

Application of statistical methods with emphasis on
Machine Learning for the analysis of experimental data
from the ATLAS experiment at the LHC at CERN
PhD Thesis Presentation

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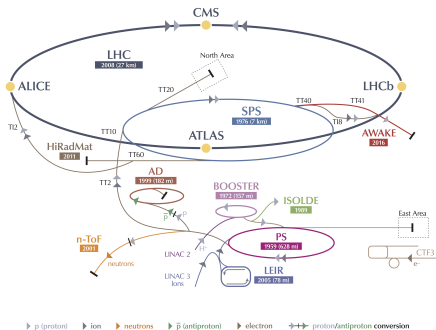
May 13, 2022

Outline

- 1 The LHC and the ATLAS experiment
- 2 Forward Muon Efficiency Scale Factors
- 3 MicroMegas Construction
- 4 $W^\pm Z$ inclusive production
- 5 $W^\pm Z$ inclusive production Fake Bkg.
- 6 VBS $W^\pm Zjj$ production
- 7 aQGC in $W^\pm Zjj$ -VBS PS

The LHC and the ATLAS experiment

Large Hadron Collider (LHC)



- pp collisions at $\sqrt{s} = 13$ TeV during Run 2
- progressive ramp-up
 - LINAC 2 ¹ → PSB → PS & SPS
- p beams circulating around 27km ring in opposite directions
 - guided by 2-pole
 - steered/focused by 4-pole
 - corrected by 6/8-pole magnets
- 4 major and 4 smaller detector systems

Luminosity

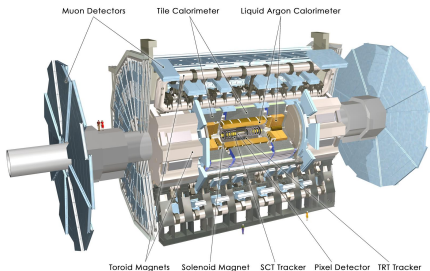
$$L = n_b f \frac{N_1 N_2}{A} \rightarrow$$

$$L_{\text{peak}}^{2018} = 19 \times 10^{33} \text{cm}^{-2} \text{s}^{-1}$$

ALICE	TOTEM
ATLAS	MoEDAL
CMS	LHCf
LHCb	FASER

¹LINAC 4 after 2018

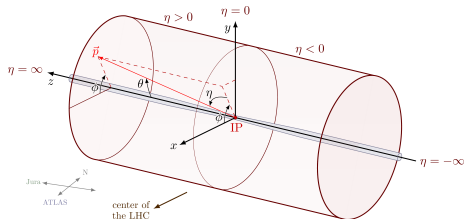
The ATLAS experiment



ATLAS - Largest volume particle collider general purpose detector

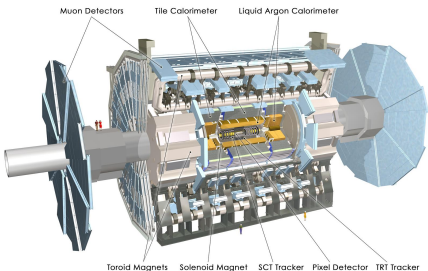
Main Components

- Inner Detector
- Calorimeter
- Muon Spectrometer
- Magnet System



- $\eta = \frac{1}{2} \ln \frac{|\rho| + p_z}{|\rho| - p_z} = -\frac{1}{2} \ln \tan \theta$
- $p_T = p \cdot \sin \theta$
- $E_T^2 = m^2 + p_T^2$
- $\Delta R = \sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$
- d_0 is the negative or positive transverse impact parameter, i.e. the point of maximum proximity to the beam
 - z_0 is its z-coordinate

The ATLAS experiment



ATLAS - Largest volume particle collider general purpose detector

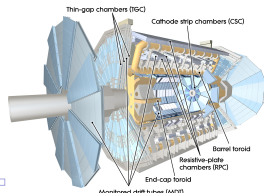
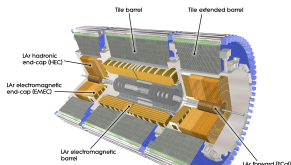
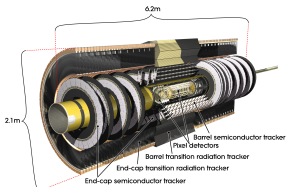
Main Components

- Inner Detector
- Muon Spectrometer
- Calorimeter
- Magnet System

- Tracking and charge information
- $|\eta| < 2.5$ ("Central")
- Pixel Detector, IBL, SCT and TRT sub-systems

- Sampling electromagnetic and hadronic calorimeter
- Energy measurement in $|\eta| < 4.9$
- Particle type identification from signal shape
- Missing E_T from negative vector sum of absorbed particles' p_T

- Gas chambers immersed 3.5T
- Momentum measurements in $|\eta| < 2.7$
- Trigger in $|\eta| < 2.4$ & $|\phi| \leq 2\pi$
- RPC, CSC, TGC, MDT



Event and Object Reconstruction in ATLAS

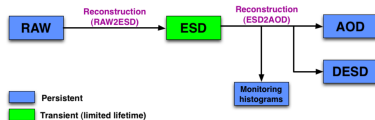
LHC: $\approx 10^9$ collisions/second



ATLAS: Three-stage Trigger co-operating with DAQ



Analyses: $\approx 10^3$ interesting events/second



Object Reconstruction

- Electrons: ID & Calorimeters (Bremsstrahlung)
- Muons: Primarily both from ID and MS, but also MS-only (MIP)
- Jets: From calorimeter energy deposit clusters matched to selected tracks from ID, after subtracting single particle deposits (ParticleFlow algorithm)²
- E_T^{miss} : Estimated by negative vector sum of p_T of:
 - hard-scatter reconstructed particles (e, μ , τ , γ , jets)
 - softer signals from unused charged particle tracks

²Previously solely calorimeter topological energy clusters (EMTopo algorithm)

Simulation of pp collisions

In theory:

- $d\sigma \propto |\mathcal{M}|^2 d\Phi$

- $$\sigma = \underbrace{\sum_{a,b} \int_0^1 dx_a dx_b}_{\text{IS PS}} \underbrace{\int d\Phi}_{\text{FS PS}} \underbrace{f_a(x_a, \mu_F) f_b(x_b, \mu_F)}_{\text{P.D.Fs}} \underbrace{\frac{1}{2\hat{s}}}_{\text{Inc. flux}} \underbrace{|\mathcal{M}(\Phi; \mu_F, \mu_R)|^2}_{\text{Sq. ME}}$$

In practice:

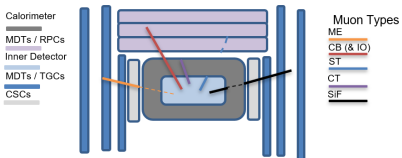
- 1 PDFs extracted from experimental fits of x - Q^2
- 2 Fixed-order perturbation theory parton-level numerical integration software with Monte Carlo sampling over user-specified phase space
- 3 Model hadronic and electroweak ISR/FSR with iterative parton showering algorithms

e.g. MADGRAPH & LHAPDF & PYTHIA , ...

- 5 Detailed entire ATLAS volume modeling with Geant4
- 6 Digitization of simulated hits, fine-tuning of detector response with component cross-talk, electronic noise, pile-up ...

Forward Muon Efficiency Scale Factors

Muon Reconstruction and Identification Algorithms

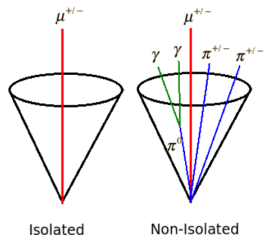
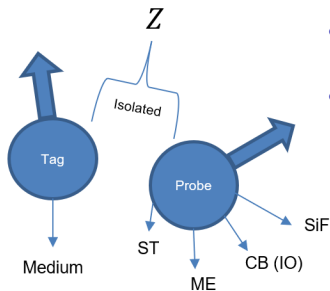


- ATLAS defines muon types based on reconstruction algorithms with various sub-system combinations allowing to measure sub-system efficiencies

- Identification algorithms are defined, on the basis of Quality WPs (acceptance modifiers)
- Selection based on sensor hit and no-hit trajectory and dedicated variables relating to charge and momentum measurements in ID and MS
 - Escalation of selection purity and background rejection efficiency (used in also in electron identification)
 - LOOSE
 - MEDIUM
 - TIGHT
 - and selection to accommodate analyses in extrema of phase space:
 - low- p_T
 - high- p_T

Central Muon Reconstruction and Identification Efficiency

Tag-and-Probe Method



- Tag-and-Probe method used to measure reconstruction and identification efficiency of each subsystem
- Selection
 - Tag is a MEDIUM quality TIGHT isolation central muon with $p_T > 26\text{GeV}$, originating from the hard-scatter vertex
 - Probe is tightly isolated central muon with $p_T > 10\text{ GeV}$, $|d_0/\sigma(d_0)| < 3$ and $|z_0| < 10\text{mm}$
 - $\Delta R_{\mu\mu} > 0.3$
 - $m_{\text{tag-probe}}$ in $61 < m_Z (\text{GeV}) < 121$ window, opposite charges
 - Probe-jet ambiguity resolution
- Probe is used to test efficiency of a sub-system, reconstructed with independent different sub-system
- Each detector sub-system efficiency is measured with specific type probes
- Probe-matching is performed with $\eta - \phi$ proximity: $\Delta R \leq 0.05$

Central Muon Reconstruction and Identification Efficiency and Scale Factors

- Using T&P, efficiency for each muon reconstruction and identification algorithm X can be estimated by:

$$\epsilon(X) = \frac{N_P^X}{N_P^{\text{All}}} \quad (1)$$

- To calculate efficiency, combine the calculated efficiencies from the sub-systems³:

$$\epsilon(X) = \epsilon(\text{ID}|\text{MS}) \times [\epsilon(X|\text{ID} \wedge \text{MS}) \times \epsilon(\text{MS}|\text{CT}) + \epsilon(X \wedge \neg\text{MS}|\text{CT})] \quad (2)$$

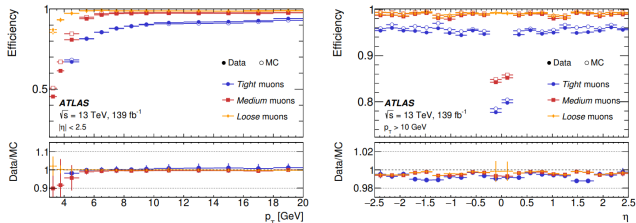
- Muon efficiency measured with the same procedure in:
 - real Run 2 $Z \rightarrow \mu\mu$ data selected using single-muon trigger ($\epsilon(X)_{\text{Data}}$)
 - and simulated $Z \rightarrow \mu\mu$ decays using POWHEG-BOX v2 + PYTHIA8 ($\epsilon(X)_{\text{MC}}$)
- Deviation of the simulation from the measured detector behavior used as correction factors to MC simulation for each working point

$$SF(X) = \frac{\epsilon(X)_{\text{Data}}}{\epsilon(X)_{\text{MC}}} \quad (3)$$

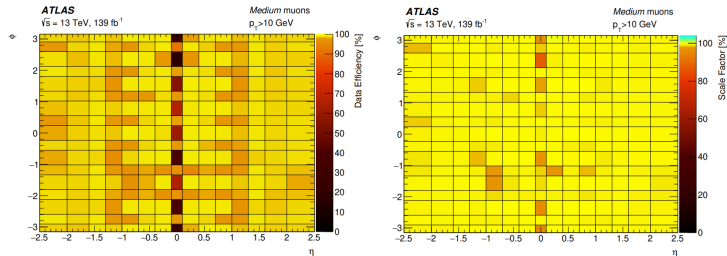
³Eur. Phys. J. C (2021) 81:578

Central Muon Reconstruction and Identification Efficiency and SF Run 2 measurements

- $|\eta| < 2.5$ "Central" muon Run 2 efficiency p_T and η distributions for LOOSE, MEDIUM and TIGHT muons



- $|\eta| < 2.5$ "Central" MEDIUM Run 2 $\eta - \phi$ maps of efficiency measured in data and Scale Factors



Forward Muon Reconstruction and Identification Efficiency

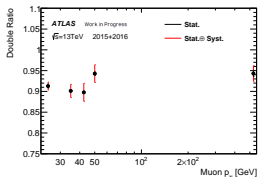
- $2.5 < |\eta| < 2.7$ "Forward" region
 - Efficiency not measured - out of ID acceptance
- Tag & Probe involving two independent detectors not applicable, instead re-defined:
 - Tag is "Central" MEDIUM isolated muon with $p_T > 25$ GeV (2015, 2016) or $p_T > 27$ GeV (2017, 2018), $d_0/\sigma(d_0) < 3$, $|z_0 \sin \theta| < 0.5$ mm
 - Probe $p_T > 20$ GeV, no isolation
 - $|M_Z^{\text{PDG}} - M_{\mu\mu}| \leq 10$ GeV
- SF estimated using "Double Ratio": ratio of forward probe count in Data over MC to "Control" central probe count in Data over MC

$$SF = \left[\frac{N(\text{Data})}{N(\text{MC})} \right]_{|\eta|>2.5}^{Z \rightarrow \mu\mu} / \left[\frac{N(\text{Data})}{N(\text{MC})} \right]_{2.2 < |\eta| < 2.5}^{Z \rightarrow \mu\mu} \quad (4)$$

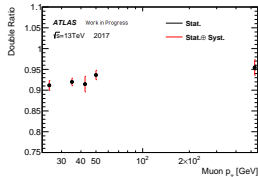
Forward Muon SF Measurements

- Studies were performed with MEDIUM quality probes
- SF Double Ratio calculated in bins of p_T and ϕ
- Forward Muon SFs - p_T , ranging from $\approx 90\%$ (low p_T to $\approx 95\%$ (high p_T)

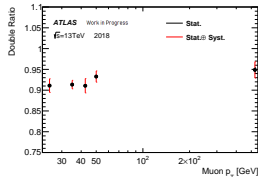
Data & MC of 2015+2016



Data & MC of 2017



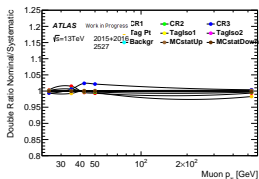
Data & MC of 2018



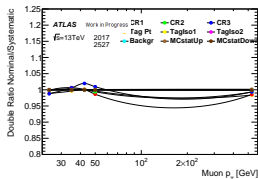
Forward Muon SF Systematics

- Systematic variation effects checked:
 - Vary w.r.t Tag p_T
 - Re-evaluate with tag $p_T > 35$ GeV, assign half difference from nominal as sys.
 - Vary w.r.t Tag Isolation
 - Re-evaluate with looser tag isolation, assign half difference from nominal as sys.
 - Vary w.r.t Central Control Region (denominator range)
 - CR1: $2.0 < |\eta| < 2.2$
 - CR2: $2.0 < |\eta| < 2.5$
 - CR3: $0 < |\eta| < 2.5$
 - Vary w.r.t MC Statistics
 - average of up/down variations
 - Vary w.r.t MC Background
 - Vary $Z \rightarrow ee, \tau\tau, t\bar{t}$ and W +jets MC subtraction $\times 0.5, \times 2$, assign half difference from nominal as sys.
 - Vary w.r.t Theory
 - Envelop of MSTW2008NL0 PDF weights - 0.5%
 - CT10 PDF instead of MSTW - 0.2%

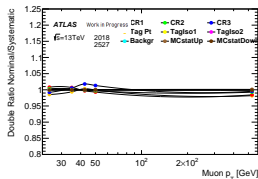
Data & MC of 2015+2016



Data & MC of 2017



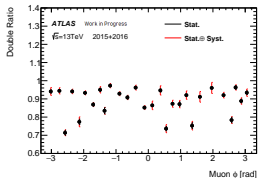
Data & MC of 2018



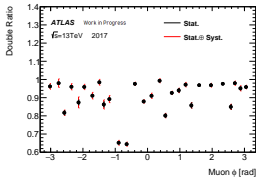
Forward Muon SF - ϕ

- SFs provided also in higher resolution in bins of ϕ
- Binning created after investigating central values in fine ϕ intervals, in order to establish a flat baseline with visible drops in the double ratio

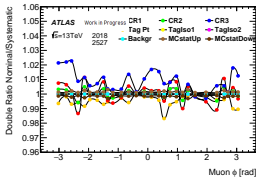
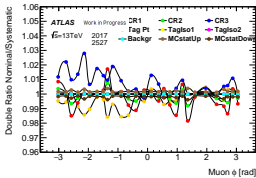
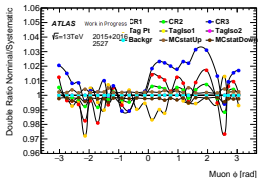
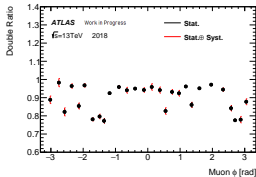
Data & MC of 2015+2016



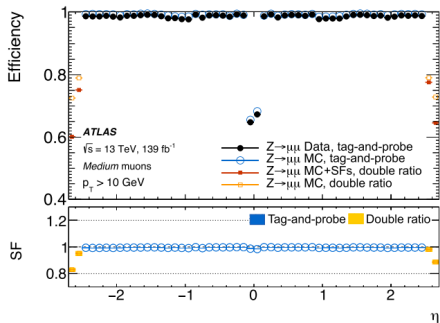
Data & MC of 2017



Data & MC of 2018



Forward Muon SF Results

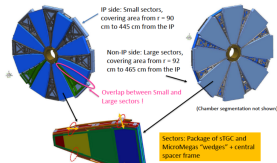
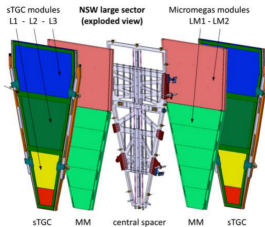
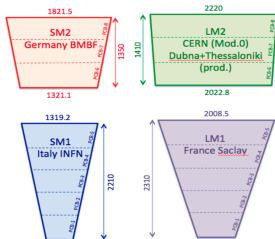
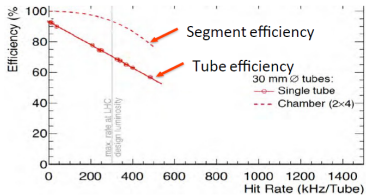


- Observed decrease in reconstruction and identification efficiency stems from stringent selection criteria applied to tracks in region where the ID coverage is partial or absent
- SFs $\eta - \phi$ maps calculated in 4 bins of eta $2.5 < |\eta| < 2.6$ and $2.6 < |\eta| < 2.7$ and the aforementioned ϕ binning
- Analyses apply forward muon SFs for $X = \text{LOOSE}/\text{MEDIUM}$ muons

MicroMegas (Micro-Mesh Gaseous Structure) Construction

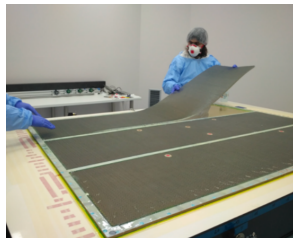
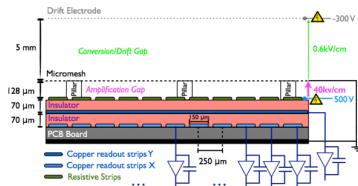
MicroMegas Construction QA/QC

- NSW will provide better tracking (MicroMegas) & triggering capabilities (sTGCs) to combat background readout rate at high-luminosity conditions that affect the end-caps
- Gas-gap chambers
 - NSW MM wedge = 2 SM (small sector) / 2 LM (large sector)
- MicroMegas detectors to be used in NSW upgrade
 - allowing $100 \mu\text{m}$ spatial and 1 mrad angular resolution; 15% muon momentum resolution at 1 TeV
- LM2 drift panels constructed in Thessaloniki
 - Greek contributions in detector Integration (AUTH, NTUA, Aegean), Electronics (NTUA, NKUA, Aegean, UWA, Demokritos)



MicroMegas Construction QA/QC

- Each MicroMegas detector consists of 2 external and 1 central drift panels (Thessaloniki), with 2 readout panels in between (Dubna)
- Key features: floating-mesh above drift panel copper surface and small amplification gap
- Construction Process:
 - Gluing of PCB sheets on inner aluminum frame, with honeycomb in-between, under 100 mbar; IC spacer gluing
 - Gas-leak test emulating gas-gap operation
 - Floating-mesh stretching, transferred and perforated (IC holes); gluing on top of outer aluminum mesh frame (5mm height)
 - Shipping for read-out instrumentation for assembly of quadruplet
- QA / QC
 - Dry-runs; smoothing, conductivity and panel planarity and thickness checks (11.5 ± 0.037 mm)
 - IC spacers (5 ± 0.050 mm) and mesh frame height (5.06 ± 0.025 mm) measurements
 - Mesh pre/post-gluing tension measurement (8.5 ± 1.5 N/cm), cleaning, passivation of IC points
 - Mesh frame preparation, drilling and gluing, HV connector hole opening;
 - HV conductivity test between floating-mesh and copper surface (at 500V: $I < 10$ nA)



$W^\pm Z$ inclusive production

$W^\pm Z$ inclusive production

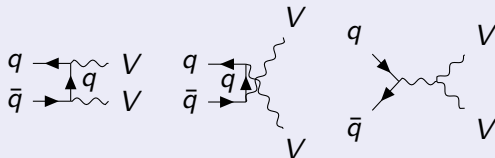
▽ Motivation for Diboson Processes:

- EWSB probe at TeV scale
- Sensitive to aTGCs / aQGCs
- Polarization

▽ and especially $W^\pm Z$:

- $\frac{\sigma_{W+Z}}{\sigma_{W-Z}}$
- NLO & NNLO corrections
(1604.08576)

Diboson Production (LO)

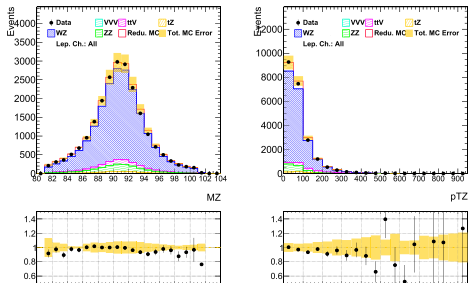


\sqrt{s}	σ_{LO} [pb]	σ_{NLO} [pb]	σ_{NNLO} [pb]	$\sigma_{\text{NLO}}/\sigma_{\text{LO}}$	$\sigma_{\text{NNLO}}/\sigma_{\text{NLO}}$
7	11.354(1) ^{+0.5%} _{-1.2%}	18.500(1) ^{+5.3%} _{-4.1%}	19.973(13) ^{+1.7%} _{-1.9%}	+62.9%	+ 8.0%
8	13.654(1) ^{+1.3%} _{-2.1%}	22.750(2) ^{+5.1%} _{-3.9%}	24.690(16) ^{+1.8%} _{-1.9%}	+66.6%	+ 8.5%
13	25.517(2) ^{+4.3%} _{-5.3%}	46.068(3) ^{+4.9%} _{-3.9%}	51.11(3) ^{+2.2%} _{-2.0%}	+80.5%	+10.9%
14	27.933(2) ^{+4.7%} _{-5.7%}	51.038(3) ^{+5.0%} _{-4.0%}	56.85(3) ^{+2.3%} _{-2.0%}	+82.7%	+11.4%

$W^\pm Z$ inclusive production - Selection

- $W^\pm Z^4 ll\nu$ signature
 - 3 sets of lepton selection cuts:
 - **Baseline:** $p_T > 5$ GeV, basic quality & isolation, overlap removal with other leptons etc.
 - **Z-type:** $p_T > 15$ GeV, better quality & isolation, OLR with selected jets etc.
 - **W-type:** $p_T > 20$ GeV, tighter quality criteria and stricter isolation
- Reconstruct resonant Z, W

W [±] Z Inclusive Event Selection	
Event Cleaning	Reject LAr, Tile and SCT corrupted / incomplete events
Trigger and Vertex	Hard scattering vertex with $N_{\text{Tracks}} \geq 2$ Event must fire e/ μ HLT
ZZ veto	< 4 Baseline-Selection Leptons
ll ν signature	Exactly 3 leptons passing Z lepton selection
Leading p_T	$p_T^{\text{lead}} > 27$ GeV (25 GeV for data / MC from 2015)
Z-decay leptons	Pair of SFOC leptons passing Z selection
Z Mass Window	$ M_{ll} - M_Z < 10$ GeV
W [±] lepton	Remaining lepton passes W [±] selection
W [±] Transverse Mass	$m_T^W > 30$ GeV



Run 2 Data - MC →

$W^{\pm}Z$ inclusive production Fake Background Estimation

Background Estimation for $W^\pm Z$ inclusive production

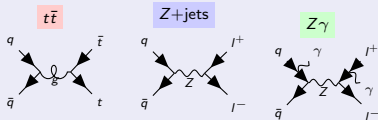
- Distinguish depending on final state (FS) leptons:

Irreducible: ≥ 3 prompt FS leptons

- ttV
- VVV
- tZ
- ZZ

Reducible: ≥ 1 non-prompt FS lepton

- 1 Heavy / Light flavour jets mis-identified as leptons
- 2 Leptons (electrons) from photon conversion



Background Estimation for $W^\pm Z$ inclusive production

- Distinguish depending on final state (FS) leptons:

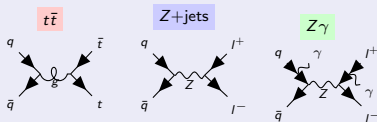
Irreducible: ≥ 3 prompt FS leptons

- ttV
- VVV
- tZ
- ZZ

Reducible: ≥ 1 non-prompt FS lepton

- Heavy / Light flavour jets mis-identified as leptons

- Leptons (electrons) from photon conversion



- The Matrix Method (MM) is a way to estimate the contribution of background processes to the SR without relying on Monte Carlo simulation.
- Background processes may not be accurately modeled by existing software
 - MM is a **data-driven method** to estimate such backgrounds

Toy single Bkg. Case

- Assuming SR selection C , expect: $\nu(C)$ events in total
- Substitute the selection efficiency

$$\nu(C) = \epsilon_C \nu_S + \epsilon_{C,B} \nu_B$$

- Create selection D targeting B :

$$\nu_{\text{sel}}(C) = \epsilon_C \nu_S + \epsilon_{C,B} \nu_B$$

$$\nu_{\text{sel}}(D) = \epsilon_D \nu_S + \epsilon_{D,B} \nu_B$$

- Solve for ν_B by inverting the efficiency matrix

$$\nu = \epsilon^{-1} \nu_{\text{sel}}$$

Matrix Method application strategy for $W^\pm Z$ inclusive production

1. Loose SR: Loosen the selection \rightarrow enhance fakes

Electrons	Muons
$p_T > 15$ GeV	$p_T > 15$ GeV
$ \eta < 2.47$	$\eta < 2.7$
$\neg(1.37 < \eta < 1.52)$	-
pass Loose LH ID	Medium LH ID
$ d_0^{BL}/\sigma(d_0^{BL}) < 5$	$ d_0^{BL}/\sigma(d_0^{BL}) < 3$ (if $\eta < 2.5$)
$z_0 < 0.5$	$z_0 < 0.5$ (if $\eta < 2.5$)

+ !isolation and/or
!identification = Loose

- Loose lepton set disjoint from tight (SR) selection set

Matrix Method application strategy for $W^\pm Z$ inclusive production

1. Loose SR: Loosen the selection \rightarrow enhance fakes

Electrons	Muons
$p_T > 15 \text{ GeV}$	$p_T > 15 \text{ GeV}$
$ \eta < 2.47$	$\eta < 2.7$
$!(1.37 < \eta < 1.52)$	-
pass Loose LH ID	Medium LH ID
$ d_0^{BL}/\sigma(d_0^{BL}) < 5$	$ d_0^{BL}/\sigma(d_0^{BL}) < 3$ (if $\eta < 2.5$)
$z0 < 0.5$	$z0 < 0.5$ (if $\eta < 2.5$)

+ !isolation and/or
!identification = Loose

- Loose lepton set disjoint from tight (SR) selection set

2. Express selection combinations

$$\begin{pmatrix} N_{TTT} \\ N_{TTL} \\ N_{TTL} \\ N_{LTT} \\ N_{TLL} \\ N_{LTL} \\ N_{LLT} \end{pmatrix} = \begin{pmatrix} e_1 e_2 e_3 & e_1 e_2 \bar{e}_3 & e_1 e_2 e_3 & \bar{e}_1 e_2 e_3 & e_1 e_2 e_3 & e_1 \bar{e}_2 \bar{e}_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ e_1 e_2 \bar{e}_3 & e_1 e_2 e_3 & e_1 \bar{e}_2 e_3 & \bar{e}_1 e_2 e_3 & e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & e_1 \bar{e}_2 e_3 & \bar{e}_1 e_2 e_3 & e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ \bar{e}_1 e_2 e_3 & \bar{e}_1 e_2 \bar{e}_3 & \bar{e}_1 \bar{e}_2 e_3 & e_1 e_2 e_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 e_2 \bar{e}_3 & e_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & e_1 \bar{e}_2 e_3 & \bar{e}_1 e_2 e_3 & e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ \bar{e}_1 e_2 e_3 & \bar{e}_1 e_2 \bar{e}_3 & \bar{e}_1 \bar{e}_2 e_3 & e_1 e_2 e_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 e_2 \bar{e}_3 & e_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \\ e_1 e_2 e_3 & e_1 e_2 \bar{e}_3 & e_1 \bar{e}_2 e_3 & \bar{e}_1 e_2 e_3 & e_1 \bar{e}_2 e_3 & e_1 e_2 \bar{e}_3 & \bar{e}_1 e_2 e_3 & \bar{e}_1 \bar{e}_2 e_3 \end{pmatrix} \begin{pmatrix} N_{RRR} \\ N_{RRF} \\ N_{RRF} \\ N_{RRF} \\ N_{RRF} \\ N_{RRF} \\ N_{RRF} \end{pmatrix}$$

- Select real as tight $\rightarrow e$
- Select fake as tight $\rightarrow f$
- Select real as loose $\rightarrow \bar{e}$
- Select fake as loose $\rightarrow \bar{f}$

\uparrow Define Fake Factors

$$F_{Z/W} = \frac{f}{\bar{f}} = \frac{N_T}{N_{fT}}$$

Matrix Method application strategy for $W^\pm Z$ inclusive production

1. Loose SR: Loosen the selection \rightarrow enhance fakes

Electrons	Muons
$p_T > 15$ GeV	$p_T > 15$ GeV
$ \eta < 2.47$	$\eta < 2.7$
!($1.37 < \eta < 1.52$)	-
pass Loose LH ID	Medium LH ID
$ d_0^{BL}/\sigma(d_0^{BL}) < 5$	$ d_0^{BL}/\sigma(d_0^{BL}) < 3$ (if $\eta < 2.5$)
$z0 < 0.5$	$z0 < 0.5$ (if $\eta < 2.5$)

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\uparrow Define Fake Factors

$$F_{Z/W} = \frac{f}{\bar{f}} = \frac{N_T}{N_{\bar{T}}}$$

3. Matrix Method N_{fake} estimate equation

$$N_{\text{fake}} = N_{TTL}^{\text{red}} F_Z + N_{TLT}^{\text{red}} F_Z + N_{LTT}^{\text{red}} F_W - N_{TLL}^{\text{red}} F_Z F_Z - N_{LTL}^{\text{red}} F_W F_Z - N_{LLT}^{\text{red}} F_W F_Z - N_{LLT}^{\text{red}} F_W F_Z$$

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Strategy

- 1 3 sources of reducible background \rightarrow 3 FFs
- 2 CRs rich in $t\bar{t}$, Z +jets, $Z\gamma \rightarrow$ Fake Factor
- 3 A value combining 3 FFs is substituted in (3) to estimate N_{fake}

Fake Factors for $t\bar{t}$ / Z +jets / $Z\gamma$

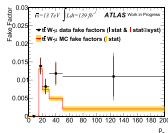
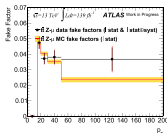
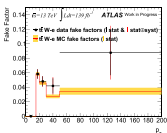
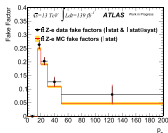
$$FF_{\text{Data}} = \frac{N_{T, \text{Data}} - N_{T, \text{RL\&ND}} t\bar{t}/Z+\text{jets}/Z\gamma - N_{T, \text{Irr. MC}}}{N_{!T, \text{Data}} - N_{!T, \text{RL\&ND}} t\bar{t}/Z+\text{jets}/Z\gamma - N_{!T, \text{Irr. MC}}}$$

$$FF_{\text{MC}} = \frac{N_{T, t\bar{t}/Z+\text{jets}/Z\gamma} - N_{T, \text{RL\&ND}} t\bar{t}/Z+\text{jets}/Z\gamma}{N_{!T, t\bar{t}/Z+\text{jets}/Z\gamma} - N_{!T, \text{RL\&ND}} t\bar{t}/Z+\text{jets}/Z\gamma}$$

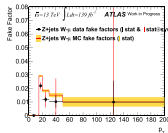
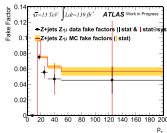
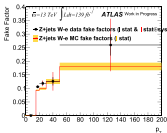
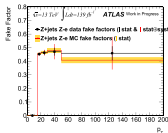
● data fake factors (| stat & | stat⊕syst)

■ MC fake factors (| stat)

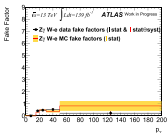
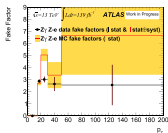
$t\bar{t}$



Z +jets



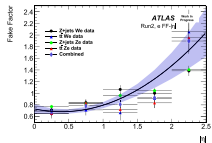
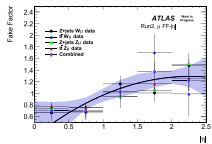
$Z\gamma$



e fakes

μ fakes

Combination and application of Fake Factors



○ Ideally: Fake Factors calculated in 2-D bins of $p_T - \eta$

□ **Alternatively:** η -dependent correction on FF

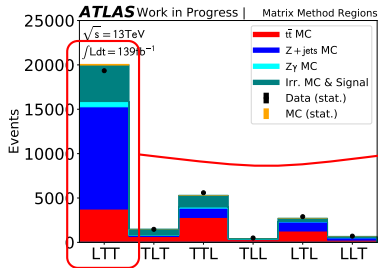
Symmetric dependence: $FF \rightarrow F(|\eta|) \times FF$

→ Combined points from weighted average of data FFs of Z +jets and $t\bar{t}$, weights are the respective statistical errors

→ Fit combined points with $y = ax^2 + bx + c$

(1σ error band used to evaluate the systematic uncertainty of this correction)

○ Utilize MC-based composition information → weighted average



Average Fake Factors with Exp. Composition

$$\begin{aligned} \text{Combined } FF = & FF_{Z+\text{jets}} \times (\% Z + \text{jets}) \\ & + FF_{Z\gamma} \times (\% Z\gamma) \\ & + FF_{t\bar{t}} \times (\% t\bar{t}) \end{aligned}$$

In the end:

1 combined FF per Loose SR region

○ FF_{LTT}, FF_{TLT} etc.

Systematics - Composition Weighted Average

Breakdown

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					

Systematics - Composition Weighted Average

1 Statistical Uncertainties of the FFs

0.5% to 4%

Breakdown

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	2.95	0.00	4.36	0.55
F_Z muon	0.00	0.00	0.32	2.31	0.31
F_W electron	3.18	0.00	5.29	0.00	3.56
F_Z electron	2.75	3.46	0.00	0.00	1.27

Systematics - Composition Weighted Average

1 Statistical Uncertainties of the FFs

0.5% to 4%

2 15% cross-section uncertainty in Irreducible Subtraction in CR and SR

17% (35% in $\mu\mu\mu$)

Breakdown

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	2.95	0.00	4.36	0.55
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Irr. subtraction	14.28	26.32	17.40	35.61	17.43

Systematics - Composition Weighted Average

- 1 Statistical Uncertainties of the FFs
0.5% to 4%
- 2 15% cross-section uncertainty in Irreducible Subtraction in CR and SR
17% (35% in $\mu\mu\mu$)
- 3 Uncertainty from $|\eta|$ correction:
9% for electron fakes
1% for muon fakes

Breakdown

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	2.95	0.00	4.36	0.55
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Irr. subtraction	14.28	26.32	17.40	35.61	17.43
Correlated η correction (e)	9.70	8.14	9.89	0.00	8.87
Correlated η correction (μ)	0.00	1.90	0.58	10.24	1.21

Systematics - Composition Weighted Average

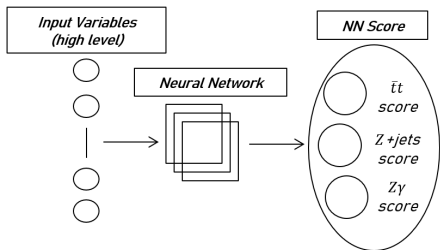
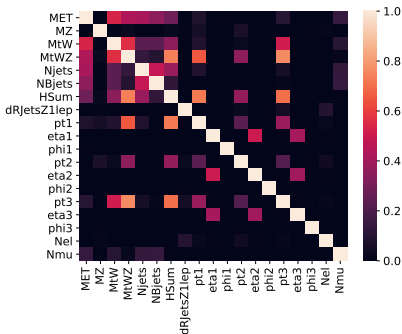
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17% (35% in $\mu\mu\mu$)
- 3 Uncertainty from $|\eta|$ correction:
9% for electron fakes
1% for muon fakes
- 4 Uncertainty assigned to Weighted Average
→ Expected Composition: 6.5%
Vary expected reducible background yields by their statistical uncertainty

Breakdown

Source	eee	$\mu e e$	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	2.95	0.00	4.36	0.55
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Correlated η correction (e)	9.70	8.14	9.89	0.00	8.87
Correlated η correction (μ)	0.00	1.90	0.58	10.24	1.21
W. Average Stat. Uncertainty	6.27	12.89	5.29	13.97	6.48
Total sys.	18.85	30.82	21.38	39.90	20.99
Stat.	2.88	5.48	1.78	1.66	1.52
Total	19.07	31.30	21.45	39.94	21.05
Absolute uncertainties					
Total	150.49	35.68	155.19	58.68	373.30

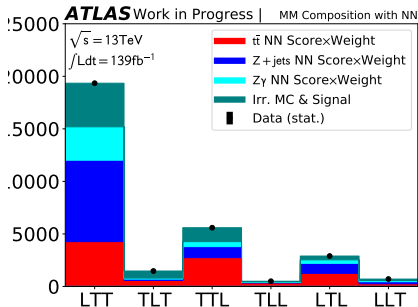
Multivariate per-event Weighted Average

- Idea: Utilize data-driven composition of Fake Background in W.A.
 - 1 Neural networks were trained on $t\bar{t}$, Z +jets, $Z\gamma$ events in the Loose SR
 - 2 Each data and Irr. Bkg. (MC) event receives a score from the trained classifier
 - 3 Use scores as weights in the weighted average of FFs



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 - ③ Use scores as weights in the weighted average of FFs



Average Fake Factors with NN Score

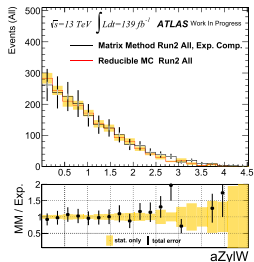
Combined $FF =$

$$FF_{Z+\text{jets}} \times (Z+\text{jets NN score}) \\ + FF_{Z\gamma} \times (Z\gamma \text{ NN score}) \\ + FF_{t\bar{t}} \times (t\bar{t} \text{ NN score})$$

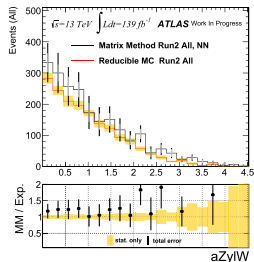
- The per-event NN score triplet can be used to provide a data-driven Reducible Background composition.

Comparison of results - Expected Comp. FF vs NN Score FF

Exp. Composition FF Weighted Average



NN Score FF Weighted Average



- NNscore combined FF is in general larger \leftrightarrow contribution from large $Z\gamma$ FF values
- Larger total errors with NN, despite no systematic from Expected Composition

Uncertainty due to limited Loose SR statistics $\leftarrow \sqrt{\sum_i (w_i \times FF_i)^2}$

- All-channel estimate still within error, per-channel discrepancies remain

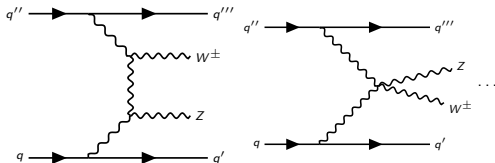
aZylW: $|y_Z - y_{W\text{-lep}}|$

$W^\pm Zjj$ Vector Boson Scattering

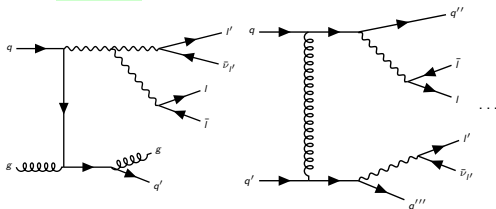
$W^\pm Zjj$ VBS

- $VV \rightarrow VV$ study 3/4-point gauge boson interaction terms

① $a_s^2 a_{EW}^6$ $VVjj$ -EW6 (i.e. VV -EW) ⁵



② $a_s^2 a_{EW}^4$ $VVjj$ -EW4 (i.e. VV -QCD) ⁶



③ $a_s^2 a_{EW}^5$ $VVjj$ -EW5 (i.e. Interference) ⁷

⁵ MadGRAPH + PyTHIA8, SHERPA222

⁶ MadGRAPH + PyTHIA8

⁷ MadGRAPH + HERWIG

$W^\pm Z_{jj}$ VBS Selection

- Basic cuts starting after $W^\pm Z$ inclusive selection
- Selection based on kinematics of jets
- 2 opposite-hemisphere energetic jets identified as VBS "tagging" jets
- $m_{jj} > 150$ GeV cut reduces VVV background

WZ_{jj} Event selection

Jet multiplicity	≥ 2
p_T of two tagging jets	> 40 GeV
$ \eta $ of two tagging jets	< 4.5
η of two tagging jets	opposite sign
m_{jj}	> 150 GeV

b-CR

$$N_{b\text{-jet}} \Big| > 0$$

QCD-CR

$$\begin{array}{l} N_{b\text{-jet}} \Big| = 0 \\ m_{jj} \Big| < 500 \text{ GeV} \end{array}$$

SR

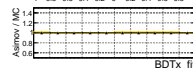
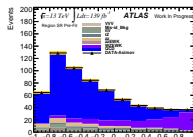
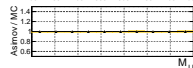
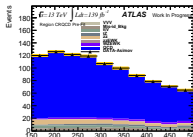
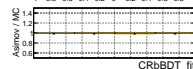
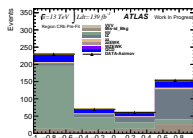
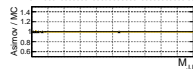
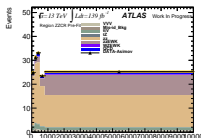
$$\begin{array}{l} N_{b\text{-jet}} \Big| = 0 \\ m_{jj} \Big| > 500 \text{ GeV} \end{array}$$

ZZ-CR

$$N_{\text{baseline leptons}} \Big| \geq 4$$

- Orthogonal CRs defined for ZZ, tZ, $W^\pm Z - \text{QCD}$

Fit Region	Variable	Binning
SR	WZ-EW BDT	[-1.0, -0.80, -0.60, -0.40, -0.20, 0.0, 0.20, 0.40, 0.60, 0.80, 1.0]
QCD-CR	m_{jj}	[150.0, 185.0, 220.0, 255.0, 290.0, 325.0, 360.0, 395.0, 430.0, 465.0, 500.0]
b-CR	$r\bar{r}V$ BDT	[-1.0, -0.50, 0.0, 0.50, 1.0]
ZZ-CR	m_{jj}	[0.0, 180.0, 300.0, 500.0, 800.0, 10000.0]



HistFactory

- Binned template probability model

$$\mathcal{P}(n_b|\mu) \propto \prod_{b \in N_{\text{bins}}} \text{Pois}\left(n_b | \mu \nu_b^{\text{sig}} + \nu_b^{\text{bkg}}\right)$$

- Signal strength $\mu \equiv \frac{\sigma}{\sigma_{\text{SM}}}$ parameter of interest (P.O.I.)
 - when observing n_{cb}
 - with expected background rate ν_{cb}
- Flexible likelihood defined to accommodate arbitrary N_{bins} , samples, regions (channels)

$$\mathcal{L}(\mathbf{n}, \boldsymbol{\alpha} | \boldsymbol{\eta}, \boldsymbol{\chi}) = \prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Poisson}(n_{cb} | \nu_{cb}(\boldsymbol{\eta}, \boldsymbol{\chi})) \prod_{\chi \in \boldsymbol{\chi}} c_{\chi}(a_{\chi} | \chi)$$

- with unconstrained parameters $\boldsymbol{\eta}$
 - with parameters $\boldsymbol{\chi}$ that produce constraint terms $c_{\chi}(a_{\chi} | \chi)$ constraining the parameter χ with aux. measurement a_{χ}
- Expected rates are modified by nuisance parameters:

$$\nu_{cb}(\boldsymbol{\phi}) = \sum_{s \in \text{samples}} \nu_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi}) = \sum_{s \in \text{samples}} \left(\prod_{\kappa \in \boldsymbol{\kappa}} \kappa_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi}) \right) \left(\nu_{scb}^0(\boldsymbol{\eta}, \boldsymbol{\chi}) + \sum_{\Delta \in \boldsymbol{\Delta}} \Delta_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi}) \right)$$

Profile Likelihood - Asymptotic Approximation

- Likelihood Ratio - widely adopted test-statistic in hypothesis testing (Neyman-Pearson Lemma)

$$\lambda = \frac{L_1}{L_0}$$

($0 \leq \lambda \leq 1$, with λ near 1 implying good agreement between the data and the hypothesized value of μ)

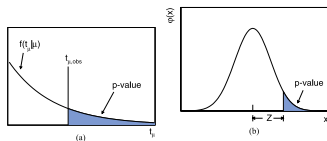
- For an alternative hypothesis as a function of signal strength μ , in the presence of nuisance parameters (due to systematics) common strategy is to profile the likelihood: maximize likelihood w.r.t. nuisance parameters for a given value of μ

$$\lambda(\mu) = \frac{L(\mu, \hat{\theta}(\mu))}{L(\hat{\mu}, \hat{\theta})}$$

- Distribution $f(t_\mu = -2 \ln \lambda(\mu))$ allows calculation of p-values, significance ...

$$p_\mu = \int_{t_{\mu, \text{obs}}}^{\infty} f(t_\mu | \mu) dt_\mu$$

- Computationally intensive: toys
- Alternative: Asymptotic approximation at large sample limit**



Integrated $\mu_{W^\pm Zjj\text{-EW}}$ Asimov Fit

WZjj-EW measurement Profile Likelihood fit Strategy

- 1 Simultaneous background CR fit-to-data⁸ with object systematics extract normalisation scale factors for $W^\pm Zjj\text{-QCD}$, tZ , ZZ , ttV
- 2 Scale these background contributions with norm. scale factors
- 3 Perform simultaneous fit in CRs and SR with exp. and theoretical systematic variations, measure $\mu_{W^\pm Zjj\text{-EW}}$

Theoretical Uncertainties

- WZjj-QCD Modelling Uncertainty
Compare MADGRAPH to SHERPA222 for QCD template
- WZjj-EW Parton Showering Uncertainty
Swap PYTHIA8 with HERWIG for EW template
- QCD-Scale Uncertainty
100 NNPDF3.0 MC replicas and alternatives, α_s variation, μ_R and μ_F variations
- EW-5 (Interference) uncertainty
estimated by comparing nominal EW template with EW+Interference MC estimation

Other fit uncertainties

- Cross-section uncertainties on MC-estimated backgrounds
 - VVV: 25%
 - ZZ – EW: 15%
 - Fake Background MC estimation: 40%
- MC statistics uncertainties
- Luminosity Run2 1.7% uncertainty

- Asimov "Observed" dataset: Artificial dataset created from expected yields for all processes, with all nuisance parameters fixed to their expected values
 - In practice: "Observed" data is sum of expected MC and data-driven estimates

⁸ Performed in python HistFactory implementation (pyhf)

Integrated $\mu_{W^\pm Z_{jj-EW}}$ Asimov Fit Results

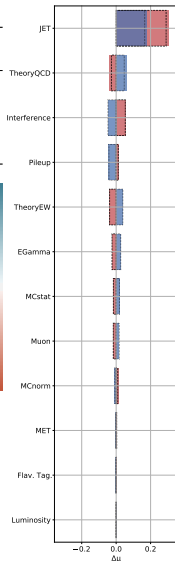
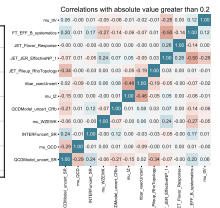
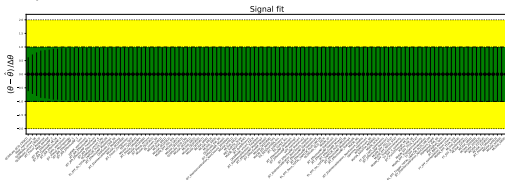
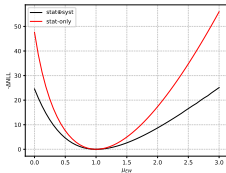
- Results of Bkg.-only and Asimov $\mu_{W^\pm Z_{jj-EW}}$ normalization factor results

CR Bkg-only Fit	
$\mu \equiv \frac{\sigma}{\sigma_{SM}}$ Normalization Results	
μ_{QCD}	0.829
μ_{ttV}	1.205
μ_{ZZ}	0.866
μ_{tZ}	0.768

Signal Cross-Section Extraction Fit	
$\mu \equiv \frac{\sigma}{\sigma_{SM}}$ Normalization Results	
μ_{EW}	1.0 ± 0.196
μ_{QCD}	1.0 ± 0.093
μ_{ttV}	1.0 ± 0.098
μ_{ZZ}	1.0 ± 0.138
μ_{tZ}	1.0 ± 0.208

- Significance $Z = \sqrt{-2 \ln \lambda(0)} = 7.01\sigma$ (Asym. Approx.)

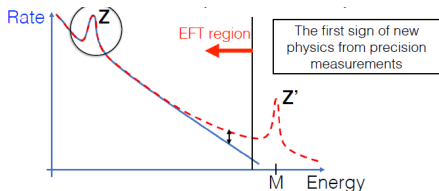
- NLL calculated 50 times in $\mu_{W^\pm Z_{jj-EW}} \in [0,3]$
- Impact per group of nuisance parameters (and per nuisance parameter)



aQGC in $W^\pm Zjj$ -VBS PS

Introduction to Effective Field Theory (EFT)

- LHC opens opportunities to study New Physics
- 2 routes for experimental New Physics searches
 - Resonances
 - Deviations in the tail



- Assume New Physics is "heavy"
- Effective field theory prescribes natural extension of the SM, new operators created from SM fields, respecting gauge symmetries and conservation laws

$$\mathcal{L} = \mathcal{L}_{\text{SM}} + \mathcal{L}_{\text{EFT}} = \mathcal{L}_{\text{SM}} + \sum_i \frac{c_i}{\Lambda^{d_i-4}} \mathcal{O}_i =$$
$$\mathcal{L}_{\text{SM}} + \sum_i \frac{c_i}{\Lambda} \mathcal{O}_i^{\text{dim-5}} + \sum_i \frac{c'_i}{\Lambda^2} \mathcal{O}_i^{\text{dim-6}} + \sum_i \frac{c''_i}{\Lambda^3} \mathcal{O}_i^{\text{dim-7}} + \sum_i \frac{c'''_i}{\Lambda^4} \mathcal{O}_i^{\text{dim-8}} + \dots$$

Anomalous Triple and Quartic Gauge Couplings in VBS PS

- Existence of dim-6 operators modifies SM TGCs, HVV

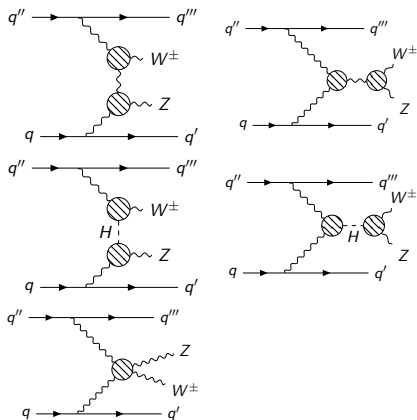
- Existence of dim-8 operators modifies SM QGCs

$$\mathcal{L}^{VV'V'} = c_0^{VV'} \mathcal{O}_0^{VV'} + c_1^{VV'} \mathcal{O}_1^{VV'}$$

- EFT allows to probe deviations from the SM-predicted QGC coefficient

$$c_i^{VV'} = c_{i,SM}^{VV'} + g^2 \Delta c_i^{VV'}$$

- we study dimension-8 EFT operators affecting aQGCs



EFT study of aQGCs in $W^\pm Zjj$ VBS PS

- Eboli-Garcia model dimension-8 operators modifying quartic vertices

	WWWW	WWZZ	ZZZZ	WWAZ	WWAA	ZZZA	ZZAA	ZAAA	AAAA
$\mathcal{L}_{S,0}, \mathcal{L}_{S,1}$	X	X	X	O	O	O	O	O	O
$\mathcal{L}_{M,0}, \mathcal{L}_{M,1}, \mathcal{L}_{M,6}, \mathcal{L}_{M,7}$	X	X	X	X	X	X	X	O	O
$\mathcal{L}_{T,0}, \mathcal{L}_{T,1}, \mathcal{L}_{T,4}, \mathcal{L}_{T,5}$	O	X	X	X	X	X	X	O	O
$\mathcal{L}_{T,2}, \mathcal{L}_{T,3}, \mathcal{L}_{T,8}$	X	X	X	X	X	X	X	X	X
$\mathcal{L}_{T,5}, \mathcal{L}_{T,6}, \mathcal{L}_{T,7}$	O	X	X	X	X	X	X	X	X
$\mathcal{L}_{T,9}, \mathcal{L}_{T,9}$	O	O	X	O	O	X	X	X	X

- of which a subset was available to be studied
- Decomposition
 - allows re-scaling existing sample to desired coefficient value

$$|A_{SM} + \sum_i c_i A_i|^2 = |A_{SM}|^2 +$$

$$\sum_i c_i^2 |A_i|^2 +$$

$$\sum_i c_i 2\text{Re}(A_{SM} A_i) +$$

$$\sum_{ij, i \neq j} c_i c_j 2\text{Re}(A_i A_j)$$

Eboli-Garcia Model $W^\pm Zjj$ -VBS study

$$\mathcal{L}_{T,0} \left| \frac{c_{T,0}}{\Lambda^4} \text{Tr} \left[\hat{W}_{\mu\nu} \hat{W}^{\mu\nu} \right] \times \text{Tr} \left[\hat{W}_{\alpha\beta} \hat{W}^{\alpha\beta} \right] \right.$$

$$\mathcal{L}_{T,1} \left| \frac{c_{T,1}}{\Lambda^4} \text{Tr} \left[\hat{W}_{\alpha\nu} \hat{W}^{\mu\beta} \right] \times \text{Tr} \left[\hat{W}_{\mu\beta} \hat{W}^{\alpha\nu} \right] \right.$$

$$\mathcal{L}_{T,2} \left| \frac{c_{T,2}}{\Lambda^4} \text{Tr} \left[\hat{W}_{\alpha\mu} \hat{W}^{\mu\beta} \right] \times \text{Tr} \left[\hat{W}_{\beta\nu} \hat{W}^{\alpha\nu} \right] \right.$$

$$\mathcal{L}_{S,1} \left| \frac{c_{S,1}}{\Lambda^4} \left[(D_\mu \Phi)^\dagger (D^\mu \Phi) \right] \times \left[(D_\nu \Phi)^\dagger (D^\nu \Phi) \right] \right.$$

$$\mathcal{L}_{M,0} \left| \frac{c_{M,0}}{\Lambda^4} \text{Tr} \left[\hat{W}_{\mu\nu} \hat{W}^{\mu\nu} \right] \times \left[(D_\beta \Phi)^\dagger (D^\beta \Phi) \right] \right.$$

$$\mathcal{L}_{M,1} \left| \frac{c_{M,1}}{\Lambda^4} \text{Tr} \left[\hat{W}_{\mu\nu} \hat{W}^{\nu\beta} \right] \times \left[(D_\beta \Phi)^\dagger (D^\mu \Phi) \right] \right.$$

- MADGRAPH + PYTHIA8
- $p_T^l > 4$ GeV, $p_T^{\text{jet}} > 15$ GeV
- Quadratic, linear terms for $M_0, M_1, S_1, T_0, T_1, T_2$
- Simultaneous non-zero pair of coefficients
 - Cross-terms for $T_0 - T_1, T_0 - T_2, T_1 - T_2, M_0 - M_1$

EFT fits in $W^\pm Zjj$ -VBS PS

- **Goal: Calculate limits on EFT-operator coefficients**
- Reco-level fit performed in EFT-FUN⁹ (quadratic fit validated with pyhf)
 - Profile Likelihood fit in SR
 - Quadratic/Full fits with/without Systematics
 - Results with/without scaling QCD, ZZ, tZ, ttV using bkg. only fit results
 - When considered, object systematics + theoretical systematics on $W^\pm Zjj$ -EW and QCD
- Expected fits and fits-to-data of Run 2

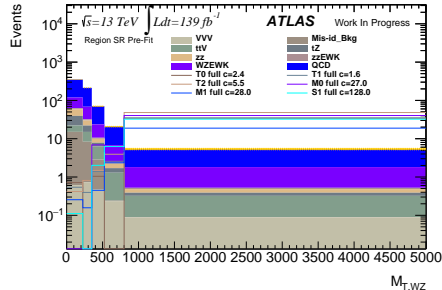
- 95% C.L. intervals for M_T^{WZ} , P_T^Z , $\sum P_T^{\text{Lep}}$, $\Delta\phi_{jj}$, $\Delta\phi_{VV}$, $\Delta\eta_{jj}$, EW-QCD BDT

- Asymptotic approximation - Wilks Theorem

$$\tilde{\epsilon}(\mu, \theta) = \text{CDF}_{\chi^2}^{-1}(0.68, \text{d.o.f} = 1) \approx 1 \quad (1\sigma)$$

$$\tilde{\epsilon}(\mu, \theta) = \text{CDF}_{\chi^2}^{-1}(0.95, \text{d.o.f} = 1) \approx 3.84 \quad (2\sigma)$$

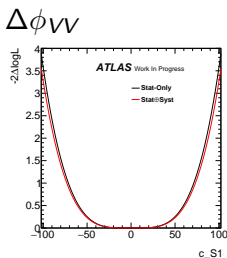
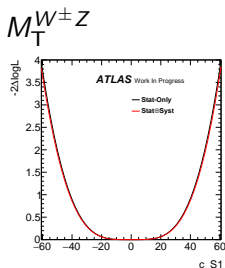
- Bin-optimization performed to select best-performing $N_{\text{bins}} = 5$ binning for each variable while enforcing $N_{\text{SM}} \geq 5$ for each bin



⁹ Developed by Hannes Mildner

Single Operator fits in EFT-FUN

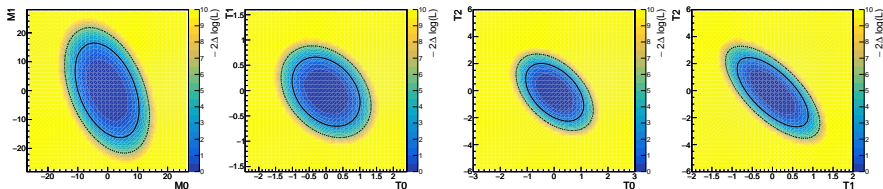
- Below: both quadratic and Interference (linear) terms used, systematics included
- M_T^{WZ} provides most restrictive results
- Applying bkg. only fit normalisation scale factors reduces tot. bkg - leads to wider limits
- Results consistent with the SM



Quad+Interf Stat+Sys.	Variable	Run2 (scaled, exp)	Run2 (unscaled, exp)	Run2 (scaled, obs)	Run2 (unscaled, obs)
T0	M_T^{WZ}	[-1.13, 1.11]	[-1.00, 0.99]	[-0.73, 0.71]	[-0.56, 0.57]
T1	M_T^{WZ}	[-0.78, 0.73]	[-0.68, 0.65]	[-0.51, 0.46]	[-0.40, 0.36]
T2	M_T^{WZ}	[-2.32, 2.11]	[-2.05, 1.87]	[-1.52, 1.31]	[-1.20, 1.02]
M0	M_T^{WZ}	[-11.60, 11.21]	[-10.49, 10.17]	[-7.56, 7.12]	[-6.02, 5.77]
M1	M_T^{WZ}	[-17.47, 17.37]	[-15.72, 15.57]	[-11.26, 11.13]	[-8.99, 8.81]
S1	M_T^{WZ}	[-60.84, 60.65]	[-55.77, 55.39]	[-39.33, 39.15]	[-32.06, 31.61]

Double Operator fits in EFT-FUN

- Grid-scan performed with two non-zero operator coefficients
- Below: quadratic+Interference terms with systematics, expected Asimov fit
- M_{WZ}^T again most performant
- 95% C.L. values for each operator slightly wider than single operator fit values



Alternative EFT fit templates

- More competitive limits with **2-variable 1-dimensional template** by combining single-variable templates
- $M_{WZ}^T - m_{jj}$ 5x2=10 bins template choice and binning follows existing CMS publication <https://arxiv.org/abs/2005.01173>
- Stat-only fits performed, few % tighter limits than using just M_T^{WZ} when either templates are using the same binning
 - Keeping in mind sys. variations not included and differences in the models used
 - up to few percent tighter than CMS limits for T0, T1, T2
 - up to 10% wider than CMS limits for M0, M1, S1
- Keeping in mind sys. variations not included and differences in the models used, expected 95% C.L. results are and up to 10% wider for M0, M1, S1.

Quad+Interf	Stat-Only	Variable	Run2 (scaled, exp)	Run2 (unscaled, exp)	Run2 (scaled, obs)	Run2 (unscaled, obs)
T0		$M_{WZ}^T - m_{jj}$	[-0.79, 0.79]	[-0.80, 0.80]	[-0.58, 0.59]	[-0.57, 0.58]
T1		$M_{WZ}^T - m_{jj}$	[-0.52, 0.49]	[-0.52, 0.50]	[-0.41, 0.37]	[-0.40, 0.37]
T2		$M_{WZ}^T - m_{jj}$	[-1.56, 1.44]	[-1.58, 1.46]	[-1.22, 1.06]	[-1.22, 1.04]
M0		$M_{WZ}^T - m_{jj}$	[-8.58, 8.30]	[-8.69, 8.43]	[-6.24, 6.05]	[-6.10, 5.96]
M1		$M_{WZ}^T - m_{jj}$	[-12.63, 12.42]	[-12.79, 12.58]	[-9.34, 9.15]	[-9.21, 9.01]
S1		$M_{WZ}^T - m_{jj}$	[-44.95, 44.77]	[-45.50, 45.33]	[-33.59, 33.38]	[-32.95, 32.70]

- Quadratic fits using multivariate **EFT NN template**
- NN trained to discriminate between EFT Quad. events and EW+QCD events
- Feature selection of 8 performant variables using ROOT TMVA suite

Rank	Variable	Importance
1	M_{WZ}^T	2.397e-01
2	$\Delta\phi_{VV}$	1.528e-01
3	DR_{jj}	1.252e-01
4	ζ_{VV}	1.222e-01
5	m_{JJ}	1.108e-01
6	$\Delta\eta_{VV}$	1.068e-01
7	ΔR_{jZ}	9.711e-02
8	N_{jets}	4.546e-02

- Promising results, slightly better discrimination in Asimov Quadratic than M_T^{WZ} when either templates are using the same binning

Operator	Quadratic Asimov Run 2 95% C.L.
T0	[-0.981, 0.981]
T1	[-0.700, 0.700]
T2	[-1.836, 1.836]
M0	[-9.854, 9.854]
M1	[-15.153, 15.153]
S1	[-50.902, 50.902]

Summary

- Details of calculations of "Double Ratio" Scale Factors used as weights for forward muon simulations were presented.
- The construction process of MicroMegas detectors to be used by the ATLAS experiment in the NSW was discussed.
- Studies in the context of $W^\pm Z$ production and $W^\pm Zjj$ VBS were shown, using ATLAS Run 2 data and simulation.

Specifically:

- An estimation of the Reducible Background for $W^\pm Z$ production, using the data-driven Matrix Method, with an application of Neural Network to estimate fake background composition in data.
- Simultaneous profile likelihood fits were performed to measure expected significance and signal strength of the purely electroweak $WZjj$ -EW6 process.
- 95% C.L. EFT dim-8 Eboli-Garcia model operator coefficient limits were calculated using kinematical variable and multivariate templates.

Thank you for your time and attention!

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- Kordas Konstantinos, Assoc. Prof. A.U.Th.
- Nicolaidou Rodanthi, Main Researcher CEA Saclay
- Bachas Konstantinos, Assoc. Prof. U.Th.
- Leisos Antonios, Assoc. Prof. H.O.U.

List of contributions to publications

- Published work

- "Muon reconstruction and identification efficiency in ATLAS using the full Run 2 pp collision data set at $\sqrt{s}=13$ TeV", ATLAS Collaboration., Aad, G., Abbott, B. et al. Muon reconstruction and identification efficiency in ATLAS using the full Run 2 pp collision data set at $s\sqrt{s}=13$ TeV. Eur. Phys. J. C 81, 578 (2021) <https://doi.org/10.1140/epjc/s10052-021-09233-2>
- "A Machine Learning approach to the EFT reinterpretation of the WZjj fully leptonic electroweak production", Konstantinos Bachas et al 2021 J. Phys.: Conf. Ser. 2105 012011 <https://doi.org/10.1088/1742-6596/2105/1/012011>
- "An overview of the ATLAS New Small Wheel Micromegas construction project at Aristotle University", C. Lampoudis (Aristotle U., Thessaloniki), D. Sampsonidis (Aristotle U., Thessaloniki), I. Karkanias (Aristotle U., Thessaloniki), S. Kompogiannis (Aristotle U., Thessaloniki), Int.J.Mod.Phys.A 35 (2020) <https://doi.org/10.1142/S0217751X20440091>
- "Construction Techniques for Large Size Gaseous Detectors for High Energy Physics Experiments", Sampsonidis D., Lampoudis C., Kompogiannis S. and Karkanias I., International Journal of Engineering Science Invention (IJESI) ISSN (Online): 2319-6734, ISSN (Print): 2319-672, Volume 9 Issue 3 Series. I, Mar.2020, 29-35

- Analyses under review

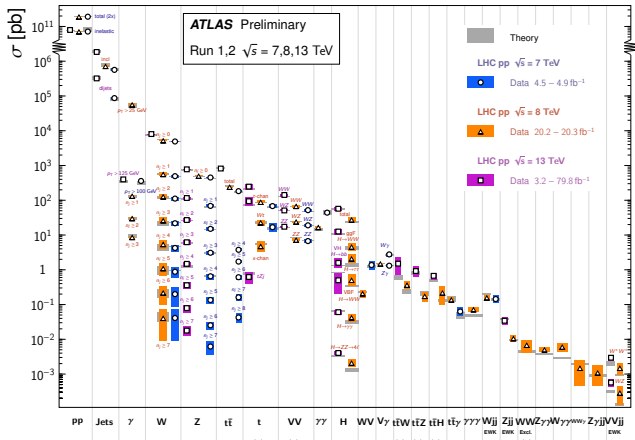
- "Study of electroweak $W\pm Z$ boson pair production in association with two jets in pp collisions at $\sqrt{s}=13$ TeV with the ATLAS Detector", Bittrich, Carsten et al.,
- "Measurement of $W\pm Z$ polarisation in pp collisions at $\sqrt{s}=13$ TeV with the ATLAS Detector", Di Ciaccio, Lucia et al.

Backup

$W^\pm Z$ production studies at the LHC

Standard Model Production Cross Section Measurements

Status: July 2018



$W^\pm Z$ Inclusive Object Selection

Electron object selection

Selection	Baseline selection	Z selection	W selection
$p_T > 5$ GeV	✓	✓	✓
Electron object quality	✓	✓	✓
$ \eta^{\text{cluster}} < 2.47, \eta < 2.5$	✓	✓	✓
LooseLH+BLayer identification	✓	✓	✓
$ d_0^{\text{BL}}/\sigma(d_0^{\text{BL}}) < 5$	✓	✓	✓
$ \Delta z_0^{\text{BL}} \sin \theta < 0.5$ mm	✓	✓	✓
FCLoose isolation	✓	✓	✓
e-to- μ and e-to-e overlap removal	✓	✓	✓
e-to-jets overlap removal		✓	✓
$p_T > 15$ GeV		✓	✓
Exclude $1.37 < \eta^{\text{cluster}} < 1.52$		✓	✓
MediumLH identification		✓	✓
HighPtCaloOnly isolation		✓	✓
$p_T > 20$ GeV			✓
TightLH identification			✓
FCTight isolation			✓
Unambiguous author			✓
DFCommonAddAmbiguity ≤ 0			✓

Muon object selection

Selection	Baseline selection	Z selection	W selection
$p_T > 5$ GeV	✓	✓	✓
$ \eta < 2.7$	✓	✓	✓
Loose quality	✓	✓	✓
$ d_0^{\text{BL}}/\sigma(d_0^{\text{BL}}) < 3$ (for $ \eta < 2.5$ only)	✓	✓	✓
$ \Delta z_0^{\text{BL}} \sin \theta < 0.5$ mm (for $ \eta < 2.5$ only)	✓	✓	✓
PFlowLoose_FixedRad isolation	✓	✓	✓
μ -jet Overlap Removal		✓	✓
$p_T > 15$ GeV		✓	✓
$ \eta < 2.5$		✓	✓
Medium quality		✓	✓
$p_T > 20$ GeV			✓
Tight quality			✓
PFlowTight_FixedRad isolation			✓

Jet object selection

	Selection
anti- k_t $\Delta R = 0.4$	✓
$p_T > 25$ GeV	✓
JVT > 0.59 (for $p_T < 60$ GeV & $ \eta < 2.4$)	✓
ΔR (jet - baseline electron) ≥ 0.2	✓
ΔR (jet with < 3 tracks - baseline muon) ≥ 0.2	✓
ΔR ("muon bug") PFlow jet with - baseline muon) ≥ 0.4	✓

Control Regions

- **Z+jets**: Create Z-pair by selecting 2 likely prompt leptons and a non-isolated lepton
- **$t\bar{t}$** : Select two likely prompt leptons from $t \rightarrow Wb$, while avoiding SFOC pairs.
- **Z γ** : Similar to Z+jets CR, however use m_{ll} window below M_Z and an m_{3l} cut.

≥ 2 Z-type leptons, same-flavour and opposite charge (e^+e^- or $\mu^+\mu^-$)

$$|m_{ll} - m_Z^{PDG} < 15| \text{ GeV}$$

fake lepton is highest- p_T Matrix Method lepton

fake electron	fake muon
$m_T^W < 30 \text{ GeV}$	$m_T^W < 30 \text{ GeV}$
$E_T^{miss} < 30 \text{ GeV}$	-
$m_{ll} > 81 \text{ GeV}$	-

≥ 1 Z-type electron e_Z

≥ 1 Z-type muon μ_Z

$$\text{charge}(\mu_Z) \cdot \text{charge}(e_Z) < 0$$

remaining highest- p_T Matrix Method lepton \equiv fake lepton ℓ_m

lepton with same flavour with fake lepton passes W-lepton requirements: ℓ_W

$$\text{charge}(\ell_m) \cdot \text{charge}(\ell_W) > 0$$

≥ 2 Z-type muons, opposite charge ($\mu^+\mu^-$)

$$55 < m_{ll} < 85 \text{ GeV}$$

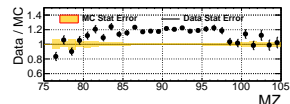
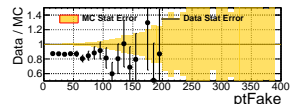
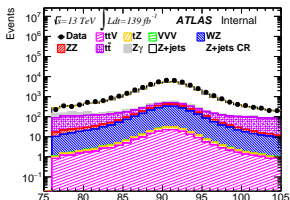
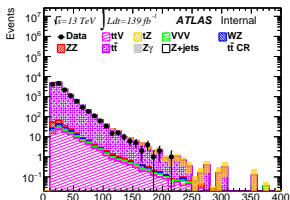
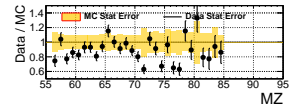
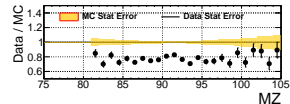
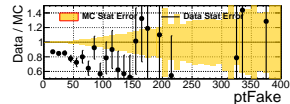
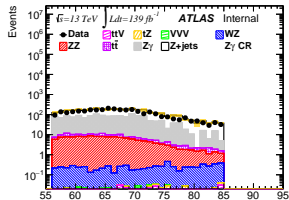
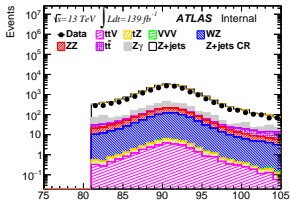
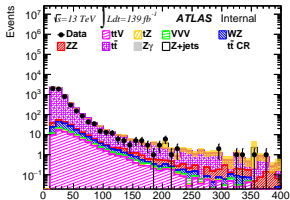
$$m_{3l} < 105 \text{ GeV}$$

fake lepton is highest- p_T Matrix Method electron

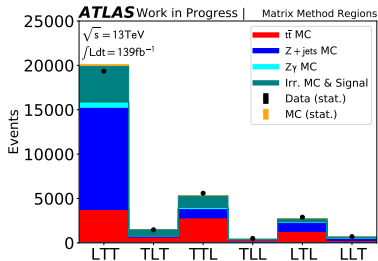
$$m_T^W < 30 \text{ GeV}$$

$$E_T^{miss} < 30 \text{ GeV}$$

$W^\pm Z$ Matrix Method Control Regions

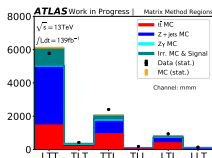
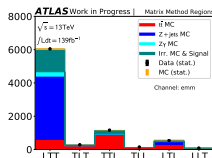
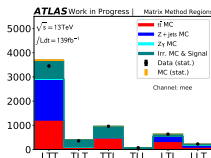
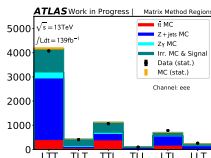


Expected Composition of Loose SR



← Z+jets fake background contribution is dominant, followed by $t\bar{t}$

↓ Composition of Loose SR, per leptonic channel



Performance of trained Classifiers

Train-Test N_{events} (80 – 20)

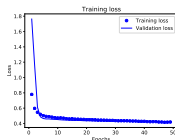
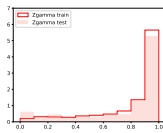
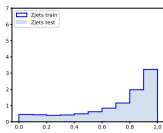
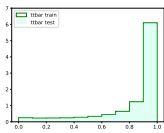
	$Z+\text{jets}$	$Z\gamma$	$t\bar{t}$
Train	41766	2988	47756
Test	10442	747	11939
Val.	13052	934	14924

NN Architecture

Num. Layers	Nodes	Drop-out	Batch Size
2	256	40%	1024

$$\text{Loss} = - \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i$$

Train-Test set performance



- Train-test distributions indicate smooth learning
- $Z+\text{jets}$ train-test curves flatter than $t\bar{t} / Z\gamma$

$Z+\text{jets}$ mis-classification as $Z\gamma$ leads to larger estimates, due to large $Z\gamma$ FF values contributing through the $Z\gamma$ score

Systematics of MM with NN

Breakdown (NN)

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	1.12	0.00	3.54	0.33
F_Z muon	0.00	0.00	0.23	2.32	0.24
F_W electron	5.30	0.00	14.63	0.00	8.18
F_Z electron	1.03	9.96	0.00	0.00	1.19
Correlated Irr. subtraction (CR)	3.26	6.92	7.36	26.71	6.73
Irr. subtraction (SR)	17.05	67.45	5.59	2.46	16.26
Correlated η correction (e)	7.28	9.10	10.39	0.00	8.22
Correlated η correction (μ)	0.00	0.89	0.46	10.28	0.92
W. Average Stat. Uncertainty	0.00	0.00	0.00	0.00	0.00
Total sys.	19.58	69.15	20.19	29.04	21.13
Stat.	6.63	24.36	2.04	1.72	3.81
Total	20.67	73.31	20.29	29.09	21.47
Absolute uncertainties					
Total	197.84	147.12	173.81	39.85	461.90

Breakdown (Exp. Comp.)

Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
Relative uncertainties [%]					
F_W muon	0.00	2.95	0.00	4.36	0.55
F_Z muon	0.00	0.00	0.32	2.31	0.31
F_W electron	3.18	0.00	5.29	0.00	3.56
F_Z electron	2.75	3.46	0.00	0.00	1.27
Correlated Irr. subtraction	14.28	26.32	17.40	35.61	17.43
Correlated η correction (e)	9.70	8.14	9.89	0.00	8.87
Correlated η correction (μ)	0.00	1.90	0.58	10.24	1.21
W. Average Stat. Uncertainty	6.27	12.89	5.29	13.97	6.48
Total sys.	18.85	30.82	21.38	39.90	20.99
Stat.	2.88	5.48	1.78	1.66	1.52
Total	19.07	31.30	21.45	39.94	21.05
Absolute uncertainties					
Total	150.49	35.68	155.19	58.68	373.30

Comparison of Expected - Neural Net compositions per channel

- Results of MC closure with Exp. Comp. Weighted Average of FFs

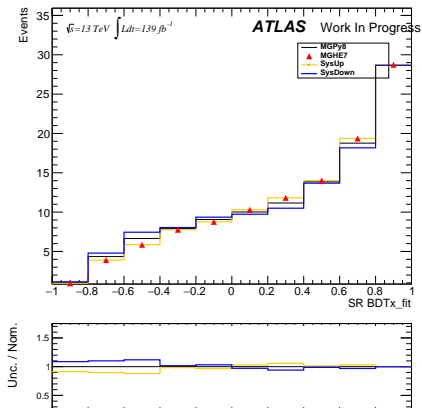
Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
$N_{LTT} \cdot F_W$	$478.3 \pm 11.0 \pm 108.9$	$23.8 \pm 0.6 \pm 26.7$	$683.5 \pm 12.8 \pm 153.2$	$44.3 \pm 0.8 \pm 43.8$	$1230.0 \pm 16.9 \pm 321.1$
$N_{TLT} \cdot F_Z$	$87.7 \pm 13.1 \pm 36.1$	$5.2 \pm 2.2 \pm 5.5$	$7.8 \pm 0.6 \pm 1.7$	$12.4 \pm 0.7 \pm 11.1$	$113.1 \pm 13.3 \pm 43.5$
$N_{TTL} \cdot F_Z$	$282.5 \pm 14.7 \pm 56.0$	$87.6 \pm 5.8 \pm 15.9$	$34.3 \pm 1.3 \pm 4.5$	$90.8 \pm 2.2 \pm 14.1$	$495.3 \pm 16.0 \pm 75.2$
-2L Terms	$-59.3 \pm 2.8 \pm 20.1$	$-2.7 \pm 0.2 \pm 1.7$	$-2.2 \pm 0.1 \pm 0.8$	$-0.6 \pm 0.0 \pm 0.4$	$-64.8 \pm 2.8 \pm 22.5$
Matrix Method result	$789.24 \pm 22.72 \pm 148.77$	$113.99 \pm 6.25 \pm 35.13$	$723.53 \pm 12.87 \pm 154.66$	$146.92 \pm 2.44 \pm 58.62$	$1773.68 \pm 26.96 \pm 372.33$
$(t\bar{t} + Z+jets + Z\gamma)$ MC \times SF	565.80 ± 25.70	198.00 ± 6.60	695.50 ± 31.60	270.60 ± 9.20	1730.00 ± 42.30

- Results of MC closure with NN-score Weighted Average of FFs

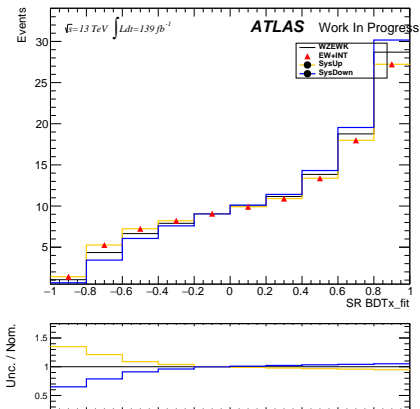
Source	eee	μee	$e\mu\mu$	$\mu\mu\mu$	All
$N_{LTT} \cdot F_W$	$582.3 \pm 14.9 \pm 123.7$	$20.9 \pm 0.5 \pm 13.8$	$818.7 \pm 17.4 \pm 171.7$	$39.7 \pm 0.7 \pm 27.2$	$1461.6 \pm 22.9 \pm 312.0$
$N_{TLT} \cdot F_Z$	$160.9 \pm 31.2 \pm 87.9$	$-1.7 \pm 24.7 \pm 56.6$	$7.4 \pm 0.5 \pm 1.8$	$12.0 \pm 0.7 \pm 3.6$	$178.7 \pm 39.8 \pm 130.9$
$N_{TTL} \cdot F_Z$	$498.4 \pm 42.3 \pm 108.0$	$215.6 \pm 35.6 \pm 91.8$	$32.5 \pm 1.2 \pm 4.4$	$85.8 \pm 2.1 \pm 12.1$	$832.2 \pm 55.3 \pm 201.3$
-2L Terms	$-284.6 \pm 32.4 \pm 112.8$	$-34.1 \pm 22.7 \pm 28.4$	$-2.0 \pm 0.1 \pm 0.6$	$-0.6 \pm 0.0 \pm 0.4$	$-321.3 \pm 39.6 \pm 137.7$
Matrix Method result	$957.05 \pm 63.49 \pm 187.37$	$200.67 \pm 48.89 \pm 138.76$	$856.58 \pm 17.47 \pm 172.93$	$137.00 \pm 2.35 \pm 39.78$	$2151.30 \pm 82.05 \pm 454.55$
$(t\bar{t} + Z+jets + Z\gamma)$ MC \times SF	565.80 ± 25.70	198.00 ± 6.60	695.50 ± 31.60	270.60 ± 9.20	1730.00 ± 42.30

$W^\pm Z \mu_{W^\pm Zjj\text{-EW}}$ Theoretical Uncertainties

- Parton Shower ($W^\pm Z_{jj\text{-EW}}$ SR)

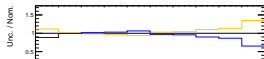
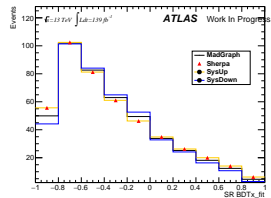
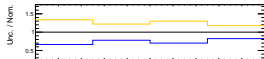
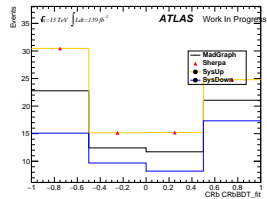
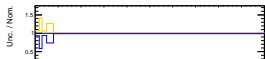
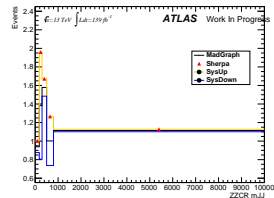
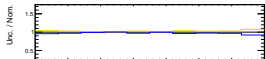
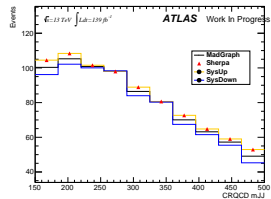


- Interference Uncertainty ($W^\pm Z_{jj\text{-EW}}$ SR)



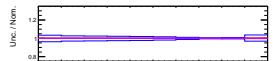
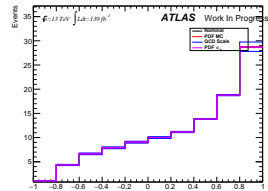
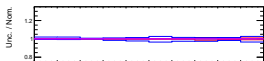
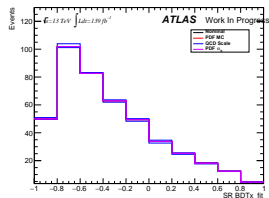
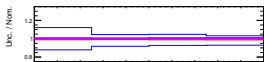
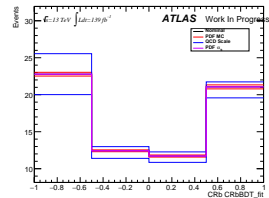
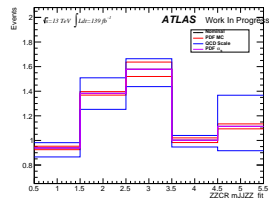
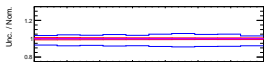
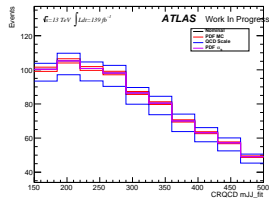
$W^\pm Z \mu_{W^\pm Zjj\text{-EW}}$ Fit Theoretical Uncertainties

- QCD Modeling ($W^\pm Zjj\text{-QCD}$ SR, CRs)



$W^\pm Z$ $\mu_{W^\pm Zjj\text{-EW}}$ Theoretical Uncertainties

- QCD Scale ($W^\pm Zjj\text{-QCD}$ SR, CRs; $W^\pm Zjj\text{-EW}$ SR)



- 100 MC replicas of NNPDF3.0 set used to compute 68% C.L. on QCD-scale cross-section
- a_s variation 0.118 ± 0.001
- Envelop of μ_R , $\mu_F \times 2$ & $\times \frac{1}{2}$

Experimental Systematics

- Electron/Photon

- EG-RESOLUTION-ALL
- EG-SCALE-ALL
- EL-EFF-ID-TOTAL-1NPCOR-PLUS-UNCOR
- EL-EFF-Iso-TOTAL-1NPCOR-PLUS-UNCOR
- EL-EFF-Reco-TOTAL-1NPCOR-PLUS-UNCOR
- EL-EFF-Trigger-TOTAL-1NPCOR-PLUS-UNCOR

- Flavor-Tagging

- FT-EFF-B-systematics
- FT-EFF-C-systematics
- FT-EFF-Light-systematics
- FT-EFF-extrapolation
- FT-EFF-extrapolation-from-charm

- Missing E_T

- MET-SoftTri-Scale
- MET-Reso-Para
- MET-Reso-Perp

- Muon

- MUON-EFF-ISO-STAT
- MUON-EFF-ISO-SYS
- MUON-EFF-RECO-STAT
- MUON-EFF-RECO-SYS
- MUON-EFF-TTVA-STAT
- MUON-EFF-TTVA-SYS
- MUON-EFF-TrigStatUncertainty
- MUON-EFF-TrigSystUncertainty
- MUON-ID
- MUON-MS
- MUON-SAGITTA-RESBIAS
- MUON-SAGITTA-RHO
- MUON-SCALE

- Pile-up

- PRW-DATASF

- Jets

- JET-BJES-Response
- JET-EffectiveNP-Detector1
- JET-EffectiveNP-Detector2
- JET-EffectiveNP-Mixed1
- JET-EffectiveNP-Mixed2
- JET-EffectiveNP-Mixed3
- JET-EffectiveNP-Modelling1
- JET-EffectiveNP-Modelling2
- JET-EffectiveNP-Modelling3
- JET-EffectiveNP-Modelling4
- JET-EffectiveNP-Statistical1
- JET-EffectiveNP-Statistical2
- JET-EffectiveNP-Statistical3
- JET-EffectiveNP-Statistical4
- JET-EffectiveNP-Statistical5
- JET-EffectiveNP-Statistical6
- JET-EtaIntercalibration-Modelling
- JET-EtaIntercalibration-NonClosure-2018data
- JET-EtaIntercalibration-NonClosure-highE
- JET-EtaIntercalibration-NonClosure-negEta
- JET-EtaIntercalibration-NonClosure-posEta
- JET-EtaIntercalibration-TotalStat
- JET-Flavor-Composition
- JET-Flavor-Response
- JET-JER-DataVsMC-MC16
- JET-JER-EffectiveNP-1
- JET-JER-EffectiveNP-2
- JET-JER-EffectiveNP-3
- JET-JER-EffectiveNP-4
- JET-JER-EffectiveNP-5
- JET-JER-EffectiveNP-6
- JET-JER-EffectiveNP-7restTerm
- JET-JvtEfficiency
- JET-Pileup-OffsetMu
- JET-Pileup-OffsetNPV
- JET-Pileup-PtTerm
- JET-Pileup-RhoTopology
- JET-PunchThrough-MC16
- JET-fJvtEfficiency

HistFactory - pyhf

Symbol	Name
$f(\mathbf{x} \phi)$	model
$\mathcal{L}(\phi)$	likelihood
$\mathbf{x} = \{\mathbf{n}, \mathbf{a}\}$	full dataset (including auxiliary data)
\mathbf{n}	channel data (or event counts)
\mathbf{a}	auxiliary data
$\nu(\phi)$	calculated event rates
$\phi = \{\boldsymbol{\eta}, \boldsymbol{\chi}\} = \{\boldsymbol{\psi}, \boldsymbol{\theta}\}$	all parameters
$\boldsymbol{\eta}$	free parameters
$\boldsymbol{\chi}$	constrained parameters
$\boldsymbol{\psi}$	parameters of interest
$\boldsymbol{\theta}$	nuisance parameters
$\kappa(\phi)$	multiplicative rate modifier
$\Delta(\phi)$	additive rate modifier
$c_\chi(\alpha_\chi \chi)$	constraint term for constrained parameter χ
σ_χ	relative uncertainty in the constrained parameter

$$\nu_{cb}(\phi) = \sum_{s \in \text{samples}} \nu_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi}) = \sum_{s \in \text{samples}} \underbrace{\left(\prod_{\kappa \in \boldsymbol{\kappa}} \kappa_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi}) \right)}_{\text{multiplicative modifiers}} \left(\underbrace{\nu_{scb}^0(\boldsymbol{\eta}, \boldsymbol{\chi}) + \sum_{\Delta \in \boldsymbol{\Delta}} \Delta_{scb}(\boldsymbol{\eta}, \boldsymbol{\chi})}_{\text{additive modifiers}} \right)$$

Modifiers and Constraints

Description	Modification	Constraint Term c_χ	Input
Uncorrelated Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Pois}(r_b = \sigma_b^{-2} \rho_b = \sigma_b^{-2} \gamma_b)$	σ_b
Correlated Shape	$\Delta_{scb}(\alpha) = f_p(\alpha \Delta_{scb, \alpha=1}, \Delta_{scb, \alpha=1})$	$\text{Gaus}(a = 0 \alpha, \sigma = 1)$	$\Delta_{scb, \alpha=1}$
Normalisation Unc.	$\kappa_{scb}(\alpha) = g_p(\alpha \kappa_{scb, \alpha=1}, \kappa_{scb, \alpha=1})$	$\text{Gaus}(a = 0 \alpha, \sigma = 1)$	$\kappa_{scb, \alpha=1}$
MC Stat. Uncertainty	$\kappa_{scb}(\gamma_b) = \gamma_b$	$\prod_b \text{Gaus}(a_{\gamma_b} = 1 \gamma_b, \delta_b)$	$\delta_b^2 = \sum_s \delta_{sb}^2$
Luminosity	$\kappa_{scb}(\lambda) = \lambda$	$\text{Gaus}(l = \lambda_0 \lambda, \sigma_\lambda)$	$\lambda_0, \sigma_\lambda$
Normalisation	$\kappa_{scb}(\mu_b) = \mu_b$		
Data-driven Shape	$\kappa_{scb}(\gamma_b) = \gamma_b$		

Correlation - Pulls - Impact Calculation

- Fit param. Correlation
 - Minuit computes inverse of the matrix of second derivatives of FCN to be minimized
 - Minuit errors: diagonal elements
 - Minuit correlations: off-diagonal elements

- Pull Plot

$$\text{Pull} = \frac{\text{MLE}_{\text{val}} - \text{init}_{\text{val}}}{\text{width}}$$
$$\text{Pull error} = \frac{\text{MLE}_{\text{error}}}{\text{width}}$$

- Impact calculation

$\Delta\theta$ = Gaus. Constraint width

$\Delta\hat{\theta}$ = Minuit param. uncertainty

$\Delta\mu = \text{MLE}_{\text{full}} - \text{MLE}_{\theta \pm \Delta\theta}$ or $\text{MLE}_{\text{full}} - \text{MLE}_{\theta \pm \Delta\hat{\theta}}$, with const. param value

BDT Fit Templates

- EW-IrrMC BDT

- Events weighted by x-section
- 15 "important" variables

- 1 m_{jj}
- 2 N_{jets}
- 3 $p_{T\text{-jet1-jet2}}$
- 4 $\eta\text{-jet1}$
- 5 $\Delta\eta_{jj}$
- 6 $\Delta\phi_{jj}$
- 7 $|y_Z - y_l, W|$
- 8 p_T^Z, p_T^W
- 9 η_W
- 10 $M_T^{W\pm Z}$
- 11 $\Delta R(j_1, Z)$
- 12 $R_{p_T}^{\text{hard}}$ (transverse momenta of 3lep+2jet/sum)
- 13 $\zeta_{\text{lep}} = \min(\Delta\eta_-, \Delta\eta_+)$ (largest/smallest η difference of leptons from jet)

- Parameters (ROC optimized)

- BoostType Grad, NTrees 300, MaxDepth 5, MinNodeSize 2%

- $tZj\text{-}t\bar{t}V$ BDT

- Events weighted by x-section
- 15 "important" variables

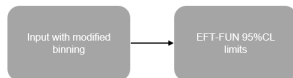
- 1 Jet-1 p_T, η, ϕ
- 2 Jet-2 p_T
- 3 $\Delta\eta_{jj}$
- 4 $\Delta\phi_{jj}$
- 5 p_T^Z, η_Z, ϕ_Z
- 6 p_T^W
- 7 $M_{W\pm Z}, \Delta\eta_{W\pm Z}, \Delta\phi_{W\pm Z}$
- 8 $N_{\text{jets}}, N_{\text{b-jets}}$
- 9 $m(3l, \text{jets})$ (from all objects with $p_T > 25$ GeV)

- Parameters (N-1 iterative ROC optimization, starting from EW-IrrMC BDT)

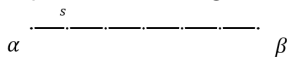
- BoostType Grad, NTrees 280, MaxDepth 4, MinNodeSize 2%

EFT fit - Binning Optimization

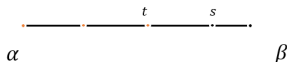
- **Strategy for brute-force optimization:**



-
- Replace the existing bins - split the interval in N_s intervals



- For each $\alpha - s$ or $s - \beta$ interval, split it in N_t intervals



- Repeat until you reach desired number of bins - while iterating for all other positions of the s, t, \dots points.
- Narrowest limit corresponds to optimized binning.

EFT fit - Binning Optimization

- **Example:** M_T^{WZ} range: [0, 5000] (5 TeV)
- For parameters $n_{\text{step}1} = 3$, $n_{\text{step}2} = 3$, $n_{\text{step}3} = 3$, $n_{\text{step}4} = 3$
 N_1, N_2, N_3, N_4 go from 1-4 independently of each other
- (round up to closest 0.005% of last bin edge - 25 GeV in this case)

- **Step1 Iteration** $N_1 = 1$:
 - $\rightarrow [0, 5000] \rightarrow$ insert a bin edge in $N_1 \times \frac{5000}{n_{\text{step}1}=3}$
- **Step2 Iteration** $N_2 = 1$:
 - $\rightarrow [0, 1675, 5000] \rightarrow$ insert a bin edge in $N_2 \times \frac{1675}{n_{\text{step}2}=3}$
- **Step3 Iteration** $N_3 = 1$:
 - $\rightarrow [0, 550, 1675, 5000] \rightarrow$ insert a bin edge in $N_3 \times \frac{550}{n_{\text{step}3}=3}$
- **Step4 Iteration** $N_4 = 1$:
 - $\rightarrow [0, 175, 550, 1675, 5000] \rightarrow$ insert a bin edge in $N_4 \times \frac{175}{n_{\text{step}4}=3}$
- **Finally:**
 - $\rightarrow [0, 50, 175, 550, 1675, 5000]$ - test - repeat

EFT fit - Multivariate template

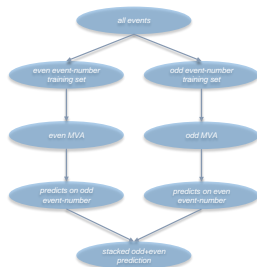
• Training events

- 20k events EFT quad - 20k events EW+QCD, or all available and weight loss based on N_{train} events in each class
- 80% train - 20% validation (for early-stopping w.r.t. val. loss)

• NN Architecture

Num. Layers	2
Nodes per layer	128
Hidden layer activation	relu
Normalization	Batch Normalization
Loss Function	binary cross-entropy
Optimizer	Adam
Max Epochs	100
Batch Size	1024

• Template creation pipeline



• Fit template

