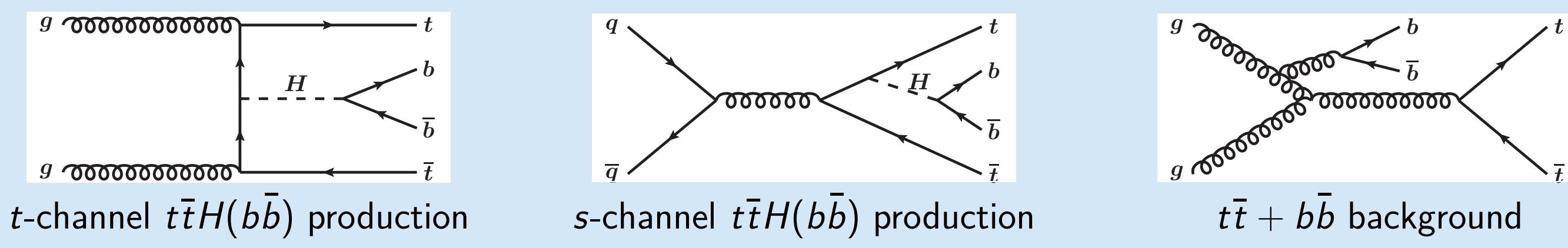


## The $t\bar{t}H(H \rightarrow b\bar{b})$ Analysis in a Nutshell

- Top quark heaviest  $\Rightarrow$  strong Yukawa coupling
- $t\bar{t}H$ : direct measurement of top Yukawa
- Subsequent  $H \rightarrow b\bar{b}$  has largest branching ratio (58%)



- $t\bar{t}H(bb)$  still to be observed - analysis measures signal strength  $\mu = \frac{\sigma_{\text{measured}}}{\sigma_{\text{SM prediction}}}$
- Simplified template cross-section (STXS) framework  $\Rightarrow$  measure in 6 STXS Higgs  $p_T$  regions the signal strength  $\mu_i$ , to probe  $p_T$  dependent deviations from SM
- Challenge: large  $t\bar{t}$  + jets background due to jets from b- or c- quarks
- Analysis done on  $140 \text{ fb}^{-1}$  of 13 TeV  $p-p$  data in 1 or 2 lepton (electron/muon) final states

Improved multivariate analysis strategy over [1] using transformer NN for

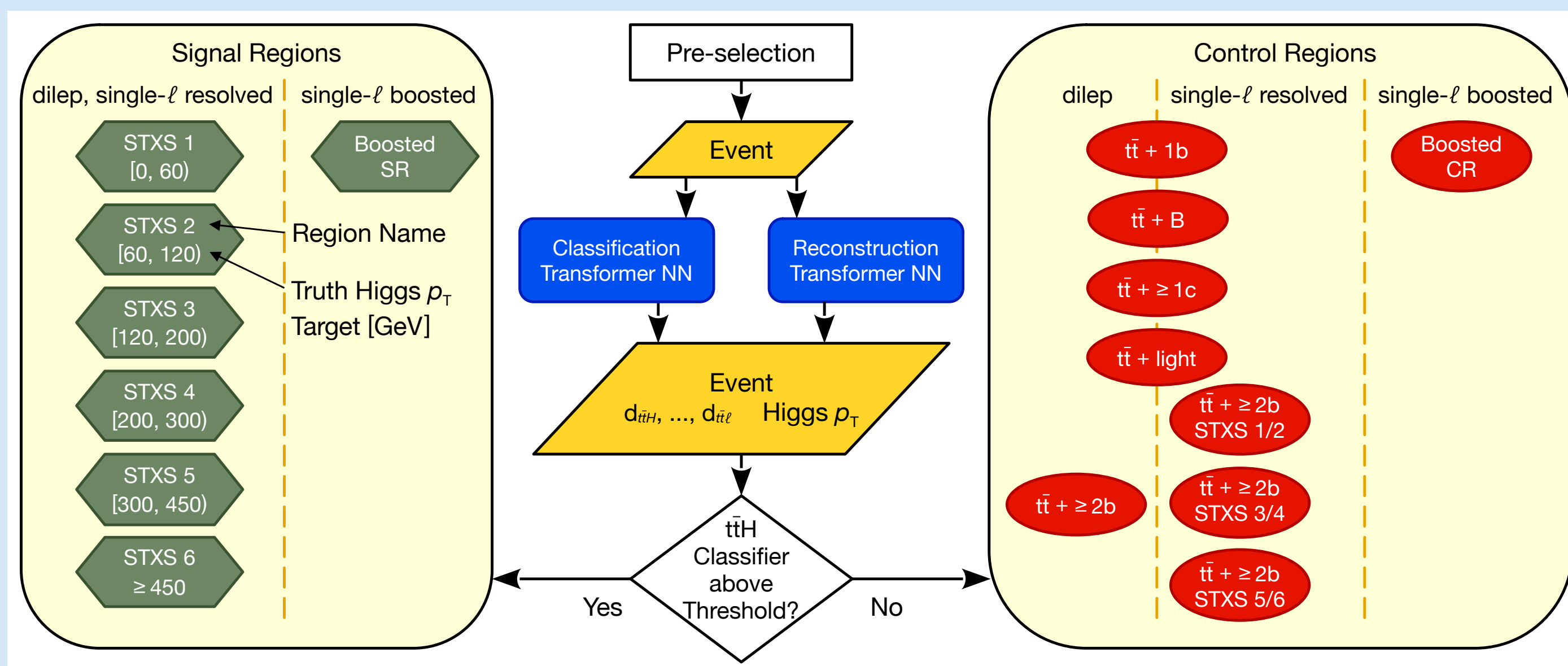
- Classification of signal and background events
- Higgs candidates reconstruction for  $p_T^H$

## Event Classification and Higgs $p_T$ Reconstruction

- Three channels: dilepton, single-lepton resolved, DNN-selected single-lepton boosted
- Pre-selection for events with certain number of jets and  $b$ -jets:

channel	# jets ( $R = 0.4$ ) at WP, in which # jets at WP	# jets ( $R = 1.0$ )
dilepton	3 at 85%	2 at 70%
single- $\ell$ resolved	5	3 at 70%
single- $\ell$ boosted	4	3 at 85%

Looser requirements than previous analysis: pre-selection efficiency for  $t\bar{t}H$  6.3% - around 3 times higher



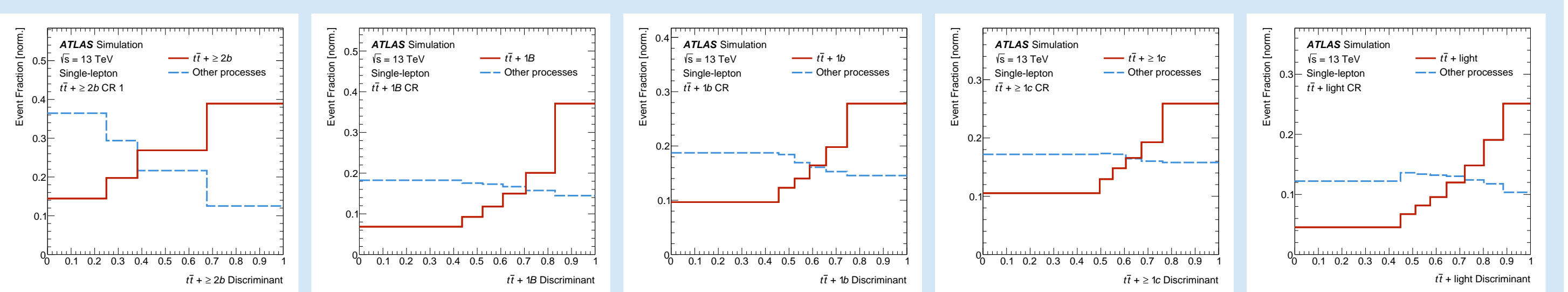
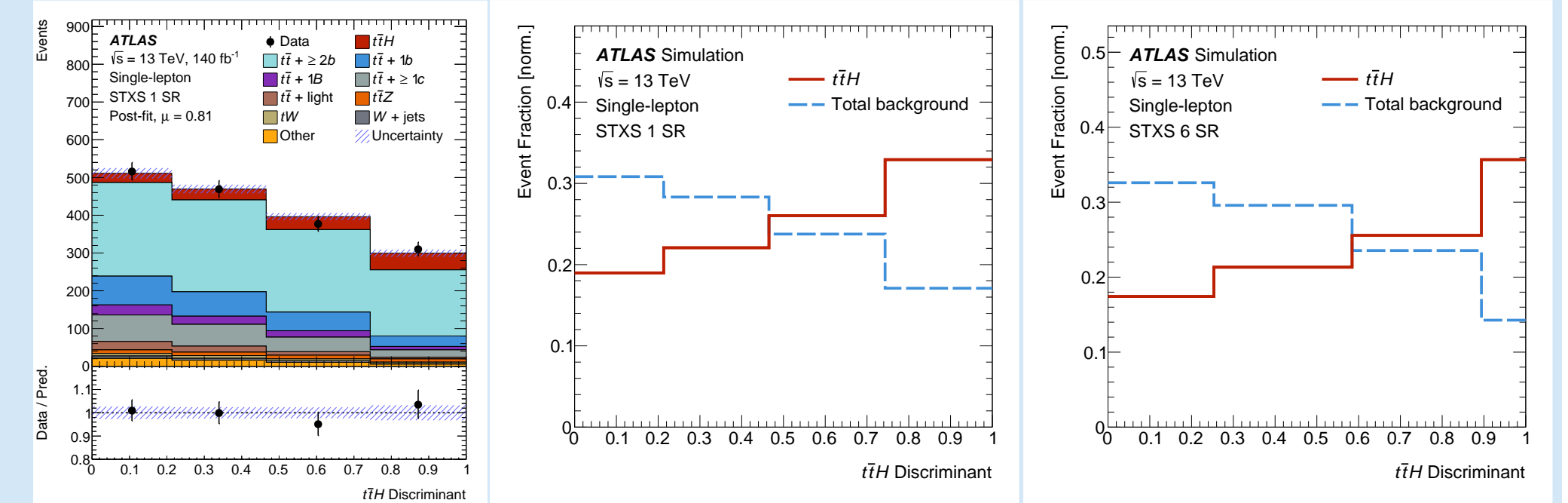
- Events separated into signal and control regions:
  - Classification transformer gives 6 discriminant values for each class:  $t\bar{t}H$  signal,  $t\bar{t} + 1b$ ,  $t\bar{t} + 1B$ ,  $t\bar{t} + \geq 2b$ ,  $t\bar{t} + \geq 1c$ ,  $t\bar{t} + \text{light}$  backgrounds

$$d_i = \frac{p_i}{\sum_{j \neq i} p_j \cdot \hat{N}_{ij}}, \text{ weights } \hat{N}_{ij} = \frac{N_j}{\sum_{k \neq i} N_k} \text{ from remaining classes} \quad (1)$$

- $p$ : probability,  $N$ : expected event yield
- Definition of discriminant function works well
- Cut values on  $d_{t\bar{t}H}$  for considering events signal-like: from  $\max(\frac{S}{\sqrt{B}})$
- Background grouping decided by the highest of the 5  $d_i$  for bkg
- Reconstruction transformer obtains  $p_T^H$ : predict which 2 jets most likely from  $H$  decay, get  $p_T^H$  from combining jet four-vectors
- Better performance than getting  $p_T^H$  from regression, whose predictions shift to central STXS bins

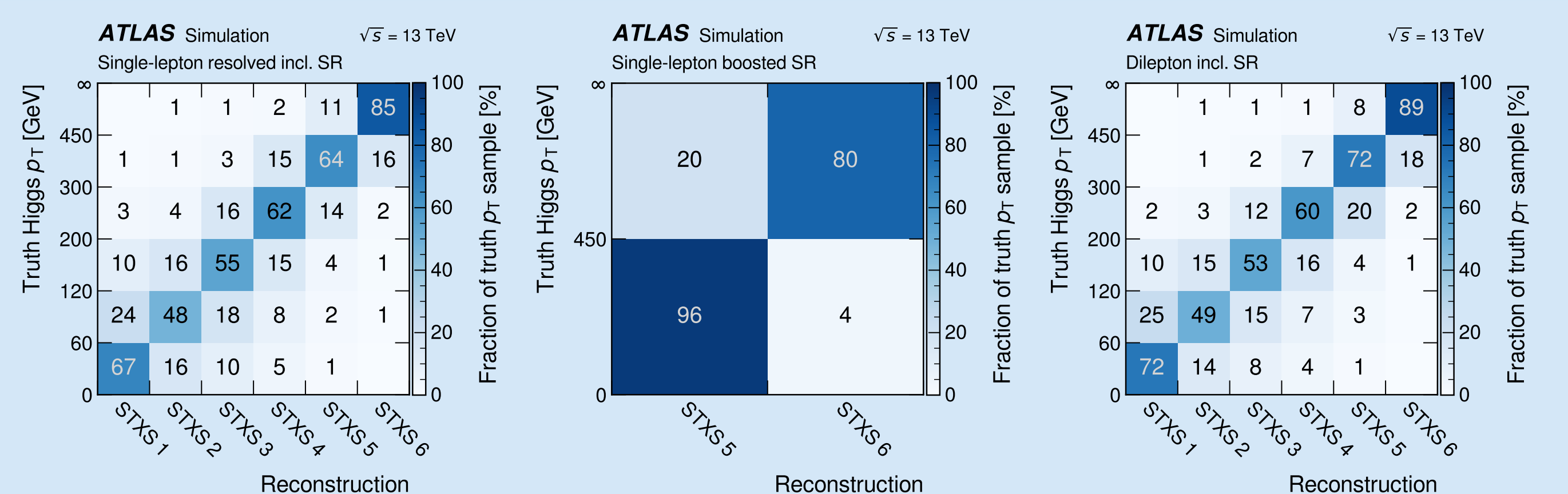
## Signal and Background Classification Performance

Data and MC comparison (single- $\ell$ ), SR  $\rightarrow$   
 Pre-fit (single- $\ell$  resolved) signal separation  $\rightarrow$   
 and bkg classification  $\downarrow$



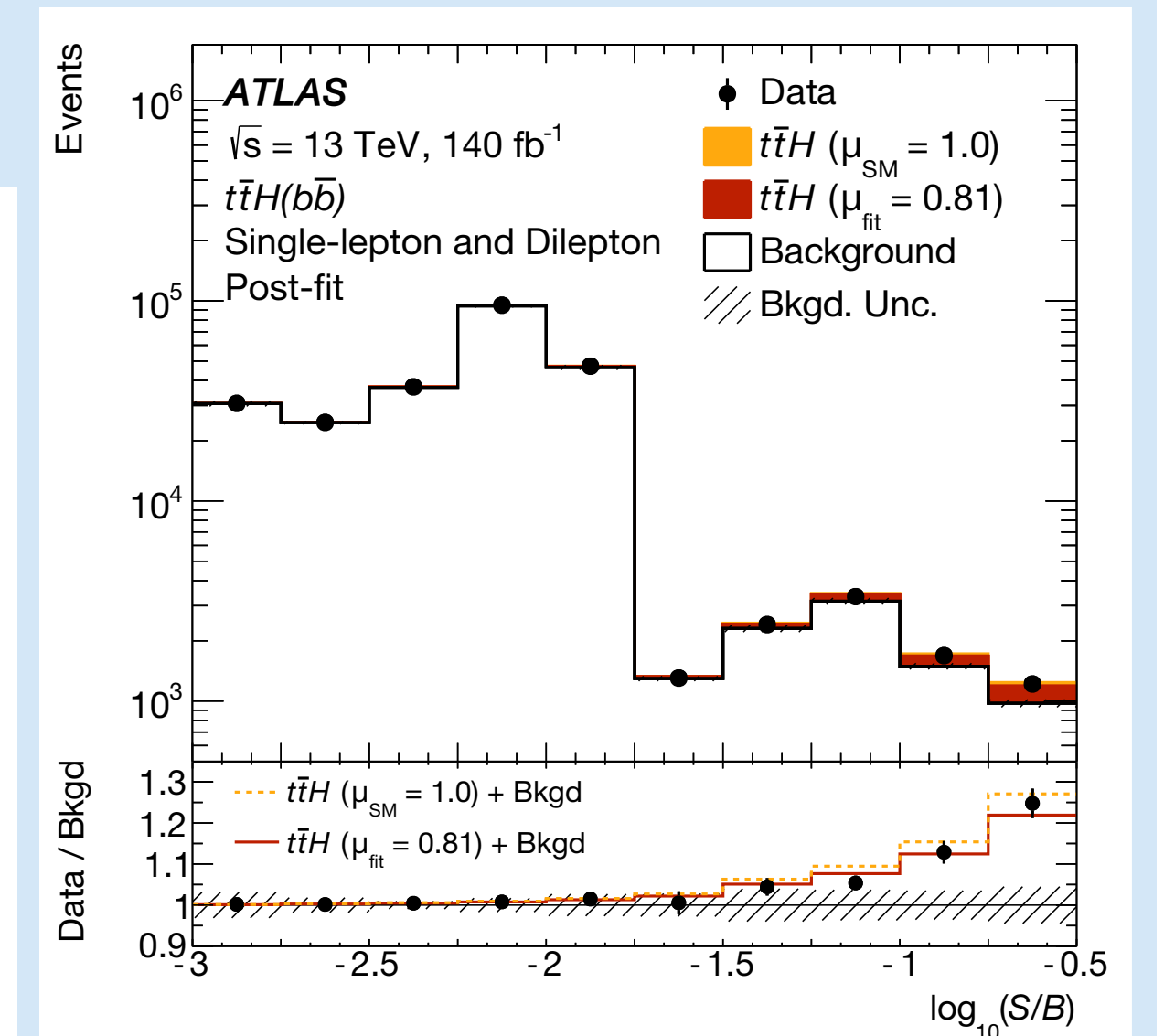
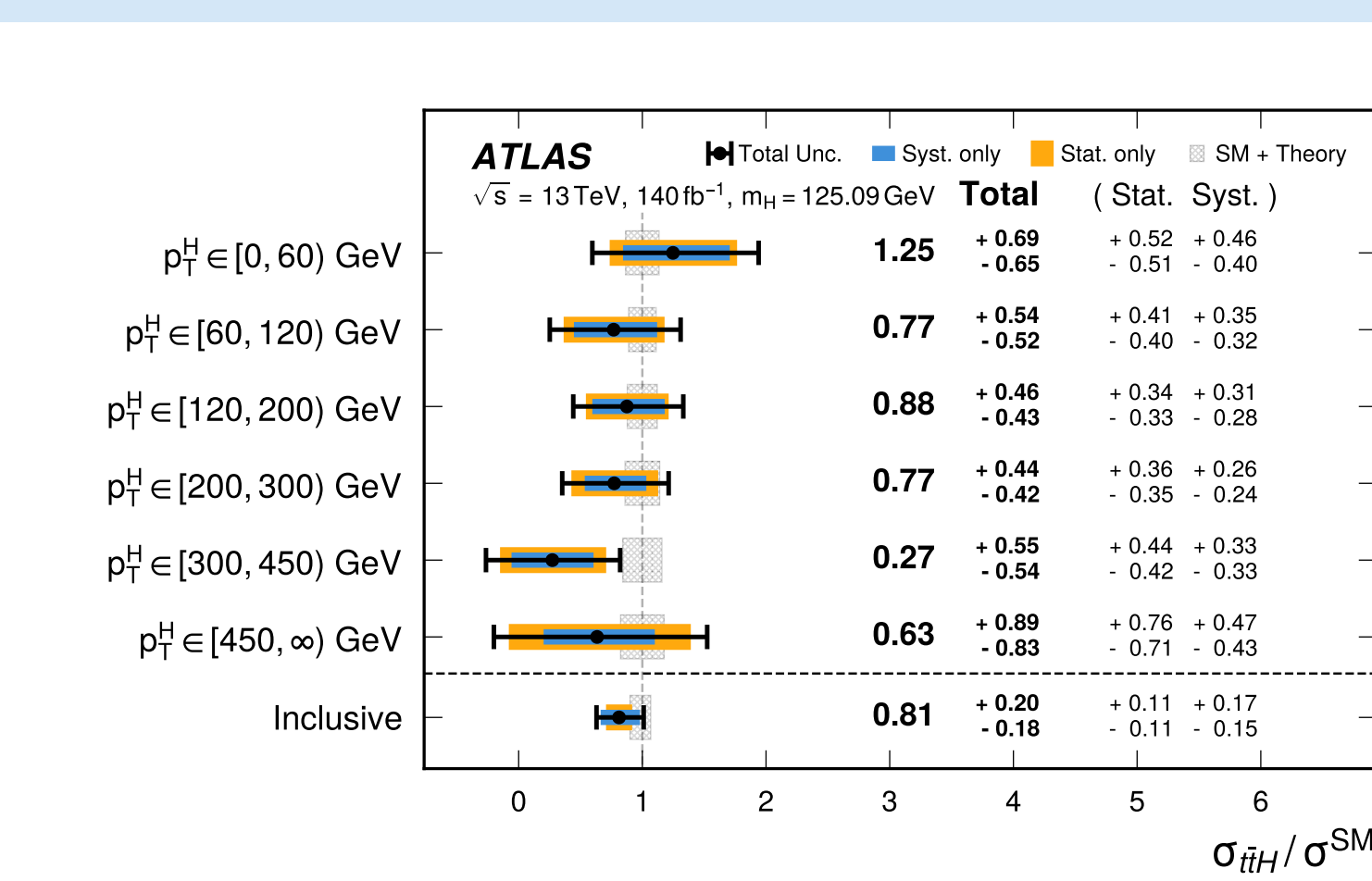
- The transformer NN approach in this analysis improved over the BDT approach as used previously [5]
- AUC 0.753 for single-lepton resolved and 0.774 for dilepton

## Higgs $p_T$ Reconstruction Performance

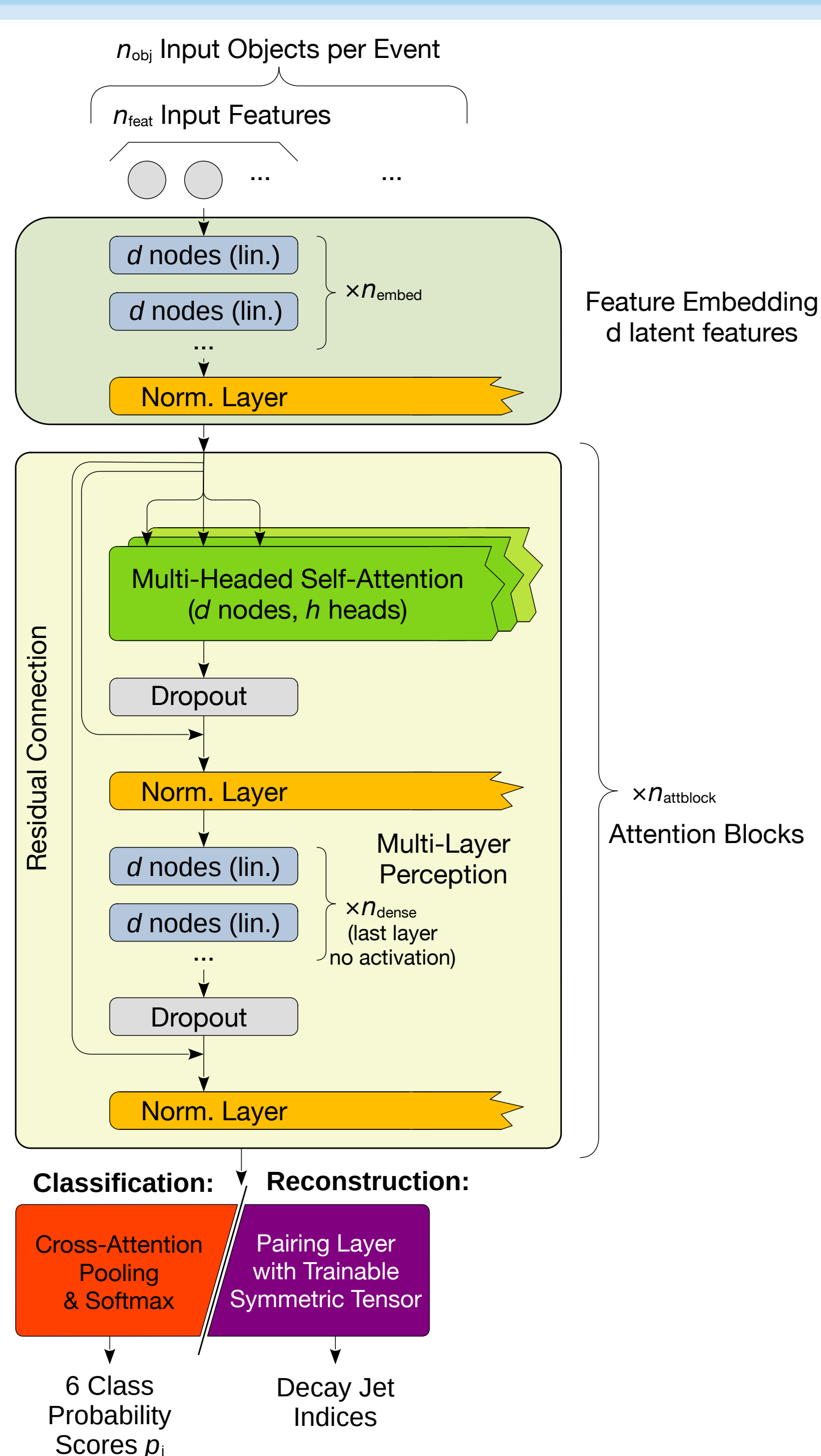


## Results of the Analysis

- Excess of  $t\bar{t}H(bb)$  events: observed (expected) significance 4.6 (5.4) std dev
- $t\bar{t}H$  signal strength for  $m_H = 125.09 \text{ GeV}$   $\mu_{t\bar{t}H} = 0.81 \pm 0.11(\text{stat.})^{+0.20}_{-0.16}(\text{syst.})$ , cross-section  $\sigma_{t\bar{t}H} = 411 \pm 54(\text{stat.})^{+85}_{-75}(\text{syst.}) \text{ fb}$ , consistent with SM
- Measured in STXS bins



## The Transformer Neural Networks



Transformer models like GPT [2] utilise attention mechanism [3]. Similar architecture used for  $t\bar{t}H(bb)$  analysis

- Permutation-invariant architecture: ordering of input objects does not matter
- Uses: kinematic information of reconstructed electrons, muons, jets,  $E_T^{\text{miss}}$ ; pseudo-continuous  $b$ -tagging score
- Trained on: classification -  $t\bar{t}H$  signal,  $t\bar{t} + \text{jets}$  bkg; reconstruction - only  $t\bar{t}H$

Residual scheme modified from [3], where two separate residual connections are employed around the multi-head self-attention and the multi-layer perception sub-layers

- Modified residual scheme results in:
  - Less dependency on earlier blocks
  - Slightly higher average classification accuracy

For  $p_T^H$  reco, pairing layer similar to [4]

## Conclusions & Outlook

- Run 2 legacy analysis, significantly improved over the last analysis [1]
- Benefited from various improvements, including transformer NN used for MVA:
  - Define signal region and control regions
  - Higgs  $p_T$  reconstruction
- Discriminant function defined for event classification performs well
- Reconstructing jets from Higgs decay: better performance than obtaining  $p_T^H$  from regression



[1] ATLAS Collaboration, Measurement of Higgs boson decay into b-quarks in associated production with a top-quark pair in pp collisions at  $\sqrt{s} = 13 \text{ TeV}$  with the ATLAS detector, JHEP 06 (2022) 097  
 [2] T. Brown et al., Language Models are Few-Shot Learners, Advances in Neural Information Processing Systems, ed. by H. Larochelle et al., 33, Curran Associates, Inc., 2020, 1877  
 [3] A. Vaswani et al., Attention is all you need, Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS'17, Long Beach, California, USA: Curran Associates Inc., 2017, 6000  
 [4] M. J. Fenton et al., Permutationless many-jet event reconstruction with symmetry preserving attention networks, Phys. Rev. D 105 (2022) 112008  
 [5] ATLAS Collaboration, Search for the standard model Higgs boson produced in association with top quarks and decaying into a  $b\bar{b}$  pair in pp collisions at  $\sqrt{s} = 13 \text{ TeV}$  with the ATLAS detector, Phys. Rev. D 97 (2018) 072016