UNIVERSITÀ DEGLI STUDI DI PADOVA

Dipartimento di Fisica e Astronomia "Galileo Galilei"

Corso di Laurea in Fisica

Tesi di Laurea

Predictive learning applied to muon chamber monitoring

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To the strength, the courage, the perseverance,
the passion, the love you infused in me.
To you.

Abstract

Cose in inglese

Sommario

Ho fatto cose per 5 mesi e non funziona niente ma i grafici sono belli check them out!

Contents

Chapter 1

Introduction

1.1 Machine Learning applications in High Energy Physics

Particle Physics, also known as High Energy Physics (HEP), is the branch of physics that studies the nature of the particles that costitute matter and radiation. Its development can be located starting from the second half of the 19^{th} century and, since then, theoretical physicists have been working on models that can accurately predict and describe the outcome of experiments. The model that better describes the experimental results is the Standard Model (SM), although it is common knowledge among the HEP community that SM is not complete. As a matter of fact, it does not describe General Relativity in terms of quantum field theories, it does not give specifics about nautrino masses and does not explain the existance of dark matter. These facts show that there are as yet undiscovered physical laws and that our understanding of the world at its most fundamental level is lacking.

In order to interrogate experimental data in the search for New Physics (NP), scientists have come to realise that employing a model-dependet approach (i.e. searching for specific NP models) has a critical disadvantage: a statistical test which is designed to be sensitive to one specific hypothesis is typically insensitive to data departures of a different nature from the one expected. This means that if new physics is present in the data, but not predicted by the specific NP model that is being tested, it would not be discovered.

A modern approach that overcomes the difficulties underlined above is the so called model-indipendent approach. For the sake of clarity, in the context of statistics, testing one hypothesis requires an alternative hypothesis to be compared with. In physics, a model is a set of physical laws that make us able to predict the distribution of a certain feature depending on free parameters. We thus define a certain approach 'model-independent' if the alternative distributions do not follow from a physical model. It means that the distributions can adapt to the true underlying data distribution for an appropriate choice of the free parameters. The main reason for which we demand a model-independent approach is the advantage of sensitivity to a large variety of new physics scenarios.

In the realm of HEP, Machine Learning (ML) techniques has been used since early 2000 (traditionally known as Multivariate Analysis) in many crucial tasks, such as event classification, track reconstruction and particle identification.

1.2 Data Quality Monitoring

Chapter 2

The Algorithm

Chapter 3

Experimental Setup and Datasets

Chapter 4

Running the Algorithm on Low Level Features

Chapter 5

Conclusions

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