Il Colle di Galileo

Machine Learning at GGI

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Abstract. Machine learning (Machine-learning) has become an important toolbox for theoretical and experimental physics, and its importance is expected to grow steadily over the years to come. Thanks to its effectiveness and extreme flexibility, it can be applied in a huge set of topics, ranging from statistical data analysis to simulation and modelling. For this reason, Machine learning has been successfully used in very different research areas, such as high-energy physics, astrophysics and cosmology, condensed matter and statistical physics. Applications in different domains often share strong similarities either in the problems to be solved or in the methodology employed. This motivates a fruitful exchange of ideas which is, however, seldom achieved in practice due to the distance separating the various research communities. The workshop brought together researchers with interest and expertise in Machine learning from different fields in physics, strongly encouraging and promoting the cross-topic exchange of ideas and collaborations.

Keywords: machine learning, artificial intelligence, particle physics, condensed matter, astrophysics.

Scientific context

One of the best-selling textbooks on Machine Learning ("Hands on Machine Learning", Aurelien Geron) starts with the example of a toddler who is taught the meaning of the name "apple"' simply by pointing to an actual apple once. This is what the author defines as "genius". Machines or – as they are more broadly defined, algorithms – do not learn as fast as a toddler yet, as they each need lots and lots of data (many, many pictures of the aforementioned apple for instance) to work at the desired level of precision in their tasks. With a limited set of data, machines are only exposed to a limited amount of "training", leading literally to the comparison of apples to pears. With proper training, on the other hand, (almost) nothing is impossible.

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Clearly, the apple is just an example, one which is dear to physicists, but machine-learning techniques have a much broader spectrum of applications. And even if "machines" don't have the same level of "genius" as of a two-year old, the boom of machine-learning algorithms is already easily visible in our everyday lives. In particular, the past decade has witnessed a prodigious rise of machine-learning-based techniques, impacting many areas of industry, including autonomous driving, healthcare, finance, manufacturing, and more. The success of machine learning was initially marked by significant improvements in some existing technologies, in the field of image recognition for example, the famous identification of the "apple". To a large extent, these advances were the first demonstrations of the impact that machine-learning methods can have on specialized tasks. More recently, applications traditionally inaccessible to automated software have been successfully enabled, in particular by deep learning technology, moving a step closer to what is expected from general artificial intelligence.

Along with the rise of machine-learning techniques in industrial applications, scientists have become increasingly interested in the potential of machine learning for fundamental research, with important consequences for physics. This is not really surprising, as both machine learning and physics share some of their methods as well as their goals. Both disciplines are concerned about the process of gathering and processing data to design models that can analyze and predict the behaviour of complex systems. The strong interplay between the two areas of research has recently received further recognition in the form of the 2024 Nobel Prize for physics, awarded to two scientists, J. Hopfield and G. Hilton, who "used tools from physics to construct methods that helped lay the foundation for today's powerful machine learning".

Thanks to its effectiveness and extreme flexibility, machine learning offers useful applications for a wide spectrum of research topics, ranging from statistical data analysis, to simulation and modelling. Surprisingly good results have been obtained in many cases, often surpass the efficacy of traditional techniques. All areas of theoretical and experimental physics have greatly profited from machine-learning applications, which are becoming a necessary ingredient of modern research. Unlike many other areas to which machine learning is applied, physics offers the huge benefit of providing a high degree of control over the quality of data and, in many cases, the underlying models. Such a combination of factors is particularly suitable for developing a robust understanding of the learning process, which continues to be one of the major unknown aspects of machine-learning techniques. Obtaining a description of the machine learning behaviour that can be understood and easily interpreted would be a huge step forward from the traditional use of machine learning as a "black box". This is clearly a cross-cutting theme with extensive consequences for all the areas of research included in the workshop.

Structure of the workshop

The workshop "Machine Learning at GGI" was held at the Galileo Galilei Institute in the late summer of 2022. The program aimed to bring together researchers with interests and expertise in machine-learning from different fields in physics and strengthen the collaboration within each research area. It also strongly encouraged and promoted a cross-topic exchange of ideas. Experts from different research branches were hosted by the GGI and several fields were covered during the activities.

The focus was on the following areas: high energy physics; astrophysics, cosmology and astro-particles; condensed matter and statistical physics (including quantum information). These three macro areas were equally represented by the talks and seminars during the daily activities and also during the conference. The scientific schedule was inspired by the distinctive trait of the workshop: a focus on a theoretical physics perspective rather than on purely experimental applications. Theoretical physics was, however, interpreted in the broad sense, including phenomenological topics, in keeping with the GGI's mission. A few experimental participants and talks were also scheduled, to provide a complete overview of machine-learning applications and their benefits for research in theoretical physics.

Participation in the workshop was numerous, with approximately thirty scientists present every day, for an overall total of around a hundred. As in the spirit of the initiatives of the GGI, most of the participants stayed in Florence for an average of two weeks.

Conference

The third week of the workshop was dedicated to an international conference. The conference lasted five days and comprised about forty plenary talks. The topics covered ranged from applied physics to cosmology (determination of cosmological parameters, dark matter detection), astrophysics (galaxy evolution), collider physics (anomaly detection, new-physics searches, Monte Carlo generators), condensed matter, quantum information and statistical physics (quantum noise, quantum machine learning), to the mathematical foundations of artificial intelligence. The recordings are available on the GGI YouTube channel.

Scientific output

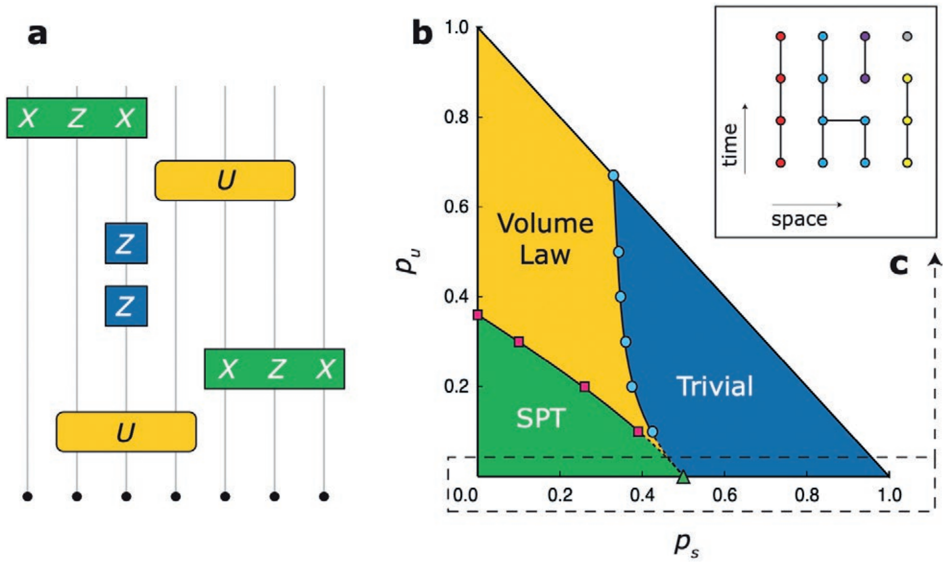
The main output of the workshop can be summarized by highlighting the main topics discussed for each of the three macro areas.

High-Energy Physics

Machine learning has been successfully applied to high-energy physics for a long time. This is particularly true for collider experiments characterized by the gathering of huge datasets, which naturally lend themselves to big-data analysis techniques. To get an idea of the vast landscape of machine-learning applications in particle physics, all you need to do is look at the hundreds of references in the "Living Review of Machine Learning for Particle Physics" (https://iml-wg.github.io/ HEPML-LivingReview/). In this context, it is worth mentioning the discussion devoted to methods of statistical analysis and inference during the workshop, such as the use of the neural network to determine the parton distribution functions, or the use of Monte Carlo integration to achieve a fast and reliable comparison between theory and data in collider experiments.

Astrophysics and cosmology

The presence of big datasets is also a feature of modern astrophysics and cosmology, which have witnessed a rapidly growing set of machine-learning applications. In this context, time was dedicated during the workshop to activities such as the use of classification algorithms aimed at source detection in astrophysics, applications of recurrent neural networks for the search for signals in pulsar timing arrays, and the use of machine learning tools for the analysis of large-scale-structure data.



Phase diagram of random quantum circuits (Lavasani, Alavirad and Barkeshli, *Nature Phys*. 17 (2021) 342-347).

Condensed matter and statistical physics

Condensed matter and statistical physics takes advantage of the effectiveness of machine-learning in simulating complex systems. A considerable amount of time was dedicated to this field for discussions during the workshop. In particular, the new and very rapidly growing field of quantum machine learning is emerging from the interplay of quantum information theory and machine-learning techniques. Discussions on how it can enhance classical algorithms, running them on the already available and much more powerful quantum computers, was one of the main topics during the workshop. Other talks focused on the use of machine learning for classifying phases of physical systems (see figure). Finally, a set of theoretical studies on the use of spectral methods for enhancing neural-network learning efficiency was presented.