Reducing the effect of nominal background samples on signal sample systematics using an adversarial neural network in the tW dilepton channel

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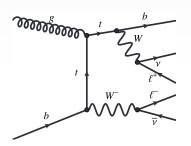


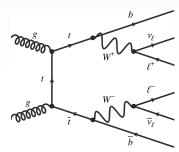


### Outline

- tW and  $t\bar{t}$  separation
- Artificial neural networks and adversarial neural networks as a possible solution
- Introduction to hyperparameters
- Preliminary training results for an adversarial neural network

# tW and tt separation





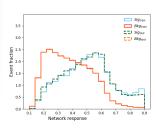
- Problem: Cross-sections of tW about 10 times smaller than  $t\bar{t}$
- Interference in NLO order
- ullet Instead of applying cut  $\longrightarrow$  Neural networks

# Setup of the classifier

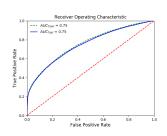
#### Hyper-parameter scan results

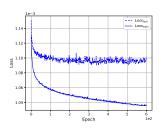
- Input: 14 variables motivated by a BDT variable scan.
- ullet Hidden layers: 6 elu layers imes 128 nodes each
- Output layer: 1 sigmoid node
- Optimisation: SGD, learning rate = 0.06, momentum = 0.3, no nesterov, no decay
- Duration: 600 epochs

# Simple network results



Separation







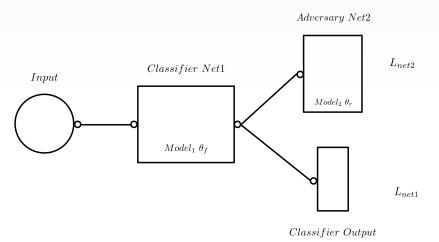
ROC curve

Losses

### Adversarial Neural Networks

- Neural networks have no info on systematic uncertainties
- Introduction of a second, adversarial network classifying between nominal and systematic
- Combined loss function  $\mathcal{L}_{adversarial}\left(\theta_f, \theta_t\right) = \mathcal{L}(\theta_f) \lambda \mathcal{L}(\theta_f, \theta_r)$
- Network 1: signal/background separation
- Network 2: nominal/systematic separation
- Expectation: network 1 succeeds, network 2 fails

# Setup of the ANN



## ANN

|       | Discriminator | Adversary |
|-------|---------------|-----------|
| tī    | 0             | 1         |
| tW DR | 1             | 1         |
| tW DS | 1             | 0         |

### ANN setup

### Discriminator setup

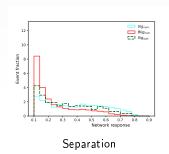
- Input: 14 variables motivated by a BDT variable scan.
- Hidden layers: 6 elu layers  $\times$  128 nodes each
- Output layer: 1 sigmoid node
- Optimisation: SGD, learning rate = 0.01, momentum = 0.3, no nesterov, no decay

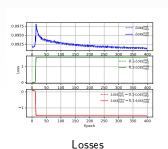
### Adversary setup

- Input: 14 variables motivated by a BDT variable scan.
- Hidden layers: 6 elu layers  $\times$  128 nodes each
- Output layer: 1 sigmoid node
- Optimisation: SGD, learning rate = 0.01, momentum = 0.3, no nesterov, no decay



### ANN results





- The separation is visibly bad.
- The agreement between nominal and systematics has barely improved
- Losses show bad behaviour

### Improvement plans

#### Assumption

Labelling  $t\bar{t}$  as a nominal sample results in a strong bias

#### Possible solution

- Randomly label tt events as either nominal or systematic
- Add additional weighting to the  $t\bar{t}$  sample for the adversarial network only
- ullet Exclude the  $t\bar{t}$  sample for the adversarial training completely

# Applied fixes

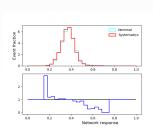
### Re-labelling

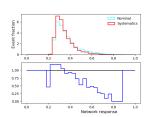
|       | Discriminator | Adversary      |
|-------|---------------|----------------|
| tī    | 0             | 1/0 (50 % mix) |
| tW DR | 1             | 1              |
| tW DS | 1             | 0              |

### Weighting tt for the adversary

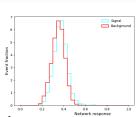
- Applying an additional weight to the  $\ensuremath{t\bar{t}}$  events for the adversarial training only
- Varied the weights between 0.0 and 1.0

# ttbar weights for the adversarial training

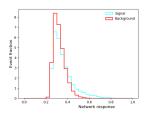




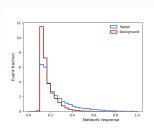


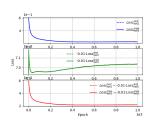


Weight = 1

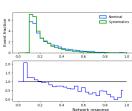


# ttbar weights for the adversarial training

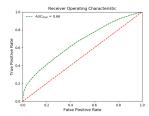




Weight = 0



Weight = 1



### Conclusions

### Improvements and insights

sdfw

### Weighting tt for the adversary

- Applying an additional weight to the  $t\bar{t}$  events for the adversarial training only
- Varied the weights between 0.0 and 1.0