

# Multivariate Analysis Using an Artificial Neural Network to Improve Sensitivity in the ATLAS $t\bar{t}H$ ( $b\bar{b}$ ) Search

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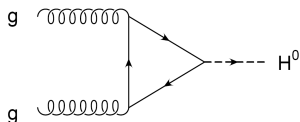


# Outline

- ① Introduction to  $t\bar{t}H$
- ② Event Categorisation
- ③ Multivariate Analysis
- ④ Results

# Motivation for $t\bar{t}H$

Higgs processes confirmed @LHC:



$$H \rightarrow \gamma\gamma$$

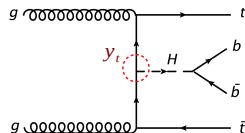
$$H \rightarrow ZZ^{(*)} \rightarrow 4l$$

$$H \rightarrow WW^{(*)} \rightarrow l\nu l\nu$$

$$H \rightarrow \tau\tau$$

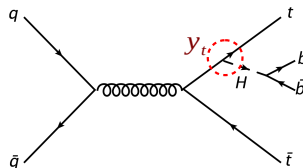
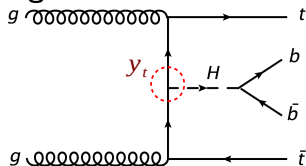
## Interesting: Yukawa coupling $q\bar{q}H$

- Not directly observed so far
- $t\bar{t}H$  ( $b\bar{b}$ ) is most probable:
  - $Y_t \propto m_t$
  - $\text{BR}(H \rightarrow b\bar{b})$  high
- Associate top production “proofs” coupling

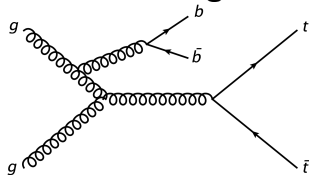


# Signal & Background

## Signal:



## Dominant background:



## Other backgrounds:

- $t\bar{t}V$
- non- $t\bar{t}$

# Outline

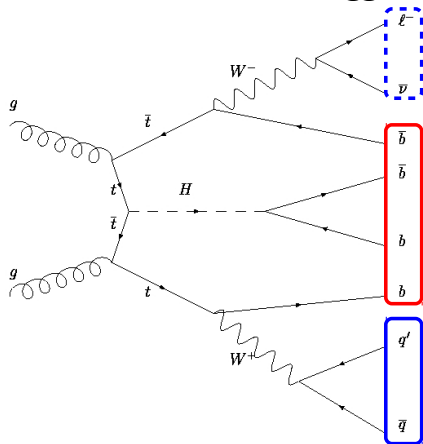
## ② Event Categorisation

Pre-Selection

Categorisation

# Basic Event Selection

Considerations: **Good to trigger & signal-like**



- Focus on **single-lepton** events:
    - $e/\mu$  with  $p_T > 25$  GeV
  - At least 4 *reconstructed jets*
  - At least 2 *reconstructed b-jets*
- 
- Classify events according to...
    - Number of **jets**
    - Number of **b-jets**

# Categorisation into Analysis Regions

Table: Nine analysis regions.

	2 b-jets	3 b-jets	$\geq 4$ b-jets
4 jets			
5 jets			rich
$\geq 6$ jets		rich	rich

## "Signal rich":

- $\frac{S}{B} > 1\%$
- $\frac{S}{\sqrt{B}} > 0.3$

## Remark:

- Technical definition of b-jet is ambiguous

## ③ Multivariate Analysis

Discriminating Variables

Motivation for Multivariate Analysis

Artificial Neural Network



# Discriminating Variables

Find differences between **signal** and **background**, possible discriminators:

## Event-shape variables

- Centrality
- Aplanarity
- ...

## Global event variables

- Scalar sum of the jets  $p_T$ s
- ...

## Object pair properties

- $\Delta R$  of jet pair with ...
  - ... largest  $\sum p_T$
  - ... largest invariant mass
- ...

There are  $\sim 20$  in the analysis. I'll only show two.

# High Transverse Momentum Jets (1)

## Definition

$$N_{40}^{\text{jet}} := N_{\text{jet}} (|p_T| > 40 \text{ GeV})$$

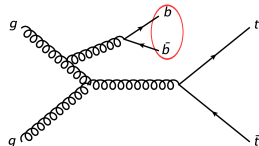
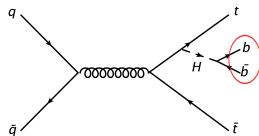
### Signal:

- Two b-jets from **higgs**  $\Rightarrow M_{b\bar{b}} = M_H$
- $|p_T|$  likely to be high

### Background:

- Two b-jets from **gluon**
- Gluon radiation tends to be “soft”
- $|p_T|$  likely to be lower

$\Rightarrow$  On average, signal has more high transverse momentum jets!



# High Transverse Momentum Jets (2)

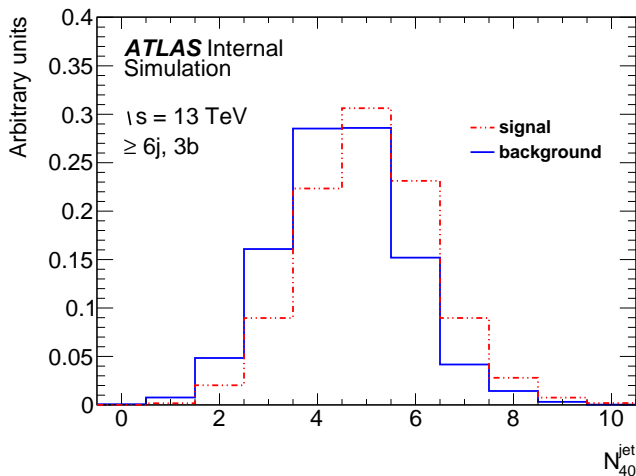


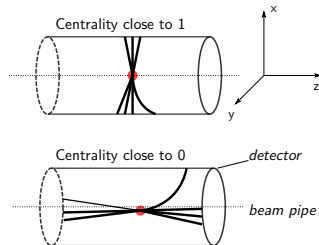
Figure:  $N_{40}^{\text{jet}}$  in the  $\geq 6$  jets 3 tight b-jets region.

# Centrality (1)

## Definition

$$\text{Centrality} := \frac{\sum_i |p_T^i|}{\sum_i E_i}$$

$i = \text{Jets, Leptons}$



- Signal:**

- $t\bar{t}H$  on-shell:  $\geq 475$  GeV
- High  $\hat{s}$  more likely for  $x_1 = x_2$  (Bjorken  $x$ )
- Less z-boosted  $\approx$  more central

- Background:**

- $t\bar{t}$  on shell:  $\geq 350$  GeV
- Lower  $\hat{s}$  are possible
- Possibly more z-boosted events

# Centrality (2)

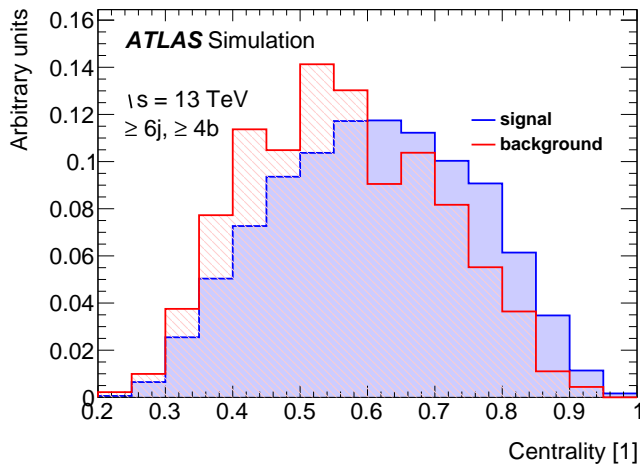


Figure: Centrality in the  $\geq 6$  jets  $\geq 4$  tight b-jets region.

# Motivation for Multivariate Analysis

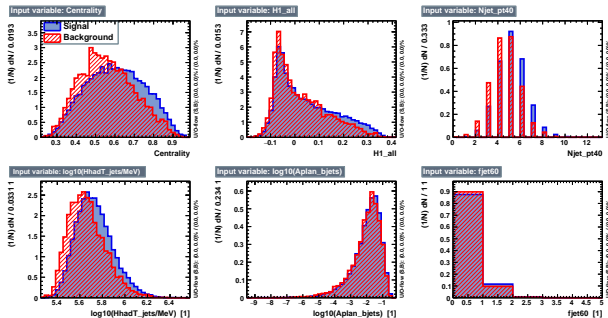


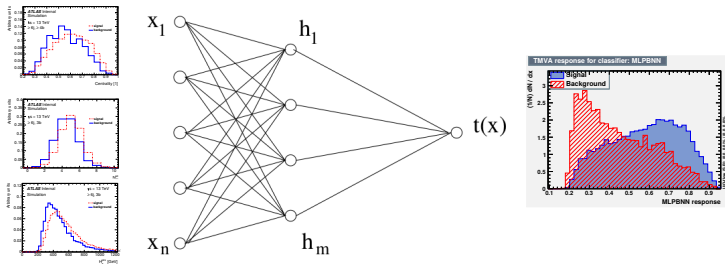
Figure: Some of the “better” variables.



Figure: Me when I look at them.

**Individual cuts won't do the job. Need more complex methods!**

# Artificial Neural Network



- Inspired by biology (i.e. the brain)
- Process information through Multilayer Network
  - Input layer: variables
  - “Hidden layer”: neurons
  - Output layer:  $t$
- **Parameters (“weights”)**  $\vec{w}$ : Strength of connections
- **Important:**  $t(\tilde{x})$  is non-linear in general!

# Artificial Neural Network - Training (simplified)

Define error function  $\epsilon$  for an input vector  $\vec{x}$ , e.g.

$$\epsilon(\vec{x}, \vec{w}) = (t(\vec{x}, \vec{w}) - \hat{t})^2$$

$$\hat{t}(\text{sig}) = 1$$

$$\hat{t}(\text{bkg}) = -1$$

Iterative training with Monte-Carlo samples:

- Start with random/guessed weights  $\vec{w}$
- Calculate error for training event
- Adjust weights  $\vec{w}$  to minimize  $\epsilon$  (i.e. backpropagation)



# Outline

## ④ Results

- Overview

- Neural Network training studies

- Sensitivity of ttH

# Overview of My Work

## Software:

- **TMVA** (4.2.1), comes with **ROOT** (6.04/02)
- Toolkit for **M**ulti**V**ariate **A**nalysis
- Set up a dedicated software tool to train & test ANNs

## Variables & training settings:

- Adapted from LHC run 1 analysis
- Started optimisation for run 2

## Impact on Sensitivity of ttH

- Calculated signal significance for estimated luminosity

# ANN with Variables and Settings of Run 1

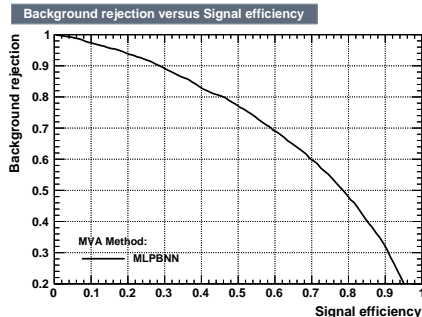
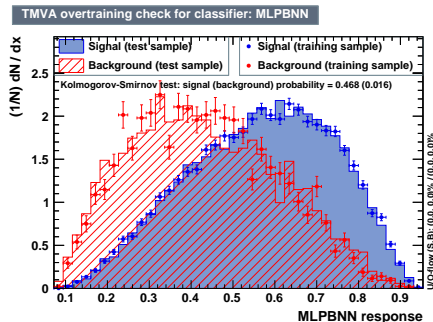


Figure: ANN output in the  $\geq 6$  jets 3 tight b-jets region.

**Receiver Operating Characteristic** := Curve on the right, showing how efficient different cuts are w.r.t. keeping signal and rejecting background.

# Signal Significance: Category + ANN

“New” category:  $\geq 6$  jets,  $\geq 3$  tight b-jets,  $\geq 4$  loose b-tags

- $\frac{S}{B} = 1.7\%$
- $\frac{S}{\sqrt{S+B}} = 0.9$

For a Luminosity of  $\mathcal{L} = 5 \text{ fb}^{-1}$ :

- Signal: 45 events
- Background: 2577 events

After applying optimal Neural Network cut:

- $\frac{S}{\sqrt{S+B}} = 1.0$

# Outlook

- Future analysis should include **all different background samples**
- ANN training with **more MC statistics**
- **New MVA variables** will possibly be added
- Inefficient: Cut on ANN output
- Better: **Likelihood fit** to ANN output distribution

Special thanks to my supervisors:

- **John Stakely Keller**
- **Judith Katzy**

Many thanks to the whole ATLAS group here at DESY!

**THANK YOU FOR YOUR ATTENTION!**

Questions?

## Appendix: Simulated Data

### Two Monte-Carlo samples

Type	Description	Generator	Events
$t\bar{t}$ (bkg.)	Semi-/dileptonic	Powheg+Pythia	$\sim 2$ million
$t\bar{t}H$ (sig.)	Inclusive higgs decay, semileptonic top decay	aMcAtNlo+Herwig++	$\sim 2$ million

- Minor bkg. contributions missing ( $t\bar{t}V$ , non- $t\bar{t}$ )
- Number of available events (after skimming):
  - Signal: ca. 400000
  - Background: ca. 450000



# Appendix: Pre-Selection Cuts

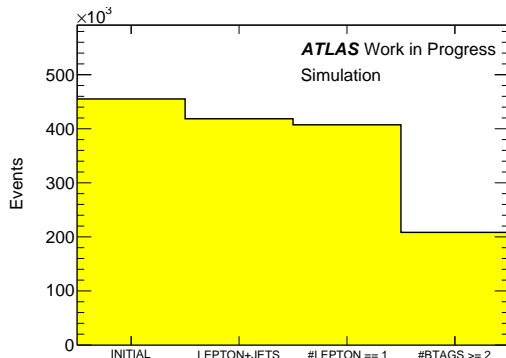


Figure: Cutflow of skimmed **bkg.** sample.

- $N_{\text{jets}} \geq 4$
- One lepton with  $|p_T| > 25 \text{ GeV}$
- Exactly one Lepton
- Require  $N_{\text{b-tags}} \geq 2$

# Appendix: Categories for ANN

## Reminder:

- Categorisation according to number of jets & number of b-jets
- Different b-tagging working points possible:
  - Loose: 85% efficiency
  - Tight: 77% efficiency

## Most promising regions:

- Good signal purity ( $\frac{S}{B} > 1\%$ ) & good signal significance ( $\frac{S}{\sqrt{B}} > 0.3$ )
- As many events as possible

## Raw MC events in examined categories

	old		new (Hyoyin)
	tight b-tags: 3	tight b-tags: $\geq 4$	tight b-tags: $\geq 3$ loose b-tags: $\geq 4$
$\geq 6$ jets	<b>sig:</b> $\sim 46000$ <b>bkg:</b> $\sim 7800$	<b>sig:</b> $\sim 22600$ <b>bkg:</b> $\sim 900$	<b>sig:</b> $\sim 35600$ <b>bkg:</b> $\sim 2300$

## Appendix: MVA in Formulas

- Each event (signal or background) has  $D$  measured variables  $\vec{x}$
- “Feature space” in  $\mathbb{R}^D$ :
  - $x_0 = \text{Centrality}$
  - $x_1 = N_{40}^{\text{jet}}$
  - ...

- Find mapping:

$$t(\vec{x}) : \mathbb{R}^D \longrightarrow \mathbb{R}$$

- $t$  is new “classifier”, desired properties:
  - Separation power, i. e.  $\langle t_{\text{sig}} \rangle \neq \langle t_{\text{bkg}} \rangle$  and  $\sigma_{t_{\text{sig}}}, \sigma_{t_{\text{bkg}}}$  small
  - Good generalization properties when applied to “unknown” events

# Appendix: Artificial Neural Network

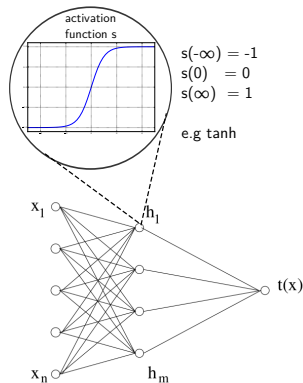
## Feed-Forward Network

$$h_i(\vec{x}) = s\left(w_{i0} + \sum_{i=1}^n w_{ij}x_i\right)$$

$$t(\vec{x}) = s\left(a_0 + \sum_{i=1}^n a_i h_i\right)$$

**ANN** as referred to in this talk:

- MLP architecture
- Feed-forward



**Figure:** MultiLayer Perceptron with one hidden layer.

# Appendix: ANN with Variables and Settings of Run 1

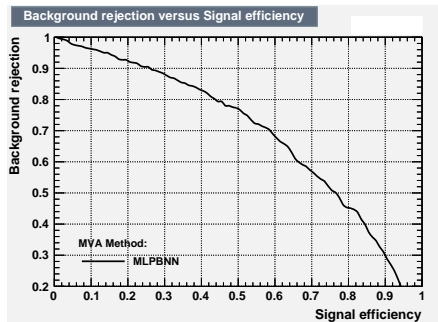
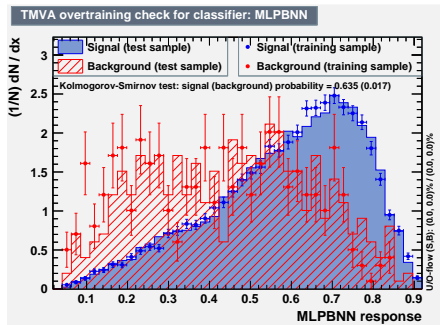


Figure: ANN output in the  $\geq 6$  jets  $\geq 4$  tight b-jets region.

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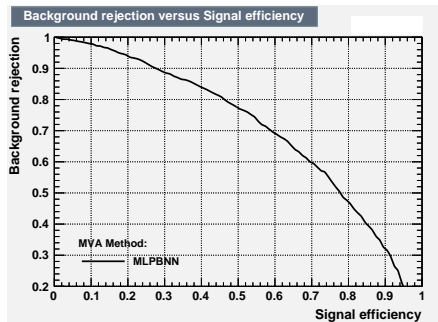
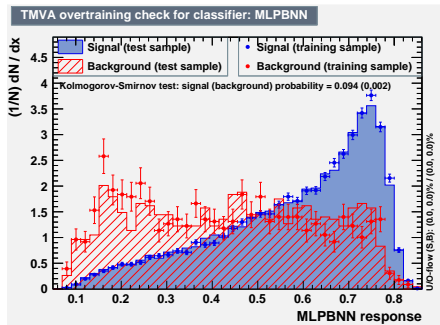


Figure: ANN output in the  $\geq 6$  jets  $\geq 3$  tight &  $\geq 4$  loose b-jets region.

# Appendix: Convergence of the ANN

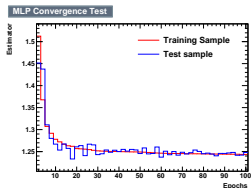


Figure: Error estimator vs. training cycles (6j 3b).

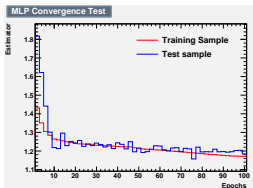


Figure: Error estimator vs. training cycles (6j 4b).

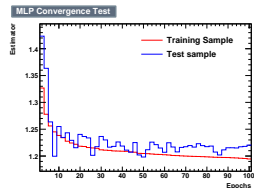
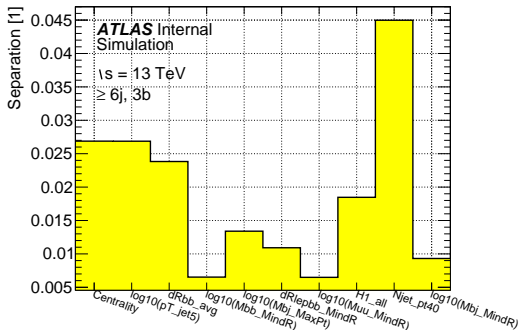


Figure: Error estimator vs. training cycles (6j 3/4b).

# Appendix: Ranking of Variables – Naive



**Figure:** Separation power of all variables used in the  $\geq 6$  jets 3 tight b-jets region.

Separation power of a discriminating variable  $\xi$ :

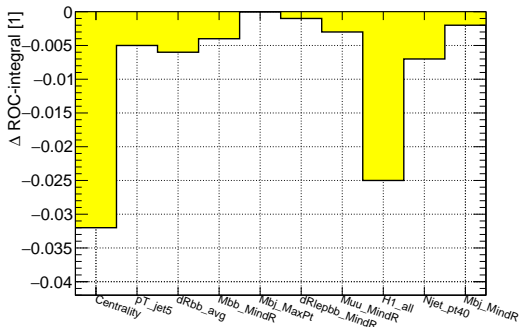
$$\int \frac{(N_{\text{sig}}(\xi) - N_{\text{bkg}}(\xi))^2}{(N_{\text{sig}}(\xi) + N_{\text{bkg}}(\xi))} d\xi$$

## Ranking

- 1  $N_{40}^{\text{jet}}$
- 2 Centrality
- 3  $p_T^{\text{jet5}}$
- 4 ...



# Appendix: Ranking of Variables



**Figure:** Separation power of all variables used in the  $\geq 6$  jets 3 tight b-jets region.

- Train ANN 10 times
- Each time, leave out one variable
- Check how quality of ANN “degrades”

## Ranking

- 1 Centrality
- 2  $H_1$  (Fox-Wolfram)
- 3  $N_{40}^{\text{jet}}$
- 4 ...

# Appendix: Ranking – Run 1 vs. Run 2 Simulation (6j3b)

## Run 1

- 1  $N_{40}^{\text{jet}}$
- 2 Centrality
- 3  $H_1$  (Fox-Wolfram moment)
- 4  $M_{bj}^{\min\Delta R}$
- 5  $\Delta R_{bb}^{\text{avg}}$
- 6  $p_T^{\text{jet5}}$
- 7  $M_{bj}^{\max p_T}$
- 8  $M_{uu}^{\min\Delta R}$
- 9  $\Delta R_{\text{lep}bb}^{\min\Delta R}$
- 10  $M_{bj}^{\min\Delta R}$

## Run 2 simulation

- 1 Centrality
- 2  $H_1$  (Fox-Wolfram moment)
- 3  $N_{40}^{\text{jet}}$
- 4  $\Delta R_{bb}^{\text{avg}}$
- 5  $p_T^{\text{jet5}}$
- 6  $M_{bb}^{\min\Delta R}$
- 7  $M_{bj}^{\max p_T}$
- 8  $\Delta R_{\text{lep}bb}^{\min\Delta R}$
- 9  $M_{bj}^{\min\Delta R}$
- 10  $M_{uu}^{\min\Delta R}$