I. INTRODUCTION

The past decade has seen a prodigious rise of machine-learning (ML) based techniques, impacting many areas in industry including autonomous driving, health-care, finance, manufacturing, energy harvesting, and more. ML is largely perceived as one of the main disruptive technologies of our ages, as much as computers have been in the 1980's and 1990's. The general goal of ML is to recognize patterns in data, which inform the way unseen problems are treated. For example, in a highly complex system such as a self-driving car, vast amounts of data coming from sensors have to be turned into decisions of how to control the car by a computer that has "learned" to recognize the pattern of "danger".

The success of ML in recent times has been marked at first by significant improvements on some existing technologies, for example in the field of image recognition. To a large extent, these advances constituted the first demonstrations of the impact that ML methods can have in specialized tasks. More recently, applications traditionally inaccessible to automated software have been successfully enabled, in particular by deep learning technology. The demonstration of reinforcement learning techniques in game playing, for example, has had a deep impact in the perception that the whole field was moving a step closer to what expected from a general artificial intelligence.

In parallel to the rise of ML techniques in industrial applications, scientists have increasingly become interested in the potential of ML for fundamental research, and physics is no exception. To some extent, this is not too surprising, since both ML and physics share some of their methods as well as goals. The two disciplines are both concerned about the process of gathering and analyzing data to design models that can predict the behaviour of complex systems. However, the fields prominently differ in the way their fundamental goals are realized. On the one hand, physicists want to understand the mechanisms of Nature, and are proud of using their own knowledge, intelligence and intuition to inform their models. On the other hand, machine learning mostly does the opposite: models are agnostic and the machine provides the 'intelligence' by extracting it from data. Although often powerful, the resulting models are notoriously known to be as opaque to our understanding as the data patterns themselves. Machine learning tools in physics are therefore welcomed enthusiastically by some, while being eyed with suspicions by others. What is difficult to deny is that they produce surprisingly good results in some cases.

In this review, we attempt at providing a coherent selected account of the diverse intersections of ML with physics. Specifically, we look at an ample spectrum of fields (ranging from statistical and quantum physics to high energy and cosmology) where ML recently made a prominent appearance, and discuss potential applications and challenges of 'intelligent' data mining techniques in the different contexts. We start this review with the field of statistical physics in Section II where the interaction with machine learning has a long history, drawing on methods in physics to provide better understanding of problems in machine learning. We then turn the wheel in the other direction of using machine learning for physics. Section III treats progress in the fields of high-energy physics and cosmology, Section IV reviews how ML ideas are helping to understand the mysteries of many-body quantum systems, Section V briefly explore the promises of machine learning within quantum computations, and in Section VI we highlight some of the amazing advances in computational chemistry and materials design due to ML applications. In Section VII we discuss some advances in instrumentation leading potentially to hardware adapted to perform machine learning tasks. We conclude with an outlook in Section VIII.

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