# IRIS-HEP Fellowship Proposal: Particle Graph Autoencoders for Real-Time Jet Anomaly Detection

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Area: Innovative Algorithms

## 1 Proposal

The CERN Large Hadron Collider (LHC) is the highest energy collider in the world. One of the main objectives behind the development of the LHC is to search for new physics at the subatomic level without the bias of hypothesized theoretical expectations that may not reflect the actual essence of new physics in nature. For this reason, there is large interest in searching for new physics by applying more generic anomaly detection techniques. One example in particular is using autoencoders. Autoencoders are composed of an encoder and decoder, that are each a neural network trained to accurately map a set of input data (representing known physics) down to a compressed latent representation (in order to encode the most significant details found within the data set) and then reverse the encodings to their original form. By quantifying how inaccurate this reconstruction is, we can determine whether potential anomalous candidates for new physics exist within the data.

Prior work by the Duarte group [1] suggests that graph neural network (GNN) based autoencoders can be effective mechanisms for reconstructing particle jets and isolating anomalous signals from background data. Rather than treating particle jets as ordered sequences or images, particle graph autoencoders (PGAEs) embed particle jet showers as a graph and exploit particle-particle relationships to efficiently encode and reconstruct particle-level information within jets.

Extending this work, my objective is to investigate different types of graph-based autoencoders as well as randomized neural network architectures, including variational autoencoders [2] or normalizing flows [3]. I will work on applying and analyzing new data sets like the public DarkMachines data set [4], or more complex CMS simulation to these new architectures in order to search for new physics.

In addition, one important application of autoencoders would be through their use in the level-1 trigger [5] (a real-time data filter system that rapidly decides which collision events to record), which requires smaller models because of the latency budget and computing resource constraints. I will investigate converting these particle graph autoencoders using `hls4ml` [6] to FPGA firmware. This will build on previous work within IRIS-HEP integrating GNNs into `hls4ml` [7–9]. One aspect of this work would be using FPGAs to test algorithms and create more optimized models for that task through compression and quantization.

This project will be conducted under the local supervision and guidance of Professor Javier Duarte (UC San Diego) with additional support from Maurizio Pierini (CERN) and IRIS-HEP members working on GNNs for event reconstruction, jet physics, and trigger applications. This work will also be done in collaboration with the Fast Machine Learning Lab [10].

## 2 Timeline

The timeline I propose is a total of three months during the summer (June 14, 2021 – September 3, 2021), during which I will work full time on this research.

- **Week 1–2**: Develop ML framework for training autoencoders and prepare DarkMachines and trigger jet datasets
- **Week 3–4**: Train and evaluate DNN/CNN autoencoders for anomaly detection

- **Week 5–6**: Train and evaluate GNN autoencoders for anomaly detection
- **Week 7–8**: Optimize models for FPGA deployment
- **Week 11–12**: Test models on FPGA development board

# References


[1] G. Kasieczka et al., "The LHC Olympics 2020: A community challenge for anomaly detection in high energy physics", arXiv:2101.08320. Submitted to *Rep. Prog. Phys.*

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[3] S. E. Park et al., "Quasi Anomalous Knowledge: Searching for new physics with embedded knowledge", arXiv:2011.03550.

[4] "Darkmachines", 2021. https://darkmachines.org/.

[5] CMS Collaboration, "The Phase-2 upgrade of the CMS Level-1 trigger", CMS Technical Design Report CERN-LHCC-2020-004. CMS-TDR-021, 4, 2020.

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[7] Y. Iiyama et al., "Distance-weighted graph neural networks on FPGAs for real-time particle reconstruction in high energy physics", *Front. Big Data* **3** (1, 2021) 44, doi:10.3389/fdata.2020.598927, arXiv:2008.03601.

[8] A. Heintz et al., "Accelerated charged particle tracking with graph neural networks on FPGAs", in *3rd Machine Learning and the Physical Sciences Workshop at the 34th Conference on Neural Information Processing Systems*. 12, 2020. arXiv:2012.01563.

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[10] "Fast machine learning lab", 2021. https://fastmachinelearning.org/.