

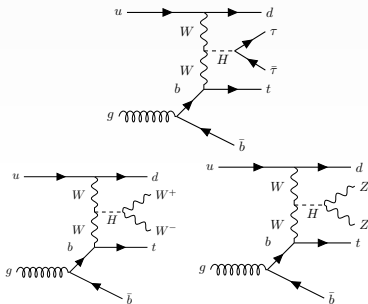
Neural network development in the analysis of single top-quark production in association with a Higgs boson and light-quark at ATLAS

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General ML selection



- n-jets: 2 (b-jets: 1)
- b-jet WP: 70 DL1r
- nLeptons & nTaus: $1e/\mu$ $2\tau_{had}$
- $E_{T,miss}$: no cut (to 800 GeV)

- jets:
 - $p_T > 35$ GeV
 - $|\eta| < 4.5$
 - EMPFlow
- electrons:
 - $p_T > 20$ GeV leading 27 GeV
 - $|\eta| < 2.5$ not in 1.37 - 1.52
 - WP: LooseAndBLayerLH ; isolation: no requirement
- muons:
 - $p_T > 20$ GeV leading 27 GeV
 - $0.01 < |\eta| < 2.5$
 - WP: Loose ; isolation: no requirement
- taus:
 - $p_T > 20$ GeV leading 27 GeV
 - $|\eta| < 2.5$ not in 1.37 - 1.52
 - WP: RNNLoose
 - ASG recommended OLR (τ_{had} remove jets)

Challenges

Handling of negative weights

- What is the origin of negative weights
- How do they affect neural networks
- How should they be handled

Weighting of background processes

- Dominating background can diminish the significance of secondary backgrounds in Training
- Adjust the network to handle several levels of background.

Accelerating network optimisation

- Exploration of new features is only possible in an optimised network
- To minimise the work of constant optimisation

Initial problems

Obstacles of optimisation processes

- Grid searches are both tedious and resource intensive
- Knowledge gained in one problem is rarely universal
- Experienced users can develop a bias towards certain hyperparameters

Applications in

- A neural network should be developed in parallel to an ongoing analysis.
- New additions need a new optimisation.

Training specifications

- Training a deep neural network
- Coarse optimisation using an evolutionary neural network
- Fine optimisation doing a grid search
- Optimised hyperparameters:
 - Number of nodes
 - Number of layers
 - Dropout percentage
 - Activation function
 - Weight initialisation
 - Optimiser
- Signal: tHq , tZq
- Background: Diboson, Z +jets, $t\bar{t}$ bar
- Using absolute weights

Evolutionary optimisation of neural networks

- Combination of a grid searches with a survival of the fittest setup
- Start with a number of random hyperparamters
- Evaluate the set of hyperparameters
- Create a a new set of networks based on the previous best
- Add recombination and variation to avoid local minima and bias

Setup

- tZq as signal against $t\bar{t}$ as background
- Using basic kinematic variables
- No specific region
- Training without weights due to some recent problems
- Testing: nodes, layers, dropout
- Fixed hyperparameters:
 - Optimizer: Adam
 - Activation: relu, sigmoid
 - Batchsize: 1000
 - Epochs: 25

An example of parameter development

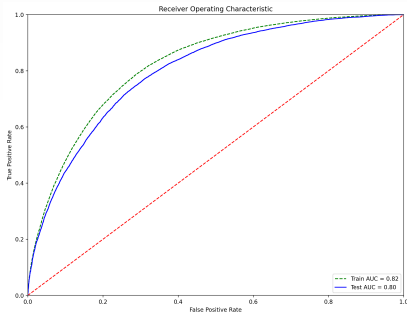
Initial parameters

- Layers: 1 – 10
- Nodes: 1 – 100
- Dropout: 0 – 1

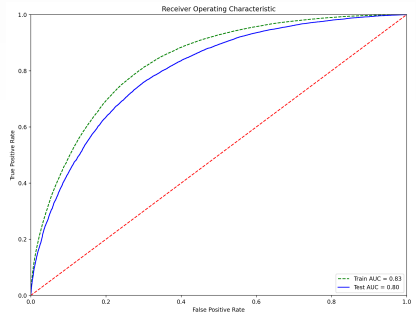
Final parameters

- Layers: 4 ± 2
- Nodes: 67 ± 33
- Dropout: 0.4 ± 0.3

Comparing to a grid search

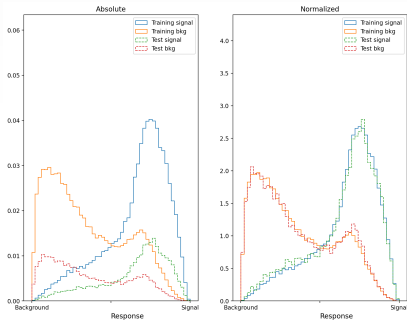


Grid search

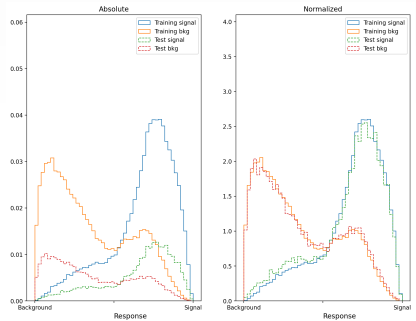


Evolutionary search

Comparing to a grid search



Grid search



Evolutionary search

Setup on baf

- Create a random set of hyperparameters
- Submit a job to baf for each configuration
- Use dagman to wait for the jobs to finish
- Evaluate the results and create the next set of configurations
- Anji's talk
- Confluence link

Setup

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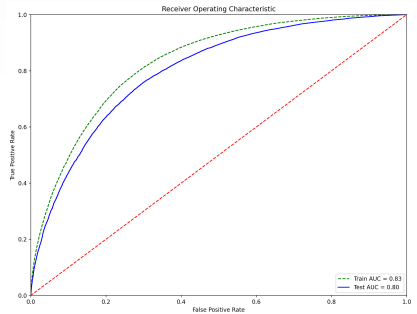
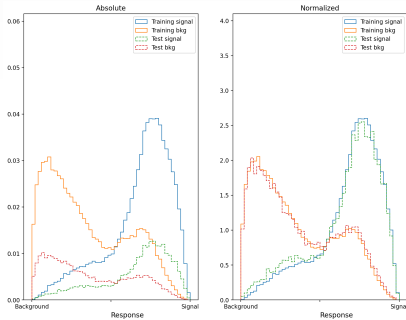
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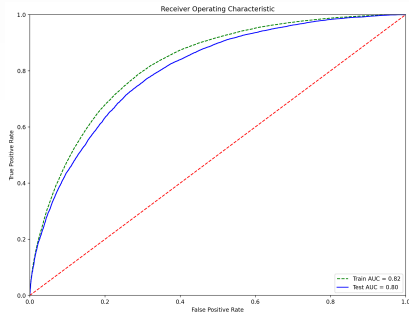
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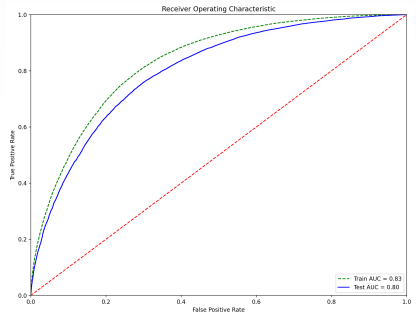
ROC and Separation



Comparing to a grid search

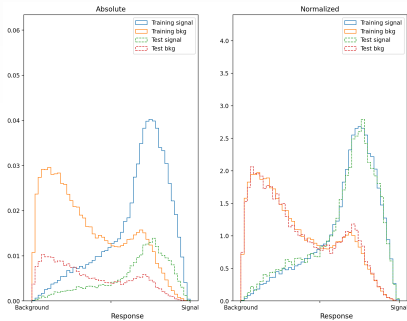


Grid search

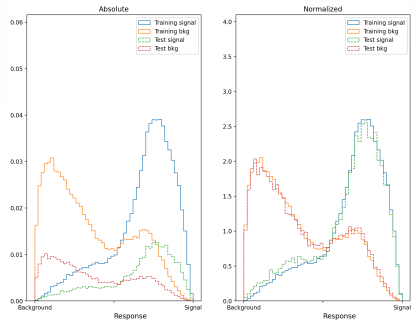


Evolutionary search

Comparing to a grid search



Grid search



Evolutionary search

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Conclusion

- Now is the time for intense testing. Can the network uphold its promises?
- There is a large number of features still to be implemented
- I have to test on a proper sample with weights and a good set of variables
- For now the code is running and shows the expected behaviour
- For a different option utilizing grid resources and ATLAS GPUs see this talk by Rui Zhang in the ATLAS ML Forum [Link](#)

Sources
