Analyses Report

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Performance report meeting:
2025-2-24

Overview

- Using machine learning (ML) models (mainly deep learning and Gen AI) in:

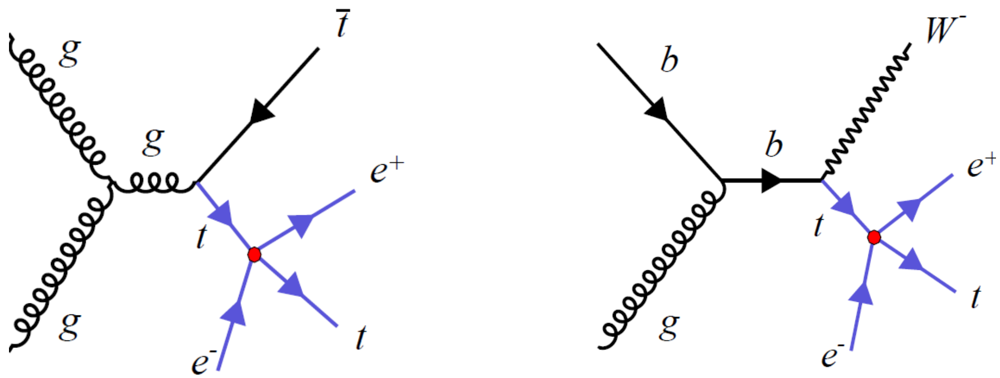
  1. Search for flavor changing (FCNC) in top sector – GitHub code

  2. Jet charge discrimination (up vs anti up quarks) – GitHub code

  3. Anomaly detection and fast simulation - GitHub code

Flavor Changing in Top sector

In this analysis we looking for FC ($t \rightarrow ull$ or $t \rightarrow cll$) in top sector as the heaviest quark which may be an indicator of new flavor physics.

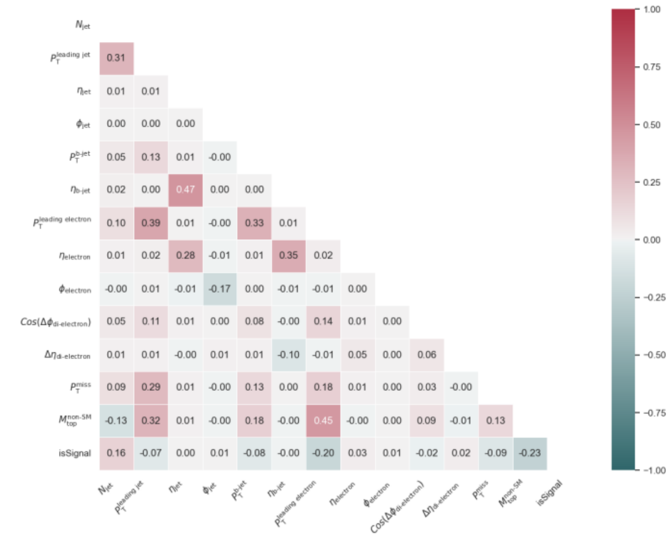


Effective Lagrangian $$\mathcal{L}_{tu\ell\ell} = \frac{1}{\Lambda_\ell^2} \sum_{i,j=L,R} \left[V_{ij}^\ell \left(\bar{\ell}\gamma_\mu P_i \ell\right)\left(\bar{t}\gamma^\mu P_j u\right) + S_{ij}^\ell \left(\bar{\ell} P_i \ell\right)\left(\bar{t} P_j u\right) + T_{ij}^\ell \left(\bar{\ell}\sigma_{\mu\nu} P_i \ell\right)\left(\bar{t}\sigma_{\mu\nu} P_j u\right)\right],$$

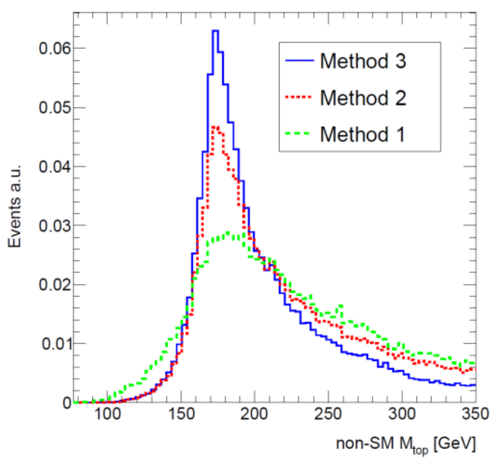
- Starting with **ttbar** and **tW**, targeting **final states** with three leptons (a pair of OS) and a b-tagged jet (one of the tops decays leptonically via w $\rightarrow l\ \nu_l$)
- There are **at least** two jets – other jets might come from showering
- The leading potential backgrounds are tZ, $t\bar{t}W$, $t\bar{t}Z$, $t\bar{t}t\bar{t}$, WZ, ZZ, $t\bar{t}$

Event generation and feature engineering

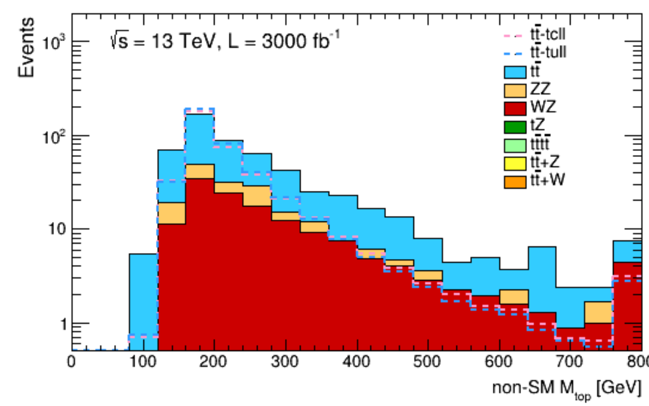
- Signal and background events are generated with MG5+PYTHIA (for PS and HAD) + Delphes (for HLLHC CMS card detection).
- Several variables are defined to be feed into the ML models for training.
- Three algorithms used to **reconstruct non-SM top mass**. The best one uses electrons and jets to get $\min(|m_{llq} - m_{top}|)$.



Feature heatmap



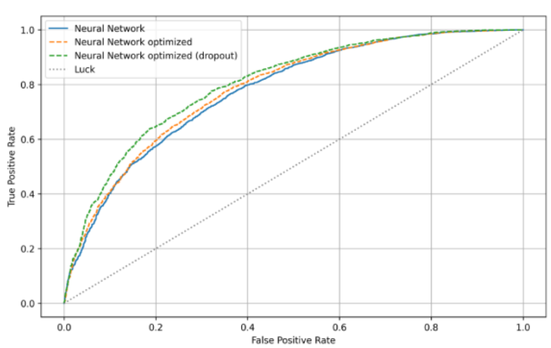
Non-SM top mass reconstruction



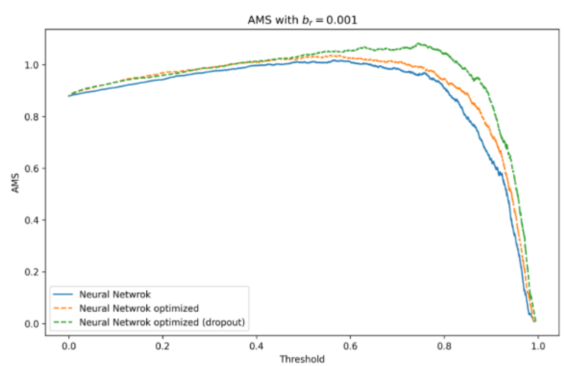
Non-SM top mass distribution

DNN and other ML classifiers

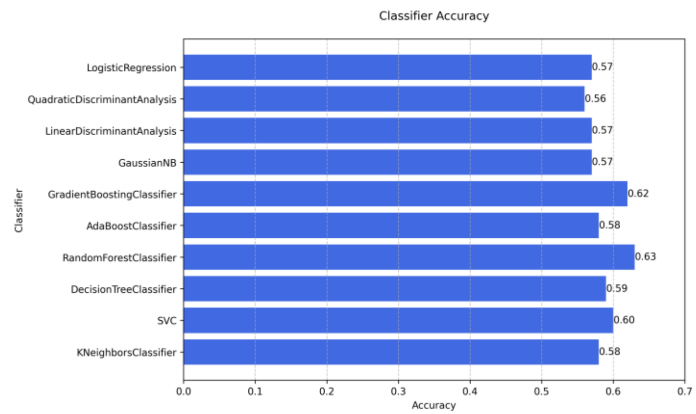
- A deep learning-based classification model (benchmark) is trained to distinguish signal from background detection).
- All hyperparameters are optimized and drop out layer + stopping layer are added to avoid overfitting. Achieves a **signal-to-background** improvement of up to 3.3x in ttbar channel.
- Other ML classifiers are trained for comparison.



ROC curve for DNN



DNN threshold using AMS

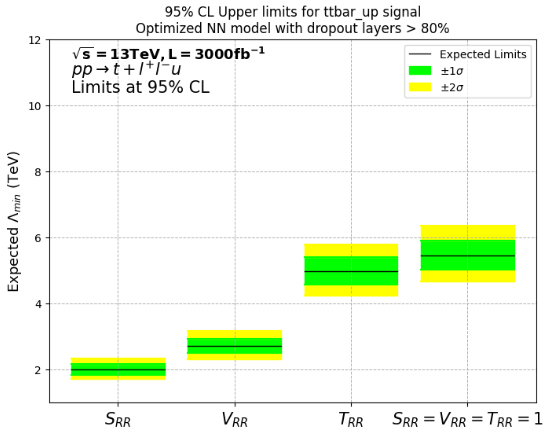


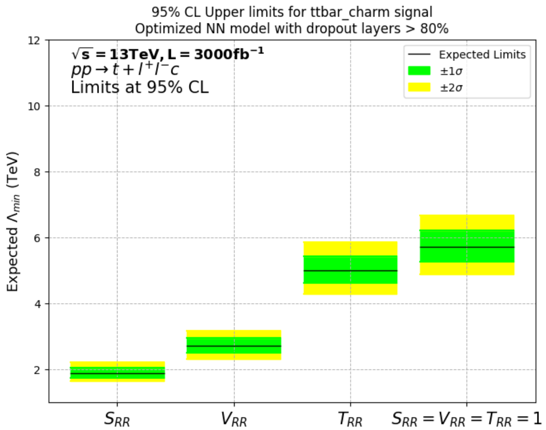
Other classifier accuracy

Exclusion limits on NP scale

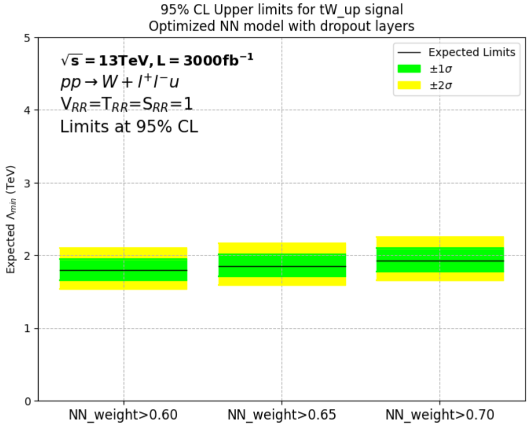
- Expected **95% CL exclusion limits** on the new physics scale (Λ) for all signal scenarios:

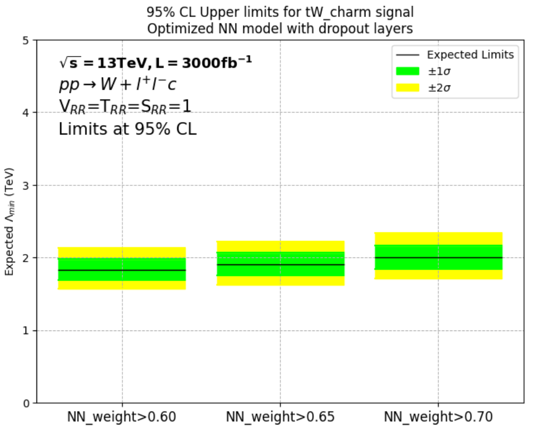
$t\bar{t}$ channel limit





tw channel limit



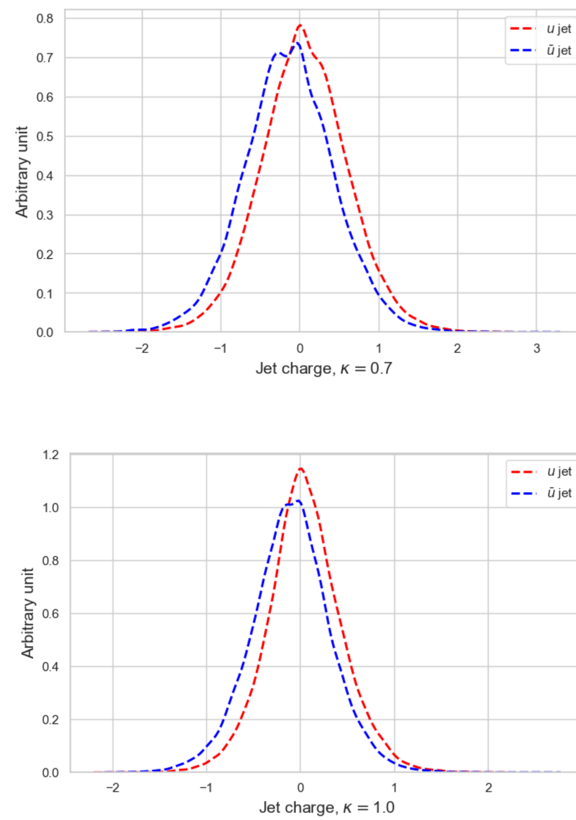


Application of Deep learning to Jet charge

- The jet charge method is crucial in verifying the top quark charge, heavy boson identification (W′/Z′), quark vs. gluon jet discrimination.
- This study explores **classical deep learning** models like DNN, CNN, GNN and **quantum ML models** for improved jet charge classification.
- The jet charge observables are defined as (where is a tunable parameter affecting charge sensitivity):

$$\mathcal{Q}_j = \frac{1}{(p_T^{\mathrm{jet}})^\kappa} \sum_{i \in \mathrm{Tr}} Q_i (p_T^i)^\kappa$$

$$Q_{3,\kappa} = \frac{\sum_{i \in Tr} q_i \, |\Delta\eta_i|^\kappa}{\sum_{i \in Tr} |\Delta\eta_i|^\kappa}$$



Momentum weighted jet charge distribution

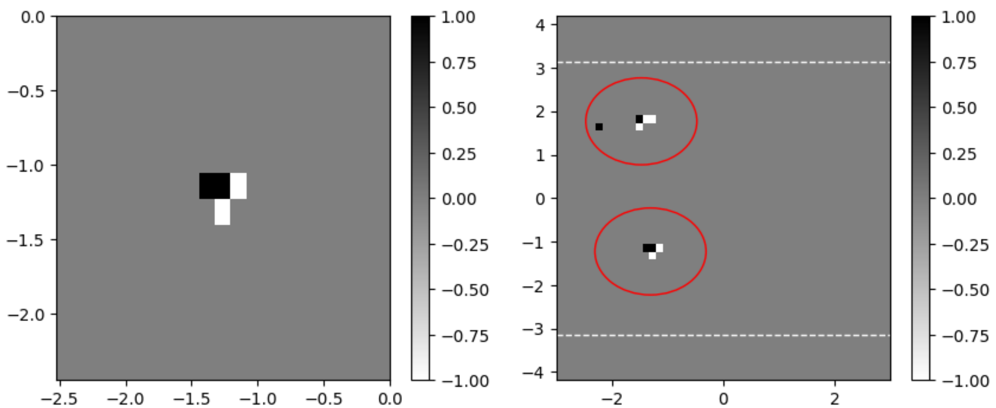
Convolutional NN and Graph NN

Convolutional Neural Networks (CNNs):

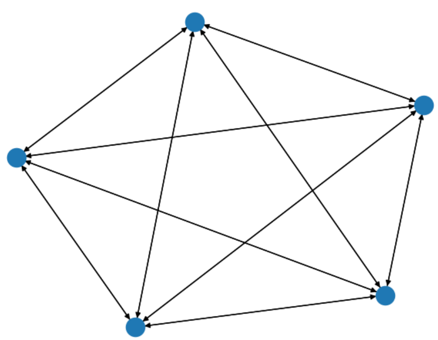
- CNNs process jet images by analyzing pixel charge distributions in **η-φ space**.
- They capture **spatial correlations** of energy deposits to classify jet charge.
- Can differentiate between quark-initiated and gluon-initiated jets using learned spatial features.

Graph Neural Networks (GNNs):

- GNNs model jets as graphs, where **tracks are nodes** and **edges encode relationships**.
- Capture relational and topological information beyond fixed-grid structures.
- Effective in handling **variable-sized track information** per jet.



Pixelated representation of jets in $\eta - \phi$ space

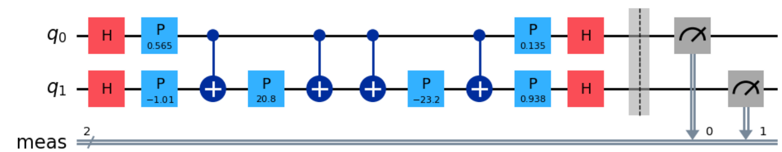


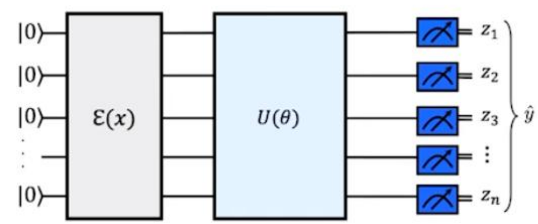
Graph representation of a leading jet

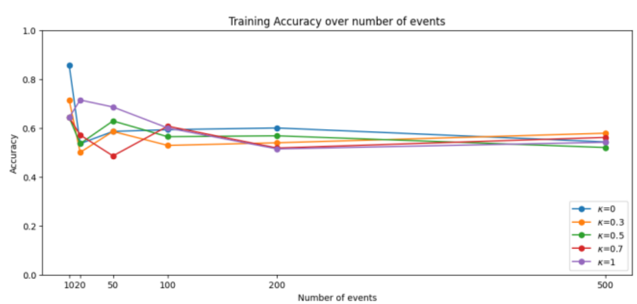
Quantum ML application

- Quantum Feature Map: Maps classical jet charge data into a higher-dimensional quantum Hilbert space using parametrized quantum circuits, enabling more expressive representations.
- Quantum Kernel: Compute similarity between quantum-embedded jets, allowing for efficient discrimination using quantum support vector machines.
- Challenges: Noisy quantum hardware, limited qubit connectivity, and circuit depth constraints impact practical implementation.

Quantum feature map and kernel





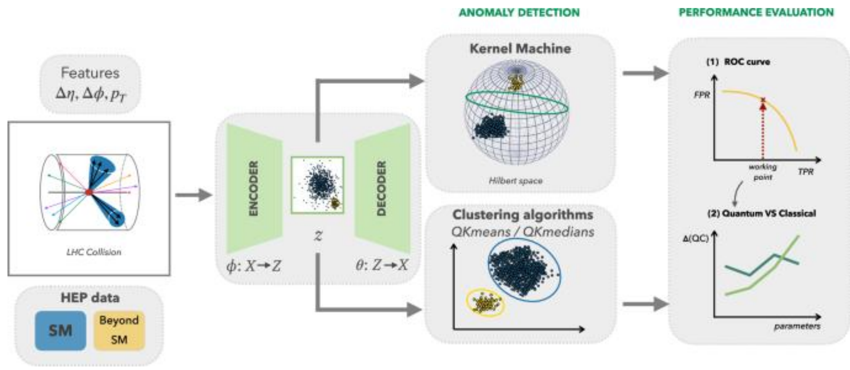


Accuracy for VQC in few events

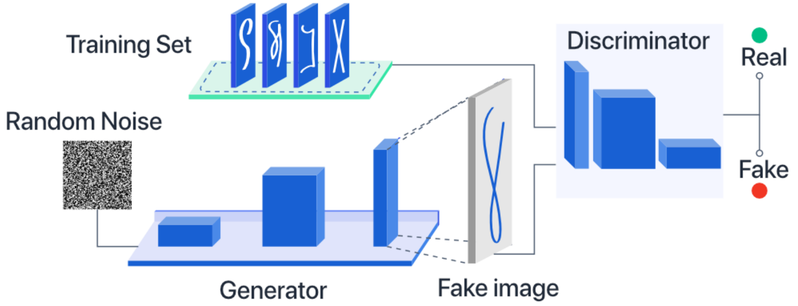
Accuracy for QSVM in few events

Anomaly detection using Gen AI

- Train Autoencoder or variational AE on SM background events and reconstruct them well.
- New Physics events, which deviate from learned patterns, lead to high reconstruction errors, signaling potential anomalies.



- In GAN-based anomaly detection, the **generator** learns to produce events that resemble Standard Model (SM) data, while the **discriminator** is trained to distinguish between real and generated events.
- if the discriminator assigns a high anomaly score (i.e., the event is unlike both real and generated SM events), it may indicate a **Beyond Standard.**



Summary & ongoing

- The paper on top FCNC is finished and ready for submission.
- The paper on classical and quantum ML applications in jet discrimination is in progress (70% complete). The remaining tasks include running QSVM on a real IBM quantum server and training GNN with GraphSAGE.
- Your feedback is welcome and greatly appreciated.