# Neural Reweighting for Monte-Carlo Events

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## Matrix Element Reweighting

Calculate the squared matrix element for new parameters of BSM physics hypothesis

Can be calculated analytically with event simulators like MadEvent for tree-level processes

Subject to technical constraints for combinatorially large and degenerate final states

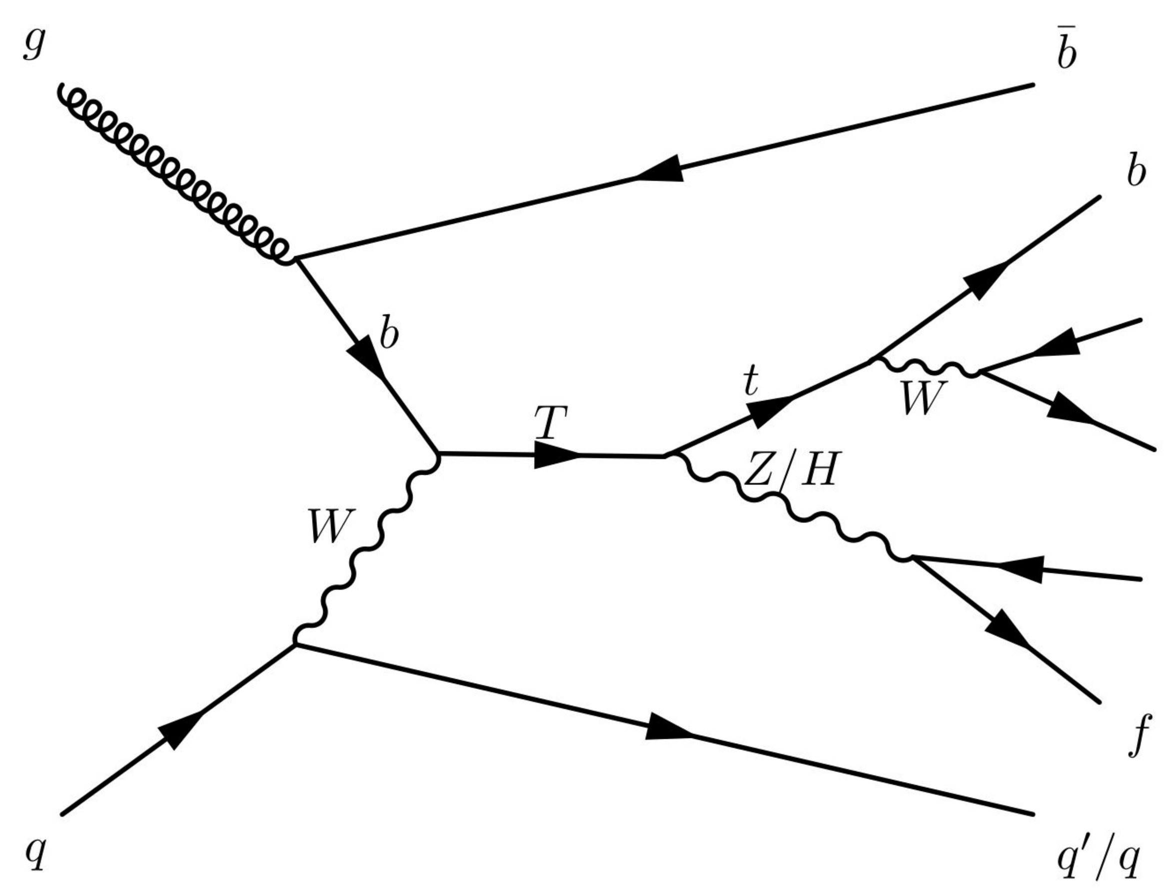
## Reweighting with Neural Networks (NNs)

NNs can be trained to learn the analytical reweighting with truth-level hard scatter process information

Can be used as a continuous interpolator (compared to usual grid interpolations) within a pre-determined parametric hyperspace

*Assumptions:* Sufficient training statistics to cover the desired phase space

*Test Case:* Single of positively charged Vector-like Quarks (T) that can decay into third generation quarks in Wb, Ht, and Zt modes

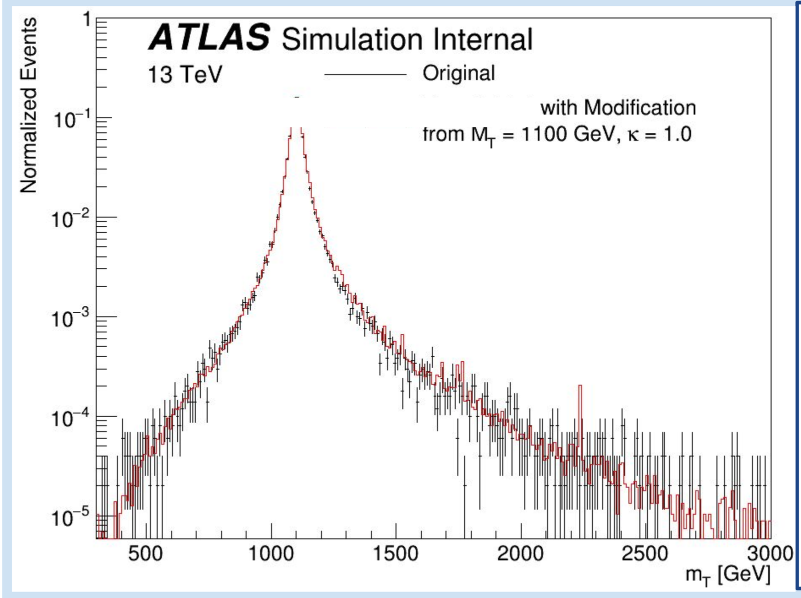


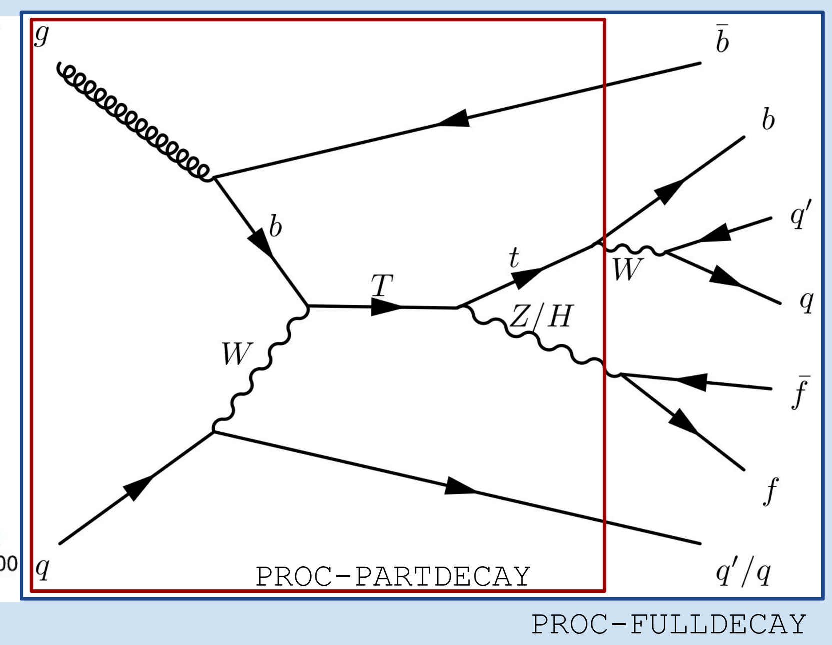

## Process Simplification

Generating training data with large combinatorial final states can require prohibitively large resources

Reweighting factors can be approximated from a simplified process where the decays of the SM bosons and quarks are ignored

$$w^{\text{new}}_{\text{PROC-FULLDECAY}} \approx \frac{|\mathcal{M}^{\text{new}}_{\text{PROC-PARTDECAY}}|^2}{|\mathcal{M}^{\text{old}}_{\text{PROC-PARTDECAY}}|^2} w^{\text{old}}_{\text{PROC-FULLDECAY}}$$




### Network Architecture

Input features: 29
- Four vectors and PIDs of the four outgoing particles
- Longitudinal momenta and PIDs of incoming partons
- True and Target VLQ mass and width
- VLQ Decay Mode (Higgs: 0, W: -1, Z: 1)

Multi-layer Perceptron with 6 hidden layers with 32, 64, 32, 32, 8, 4 nodes, LeakyReLU activation and Huber Loss

Training data includes VLQ samples between 1.1 and 2.3 TeV with relative decay widths less than 50%; trained to reweight to any mass-width within ± 200 GeV of true simulation mass

## Signal Grid Extrapolation

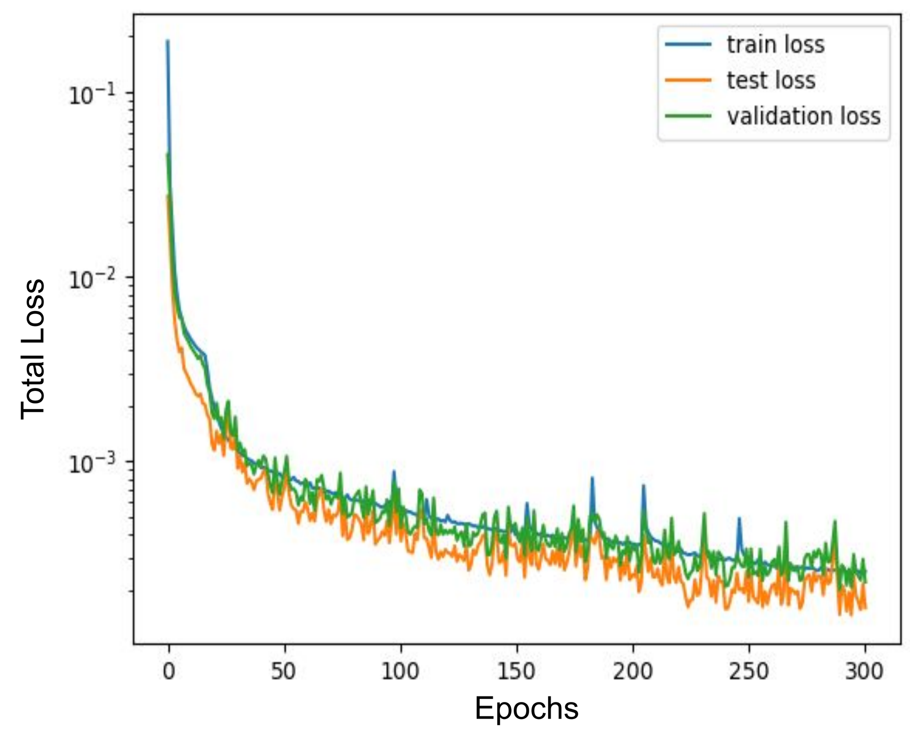
Often required by physics analyses to extend the reach of physics analyses

Needed *post-hoc* i.e. only after unblinding data in the most sensitive phase space

Calculating exact reweighting factors or generating new signal Monte-Carlo can be prohibitively time consuming

## Model Performance

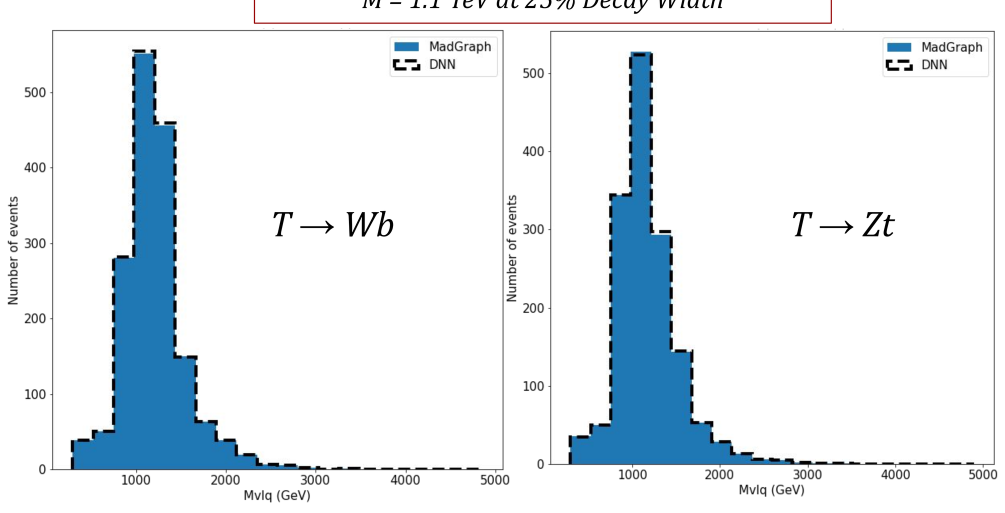
The test set includes certain mass-width combinations that are not included in the training data

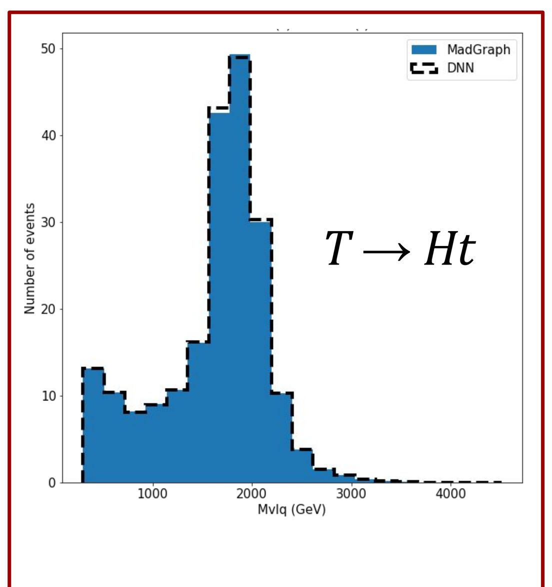



Convergence Performance

Closure Test

*Reweighting M = 1.3 TeV at 50% Decay Width to M = 1.1 TeV at 25% Decay Width*



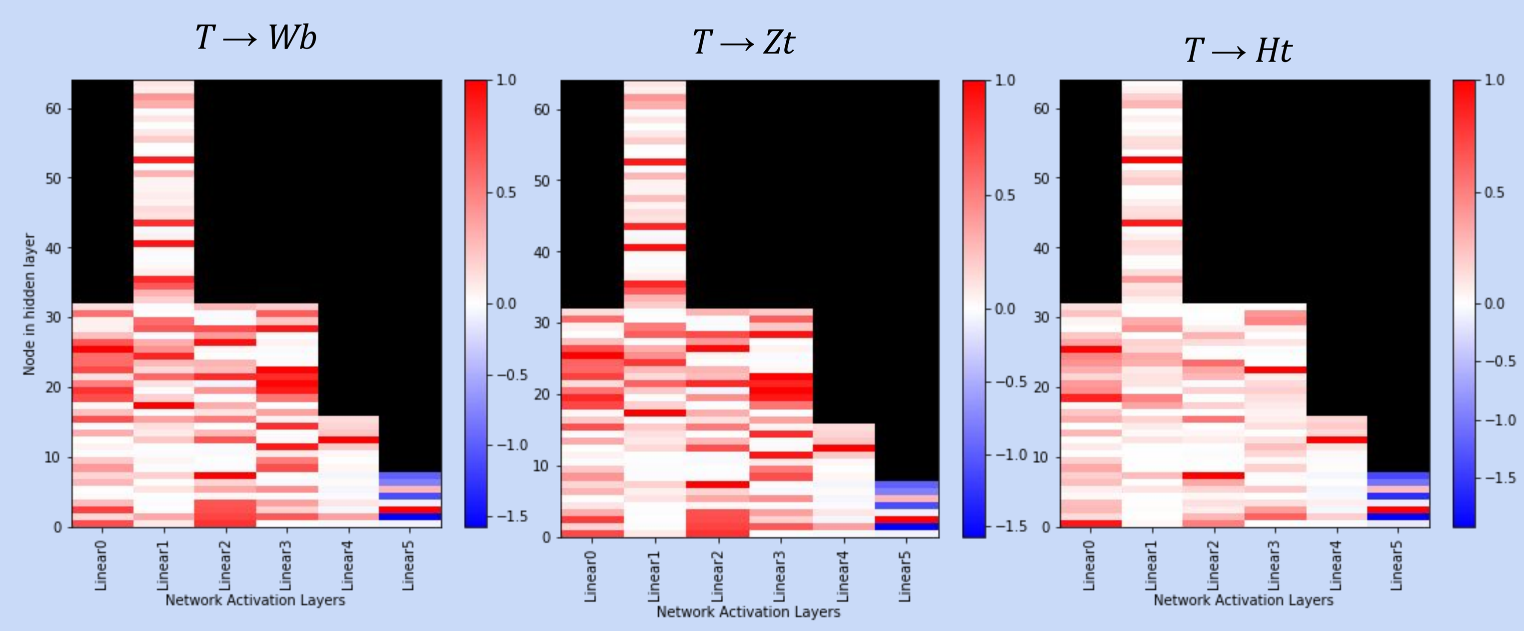




*Reweighting M = 1.9 TeV at 50% Decay Width to M = 2.1 TeV at 30% Decay Width*

Interpolation Test

## Model Interpretation

Inspecting the information propagation pathways of the NN using Relative Neural Activity (RNA) Score




Neural pathways are almost identical for vector bosons and significantly different for the Higgs mode

The underlying physics leaves its imprint on the NN – the path is chosen by the physics!

## Acknowledgements

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