

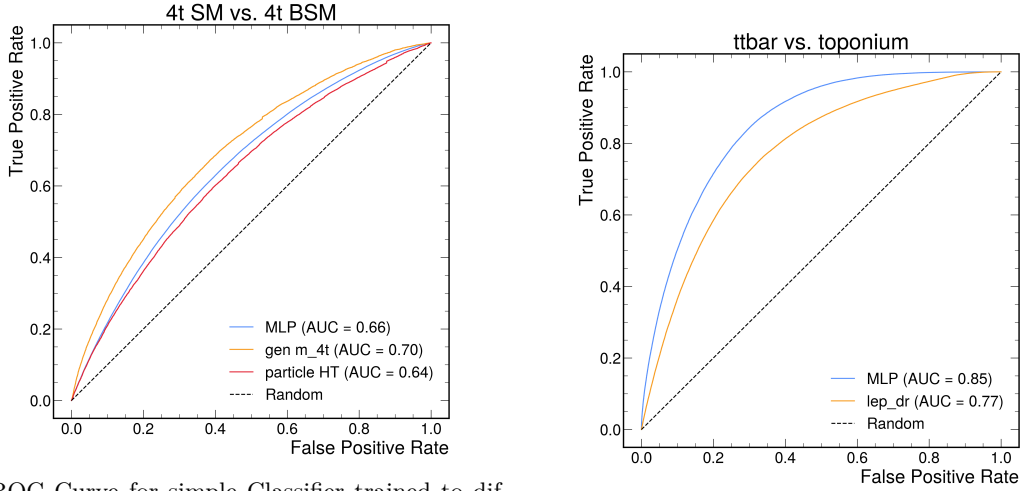
# Optimal observables for searches for top-philic resonances in $t\bar{t}t\bar{t}$ and $t\bar{t}$ production

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(a) ROC Curve for simple Classifier trained to differentiate SM from Resonance  $t\bar{t}t\bar{t}$  events. As a comparison, the curve is also shown for  $H_T$  and the generator-level  $m_{4t}$

(b) ROC Curve for simple Classifier trained to differentiate  $t\bar{t}$  vs. toponium. As a comparison, the curve is also shown for  $\Delta R_{\ell\ell}$

## 1 Introduction

Given the recent excess of  $t\bar{t}$  events [1], extensions to the Standard Model (SM) involving a change in the coupling to the top quark have gained academic interest. While the most likely explanation is a quasi-bound toponium state, the excess could also be due to a new pseudoscalar resonance [2]. In this project, a top-philic pseudoscalar resonance is investigated in four top events, which provide the phase space to differentiate the two hypotheses. A machine learning (ML) classifier is trained to differentiate SM events from BSM events. Furthermore, an uncertainty-aware training is completed to maximize the sensitivity towards the resonance. As a second approach, the MLP is also trained on a  $t\bar{t}$  dataset to differentiate NLO SM events without bound state toponium from events with one. The sensitivity to new physics is increased by a differential measurement with the MLP output as an optimal observable.

## 2 $t\bar{t}t\bar{t}$ pseudoscalar singlet

A sample of  $t\bar{t}t\bar{t}$  events was used that was produced in Madgraph, using Pythia8 for parton showering and Delphes for fast detector simulation. Every event was reweighted using a simplified model for a top-philic pseudoscalar singlet at  $m_{P_1} = 345 \text{ GeV}$  with different coupling strengths  $y$ . The first step is to convert the resulting root file into a dataframe with more information. Additional variables that are not produced in the simulation, but can be used as input features and selection masks (e.g. for the 2lSS channel) are calculated and organized into a format that is suitable for machine learning. The weights for the events are also reparametrized as a SM contribution, an interaction term, and the resonance term:

$$N = N_{\text{SM}} + y^2 N_{\text{Int}} + y^4 N_{\text{Res}} \quad (1)$$

Lastly, variations are applied to the input features to mimic jet energy scale uncertainties. The variables influenced by this are stored with an upward and a downward fluctuation, to later be used in the uncertainty-aware training.

The first step, once the dataset has been built, is to train a simple cross-entropy classifier MLP on the nominal data to see if everything works. As seen in Figure 1a, the model is able to differentiate between SM and BSM, where SM events are drawn from the sample according to their SM weight and the BSM samples are drawn according to their resonance weight for simplicity. The network is able to find a complex combination of angular and energy-related features, as confirmed by feature importance, and improve the separation compared to simple input features such as  $H_T$ . Since the MLP is only given reconstruction-level information, it performs worse than using the generator-level invariant mass of the four tops  $m_{4t}$ .

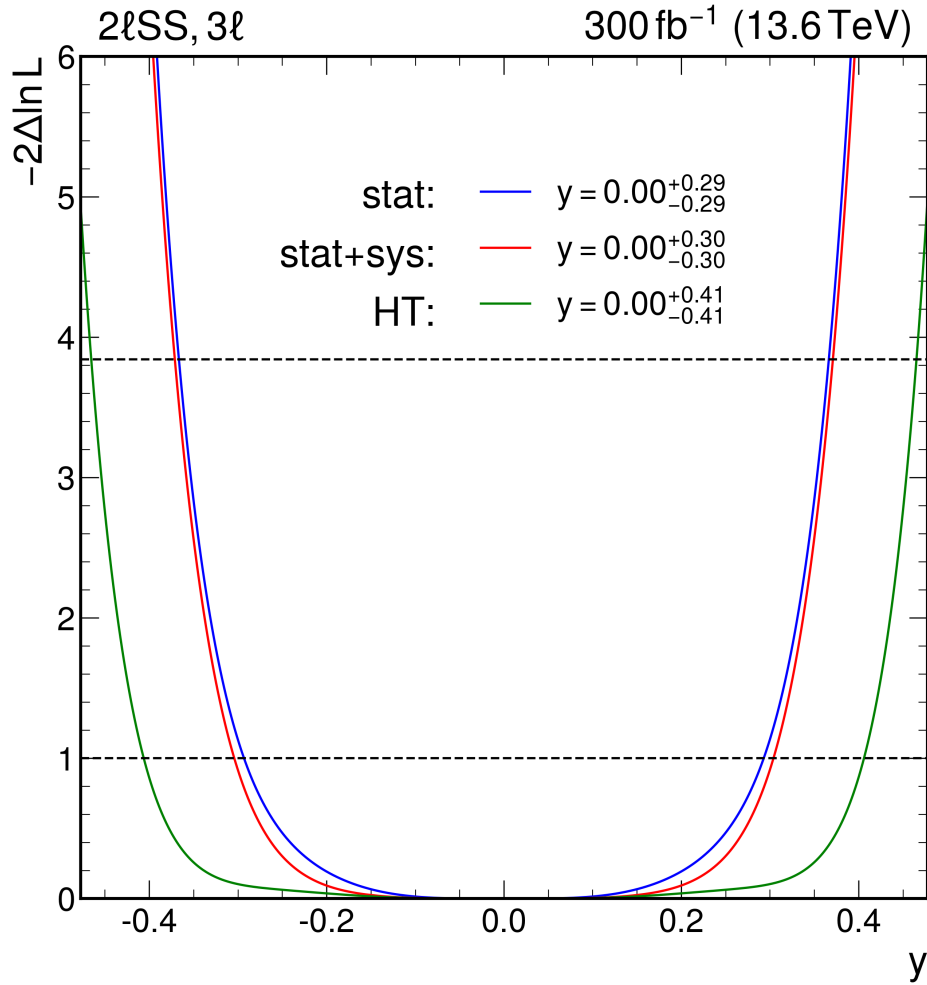


Figure 2: Likelihood Scan as a function of coupling strength for data without BSM. Shown are the lines with only statistical uncertainties, statistical and systematic uncertainties and based on  $H_T$  instead of the MLP output as a comparison

After confirming that the model is capable of differentiating the signals, a more complex training is started, which involves the dominant uncertainties: Initial- and final-state radiation are simulated by additional weights from the original simulation, Jet energy scale uncertainties are modeled by shifting the input features, as discussed above, and the dataset is mixed with additional  $t\bar{t}W$  events. The loss of the network is defined such that it achieves the lowest uncertainty on the signal strength, effectively maximizing the sensitivity. Finally, the results are evaluated using COMBINE with the AnalyticAnomalousCoupling framework, to handle the potentially negative interference term. The Likelihood scan for "observed" data without BSM is shown in Figure 2. One can see a clear improvement over just using  $H_T$ , which shows the possible gain in sensitivity by exploiting all the available information, including angular features. The second thing to note is that the result is dominated by statistical uncertainties. For this reason it was interesting to project the sensitivity for higher luminosities, but it was found that the limits only decrease slowly with higher luminosities.

### 3 Toponium bound state

After the investigation into the 4 top sample was finished, the next step was to look into resonant top pair production directly. By simulating a model of a bound toponium state, a sample with a clear peak at the

top pair production threshold was produced. A variable with an almost perfect separation power to the SM  $t\bar{t}$  dataset simulated at NLO, is the invariant mass of the top pair on generator-level. While the model was only given reconstruction-level information, it still showed great performance, as seen in Figure 1a, if trained to differentiate both datasets. The challenging part came after defining a threshold region and only training on events with  $340 \text{ GeV} < m_{t\bar{t}} < 400 \text{ GeV}$  to see if the model is able to find energy-independent variables. The performance of the network degraded, but still outperformed a simple variable or a Boosted Decision Tree in separation power.

In an effort to reproduce the results from Ref. [1], the spin variables  $c_{\text{hel}}$  and  $c_{\text{han}}$  were created. The calculation on generator-level was rather straightforward, but in order to calculate the variables on reconstruction-level a kinematic reconstruction of the tops from their decay products and the missing energy is necessary. With the constraints,

1. that the invariant mass of the lepton and the neutrino should each sum to the W boson mass,
2. that the invariant mass of the lepton, the neutrino and the b jet should sum to the top mass
3. and that the sum of the neutrino momenta explains the entirety of the missing transverse momentum,

the 4-momenta of the tops and the neutrinos can be algebraically solved. Since it is not clear which jet comes from which b quark, all combinations are tried, and the one with the invariant mass of the lepton and b quark with the highest likelihood is taken. The likelihood for  $m_{\ell b}$  is determined from generator-level data on the  $t\bar{t}$  dataset. In order to account for the imprecision of the input values, and to increase the efficiency since sometimes the solutions are in the nonphysical regime, the energy and angle of the jets and leptons are smeared. The top and W mass for the constraints are also sampled from a Breit-Wigner distribution. The reconstruction step is repeated 100 times with the smeared inputs and the final solution is taken as the average of all 100 smeared solutions, weighted by their individual smeared  $m_{\ell b}$ -likelihoods.

As another option, an MLP for the reconstruction step was also investigated. Instead of solving for the 4-momenta as described above, a neural net is trained to predict the relevant quantities directly. The loss is defined as the MSE of the prediction, but with the limited time invested, no improvements were gained over the analytic approach.

Despite not including systematic uncertainties in this stage of the project, at least the statistical significance can be calculated. Figure 3 shows the significance as a function of cross-section for different variables. One can already see a high significance by merely using the number of events, a 2D histogram of the reconstructed  $m_{t\bar{t}}$  and  $c_{\text{hel}}$  or  $\Delta R_{\ell\ell}$ . But the MLP, trained on a cross-entropy loss achieves the highest confidence level, since it can effectively utilize all the available information.

## 4 Conclusion

This project showed that modern machine learning techniques are able to aid high energy physics research. The sensitivity to top-philic resonances in  $t\bar{t}t\bar{t}$  and  $t\bar{t}$  events can be increased, by using the network output as an optimal observable. The effective exploitation of angular features in addition to energy features proved itself useful for the investigation of open questions in particle physics.

## Acknowledgments

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## References

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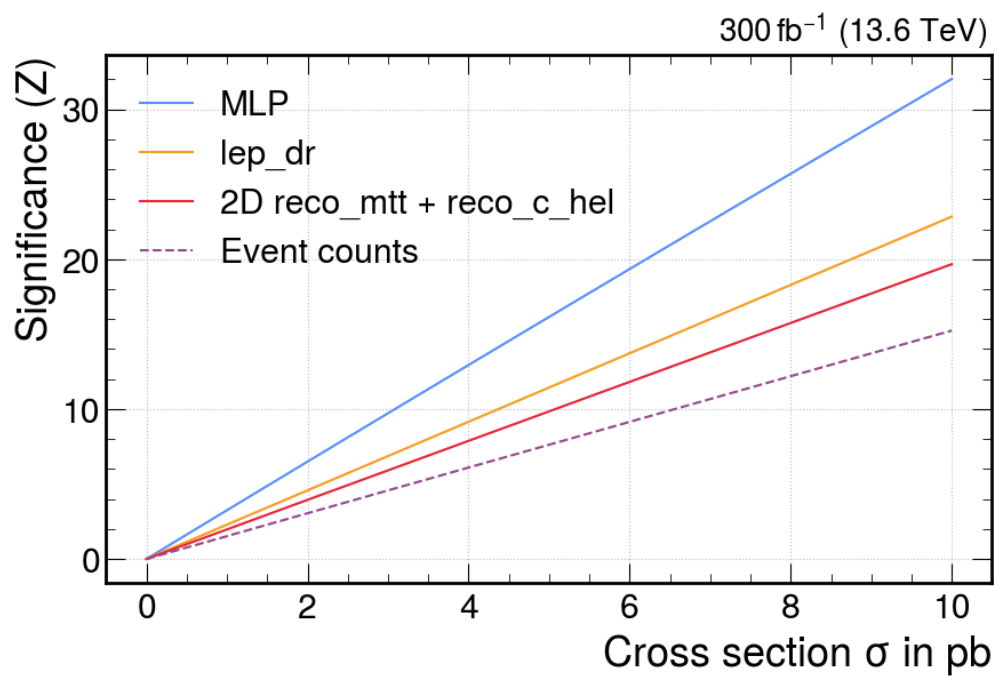


Figure 3: Sensitivity to toponium as a function of the cross-section. Shown are the curves based on the histogram from the MLP, from  $\Delta R_{\ell\ell}$ , from a 2D histogram of the reconstructed  $m_{tt}$  and  $c_{hel}$ , and just based on the difference in event counts