Jet Tagging Using Deep Learning

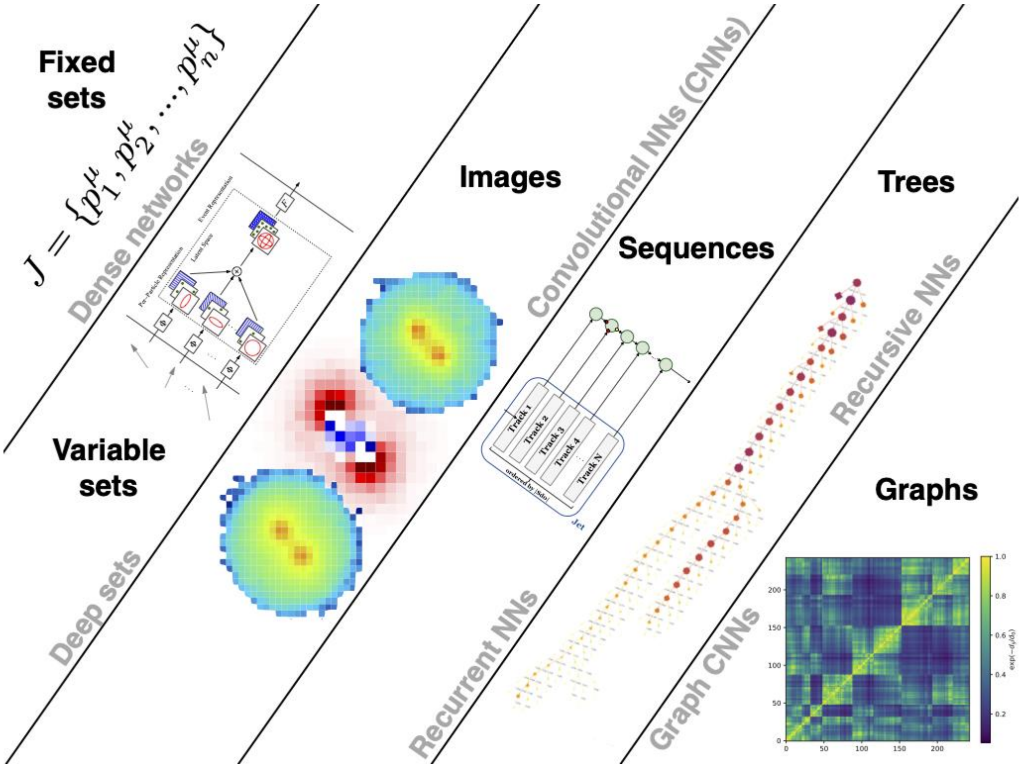


Fig. 1 Figure reference: Jet Substructure at the Large Hadron Collider

Deep learning is a subfield of artificial intelligence that uses neural networks to parse data, learn from it, and then make predictions about something in the world. This framework has led to significant advances in computer vision, natural language processing, and reinforcement learning in the last decade.

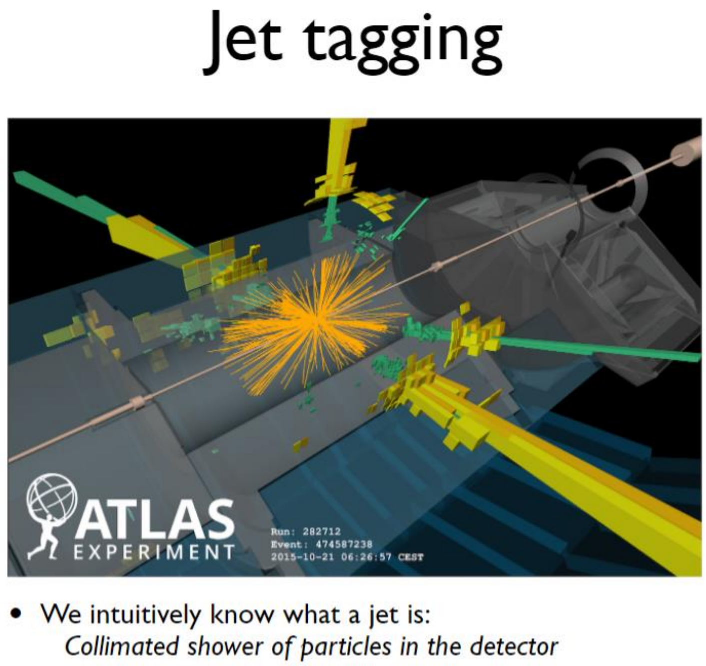
In this Project, I have focused on the following main tasks and how we can use deep learning.

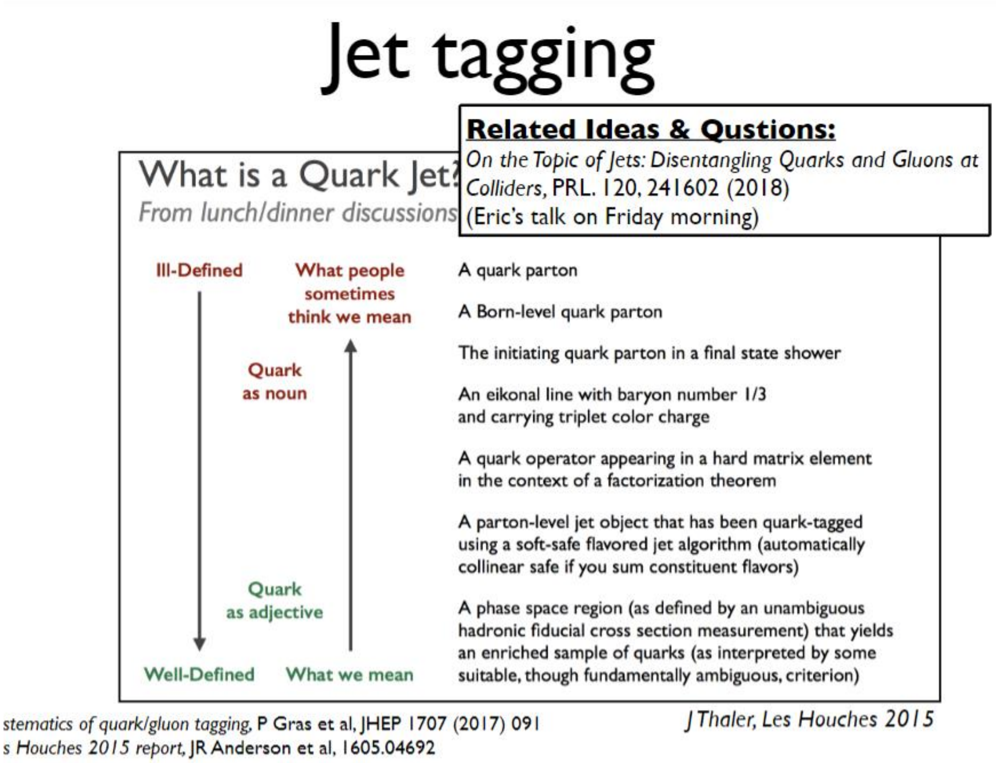
- Jet tagging with convolutional neural networks
- Transformer neural networks for sequential data
- Normalizing flows for physics simulations such as lattice QFT

I have divided the Project into 6 tasks and implemented deep learning into them. Lets see how we have performed every task.

The dataset for the Project i have used from the https://github.com/huggingface/datasets library of hugging face.

Jet tagging is the process of identifying the type of elementary particle that initiates a "jet", i.e., a collimated spray of outgoing particles. It is essentially a classification task that aims to distinguish jets arising from particles of interest, such as the Higgs boson or the top quark, from other less interesting types of jets.(Refer to - jet-universe/particle_transformer)





There are various types of tagging:

1. **Flavour Tagging**
2. **QG Tagging**
3. **Heavy Resonance Tagging**
4. **Jet Tagging**

And in this Project, we have specifically focused on the Jet Tagging)Reference- https://indico.cern.ch/event/745718/contributions/3205082/attachments/1753205/2841505/JetTagging_Overview.pdf)

Introduction:

To download the top Quark tagging from the Hugging face Hub(https://colab.research.google.com/corgiredirector?site=https%3A%2F%2Fhuggingface.co%2Fdatasets%2Fdl4phys%2Ftop_tagging) i have used the *load_dataset ()* function.

Jet Tagging with Neural Networks

Overview

This repository serves as a resource for learning about jet tagging using deep neural networks in the context of high-energy physics, particularly proton-proton collisions. The project includes code, and datasets aimed at providing a comprehensive understanding of the process of training and evaluating neural networks for jet classification tasks.

Machine learning, particularly deep learning, has sparked a revolution in the analysis of large-scale data samples within the field of particle physics, significantly enhancing the potential for discovering new fundamental laws of nature (Radovic et al., 2018). In particular, deep learning techniques have revolutionized the approach to jet tagging, a crucial classification task conducted at high-energy particle colliders like the CERN Large Hadron Collider (LHC), resulting in a remarkable enhancement in performance (Kogler et al., 2019; Larkoski et al., 2020).

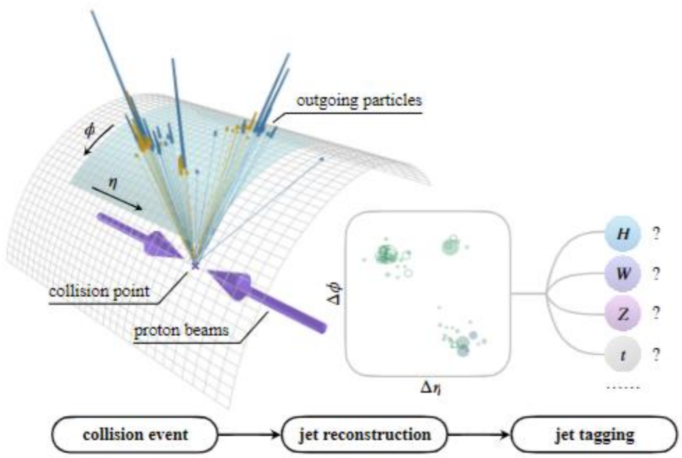


Figure 1. Illustration of jet tagging at the CERN LHC. High-energy proton-proton collisions at the LHC can produce new unstable particles that decay and yield a collimated spray of outgoing particles. These outgoing particles are measured by complex particle detector systems, and jets can be built ("reconstructed") from these measured particles. The goal of jet tagging is to classify the jets and identify those arising from particles of high interest, e.g., the Higgs boson, the W or Z boson, or the top quark.

At the CERN Large Hadron Collider (LHC), high-energy proton beams collide at an astounding frequency of 40 million times per second (40 MHz), producing sprays of outgoing particles. To analyze the resulting collision data, complex detector systems like ATLAS and CMS are employed, consisting of over 100 million individual sensors. These detectors measure various properties of the outgoing particles, allowing researchers to reconstruct collision events and identify novel physics processes, **such as the discovery of the Higgs boson.**

A crucial step in the analysis process is jet tagging, which involves identifying the type of particle that initiates a jet. Jets are collimated sprays of outgoing particles, and tagging them correctly is essential for distinguishing particles of interest, like the Higgs boson or the top quark, from other types of jets. However, jet tagging is challenging due to the radiation and subsequent particle production within jets, leading to a cascade of particles and smearing of the initial particle's characteristics.

Traditional jet tagging approaches rely on hand-crafted features based on the principles of quantum chromodynamics (QCD). However, the emergence of deep learning has introduced new methods that represent jets as unordered sets of outgoing particles. ParticleNet, for instance, adapts the Dynamic Graph CNN architecture and has shown substantial performance improvements on jet tagging benchmarks. Despite subsequent model proposals, no significant performance gains have been achieved, largely due to the lack of large public datasets.

Contents:

Gradient Descent Optimization:

I have implemented the fundamentals of gradient descent optimization for optimizing functions. The main objective of this Task is to understand the optimization process and its relevance to training neural networks.

Neural Network Deep Dive:

Delve into the intricate workings of neural networks with a deep dive into their architecture and optimization techniques. The motive of this task is to gain insights into implementing neural networks from scratch and defining learners in fastai tailored for high-energy physics tasks.

Jet Images and Transfer Learning with CNNs:

Here i have implemented the conversion of jets into images and their classification using convolutional neural networks (CNNs) to learn about transfer learning, its advantages compared to training from scratch, and the main steps needed to fine-tune CNNs for jet classification tasks.

Convolutional Neural Networks (CNNs):

Here i have trained the CNNs specifically designed for jet tagging to understand advanced CNN concepts such as 1-cycle training policy, batch normalization, and debugging unstable training runs with activation statistics.

Generating hep-ph Titles with Transformers:

Jet tagging is a critical yet challenging classification task in particle physics. While deep learning has transformed jet tagging and significantly improved performance, the lack of a large-scale public dataset impedes further enhancement. In this work, we present JetClass, a new comprehensive dataset for jet tagging. The JetClass dataset consists of 100 M jets, about two orders of magnitude larger than existing public datasets. A total of 10 types of jets are simulated, including several types unexplored for tagging so far. Based on the large dataset, we propose a new Transformer-based architecture for jet tagging, called Particle Transformer (ParT). By incorporating pairwise particle interactions in the attention mechanism, ParT achieves higher tagging performance than a plain Transformer and surpasses the previous state-of-the-art, ParticleNet, by a large margin. The pre-trained ParT models, once fine-tuned, also substantially enhance the performance on two widely adopted jet tagging benchmarks

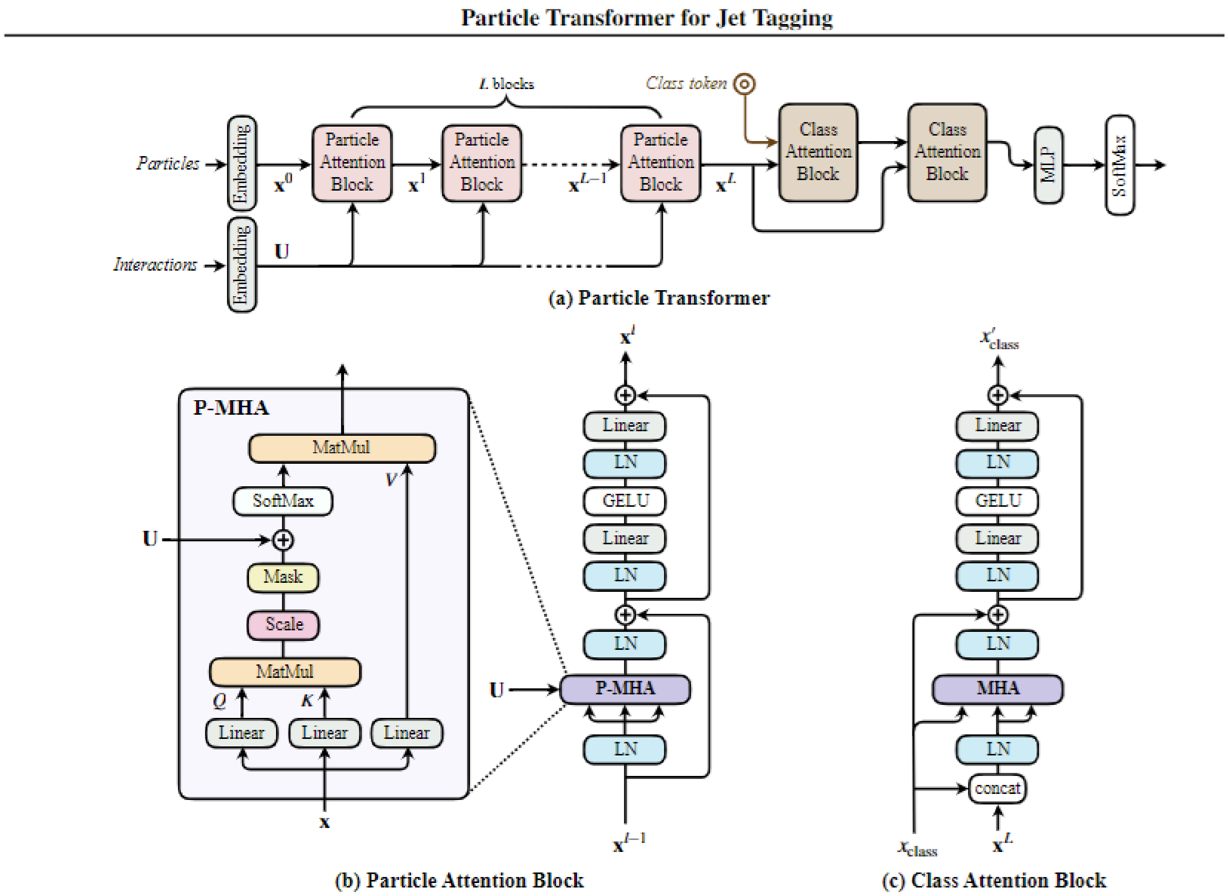


Figure 3. The architecture of (a) Particle Transformer (b) Particle Attention Block (c) Class Attention Block.

References:

Particle physics

- The Particle Data Group has a wonderfully concise review on machine learning. You can find it under *Mathematical Tools > Machine Learning*.
- *Jet Substructure at the Large Hadron Collider* by A. Larkowski et al (2017). Although ancient by deep learning standards (most papers are outdated the moment they land on the arXiv 😳), this review covers all the concepts we'll need when looking at jets and how to tag them with neural networks.

- *HEPML-LivingReview*. A remarkable project that catalogues loads of papers about machine learning and particles physics in a useful set of categories.

- *Physics Meets ML*. A regular online seminar series that brings together researchers from the machine learning and physics communities.

- *Machine Learning and the Physical Sciences*. A recent workshop at the NeurIPS conference that covers the whole gamut of machine learning and physics (not just particle physics).

- *Graph Neural Networks in Particle Physics* by J. Shlomi et al (2020). A concise summary of applying graph networks to experimental particle physics - mostly useful if we have time to cover these exciting architectures.

Deep learning

- Deep Learning for Coders with Fastai and PyTorch by Jeremy Howard and Sylvain Gugger. A highly accessible and practical book that will serve as a guide for these lectures.

- Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow by Aurélien Géron. An excellent book that covers both machine learning and deep learning.