Chapter 1

Author's Note

"The party is over." Chen-Ning Yang, one of the most significant physicists, expressed his opposition to funding the Circular Electron Positron Collider and Super Proton-Proton Collider (CEPC-SppC) project, which is briefly presented in Fig 1.1. He gives explicit reasons why he does not embrace the ambitious programme. It is the worst of times. Pioneers, in the 20th century, built a more-or-less complete model of all the detected particles and forces in our universe. They were so spectacularly successful that it is tough for us to improve the model, which is called the Standard Model (SM) of particle physics nowadays. It is the epoch of incredulity. Modern physicists build dozens of models, hold hundreds of conferences, write thousands of papers (and of course cite each other). Unluckily, none of their confident predictions has been witnessed. It is the age of foolishness. Several far-reaching significance research projects have been terminated or delayed. What is even more tragic is that both the funds and the international cooperation for HEP research are decreasing year by year, due to the volatility of international relations and the turbulent world economy. These facts almost frighten me, these reasons almost convinced me, until I witnessed High Energy and Nuclear Physics (HENP) meets Deep Learning (DL), which is a class of Artificial Intelligence (AI) technologies, as slightly introduced in Fig 1.2. AI and HENP are not strangers. Experimental particle physicists started working with massive datasets since the 1990s. They employed conventional programming, which means researchers

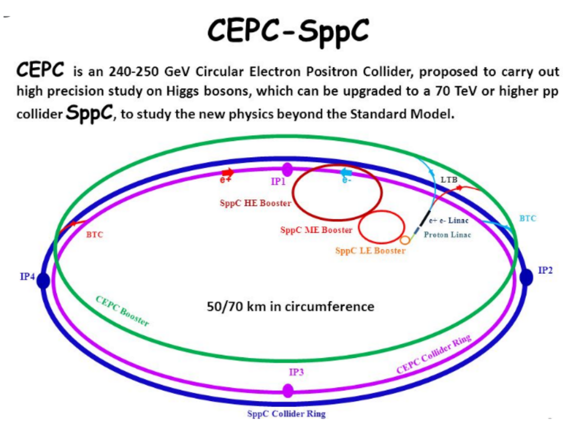

FIGURE 1.1: The overall CEPC-SppC schematic Diagram. Image Credit: Qingjin Xu

need to tell the computer how to perform the tasks step by step, to reconstruct high-level physics features and identify various particles. Soon after, about the 2000s, simply neural networks (NN), a type of beautiful biologically-inspired algorithms, have been used to classify particle interactions. The NN algorithms can automatically perform learning from observational data and then figure out their solutions to the problem at hand. Is it too good to be true? De facto, until 2006, neither AI nor HENP community has a solution to train the NN algorithms to surpass more traditional approaches, for instance, decision tree algorithms. What changed since 2006 is the discovery and application of a series of techniques, which are broadly known as deep learning nowadays, for learning in deep neural networks. This revolution starts from the AI community. Meanwhile, it has significantly changed how scientific data analysis is performed and has brought deep learning, the light at the end of the tunnel, to the forefront of HENP research [1]. It is my sincere belief that when the history of our time is written, not too far from now, it will be regarded as the golden age of physics. We are fortunate to live in such an exciting time period and to play our part in applying AI revolution results in physics discoveries. The aim of this book or this project is to share and gain knowledge in applying deep learning in neutrino physics researches. We present our experience with DL-related algorithms training that combines neutrino interactions simulation, real-time decision making, particle reconstruction/identification/calibration, and theoretical calculation based on the off-the-shelf frameworks, services, and tools. Some of these end-to-end exploratory (data) analyses employed observational data from two open HEP data sets[2]. When writing this book, we have always followed the following principles.

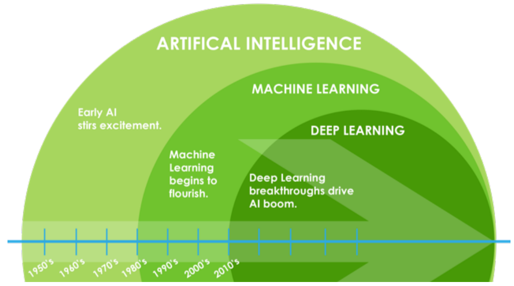

FIGURE 1.2: Deep learning is a subset of machine learning technologies, which have been employed into training deep neural network algorithms. Nowadays, deep learning is bringing new levels of performance to the analysis of growing datasets in high energy and nuclear physics[1]. Image Credit: Tuples Edu

1.1 One for All, All for One

https://github.com/A-I-AI/Open-AIHENP-Community

[2]CERN Open Data has been employed for Hadron physics related analyses, and Deep Learn Physics data has been used for neutrino physics analyses.There are barriers to open HENP data sets, but doing so has already contributed to scientific progress. We take our hats off to heroes who are from these two groups. I propose honoring them, who are the first to open HEP data sets, Data-Man/Data-Woman.

While in quarantine from the COVID-19 pandemic, I learned an intriguing story about Galileo Galilei from Michael Nilson's Ted talk. Galileo turned his telescope up at the sky towards Saturn and found the rings of Saturn for the first time in history. Instead of spreading the epoch-making discovery to the astronomical community, he wrote down a description into an anagram and sent it to several of his astronomer rivals. So, if those astronomers find the same discovery later, he still can get the credit by unveiling that anagram. At the same time, he did not share any knowledge with his community. Such was the culture of science at that time. That culture hindered the spread of scientific knowledge and, therefore, the development of science. Fortunately for us, a revolution in scientific knowledge sharing started from the 17th century, consequently it became expected that when a scientist made a discovery, he/she will publish the result in a journal directly, not email an anagram instead. Nevertheless, sadly, the revolution has not yet succeeded. Nevertheless, sadly, the revolution has not yet succeeded. Hitherto, very few we can see transparency HENP projects, very often we can see various types of pride and prejudices in HENP communities. It is routine that scientists hoard their data sets, hide their codes, even conceal the descriptions of the problems that they think are most exciting. In other words, scientists in our time are still trying to hoard everything which could be useful, potentially, to their rivals. History taught us that it is not the right way to chase our dream to deep understanding physics, but it is the best way to get a permanent job. We consider Open Science effort seriously to make our research as transparent as possible. This website provides a variety of supplementary material, including corresponding codes, employed datasets, application ideas, exercises, and other resources that share our experience and exciting findings. We also hope this website can be a platform for Open HENP/reproducible research fans. We respectfully require your comments, suggestions, and feedback for this book/project. Let us work together to reduce discrimination and open data in the HENP community.

1.2 Two-way Street

HENP and DNNs Open science is also conducive to the promotion of interdisciplinary researches. We not only understand DNNs can be beneficial for a broad scope of tasks in HENP but also aware that the AI community can benefit from solving these tasks. Geoffrey Hinton, the Google AI Shifu, said in an interview that current computer vision systems are prone to adversarial errors. For instance, there is a Po's picture. If we change a few pixels slightly, he still looks exactly like a panda, but the trained DNN model may suddenly say this is Mr. Ping. The way we change the pixels is cleverly designed to fool the model into thinking it is another animal. But the point is, Po still looks like a panda to we human being. Part of the problem, as Hinton pointed out, is that the DNN model does not try to reconstruct the picture from the high-level representations. DNNs only try to do discriminative learning, where the trained model learns layers of feature detectors, and the whole objective is to change the weights. Recently, the AI community has started to talk about introducing a reconstruction on the observational data, and then it may help the trained model be more resistant to adversarial attacks. HENP communities have been developing dedicated solutions for processing massive experiment data sets over decades, whose core function is doing reconstruction. By cooperating with the common challenges, such as the reconstruction, the two fields can further improve in solving such problems. From the HENP side, our knowledge of the underlying physics laws and the detected or simulated data provide us the clean input datasets and organized environment to study the DNN architectures, therefore help both communities to understand better how DL operates, and potentially to design more powerful network architectures. We hope to encourage cooperation between AI and HENP communities by making our effort available in the public domain. We wish to contribute to both sides of this two-way street.

1.3 Three Approaches

Principle Oriented Getting started in deep learning, generally speaking, means install TensorFlow or PyTorch, download codes from others[3] [4], and finally, start training your first DNN model. It is not a bad way to walk into the AI world. Many of our colleagues did this due to it has an immediate problem-solving payoff. On the other hand, a deep understanding of the underlying mathematical theories is still necessary to develop efficient neural network architecture for the task considered. We focus on all the necessary nuts and bolts of DNNs: how they work, and how they can be used to solve some specified problems.

Application Oriented We learn the core principles behind deep neural networks by working on a series of problems, the problem of training a Not so simple neural network to classify various neutrino interactions. We will introduce the training phase step by step in python. Once you have finished the examples, you will be able to employ more feature-complete neural network libraries in PyTorch or TensorFlow intended for use in production.

[3] Your First Deep Learning Project in Python with Keras Step-By-Step
[4] Inspirational Applications of Deep Learning

Always To Be Continued Neutrino physics and DL are all motivated by challenges. They also share the same ambition: build mathematical models who can best fit the input observational data sets and make principled predictions of similar outcomes. It is easiest to understand both fields with some historical context. Rather than providing a detailed history, we will go through the key historical issues which troubled our pioneers, and we will see how the pioneers conquer the issues.