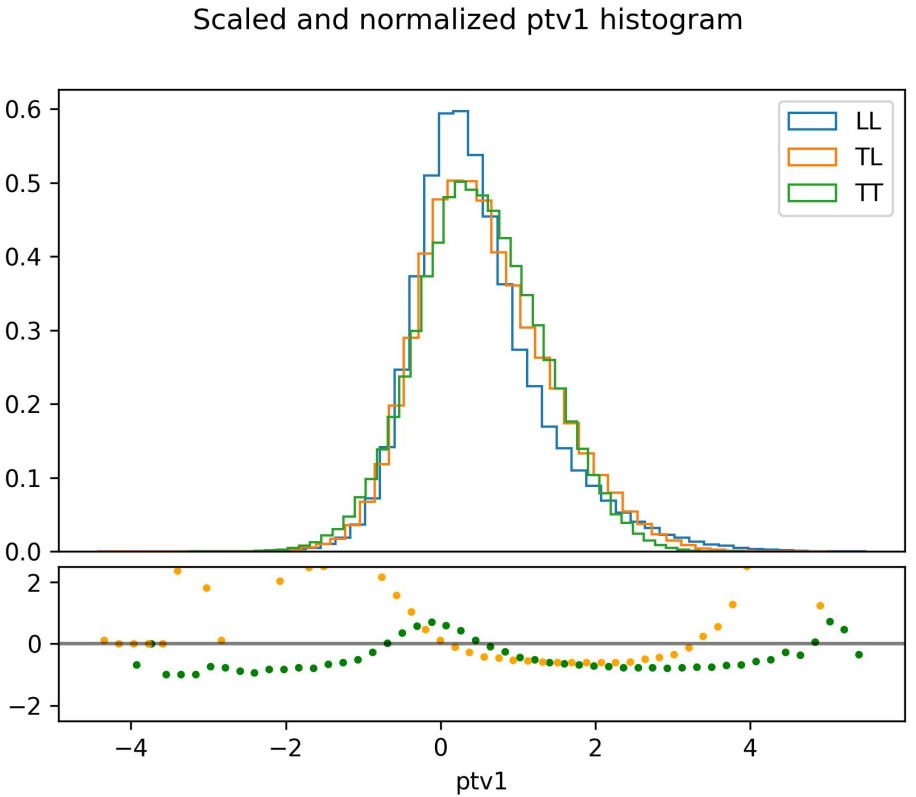
Some examples in the following

# Most important features visualization

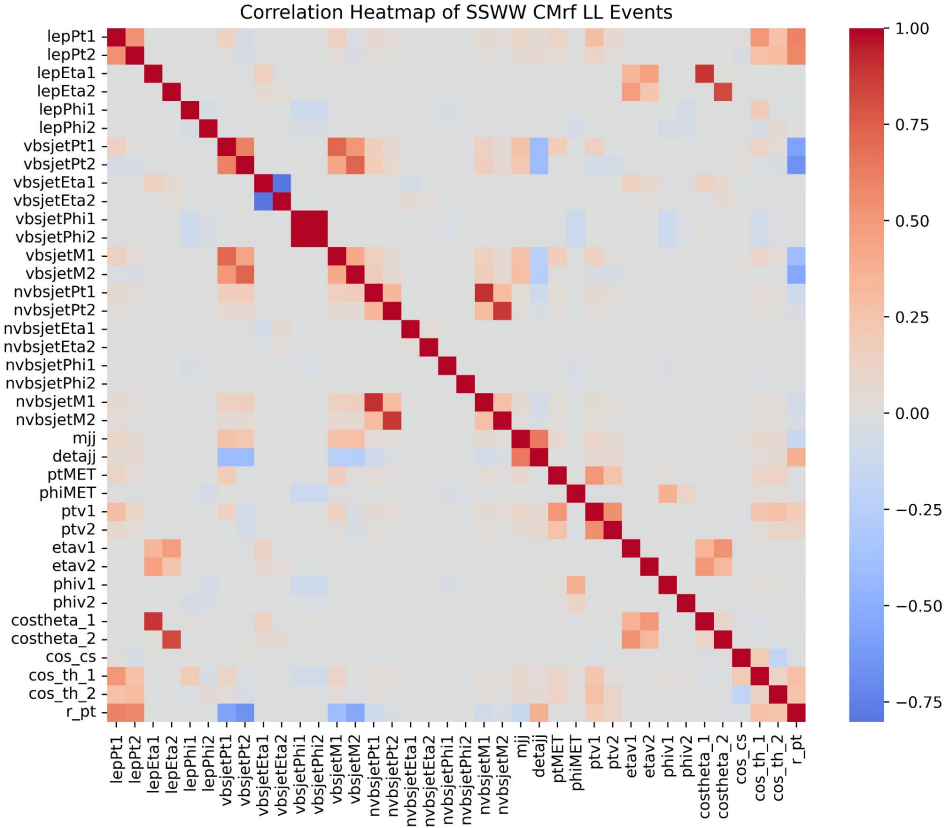


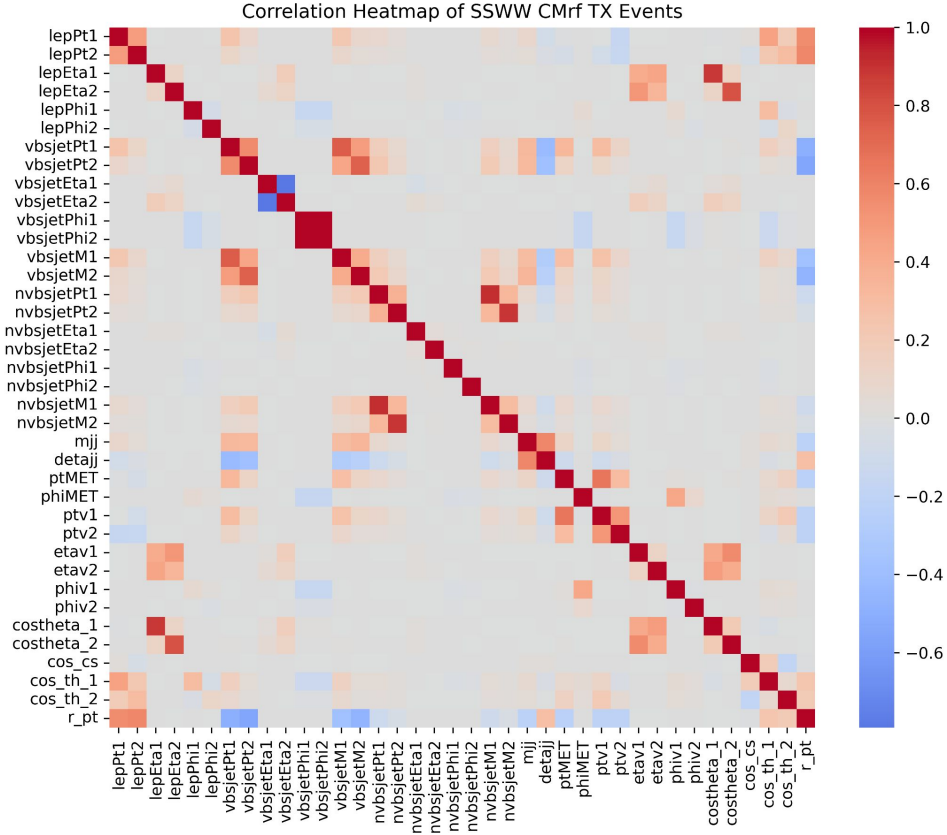
# Most important features visualization



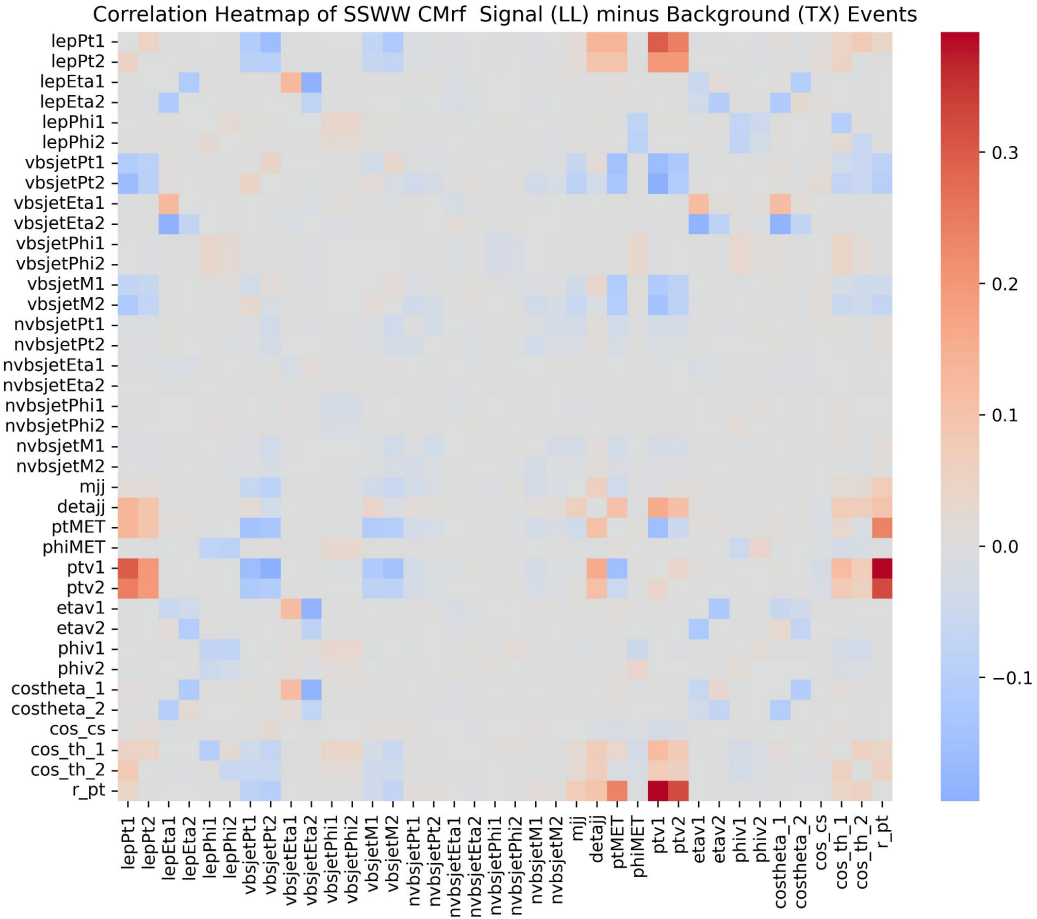
# Correlation (1/3)




Feature correlation is apparently similar in signal events and background ones

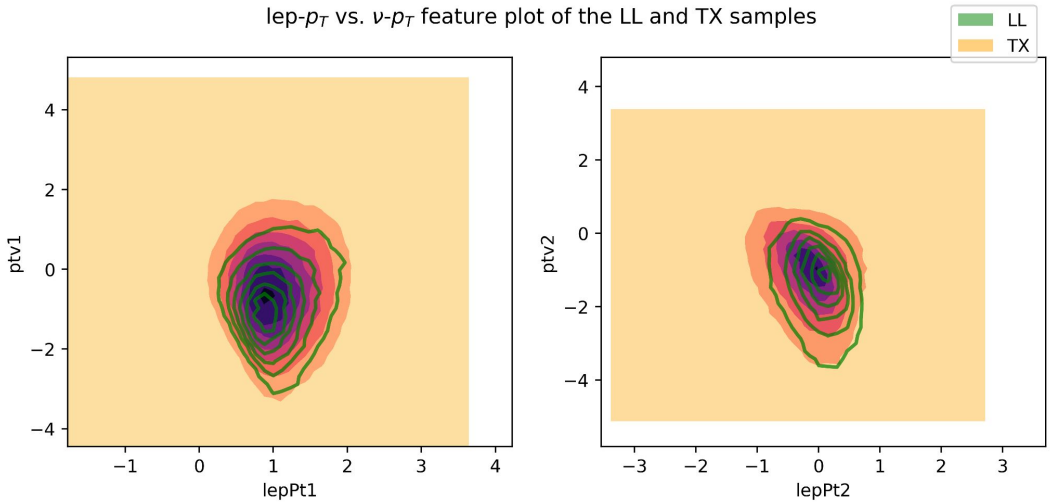
# Correlation (2/3)

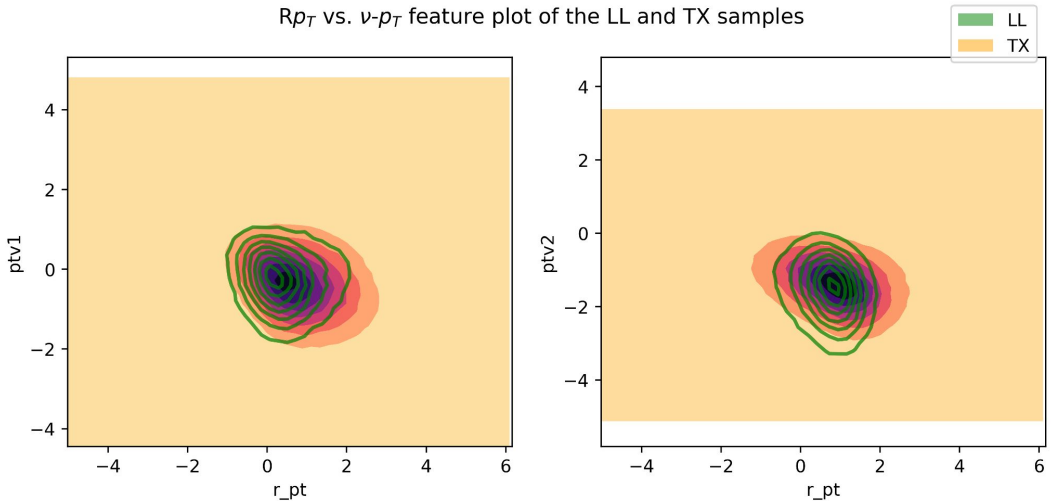



But if we plot the difference of the correlation matrices, we can observe that certain features present higher correlation amongst the signal (LL) events compared to the background (TX) ones, or viceversa.

# Correlation (3/3)

In particular, we see that the main difference in correlation is between leptons and the correspondent neutrinos transverse momenta, and between $R_{pT}$ and neutrino momenta



# Model (1/3)

The ML model we built is a DNN in pytorch: we included multiple hidden layers with Dropout and Batch Normalization

| | |
|---|---|
| Number of hidden layers | 3 |
| Hidden layers depth | 64, 48, 32 respectively |
| Dropout | 0.1 for each layer |
| Batch Normalization | in each layer |
| Output function | Sigmoid |
| Optimizer | Adam |
| Learning rate | 5e-4 |

# Model (2/3)

| | |
|---|---|
| Dataset shuffling and splitting | train_test_split scikitlearn function, with a train/test ratio of 75/25 |
| Training batches size | 100 |

We implemented Early Stopping in order to prevent overfitting: specifically, the validation loss is monitored, with a patience of 5 epochs and a delta of 0.01 (i.e. the training stops if the validation loss does not decrease more than 0.01 in 5 epochs)

| | |
|---|---|
| Value monitored | Validation loss |
| Patience | 5 epochs |
| Delta | 0.01 |

# Model (3/3)

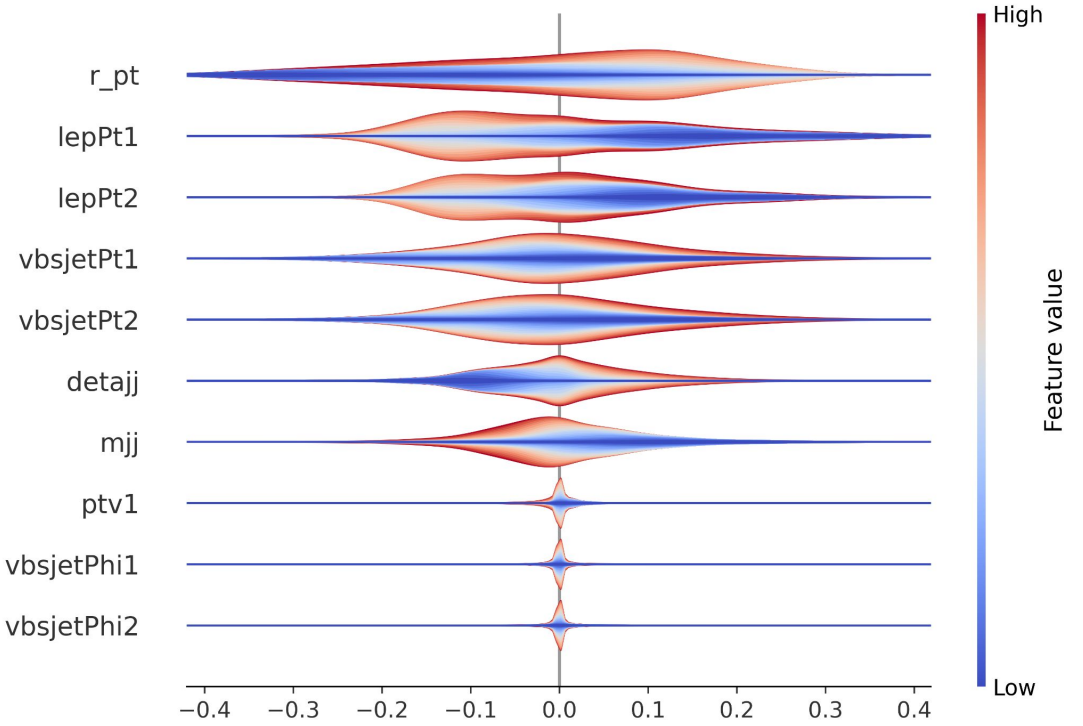
We present the AUC resulting from distinct training runs, differing by the inclusion or exclusion of certain features in the training dataset

| AUC | without $R_{pT}$ | with $R_{pT}$ |
|---|---|---|
| without neutrinos | 0.914 | 0.994 |
| with neutrinos | 0.935 | 0.996 |

One of the hypotheses we made before starting the work is that the GEN neutrino features could play an important role in the training, but we didn't observe such a strong dependence. Instead, we note the importance of the $R_{pT}$ feature

# SHAP (1/2)

After the training we used the SHAP library (in particular the KernelExplainer) to better understand what are the variables the influence the model the most

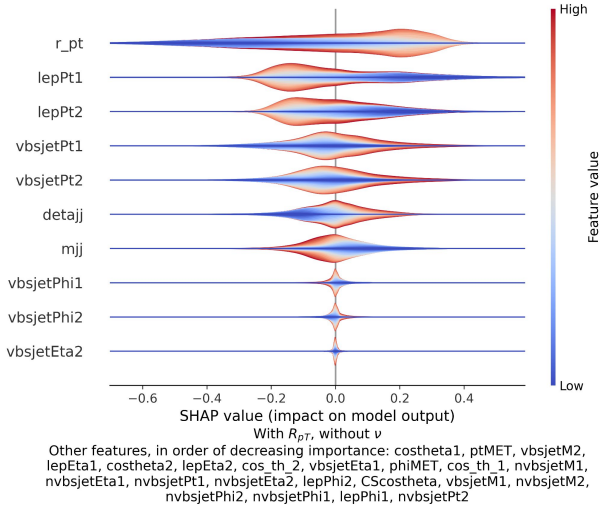



With $R_{pT}$, with $\nu$

Other features, in order of decreasing importance: ptMET, vbsjetEta2, etav1, costheta1, etav2, vbsjetEta1, lepEta1, costheta2, cos_th_1, nvbsjetEta1, nvbsjetPhi2, nvbsjetM1, vbsjetM2, ptv2, phiv1, nvbsjetEta2, CScostheta, vbsjetM1, nvbsjetPhi1, phiMET, nvbsjetPt1, lepPhi1, nvbsjetM2, cos_th_2, phiv2, lepEta2, nvbsjetPt2, lepPhi2

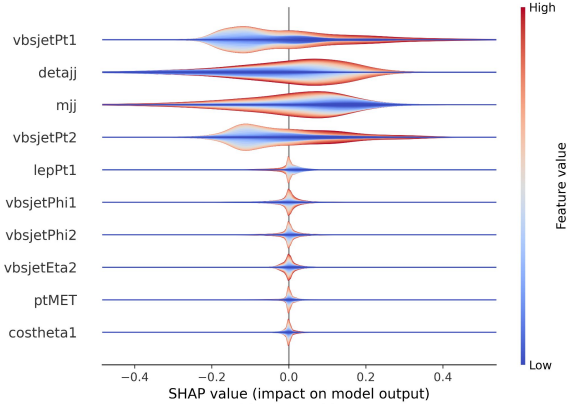
# SHAP (2/2)

As stressed above, we see that the $R_{pT}$ variable is strong in helping the model in this classification task. It is interesting to note how the importance of the other variables changes when we include $R_{pT}$



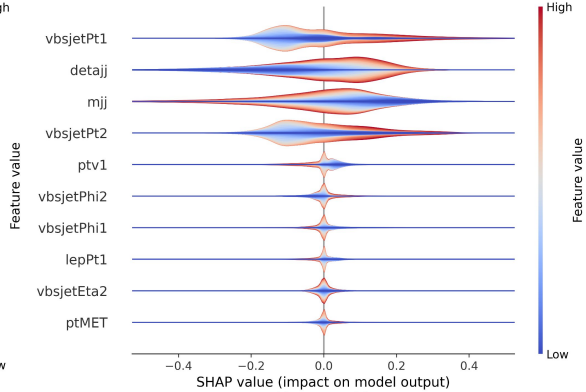

With $R_{pT}$, without $\nu$

Other features, in order of decreasing importance: costheta1, ptMET, vbsjetM2, lepEta1, costheta2, lepEta2, cos_th_2, vbsjetEta1, phiMET, cos_th_1, nvbsjetM1, nvbsjetEta1, nvbsjetPt1, nvbsjetEta2, lepPhi2, CScostheta, vbsjetM1, nvbsjetM2, nvbsjetPhi2, nvbsjetPhi1, lepPhi1, nvbsjetPt2




Without $R_{pT}$, without $\nu$

Other features, in order of decreasing importance: vbsjetEta1, phiMET, lepEta1, lepPhi1, lepPt2, CScostheta, lepEta2, cos_th_1, costheta2, cos_th_2, vbsjetM2, lepPhi2, nvbsjetPt2, vbsjetM1, nvbsjetPt1, nvbsjetEta1, nvbsjetM1, nvbsjetPhi1, nvbsjetPhi2, nvbsjetM2, nvbsjetEta2




Without $R_{pT}$, with $\nu$

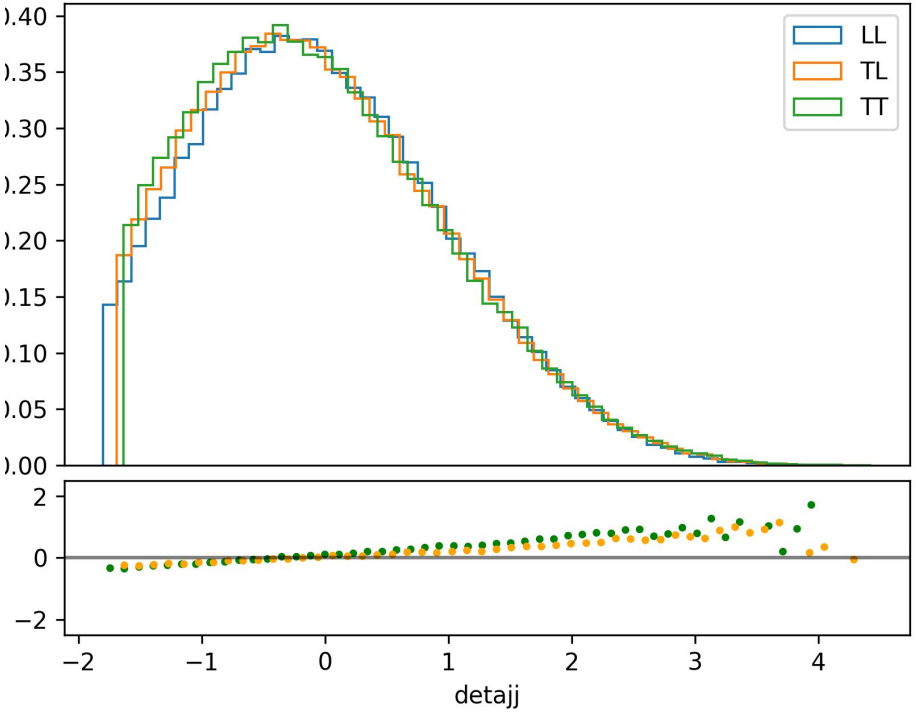
Other features, in order of decreasing importance: etav1, etav2, vbsjetEta1, ptv2, costheta1, lepEta1, costheta2, lepEta2, lepPt2, CScostheta, cos_th_1, lepPhi1, nvbsjetPt1, phiMET, cos_th_2, lepPhi2, nvbsjetPt2, vbsjetM2, vbsjetM1, nvbsjetM1, phiv2, nvbsjetPhi1, nvbsjetPhi2, nvbsjetEta1, nvbsjetM2, nvbsjetEta2, phiv1

For the code see the repo
https://github.com/marcortinovis/MLforPolarizedVBS

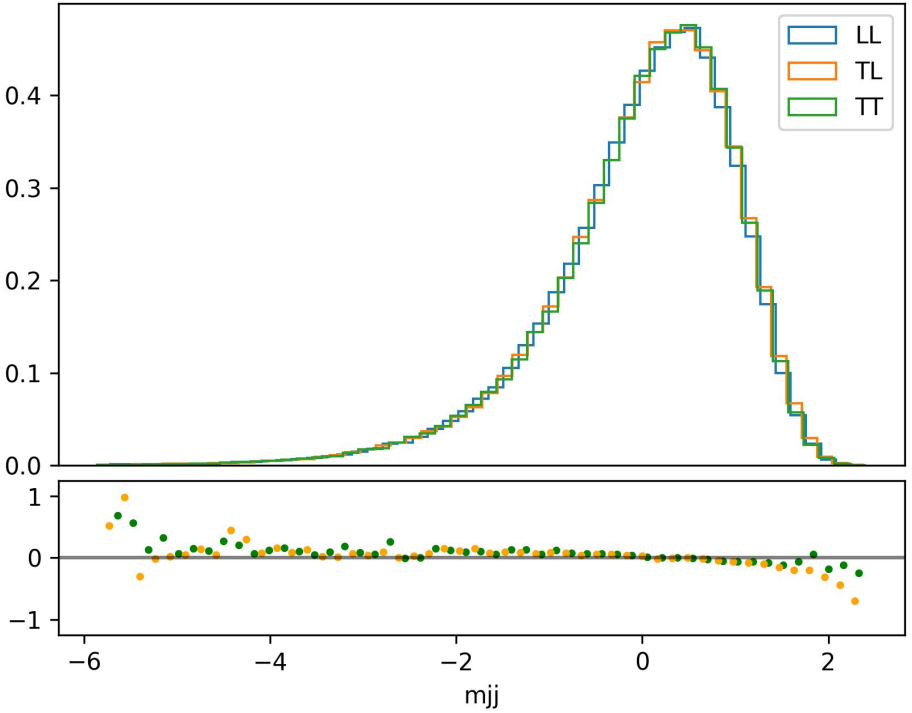
# Backup

# Most important features visualization

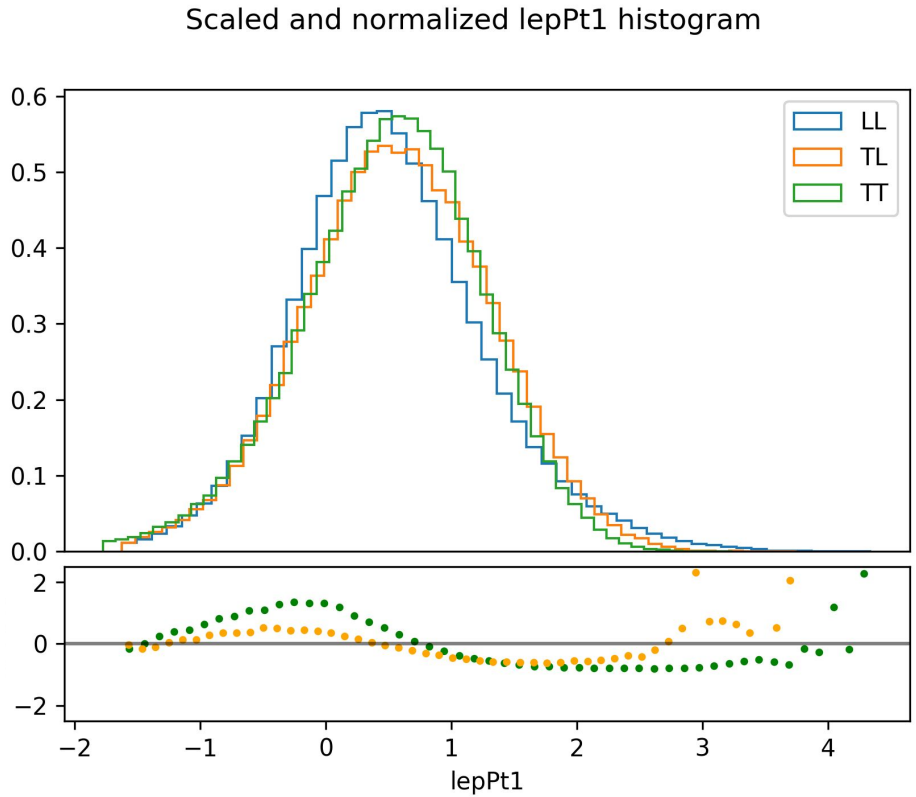
Scaled and normalized detajj histogram

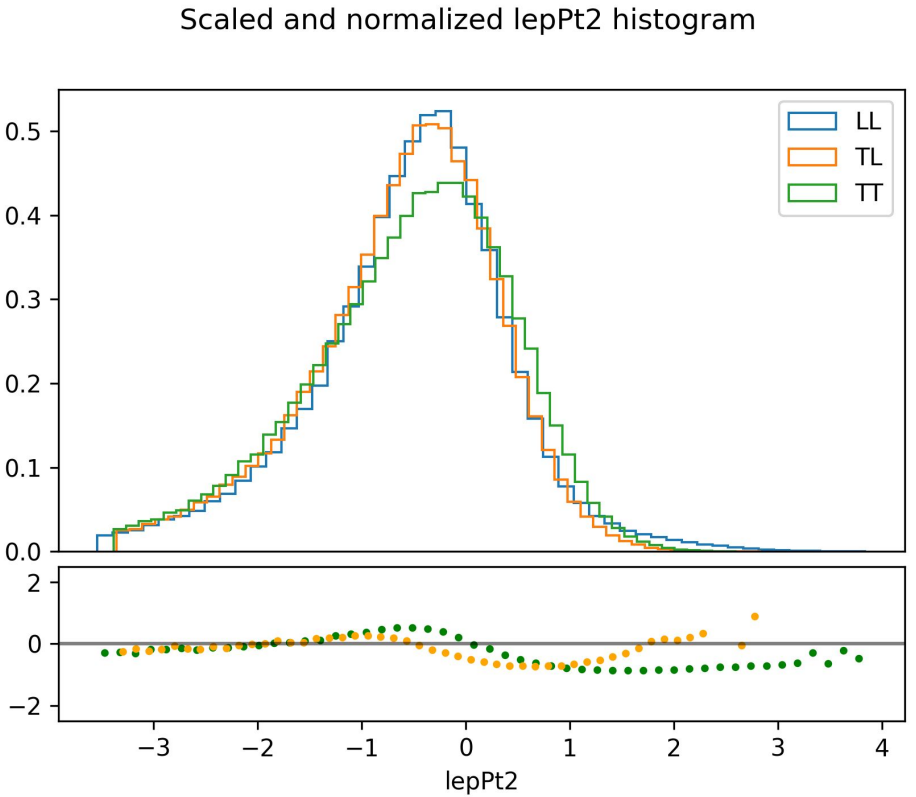



Scaled and normalized mjj histogram

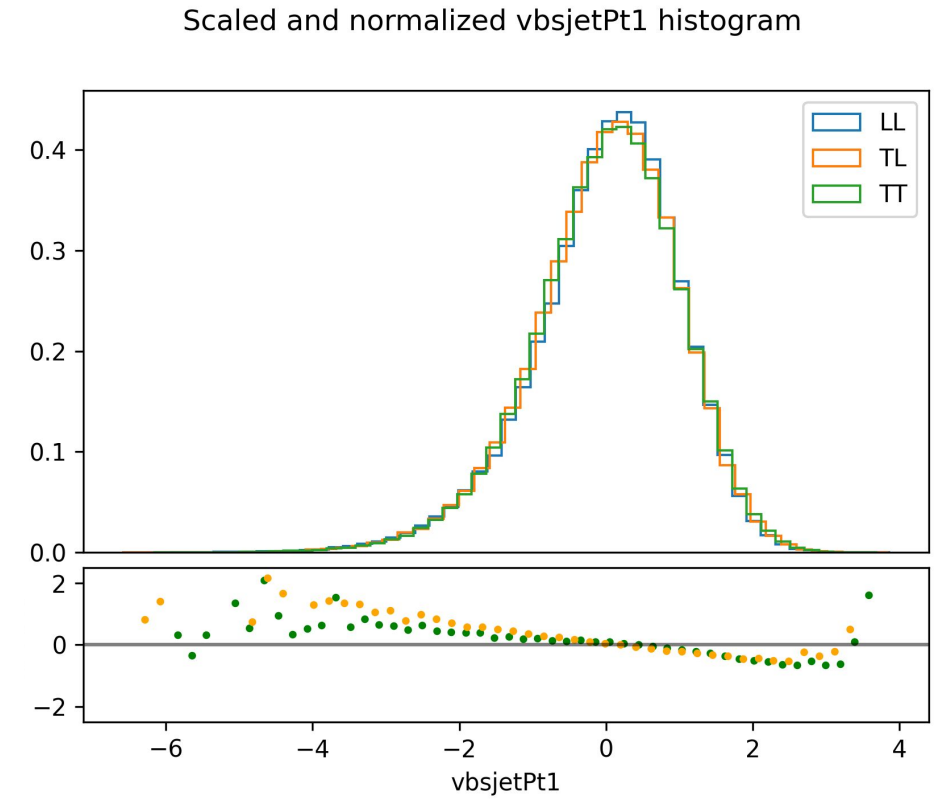


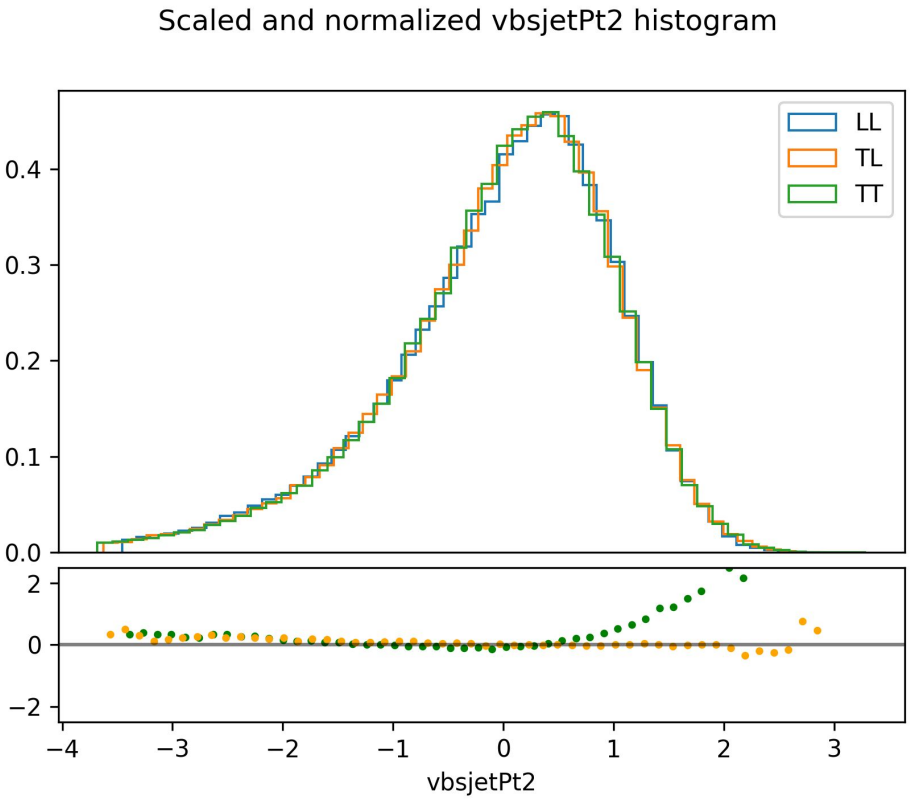
# Most important features visualization



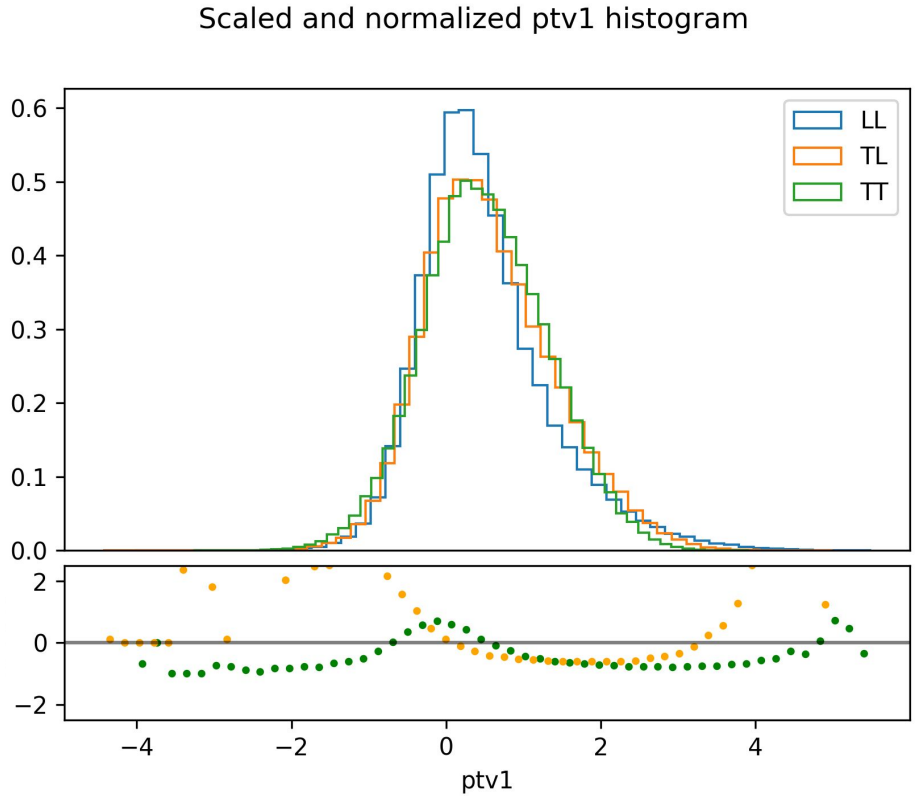



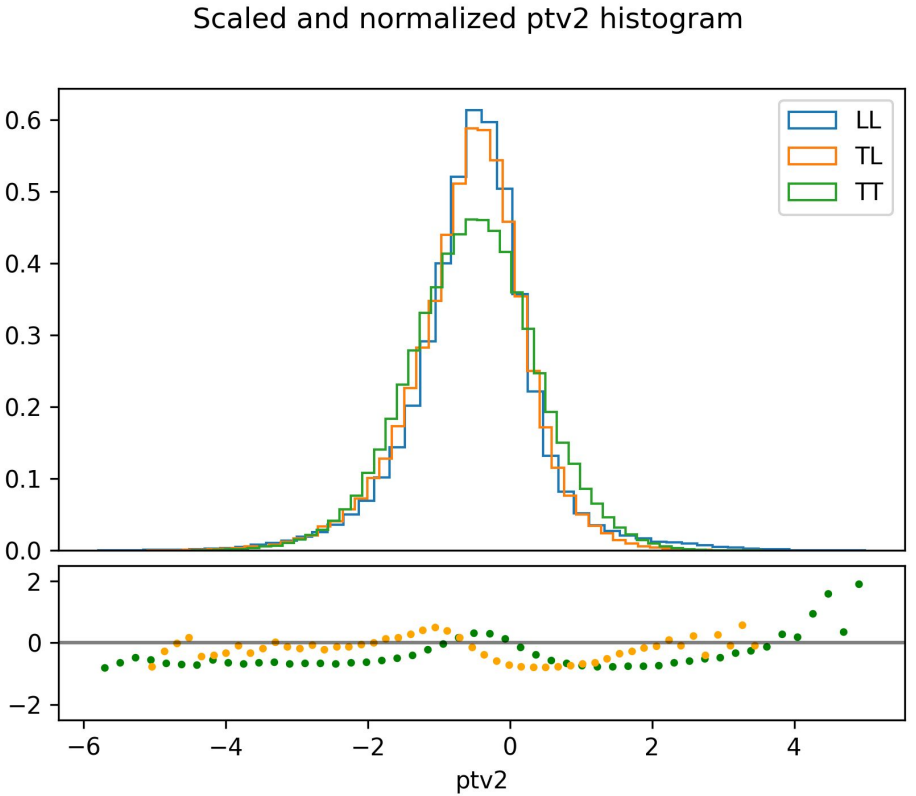
# Most important features visualization



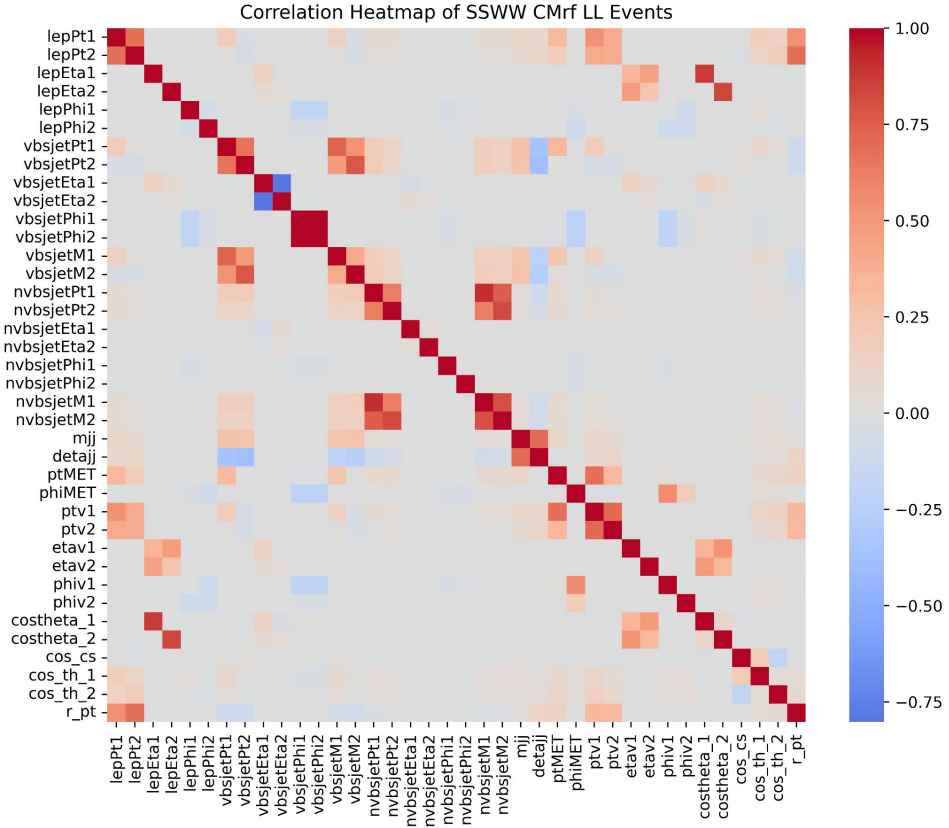



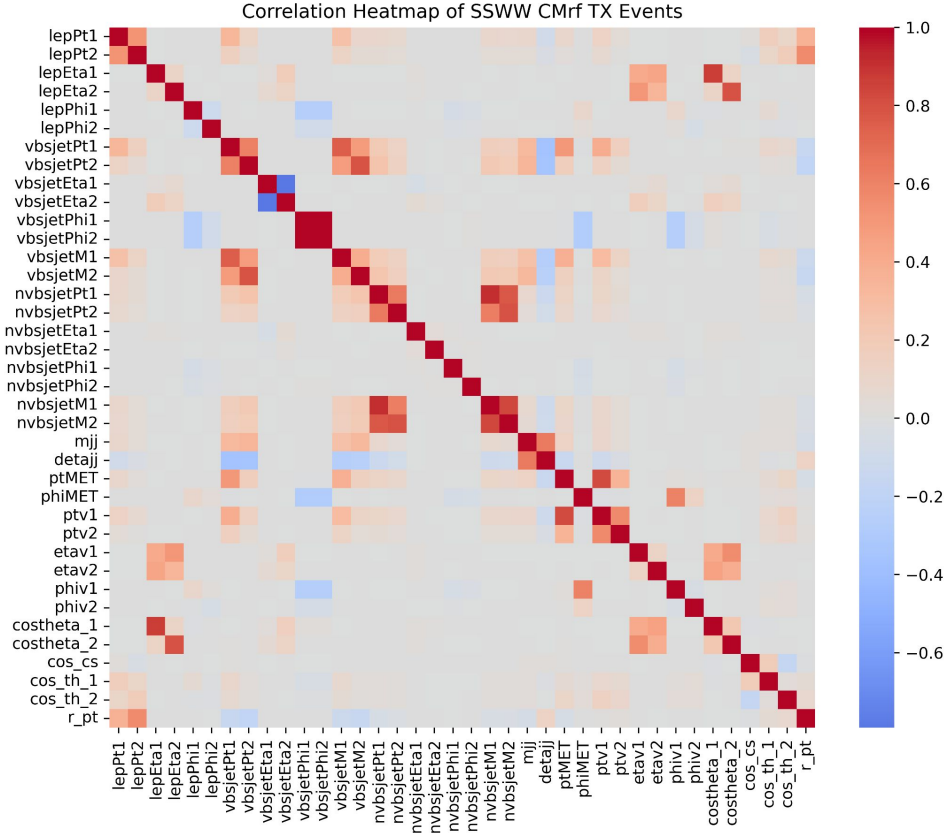
# Most important features visualization



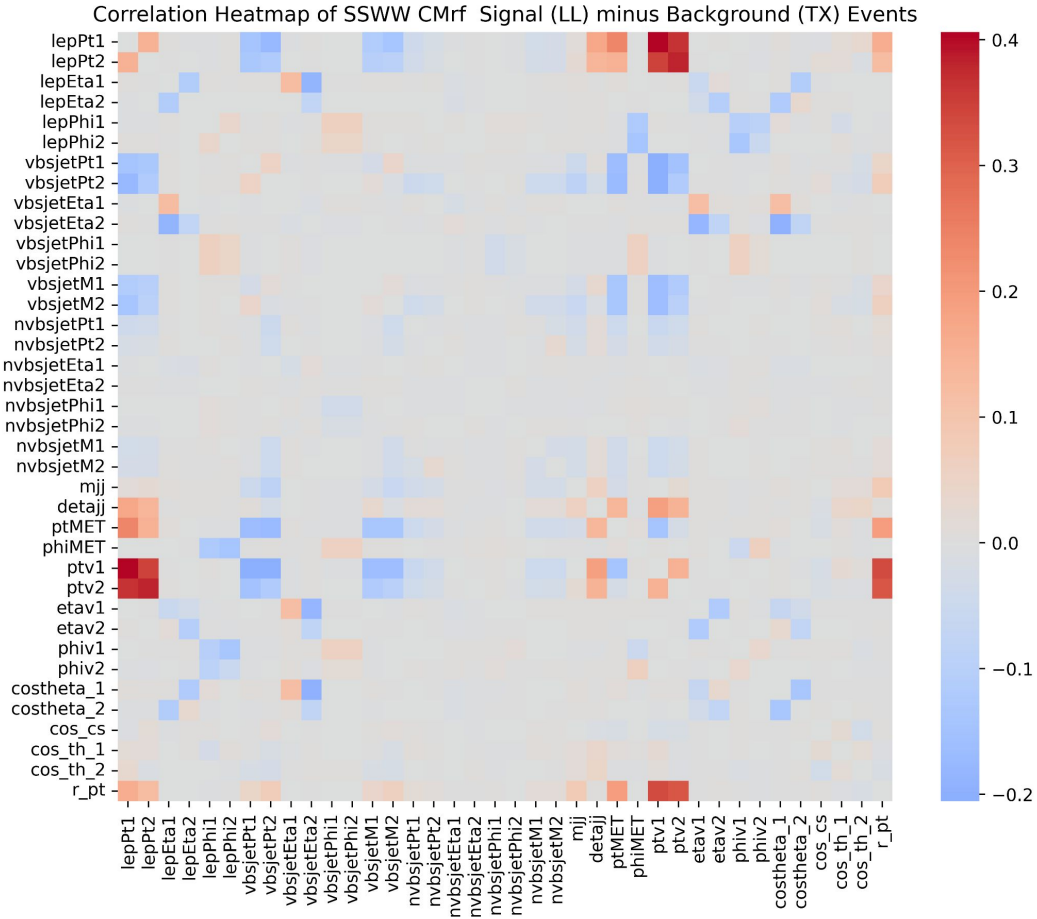
# Correlation, source data



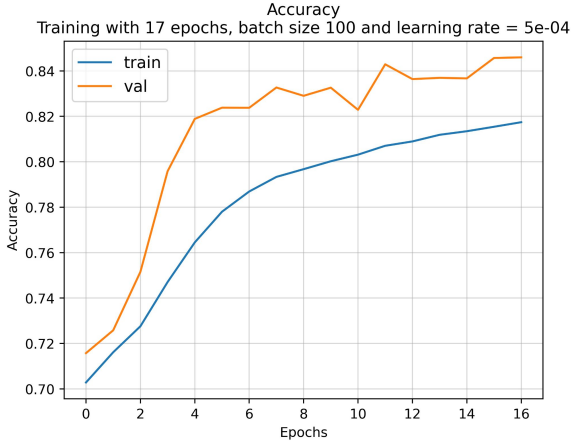

We see no difference with the correlation of scaled and normalized data.

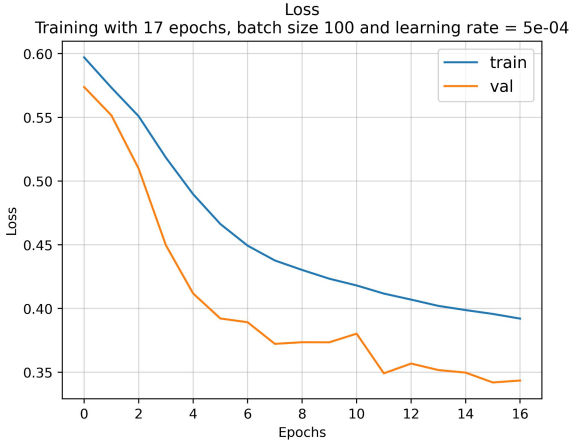
# Correlation, source data



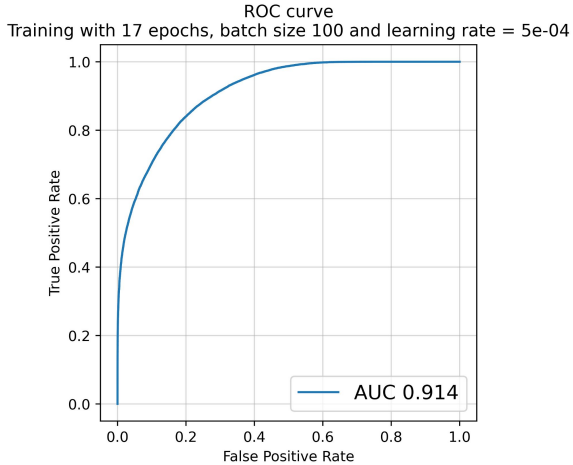

We see no difference with the correlation of scaled and normalized data.

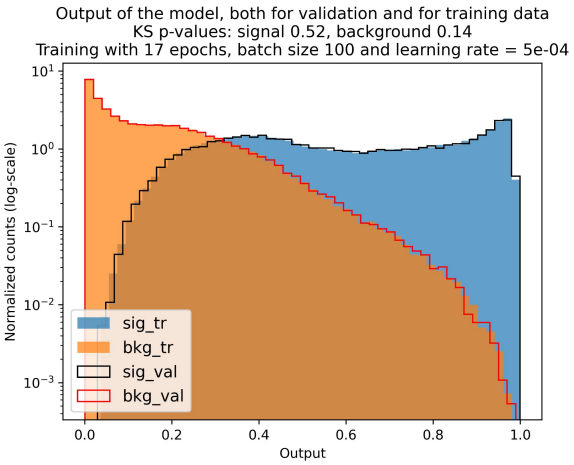
# Training results: without $R_{pT}$ and without neutrinos



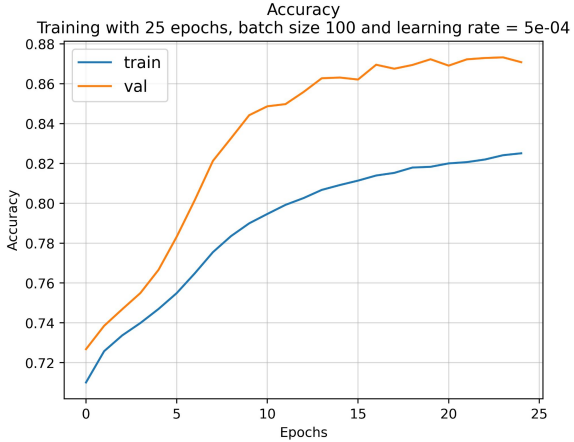

Note: the validation loss is systematically lower than the training one because of the dropout

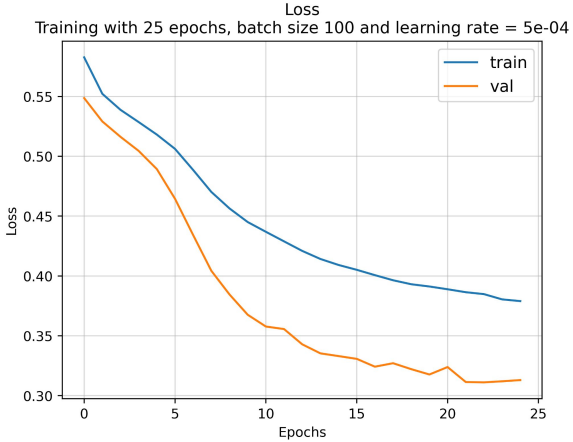


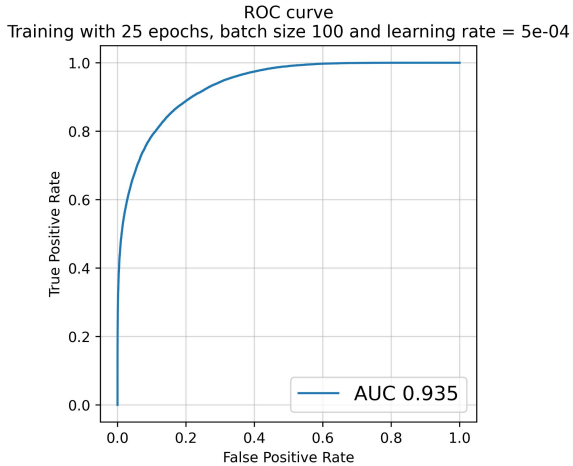



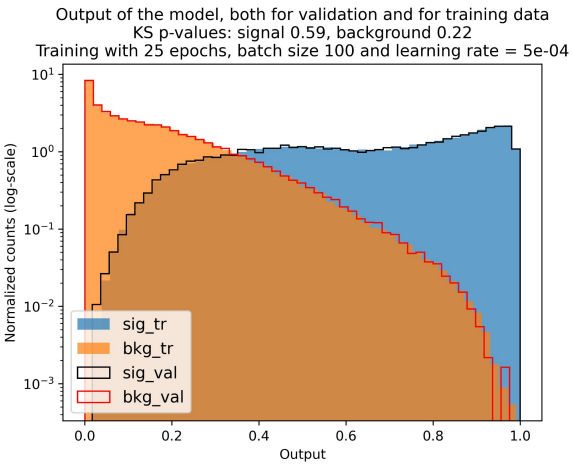

The double secondary peak at ~0.3 still has no clear explanation, but with a better choice of features it decreases

# Training results: without $R_{pT}$ and with neutrinos

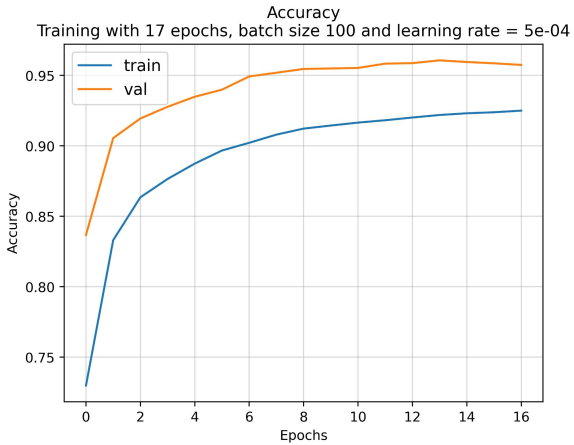


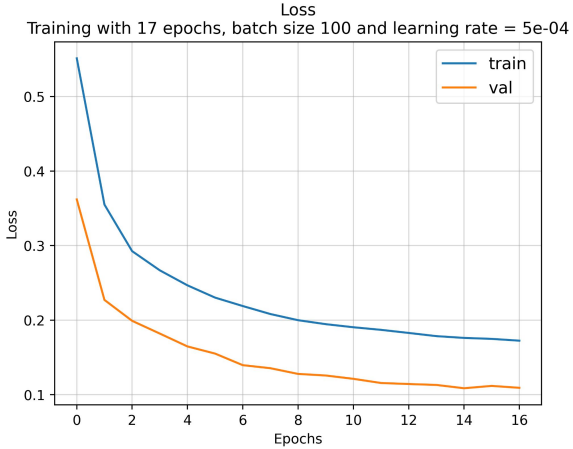



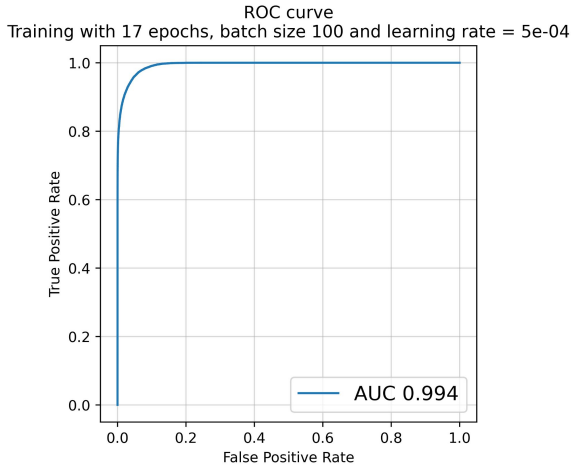



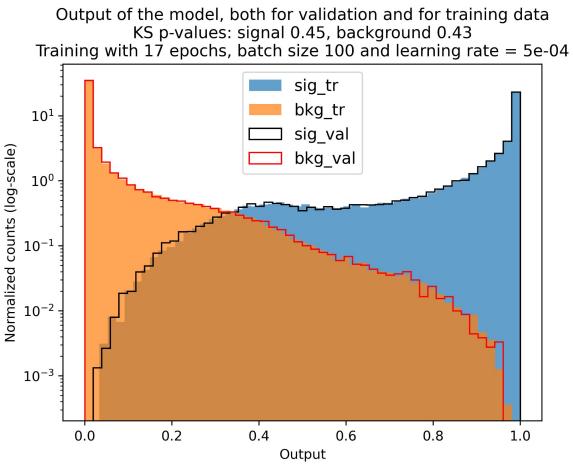



# Training results: with $R_{pT}$ and without neutrinos



# Training results: with $R_{pT}$ and with neutrinos