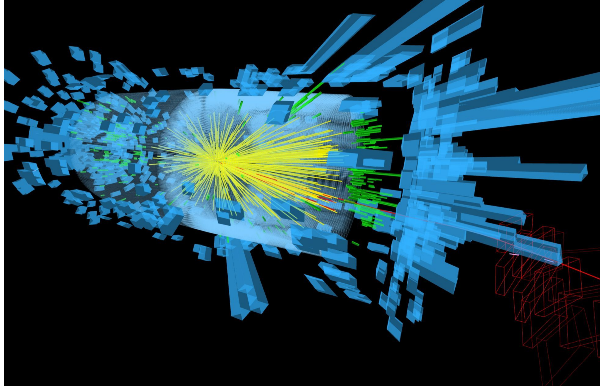

Particle Graph Autoencoders for Real-Time Jet Anomaly Detection

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Mentor: Dr. Javier Duarte

IRIS-HEP Fellowship
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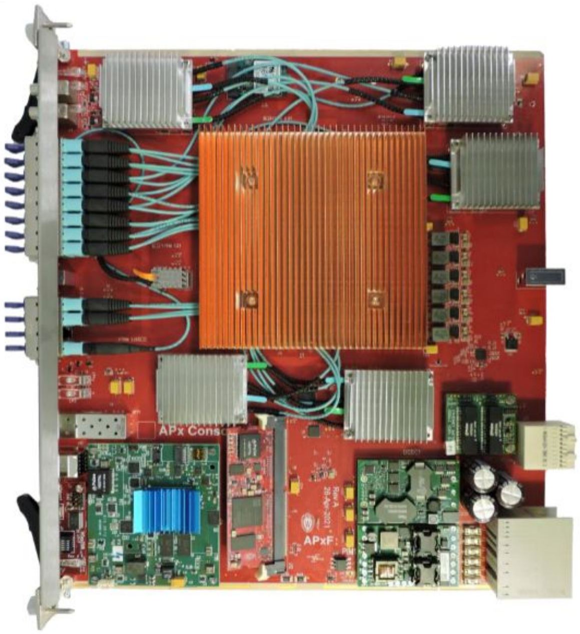
UCSD

L1 Trigger

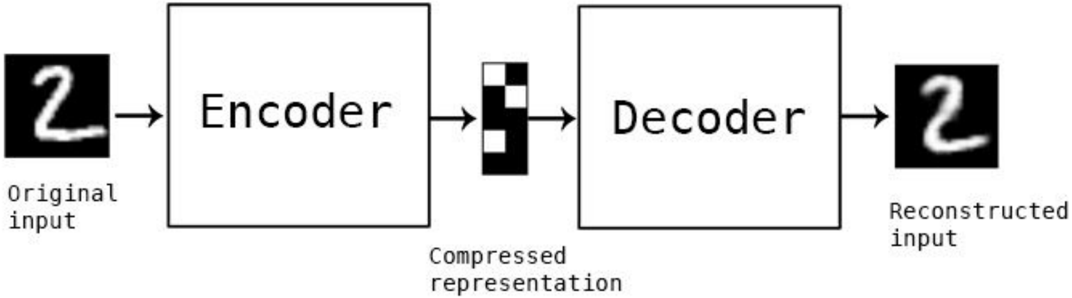
- Role: a real-time data filter system that rapidly decides which collision events to record
- Restrictions
    - Has low latency requirement - 4 microseconds
    - Computing resource constraints

- Test on FPGA to put autoencoders for anomaly detection onto the trigger.



Autoencoders (AEs)

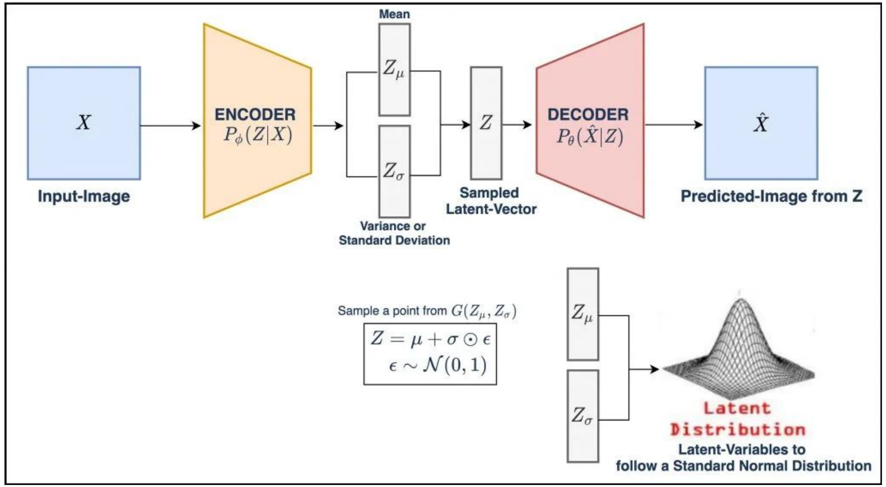
- Neural net architectures designed to form a compressed representation of input data → to learn important attributes of that input data.
- Accurately reconstruct input from that learned encoding.
- For anomaly detection: measuring the difference between the original data point and the reconstruction → reconstruction error (anomaly score).
  - Data points with high reconstruction error are considered anomalies



https://blog.keras.io/building-autoencoders-in-keras.html

Variational Autoencoders (VAEs)

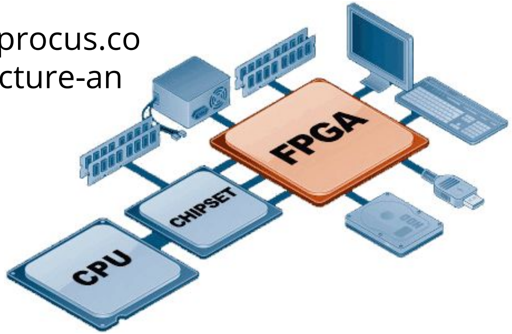
- Make both the encoder and the decoder probabilistic.
  - Represent different latent attributes as a probabilistic distribution
  - Sampled distribution is used to construct the decoder model
- Latent variables (z) outputted from a probability distribution on the input , x; Reconstruction formed probabilistically from z
- KL divergence - how different probability distributions are from each other



https://learnopencv.com/variational-autoencoder-in-tensorflow/

Introduction to Project

https://www.elprocus.com/fpga-architecture-and-applications/



Project Goal:

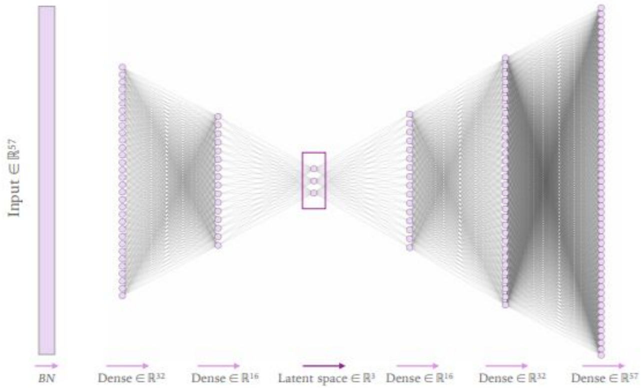
- finding a network is small enough to fit in FPGA (to meet L1 trigger requirements) that is also good at anomaly detection
  - Evaluate variations of autoencoder and variational autoencoder structures on:
    - which structure can be best optimized to minimize the reconstruction loss
    - which structure is best at anomaly detection - based on ROC curves
- Looking at graph neural network as an alternative for anomaly detection

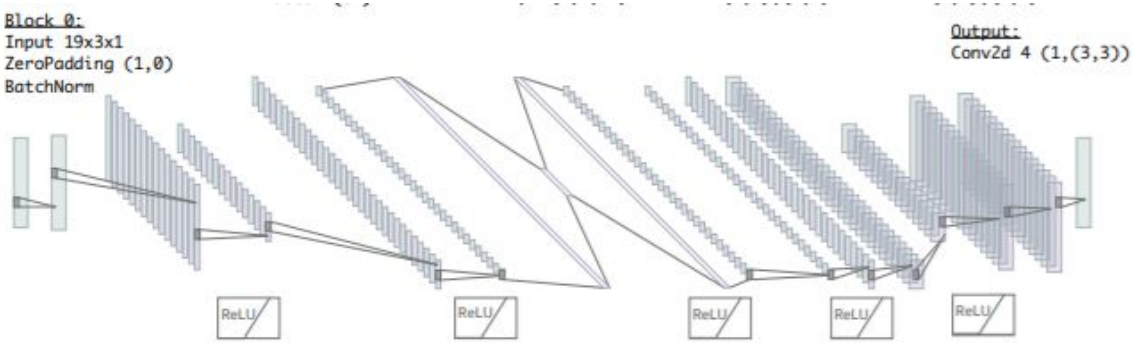
Dataset

- Trained on CMS simulated dataset: QCD background and multiple signal samples (representing new physics)
- Represents 19 objects
  - 1 met, 4 electrons, 4 muons, 10 jets
    - p_T (linear momentum)
    - eta (angle event is at on the plane in reference to the z-axis)
    - phi (angle event is at on the plane in reference to pT and x-axis)

Baseline Models

- Dense ae + vae
  - (one-to-one) - learns using every input in relation to output
- Conv ae + vae
  - learns based on relationship with neighboring data points by applying conv filters
  - Applied on a matrix of nobjects x nfeatures

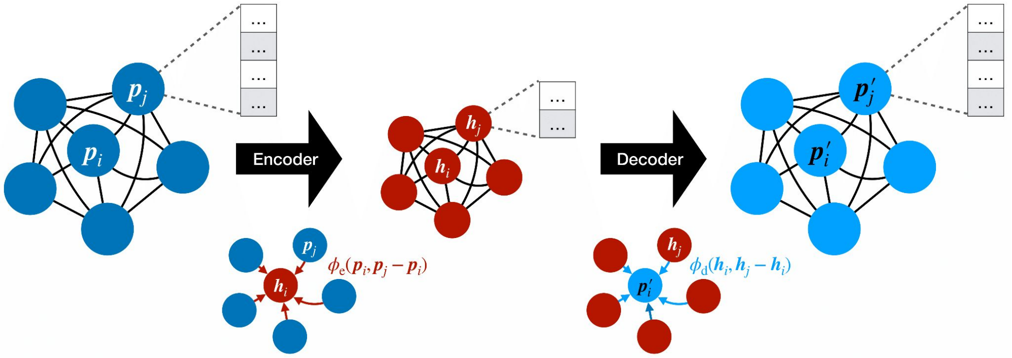




arXiv:1908.05318
[hep-ex]

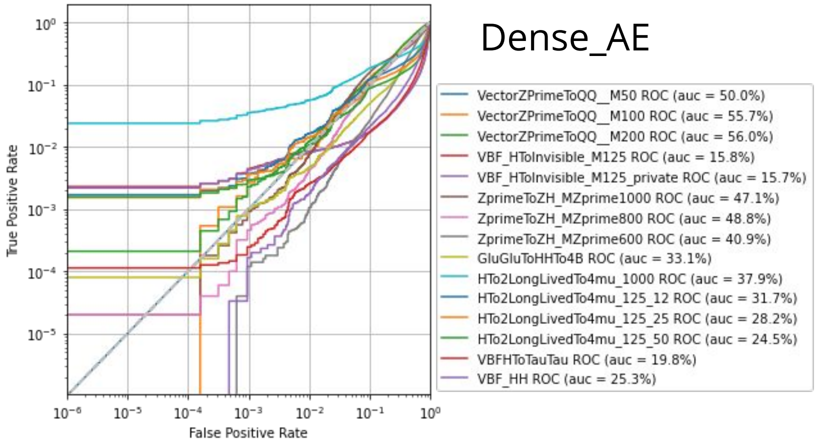
IN Model

- Interaction networks (INs) are designed to analyze the interactions or properties of distinct objects and relations in complex systems
- Key Features of model architecture:
  - Two neural network inferences --
    - Run the NN on each edge (each pair of nodes) and output a vector for each edge
    - On a certain # of features for each node, sends out a certain number of output features
  - Message passing steps --
    gets the summation of latent features for each edge that will be sent to the receiver node

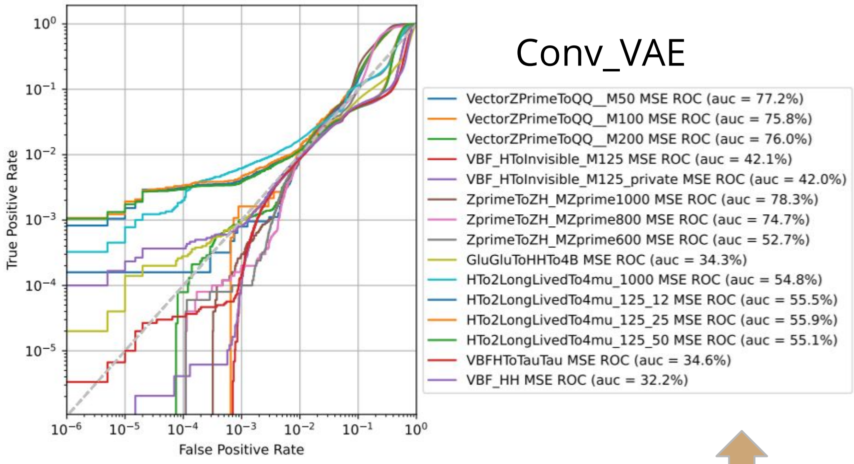


ROC curves

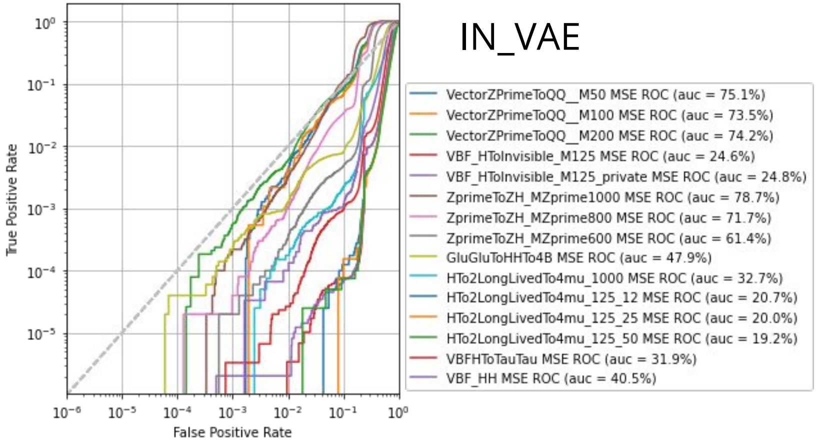
Dense_AE



Conv_VAE



IN_VAE



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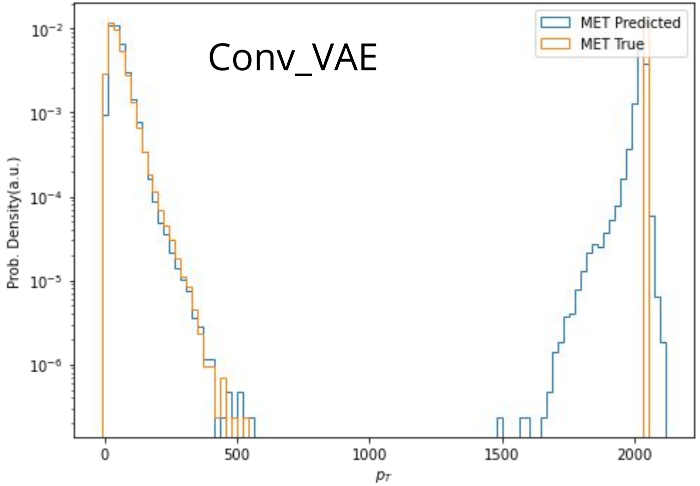
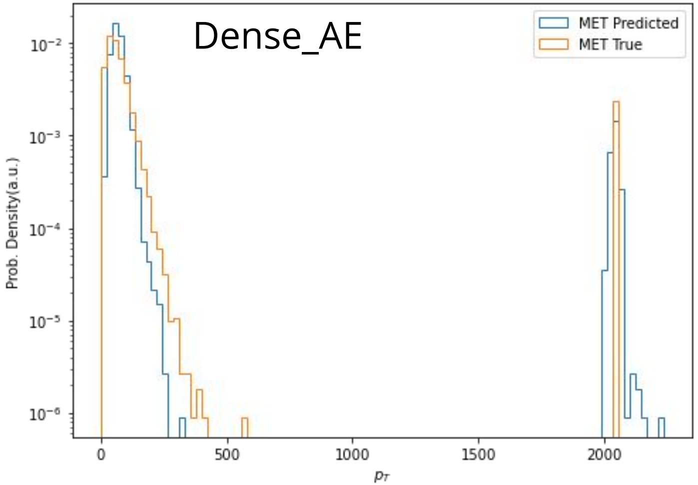
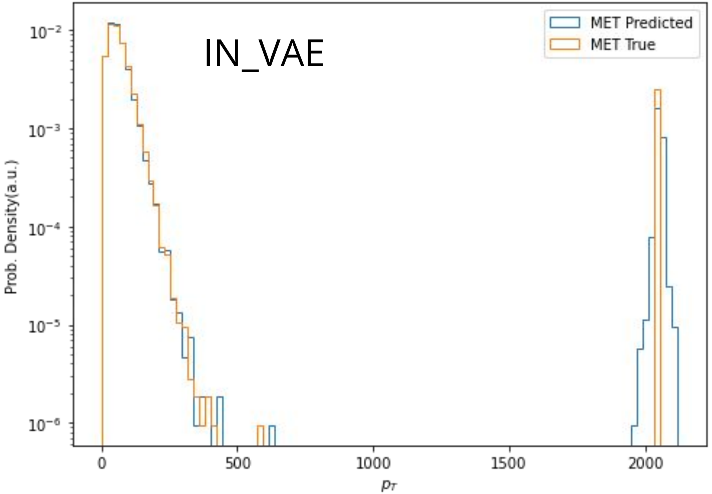
Reconstruction plots for MET







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Summary + Outlook

- Experimented with dense, conv, and in ae and vae architectures
- Results indicate better reconstruction performance by the in_vae, but the conv_vae has better anomaly detection results

Next Steps:

- Validate performance of these models with existing results
- Using hls4ml, convert model and deploy on FPGA

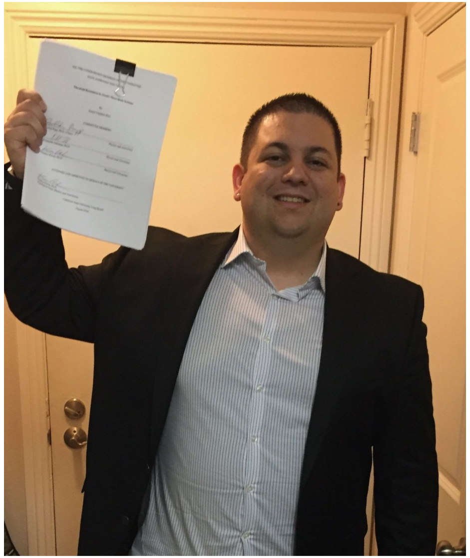
- Common git repository: https://github.com/jmduarte/L1_anomalyDetection

Acknowledgements

Thank you!!!!!!!

Dr. Javier Duarte

Dr. Daniel Diaz



Raghav Kansal

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(IRIS-HEP)