Hunting the Higgs with an Adversary

Stefan Katsarov

Supervisor: Liza Mijovic



Outline

- Standard model, LHC and ATLAS
- Higgs discovery and production
- Event classification with neural networks
- The study:
 - A problem with Higgs classification
 - ATLAS solution and my solution
 - Comparing the two results
- Summary

The Standard Model of particle physics

The standard model (SM) is the **most** complete theory we have of the universe

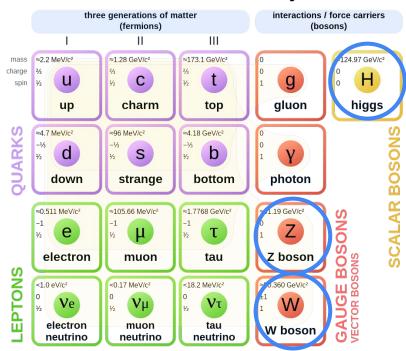
Describes the **electromagnetic**, **strong** and **weak** forces

Classifies all known elementary particles

Higgs boson was the last SM particle discovered

Will consider **Higgs boson** interaction with the **weak force** mediating **W and Z bosons**

Standard Model of Elementary Particles



The LHC and ATLAS

LHC is a 27 km ring accelerating protons to high energies

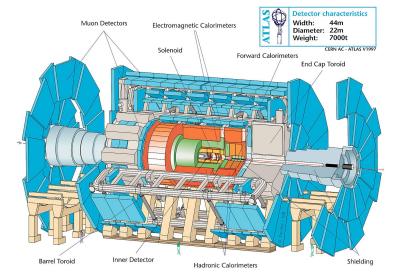
Collisions in middle of ATLAS detector

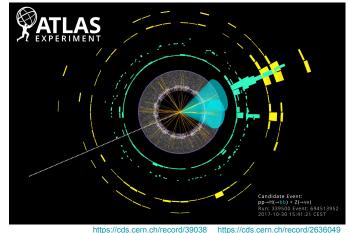
Energy can be converted to mass (E=mc²)

Spray new particles in all directions

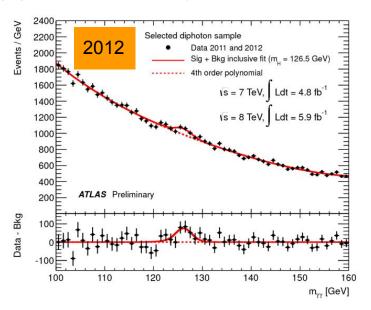
Background = boring

Signal = interesting



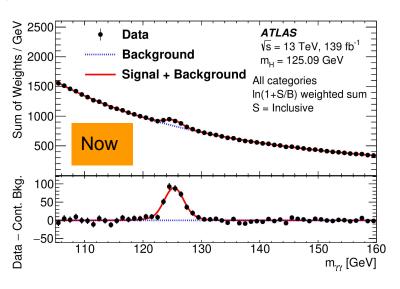


Higgs discovery: diphoton decay channel





Two well reconstructed photons, accurately measured kinematics



More data has greatly **reduced statistical uncertainty**

Significant contribution to current Higgs measurements

Vector-boson fusion Higgs motivation

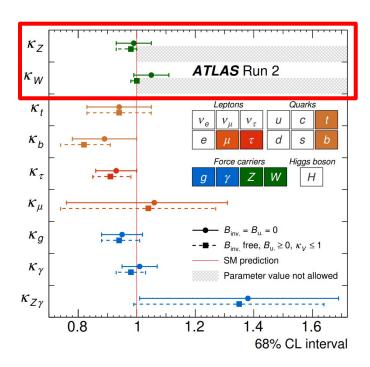
Higgs boson introduced in SM to give W and Z boson (vector-bosons) their masses

SM predicts **strict constraints** on Higgs to W and Z coupling strengths

Measuring these coupling strengths is a **powerful test for the SM**

Problem: A large uncertainty in Higgs to W and Z boson couplings

Solution: Improve classification of vector-boson fusion (VBF) Higgs events



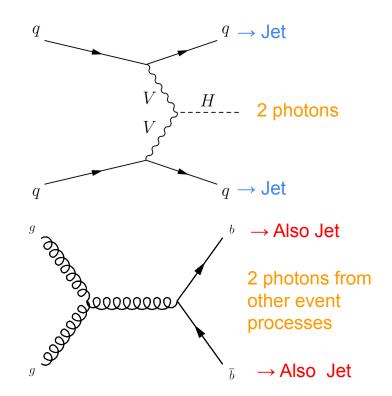
VBF Higgs production and background sources

Higgs produced via VBF 7% of the time

Clear detector signature

VBF forms two energetic jets

Background has many sources, can radiate VBF-like jets



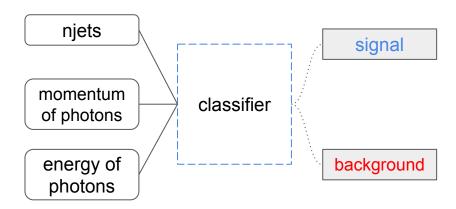
Classification using Neural Networks

Significantly improves classification over manual approach

Trains on simulated signal and background event features

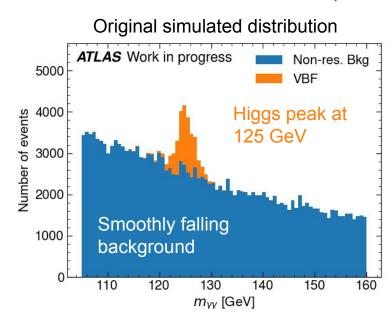
Learn patterns in input features by minimising a loss function

Can then predict if new events are signal

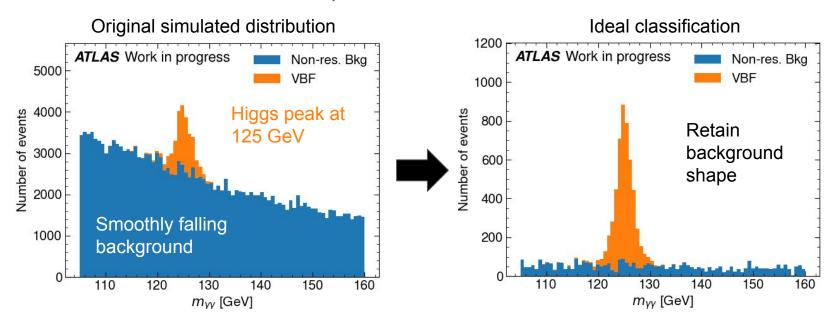


Study: A problem in classification between VBF Higgs and non-resonant background events

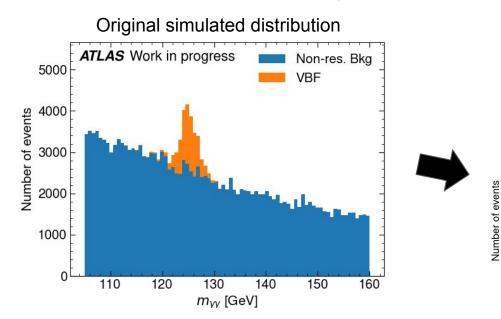
Signal and background obtained through simulated LHC collisions and ATLAS detector response

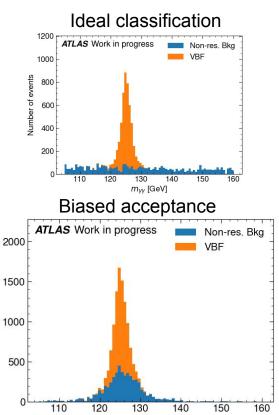


Signal and background obtained through simulated LHC collisions and ATLAS detector response



Signal and background obtained through simulated LHC collisions and ATLAS detector response





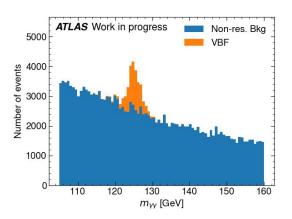
mw [GeV]

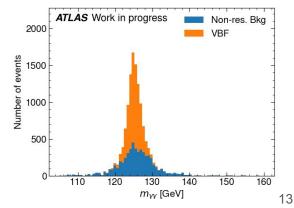
Problems:

Shape of accepted background distribution significantly distorted (background sculpting)

Introduces uncertainties in modelling of the background using non-signal regions

Leads to uncertainty in number of VBF events selected



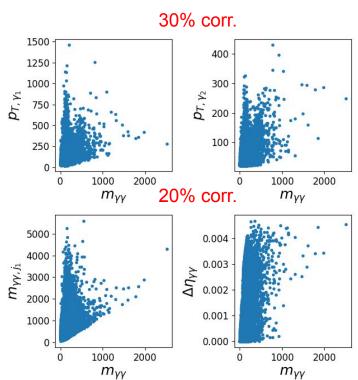


Why does background sculpting happen?

Reason: Many background features are **highly** correlated with the mass

Take the network's perspective:

- mγγ signal peak, background flat ⇒ very good classification variable
- Network indirectly learns mass of background
- Can then learn mass of signal
- Good performance = reject everything outside Higgs region, accept rest



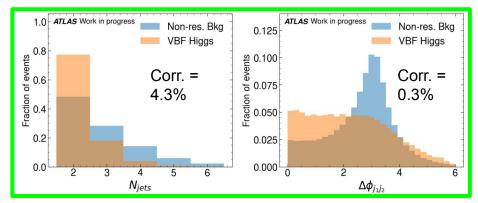
Performing mass de-correlation (ATLAS)

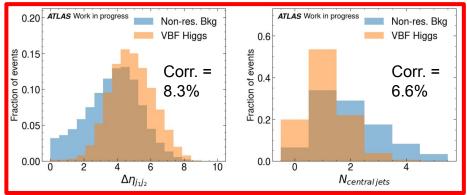
Current solution: Removing variables with mass correlation > 5%

No information left for classifier to learn mass

Problem: Only 1/3 of features left to train classifier

Limits classifier from learning differences between signal and background





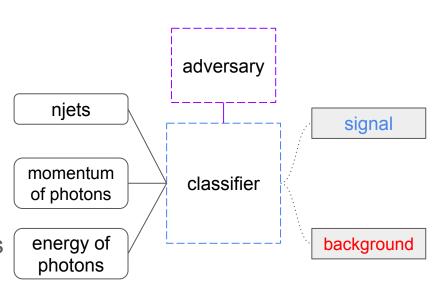
Performing mass de-correlation (This study)

Improved solution: Training the classifier by controlling training objectives

Include an **adversarial neural network** (ANN) to train with classifier

Monitor sculpting and regularise training by **modifying loss function**

Penalise the classifier if it learns the mass by increasing its loss function



Performance metrics

Discriminating power:

Background efficiency at 80% signal efficiency

Level of background sculpting:

- Measure entropy between original and accepted background distributions
- Jensen-Shannon divergence metric will be used
- Report entropy for inclusive region (105 GeV to 160 GeV) and Higgs region (121 GeV to 129 GeV)

Results with the ATLAS approach

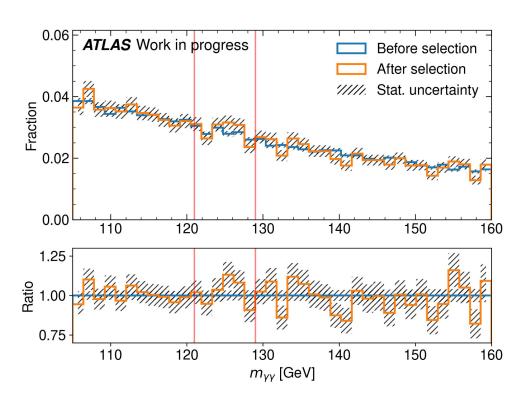
JSD inclusive = $7\pm4 \times 10^{-4}$

JSD Higgs = $3\pm3 \times 10^{-4}$

No visible background sculpting

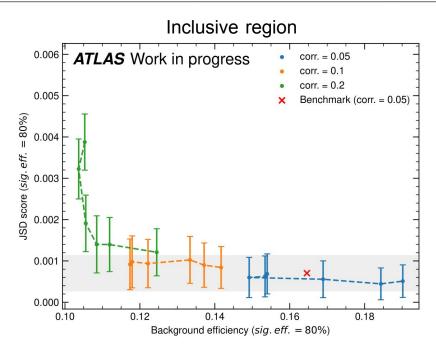
Background efficiency = **0.165 ±0.002**

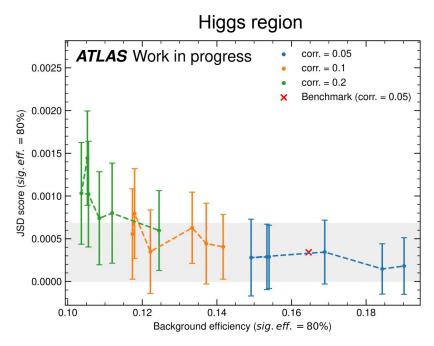
Will be used as a benchmark



Optimising the ANN

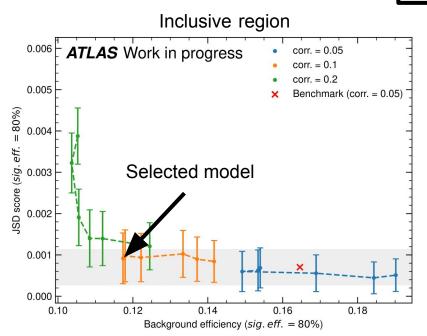
Parameter	Value	Selected value
Training set correlation	[0.05, 0.1, 0.2]	0.1
Regularisation strength	[0.1875, 0.375, 0.75, 1.5, 3, 6]	0.1875

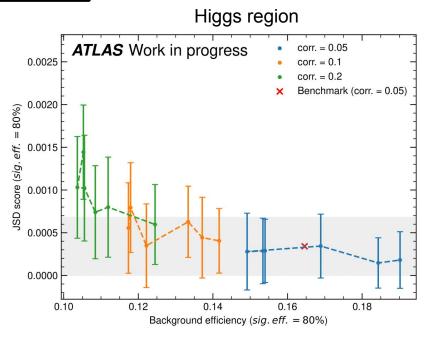




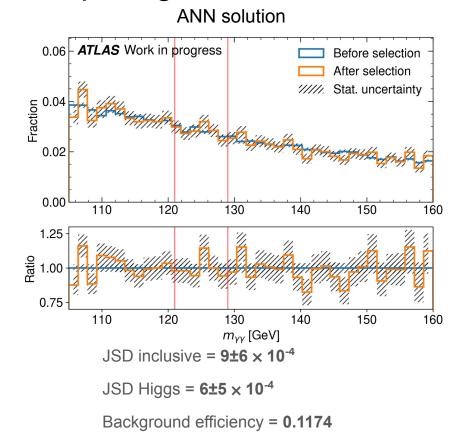
Optimising the ANN

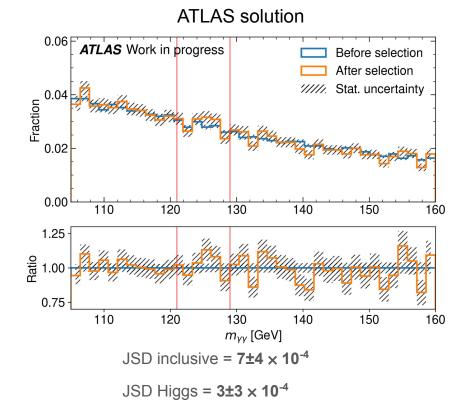
Parameter	Value	Selected value
Training set correlation	[0.05, 0.1, 0.2]	0.1
Regularisation strength	[0.1875, 0.375, 0.75, 1.5, 3, 6]	0.1875





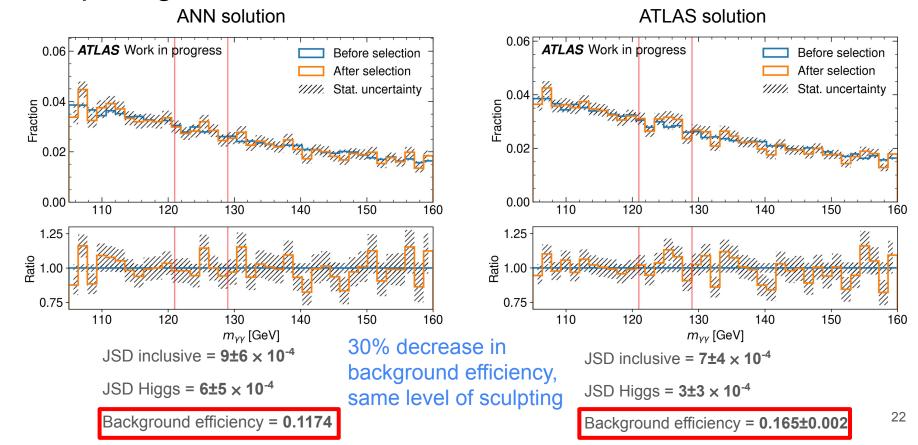
Comparing ANN with ATLAS solution





Background efficiency = 0.165±0.002

Comparing ANN with ATLAS solution



Summary

Diphoton channel currently makes a significant contribution to **Higgs** measurements

VBF Higgs measurements in the diphoton channel create a powerful test for the SM

Large VBF Higgs measurement uncertainties can arise in the diphoton channel from background sculpting due to mass correlation

Classifier training was modified by an adversarial network to penalise background sculpting

The ANN solution achieves 30% lower background efficiency over ATLAS solution at same level of sculpting

Back up