Project Proposal

Project Name

Exploring Underlying Symmetries in Particle Physics with Equivariant Neural Networks

Contact Information

Exploring Underlying Symmetries in Particle Physics with Equivariant Neural Networks
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Synopsis

The proposed project will apply equivariant neural networks to investigate underlying symmetries in particle physics, with a focus on identifying and reconstructing single particles, jets, and event topologies in collision events at the Large Hadron Collider (LHC). By capitalizing on the inherent symmetries of these phenomena, equivariant neural networks hold the potential to enhance the efficiency and accuracy of particle identification and reconstruction.

Benefits to Community

This research will contribute to the End-to-End Deep Learning (E2E) project within the CMS experiment, advancing the current state of deep learning approaches for particle identification and reconstruction. Moreover, the project's results could be applicable to other high-energy physics experiments and may have broader implications for the scientific community. By enhancing our comprehension of symmetries and asymmetries in particle physics data, we can gain insights into the fundamental properties of the universe and lay the groundwork for future discoveries.

Deliverables

1. Investigation of suitable datasets and exploration of different equivariant neural network models for particle identification and reconstruction (Required, Weeks 1-2)
2. Development and training of equivariant neural network models using collision data (Required, Weeks 3-6)
3. Benchmarking of the equivariant neural network against vision transformers and convolution-based models (Required, Weeks 7-9)
4. Extension of the equivariant neural network to exploit symmetries for finding and understanding symmetries and asymmetries in the data (Required, Weeks 10-14)
5. Documentation of the developed models, including methodology, results, and potential applications (Required, Weeks 15-16)

Related Work

In recent years, machine learning techniques have increasingly been applied to the analysis of data from particle detectors at the LHC. One notable example is the work of Andrews et al. (2020), who developed end-to-end image-based classifiers that directly leverage low-level simulated detector data to discriminate signal and background processes in proton-proton collision events at the LHC. Their approach involves constructing images from maps of the actual recorded particle showers or energy deposits in the detector and using these images as inputs to a convolutional neural network (CNN). The authors demonstrate that their end-to-end classification method can learn from the angular distribution of the photons recorded as electromagnetic showers, their intrinsic shapes, and the energy of their constituent hits, even when the underlying particles are not fully resolved. Additionally, deep learning models such as ResNet-15 have shown great promise in improving our understanding of jet image substructure at the LHC (Andrews et al.). These models can automatically learn and extract relevant features from jet images, allowing for more accurate discrimination between quark- and gluon-initiated jets. By leveraging the power of deep learning, researchers can achieve competitive performance compared to existing state-of-the-art jet classifiers.

Project Timeline

- May 29: Coding officially begins
- June 11: Complete investigation of suitable equivariant neural network models

- June 25: Complete development and training of equivariant neural network models
- July 9: Complete benchmarking against vision transformers and convolution-based models
- August 4: Complete extension of equivariant neural network for exploiting symmetries in data
- August 18: Complete documentation of developed models, methodology, results, and potential applications

Biographical Information

I am a computer science graduate student at New York University with a strong interest in machine learning and artificial intelligence.

I hold a Bachelor's degree in Mathematics from The Chinese University of Hong Kong. I have also gained experience as a software engineering intern at HireBeat, where I developed and optimized the company's AI-based resume scanning system using advanced NLP techniques and deep learning models.

I am proficient in programming languages such as Python, Java, and C++, and have experience with database systems like MySQL, PostgreSQL, and MongoDB. Additionally, I am familiar with frameworks and libraries like PyTorch, TensorFlow, and Scikit-learn, as well as development tools like Git, Linux, Elasticsearch, Docker, and AWS.

My research experience in machine learning includes work on equivariant neural networks. I have contributed research ideas by reproducing top conference papers from CVPR and ICML in PyTorch. I researched and experimented with an equivariant neural network architecture for grayscale image denoising using partial differential operators and wavelet transforms, improving the peak signal-to-noise ratio (PSNR) to 32.94 compared to 32.37 through the benchmark algorithm (BM3D) under noise level $\sigma = 15$ on Set12.

I have presented at student seminars on topics such as algebraic topology and probability theory. In September 2019, I gave a 60-minute presentation on the applications of winding numbers at CUHK. In March 2019, I presented a 90-minute combinatorial proof for Wigner's semicircle law at ETH Zurich.