Multivariate analysis of the EW gauge bosons' polarisation at the LHC

Comité de Suivi Individuel

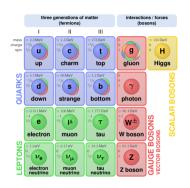
Mathis DUBAU Laboratoire d'Annecy de Physique des Particules

20 June 2025

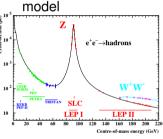




Standard Model

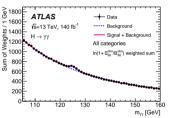


 Theory used in particle physics Highly accurate and extensively tested



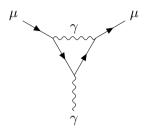
Cross section of $e^+e^- \rightarrow$ hadrons processes as a function of center-of-mass energy [1]

Invariant mass distribution of di-photon candidates for data at $\sqrt{s}=13~{\rm TeV}~[{\bf 2}]$



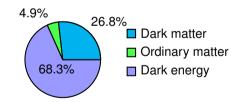
 Successfully confirmed by the discovery of the Higgs Boson in 2012 at the LHC by the ATLAS [3] and CMS [4] experiments

Tensions in the Standard Model



• 4.2σ deviation between the Fermilab measurement of the muon's magnetic moment [5] and the prediction by the Muon g-2 Theory Initiative [6]

Lack of a dark matter candidate particle



Energy density distribution of the Universe [7]

Plan

- 1 Vector Boson Scattering and Polarisation
- e/γ
- 3 Scan of hyper-parameter space in BSM
- 4 Other works and Next steps

- 1 Vector Boson Scattering and Polarisation

 Motivation

 DNN
- $2 e/\gamma$
- Scan of hyper-parameter space in BSM
- 4 Other works and Next steps

1 Vector Boson Scattering and Polarisation
Motivation
DNN

2 e/~

Scan of hyper-parameter space in BSM

4 Other works and Next steps

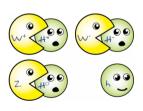
Representation for Polarisation

Spin

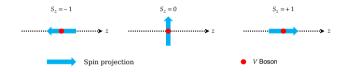
Intrinsic property of a particle

Massive vector bosons

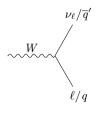
3 degrees of freedom represented by 3 different polarizations, one arise from the Higgs mechanism when the bosons acquire mass



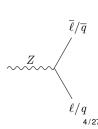
$$\epsilon_{-}^{\mu} = \frac{1}{\sqrt{2}} (0, 1, -i, 0) \quad \epsilon_{0}^{\mu} = \frac{1}{m_{V}} (k_{z}, 0, 0, E) \quad \epsilon_{+}^{\mu} = -\frac{1}{\sqrt{2}} (0, 1, i, 0)$$



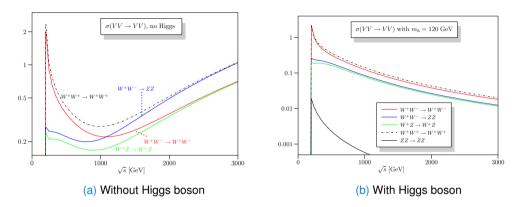
Representation of transverse (T or \pm) and longitudinal (0) polarisation states



The decay products of W or Z bosons retain traces of the bosons' polarisation



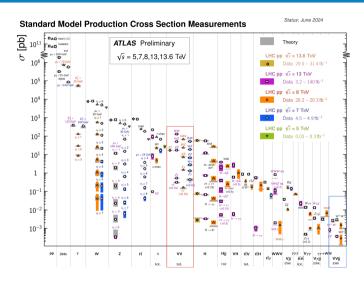
Why study Vector Boson Polarisation?



Effective cross-section (in nb) for five different longitudinally polarized weak interaction gauge boson scattering (Vector Boson Scattering or VBS) processes [8]

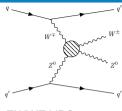
Measuring polarisation in boson scattering (WZ production, for example) provides a direct probe of EW symmetry breaking mechanism

Standard Model cross section



Summary of several Standard Model cross-section measurements [9]

My Analysis



EWWZ VBS process

- The ATLAS team at LAPP (Emmanuel, Iro, Lucia ...) has been analyzing WZ boson pairs for several years, in particular
 - the first observation of the production of a WZ pair in an electroweak process [10]
 - the first observation of the joint polarization states of gauge bosons in the WZ production [11]

- The main idea is to continue the previous work and try to measure now the fraction of polarisation in WZ VBS EW processes
- We focus on the WZjj $ightarrow \ell\ell\ell\nu$ jj decay channel with ℓ only e and μ
- Main challenge is the low cross section of this process

Analysis strategy

Work in parallel on two aspects

- Study machine learning techniques to maximize the sensitivity of WZjj-EW polarisation measurement → done using existing published Run-2 WZ VBS analysis
- Develop analysis of Run-3 data for WZjj-EW measurement

1 Vector Boson Scattering and Polarisation Motivation DNN

2 e/ γ

Scan of hyper-parameter space in BSM

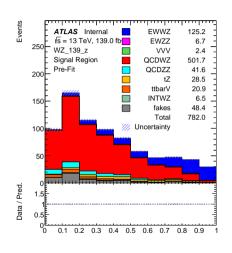
4 Other works and Next steps

Signal vs Background DNN



- 4 classes one-hot encoded → WZjj-EW, WZjj-QCD, ZZ-QCD, and other minor background, 1 for each process, 0 otherwise
- Softmax activation function for output
- ZZ-EW is not used for the training since it's signal-like
- output WZjj-EW used for y
- Weight event by event used, using the absolute value and matching NSignal and NBackground

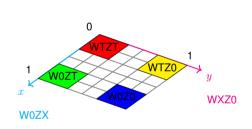




Signal vs Background template

Polarisation DNN - V1

- 4 output, one for each polarisation state
 - Weight event by event used, using the absolute value and matching $N_{\text{EW00/EW0T/EWT0}}$ and N_{EWTT}

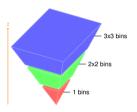


polarisation discrimination \rightarrow (xy) plan

$$x = \frac{00 + 0T \times (1 - T0)}{00 + 0T + T0 + TT} \quad y = \frac{00 + T0 \times (1 - 0T)}{00 + 0T + T0 + TT}$$

Technical details on Backup Slides 3-4 and Variables in Table 2

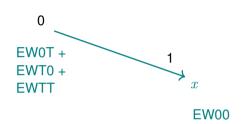
Softmax activation function for output



Custom binning in pyramidal shape

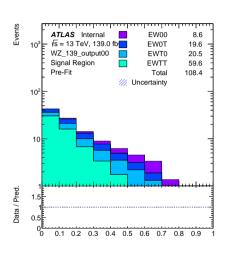
- 3 norm factor related to polarisation (despite other μ)
- more complex fit
- give a measurement on the 4 polarisation at the same time

Polarisation DNN - V2

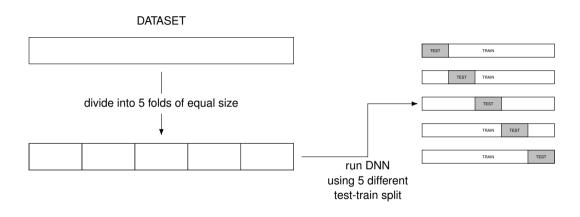


EW00 vs (EW0T+EWT0+EWTT) \rightarrow x axis

- 1 single output \rightarrow EW00 = 1 and EW0T+EWT0+EWTT = 0
- Sigmoid activation function for output
- Weight event by event used, using the absolute value and matching $N_{\rm EW00/EW0T/EWT0}$ and $N_{\rm EWTT}$

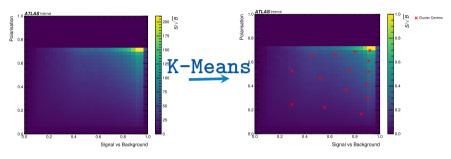


Polarisation template



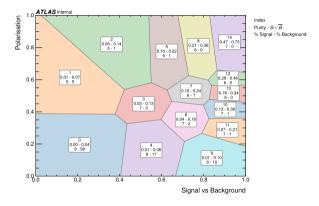
Implementation of a k-fold procedure \longrightarrow suppression of any overfitting bias

S/\sqrt{B} and K-Means



 S/\sqrt{B} 2D map

Voronoi Diagrams

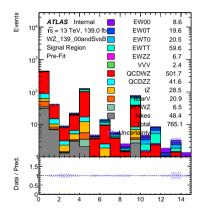


Voronoi Diagrams of our 2D map

- We construct a Voronoi Diagram using the function Voronoi from SciPy
- The seeds are the clusters centres computed before
- For each Voronoi region we present:

 - the purity, S/(S+B), with weight
 - the ratio S/\sqrt{B} , with weight
 - the % of Signal and Background, with weight

2D Fit - Joint Polarisation



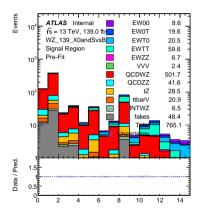
2D unrolled template for EW00

Туре	Date	Bins	Significance		
			Run-2	Run-3	Run-2+3
3D map - first stage of the fit	10/2024	27	0.54	0.88	1.30
3D map - actual fit setup	02/2025	27	0.54	0.80	0.97
3D map - binning optimisation	04/2025	14	0.60	0.89	1.07
2D map - multi-output polarisation	06/2025	14	0.69	1.03	1.24
2D map - single-output polarisation	06/2025	15	0.91	1.33	1.59

- Constant optimisation and improvement → improvement of the significance
- Over 160% improvement since the first fit
- Non linear binning optimisation is functional

Fit details on Backup Slides 7, 9, 10

2D Fit - Single Polarisation



2D unrolled template for EWX0

Туре	Bins	Significance				
		Run-2	Run-3	Run-2+3		
2D map - EW0X	15	1.84	2.68	3.20		
2D map - EWX0	15	2.28	3.33	4.0		

- More than 3σ for Run-2+3
- Non linear binning optimisation is functional

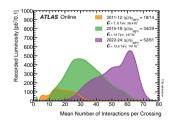
Fit details on Backup Slides 7, 8, 10

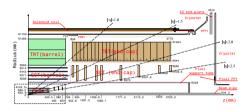
- Vector Boson Scattering and Polarisation
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- Scan of hyper-parameter space in BSM
- Other works and Next steps

Forward electrons ID

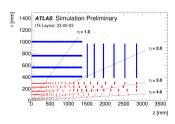
Improved $|\eta|$ coverage rate from 2.5 to 4.0 during ATLAS Phase-II Upgrade, enabling more "forward" e/μ to be used

- QT: based on the Forward electron ID in Run-4 with ITk and HGTD with definition of working point
- An issue in p_T calibration was observed and we proposed a DNN for calibrating it (only in Run-4)
- Portage of the ID technique to Run-3 and proposition of working point





Current Trajectograph [12]



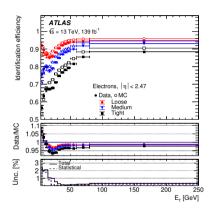
Inner Tracker (ITk) [13]

Methodology

- Trying to set up a discriminant:
 - with variables uncorrelated to p_T
 - trained over all p_T

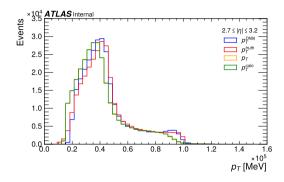
In order to:

- Be able to measure a distortion of shape from a unique DNN in order to compute selection efficiency for all p_T in a correlated way (hope is that, as the discriminant is less p_T-dependent, the mis-modeling would also be much less p_T dependent)
- Allow extrapolation at high-p_T for working point



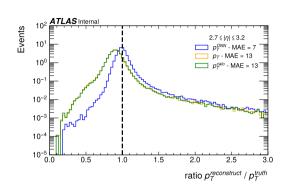
Identification efficiencies of electrons from $Z \longrightarrow ee$ decays as a function of the electron's $E_{\rm T}$ [14]

Run-4 - Calibration



 p_{T} from different methods

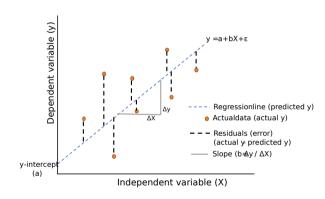
$$MAE = \frac{\sum_{i=1}^{N} |y_i - s(x_i)|}{N}$$



Ratio between p_T^{truth} and $p_T^{\mathrm{reconstruct}}$

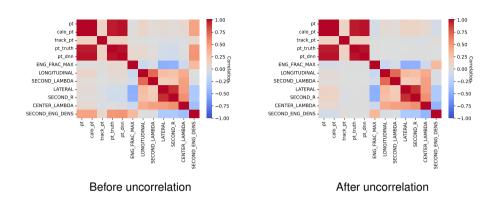
- y_i the label $\longrightarrow p_T^{\mathsf{truth}}$
- x_i is the vector of input variables
- $s(x_i)$ the prediction made by the DNN $\longrightarrow p_T^{\mathsf{DNN}}$

Decorrelation



Linear regression and residuals

- Decorrelation between $p_T^{\rm calo}$ for Run-3 and $p_T^{\rm DNN}$ for Run-4 and the seven clusters moments
- Training a linear regression model to fit p_T versus the 7 C.M (for signal only)
- We take the residuals to subtract them to the C.M (background and signal)
- The p_T variable is then unchanged, and is uncorrelated from the 7 C.M

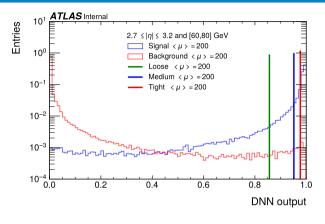


Correlation matrix between p_T and the seven clusters moments for the signal before and after uncorrelated them with a linear regression model

example for Run-4 with $2.7 \leq |\eta| \leq 3.2$ and $\langle \mu \rangle = 200$

As expected, the decorrelation process allows for using in the DNN these 7 input variables independent of pT

WP cuts

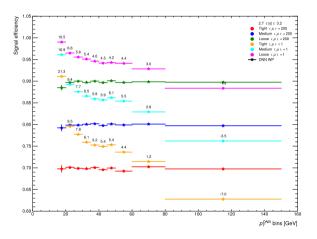


DNN prediction for signal and background at $\langle \mu \rangle = 200$ with cut on signal efficiency example for $2.7 \leq |\eta| \leq 3.2$ and $p_T \in [60;80]$ GeV

- Cut on the DNN predictions for the signal at $\langle \mu \rangle = 200$ for Run-4 and $\langle \mu \rangle \in [40;60]$ for Run-3
- Background is not take into acount on the cut
- loose WP as 90% signal efficiency
- medium WP as 80% signal efficiency
- tight WP as 70% signal efficiency

Variables in Table 3

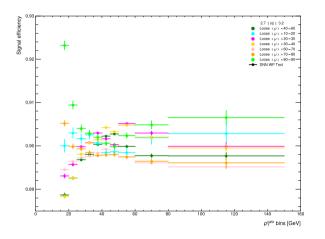
Run-4 - DNN WP Signal efficiency



Signal efficiency for DNN WP for data test at $\langle \mu \rangle = 200$ and $\langle \mu \rangle = 1$

- Signal efficiency at $\langle \mu \rangle = 1$ is a few percent higher than $\langle \mu \rangle = 200$ for loose and medium
- The sensitivity of the signal selection to pile-up is only a few percent
- No interpolation possible \longrightarrow missing samples at different $\langle \mu \rangle$

Run-3 - DNN Loose WP Signal efficiency



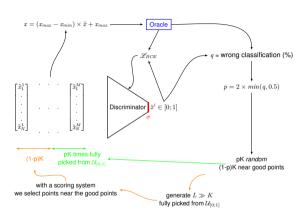
Signal efficiency for the Loose DNN working points on the test dataset at every $\langle \mu \rangle$ bins

 Overall the interpolation on the pile-up is working well and allow us to bring back the working points efficiencies within ~ 1% of the desired values.

- Vector Boson Scattering and Polarisation
- 2 e/~
- 3 Scan of hyper-parameter space in BSM
- 4 Other works and Next steps

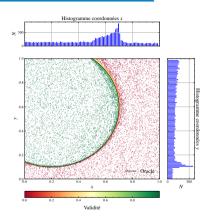
Active Learning





Schema of AL using DNN

- Scoring methods based on [15]
- Collaboration with Ugo de Noyers and Björn Herrmann from LAPTh



Toy model with the DNN and the AL algorithm

- Scan of Scotogenic Models [16] using MCMC
- Paper to be published and Ugo's PhD Thesis

- Vector Boson Scattering and Polarisation
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Other works

ADUM hours

- Research ethics 15h
- Researh integrity 15h
- Fundamentals of Big Data 24h
- Gif School 2023 24h
- PhD and career development 24h
- Introduction to parallel computing 36h
- European School of High Energy Physics 40h
- Teach TD efficiently 7h
- 21h30 of lectures on Introduction to python for 1st year student at the USMB

Talks

- COPIN-IN2P3 Talk in Cracaw on WZ inclusive polarisation studies [11]
- e/γ workshop 2025
- Physics ATLAS France (PAF)

Extra Work

- Qualified ATLAS author
- Vulgarisation scientifique pour Fête de la science of LAPP 2023 and at Mercredi du LAPP
- CERN Guide
- Shift in the control room for the Calorimeter / Forward detector desk - 208h
- Develop a website to visualise our datasets
- e/γ workshop 2024

Next Steps

e/γ

 Implementation of the DNN for Identification and Calibration inside ATLAS Athena Framework

The analysis

- Update (reconstructed) object systematics for Run-3 data
- Study of associated systematic uncertainties through the statistical treatment
- Follow the ATLAS procedures in order to eventually uncover the data and get the physics results

Work on the side

- Finish paper publication with Ugo and Björn
- Write the thesis

Summary

VBS and Polarisation

- DNN optimisation is done → gain of significance
- k-fold and binning optimisation is showing good results
- Implementation done in the framework
- The fit setup is done, we need to add the systematics now
- Best significance ever presented with more than 1.5σ for joint polarisation and more than 3σ for single polarisation for Run-2+3
- Joint and Single Boson polarisation measurement

e/γ

- Calibration of the p_T work well and give us a more precise value rather than the existing methods
- DNN WP outperform the pre-existing WP
- WP efficiency works well at different $\langle \mu \rangle$ and the interpolation if successfully by giving us overall \sim 1% difference in signal efficiencies

BSM

- New methods to scan an hyper-parameter space
- Show good results and comparison with MCMC
- Paper soon to published

References

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- [7] G. Hinshaw et al., Nine-Year Wilkinson Microwave Anisotropy Probe (WMAP) Observations: Cosmological Parameter Results, Astrophys. J. Suppl. 208 (2013) 19, arXiv: 1212.5226 [astro-ph.CO] (Cited on slide 3).
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- ATLAS Collaboration, Observation of gauge boson joint-polarisation states in $W^{\pm}Z$ production [11] from pp collisions at $\sqrt{s}=13$ TeV with the ATLAS detector, 2022, arXiv: 2211.09435 [hep-ex] (Cited on slides 10, 32).
- [12] The ATLAS Experiment at the CERN Large Hadron Collider, JINST 3 (2008) S08003, Also published by CERN Geneva in 2010. URL: https://cds.cern.ch/record/1129811 (Cited on slide 21).

- [13] Expected tracking and related performance with the updated ATLAS Inner Tracker layout at the High-Luminosity LHC, tech. rep., All figures including auxiliary figures are available at https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/PUBNOTES/ATL-PHYS-PUB-2021-024: CERN, 2021, URL: https://cds.cern.ch/record/2776651 (Cited on slide 21).
- [14] Electron and photon efficiencies in LHC Run 2 with the ATLAS experiment, Journal of High Energy Physics 2024 (2024),
 URL: http://dx.doi.org/10.1007/JHEP05 (2024) 162 (Cited on slide 22).
- [15] Mark D. Goodsell and Ari Joury, *Active learning BSM parameter spaces*, Eur. Phys. J. C 83 (2023) 268, arXiv: 2204.13950 [hep-ph] (Cited on slide 30).
- [16] Ugo de Noyers, Maud Sarazin, and Björn Herrmann, *Phenomenology of a singlet-doublet-triplet scotogenic framework*, (2024), arXiv: 2410.23712 [hep-ph] (Cited on slide 30).
- [17] Louis Portales, Observation of electroweak WZjj production and studies on pile-up mitigation with the ATLAS detector, Theses: Université Savoie Mont Blanc, 2020, URL: https://theses.hal.science/tel-03550156 (Cited on slide 47).
- [18] Martín Abadi et al., TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems, Software available from tensorflow.org, 2015, URL: https://www.tensorflow.org/ (Cited on slide 44).

[19]	François Chollet et al., <i>Keras</i> , https://keras.io, 2015 (Cited on slide 44).

Framework DNN configuration Fit details e/γ

Muon g-2

The Dirac equation predict g=2In nature, radiate corrections make $g \neq 2$

We can compute a the anomaly:

$$a = \frac{g-2}{2}$$

with g the Landé factor that arise from:

$$\vec{\mu}_S = g \frac{q}{2m} \vec{S}$$

The values observed for now are the following:

- $a_{\mu}(\mathsf{Exp}) = 116592061(41) \times 10^{11}$ [5]
- $a_{\mu}(SM) = 116591810(43) \times 10^{11}$ [6]

Analysis set-up, phase space and events selection

- Exactly same event selection as used for Run-2 (inclusive and VBS), see below
- CP recommendations and ID/ISO WP points adapted to Run-3
- lepton / boson / jet information

Event selection

Phase space definition

Variables	Fiducial WZjj-EW
Lepton $ \eta $	< 2.5
p_T of l_Z , p_T of l_W [GeV]	> 15, > 20
m_Z range [GeV]	$\left \left m_Z - m_Z^{PDG} \right < 10 \right $
m_T^W [GeV]	≥ 30
$\Delta R(l_Z^-, l_Z^+), \Delta R(l_Z, l_W)$	> 0.2, > 0.3
p_T two leading jets [GeV]	> 40
$ \eta_j $ two leading jets	< 4.5
Jets multiplicity	≥ 2
$\eta_{j1}\cdot\eta_{j2}$	< 0
m_{jj} [GeV]	> 500
$\Delta R(j,l)$	> 0.3
$N_{b-quark}$	= 0

Criteria
Less than 4 baseline leptons
Exactly 3 leptons passing the Z selection
$p_T^{lead} > 25$ GeV in 2015 and $p_T^{lead} > 27$ GeV in 2016-2018
Two same flavor oppositely charged leptons passing Z-lepton selection
$ m_{\ell\ell}-m_Z <10~{\sf GeV}$
Remaining lepton passes W lepton selection
$m_T^{W} > 30 \text{ GeV}$
$^{\prime}\geq 2$
$>40~{\sf GeV}$
> 4.5
opposite sign
> 150 GeV

- ZZ CR: >4 baseline leptons
- b CR: $N_{b-quark} > 0$
- WZjj-QCD VR: $m_{jj} < 500 \text{ GeV}$

Framework

DNN configuration

Fit details

 e/γ

Setup

We use Tensorflow [18] and his API Keras [19] to compute deep neural networks

The dataset, signal + background, is normalised for better performance with following normalization:

$$x_{norm} = \frac{x - x_{max}}{x_{max} - x_{min}}$$

to scale them between 0 and 1

For multiple output DNN, we one-hot encoded each output as 1 for the corresponding process and 0 otherwise. We use in this way the categorical cross entropy function:

$$\mathscr{L} = \frac{-1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} x_{i,c} \cdot \ln\left(\hat{x}_{i,c}\right)$$

For multiple output DNN, we use the binary cross-entropy loss function:

$$\mathscr{L} = \frac{-1}{N} \sum_{i=1}^{N} \left[(1 - y_i) \ln (1 - s(x_i)) + y_i \ln s(x_i) \right]$$

We split the dataset as 80% of it for training and 20% for validation following a k-fold procedure

Neural Network Architecture

Feed-Forward fully connected DNN

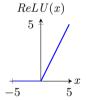
- number of hidden layers 6 each of them with ReLU activation function
- number of neuron per hidden layers 256
- a dropout layer after each hidden layer with a dropout of 0.25 except the last layer
- output layer with:
 - one single output with Sigmoid activation function
 - multiple output with Softmax activation function

The training was then done with the following settings:

- The optimizer for the loss function is ${\tt Adam}$ with an initial learning rate of 10^{-3} and a weight decay of 0.5
- We use a learning rate scheduler to decrease it by a facotr by 0.33 value when val_loss don't improve for 5 epochs and with a lower limit at 10^{-10}
- The input layer is made of N_{input} neurons
- We use an early stopper to prevent overfitting with a patience of 10 epochs
- Batch size of 10240

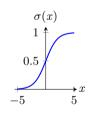
Activation Function

$$ReLU(x) = \left\{ egin{array}{ll} x & \mbox{if } x > 0 \\ 0 & \mbox{else} \end{array} \right.$$



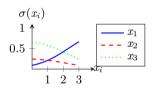
ReLU (*Rectified Linear Unit*) function

$$\sigma(x) = \frac{1}{1 + \exp^{-x}}$$



Sigmoid function

$$\sigma(x_i) = \frac{e^{x_i}}{\sum_{j=1}^C e^{x_j}}$$



Softmax function for three input values (x_1 , $x_2 = 1$, $x_3 = 2$)

Variables

Table 1: Signal vs Background DNN variables

Symbol	Description
$N^{ m jets}$	Multiplicity of jets
m_{ii}	Mass of the di-jet system
$\Delta \eta_{jj}$	Difference in pseudorapidity between the two tagging jets
$\Delta \phi_{jj}$	Difference in azimuth angle between the two tagging jets
p_T^W	Transverse impulse of the W
$p_T^{ ext{jet-1}}$ $\eta^{ ext{jet-2}}$	Transverse impulse of the tagging jet 1
$\eta^{\text{jet-2}}$	Pseudorapidity of the tagging jet 2
Clep	Centrality of leptons with respect to the di-jet system
$ y_lw-y_Z $	Difference in rapidity between Z boson and lepton from W
$\cos \theta_V$	Cosine of emission angle in the WZ rest frames
$R_{p_T}^{hard}$	Transverse component of vector sum of moments divided by their p_T sum
η_{W_l,Z_1}	Pseudorapidity of the first leptons from W and Z
p_T^{WZ}	Transverse impulse of the WZ system
$\Delta \phi(l_1^Z, l_2^Z)$	Difference of azimuthal angle ϕ of leptons from Z
$\Delta \phi(l^W, l^{\nu})$	Difference in azimuthal angle ϕ of leptons from W
$E^{\text{jet-1}}$	Energy of of the tagging jet 1
$A_{p_T^{ij}}$	Asymmetry between the p_T of the two tagging jets

Table 2: Polarisation DNN variables

Symbol	Description
$\Delta \eta_{ij}$	Difference in pseudorapidity between the two tagging jets
$\Delta \phi_{jj}$	Difference in azimuth angle between the two tagging jets
$p_T^{W,Z}$	Transverse impulse of the W and Z bosons
$\eta^{\text{jet-1/2}}$	Pseudorapidity of the tagging jet 1 and 2
ΔR_{jZ}	Angular separation between the first tagging jet and the Z boson
m_T^{WZ}	Transverse mass of system WZ
$ y_{lW} - y_{Z} $	Difference in rapidity between Z boson and lepton from W
$\cos \theta_{W,Z,V}$	Cosine of emission angle in the W , Z , and WZ rest frames
$p_T^{Z_1}$	Transverse impulse of the first lepton from Z
η_{W_l,Z_l}	Pseudorapidity of the three leptons from W and Z
p_T^{WZ}	Transverse impulse of the WZ system
$\Delta \phi(l_1^Z, l_2^Z)$	Difference of azimuthal angle ϕ of leptons from Z
$A_{n^{ij}}$	Asymmetry between the p_T of the two tagging jets
r^{21}	Ratio of p_T of leading to sub-leading boson

Variables from BDT [17]

DNN configuration

Fit details

 e/γ

Samples of the fit

Signal

- VBS WZjj-EW
 - SR: 4 polarised "new" with a rescaling to match previous samples number of events
 - bCR and ZZCR: unpolarised "noSkim"

Background

- VBS WZjj-EW off-shell
 - SR: unpolarised "noSkim" rescale to HT/2 and substract by unpolarised "new"

 not implemented due to yields issues
 on "new" polarised samples
- VBS WZjj-EW interference between polarisation states
 - SR: unpolarised "new" substract by 4 polarised "new" → not implemented due to yields issues on "new" polarised samples
- ZZ-EW, VVV, WZjj-QCD, ZZ-QCD, tZ, ttV, WZ-INT
 - SR
 - bCR and ZZCR
- Fakes tt̄, Zγ, Zℓℓ
 - SR: rescaling of 1.8 for the MC estimate to match the numbers of events expected by the Matrix Method
 - bCR: Matrix Method estimate
 - ZZCR: MC estimate since low in this region

Single Boson polarisation

POI:
$$N_{\mathsf{EW}}^{\mathsf{observed}}$$
 , f_1

$$rac{N_{ ext{EW}}^{ ext{observed}}}{N_{ ext{DX/X0}}^{ ext{predict}}}*f_1 \ rac{N_{ ext{EW}}^{ ext{observed}}}{N_{ ext{TX/XT}}^{ ext{predict}}}*(1-f_1)$$

Parameters that are floating unconstrained in the fit, others ones are constant

$$f_1$$
 is set to be f_{0X}/f_{X0} so $f_{00} + f_{0T}/f_{00} + f_{T0}$

The first norm factor is applied to EW0X/EWX0 while the second to EWTX/EWXT

Joint Boson polarisation

POI:
$$N_{\mathsf{EW}}^{\mathsf{observed}}$$
 , f_1

$$rac{N_{ ext{EW}}^{ ext{observed}}}{N_{ ext{predict}}^{ ext{predict}}}*f_1 \ rac{N_{ ext{construct}}^{ ext{observed}}}{N_{ ext{predict}}^{ ext{predict}}}*(1-f_1)$$

Parameters that are floating unconstrained in the fit, other ones are constant

 f_1 is set to be f_{00}

The first norm factor is applied to EW00 while the second to EW0T, EWT0 and EWTT

Parameters of the fit

NormFactor

A floating norm factor μ if given for (as from previous analysis):

- tīV
- tZ

- WZjj-QCD
- ZZ-QCD only for ZZCR

Fit

The fit is done using a SR and two control region:

- SR: unrolled 3D map from the DNN
- ZZCR: m_{JJ}
- bCR: BDT_b

all are compute directly from the output of the framework

Hybrid-Asimov fit (only CR have data unblinded)

Higher significance is done using a Lumi

 e/γ

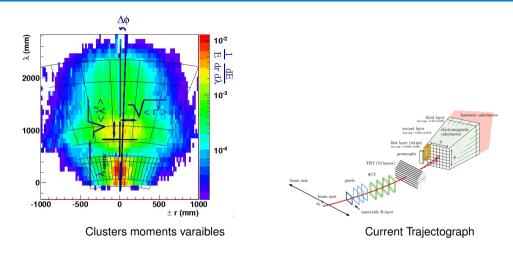
Variables

Detector	Variables names	Variables information
HGTD	Time	HGTD time information
	$\eta^{ m calo}$	η from CaloCluster
	ϕ^{calo}	ϕ from CaloCluster
	f_i^{EM}	Deposit energy on the i-th layer of the EMCalo for $i \in [1;2;3]$
	f_l^{HAD}	Deposit energy on the i-th layer of the HADCalo for $i \in [1;2;3;4]$
	f _{em}	Fraction of the cluster energy that is deposited in the most energetic cell of the cluster
Calorimeter	longitudinal	Shower shape in the clusters' longitudinal direction, based on the distance of each cell to the shower core
	$<\lambda^2>$	Second moment in λ - the distance of each cell to the cluster center along the shower axis
	lateral	Lateral moment of the shower taking into account the two most energetic cells (which constitutes the shower core)
	$< r^2 >$	Second moment in $\it r$ - the radial distance of each cell to the shower axis
	λ_{center}	The distance of the shower center from the front of the calorimeter along the shower axis
	$< \rho^2 >$	Second moment in energy density
	η^{track}	η from trackParticle
Tracker	ϕ^{track}	ϕ from trackParticle
Iracker	pixels	Number of pixels hits
	strips	Number of strips hits
	$\Delta \eta$	Delta in η for the point of impact of the trace in layer 2 of the calo and the energy deposit in this same layer
T	$\Delta \eta$	Delta in ϕ for the point of impact of the trace in layer 2 of the calo and the energy deposit in this same layer
Track-Calo match	$\Delta \eta^{ m rescaled}$	Delta in ϕ for the point of impact of the trace rescaled by the energy give by the calorimeter
	$\Delta \eta^{ m last}$	

Table 3: Variables used as input for Run-4 and Run-3

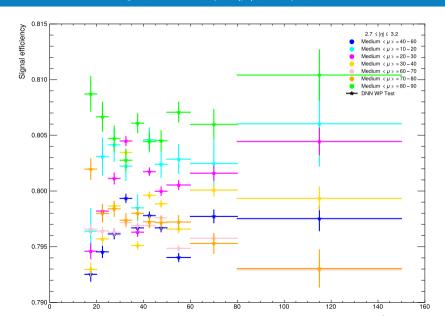
Six first Cluster Moments (f_{fem} , longitudinal, $<\lambda^2>$, lateral, $< r^2>$ and λ_{center}) are the ones to ID the electron in the forward region presently

Variables examples



Example of variables we can get from the detectors

Run-3 - DNN Medium WP Signal efficiency - $\langle \mu \rangle$ interpolation



Run-3 - DNN Tight WP Signal efficiency - $\langle \mu \rangle$ interpolation

