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Z boson mass estimation using Machine Learning

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***Abstract* - In this work we try to demonstrate the use of Machine Learning (ML) by estimating the mass of Z boson using Machine Learning (ML).**

***keywords* - Machine Learning (ML), Z boson**

I. INTRODUCTION

Machine Learning (ML) is quite promising now days. It has found applications almost in all disciplines. ML algorithms develop a scientific model of sample data, known as 'training data', to perform predictions or take decisions without being programmed to play out the task. In short, it is all about taking decisions which allow us to accurately predict things using simple statistical methods, algorithms, and modern computing power. The Z boson has been discovered in 1983 at CERN [58, 59]. It is a very important part of the standard model jigsaw puzzle [58, 59, 60, 61, 62, 63]. The Z boson is one of the elementary particles incorporated into the standard model. There are two fundamental sorts of particles in this model: the fermions or matter particles and the bosons or force particles. The Z boson, along with the $W^{\pm}$ bosons, communicates the weak force which is one of the four fundamental forces and is in charge of beta decay and nuclear fusion processes. It is a force much like the electromagnetic force yet its range is very short. The Z boson is an electrically neutral particle i.e. it is its own antiparticle. It is a large particle that is almost ninety times as large as a proton. The Z boson was a vital particle engaged with the unification of the electromagnetic and the weak force into the electroweak force. Before the proposed Z particle was brought into reality it was surely known that the $W^{\pm}$ particles mediated interactions with neutrinos that transformed into electrons which enabled them to interact with matter, a procedure called charged current interaction. With the presence of the Z particle, in any case, it was trusted that a neutrino could interact without transforming itself. This procedure of non-transformation was called neutral current interaction. In 1973 investigations utilizing bubble chambers were conducted to discover proof of this interaction, which gave physical confirmation to electroweak unification. Additionally, from these investigations, utilizing the ration of the neutral and the charged currents, the clue was emerged out to evaluate the masses of the $W^{\pm}$ and Z particles. The complicated Feynman diagram of the process of creation of Z boson is represented in the Fig.1.1.

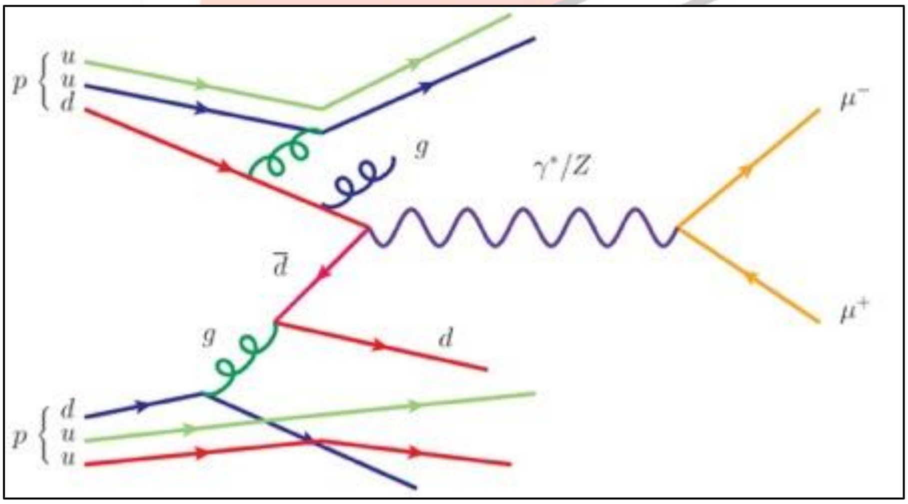

Fig.1.1: Feyanman diagram representing decay of Z boson from qark-quar interaction (Source-www.quantumdiaries.org/Zboson).

The protons that collide with each other as shown in the figure comprises of three quarks which are up, up and down quarks. Out of those three quarks, one ends up connected with the other quark originating from the other proton. The two down quarks collaborate with one another and transform either into a gamma quant or a Z boson, which in the end decays into a muon, anti-muon pair. The process of decay of Z boson into a muon, anti-muon pair is known as resonance. The probability of such a process can be estimated from a formula given by,

$$P \propto \frac{1}{\left(p_z^2 - m_z^2\right)^2 + \varepsilon} = \frac{1}{\left[\left(p_{\mu^+} + p_{\mu^-}\right)^2 - m_z^2\right]^2 + \varepsilon} \qquad (1.1)$$

where m_z is the mass of the Z boson, p_z and p_μ are the momentum of Z boson and muon respectively, and ε is the error in the measurement. The important part of such process is that the probability of decay is highest when the invariant mass of the two muons is equal to the mass of the Z boson, which creates the two muons. The probability distribution about the mass axis is something like Gaussian. However, these two muons can appear out of the two down quarks through a gamma quant also which is called Drell-Yan process as given by,

$$d + d \rightarrow \gamma \rightarrow \mu\mu \qquad (1.2)$$

The gamma quant doesn't have mass. Therefore there is no particular peak at any specific region of the mass scale. Therefore, in general, we see a blend of two processes together, a mixture of Gaussian like shape (signal) and exponential-like shape (background) as appeared in the Fig.1.2.

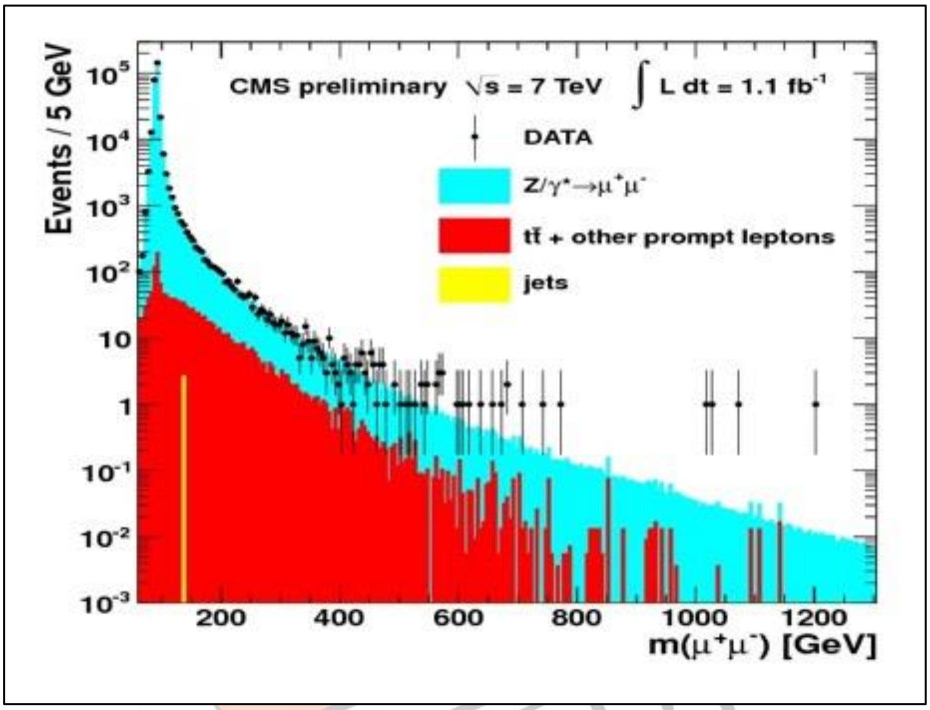

Fig.1.2: Combination of signal and background processes (Source: CMS @CERN)

So, if we can extract the information about the Gaussian from the blend of the model, the most fascinating parameter we can separate is the mass of the Z boson. We can basically do it by fitting a Gaussian and some exponential shape into the histogram that we got from the experiment.

II. Data Analysis and results:

We collect a sample of Z boson candidates recorded by CMS detector in 2011 [9] and published at CERN open data portal. It comes from the double muon dataset with the following selection applied:

- Both muons are Global muons.
- Invariant mass sits in range: 60 GeV< Mμμ < 120 GeV.
- |η| < 2.1 for both the muons.
- p_T > 20 GeV.

The following variables are output to a CSV file: Run, Event, Pt1, eta1, phi1, Q1, dxy1, iso1, Pt2, et2, phi2, Q2, dxy2, iso2, where,

- Run and Event are run and event number respectively,
- Pt1, Pt2 are transverse momenta of the muons,
- eta1, eta2 are pseudorapidities of the muons,
- phi1, phi2 are the angles of the muon direction,
- Q1, Q2 are the charges of the muons,
- dxy1, dxy2 are the impact parameters in the transverse plane and
- iso1, iso2 are the track isolation.

We read in the CSV file into a data frame using Python with the help of Pandas library [64] and calculate the invariant mass of the two muons using the following formula:

$$M = \sqrt{2 p_T^1 p_T^2 \left[\cosh(\eta_1 - \eta_2) - \cos(\phi_1 - \phi_2)\right]} \qquad (2.1)$$

and add the mass column to the data frame. The Fig.2.1(a) represents the distribution of Z boson mass calculated from the data set.

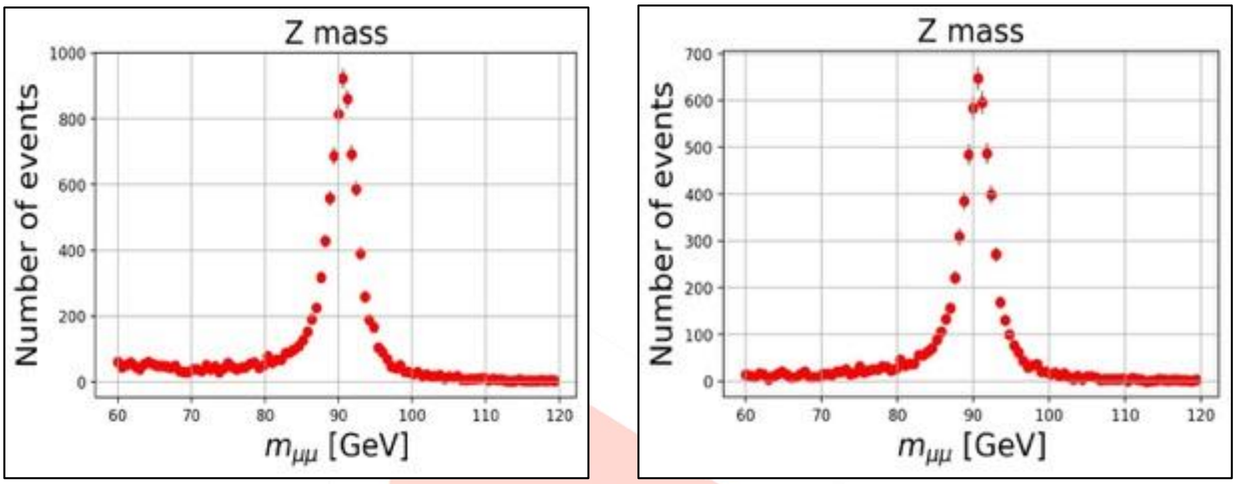

Fig.: 2.1 (a) Mass distribution of Z boson without selection criteria and (b) distribution of Z boson mass for oppositely charged muons , $I_{Track} < 3$ and $d_{xy} < 0.2$.

Again we clean the data set a little bit by taking only oppositely charged muons and taking $I_{Track} < 3$ and $d_{xy} < 0.2$, where Itrack is the particle track isolation parameter (see [9]). Fig.2.1 (b) shows the distribution after this selection criterion is applied. Next, we define a parameterized model which represents the mixture of Gaussian signal and background, that for simplicity we considered flat over mass as follows:

$$f(x) = a_0 + \frac{A}{\sqrt{2\pi}\sigma} e^{-\frac{(x-m_0)^2}{2\sigma^2}} \qquad (2.2)$$

where a_0 is the height of background, σ is the standard deviation of the Gaussian distribution, m_0 is the center of the Gaussian distribution, A is the height of the peak of the distribution.
We optimize this model using the ML library scikit-Optimize [8] to fit our model to the distribution of mass obtained from the dataset after the selection criteria applied as mentioned above. The procedure for optimization can be found in the online documentation of ’scikit-Optimize’[8]. We use ”lbfgs” as acquisition optimizer, ”EI” as acquisition function and ”GP” as base estimator. The results after optimization are shown in the Fig.2.2, where the convergence plot of the optimization process is shown in Fig.2.2(a) and Fig.2.2(b) represents the fitted model to the distribution. The fitting parameters obtained in the process are as follows:

m_0 = 91.08651947478343
σ = 1.7777781139910542
A = 2698
a_0 = 8

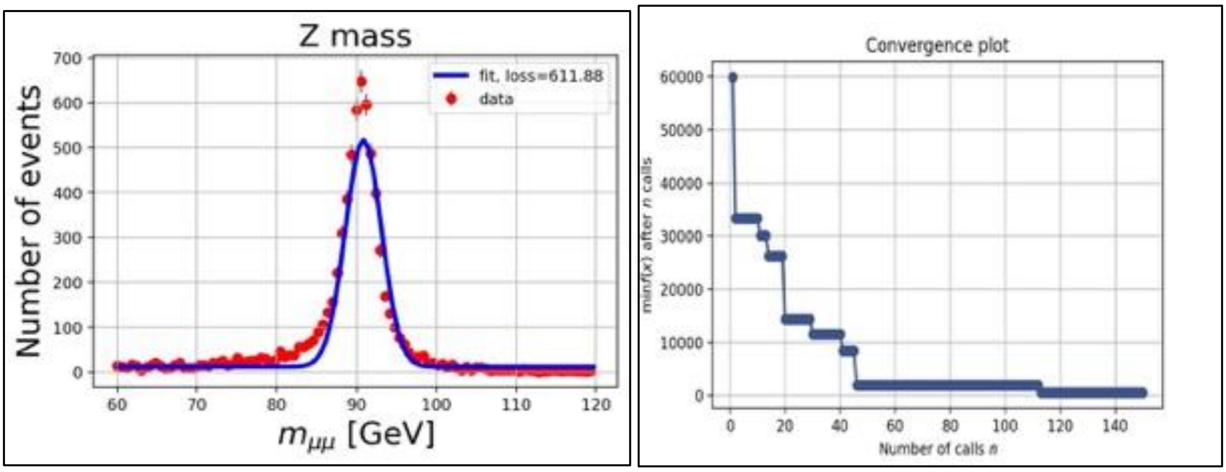

Fig.2.3(a) Convergence plot of the optimization process and (b) fitting of Z boson mass Distribution with our model (2.2) using Machine Learning.

III. CONCLUSION

In this work we try to demonstrate the use of Machine Learning (ML) for estimation of Z boson of mass. Comparing with Particle Data Group (PDG) we can see that ML is doing a good job in the prediction of mass of Z boson by using data obtained from CMS detector. We can conclude that ML will be helpful in such kind of other analysis in High Energy Physics.

REFERENCES

[1] atlas.physicsmasterclasses.org/en/lhcphysics2.htm
[2] https:// CERN.org.
[3] D. Denegri, Physics Reports 403, 107 (2004)
[4] M. Krasny et al., The European Physical Journal C 51, 607 (2007)
[5] G. Abbiendi et al., Eur. Phys. J. C 14, 187 (2000).
[6] https://www.symmetrymagazine.org/z-boson.
[7] W. McKinney, http://pandas.sourceforge.net.
[8] scipy.optimize.OptimizeResult-SciPy v1.2.0 Reference Guide.
[9] CMS Collaboration, DoubleMu primary dataset in AOD format from RunA of 2011 (/DoubleMu/Run2011a-12oct2013-v1/AOD) (2016)
[10] A. M. Sirunyan et al., physical Review C 98, 044902 (2018).
[11] S. Bentvelsen et.al, JINST 3, S08003 (2008).
[12] K. Aamodt et.al, JINST 3, S08002 (2008)
[13] S. Chatrchyan et al., JINST 3, S08004 (2008).
[14] E. Focardi, Physics Procedia 37, 119 (2012)
[15] M. Tanabashi et al., Phys. Rev. D 98, 030001 (2018)
[16] A. Augusto et.al, JINST 3, S08005 (2008).
[17] A. M. Sirunyan et al., physical Review C 98, 044902 (2018).
[18] J. Gonzalez et al., Physical Review D 98, 11 (2018)
[19] K. J. Millman and M. Aivazis, Computing in Science and Engineering 13, 9 (2011)
[20] G. Louppe et al., Journal of High Energy Physics 1, (2019)