

Intelligent Triggers for Rare Event Detection in Liquid Argon Detectors

Seokju Chung, Columbia University

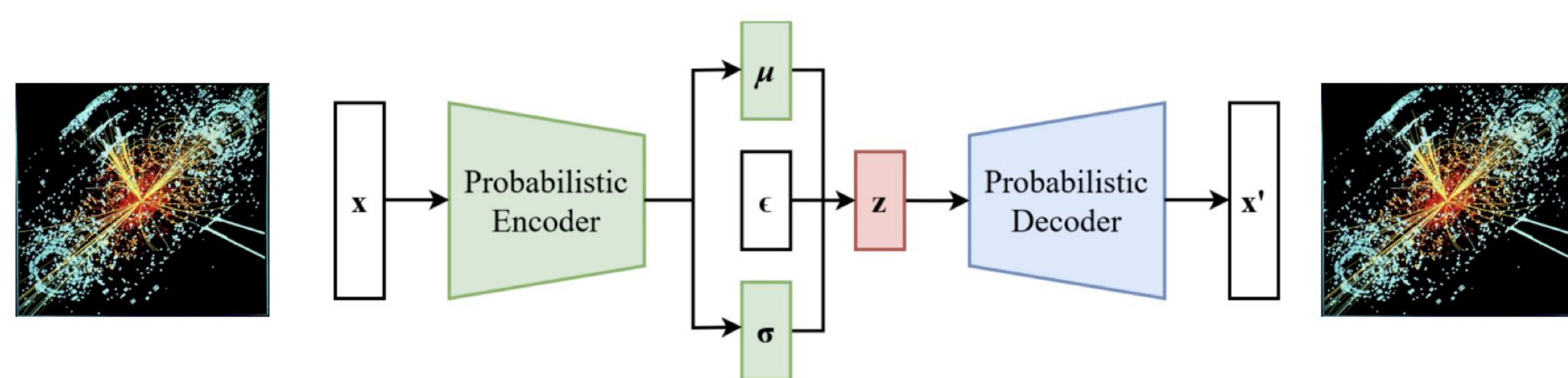
COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK



FERMILAB-POSTER-25-0060-V

Anomaly Detection with Machine Learning

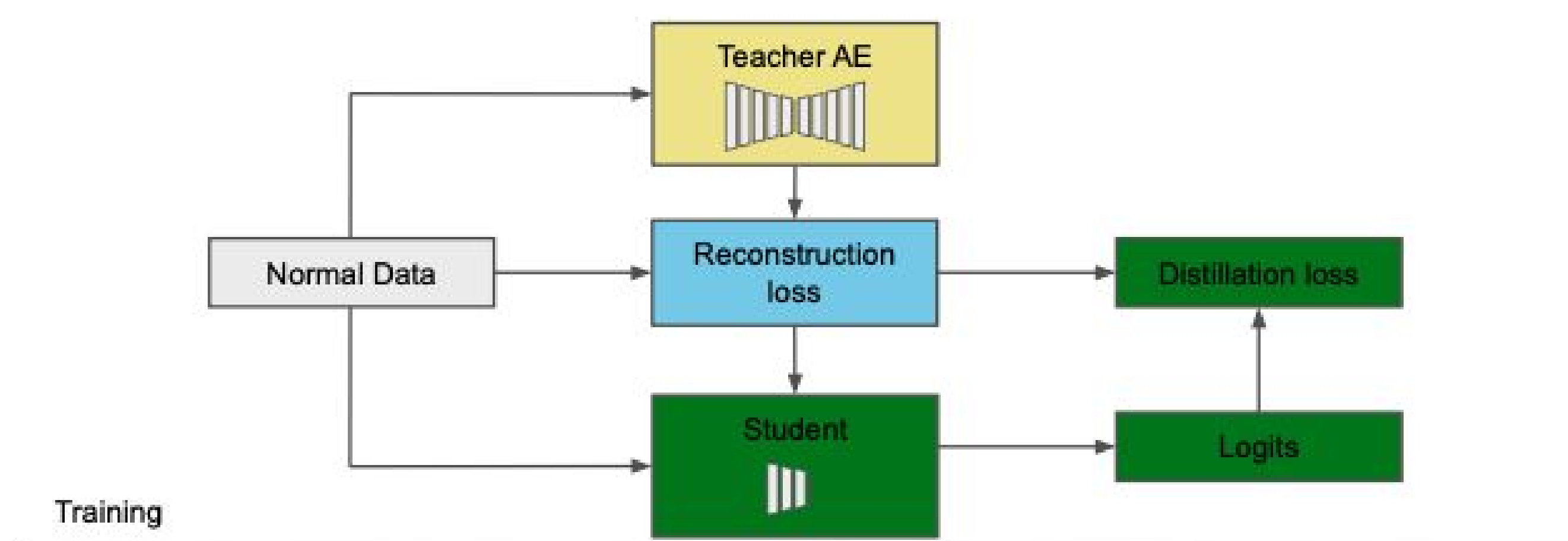
We explore anomaly detection using Convolutional Neural Network (CNN) autoencoders, which flag unusual, rare activity (Anomaly) based on reconstruction loss. This loss, or anomaly score, captures how poorly the model reproduces an input image, with large differences indicating potential anomalies. This approach is model-agnostic and data-driven, allowing us to identify unexpected signals without relying on specific assumptions. This is essential when searching for unknown signatures of new physics.



Schematic of an autoencoder network. The network encodes the input into a simpler latent space and decodes the latent space into an output resembling the input. In this process, the network learns common features of the input dataset.

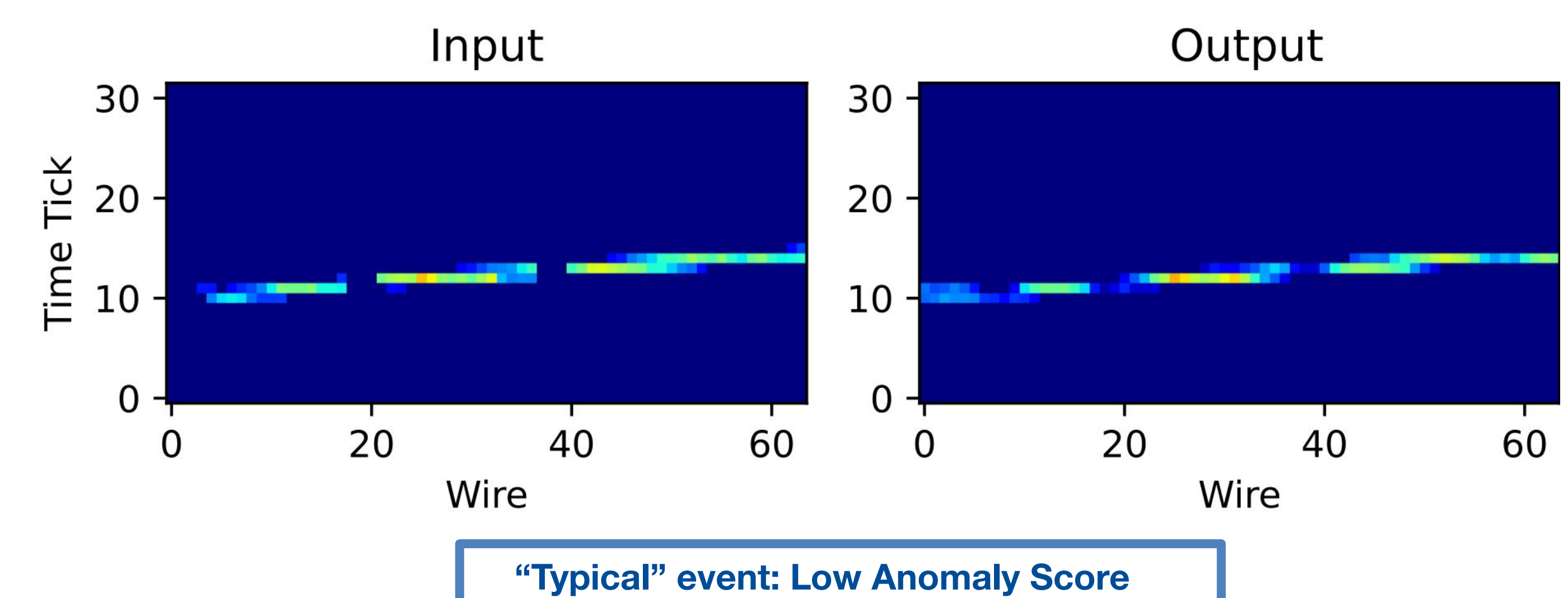
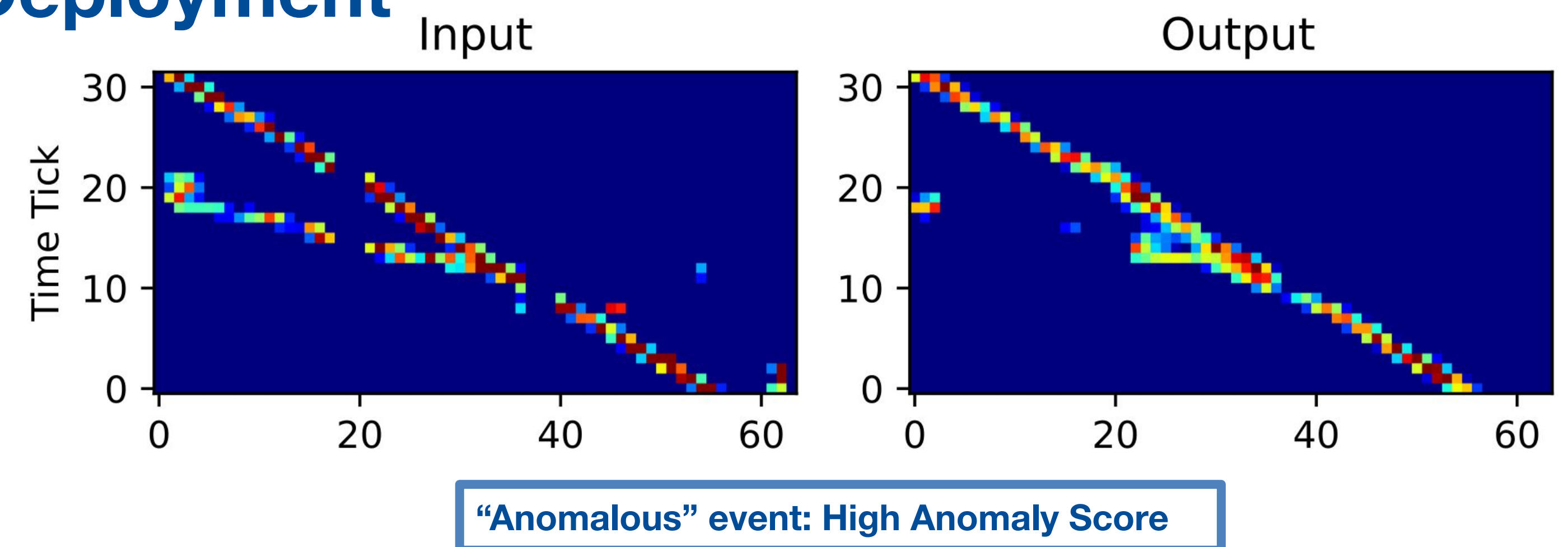
Real-time Triggering on Constrained Systems

The Deep Underground Neutrino Experiment (DUNE) will stream several terabytes of high-resolution data per second, requiring real-time data reduction by over four orders of magnitude while maintaining sensitivity to rare signals like supernova neutrinos. To meet these demands, we deploy lightweight models using techniques such as quantization and Knowledge Distillation. In our Student-Teacher framework, a smaller, quantized Student network is trained to replicate the Teacher's output with minimal resources. This approach enables fast, low-latency inference on constrained hardware such as FPGAs, bringing intelligent triggering closer to real-time operation in large-scale neutrino experiments.

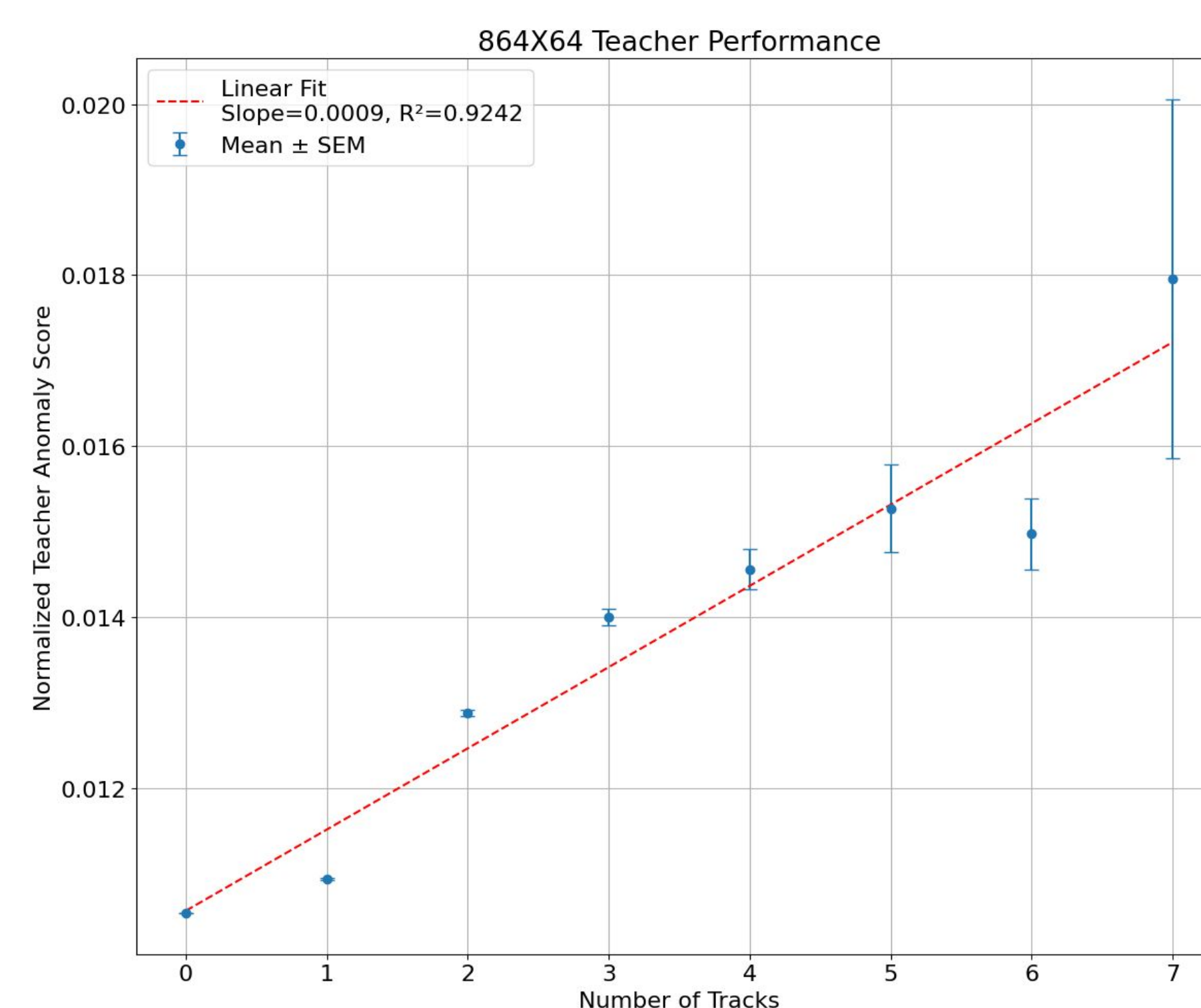


Schematic of the Knowledge Distillation process. The unsupervised Teacher autoencoder is distilled by using its anomaly score as an additional input for the supervised training of the Student. Through this process, a high-performance network with low resource consumption is achieved.

Network Performance and Hardware Deployment



Example of typical and anomalous event. By comparing the input and output of the teacher autoencoder, anomalous features, such as multiple particle tracks can be identified. The teacher is trained with publicly available raw data from the MicroBooNE experiment.



Correlation plot between number of tracks and anomaly score. The plot shows that a greater number of tracks results in a higher anomaly score, indicating that the network is sensitive to certain physical features of the data.

Status report of a small Student network deployment simulation to a FPGA. Currently, the network is over-utilizing the available DSP. Work in process to reduce network size while maintaining performance

Summary					
Name	BRAM_18K	DSP	FF	LUT	URAM
DSP	-	-	-	-	-
Expression	-	-	0	6	-
FIFO	-	-	-	-	-
Instance	0	5329	127014	305312	0
Memory	-	-	-	-	-
Multiplexer	-	-	-	54	-
Register	-	-	19129	-	-
Total	0	5329	146143	305372	0
Available	5376	12288	3456000	1728000	1280
Available SLR	1344	8772	864000	432000	320
Utilization (%)	0	43	4	17	0
Utilization SLR (%)	0	173	16	70	0

Conclusion and Summary

- Future particle experiments will generate huge amount of data, requiring real-time triggering
- Autoencoders enable model-independent anomaly detection
- Knowledge Distillation allows compression of large network onto a hardware-deployable smaller network
- Our model successfully detects anomalies, particularly multi-track events based on LArTPC wire data

This work was supported by the National Science Foundation under Grant No. OAC-2209917. We acknowledge the MicroBooNE Collaboration for making publicly available the data sets [10.5281/zenodo.7262009] employed in this work. These data sets consist of simulated neutrino interactions from the Booster Neutrino Beamline overlaid on top of cosmic data collected with the MicroBooNE detector [2017 JINST 12 P02017].

