Status and Outlook of the Type II Seesaw Search in Run 2 and Run 3

Lara Calic

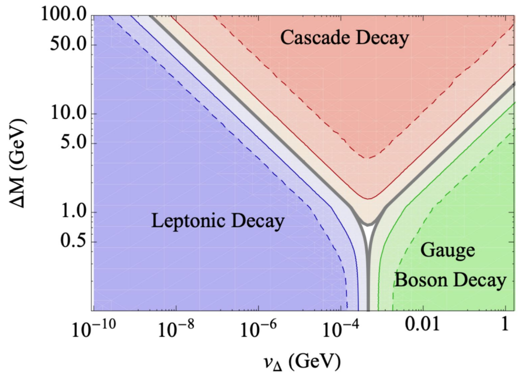
PhD student day

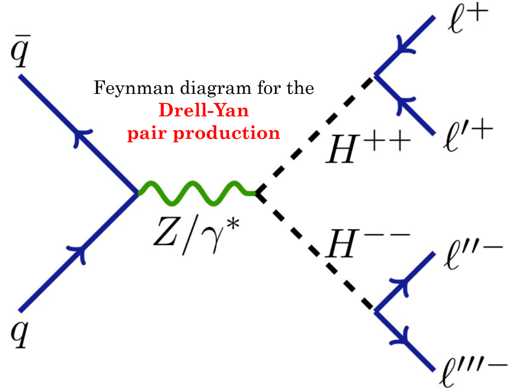
11th of December, 2025

Studying Type II SeeSaw model

- Main motivation behind the model is the explanation of neutrino masses
- Type II: introduces a new scalar triplet containing a doubly charged Higgs boson
- Predicts lepton number violation and lepton flavor violation
- We focus on the following final states:
    - 4 leptons
    - assume *Br(H±± → ℓ±ℓ±) = 1/6*, where we consider all possible lepton combinations (e, μ and τ)
- Interested in e, μ and τ final leptonic states
- Previous, similar, and published Run 2 search:
    - Type II: published paper (limit at $m_{H\pm}$ > 1080 GeV)
    - Previous published analysis for Run 2 (considered final states which only included e and μ)

Leptonic decays: set vev $v_\Delta \approx 10^{-8}$ and set $\Delta M = m_{H\pm} - m_{H\pm\pm}$ to zero





Feynman diagram for the **Drell-Yan pair production**

Generates neutrino masses **directly through Higgs interactions**

Common points that must “tick the box” for the analysis to be publishable:

- Signal MC modeling and samples
- VR, CR and SR regions (cut-based approach)
- Background estimations (dedicated paper on ML-based fakes approach, submitted on arXiv)
- Systematics (including Run 2/3)

New improvements

- Add **hadronically decaying taus*** as final-state leptons
- Introduce **ML at different levels** of analysis (selection, background determination)
- Use **Run 3 data** (target integrated luminosity of **~300 fb^{-1} for Run 3**, compared to **139 fb^{-1} in Run 2** → a factor **~2.2 increase)**

*** described in more details on the next slides**

Classical approach

Background Estimations: Binned approach

Electrons (Type II studies)

Note: A similar approach was used for muons (see backup slides)

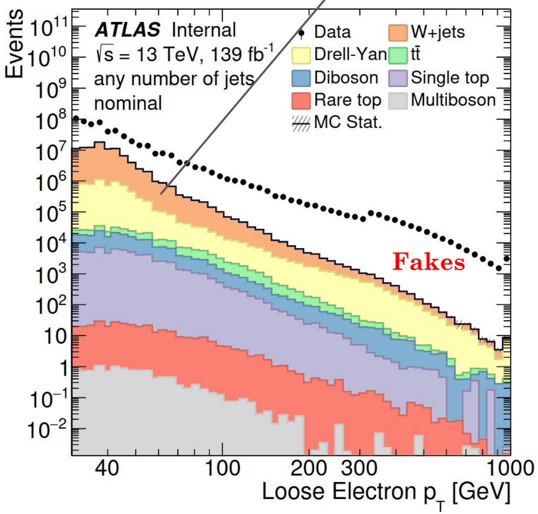
Main SM backgrounds contributing to the multi-lepton final state:

- Diboson production
- ttbar, single-top
- Drell-Yan + jets
- Misidentified (“fake”) leptons
    - jets, non-prompt leptons, or photon conversions reconstructed as electrons or muons

What are the main challenges?

- **Fake leptons are difficult to model in MC (large uncertainties and mismodelling)**
- Fakes appear in many regions due to relaxed isolation or jet → lepton mis-ID
- The Type II Seesaw analysis is highly sensitive to even small fake-lepton contributions
- We need data-driven method to solve this

W+jets dominates → large fake-electron contribution



Data >> prompt MC

We can’t rely only on MC to describe this region!

Background Estimation: Binned Fake Factor Estimation

Fake-factor method is a simplified matrix method — we define **loose** (not tight) and **tight** regions which are orthogonal.

Two lepton definitions:

- Tight: nominal signal selection
- Loose: relaxed identification, isolation cuts
- Strictly loose: tight not loose region, used for fake estimation

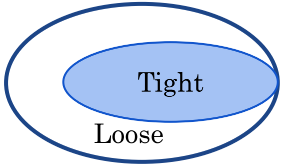
Gives us an estimated number of fake events in the signal region!

2 lepton case

	Tight	Loose
Loose	LT 1 fake lepton $F_1(N_{LT}^{\text{data}} - N_{LT}^{\text{MC, prompt}})$	LL 2 fake leptons $-F_1F_2(N_{LL}^{\text{data}} - N_{LL}^{\text{MC, prompt}})$
Tight	TT SR	TL 1 fake lepton $F_2(N_{TL}^{\text{data}} - N_{TL}^{\text{MC, prompt}})$

$$N_{TT}^{\text{fakes}} = F_1(N_{LT}^{\text{data}} - N_{LT}^{\text{MC, prompt}}) + F_2(N_{TL}^{\text{data}} - N_{TL}^{\text{MC, prompt}}) - F_1F_2(N_{LL}^{\text{data}} - N_{LL}^{\text{MC, prompt}})$$

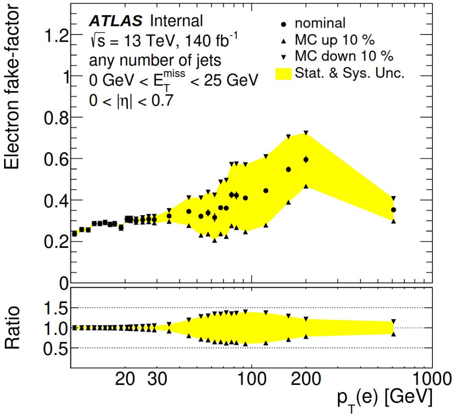
The fake factor F is defined as the ratio f /(1 – f) of fake lepton efficiencies.



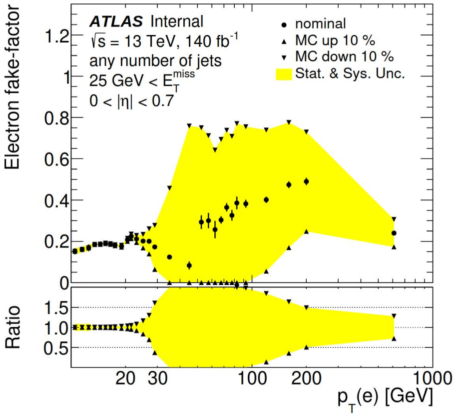
F needs to be extracted in a **control region**, where the fake lepton can be identified reliably

Electron Fake Factors

E^{miss}_{T} < 25 GeV

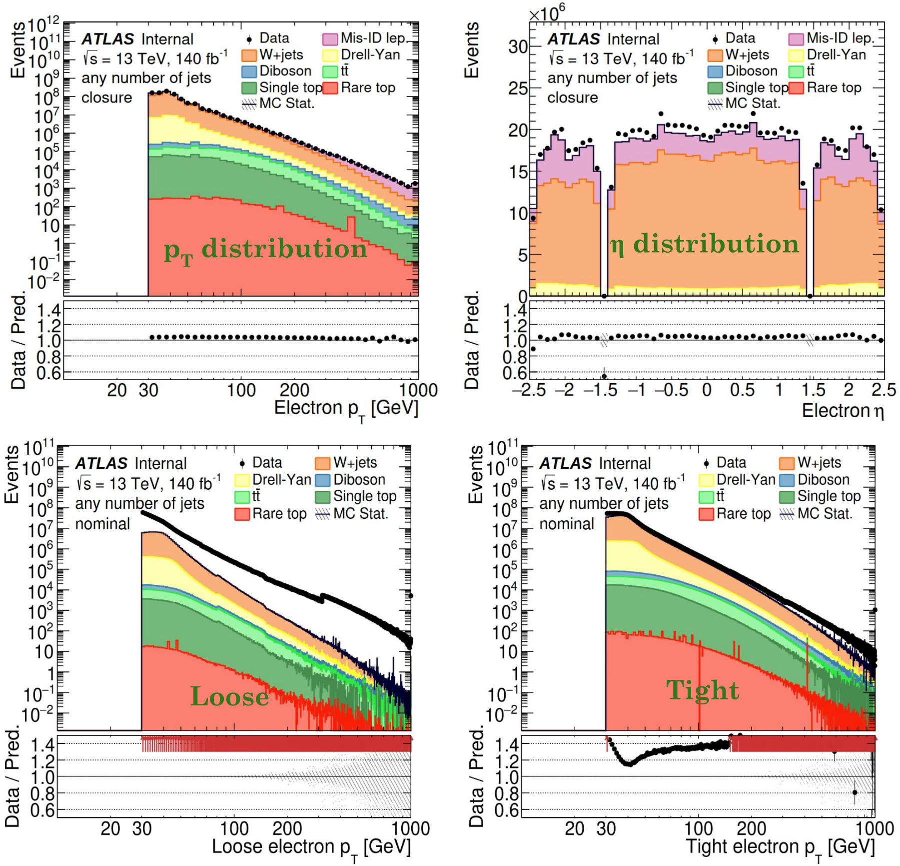


E^{miss}_{T} > 25 GeV



- Both plots show the electron fake factor vs. electron p_T (η bin (0< |η|< 0.70) split into two MET regions)
- High MET region: at low p_T the fake factor is smaller
- Low MET region: for low p_T (~40–60 GeV), the fake factor is ~ 0.3–0.35
- Varying all prompt MC by ±10% is the dominant systematic
- For high p_T, uncertainties are large (~less fakes)

Closure Test for Electrons



- We perform **closure test** in signal region to validate the FF method
- Closure is performed on **Monte Carlo only**, not on blinded data (we know which leptons are prompt and fake)
- Closure shows overall good agreement between data and MC
- Tight p_T distribution (is our signal region)
- **Data – MC = fakes**

Validated the approach on muons as well

ML based approach

Background Estimations: Fake Factor Estimation with Machine Learning

Electrons (Type II studies)

Note: for more technical details, you can check the paper on arxiv

More details: arXiv

- The standard ATLAS fake-factor method estimates the fake rate in bins of p_T, $|\eta|$ and E_T^{miss}
- The fake factor is defined as

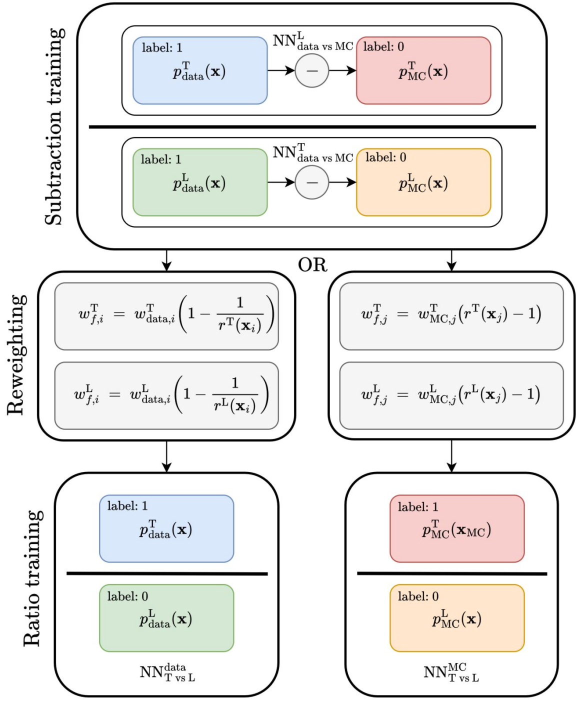
$$\mathrm{FF} = \frac{(\mathrm{data} - \mathrm{MC}_{\mathrm{prompt}})^{\mathrm{tight}}}{(\mathrm{data} - \mathrm{MC}_{\mathrm{prompt}})^{\mathrm{loose}}} = \frac{N^{\mathrm{tight}}}{N^{\mathrm{loose}}}$$

- **Limitation**: extrapolation issue, requires binning (problematic in terms of interpolation), etc.

- An idea: **replace binned fake factor estimation with ml approach – unbinned (continuous) ratio from data**

- ML learns the density ratio (or weights)

$$r(\mathbf{x}) \equiv w(\mathbf{x}) = \frac{p(\mathbf{x}^{\mathrm{tight}}_{\mathrm{data}}) - p(\mathbf{x}^{\mathrm{tight}}_{\mathrm{MC}})}{p(\mathbf{x}^{\mathrm{loose}}_{\mathrm{data}}) - p(\mathbf{x}^{\mathrm{loose}}_{\mathrm{MC}})}$$



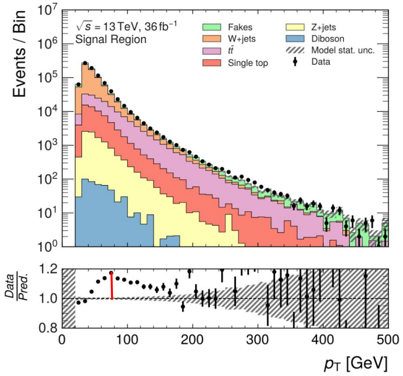
Step 1: learn numerator (tight) distribution difference

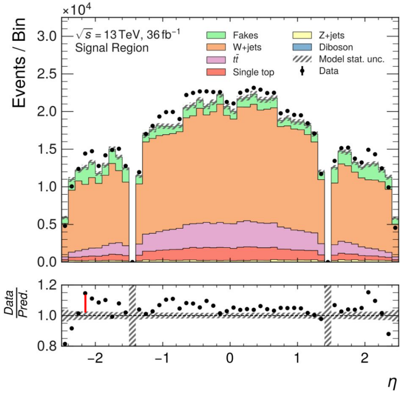
Step 2: learn denominator (loose) distribution difference

Step 3: learn the ratio (continuus)

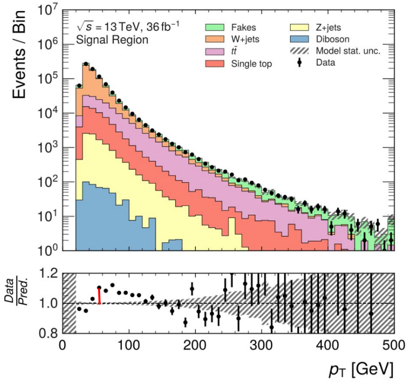
Results: Comparison between Binned and ML Fake Factor Method (Signal Region)

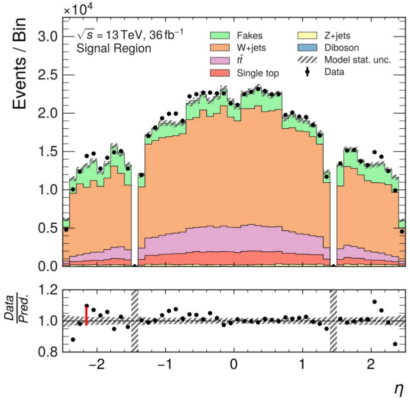
Binned Method





ML Method





Signal region – Binned method:

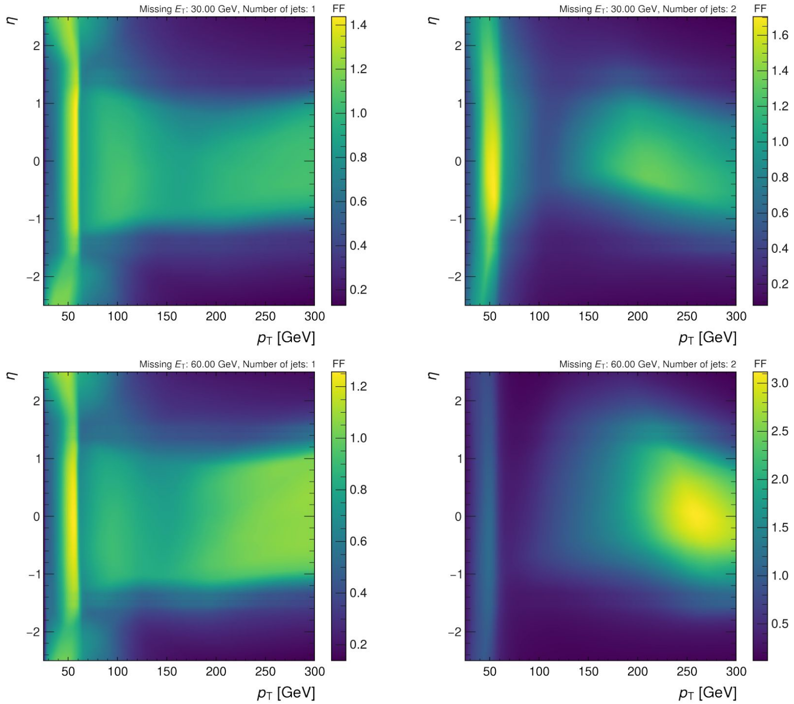
- Systematically underestimate the fake contribution
- E_T and m_T distributions show **significant shape and normalization mismodelling**
- Works “better” in CR

Signal region – ML method:

- **Much better agreement** with data in the SR (across all the variables)
- $N_{jets,}$ E_T , m_T **kinematic dependence captured**
- Extrapolation from CR → SR is **more robust**

Results: 2D projection of the fake factor (p_T - η plane)

2D projections: p_T– η slices



Conclusions:

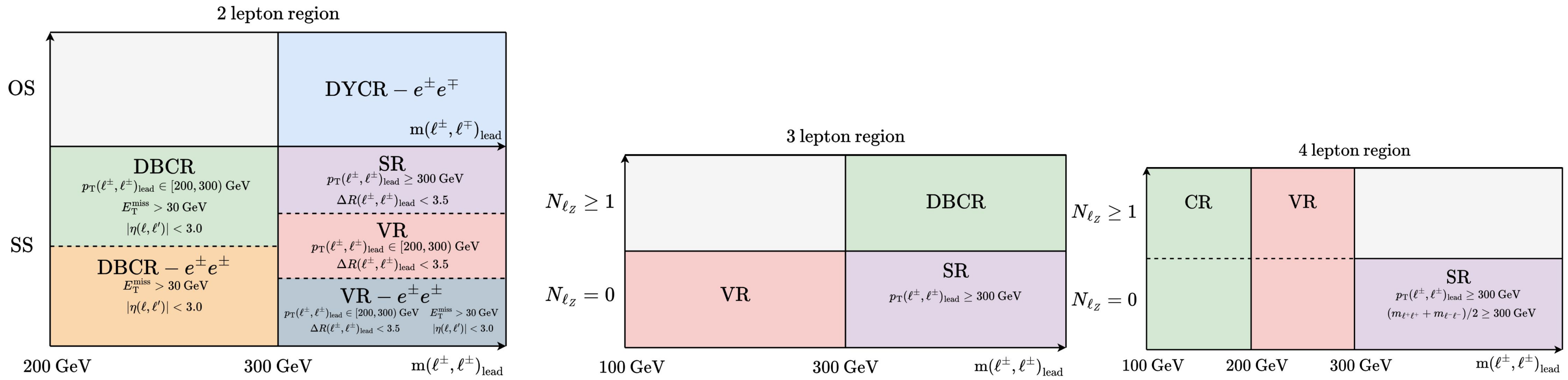
- **Smooth, continuous FF across (p_T, η)** → no binning artefacts
- Symmetric behaviour in η
- Non-trivial p_T dependence (learned directly from data)
- Fake factor increases with N_{jets}
- Stable behaviour even in low-stat regions (high p_T, large $|\eta|$)
- Improved CR → SR extrapolation due to multi-dimensional modelling

Note: A similar approach was used for p_T– MET (see backup slides)

Analysis Regions (prefit, Run 2)

Control (CR), Validation (VR) and Signal (SR) region in the type II Seesaw analysis

**Note: One representative distribution is shown for each region*



SR, VR, and CR are defined in the 2ℓ, 3ℓ, and 4ℓ channels

- To define them we are using the leading-lepton p_T, invariant mass, charge, and Nℓ requirements

Validation region (VR)

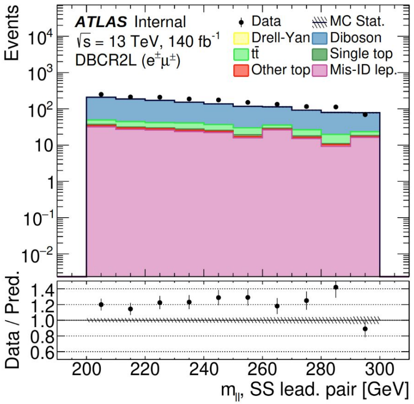
- Close to SR selections but signal-depleted; used to **validate background modelling** (MC + data-driven fakes)

Control Regions (CR / DBCR / DYCR)

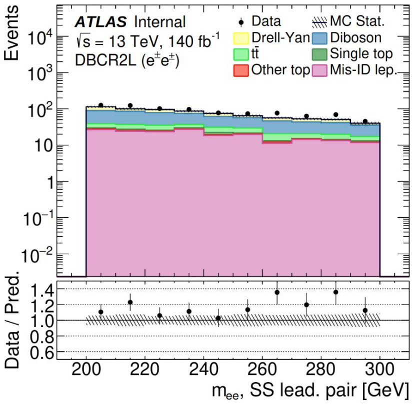
- Enriched in specific backgrounds (diboson, Drell–Yan, charge-misID) and used to **normalise backgrounds**

Analysis Strategy: Same-sign lepton pair invariant mass in Control Region

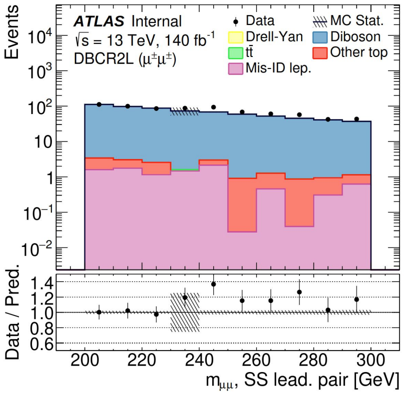
eμ



ee



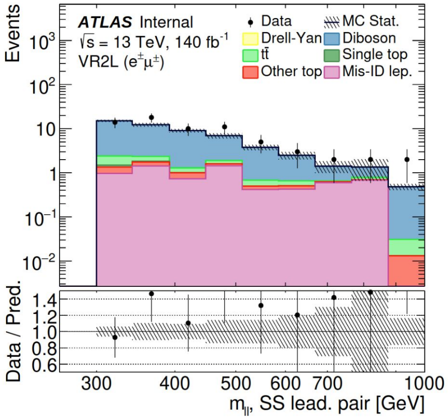
μμ



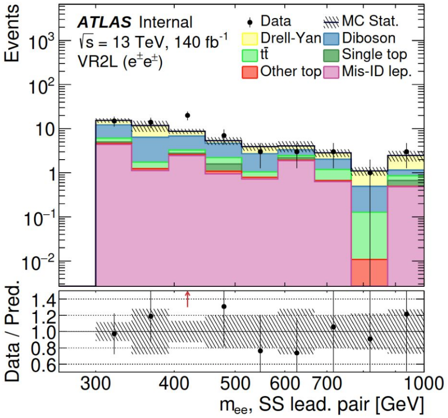
- **Overall good data–MC agreement** in all three channels for the same-sign leading lepton-pair mass in the DBCR2L region
- As expected, **diboson is dominant** (some other backgrounds that contribute are Drell-Yan, ttbar, fakes (Mis-ID) leptons)
- No notable discrepancies are observed in the data/prediction ratios

Analysis Strategy: Same-sign invariant mass of the lepton pair in Validation Region

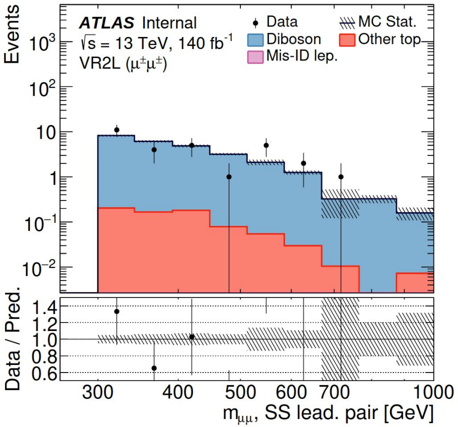
eμ



ee



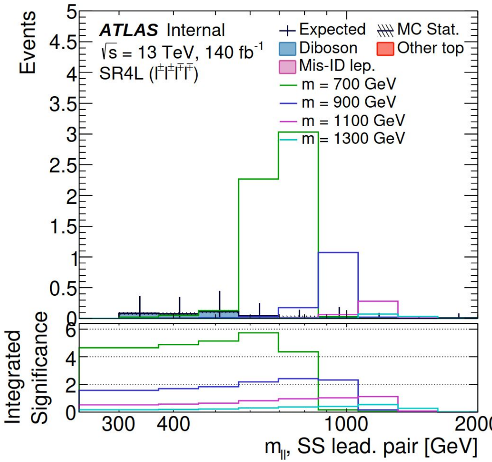
μμ



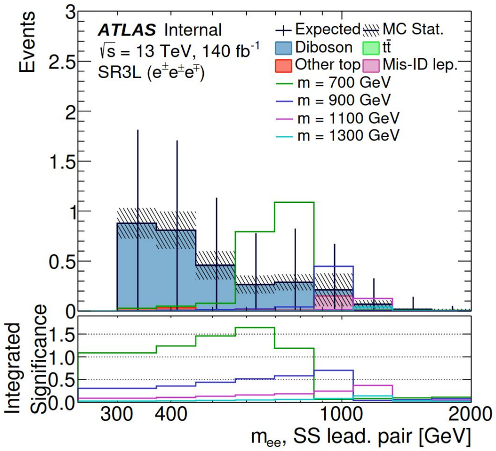
- **Good overall data–MC agreement** in the VR2L region across all same-sign channels, within the statistical uncertainties
- Diboson still dominant process, and fakes are contributing mainly in electron channels
- The data/prediction ratio is relatively flat and agrees within a ~20% normalisation offset

Analysis Strategy: Same-sign invariant mass of lepton pair in Signal Region

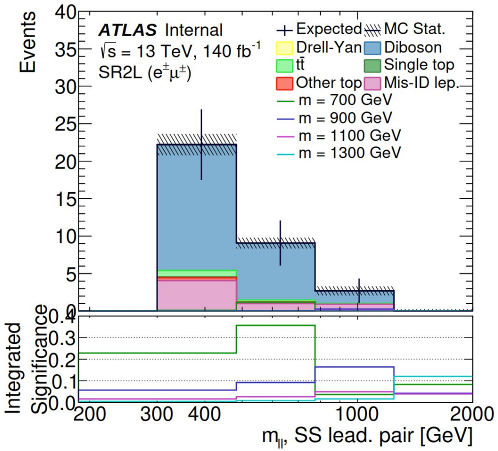
4ℓ



3ℓ



2ℓ



- The **background prediction** (diboson, mis-ID leptons, other top) is **low and dominated by statistical uncertainties** across all variables

- Most sensitive channel for Type II Seesaw → strong separation between signal and backgrounds

- Planned improvements using neural-network methods

Hadronic τ Decays*

On-going Work: New improvements in the type II Seesaw analysis

Hadronic taus were not included in previous versions due to reconstruction challenges!

More details and all plots shown here are taken from:
[1] Tau reconstruction and ID performance, 13 TeV
[2] ATLAS Tau reconstruction paper

*Identification working points are predefined levels of how strict the detector is when deciding whether something is a real lepton or a background object.

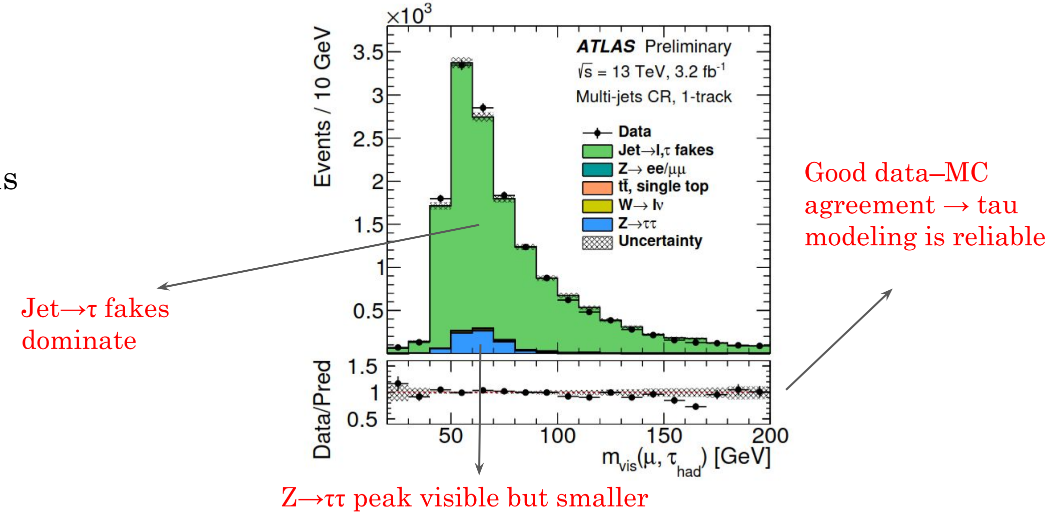
Why weren't they used before?

- Reconstruction is more challenging (jet-τ confusion, ID* working points)
- Hadronic taus are **more difficult to reconstruct** (have backgrounds from jets faking taus → require dedicated algorithms and calibration)

Why do we want to include them?

- Run 3 provides improved τ-ID, calibration, and performance
- Adding hadronic τ increases **signal efficiency**
- Adds **significant physics reach** of the analysis

Visible mass of the (muon, hadronic-tau) in control region



* Hadronic taus are reconstructed reliably, even in challenging multijet environments

* Jet→τ fakes are the **main background** but are well understood and data-constrained

Conclusions

- Type II Seesaw predicts clear multi-lepton signatures accessible with ATLAS detector

- Fake leptons are a major background challenge and we need data-driven estimation techniques for them
- The machine-learning fake-factor method provides a continuous, multi-variable model that outperforms the binned approach (in one variable), especially when extrapolating to the signal region

- Hadronic τ decays significantly increase the analysis's flavour coverage and sensitivity, and can now be included thanks to improved Run 3 tau reconstruction

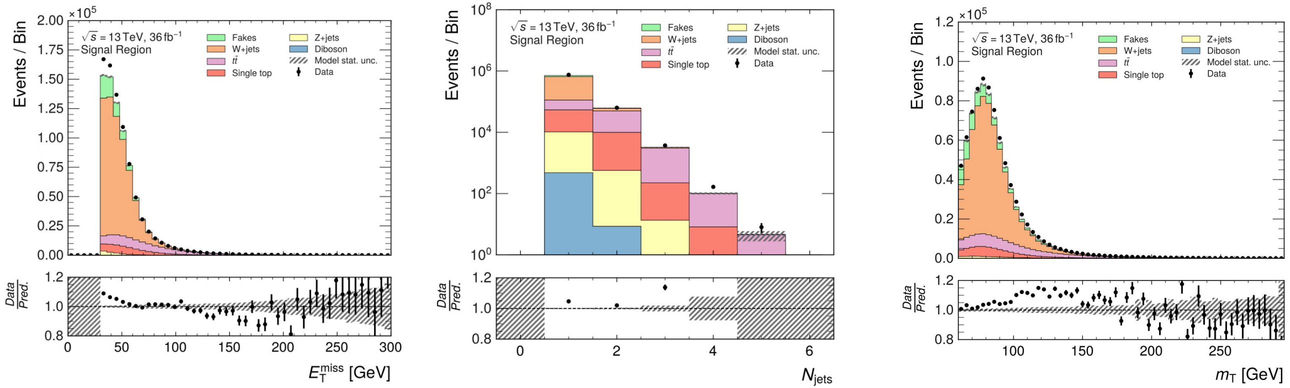
- Run 3 data and these improvements together enhance the discovery potential of the Type II Seesaw search

Backup

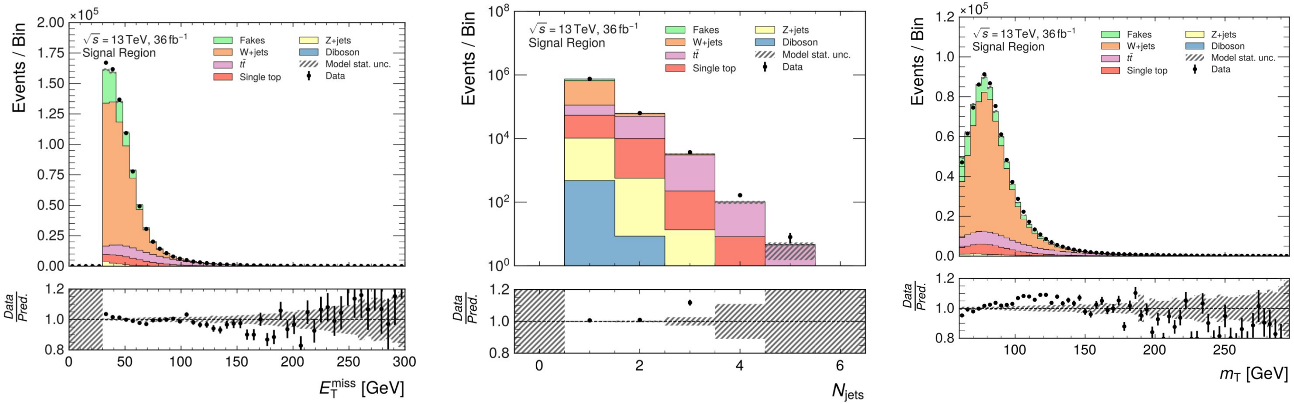
(Type II studies)

Results: Comparison between Binned and ML Fake Factor Method (in Signal Region)

Binned Method



ML Method



Conclusions

ML method shows a good agreement with binned where **statistics are good**, but also **outperforms** it when extrapolating to the SR and in sparse/high-dimensional regions

Results: Comparison between Binned and ML Fake Factor Method (in Control Region)

- Both methods show **good closure** in the CR, as expected

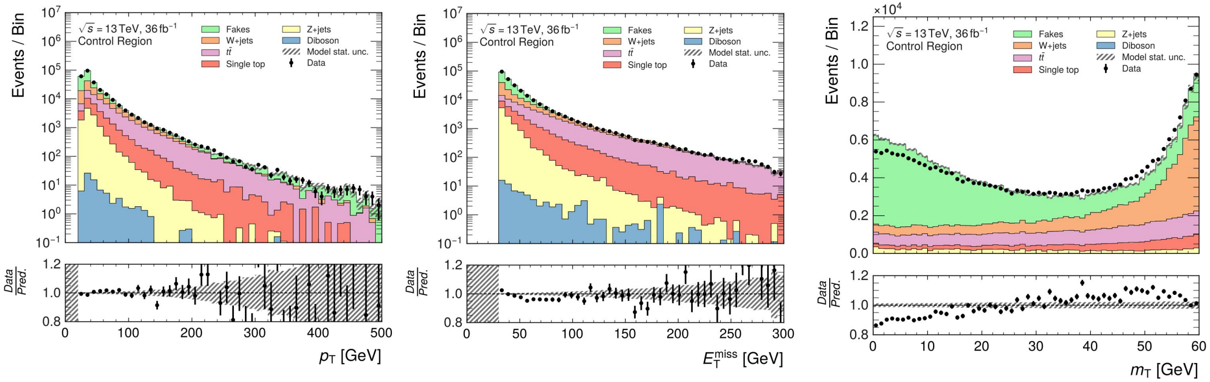
- The **binned method** performs well for variables it is explicitly binned in (p_T, $|\eta|$)

- The **ML method** achieves **overall better closure**, especially for **MET** and $\mathbf{m_T}$, capturing their multivariate dependence

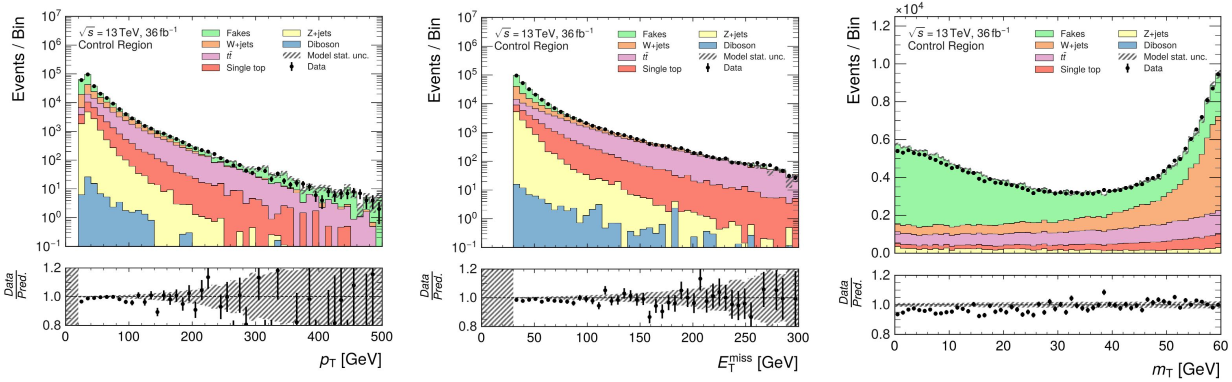
- ML reduces visible mismodelling in variables **not** included in the binned parameterisation

- Confirms that ML learns a **physically meaningful fake factor** in the region where statistics are high

Binned Method



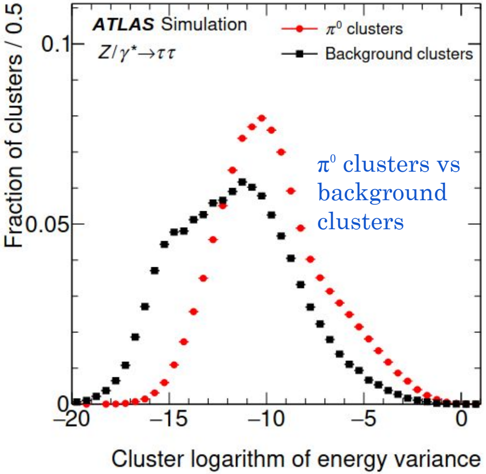
ML Method

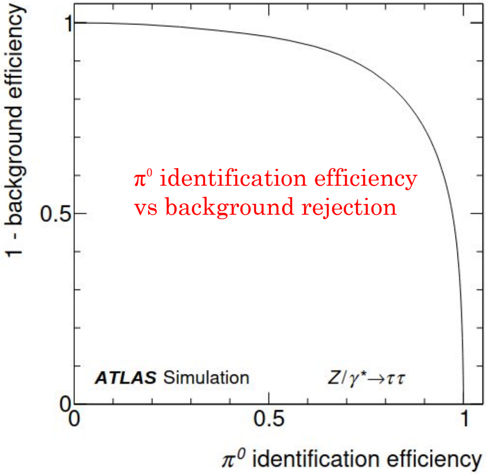


Physics motivation

- In **type II Seesaw model**: expect heavy scalar boson ($H^{\pm}$) that couple to all lepton flavours (e, μ,τ)
- Hadronic decays represent ~ 65% of all tau decays → important part of the signal
- Including τ_had extends coverage to all flavour combinations and maximizes signal sensitivity
- By adding them, we will have **a new final state** (additionally to e and μ)

How ATLAS distinguishes hadronic τ decays from jets?

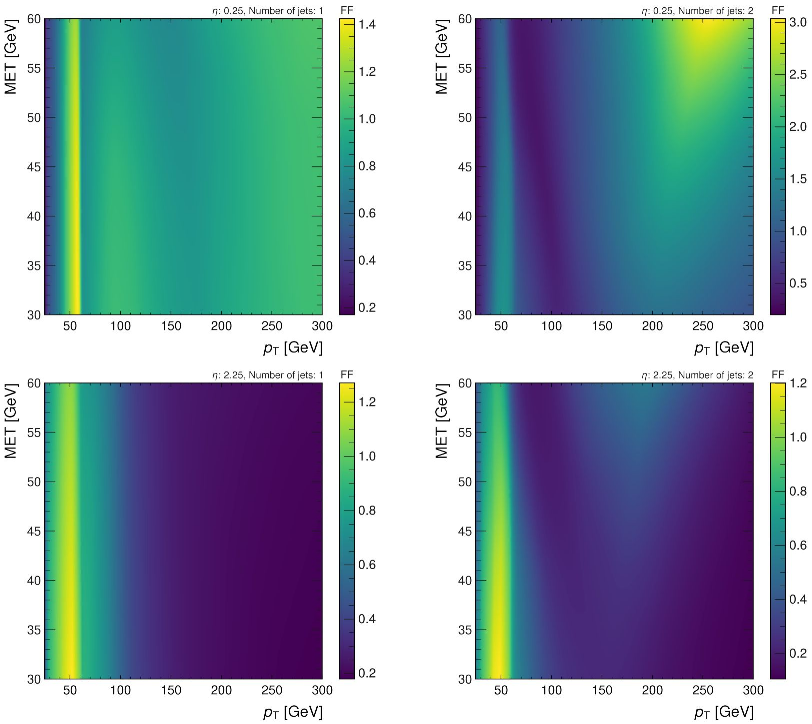




* Hadronic τ decays leave a very specific calorimeter signature, dominated by charged pions and $\pi^0 \rightarrow \gamma\gamma$
* Jet backgrounds have different cluster shapes and energy variance distributions

To conclude here … ATLAS can **identify τ_had with high efficiency** while strongly rejecting jet backgrounds!

2D projections: p_T– MET slices



Conclusions:

- **Strong MET dependence captured — a major limitation of the binned FF**
- Higher MET → larger FF, consistent with W+jets and $t\bar{t}$ fake-rich regimes
- Smooth behaviour in sparse, high-MET regions (binned method unstable there)
- Clear correlation with N_{jets} and MET jointly → true multivariable learning
- Stable behaviour even in low-stat regions (high p_T, large $|\eta|$)
- More robust SR predictions thanks to improved modeling of MET tails

Electrons

Fake-enriched region

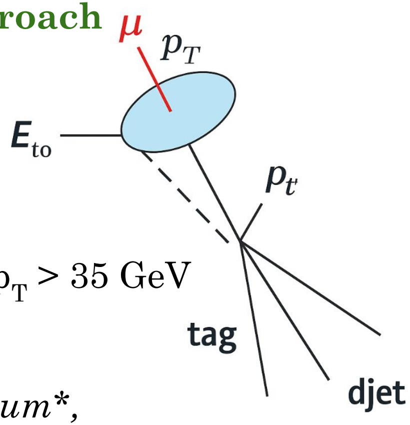
- Exactly one electron, no muons
- $N_{\text{b-jets}} = 0$ (b-jet veto)
- $p_T > 10$ GeV

Identification for tight electrons: *LHTight**.
Loose electrons: *Loose_VarRad**+ *prescaled triggers (lhvloose)*

Muons

Fake-enriched region
Tag-and-probe approach

- Exactly μ, no e
- $N_{\text{b-jets}} = 0$ (b-jet veto)
- $E_T^{miss} < 40$ GeV
- $p_T > 10$ GeV
- At least one jet with $p_T > 35$ GeV
- $\Delta\phi(\mu, j_{\text{lead}}) > 2.7$



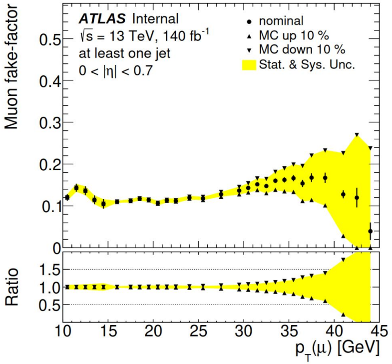
Muon reconstruction: *Medium*, isolation: Tight_VarRad.*

*LHTight** → *"our strict electron selection",*
*Loose_VarRad** → *"a loose electron selection with relaxed identification and isolation cuts"*

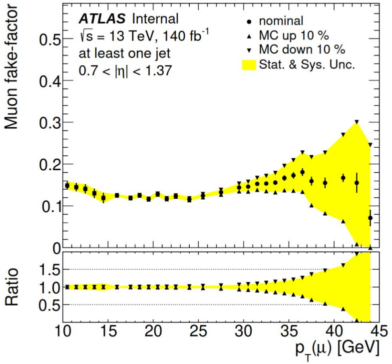
*Medium** *is the default muon ID: not too loose, not too tight*

Muons Fake Factors

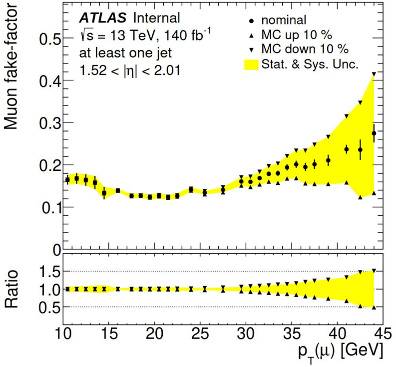
Different η slices



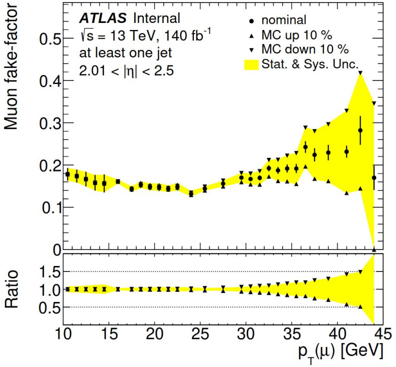
Central region



Crack region



Endcap region



Forward region

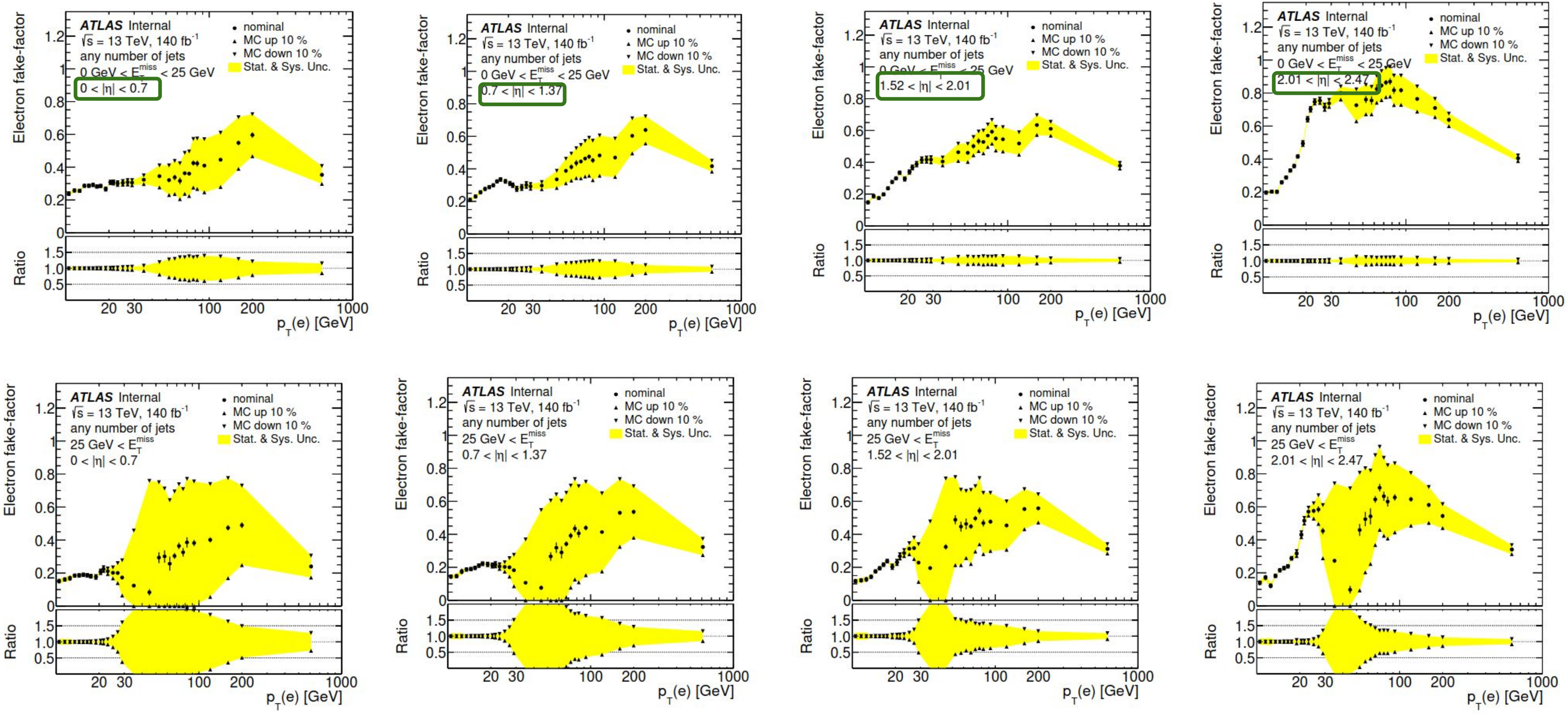
Similar shapes, forward region has slightly higher fake factors at high p_T

Less η-dependence

Electron Fake Factors

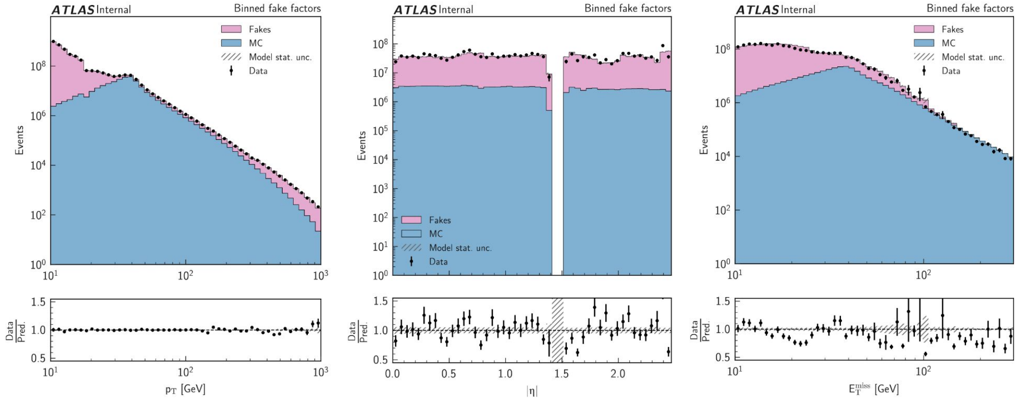
$E_T^{miss} < 25$ GeV

$E_T^{miss} > 25$ GeV

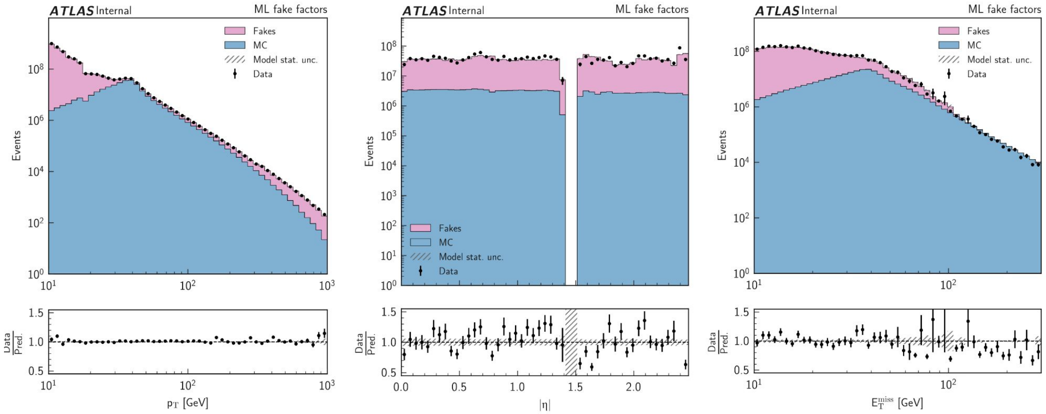


Closure: Comparison between Binned and ML Fake Factor Method

Binned Fake Factors

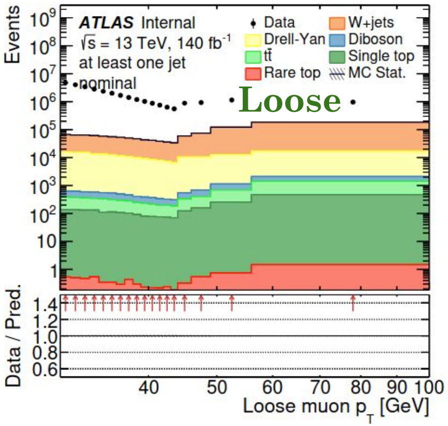


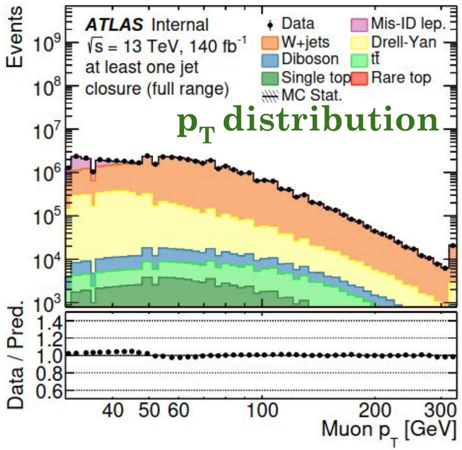
ML Fake Factors

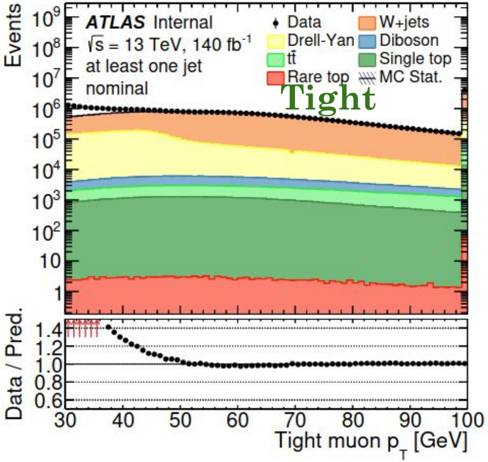


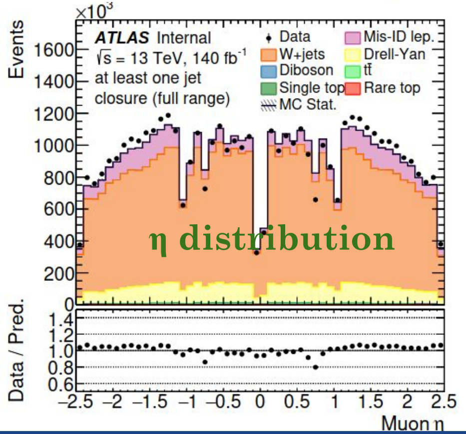
- Computed the fake factors using the training sample (50% of the dataset) and apply them to the test sample (25% of the dataset)
- The binned and ML fake factors show **comparable performance** in p_T and $|\eta|$
- The MET distribution shows **much stronger performance** for the ML method
- The same approach was applied for muons

Tight and Loose Distributions for Muons



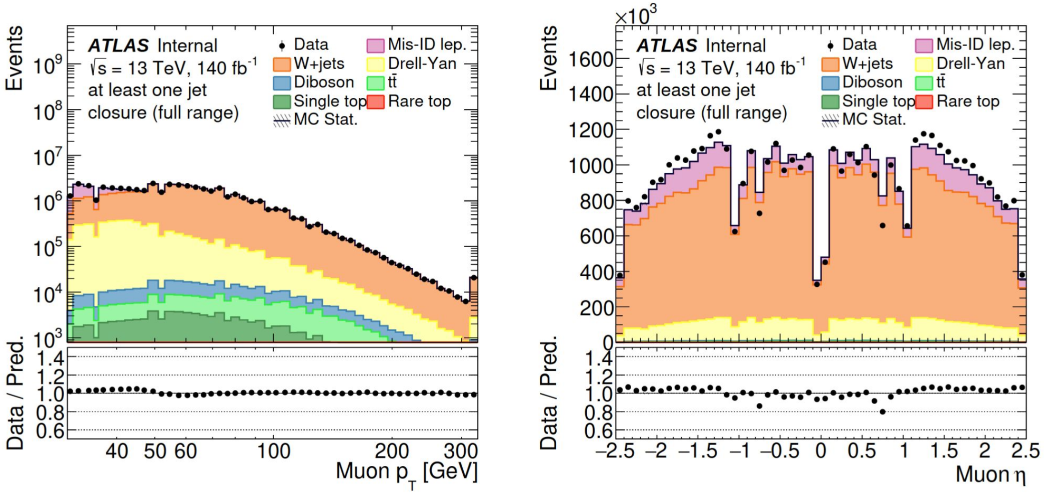






- Preformed closure test to validate of FF method
- As shown, we observed a very good agreement between MC and data

Closure Test for Muons



- In the closure test: Closure test: flat p_T , good η modeling
- Above > 40 GeV, there is very less fakes

Tau Decays

Diagrams taken from [PhD thesis]

Hadronic decays (~65%)

- 1-prong:
  - $\tau^- \rightarrow \pi^- \nu\tau$
  - $\tau^- \rightarrow \pi^- \pi^0 \nu\tau$
- 3-prong:
  - $\tau^- \rightarrow \pi^- \pi^+ \pi^- \nu\tau$

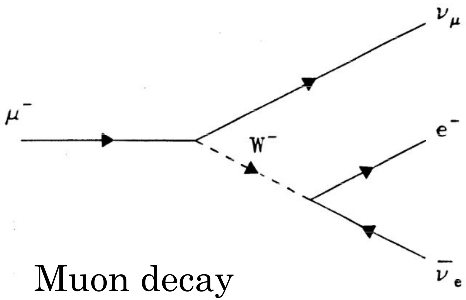
- Neutral pions decay as: $\pi^0 \rightarrow \gamma\gamma$
  → leads to **narrow calorimeter clusters + tracks** (this is what ATLAS τ-ID uses)

Leptonic decays (~35%)

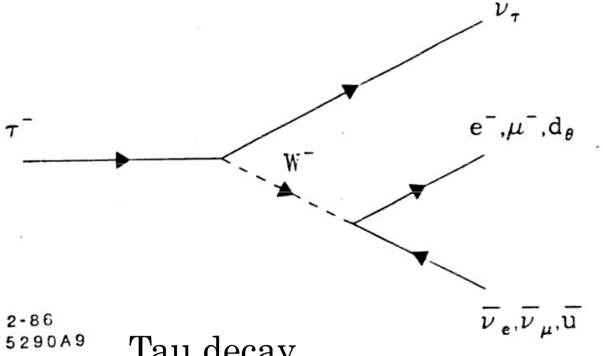
- $\tau \rightarrow e\, \nu\bar{\nu}$ (~17.8%)

- $\tau \rightarrow \mu\, \nu\bar{\nu}$ (~17.4%)

Leptonic τ decays appear as electrons or muons



Muon decay



Tau decay