The Machine Learning role in High Energy Physics

Javier Andres Orduz-Ducuara
Mathematics and Engineering department
Higher Studies Faculty of Acatlan
UNAM

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Abstract

We explore some Standard Model (SM) extensions considering Machine Learning (ML) techniques. This is stage one, looking for recents papers, collaborations and events to build the framework and the contributions in this exciting field which combines: Physics, Computing, Mathematics and Artificial Intelligence. Our main expectations (stage two of the project) are to explore some of the new physics scenarios such as THDM, gauge extended models and vector-like models, and we investigate the observables and parameters using some ML techniques to place some bounds and define exclusion regions for the models. These techniques could prove to be useful in the understanding of flavor-changing scalar interactions, the detection of new particles and precise measurements of SM particles.

1 Introduction

The scientific community accept the SM and its predictions because of the high grade of precision despite the unrevealed questions. Recent results as Higgs observation by CMS and ATLAS at CERN support the SM as a framework to describe the interactions among particles at scale $\mathcal{O}(10^2\,\mathrm{GeV})$. Big machines are necessary to investigate the universe at this (or higher energy) scale. Currently, the technological development allows the exploration through the computer: Simulations, high performance, big data, artificial inteligence, among others. Fig. **??** shows a sketch for the Artificial Inteligence, Machine Learning and Deep Learning.

The evolution on calculation techniques and the new sotfware tools allow to probe the SM (and its extended models) and the experimental results. In fact machine learning (ML) becomes one of the most interesting and powerful set of techniques and tools (sometimes called paradigm) for investigating the phenomena regarding experimental and theoretical High Energy Physics (HEP).

The ML paradigm works to: 1. obtain a deep insights, 2. recognize unknown patterns and 3. create high perform predictive models from data. In this paradigm there are different learning types: Supervised, such as regression and classification; and unsupervised, implemented to find a pattern more than prediction.

In HEP the ML can be implemented in a theoretical and experimental view:

1. Higher order computational methods: OneLoop, QCDLoop, LoopTools; parton level generators NNLO, DYNNLO, N3LO [1, 2]

2. Monte Carlo event generators and deep inelastic inclusive cross-sections: MadGrap, POWHEG and HERA [1, 3]

In the theoretical and phenomelogical view, researchers face on some challenges to implement this ML paradigm for scrutinizing the models and the theory, however in ref. [4] shows an application in a beyond standard model with new neutral gauge boson but it is toy model. Actually in ref. [5] is shown an interesting analysis to $t\bar{t} \to W^+ b W^- \bar{b}$ looking at the physical parameters as mass.

In this work we want to explore some models and implement novel techniques to investigate the behavior of the physical parameters for Two-Higgs Doublet model (THDM), new gauge group and vector-like models. In particular we focus on THDM-III.

2 Models, methods or materials

We expose some models to study using ML. In particular we write down the Lagrangian for the THDM type III because we want to explore the flavor-changing parameters. In a general way, the Yukawa sector for the THDM-III is given by

$$\begin{aligned}
\mathcal{L}_n^{THDM-III} &= \frac{g}{2}\left(\frac{m_i}{m_W}\right)\bar{d}_i\left[\frac{\cos\alpha}{\cos\beta}\delta_{ij}+\frac{\sqrt{2}\sin(\alpha-\beta)}{g\cos\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^d\right)_{ij}\right]d_jH^0 \\
&+ \frac{g}{2}\left(\frac{m_j}{m_W}\right)\bar{d}_i\left[-\frac{\sin\alpha}{\cos\beta}\delta_{ij}+\frac{\sqrt{2}\cos(\alpha-\beta)}{g\cos\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^d\right)_{ij}\right]d_jh^0 \\
&+ \frac{ig}{2}\left(\frac{m_i}{m_W}\right)\bar{d}_i\left[-\tan\beta\delta_{ij}+\frac{\sqrt{2}}{g\cos\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^d\right)_{ij}\right]\gamma^5d_jA^0 \\
&+ \frac{g}{2}\left(\frac{m_i}{m_W}\right)\bar{u}_i\left[\frac{\sin\alpha}{\sin\beta}\delta_{ij}+\frac{\sqrt{2}\sin(\alpha-\beta)}{g\sin\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^u\right)_{ij}\right]u_jH^0 \\
&+ \frac{g}{2}\left(\frac{m_u}{m_W}\right)\bar{u}_i\left[-\frac{\cos\alpha}{\sin\beta}\delta_{ij}+\frac{\sqrt{2}\cos(\alpha-\beta)}{g\sin\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^u\right)_{ij}\right]u_jh^0 \\
&+ \frac{ig}{2}\left(\frac{m_u}{m_W}\right)\bar{u}_i\left[-\cot\beta\delta_{ij}+\frac{\sqrt{2}}{g\sin\beta}\left(\frac{m_W}{m_i}\right)\left(\tilde{Y}_2^u\right)_{ij}\right]\gamma^5u_jA^0. \qquad (1)
\end{aligned}$$

where $\left(\tilde{Y}_2^u\right)_{ij}$ are some of parameters that we could study in the ML paradigm. As we will show this kind of model may have a special general potential depending on, λ_i parameters and different relations between the scalar fields, Φ_1 and Φ_2.

3 Results

I will show some results using machine learning for the high-loop level in particle physics, in particular some concepts and ideas in a theoretical view.

References

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