

Search for heavy neutrinos in a 3-lepton final-state

Applications using supervised machine learning

by

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Abstract

This will be the abstract.

Acknowledgments

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Introduction

The standard model (SM) is perhaps one of the most successful scientific theories ever created. It accurately explains the interactions of leptons and quarks as well as the force carrying particles which mediate said interactions. In 2012 the SM achieved one of its crowning achievements when we discovered the Higgs boson. Much of the accolade was rightfully given to the theoretical work on the SM, but another aspect of the discovery was equally important. Data analysis was and is a crucial part of any new discovery in physics. One of the most important and exiting tools is machine learning.

Outline of the Thesis

Chapter 1

The Standard model of elementary particles

1.1 Phenomenology - What is it?

1.2 The background channels

The dominant SM backgrounds can be divided into two categories: (i) from leptonic τ decays and (ii) from fake leptons. In the first category, the dominant process is the pair production of WZ with W decaying leptonically and $Z \rightarrow \tau\tau$. The trilepton final states with no-OSSF pairs can arise from the subsequent leptonic decay of τ 's. We estimate this background process via Monte Carlo simulations.

The dominant processes of the second category are γ^*/Z + jets and $t\bar{t}$, where two leptons come from $\gamma^*/Z \rightarrow \tau\tau$ or the prompt decay of t and \bar{t} , and a third lepton is faked from jets containing heavy-flavor mesons.

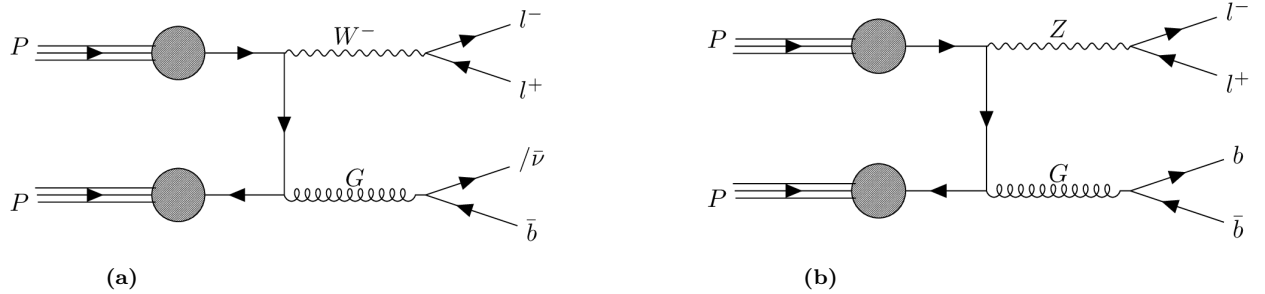


Figure 1.1: The Feynman diagram of both the W +jets [1.1a](#) and the W +jets [1.1a](#).

Chapter 2

Beyond the standard model - Heavy neutrinos

2.1 Why look beyond?

2.2 Neutrinos

2.3 Dirac and Majorana

2.3.1 How to distinguish the two?

Chapter 3

Statistical and multi-variabel analysis

The standard model (SM) is perhaps one of the most successful scientific theories ever created. It accurately explains the interactions of leptons and quarks as well as the force carrying particles which mediate said interactions. In 2012 the SM achieved one of its crowning achievements when we discovered the Higgs boson. Much of the accolade was rightfully given to the theoretical work on the SM, but another aspect of the discovery was equally important. Data analysis was and is a crucial part of any new discovery in physics. One of the most important and exiting tools is machine learning.

3.1 Discovery and significance

3.2 Exclusion

3.2.1 Likelihood

3.3 High- and Low-level features

Chapter 4

Introduction to supervised and unsuperised machine learning

This will give a brief intoruction to the concept of machine learning as well as the difference between supervised and unsuperised.

4.1 Neural Networks in physics

4.1.1 Deep vs Shallow networks

4.2 Gradient Boosting and decision trees

In this rapport I will use the XGBoost-classifier which uses gradient-boosted trees. Gradient-boosting is a machine learning algorithm which uses a collective of "weak" classifiers in order to create one strong classifier. In the case of gradient-boosted trees the weak classifiers are a collective of shallow trees, which combine to form a classifiers that allows for deeper learning. As is the case for most gradient-boosting techniques, the collecting of weak classifiers is an iterative process.

We define an imperfect model \mathcal{F}_m , which is a collective of m number of weak classifiers, estimators. A prediction for the model on a given data-points, x_i is defined as $\mathcal{F}_m(x_i)$, and the observed value for the aforementioned data is defined as y_i . The goal of the iterative process is to minimize some cost-function \mathcal{C} by introducing a new estimator h_m to compensate for any error, $\mathcal{C}(\mathcal{F}_m(x_i), y_i)$. In other words we define the new estimator as:

$$\tilde{\mathcal{C}}(\mathcal{F}_m(x_i), y_i) = h_m(x_i), \quad (4.1)$$

where we define $\tilde{\mathcal{C}}$ as some relation defined between the observed and predicted values such that when added to the initial prediction we minimize \mathcal{C} .

Using our new estimator h_m , we can now define a new model as

$$\mathcal{F}_{m+1}(x_i) = \mathcal{F}_m + h_m(x_i). \quad (4.2)$$

The XGBoost [?] framework used in this analysis enables a gradient-boosted algorithm, and was initially created for the Higgs ML challenge. Since the challenge, XGBoost has become a favorite for many in the ML community and has later won many other ML challenges. XGBoost often outperforms ordinary decision trees, but what is gains in results it looses in interpretability. A single tree can easily be analysed and dissected, but when the number of trees increases this becomes harder.

Appendices

Appendix A

A.1 Light-Cone Coordinates

Light-cone coordinates is specifically useful in high energy scattering processes where one want to decompose the momentum of the involving particles. For a general four vector p^μ , one defines

$$p^\mu = (p^+, p^-, p_\perp), \quad (\text{A.1})$$

where

$$p^+ = \frac{1}{\sqrt{2}}(p^0 + p^3) \quad (\text{A.2})$$

$$p^- = \frac{1}{\sqrt{2}}(p^0 - p^3) \quad (\text{A.3})$$

$$p_\perp = (p^1, p^2). \quad (\text{A.4})$$

Scalar products are given by

$$p \cdot k = p^+ k^- + p^- k^+ - p_\perp \cdot k_\perp \quad (\text{A.5})$$

$$p^2 = 2p^+ p^- - p_\perp^2, \quad (\text{A.6})$$

where the transverse contraction $p_\perp \cdot k_\perp$ is understood from the definition of the transverse vector and must not be mistaken as the same as the four momentum contraction $p \cdot k$. We will usually parametrize our momenta in terms of plus-components and from Eq. (A.6) it follows that the minus component can be written as

$$p^- = \frac{p^2 + p_\perp^2}{2p^+}. \quad (\text{A.7})$$

The d -dimensional Jacobian takes the form

$$d^d p = dp^+ dp^- d^{d-2} p_\perp. \quad (\text{A.8})$$

From the above relations the light-cone metric takes the form

$$g_{\text{LC}}^{\mu\nu} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}, \quad (\text{A.9})$$

where the index runs over $\mu = +, -, 1, 2$. We will elsewhere drop the subscript LC as it will always be clear from the context when we are using light-cone coordinates. One can also define light-like basis vectors

$$n_+^\mu = (1^+, 0^-, 0_\perp), \quad n_{+\mu} = (0^+, 1^-, 0_\perp), \quad (\text{A.10})$$

$$n_-^\mu = (0^+, 1^-, 0_\perp), \quad n_{-\mu} = (1^+, 0^-, 0_\perp), \quad (\text{A.11})$$

giving

$$n_+^2 = 0, \quad n_-^2 = 0, \quad n_+ \cdot n_- = 1. \quad (\text{A.12})$$

These basis vectors project out the following components of a vector

$$p \cdot n_+ = p^- , \quad p \cdot n_- = p^+ . \quad (\text{A.13})$$

We can also construct a transversal metric

$$g_{\perp}^{\mu\nu} = g^{\mu\nu} - (n_+^\mu n_-^\nu + n_+^\nu n_-^\mu) = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix} , \quad (\text{A.14})$$

from which it follows that

$$g_{\perp}^{\mu\nu} g_{\perp\,\mu\nu} = 2 . \quad (\text{A.15})$$

We can also define the gluon polarization sum in light-cone gauge, i.e $A^+ = 0$, as

$$\sum_{\text{pol}} \varepsilon_\alpha(k') \varepsilon_\beta^*(k') = -g_{\alpha\beta} + \frac{k'_\alpha n_{-\beta}}{k' \cdot n_-} + \frac{k'_\beta n_{-\alpha}}{k' \cdot n_-} . \quad (\text{A.16})$$

Bibliography