Stop(Zh) Neural Networks!

A case study in 3rd generation SUSY searches using Machine Learning

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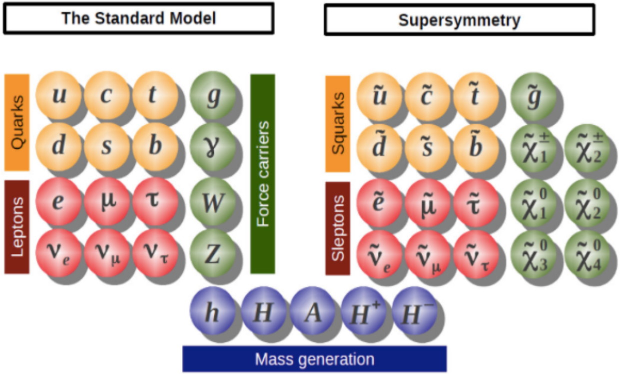
A bit of Context

A very short introduction on supersymmetry

Supersymmetry introduces a new set of particles coupling the "old" SM particles and the new hypothetical "SUSY" partners in the so-called **supermultiplets**.

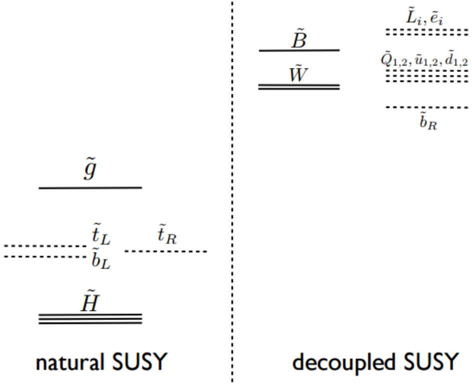
- Bosonic quark (**squarks**) and lepton (**sleptons**) partners
- Mixing of Gauge partners (Gauginos) in **Neutralinos** $\chi^0_{1,2,3,4}$ and **Charginos** $\chi^\pm_{1,2}$
- 5 Higgs bosons
- SUSY particles may have **very large masses** (above the reach of LHC)



Minimal MSSM discussion

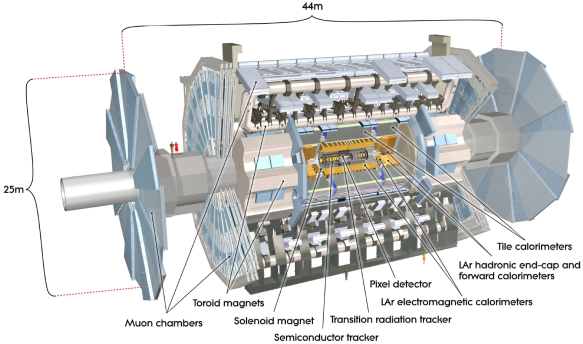
MSSM: Minimal extension of the current theory consistend with SUSY theory and observed phenomenology

- Lightest susy squark expected to be the top quark partner, the stop $\widetilde{t}$
- The super-partners of the top mix in two mass eigenstates, $\widetilde{t}_1$ and $\widetilde{t}_2$ (with $\widetilde{t}_1$ lighter by convention)
- Looking for direct pair production of stop1 and 2 using Z/h as "handles"
- Higgs boson expected to decay into two b quarks, originating b-jets



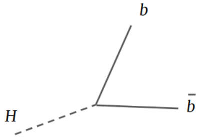
Experimental Context

The **ATLAS** detector at LHC



Data acquired in proton-proton collision at $\sqrt{s} =$ 13 TeV during 2015 - 2018 period

Higgs candidate reconstruction:



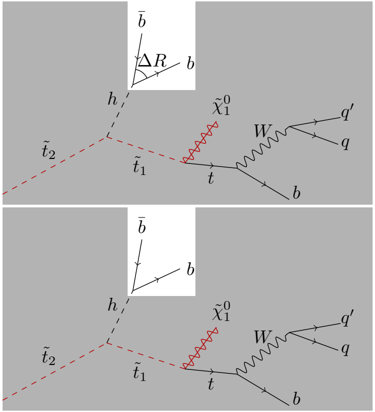
- Consider all the particle jets reconstructed as coming from the hadronization of b-quarks
- Look at all the possible combinations of two b-jets
- Find a way to discriminate which b-jet pair combination is most likely to come from the decay of Higgs

HTag: the idea

In 2018 we published a search for direct stop pair production and decay in Higgs

- Hard to reconstruct Higgs candidates starting from b-jet pairs
- Pair of b-jets with the highest combined p_T^{jj} or most collimated pair of b-jets?
- Cut on the combined invariant mass close to m_h? (introduces mass bias)
- Combining methods proved very inefficient due to low statistics

Kinematic properties of the candidates barely used. Need a way to reconstruct $h \to \bar{b}b$ without biases



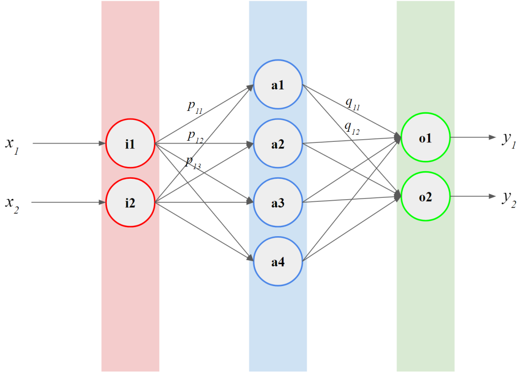
What about **Neural Networks**?

SIXTY SECONDS FOR THEORETICAL FOUNDATION OF NN

Neural Network: *Artificial Neurons* arranged in layers
Vector of inputs x_i transferred between layers; Connection between a Neuron on input layer and one on Hidden Layer is associated to weight w_{ij}
Each neuron produces an output signal described as:

$$S_j = f(\sum w_{ij} x_i + b_i) \tag{1}$$

where f(x) is the *Activation Function.*
Once information is transferred through all layers, we obtain a *prediction* (output)

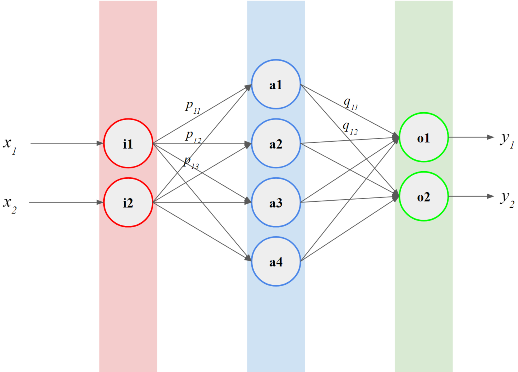


Sixty seconds for theoretical foundation of NN

Training: the value of the weights w_{ij} and biases gets iteratively adjusted multiple times (*epochs*) by comparing the Neural Network output to the expected output using a test sample of known composition. To prevent *overtraining*, a second sample (validation) is evaluated in parallel

Inference: the process of obtaining a prediction (output) from a trained neural network on an unknown dataset

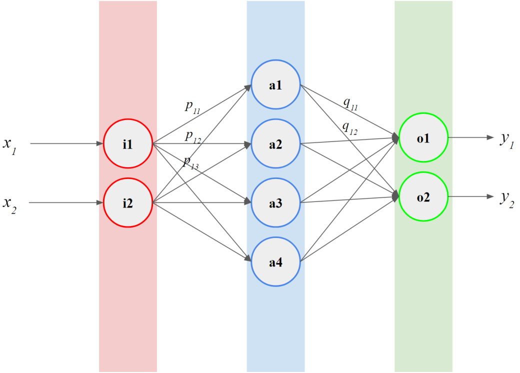
Training sample must be statistically independent yet similar to the dataset of interest



Yet another introductory slide on NN in HEP

Not quite the new kid on the block: been around since the '60, massive spike of uses during the last 10-20 years. Coming out right now from the Machine Learning Wild West.

- Regularize and rationalize use Machine Learning
- Parallelization and Deeper Networks (DNN)
- Explore new topologies
- Develop tools for easier implementation and User Experience



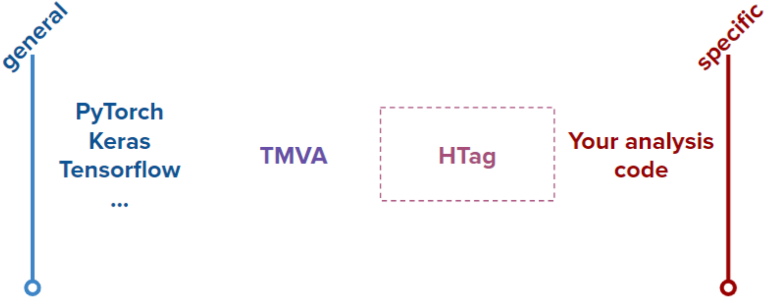
Neural Networks in HEP

Used in:

- Real-Time/Fast Trigger
- Detector Simulation
- Data Analysis

Widely used at different levels of complexity and expertise by the community

Essential for Machine Learning techniques to be effortless **implementable in our frameworks** and **easy to understand** for everyone in HEP without reinventing the wheel every time



Let's reconstruct some **Higgs** candidates!

HTag Neural Network

Goals

HTag is an Artificial Neural Network combinatorial solver framework for:

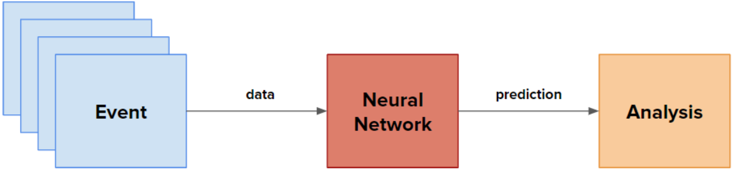
- Reconstruction of the H→ $b\bar{b}$ decay
- Goal is to improve reconstruction efficiency and reduce invariant mass bias with respect to traditional reconstruction methods
- **Training:** Implemented using **PyTorch 1.1.0**. Python-based library, providing tensor computation and strong GPU acceleration
- **Inference:** custom implementation in C++11/ROOT
- Evaluate combinations (jet-pairs), as opposed to event selection

HTag Neural Network

Data selection

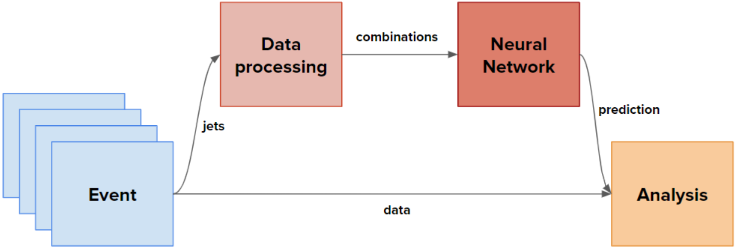
- **Event based selection:** NN makes predictions based on kinematic of the entire event

  Reconstructs **Processes**



- **HTag:** NN makes prediction based only on the kinematic of the jets

  Reconstructs **Higgs Candidates**



HTag Neural Network

Training samples

- MonteCarlo generated training sample enriched in signal with a 1:1 Signal-to-Background ratio
- Statistically independent validation sample used to prevent overtraining
- Order of jet combinations randomized each epoch

Training Sample:

- 600k combinations
- 50% jet pairs from $t\bar{t}$ sample (Background)
- 50% jet pairs from H selected in ttH fully hadronic sample (Signal)

Totally blind to SUSY!

Validation Sample:

- 400k combinations
- 50% jet pairs from $t\bar{t}$ sample (Background)
- 50% jet pairs from H selected in ttH semileptonic sample (Signal)

HTag Neural Network

Optimization

Each jet-pair classified with a **NN score** as Bkg (0) or Higgs (1)
Predictions confronted to truth-level origin of jets combination

Loss function: quantifies how well our prediction matches the target. Based on Binary Cross Entropy Loss (BCELoss) classifier

Optimizer: weight back-propagation optimized with Stochastic Gradient Descent (SGD) algorithm

$$w_j = w_j - LR\frac{\partial L}{\partial w_j}$$

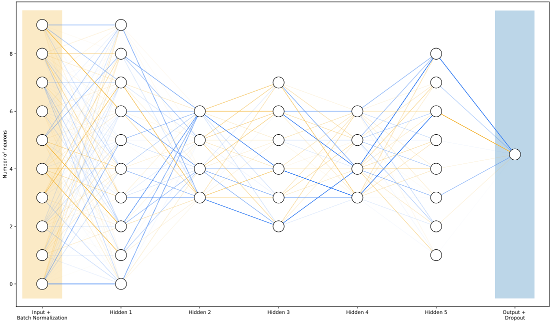
with a Learning Rate (LR) parameter of 0.005. For faster convergence, Nesterov Momentum (0.9) has been applied to the computation

HTag Neural Network

Input features

Model 5Lx10
5 Hidden Layers with 10 Features, 5 for each jet of the combination

- Reduced Momentum $\frac{p_T}{m^{jj}}$
- Jet η
- Jet ϕ
- Jet mass m
- Pseudo-Continuous b-tag score



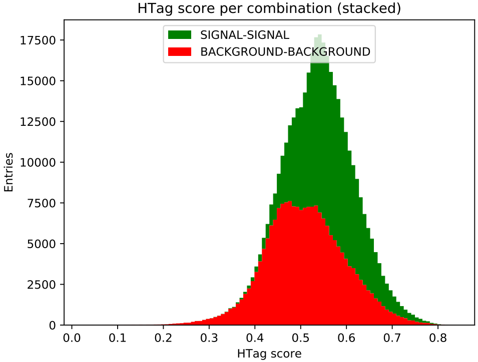
Pseudo-Continuous b-tag is a score (1 to 5) indicating different levels of tightness in the requirements for the identification of a jet as b-jet

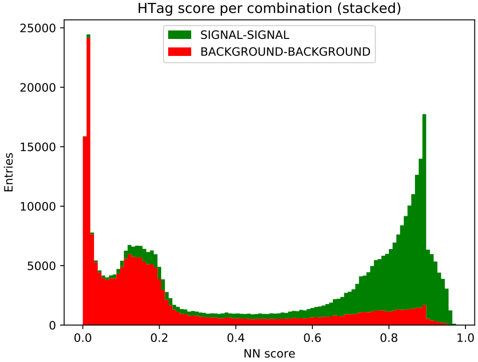
Ok, but does it **work**?

HTag Neural Network

Prediction evolution

Neural network prediction (*score*) for Validation Sample at **epoch 0** and **epoch 10**. Score distribution is classified based on the truth information.

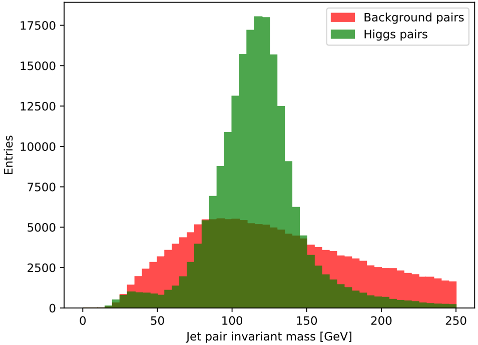




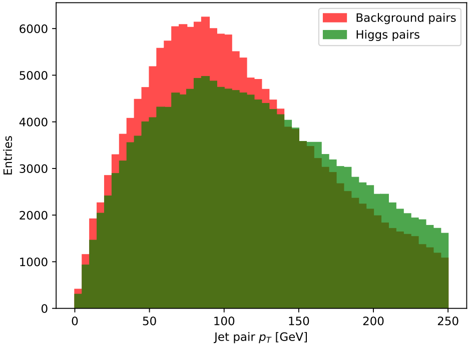
HTag Neural Network

Reconstructed kinematic quantities

Jet pair **invariant mass** m^{jj}



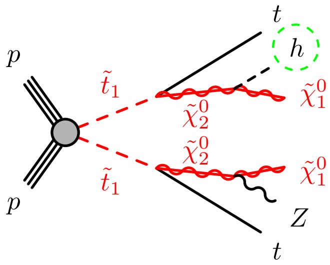
Jet pair **transverse momentum** p_T^{jj}



Introduction

Signal Models

Search for stop squark pair ($\tilde{t}_1\tilde{t}_1$) production in final states with Z or h boson:



$$\tilde{t}_1\tilde{t}_1 \rightarrow t\bar{t} + \tilde{\chi}_2^0\tilde{\chi}_2^0$$

$$\tilde{\chi}_2^0 \rightarrow Z/h + \tilde{\chi}_1^0$$

Two selections targeting different bosons:

StopH (multi-b):

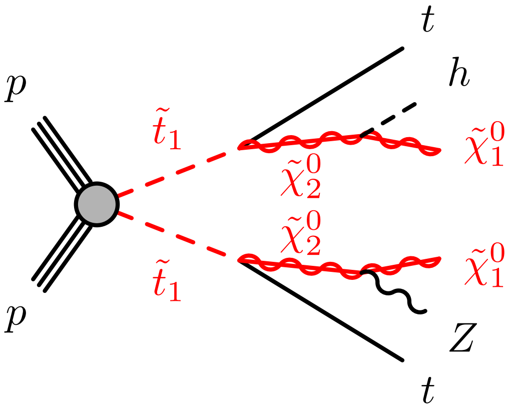
- $1\ell + 4$ b-jets
- $h \rightarrow b\bar{b}$

StopZ (multi-ℓ):

- $3\ell + 1$ b-jet
- $Z \rightarrow \ell^+\ell^-$

Signature

Multi-b selection



Final state:

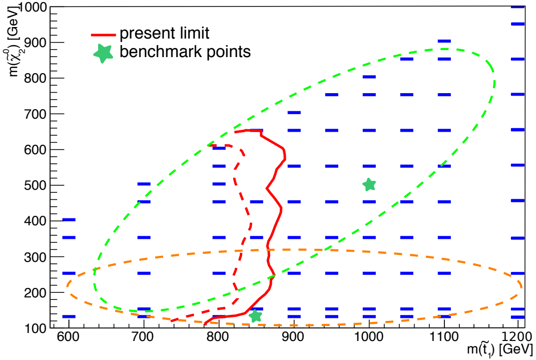
- 1 lepton (e, μ) from either one t or the other Z
- ≥ 4 b-jets
- high-jet multiplicity
- E_{T}^{miss} from Neutralinos, etc.
- $H \rightarrow b\bar{b}$ reconstructed with NN technique

Masses? Branching ratios?

StopZh analysis

Signal mass grid

- **Simplified model** containing only $\tilde{t}_1$
- $m_{\tilde{\chi}_1^0} = 0.5$ GeV
- BR of the $\tilde{t}_1$ decay is fixed to 50% in Z and 50% in Higgs.
- Present exclusion limits up to $m_{\tilde{t}_1} \approx 850$ GeV
- Benchmark points for search optimisation at different $m_{\tilde{\chi}_2^0}$
  SRL = low $\tilde{\chi}_2^0$ mass
  SRH = high $\tilde{\chi}_2^0$ mass
- Need some tight requirement to reconstruct events with Higgs!!!

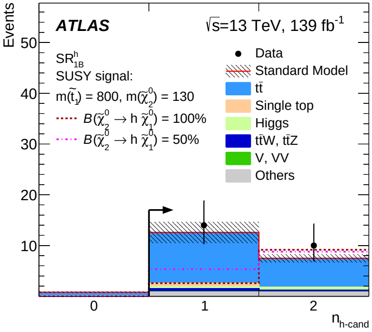


Selection strategy

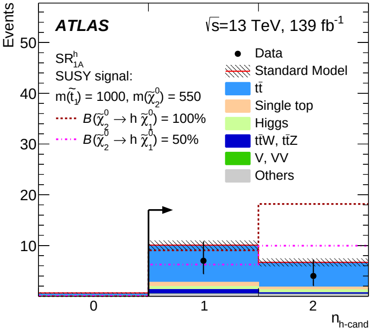
Higgs counting

In decays with many (> 1) Higgs bosons, the multiplicity of Higgs candidates passing a NN score selection can be a powerful discriminating variable (*Higgs counting*).

nHiggs^{SRL}(score > 0.7)



nHiggs^{SRH}(score > 0.7)



Selection strategy

Discovery Signal Regions

SR optimisation done scanning a set of discriminant variables, assuming a 30% systematic uncertainty on the expected SM backgrounds and aiming at maximising the discovery sensitivity

Definition	SRL	SRH
Number of leptons ($p_T > 4$ GeV)	1	
obj. E_{T}^{miss} sig	> 7	> 12
Number of jets ($p_T > 60$ GeV)	≥ 6	≥ 4
Number of b-jets ($p_T > 30$ GeV)	≥ 4	
m_T [GeV]	> 150	
Number of Higgs (**NN score** > 0.7)	≥ 1	

$$m_T \equiv \sqrt{2\ p_T\ E_T^{miss}(1 - cos(\Delta\phi_{p_T, E_T^{miss}}))}$$

Object-based E_{T}^{miss}-significance discriminates events where the E_{T}^{miss} is due to invisible particles in the final state

Fit Results

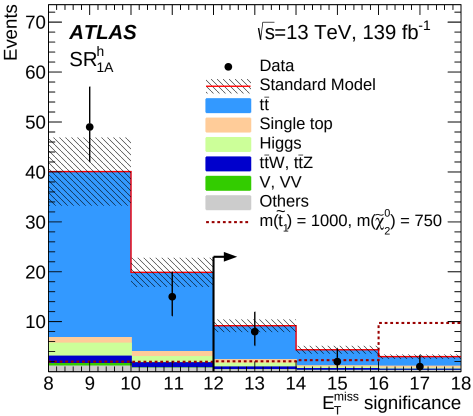
Results

Discovery Signal Regions

Analysis performed using proton-proton collision data at $\sqrt{s} = 13$ TeV collected by the ATLAS experiment during the LHC Run-2 (integrated luminosity of 139 fb^{-1}).

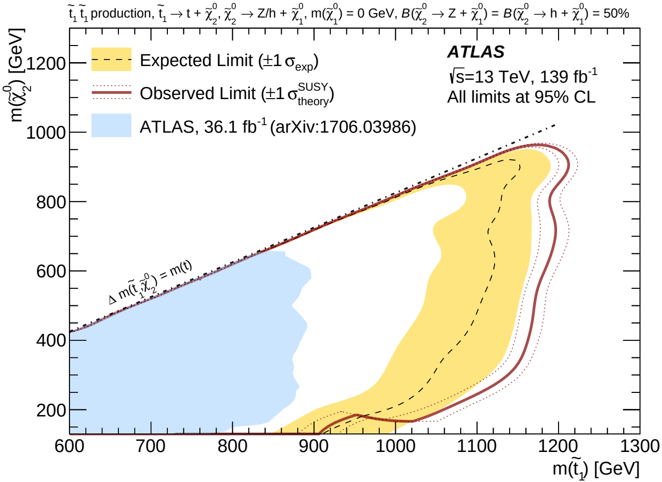
Expected and observed events in discovery SRs. Errors quoted include all the uncertainties.

	SRH	SRL
Observed events	11	24
Fitted bkg events	16.54 ± 3.14	19.48 ± 4.99



- StopZ and StopH designed to perform statistical combination
- Limits on the $\tilde{t}_1$ model obtained from the **best expected combination** of the StopZ and StopH likelihoods

Best expected combination



Conclusions

- HTag NN is a suitable option as $h \to b\bar{b}$ finding algorithm, with potential in a wide variety of scenarios, not bound to SUSY
- Higgs multiplicity from Neural Network is a powerful discriminant
- Search for new physics in final states with 1 lepton, high jet and b-jet multiplicities, and E_{T}^{miss} using the full ATLAS Run 2 dataset found in **agreement with SM predictions**
- Limits have been **statistically combined** with a search for new physics in $\tilde{\chi}_2^0$ decaying into Z to increase the exclusion reach
- Results put **limits** up to ∼1100 GeV on $\tilde{t}_1$ masses with $\tilde{\chi}_2^0$ decaying in h with 50% BR
- Paper went Public Today on arXiv!: *Search for top squarks in events with a Higgs or Z boson using 139 fb-1 of pp collision data at $\sqrt{s}$=13 TeV with the ATLAS detector*

Where do we go from **here**?

HTag

Future developments and ideas

- **Portability:** the code needs to become easier to share among different analyses and groups
- **Understand the backgrounds:** a second NN can be created and used as *Adversarial Neural Network*; one NN reconstructs the likelihood of a combination being a Higgs, while the other the likelihood of it coming from the background
- **More flexibility in the classification:** use of multi-level discrimination to reconstruct likelihood of different processes

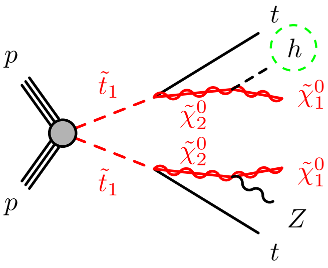

THANKS
FOR YOUR ATTENTION
quickmeme.com

Backup

Introduction

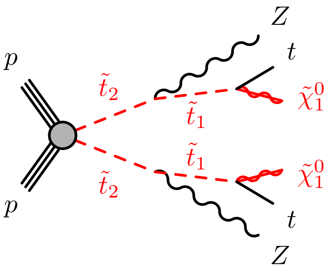
Signal Models

Search for stop squark pair ($\tilde{t}_x\tilde{t}_x$) production in final states with Z or h boson:



$$\tilde{t}_1\tilde{t}_1 \rightarrow t\bar{t} + \tilde{\chi}_2^0\tilde{\chi}_2^0$$

$$\tilde{\chi}_2^0 \rightarrow Z/h + \tilde{\chi}_1^0$$



$$\tilde{t}_2\tilde{t}_2 \rightarrow \tilde{t}_1\tilde{t}_1 + ZZ$$

$$\tilde{t}_1 \rightarrow t + \tilde{\chi}_1^0$$

Two selections targeting different bosons:

StopH (multi-b):

- $1\ell + 4$ b-jets
- $h \rightarrow b\bar{b}$

StopZ (multi-ℓ):

- $3\ell + 1$ b-jet
- $Z \rightarrow \ell^+\ell^-$

HTag Neural Network

Model initialization

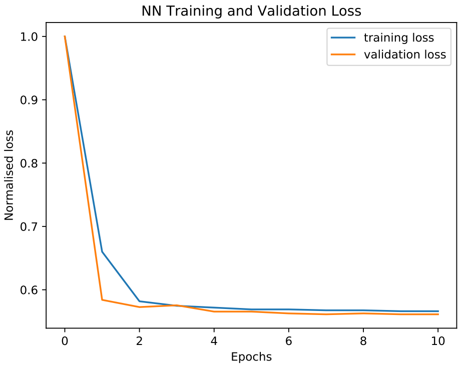
- Feed Forward Linear NN initialized with **Kaiming weight initialization** to prevent saturation of input neurons
- Input and Hidden layers based on **Leaky ReLU** activation function
- Output layer prediction obtained by a **Sigmoid** activation function
- **Dropout** layer (20%) to prevent overfitting (*"Learn less to learn better!"*)

HTag Neural Network

Batching

Evolution of training and validation losses as a function of the epoch evaluated respectively on the Training Sample and Validation Sample

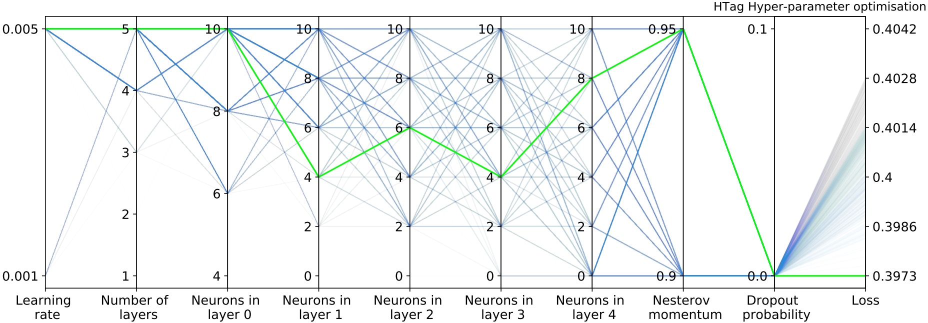
- Input layer act as a **batch normalization** layer: prevent "big variables"(pT, mass) to eclipse smaller ones (eta, phi)
- Data split in **batches** of 256 combinations each for faster convergence
- Training now takes 10 minutes on a laptop CPU instead of 3 hours on GPU farm



HTag Neural Network

Hyperparameter Optimization

Scan over the NN parameters minimizing the Loss to determine the best set of parameters (sim250k parameter combinations tested)



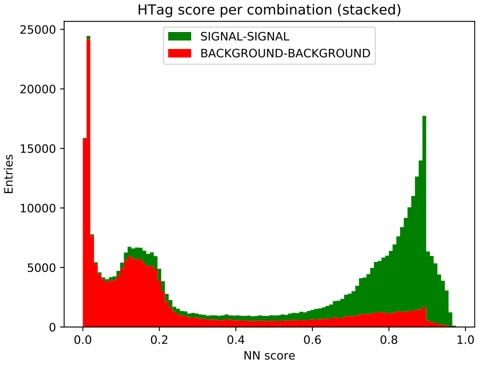
HTag Neural Network

Reconstruction efficiency

HTag is trained on SM Higgs samples, no SUSY sample used in the process.

Reconstruction efficiency for events with ≥ 2 b-jets passing score ≥ 0.7 selection:

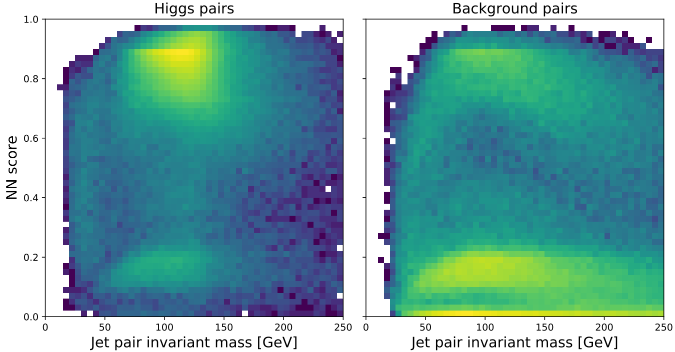
- $\epsilon_{t\bar{t}h}^{0.7} = 0.78$
- $\epsilon_{susy\ sig}^{0.7} = 0.54$ (grid average)
- $\epsilon_{bkg}^{0.7} = 0.13$



HTag Neural Network

Reconstructed Di-Jet mass distribution

Distribution of the NN score as a function of the jet pair invariant mass in Validation Sample



Training selected as the least correlated with the di-jet invariant mass between the best performing solutions.

In an unbiased m^{jj} distribution, the sidebands around the Higgs peak could be used to aid the background estimation

Background estimation

Composition

Main **backgrounds** are the processes with high b-jet multiplicity:

- $t\bar{t}$ ($> 70\%$)
- Single top
- Mixed Higgses production modes
- VV (including $Z{+}jets$ and $W{+}jets$)
- Others (minor contributions from rare top processes)

$t\bar{t}$ background normalisation determined with data-driven fit in dedicated CR. Other backgrounds determined from MC simulations due to low yield after selections are applied.

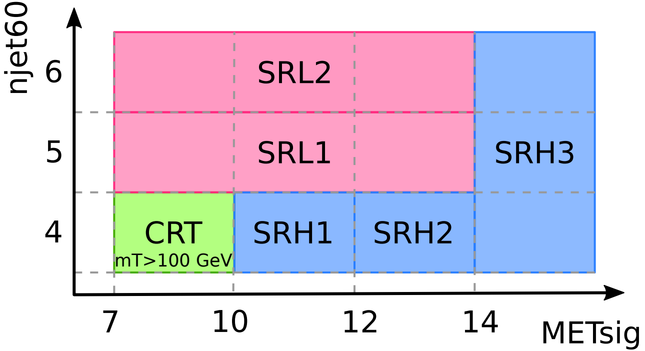
$$N^{obs}(CR) = \mu_{t\bar{t}} N^{MC}_{t\bar{t}}(CR) + N^{MC}_{Singletop}(CR) + N^{MC}_{VV}(CR) + N^{MC}_{MixedHiggses}(CR) + N^{MC}_{Others}(CR)$$

Control region $t\bar{t}$

CRT

Summary of selection criteria for the $t\bar{t}$ CR and comparison with the SR selections. The cuts on the METsig and on the number of jets reported is the minimum cut applied in the binned version of the SRs.

	CR
Num of leptons	1
obj. E_{T}^{miss} sig	$(7, 10]$
Num jets (p_T >60 GeV)	$== 4$
Num b-jets (p_T >30 GeV)	≥ 4
m_T [GeV]	> 100
Num Higgs (score > 0.7)	≥ 0



Control region $t\bar{t}$ Yield

$\mu_{t\bar{t}} = 1.09 \pm 0.13$	CRT
Observed events	119
Fitted bkg events	118.93 ± 10.90
Fitted ttbar events	104.93 ± 10.93
Fitted VandVV events	0.60 ± 0.04
Fitted ttV events	2.99 ± 0.18
Fitted MixedHiggses events	5.10 ± 0.31
Fitted singletop events	4.58 ± 0.28
Fitted Others events	0.73 ± 0.04
MC exp. SM events	109.82 ± 6.71
MC exp. ttbar events	95.82 ± 5.86
MC exp. VandVV events	0.60 ± 0.04
MC exp. ttV events	2.99 ± 0.18
MC exp. MixedHiggses events	5.10 ± 0.31
MC exp. singletop events	4.58 ± 0.28
MC exp. Others events	0.73 ± 0.04

Selection strategy

Discovery Signal Regions Yields

	SRL	SRH
MC exp. T1T1_onestepN2N2_800_130 events	14.12 ± 0.00	8.86 ± 0.00
MC exp. T1T1_onestepN2N2_1000_550 events	13.53 ± 0.00	16.22 ± 0.00
MC exp. SM events	15.49 ± 2.53	18.15 ± 4.43
MC exp. ttbar events	11.04 ± 2.44	13.91 ± 3.89
MC exp. VandVV events	$0.05^{+0.05}_{-0.05}$	0.13 ± 0.08
MC exp. ttV events	1.15 ± 0.26	0.95 ± 0.25
MC exp. MixedHiggses events	1.19 ± 0.21	0.88 ± 0.44
MC exp. singletop events	1.38 ± 0.23	0.74 ± 0.22
MC exp. Others events	0.68 ± 0.13	1.53 ± 0.32

Yield tables

Binned SRL Regions

Expected and observed events in the binned version of SRL. Errors quoted include all the uncertainties

	SRL1A	SRL1B	SRL2A	SRL2B
Observed events	19	9	14	9
Fitted bkg events	19.29 ± 5.72	9.44 ± 2.51	11.13 ± 4.06	6.68 ± 1.86
Fitted ttbar events	16.64 ± 5.52	7.26 ± 2.40	9.04 ± 3.74	5.12 ± 1.81
Fitted VandVV events	$0.14^{+0.26}_{-0.14}$	0.00 ± 0.00	0.07 ± 0.04	0.05 ± 0.04
Fitted ttV events	0.76 ± 0.35	0.36 ± 0.09	0.53 ± 0.24	0.29 ± 0.18
Fitted MixedHiggses events	0.99 ± 0.29	0.98 ± 0.22	0.36 ± 0.19	0.48 ± 0.26
Fitted singletop events	0.26 ± 0.14	0.48 ± 0.07	0.47 ± 0.18	$0.04^{+0.08}_{-0.04}$
Fitted Others events	0.49 ± 0.10	0.36 ± 0.08	0.67 ± 0.16	0.70 ± 0.16
MC exp. SM events	17.84 ± 5.06	8.81 ± 2.24	10.35 ± 3.70	6.23 ± 1.63
MC exp. ttbar events	15.20 ± 4.81	6.63 ± 2.10	8.25 ± 3.33	4.67 ± 1.54

Yield tables

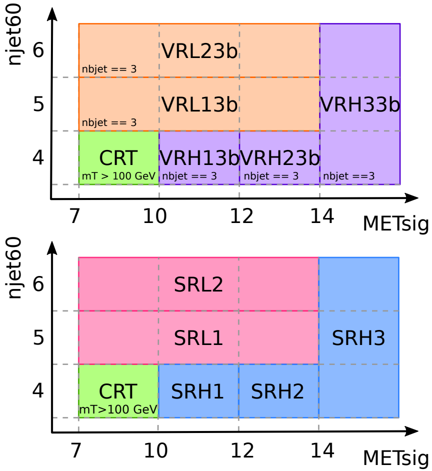
Binned SRH Regions

Expected and observed events in the binned version of SRH. Errors quoted include all the uncertainties

	SRH1A	SRH1B	SRH2A	SRH2B	SRH3A
Observed events	2	5	3	2	3
Fitted bkg events	7.17 ± 1.76	4.27 ± 1.82	2.64 ± 0.60	2.16 ± 1.30	7.36 ± 1.24
Fitted ttbar events	5.78 ± 1.80	3.45 ± 1.70	2.03 ± 0.52	1.65 ± 1.17	5.24 ± 1.19
Fitted VandVV events	$0.04^{+0.26}_{-0.04}$	$0.02^{+0.03}_{-0.02}$	0.00 ± 0.00	0.00 ± 0.00	0.04 ± 0.02
Fitted ttV events	0.39 ± 0.16	0.21 ± 0.14	0.21 ± 0.12	0.14 ± 0.10	0.60 ± 0.29
Fitted MixedHiggses events	0.38 ± 0.08	0.42 ± 0.13	0.20 ± 0.05	0.19 ± 0.07	0.47 ± 0.09
Fitted singletop events	0.51 ± 0.19	0.10 ± 0.04	0.17 ± 0.08	0.17 ± 0.06	0.66 ± 0.12
Fitted Others events	0.08 ± 0.03	0.06 ± 0.02	0.03 ± 0.03	$0.02^{+0.03}_{-0.02}$	0.36 ± 0.07
MC exp. SM events	6.66 ± 1.46	3.97 ± 1.68	2.46 ± 0.53	2.02 ± 1.17	6.90 ± 0.97
MC exp. ttbar events	5.28 ± 1.49	3.15 ± 1.55	1.85 ± 0.42	1.50 ± 1.04	4.79 ± 0.89

Validation regions $t\bar{t}$

Definitions



Two set of validation regions designed to validate $t\bar{t}$ modelling:

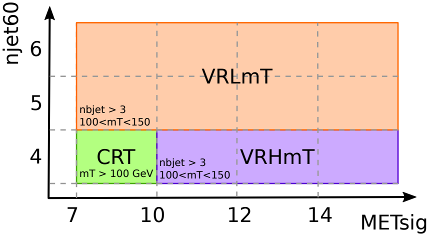
VR*3b
(VRL13b, VRL23b, VRH13b, VRH23b, VRH33b)

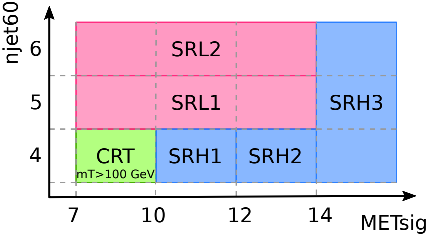
- same m_T cut as in the SRs, orthogonality obtained by requiring the presence of exactly 3 b-tagged jets
- High statistics in the region allows to design one VR for each of the bin of the SRs (50 - 170 events each VR)

(Full VR definitions in the backup)

Validation regions $t\bar{t}$

Definitions





Two set of validation regions designed to validate $t\bar{t}$ modelling:

VR*mT
(VRLmT, VRHmT)

- Designed with the goal to prove the modelling for events with nbjet > 3
- Mimic SR cuts with the exception on the cut on m_T, which is $100 < m_T < 150$ to ensure orthogonality

(Full VR definitions in the backup)

List of systematics

Statistical uncertainty coming from the limited MC statistics is the main contribution to uncertainties.
Systematic uncertainties are described by nuisance parameters not constrained by the fit:

Main experimental:

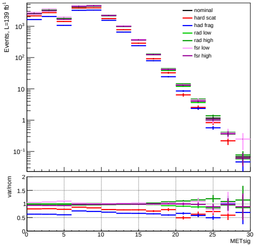
- *Jet energy scale*
- *Jet energy resolution*
- E_{T}^{miss} *soft track scale*
- E_{T}^{miss} *soft track resolution*
- *Flavour tagging efficiencies*
- All other systematics with smaller impact included (list in backup)

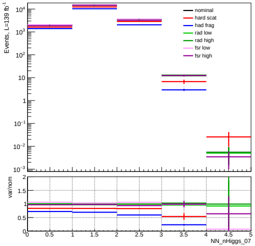
Each source of systematics is handled following the latest combined performance group recommendations.

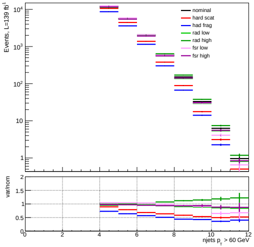
Theoretical ($t\bar{t}$):

- *Hard scattering:* compare nominal $t\bar{t}$ Powheg+Pythia8 sample with the $t\bar{t}$ aMcAtNlo+Pythia8 sample
- *Parton shower:* compare nominal $t\bar{t}$ Powheg+Pythia8 sample with the $t\bar{t}$ Powheg+Herwig7 sample (**dominant syst**)
- *Radiation High/Low:* computed comparing nominal Powheg+Pythia8 with the samples obtained doubling the renormalization and factorization scales and the varying the showering
- *FSR High/Low:* computed looking at the Var2 variation in Pythia8

Theory systematics







	SRH	SRH1	SRH2	SRH3	SRL	SRL1	SRL2
Hard Scatter	**-13.6**	**-14.7**	-10.5	-1.1	**-16.0**	**-14.6**	-18.3
Parton Shower	-12.5	-3.3	**-11.9**	**-13.9**	-14.5	-9.6	**-21.7**
Radiation Low	-5.2	-3.0	-2.4	-6.4	-6.2	-3.8	-9.5
Radiation High	7.3	4.2	3.3	8.7	8.4	5.2	13.0
FSR Low	-10.2	-13.3	1.4	-8.8	-8.5	-4.7	-14.4
FSR High	3.2	4.5	3.6	3.3	0.9	0.5	1.8

Total impact of systematics is 15-30%, mainly from HS, PS and JER *(tables in the backup)*

Theory syst impact

Impact (in %) on the TF of the $t\bar{t}$ theory uncertainties in each signal region:

	SRH	SRH1	SRH2	SRH3	SRL	SRL1	SRL2
Hard Scatter	-13.6	-14.7	-10.5	-1.1	-16.0	-14.6	-18.3
Parton Shower	-12.5	-3.3	-11.9	-13.9	-14.5	-9.6	-21.7
Radiation Low	-5.2	-3.0	-2.4	-6.4	-6.2	-3.8	-9.5
Radiation High	7.3	4.2	3.3	8.7	8.4	5.2	13.0
FSR Low	-10.2	-13.3	1.4	-8.8	-8.5	-4.7	-14.4
FSR High	3.2	4.5	3.6	3.3	0.9	0.5	1.8

Impact (in %) on the TF of the $t\bar{t}$ theory uncertainties in each validation region:

	VRH13b	VRH23b	VRH33b	VRL13b	VRL23b	VRHmT	VRLmT
Hard Scatter	-16.6	16.0	-9.3	-17.2	-23.2	-21.3	-28.2
Parton Shower	19.6	22.9	1.0	17.9	-5.5	-13.7	-13.3
Radiation Low	-3.1	-5.4	-8.0	-5.3	-10.4	-8.9	-8.2
Radiation High	3.9	6.3	11.9	7.0	14.7	12.7	10.9
FSR Low	-3.2	-2.7	-8.0	-9.7	-12.4	-10.9	-14.0
FSR High	3.0	4.8	0.5	2.5	6.7	-2.7	-0.5

Validation regions $t\bar{t}$

Definitions

<table>
<tr><th></th><th>VRL13b</th><th>VRL23b</th><th>VRH13b</th><th>VRH23b</th><th>VRH33b</th><th>VRLmT</th><th>VRHmT</th></tr>
<tr><td>Num leptons</td><td colspan="7">1</td></tr>
<tr><td>Num b-jets (p_T >30 GeV)</td><td colspan="5">$= 3$</td><td colspan="2">≥ 4</td></tr>
<tr><td>m_T [GeV]</td><td colspan="5">>150</td><td colspan="2">$100 - 150$</td></tr>
<tr><td>Num Higgs (score > 0.7)</td><td colspan="7">≥ 1</td></tr>
<tr><td>E_T^{miss} sig</td><td colspan="2">$7 - 14$</td><td>$10 - 12$</td><td>$12 - 14$</td><td>> 14</td><td>> 7</td><td>> 10</td></tr>
<tr><td>Num jets (p_T >30 GeV)</td><td>$= 5$</td><td>≥ 6</td><td colspan="2">$= 4$</td><td>≥ 4</td><td colspan="2">–</td></tr>
<tr><td>Num jets (p_T >60 GeV)</td><td colspan="5">–</td><td>≥ 5</td><td>$== 4$</td></tr>
</table>

Validation regions $t\bar{t}$ for b-jets

Yield

	VRH13b	VRH23b	VRH33b	VRL13b	VRL23b
Observed events	75	54	53	167	48
Fitted bkg events	83.04 ± 3.78	41.56 ± 3.05	48.13 ± 1.82	154.89 ± 7.02	62.13 ± 2.71
Fitted ttbar events	72.68 ± 3.78	35.45 ± 2.77	34.91 ± 1.82	134.95 ± 7.02	52.01 ± 2.71
Fitted VandVV events	0.52 ± 0.00	0.25 ± 0.01	0.65 ± 0.00	1.24 ± 0.00	0.62 ± 0.00
Fitted ttV events	2.72 ± 0.00	2.12 ± 0.12	5.29 ± 0.00	5.40 ± 0.00	2.30 ± 0.00
Fitted MixedHiggses events	1.89 ± 0.00	1.00 ± 0.06	1.08 ± 0.00	3.55 ± 0.00	1.55 ± 0.00
Fitted singletop events	4.89 ± 0.00	2.53 ± 0.15	5.55 ± 0.00	8.34 ± 0.00	3.76 ± 0.00
Fitted Others events	0.34 ± 0.00	0.21 ± 0.01	0.65 ± 0.00	1.39 ± 0.00	1.89 ± 0.00
MC exp. SM events	76.99 ± 0.01	38.61 ± 2.25	45.23 ± 0.00	143.66 ± 0.01	57.81 ± 0.00
MC exp. ttbar events	66.64 ± 0.01	32.50 ± 1.90	32.00 ± 0.00	123.73 ± 0.01	47.68 ± 0.00
T1T1_onestepN2N2_1000_550	0.71 ± 0.00	0.45 ± 0.02	14.72 ± 0.00	2.71 ± 0.00	5.86 ± 0.00
T1T1_onestepN2N2_800_130	2.63 ± 0.00	2.20 ± 0.12	12.65 ± 0.00	7.35 ± 0.00	11.58 ± 0.00

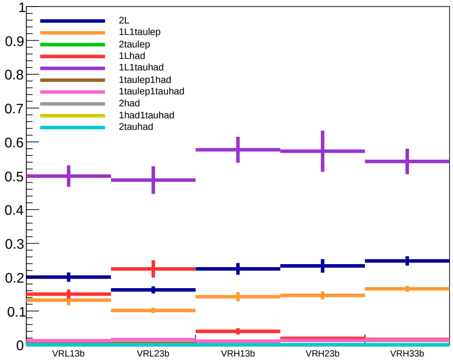
Validation regions $t\bar{t}$ for M_T

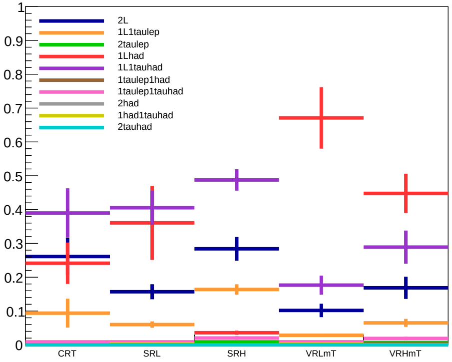
Yield

	VRHmT	VRLmT
Observed events	25	77
Fitted bkg events	27.85 ± 1.19	73.12 ± 6.27
Fitted ttbar events	22.88 ± 1.19	63.94 ± 5.71
Fitted VandVV events	0.22 ± 0.00	0.36 ± 0.03
Fitted ttV events	1.17 ± 0.00	1.98 ± 0.14
Fitted MixedHiggses events	1.10 ± 0.00	2.84 ± 0.21
Fitted singletop events	2.02 ± 0.00	2.62 ± 0.19
Fitted Others events	0.47 ± 0.00	1.39 ± 0.10
MC exp. SM events	25.95 ± 0.00	67.80 ± 4.92
MC exp. ttbar events	20.98 ± 0.00	58.62 ± 4.26
MC exp. T1T1_onestepN2N2_1000_550 events	1.88 ± 0.00	3.40 ± 0.20
MC exp. T1T1_onestepN2N2_800_130 events	3.05 ± 0.00	9.00 ± 0.52

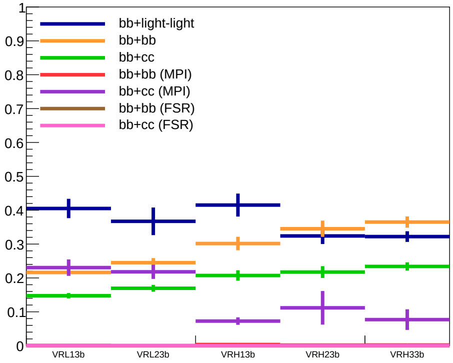
	Selection
Jets	$p_{\mathrm{T}} > 20$ GeV
	$\lvert\eta\rvert < 2.8$
	Medium JVT if $p_{\mathrm{T}} < 120$ GeV and $\lvert\eta\rvert < 2.5$
B-jets	$p_{\mathrm{T}} > 30$ GeV
	$\lvert\eta\rvert < 2.5$
	MV2c10 > 0.63 WP ($\epsilon_b \sim 77\%$)
Baseline Electrons	$E^{\mathrm{clust}}/\cosh(\eta) > 4.5$ GeV
	$\lvert\eta\rvert < 2.47$
	`LooseAndBlayerLH`
	$\lvert z_0 \sin\theta\rvert < 0.5mm$ and $\lvert d_0/\sigma\rvert < 5$
Signal Electrons	$E^{\mathrm{clust}}/\cosh(\eta) > 4.5$ GeV
	`MediumLH`
	`FCTight` isolation
	$\lvert z_0 \sin\theta\rvert < 0.5mm$ and $\lvert d_0/\sigma\rvert < 5$
Baseline Muons	$p_{\mathrm{T}} > 4$ GeV
	$\lvert\eta\rvert < 2.4$
	$\lvert z_0 \sin\theta\rvert < 0.5mm$ and $\lvert d_0/\sigma\rvert < 3$
Signal Muons	$p_{\mathrm{T}} > 5$ GeV
	Medium
	`FCTightTrackOnly` isolation
	$\lvert z_0 \sin\theta\rvert < 0.5mm$ and $\lvert d_0/\sigma\rvert < 3$

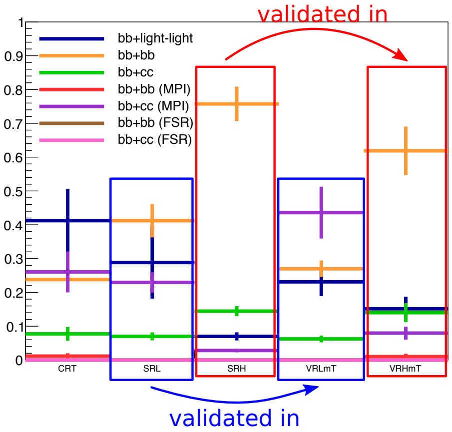
$t\bar{t}$ decay composition





$t\bar{t}$ HF composition





StopH exclusion limits

Model independent limits set on:

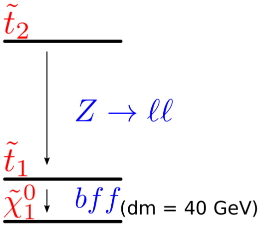
- Visible σ at 95% CL
- Number of observable events
- Number of signal events
- CL_B for the background-only hypothesis
- Discovery p-value ($p(s=0)$)

Signal channel	$\langle\epsilon\sigma\rangle^{95}_{obs}$ [fb]	S^{95}_{obs}	S^{95}_{exp}	CL_B	$p(s=0)$ (Z)
SRH	0.05	7.0	$10.3^{+4.4}_{-3.2}$	0.15	0.50 (0.00)
SRL	0.13	18.1	$14.2^{+6.0}_{-3.8}$	0.74	0.25 (0.67)

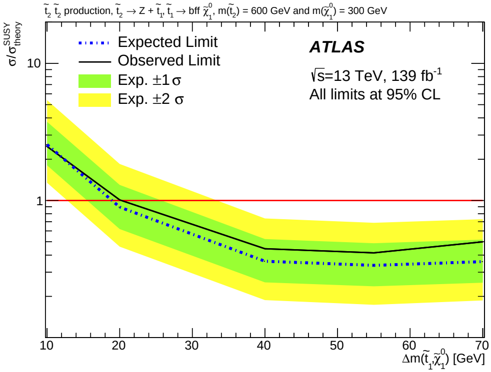
$\tilde{t}_2$ signal model reinterpretation

$\Delta m(\tilde{t}_1, \tilde{\chi}_1^0)$ sensitivity scan

$\tilde{t}_2$ reinterpretation based on StopZ decay, with
$\Delta \mathrm{m}(\tilde{t}_1, \tilde{\chi}_1^0) = 40$ GeV



Result can be extended by scanning sensitivity when varying $\Delta \mathrm{m}(\tilde{t}_1, \tilde{\chi}_1^0)$ for signal point $\mathrm{m}(\tilde{t}_2, \tilde{\chi}_1^0) = (600, 300)$ GeV with different
$\Delta \mathrm{m}(\tilde{t}_1, \tilde{\chi}_1^0) = 10, 20, 30, 40, 55, 70$ GeV

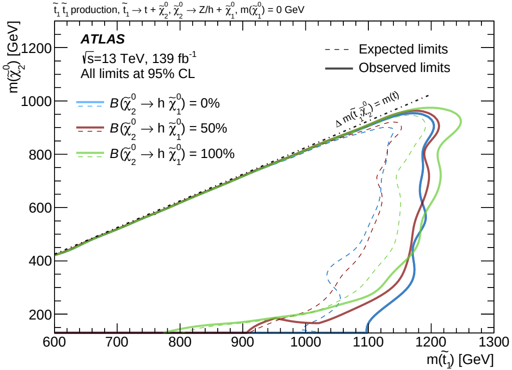


Combination with StopZ

Exclusion limit BR scans

Main interpretation performed with $\tilde{t}_1$ decay with 50% BR in either Z or h.
Sensitivity of the analysis to models with **different branching ratios** (0%, 100%) studied by re-weighting $\tilde{\chi}_2^0$ decays using their truth information

StopH + StopZ



Selection strategy

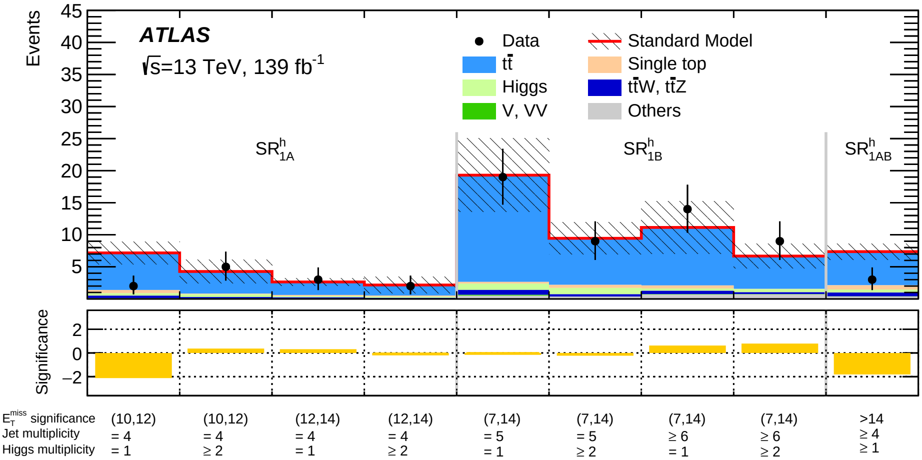
Exclusion Signal Regions

In order to take advantage of the different signal-to-background ratios in the different bins, multi-bin regions are defined starting from the SRL and SRH definitions. Discovery signal regions binned in $njet60$, $nHiggs$, and $METsig$:

Definition	SRL1A	SRL1B	SRL2A	SRL2B	SRH1A	SRH1B	SRH2A	SRH2B	SRH3A
Num_{ℓ}	1								
Num^{30}_{b-jets}	≥ 4								
m_T [GeV]	> 150								
E_{T}^{miss} sig	$7 - 14$				$10 - 12$		$12 - 14$		> 14
Num^{60}_{jets}	$= 5$		≥ 6		$= 4$				≥ 4
$\text{Num}^{0.7}_{Higgs}$	$= 1$	≥ 2	$= 1$	≥ 2	$= 1$	≥ 2	$= 1$	≥ 2	≥ 1

Results

Pull plot



Results

Stop2