

# Search for $t\bar{t}H/A \rightarrow t\bar{t}t\bar{t}$ production in the final state with one or two opposite-sign leptons using the full Run 2 $pp$ collisions data at $\sqrt{s} = 13\text{TeV}$

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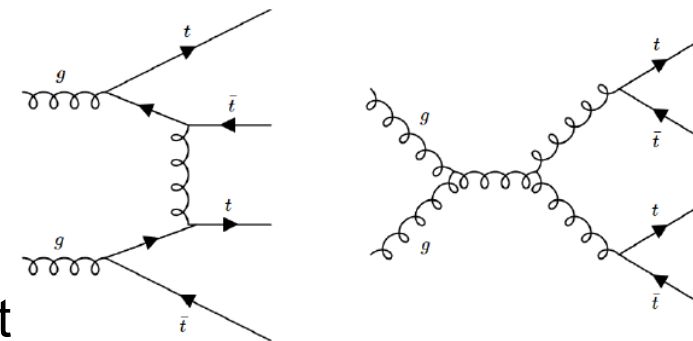
## Theoretical

- Problems with the Standard Model (SM):
  - Naturalness problem, hierarchy problem, neutrinos masses...
- Two-Higgs-Doublets-Models (2HDM) as a typical BSM scenario:
  - Simplest model to extend the number of Higgs boson

$$\mathcal{L}_{2\text{HDM}}^{\text{scalar}} = \sum_{i=1,2} (D_\mu \Phi_i)^\dagger (D^\mu \Phi_i) - V(\Phi_1, \Phi_2)$$

## Experimental

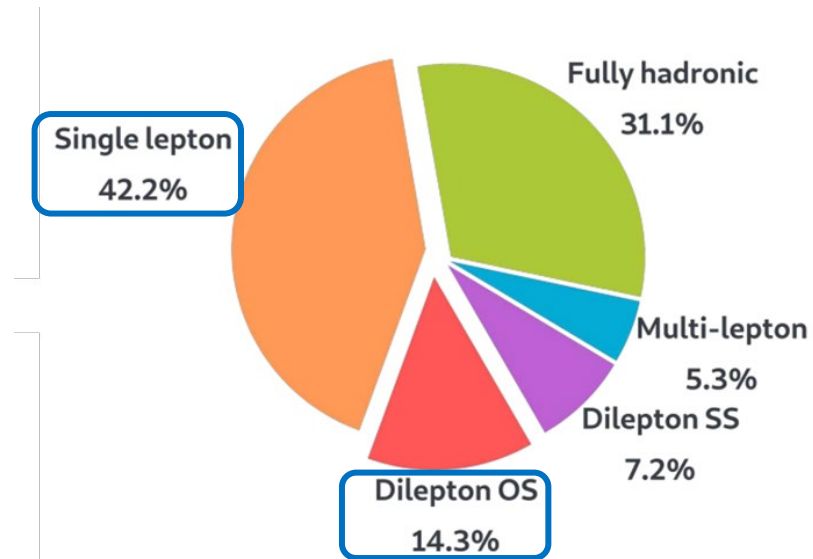
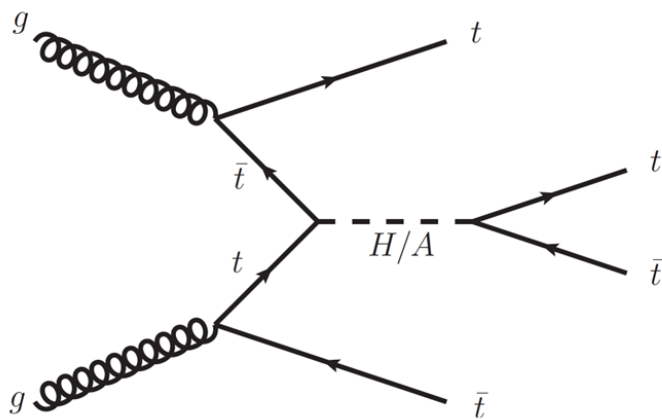
- Standard model **4-tops process**
  - SM cross section expectation:  $\sigma_{t\bar{t}t\bar{t}} = 13.37_{-1.78}^{+1.04} fb$
  - Latest measurement in ATLAS:  $\sigma_{t\bar{t}t\bar{t}} = 22.5_{-5.5}^{+6.6} fb$
  - Inconsistence arises between the theory and the experiment



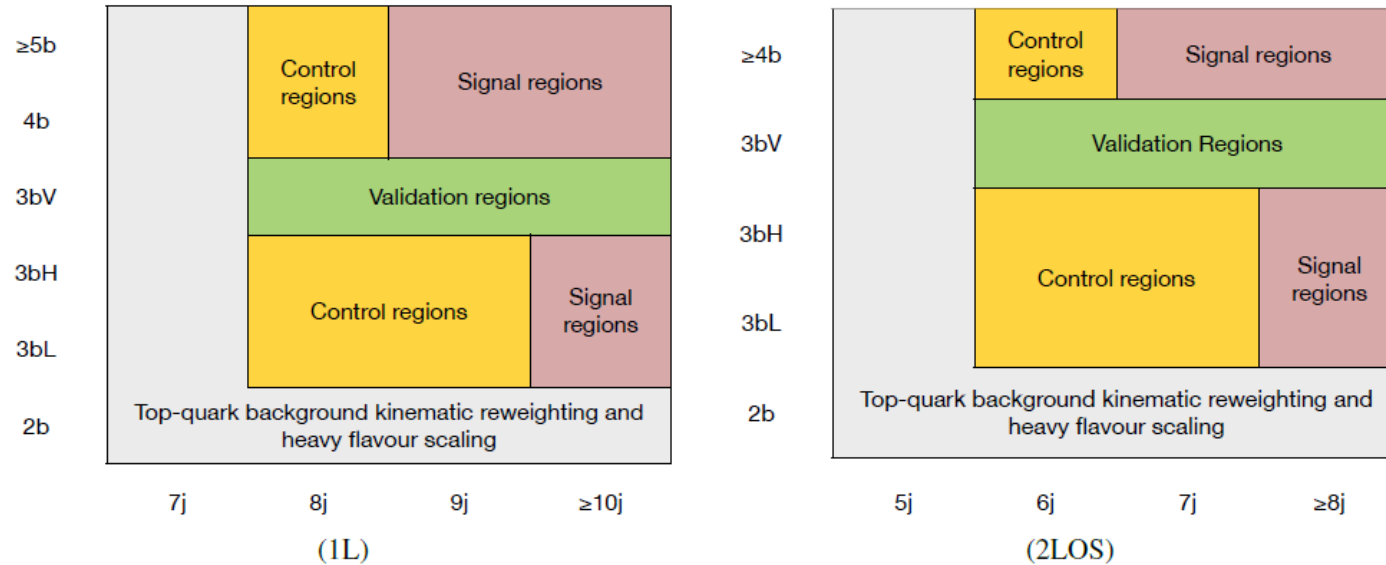
# Introduction



- **Aim:** Search for Heavy Higgs by 4tops production with the one-lepton/di-lepton opposite-sign final states
  - **Higgs mass:** 400GeV to 1000GeV with 100GeV granularity
  - **Main background:**  $t\bar{t} + jets$
  - **Final state signature:** High jet & b-jet multiplicity
- Published for the same search in the di-lepton same-sign/multi-lepton channel (SSML channel) ([link](#))



# Analysis Strategy



Name	$N_b^{60\%}$	$N_b^{70\%}$	$N_b^{85\%}$
2b	-	= 2	-
3bL	$\leq 2$	= 3	-
3bH	= 3	= 3	> 3
3bV	= 3	= 3	= 3
$\geq 4b$ (2LOS)	-	$\geq 4$	-
4b (1L)	-	= 4	-
$\geq 5b$ (1L)	-	$\geq 5$	-

- Two types of data-driven correction factors:
  - Heavy flavor (HF) normalization factors
  - Neural network (NN)-based kinematic reweighting
- Trained H/A-mass-parameterized GNN to separate signals from background
- Profile likelihood fit in all CRs and SRs simultaneously, using  $H_T$  in CR and **GNN-score** in SR

# Data & MC Samples and Event Selection



- Data: Full Run2 (2015-2018)  $\sim 139\text{fb}^{-1}$ , using single lepton triggers
- MC samples:
  - $t\bar{t}$  + jets, SM4t, ttW, ttZ, Single top, V + jets, ttt, Other top, VV, Signal
- Object definition & event selection:

Object	Baseline selection
Lepton	$p_T > 28\text{GeV}$ , $ \eta  < 1.37$ or $1.52-2.47$ (e), $ \eta  < 2.5$ ( $\mu$ ) Identification: TightLH(e)/Medium( $\mu$ ), Isolation: FCTight(e)/FCTightTrackOnly( $\mu$ ) Impact parameter: $z_0 < 0.5\text{mm}$ , $\sigma_{d0} < 5(3)$ for e( $\mu$ )
Jet	$p_T > 25\text{GeV}$ , $ \eta  < 2.5$ , JVT $> 0.5$ for $p_T < 60\text{ GeV}$ , $ \eta  < 2.4$ Algorithm: Anti- $k_T$
b-jet	$p_T > 25\text{GeV}$ , $ \eta  < 2.5$ , JVT $> 0.5$ for $p_T < 60\text{ GeV}$ , $ \eta  < 2.4$ Algorithm: DL1r
Event	Exactly one lepton (1L) / two opposite-charge leptons (2L) with $\geq 2$ jets with b-tagging passing 70% OP

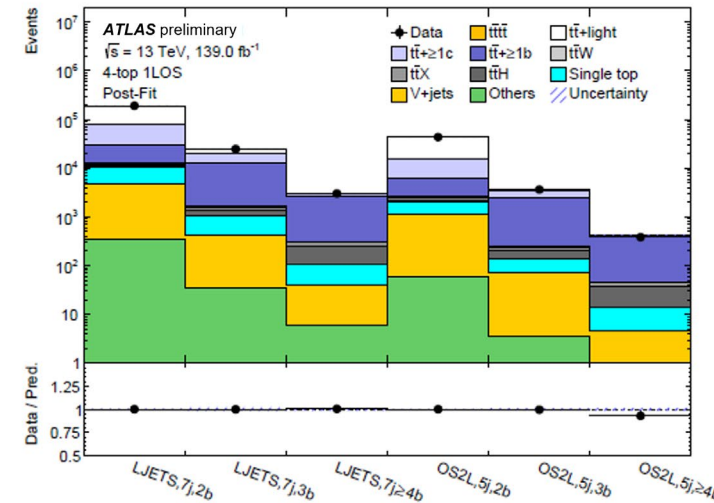
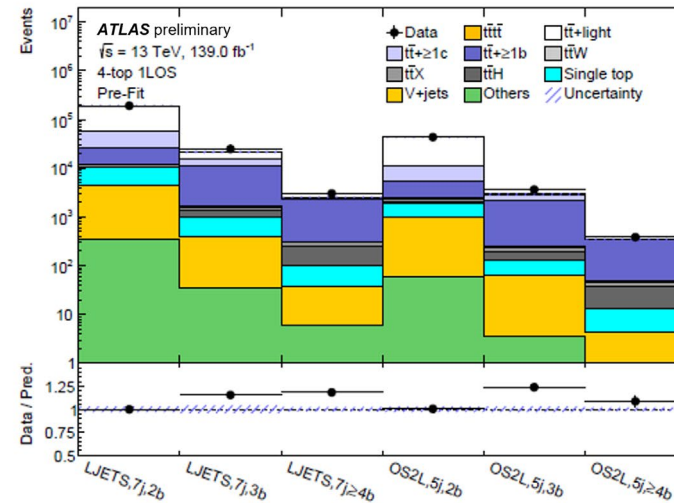
# Background Modelling (HF normalization)



- To correct the under-estimation of the  $t\bar{t}$  + HF production rate in MC prediction
- $t\bar{t}$  + HF includes:
  - $t\bar{t}$  +  $\geq 1b$  (TTB):  $t\bar{t}$  + at least one jet matched with b-hadron(s)
  - $t\bar{t}$  +  $\geq 1c$  (TTC):  $t\bar{t}$  + at least one jet matched with c-hadron(s)
  - $t\bar{t}$  + light (TTL):  $t\bar{t}$  + jets do not match with b or c-hadrons
- Data-driven fit to sum of pseudo-continuous b-tagging scores of 3rd and 4th jets
- Regions:  $7j(5j) = 2b, =3b, \geq 4b$  for 1L(2LOS) channel

- Scale factor  $\frac{t\bar{t}_{postfit}^{nominal}}{t\bar{t}_{prefit}^{nominal}}$  &  $\frac{t\bar{t}_{postfit}^{nominal}}{t\bar{t}_{prefit}^{alternative}}$  :

	TTL (1L)	TTL (OS)	TTC	TTB
Nominal	$0.84 \pm 0.04$	$0.87 \pm 0.03$	$1.61 \pm 0.13$	$1.18 \pm 0.03$
ttbb 4FS	$0.83 \pm 0.04$	$0.87 \pm 0.04$	$1.60 \pm 0.10$	$1.17 \pm 0.02$
aMcAtNloPy8	$0.94 \pm 0.04$	$0.96 \pm 0.04$	$1.78 \pm 0.11$	$1.27 \pm 0.01$
PhHerwig	$0.66 \pm 0.03$	$0.73 \pm 0.03$	$2.21 \pm 0.14$	$1.56 \pm 0.02$



Pre-fit & post-fit yields for HF normalization

# Background Modelling (NN-reweighting)



- Kinematic reweighting based on Neural Network (NN)

- NN output: a-posterior Bayesian probability

$$o(\mathbf{x}) \simeq P(\text{data}|\mathbf{x}) = \frac{\alpha_{\text{data}} P_{\text{data}}(\mathbf{x})}{\alpha_{\text{data}} P_{\text{data}}(\mathbf{x}) + \alpha_{\text{MC}} P_{\text{MC}}(\mathbf{x})}$$

- Input list: Njets, NRCjets, each jets & lep pT, missing ET
- Training regions:  $\geq 7j(5j)$ , = 2b for 1L(2LOS)

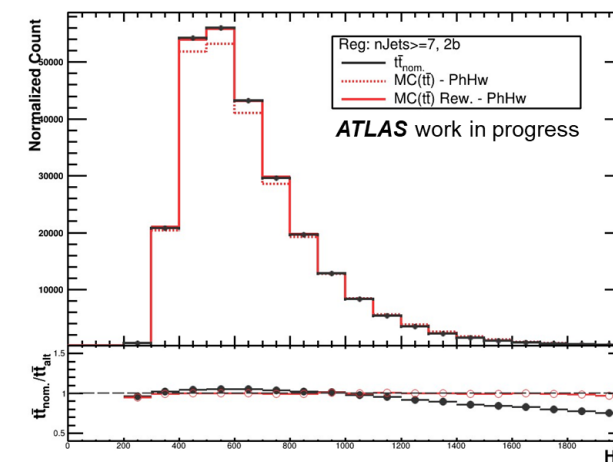
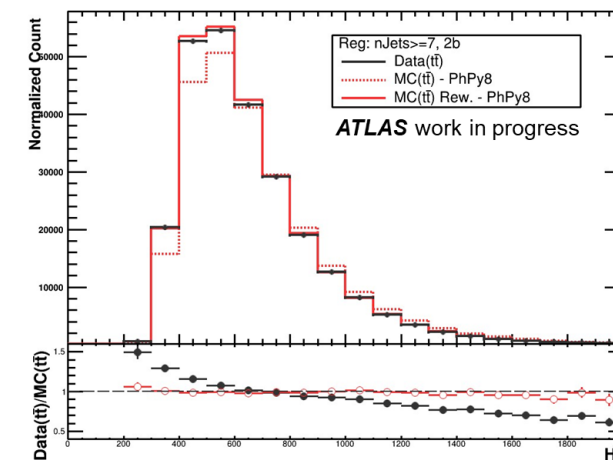
- Using an exponential lose function:

$$\mathcal{L} = P_{\text{data}} e^{-o(\mathbf{x})/2} + P_{\text{MC}} e^{o(\mathbf{x})/2} \frac{d\mathcal{L}}{do(\mathbf{x})}$$

$$\mathcal{L} = 0 \Rightarrow -\frac{P_{\text{data}}}{2} e^{-\frac{o(\mathbf{x})}{2}} + \frac{P_{\text{MC}}}{2} e^{\frac{o(\mathbf{x})}{2}} = 0$$

- Reweighting factor can be derived as:

$$w(\mathbf{x}) = \frac{P_{\text{data}}}{P_{\text{MC}}} = e^{o(\mathbf{x})}$$



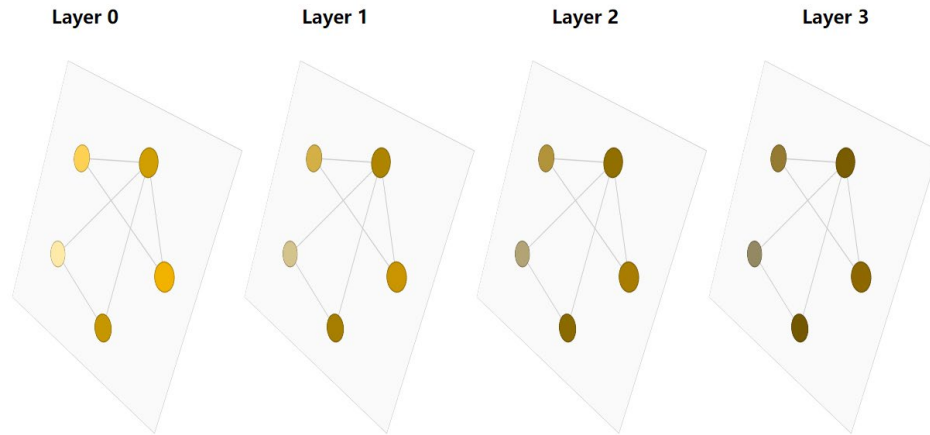
NN-reweighting effect of nominal sample (up)  
& alternative sample (down)



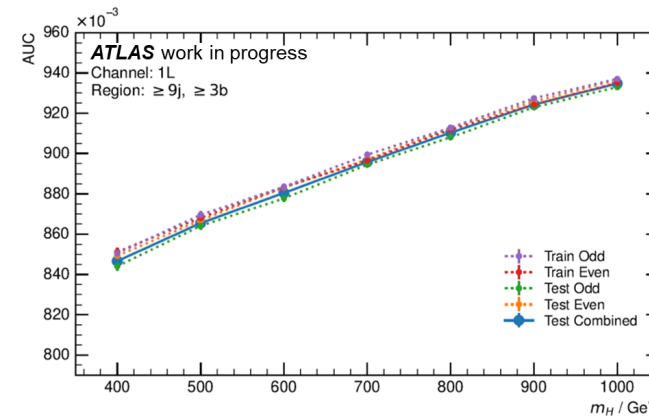
# Signal Background Discrimination (GNN)



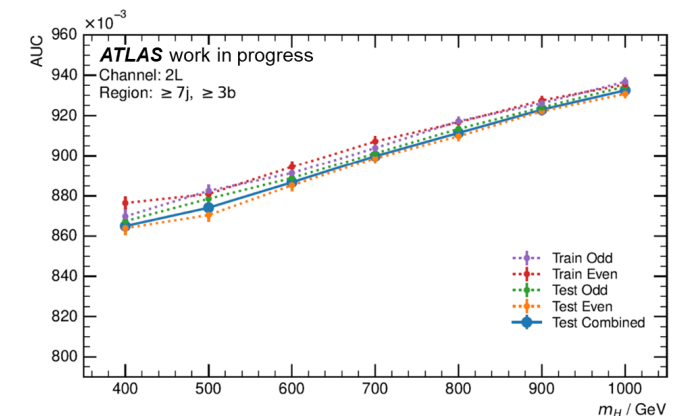
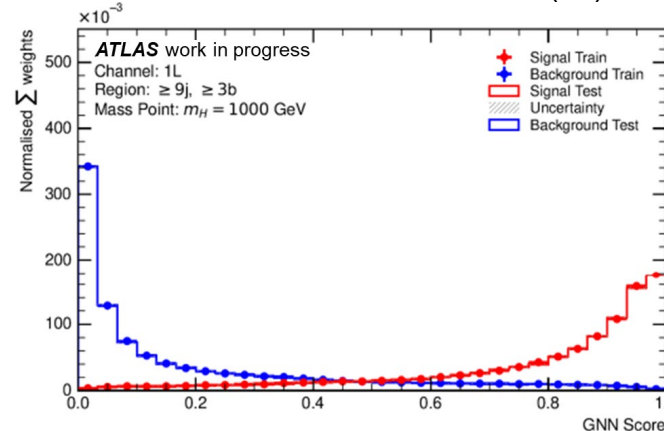
- For signal discrimination, **GNN (graph neural network)** has been used
  - GNN is agnostic to the number of nodes and are permutation invariant.
  - A relatively simple model can be used on events of varying multiplicity/topologies
  - Well **suitable** in our case with complex jet & b-jet multiplicity and structure



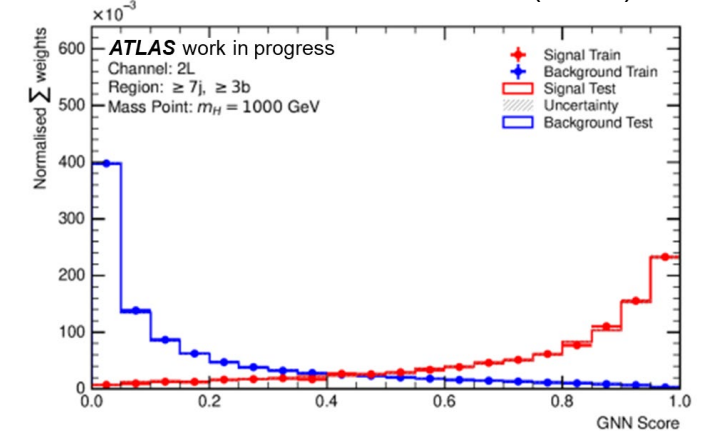
Simple sketch of node information accumulation through the network



AUC curve & score of GNN (1L)



AUC curve & score of GNN (2LOS)







- **$t\bar{t}$  theoretical uncertainties:**

- $t\bar{t}$  modelling:  $\mu_F/\mu_R/ISR/FSR$  (decorrelated to  $t\bar{t} + \geq 1b$ ,  $t\bar{t} + \geq 1c$  and  $t\bar{t} + \text{light}$  based on  $t\bar{t}$  event classification)
- $t\bar{t}$  MC choice (decorrelated to  $t\bar{t} + b$ ,  $t\bar{t} + bb$ ,  $t\bar{t} + bbb$ ,  $t\bar{t} + B$ ,  $t\bar{t} + \geq 1c$  and  $t\bar{t} + \text{light}$  based on  $t\bar{t}$  event classification)
  - ME: (PhPy8 as nominal v.s Mg5Py8 as alternative)
  - PS: (PhPy8 as nominal v.s PhHw as alternative)
  - FS: (ttbb 5FS as nominal v.s ttbb 4FS as alternative)
- $t\bar{t} + \geq 1b$  and  $t\bar{t} + \geq 1c$  XS (50%),  $t\bar{t} + \text{light}$  XS (5%, decorrelated to 1L & 2LOS channels)
- NN-reweighting
  - Statistic uncertainties extrapolation
  - Non- $t\bar{t}$  subtraction

- **Non- $t\bar{t}$  theoretical uncertainties:**

- Modelling & cross section

- **SM  $t\bar{t}t\bar{t}$  :**

- Generator, PS, scale, XS (+7.8%, -13.3%)

- **Experimental uncertainties:**

- Luminosity, pileup reweighting, object reconstruction, jet tagging, etc.

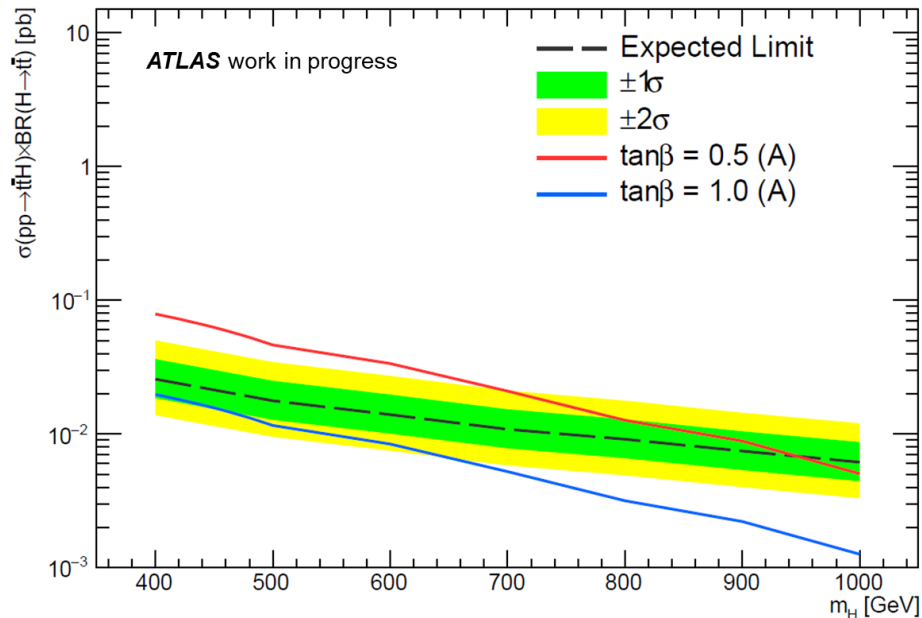
- **Signal modelling:**

- PDF (1%)
- Renormalization and factorization scales

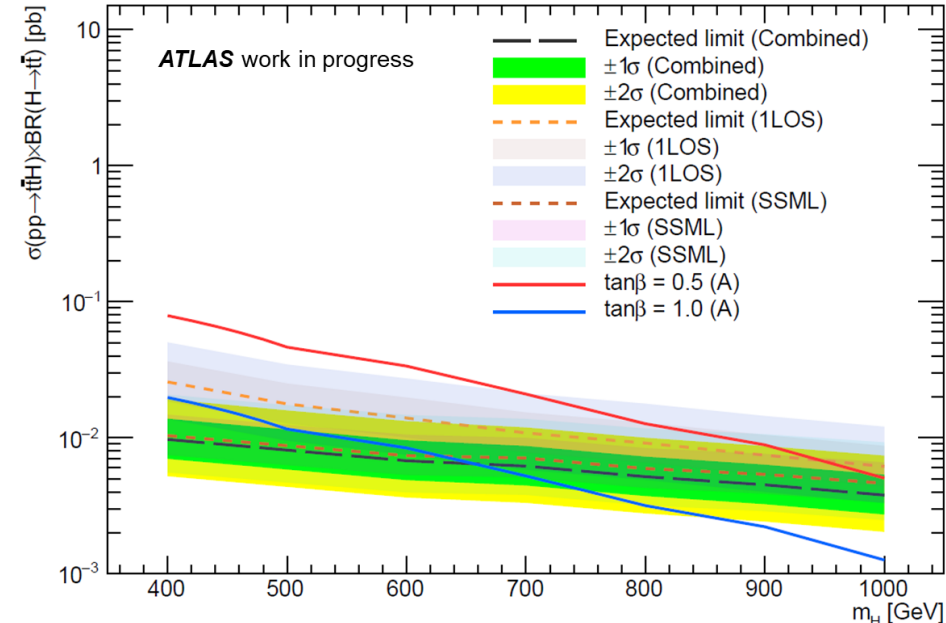
# Expected Fit Results



- Expected upper limit of the cross section extracted from Asimov data fit
  - Ranged between 25.7 fb to 6.1 fb for heavy Higgs mass between 400 GeV and 1000 GeV, respectively
- Combination with SSML channel
  - Ranged between 9.7 fb to 4.6 fb for heavy Higgs mass between 400 GeV and 1000 GeV, respectively



Expected upper limit of 1LOS channel



Expected upper limit of 1LOS + SSML channel

# Summary



- Heavy Higgs production in the 4-top process has been searched using ATLAS full run-2 data
- Background correction with 2 data-driven factors
  - HF normalization
  - NN-reweighting
- Signal-background discriminated by GNN
- Systematics has been robustly studied

- Expected upper limit of the cross section:
- Under collaboration review

	400 GeV	1000 GeV
1LOS	25.7fb	6.1fb
Combined	9.7fb	4.6fb

# BACKUP

# Samples



- Recent p-tag from the TOPQ1 has been used for over all MC/Data samples.
- AnalysisBase 21.2.169.
- Framework: TTHbb analysis ([Link](#)).
- Only prompt SM processes modelled with MC for background:

	Nominal	Alternative
$t\bar{t}$ + jets	PhPy8 (5FS ttbb, inclusive + HF filtered +HT sliced)	Mg5Py8, PhHw, PhPy8 (4FS ttbb)
SM4t	aMcAtNloPy8	aMcAtNloHerwig7, Sherpa
ttW	Sherpa	aMcAtNloPy8
ttZ	aMcAtNloPy8	Sherpa
Single top	PhPy8	PhH7, aMcAtNloPy8
V + jets	Sherpa	-
ttt	Mg5Py8	-
Other top, VV	MgPy8, aMcAtNloPy9	-
Signal	Mg5Py8	-

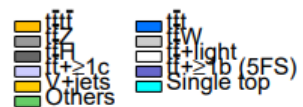
# Background Composition



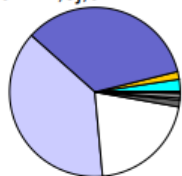
**ATLAS** Simulation Internal

$\sqrt{s} = 13$  TeV

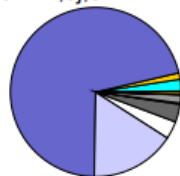
4-top 1LOS



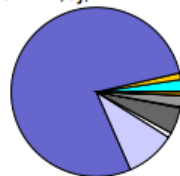
LJETS,8j,3bL



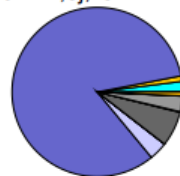
LJETS,8j,3bH



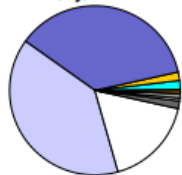
LJETS,8j,4b



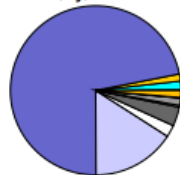
LJETS,8j,≥5b



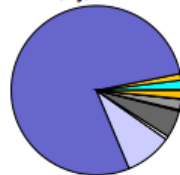
LJETS,9j,3bL



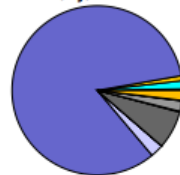
LJETS,9j,3bH



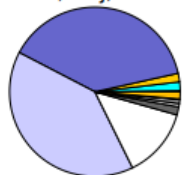
LJETS,9j,4b



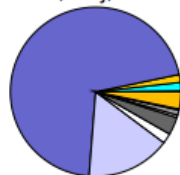
LJETS,9j,≥5b



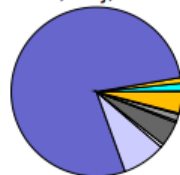
LJETS,≥10j,3bL



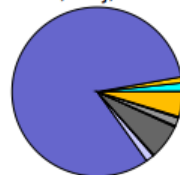
LJETS,≥10j,3bH



LJETS,≥10j,4b



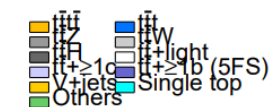
LJETS,≥10j,≥5b



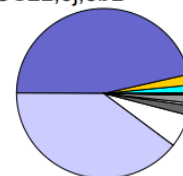
**ATLAS** Simulation Internal

$\sqrt{s} = 13$  TeV

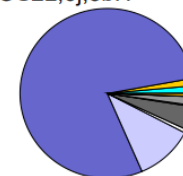
4-top 1LOS



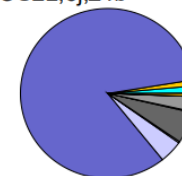
OS2L,6j,3bL



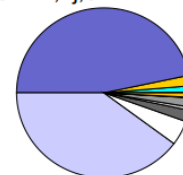
OS2L,6j,3bH



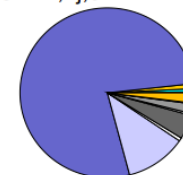
OS2L,6j,≥4b



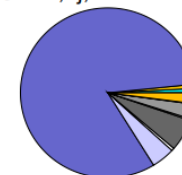
OS2L,7j,3bL



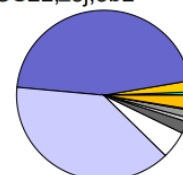
OS2L,7j,3bH



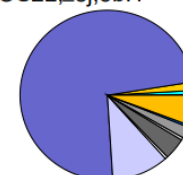
OS2L,7j,≥4b



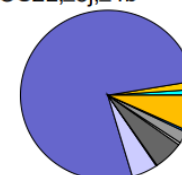
OS2L,≥8j,3bL



OS2L,≥8j,3bH



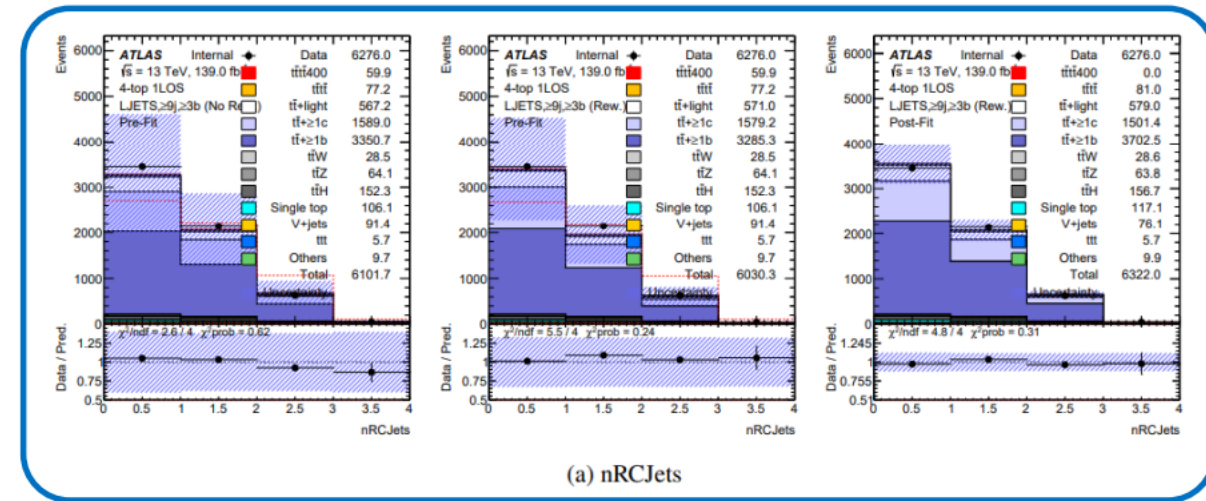
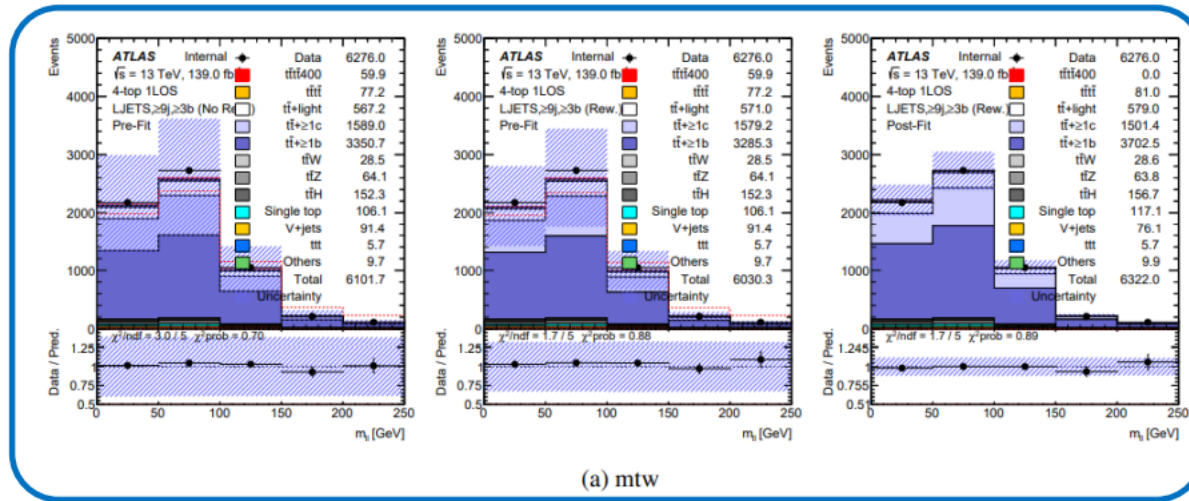
OS2L,≥8j,≥4b



# Performance of NN-reweighting



- Added several Data/MC comparison plots for the variables used in the MVA training (Appendix K.2)
  - Pre-fit plots without reweighting (left), pre-fit plots with reweighting (middle), post-fit plots (right)



Example plots

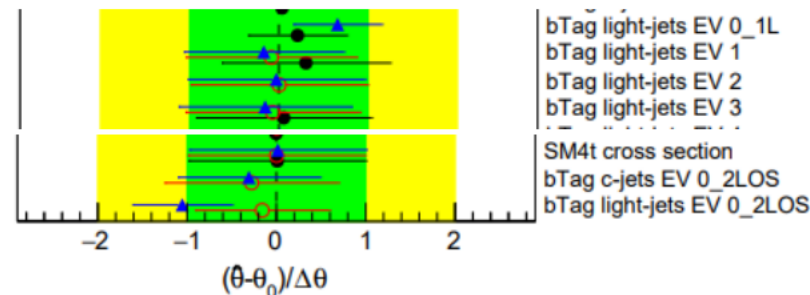
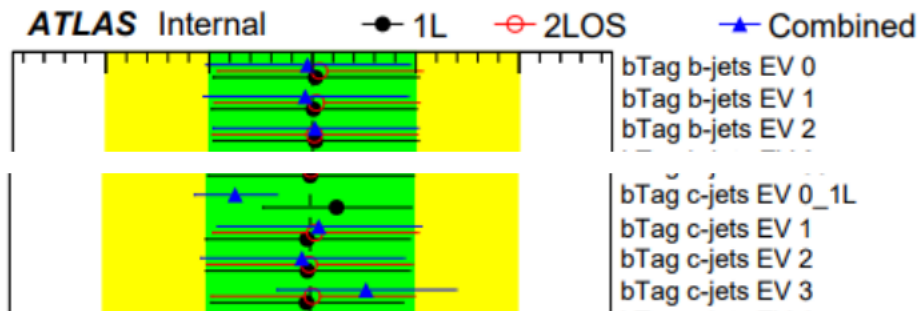
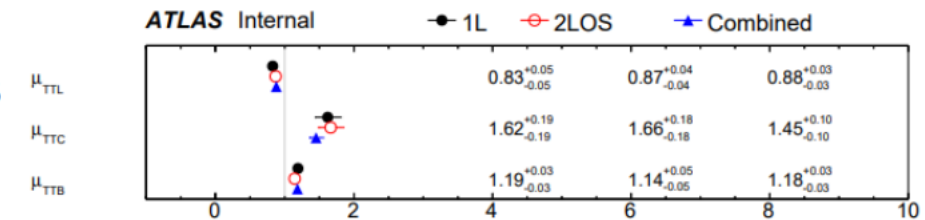
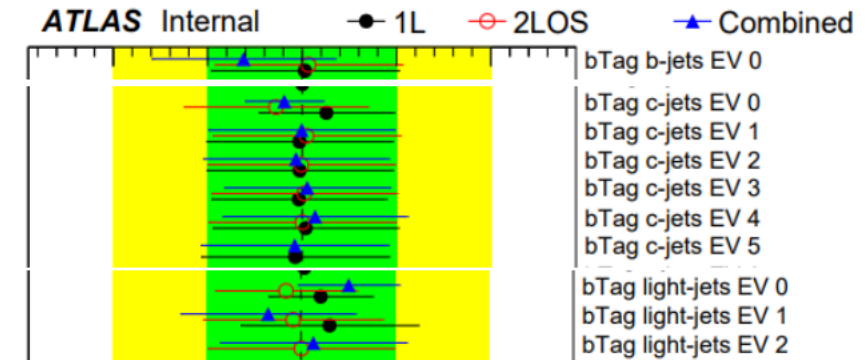
- Shows good modelling after NN-reweighting and fitting



# Heavy Flavor Correction Factor



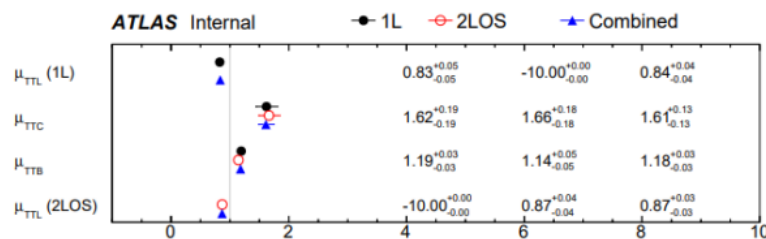
- Regions: 7j (5j) for 1L (2LOS) with 2b, 3b,  $\geq 4b$
- Combined Fit with Nuisance Parameters Correlated among Channels
  - Unstable pulls is come from the performance differences among the two channels.
  - major differences can be found in NP bTag c-jets EV0 (C0) and bTag light-jets EV0 (L0)
- Combined Fit with C0 and L0 Decorrelated among Channels
  - Do not entirely resolve the issue



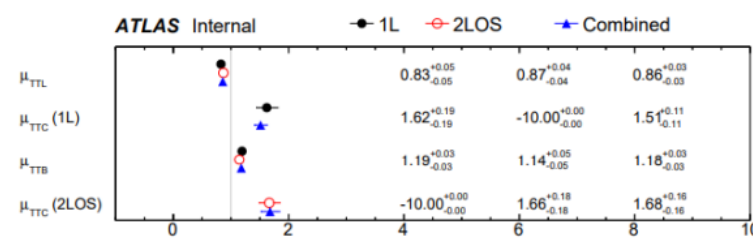
# Heavy Flavor Correction Factor



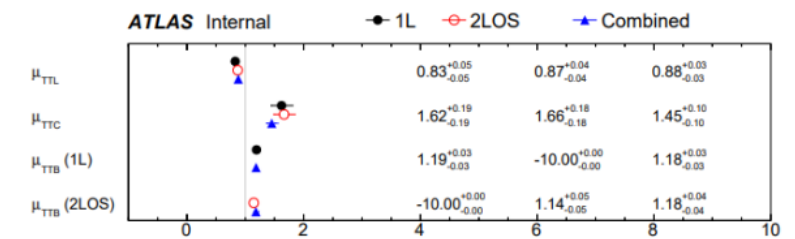
- Combined Fit with Different Correction Factors Decorrelation among Channels:
  - ✓ **Decorrelated TTL:**
    - The correction factors derived from the combined fit are closed to and in between the results derived from 1L and 2LOS separated fits.
  - **Decorrelated TTC:**
    - C0 pulls in the combined fit are opposite to the separated fits
    - $\mu_{TTC}$  (1L) derived in the combined fit is deviated from the result derived in the 1L separate fit
  - **Decorrelated TTB:**
    - The NP pulls and the HF correction factors are nearly the same as the case of without decorrelating the correction factors.



Decorrelated TTL



Decorrelated TTC

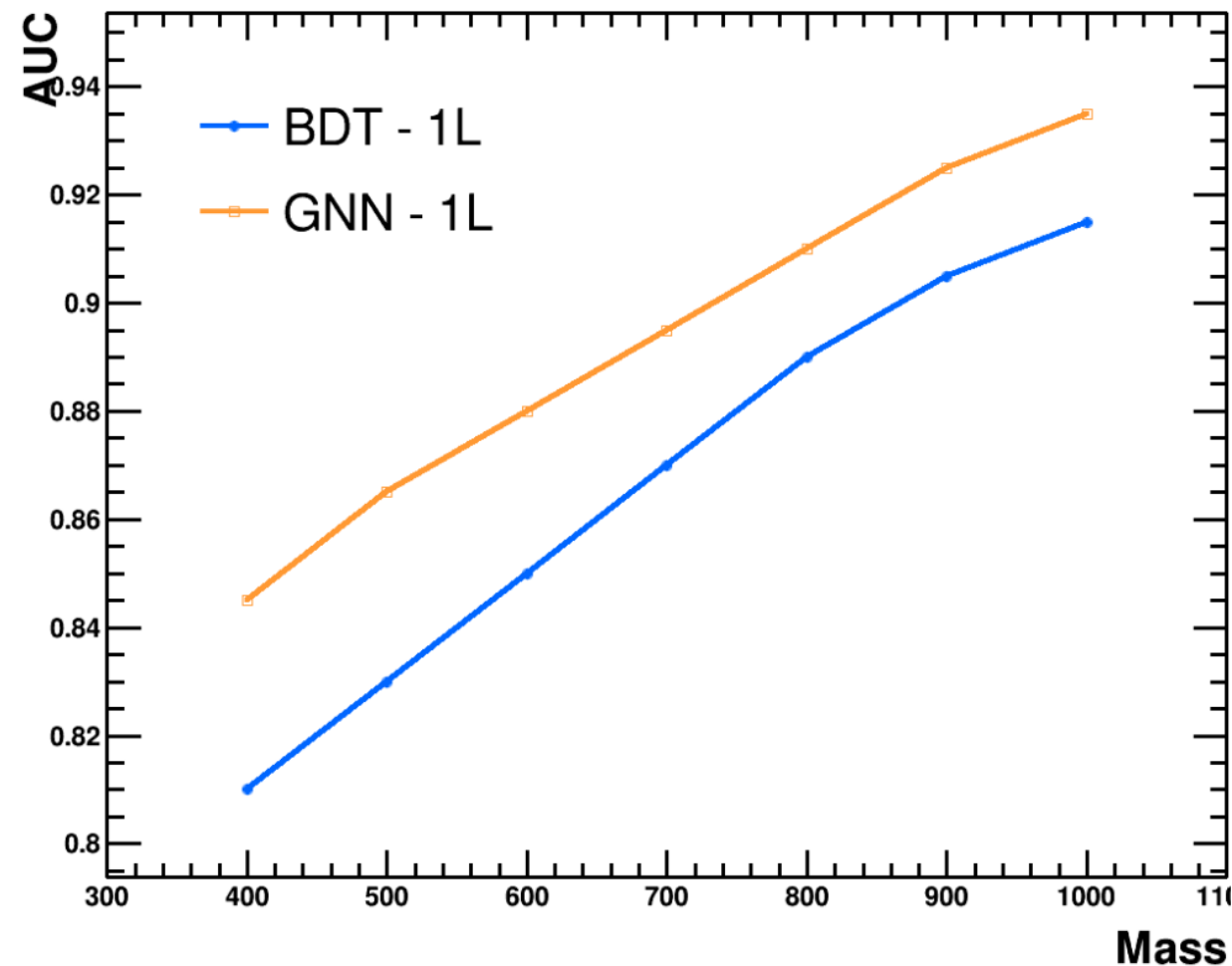


Decorrelated TTB

# GNN VS BDT



- SM4top like BDT has been also studied with the same input list used as global feature in GNN
- Purposed as a benchmark, and used only for control
- GNN shows significant improvement comparing to BDT
- GNN and BDT shows same level agreement over the data/MC in SR
- Observed same level of pulls/constraints in fits using BDT or GNN
- GNN found to be more sensitive



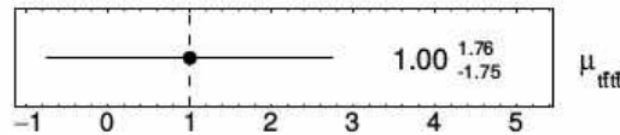
# Validation Regions



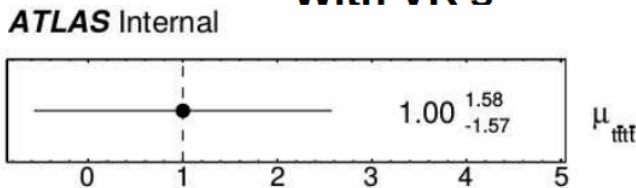
- Validation region defined in SM 4-top is studied 3bV(SM 4-top)
  - In our analysis this region found to be more sensitive than 3bH
  - Simply this two region definition swapped in our analysis
    - 3bV (SM 4-top) = 3bH & 3bH(SM 4-top) = 3bV

Name	$N_b^{60\%}$	$N_b^{70\%}$	$N_b^{85\%}$
2b	-	= 2	-
3bL	≤ 2	= 3	-
3bH	= 3	= 3	= 3
3bV	= 3	= 3	≥ 4
≥4b (2LOS)	-	≥ 4	-
4b (1L)	-	= 4	-
≥5b (1L)	-	≥ 5	-

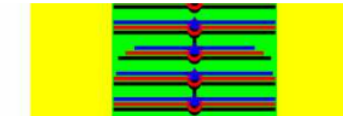
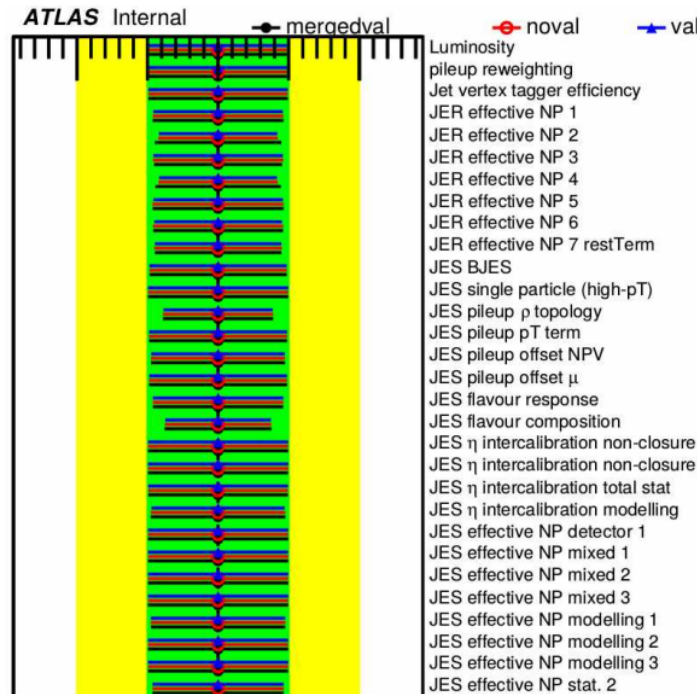
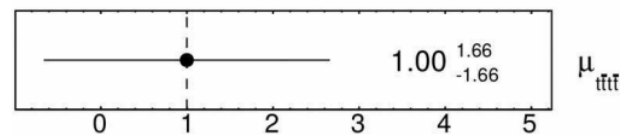
ATLAS Internal No VR's



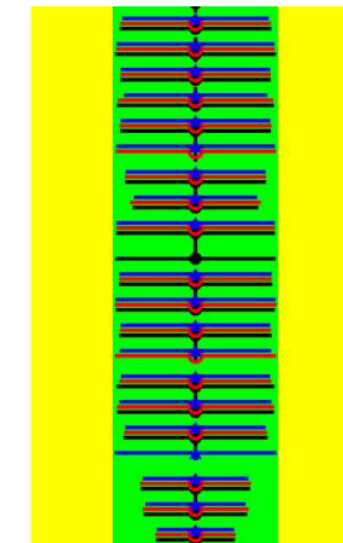
With VR's



ATLAS Internal Merged VR's



bTag c-jets EV 17  
bTag light-jets EV 0  
bTag light-jets EV 1  
bTag light-jets EV 2



tt+>= 1c gen. choice Acc.  
tt+>= 1c gen. choice Shape  
ttb gen. choice Acc.  
ttb gen. choice Shape  
ttB gen. choice Acc.  
ttB gen. choice Shape  
ttbb gen. choice Acc.  
ttbb gen. choice Shape  
tt+>= 3b gen. choice Acc.  
tt+>= 3b gen. choice Shape  
tt+light PS choice Acc.  
tt+light PS choice Shape  
tt+>= 1c PS choice Acc.  
tt+>= 1c PS choice Shape  
ttb PS choice Acc.  
ttb PS choice Shape  
ttB PS choice Acc.  
ttB PS choice Shape  
ttbb PS choice Acc.  
ttbb PS choice Shape  
tt+>= 3b PS choice Acc.

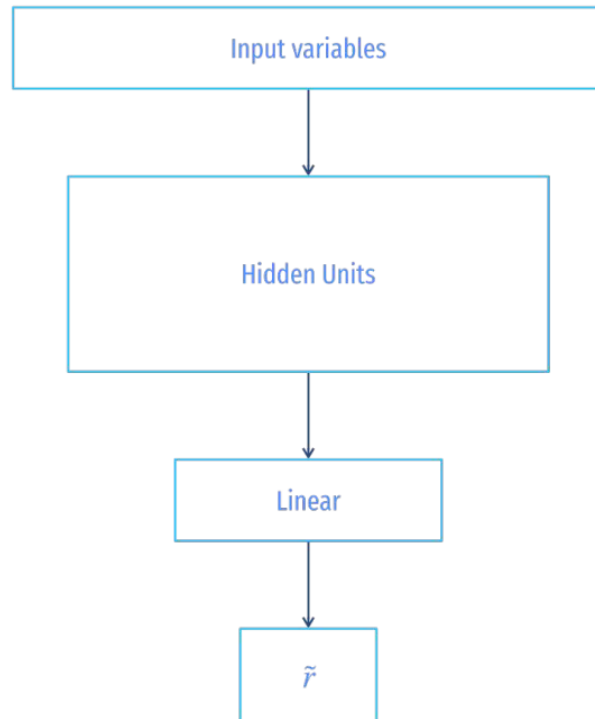
# NN-reweighting (loss function)



## Exponential Loss

$$\mathcal{L} = p_A e^{-r'/2} + p_B e^{r'/2}$$

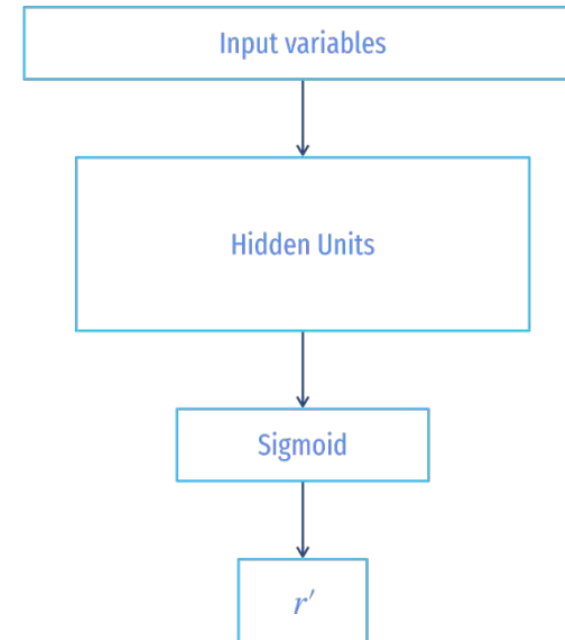
$$\frac{\partial \mathcal{L}}{\partial r'} = -\frac{p_A}{2} e^{-r'/2} + \frac{p_B}{2} e^{r'/2} = 0 \rightarrow e^{r'} = \frac{p_A}{p_B} = r$$



## Binary Cross Entropy

$$\mathcal{L} = -p_A \log r' - p_B \log(1 - r')$$

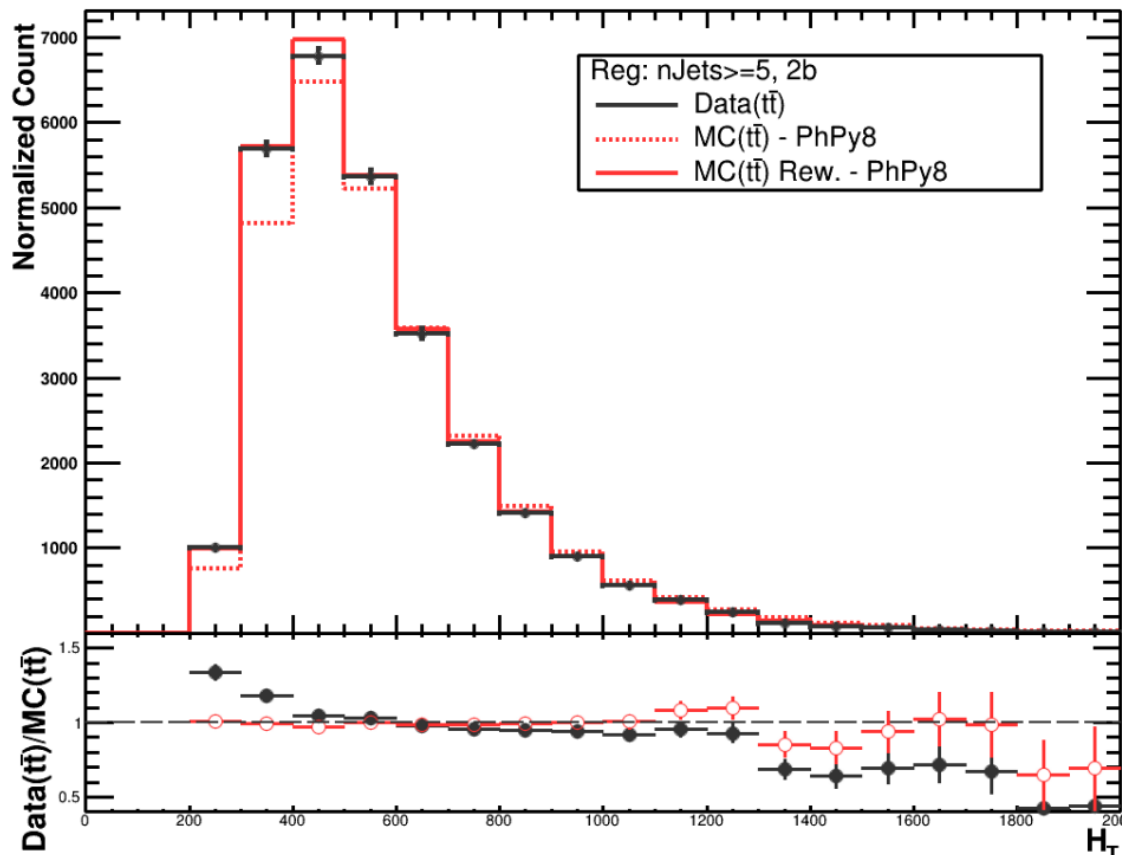
$$\frac{\partial \mathcal{L}}{\partial r'} = -\frac{p_A}{r'} + \frac{p_B}{1 - r'} = 0 \rightarrow r' = \frac{p_A}{p_A + p_B} \rightarrow r = \frac{r'}{1 - r'}$$



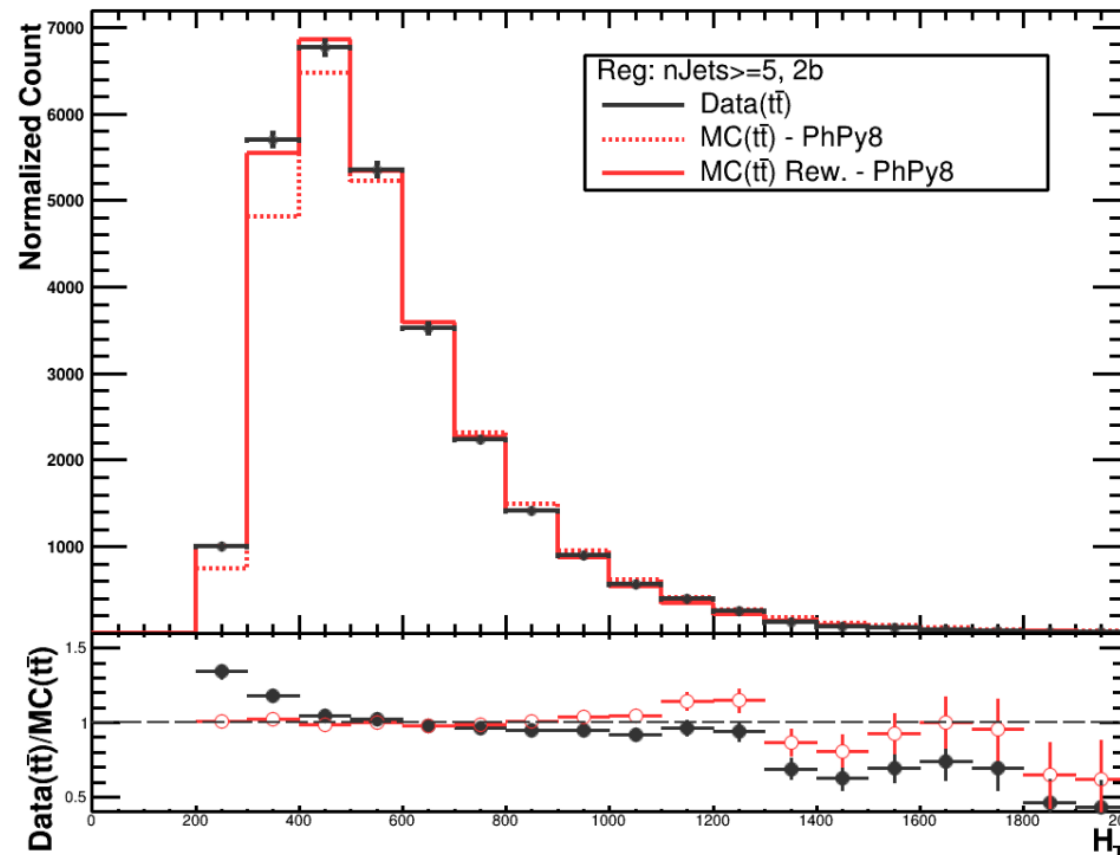
# NN-reweighting (loss function)



## Exponential Loss



## Binary Cross Entropy



# Expected significance

