Using Deep Neural Networks for matrix element reweighting of Vector-Like Quark Decay Events

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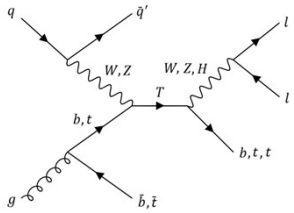
BACKGROUND

- When matrix elements are calculated using monte carlo simulations, we often wish to reweight the bins to predict kinematic behavior for alternative physics hypotheses.
- Although this can be done exactly through MadGraph, it optimally needs to be done while generating the events and is a very time and resource consuming process. Neural Networks could be used to bridge the gap by providing us a technique to find reweighting factors in a post-hoc manner.
- Vector-like quarks, quarks that do not exhibit chiral behavior, are predicted by a variety of Beyond Standard Model theories.
- In this work, we consider the singlet (EWK) production process, which is expected to dominate at higher masses:



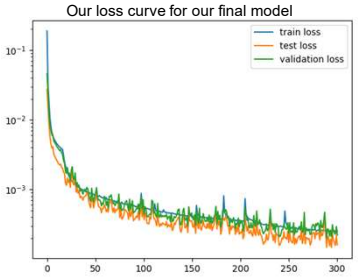
- It is generally assumed that the VLQ exclusively decays to third generation quarks. The branching ratio of the $T \to Wb$, $T \to Zt$, and $T \to Ht$ decay modes is dependent on the model; we investigate the reweighting of these process events.

DATA

- Our data consisted of 10.5 million entries, out of which 9 million were used in the training process and 1.5 million entries were prepared with more unique reweighting scenarios to test the robustness of our model.
- These events were generated with the MadGraph software using a UFO VLQ model with a 4 flavour scheme.

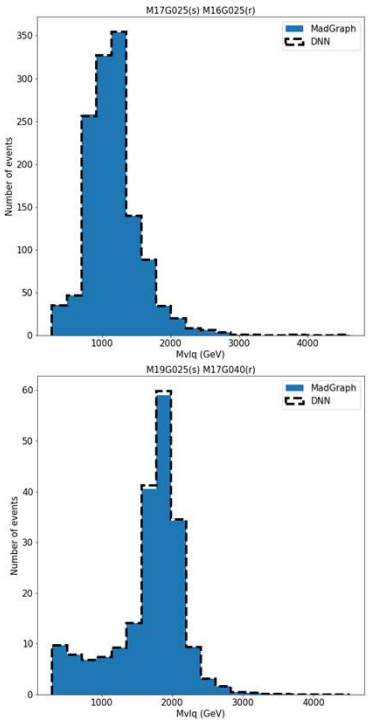
Our github repository is available at
https://github.com/abhinaya-sinha/VLQ-NN-Reweighting

MODEL TRAINING



We trained a fully connected deep neural network with the following hyperparameters:

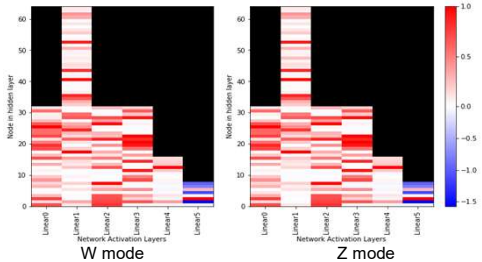
- 6 hidden layers
- Adam optimization with 1e-3 initial LR
- A dropout rate of 0.8 while training
- Batch sizes of 2048 samples each
- Huber Loss function



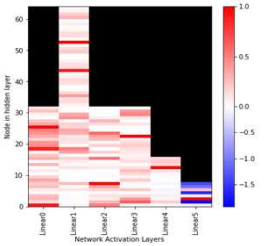
Two examples of reweighted histograms

EXPLAINABILITY

- We plotted the Neural Activity Pattern (NAP) of the network, which is a heatmap representing the relative activation strength of each node in the activation layers of the model.
- We divided our database by the W, H, and Z modes and generated NAP diagrams for each of them.



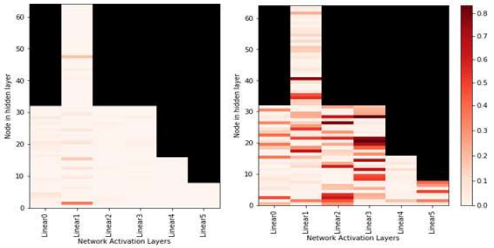
W mode Z mode



H mode

The results show that the network is sparser for the H mode than the W and Z modes, at 35% and 27% respectively.

- We also plotted the difference in RNA scores between the W and H modes and W and Z modes.
- We see a large difference between the RNA scores of the W mode and the Higgs mode, but only a minor difference between the W and Z modes.

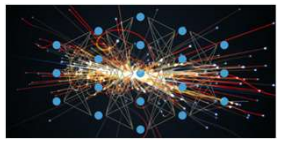


Difference plot between W & Z modes

Difference plot between W & H modes

CONCLUSIONS AND FUTURE WORK

- In our work, we found that neural networks are a viable post-hoc alternative for reweighting matrix elements for vector-like quark models.
- We found that our network, was robust towards various reweighting scenarios for vector-like quarks.
- We also showed that the mode of decay has a significant effect on the reweighting factor, which is clearly visible in the structure of the network.
- We are working on generalizing these results to other effective field theories and BSM models.



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