Hyperparameter optimization of Adversarial Neural Networks in the tW dilepton channel using the ATLAS detector

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ATLAS EXPERIMENT

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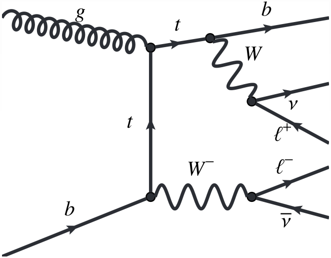
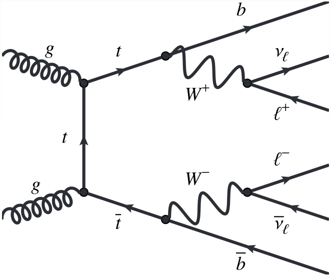
Outline

- 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 $t\bar{t}$ separation

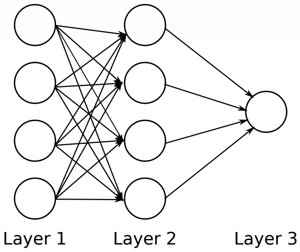




- Problem: Cross-sections of tW about 10 times smaller than $t\bar{t}$
- Interference in NLO order
- Instead of applying cut $\longrightarrow$ Neural networks

Neural Networks

- Built of layers of simple processors called nodes
- Each node is connected to each node in the previous and next layer
- Connection: linear function with a weight ω and a bias b and a non linear activation function σ
- Learning accomplished by backpropagation



Loss function and backpropagation

- Loss = performance estimation, deviation of the model from the truth tag

$$\mathcal{L} = -(y \log p + (1-y)\log(1-p))$$

- Backpropagation estimates the parameters' impact on the cost function using the partial derivatives

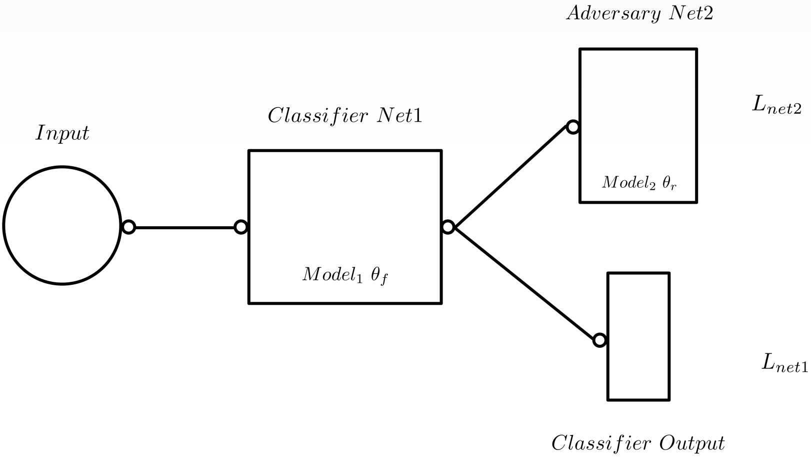
$$\frac{\partial \mathcal{L}}{\partial a_k^{L-1}} = \sum_{j=1}^{N} \frac{\partial z_j^L}{\partial a_k^{L-1}} \frac{\partial a_j^L}{\partial z_j^L} \frac{\partial C}{\partial a_j^L}$$

- Parameter update following negative gradient

Adversarial Neural Networks

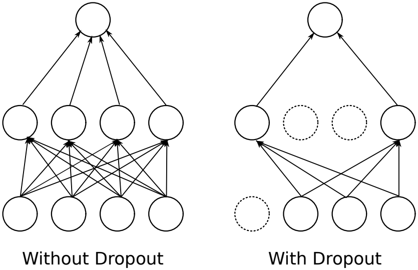
- Neural networks have no info on systematic uncertainties
- Introduction of a second, adversarial network classifying between nominal and systematic
- Combined loss function
  $\mathcal{L}_{adversarial}(\theta_f, \theta_t) = \mathcal{L}(\theta_f) - \mathcal{L}(\theta_f, \theta_r)$
- Network 1: signal/background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

Setup of the ANN

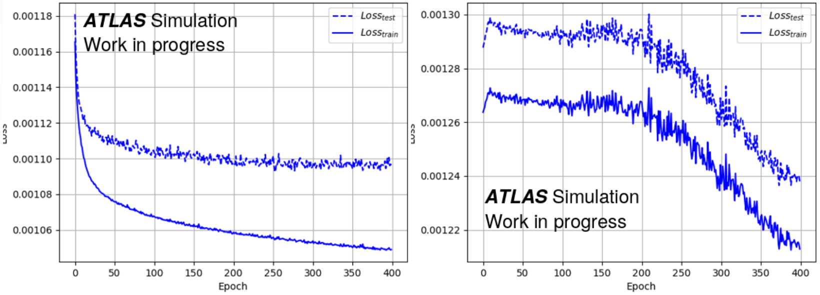


Dropout

- Long training and complicated architecture $\rightarrow$ focus on sub-dominant features or mask of the training set
- Removes a percentage of nodes for each training step
- Disincentives mask of the set or wrong features



Impact of dropout on the loss function



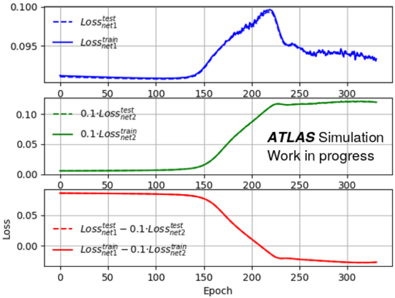
Loss curve for dropout = 0.1 Loss curve for dropout = 0.8

- For low dropout the training saturates fast
- High dropout makes the losses more linear as the training keeps on running

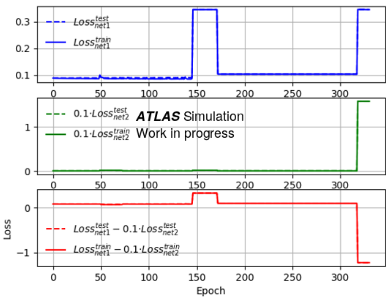
Optimisers

- Gradient based optimisation
  - for example SGD, stochastic gradient descent
  - updates based on negative gradient
  - Learning rate determines step-size
  - Step-size does not automatically decay
- Adaptive optimisation
  - for example Adam, adaptive momentum estimation
  - learning rate and other parameters get updated based on the past gradients

Results for switching from SGD to Adam



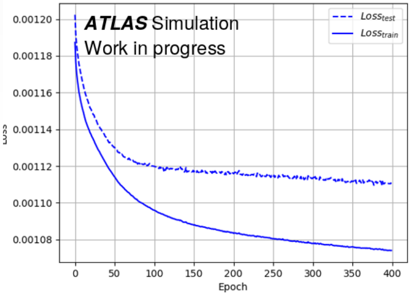
Loss curve using SGD



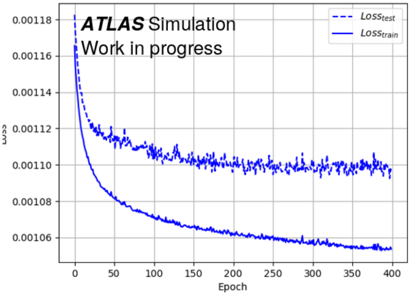
Loss curve using adam

- Default optimiser setup is definitely not always a good choice
- Also Adam sounds superior to SGD it is not easily interchangeable

Learning rate impact



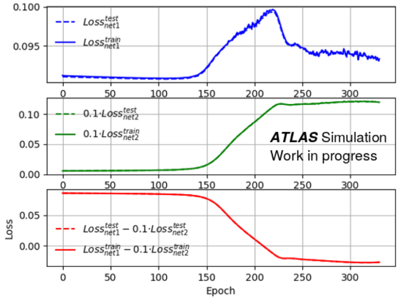
Using lr $= 0.02$



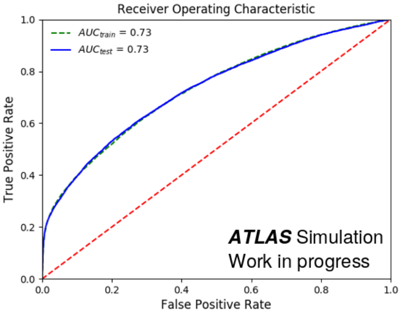
Using lr $= 0.1$

- High learning rate induces oscillations that might lead to missing a minimum
- A low learning rate makes the training converge very slowly

Losses and ROC curve for the adversarial training



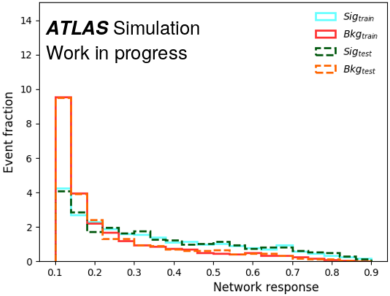
Loss curves, from top to bottom: Signal/background separation, nominal/systematics separation, combined losses



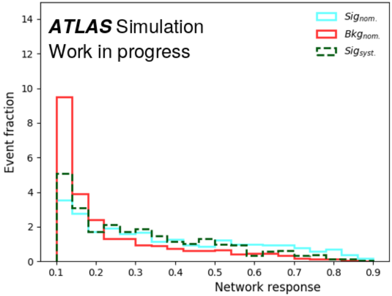
ROC curve

- Maximum for adversary is found
- Bad classififer training

Separation and Systematics



Separation



Nominal systematics agreement

- The separation is visible. Both networks train.
- Neither separation nor nom/sys agreement is very convincing

Conclusions

- Hyperparameters of optimisers and optimisers in general are not always a trivial problem
- The architecture and setup of the network have to be carefully tested and thought out for every problem
- Adversarial neural networks are a promising approach to limit the impact of problematic systematic uncertainties
- In this work the classifier cannot find a model that controls the systematics properly