# Probing HNLs at the FCC-ee using Machine Learning Methods

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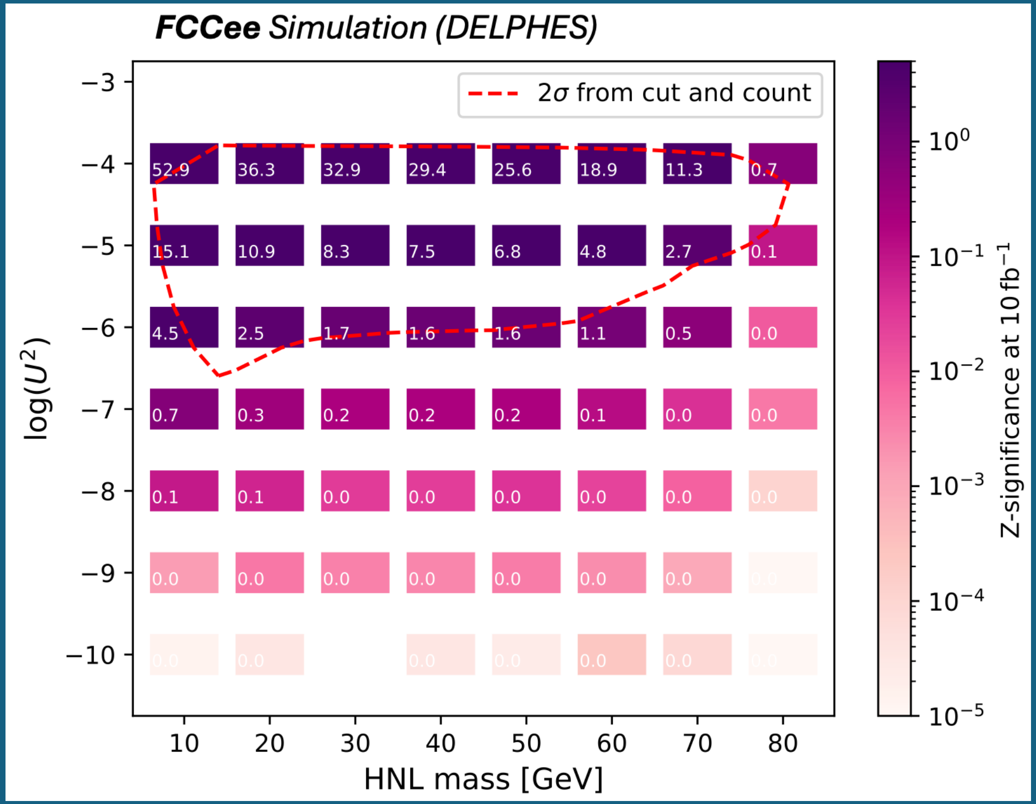
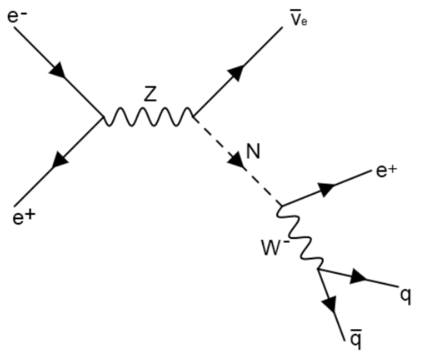
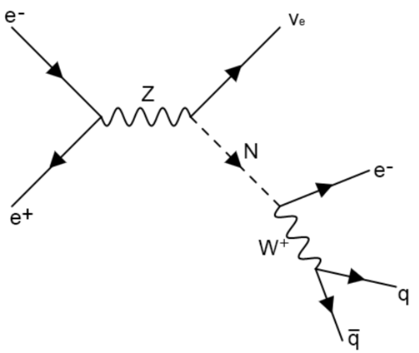
# Introduction

† arXiv:2403.00100

- HNLs introduced as a massive, sterile RH object that can generate small SM neutrino masses via Type I see-saw mechanism (Dirac or Majorana).
- Consequential lifetime ($\tau \propto M^{-5}|U|^{-2}$)† can result in displaced signatures giving us LLPs to search for at the FCC in this framework
- We look for Dirac HNLs in the mass range 10 – 80 GeV with $10^{-4} < |U_{eN}|^2 < 10^{-10}$ in electron dijet final state




| Variable | Selection |
|---|---|
| Missing energy | > 12 GeV |
| Leading electron energy | > 35 GeV |
| 3D di-jet Angle | < 2.4 rad |
| Di-jet – Electron $\Delta R$ | < 3 |

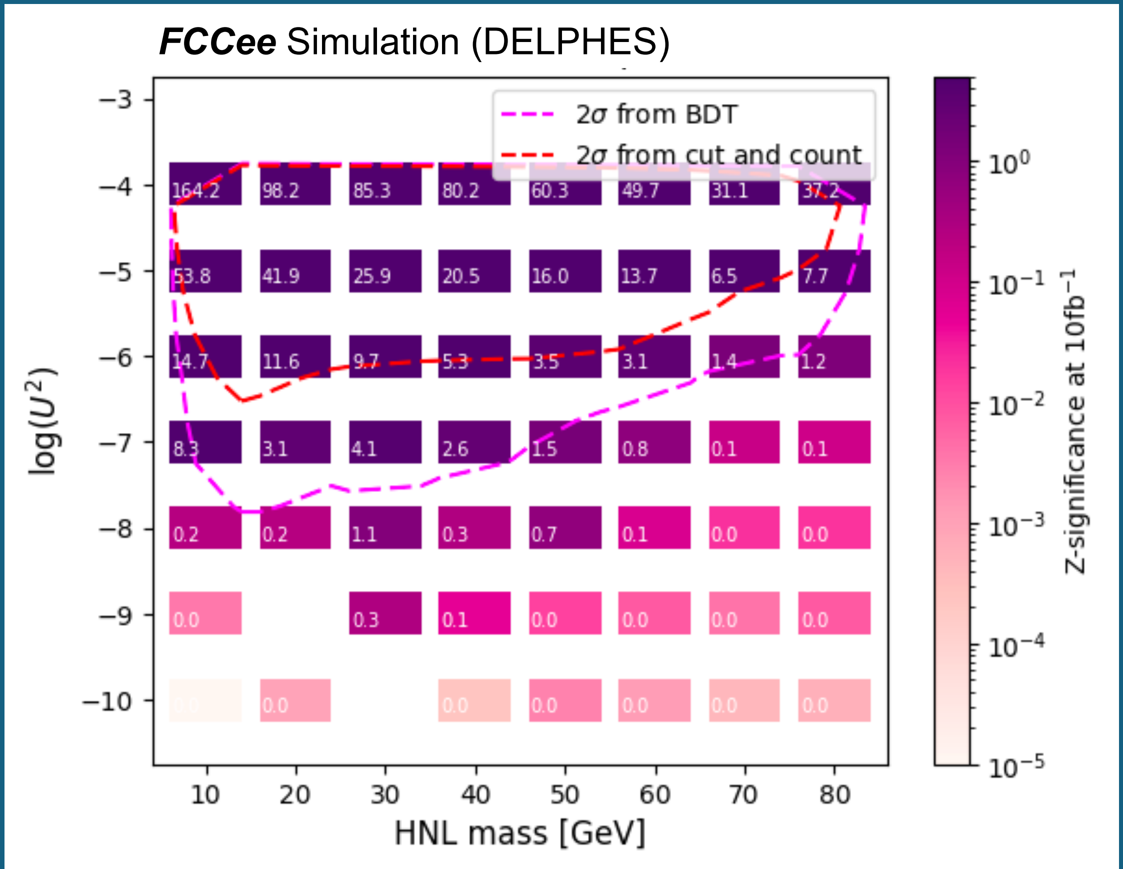
# ML approaches to HNLs: BDT

- A unique BDT model was trained using XGBoost with TMVA for each signal mass point and compared with the background proccess (4 lepton, Z →bb and Z → cc) and normalised to 10 $fb^{-1}$

- BDT Hyperparameters optimised via gridsearch cross-validation → final result ~20% improvement on cut and count method

- Input features for BDT :

| Object | Variables |
|---|---|
| Leading electron | $E, \phi, D_0, \sigma_{D_0}, \Delta R_{ejj}$ |
| Neutrino | $E_{\text{miss}}, \theta, \phi$ |
| Di-jet system | $\Delta R_{jj}, \phi$ |
| Vertex and tracks | $n_{\text{tracks}}, n_{\text{primary tracks}}, \chi^2_{\text{vertex}}$ |



# ML approaches to HNLs: DNN

- A DNN is being trained using keras for the same classification task – optimisation of the model underway, fine tuning of the hyperparameters necessary to match or improve upon BDT performance.

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- Input features for the DNN (same as BDT so far):

| Object | Variables |
|---|---|
| Leading electron | $E, \phi, D_0, \sigma_{D_0}, \Delta R_{ejj}$ |
| Neutrino | $E_{\text{miss}}, \theta,\ \phi$ |
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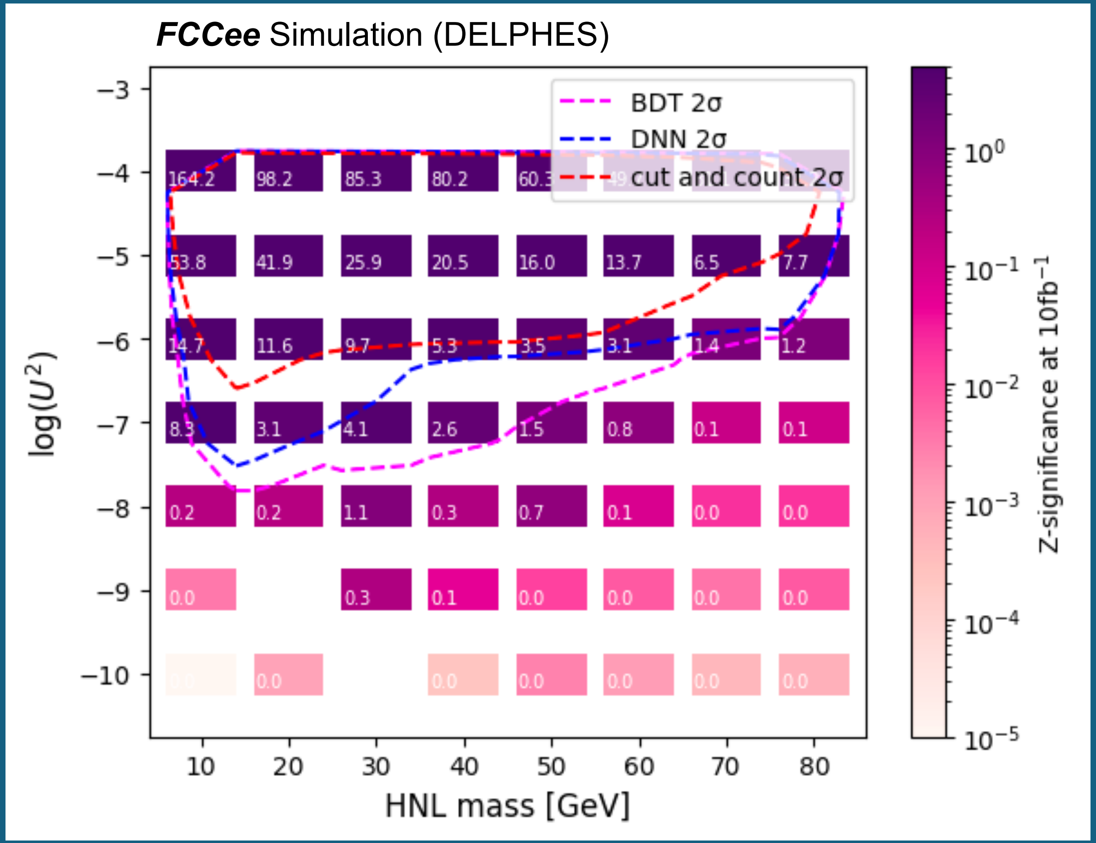
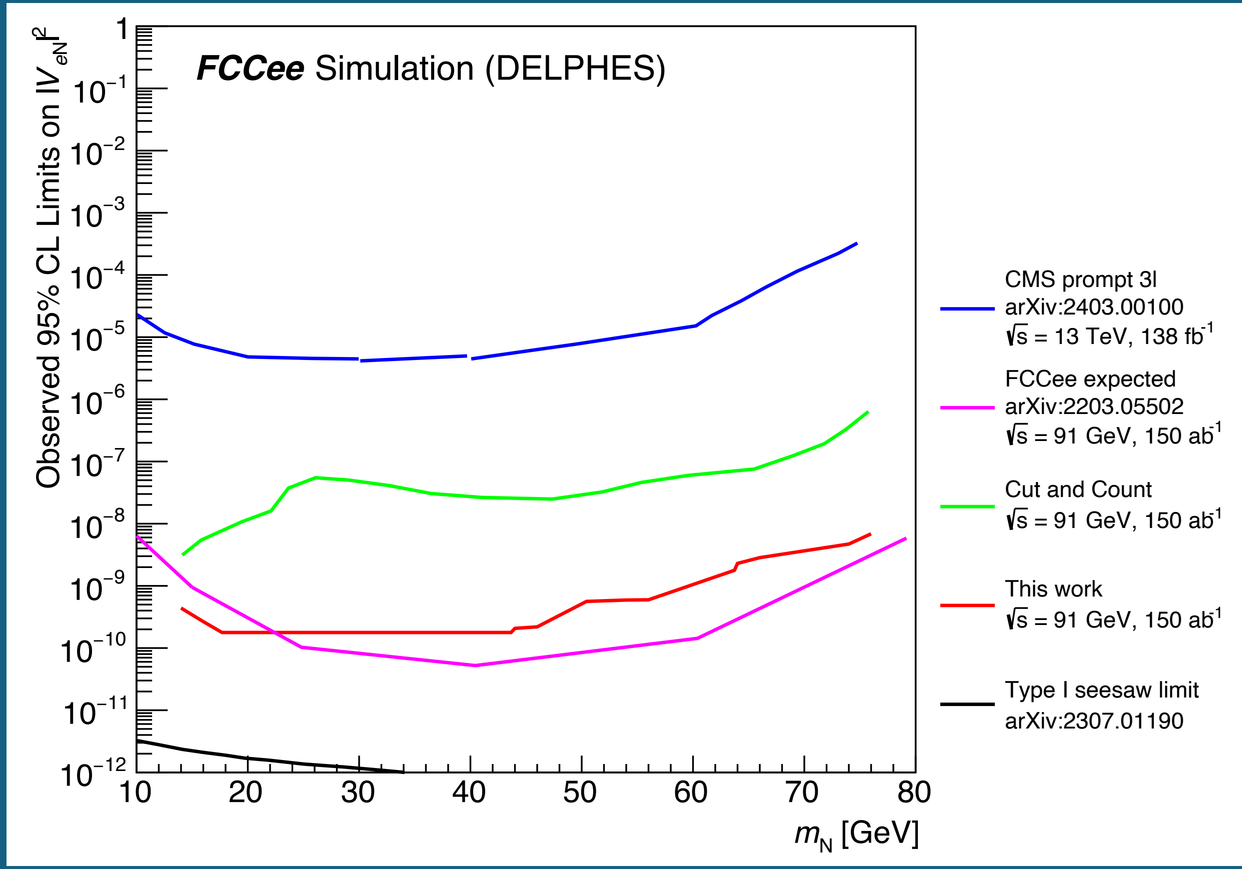


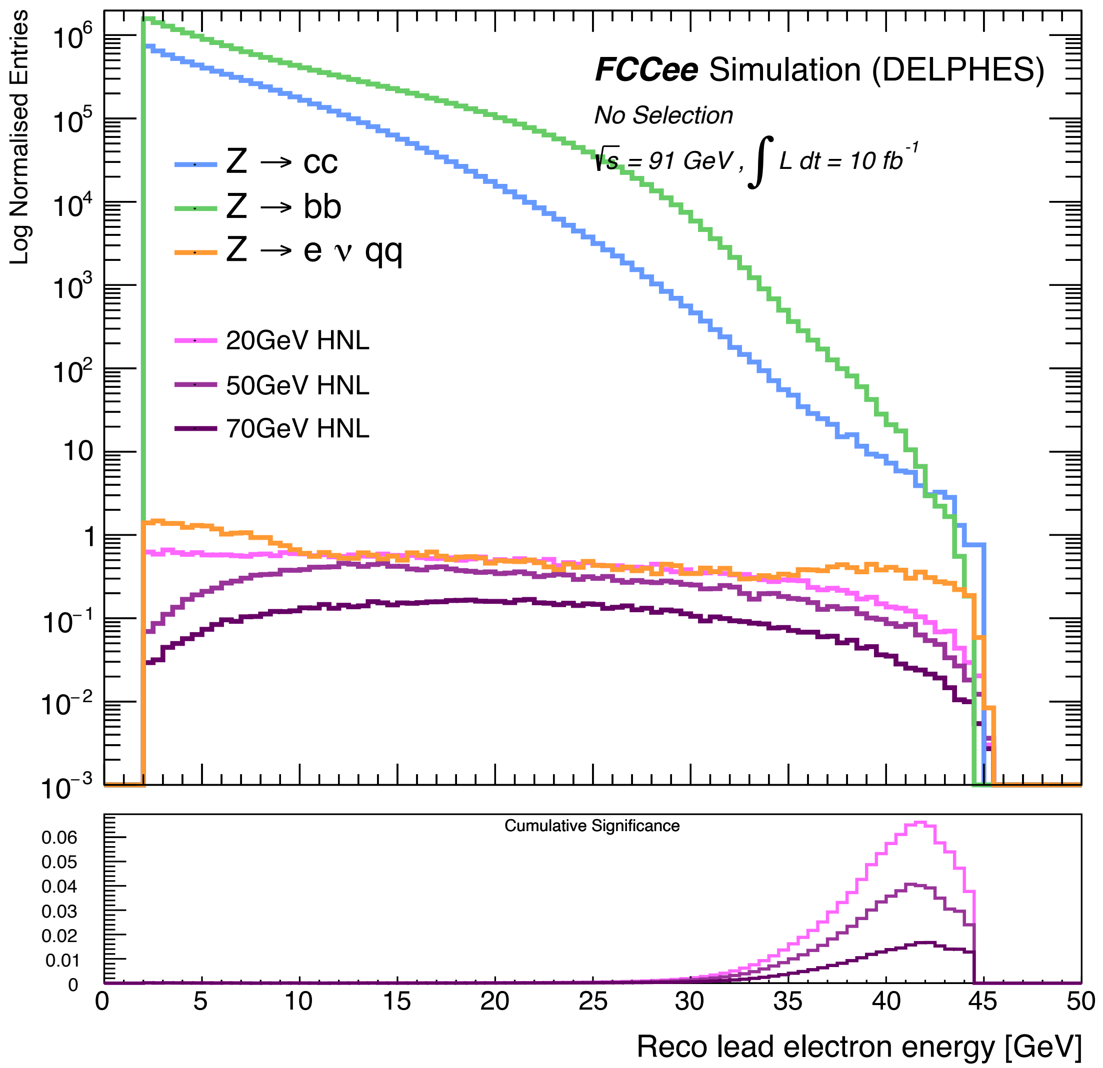
# Improved Limits

- Most successful improvement (so far) from the use of BDTs
- ~20% improvement on existing 95% CL limits compared with the same final state for cut and count study
- ejj only ~15% of the total HNL branching ratio, hence we do not see the same full coverage as for expected FCC
- Next steps: DNN optimisation and searches for viable filters working with Sarah, improving our ability to scale to full lumi

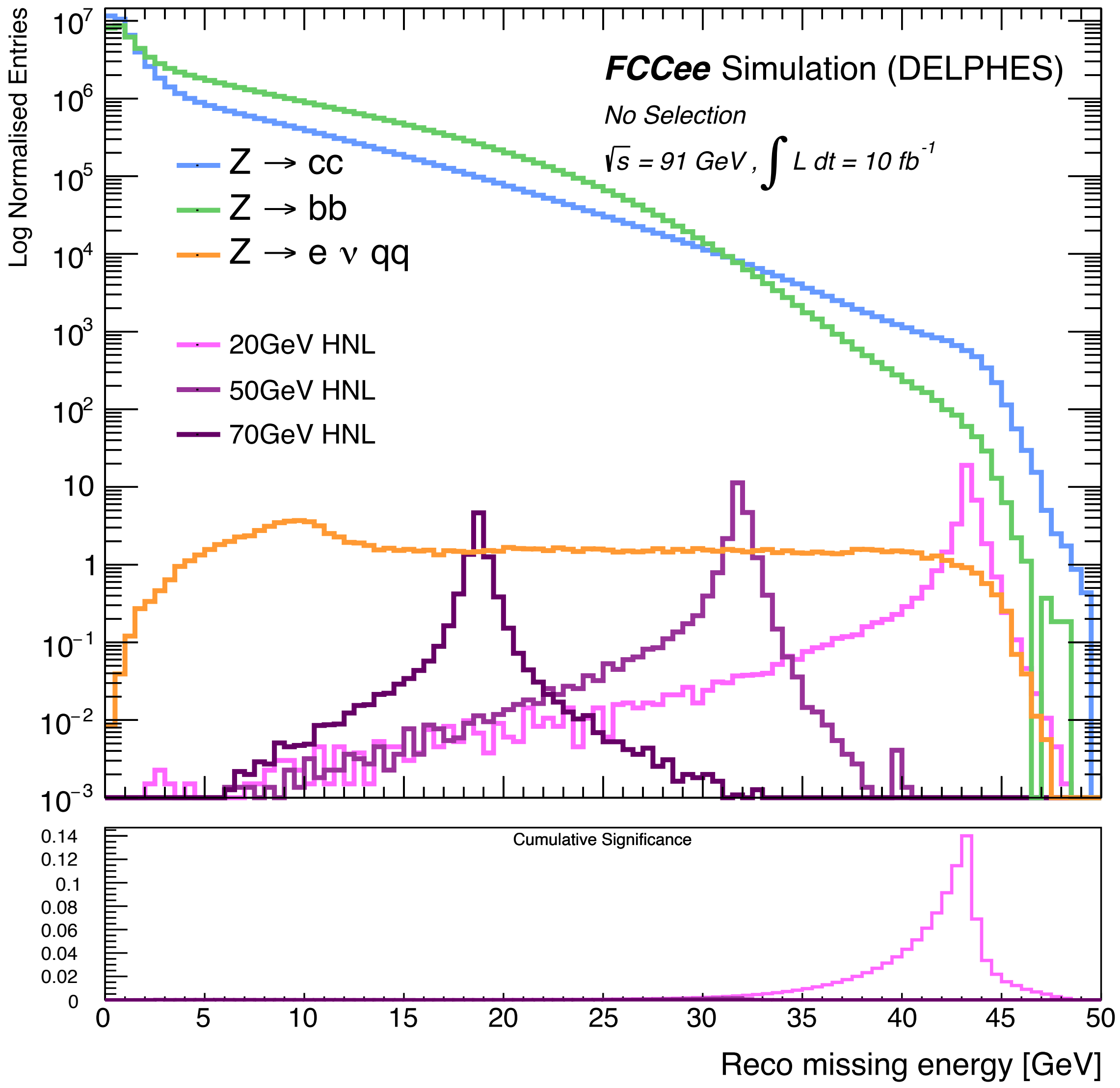


# Backup slides

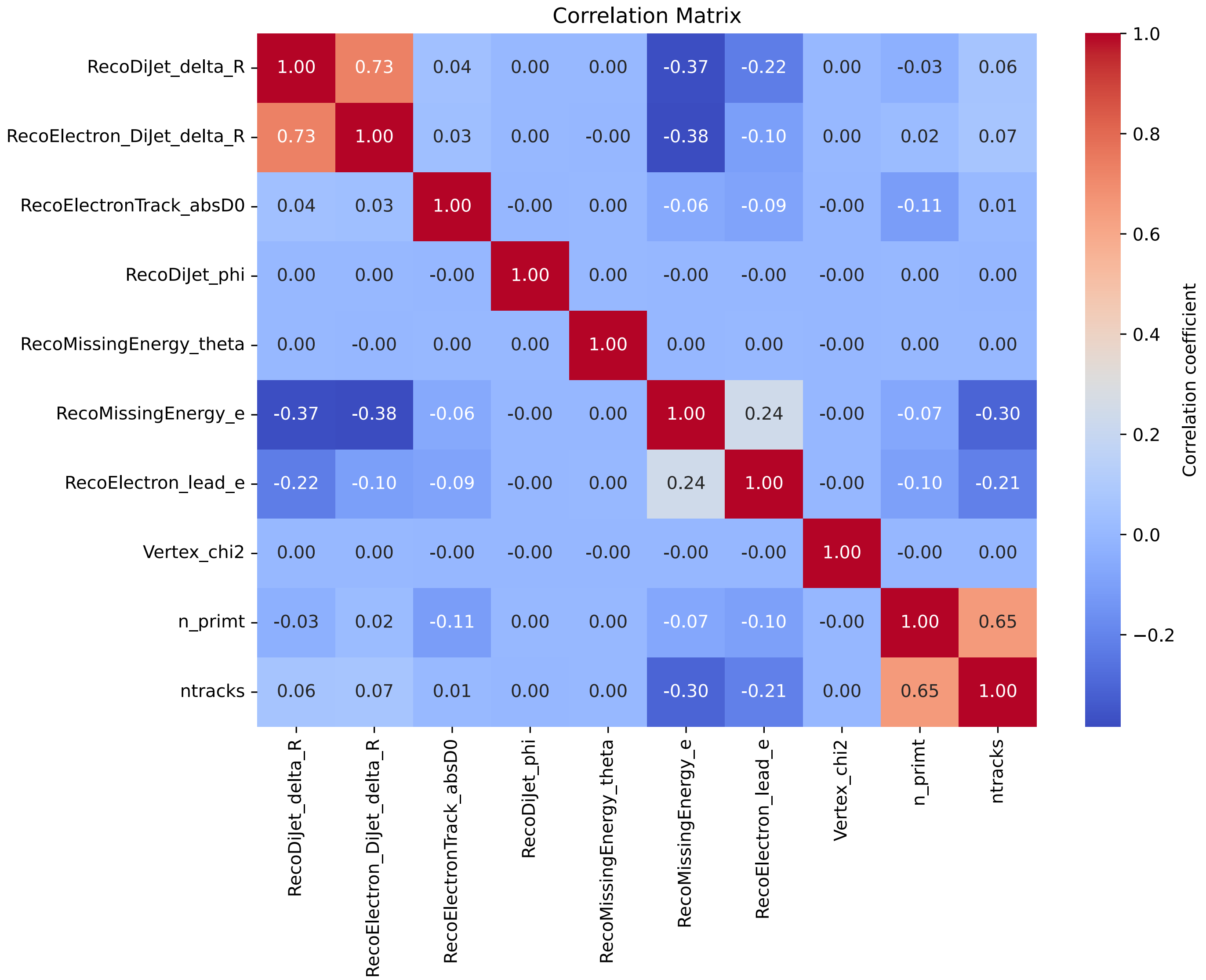
# Lead electron energy distribution



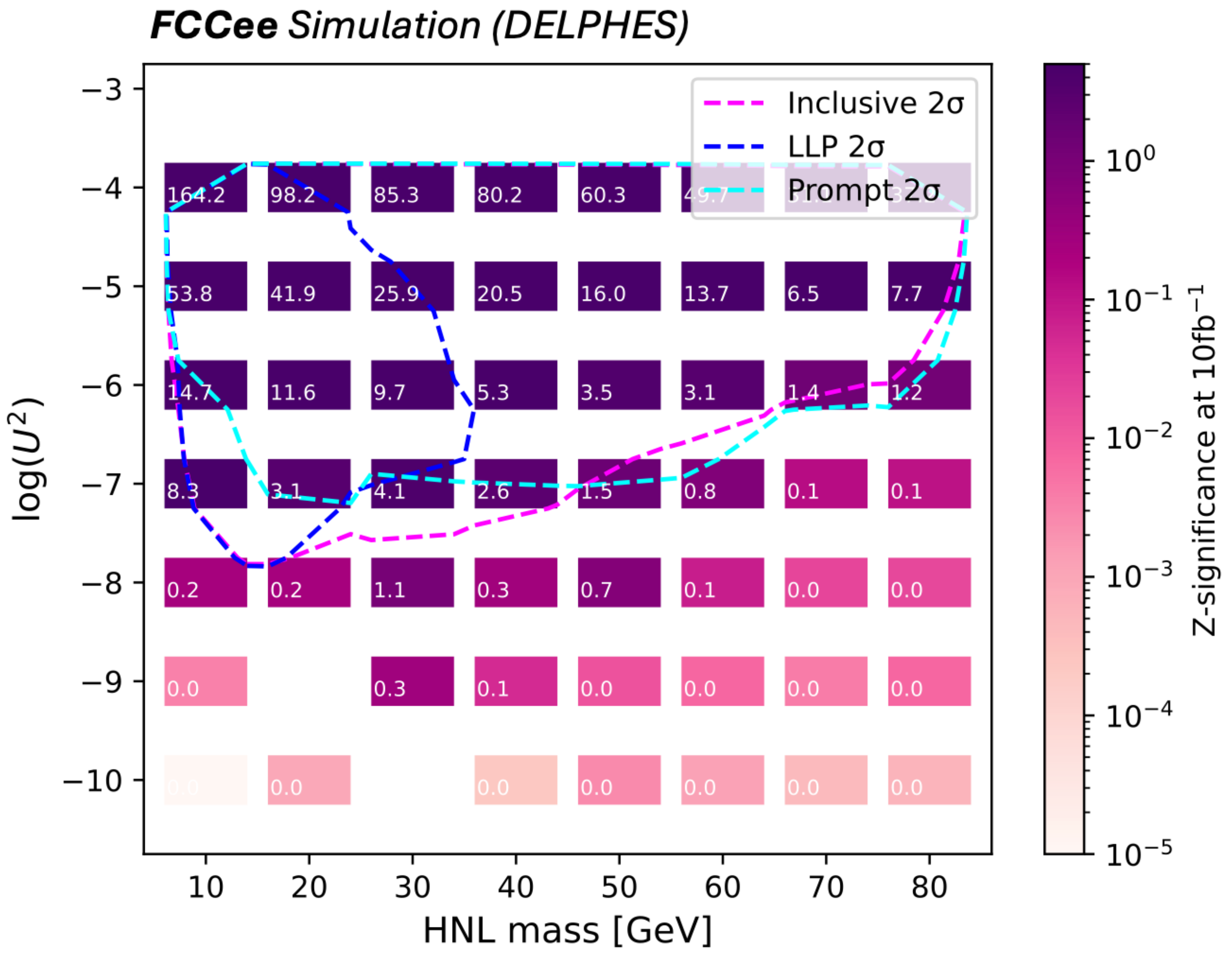
# Missing energy distribution



# Correlation matrix (50 GeV $|V_{eN}|^2 = 10^{-6}$)



# LLP vs Prompt Decay BDTs




Use of a lead electron energy filter E > 15 GeV for inclusive BDT output

Combined with $D_0$ significance > 5 for LLP

Combined with $D_0$ significance < 5 for Prompt decay

Not much improvement from seperating processes – likely because BDT trains for each signal point → displaced vertex mass points already have the $D_0$ as their most important input feature for the inclusive BDT