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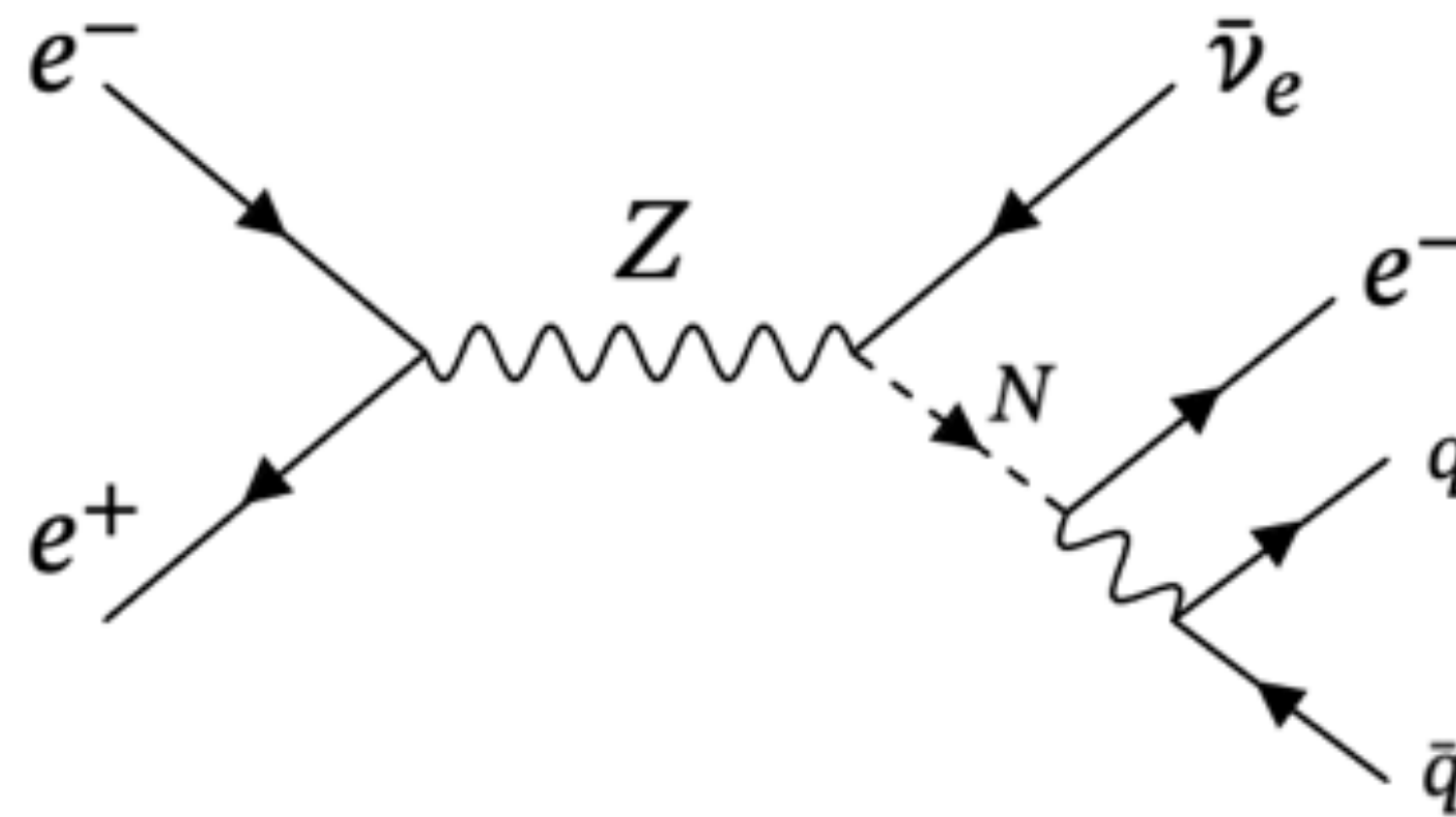
Machine Learning Techniques to Probe Heavy Neutral leptons in the electron channel at FCC-ee (Brief Summary)

Pantelis Kontaxakis
on behalf of the HNLs (evjj) team

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Introduction

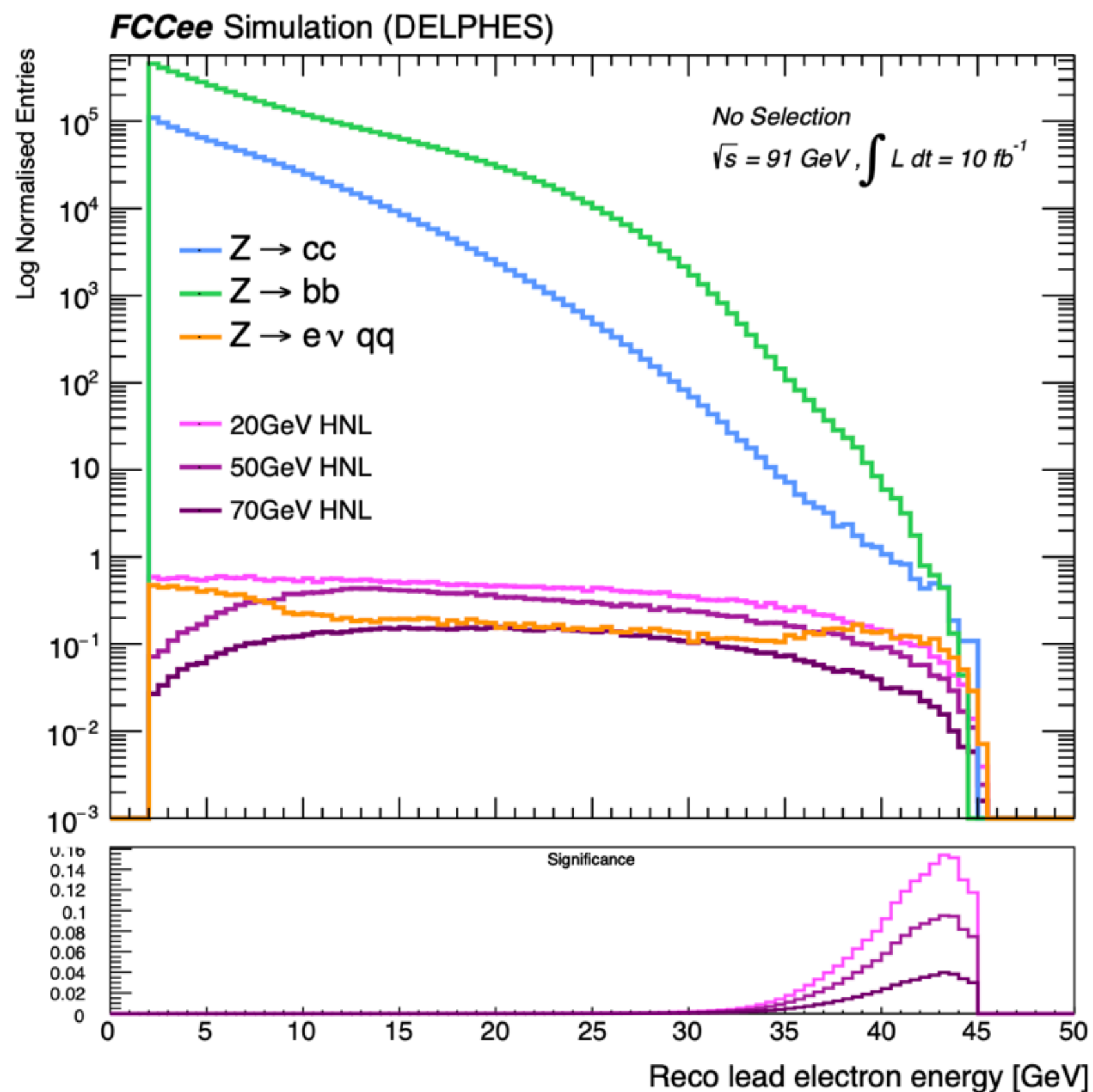
- ◎ **Low-scale** inverse seesaw mechanism enables the search for heavy right-handed neutrinos with Yukawa couplings $O(10^{-6})$ in the mass range of **10 to 100 GeV**
- ◎ Our analysis focuses on **the electron final state with two jets**, investigating the (pseudo-) **Dirac** HNL model between **10-80 GeV** with mixing angles between **$10^{-4} < |U_{eN}|^2 < 10^{-10}$**



Background Processes

● **Three** dominant SM background processes considered:

- $Z \rightarrow bb$, cc or $Z \rightarrow 4$ body final state (instead of heavier quark final states like $Z \rightarrow \tau\tau$)
- The 4-body bkg and all signal samples are privately generated using MadGraph



Process	σ (pb)	Monte-Carlo events	Production \mathcal{L} (fb^{-1})
$Z \rightarrow b\bar{b}$	6.65×10^3	4.39×10^8	6.60×10^1
$Z \rightarrow c\bar{c}$	5.22×10^3	4.98×10^8	1.15×10^2
$Z \rightarrow 4\text{body}$	1.40×10^{-2}	1.00×10^5	7.14×10^3

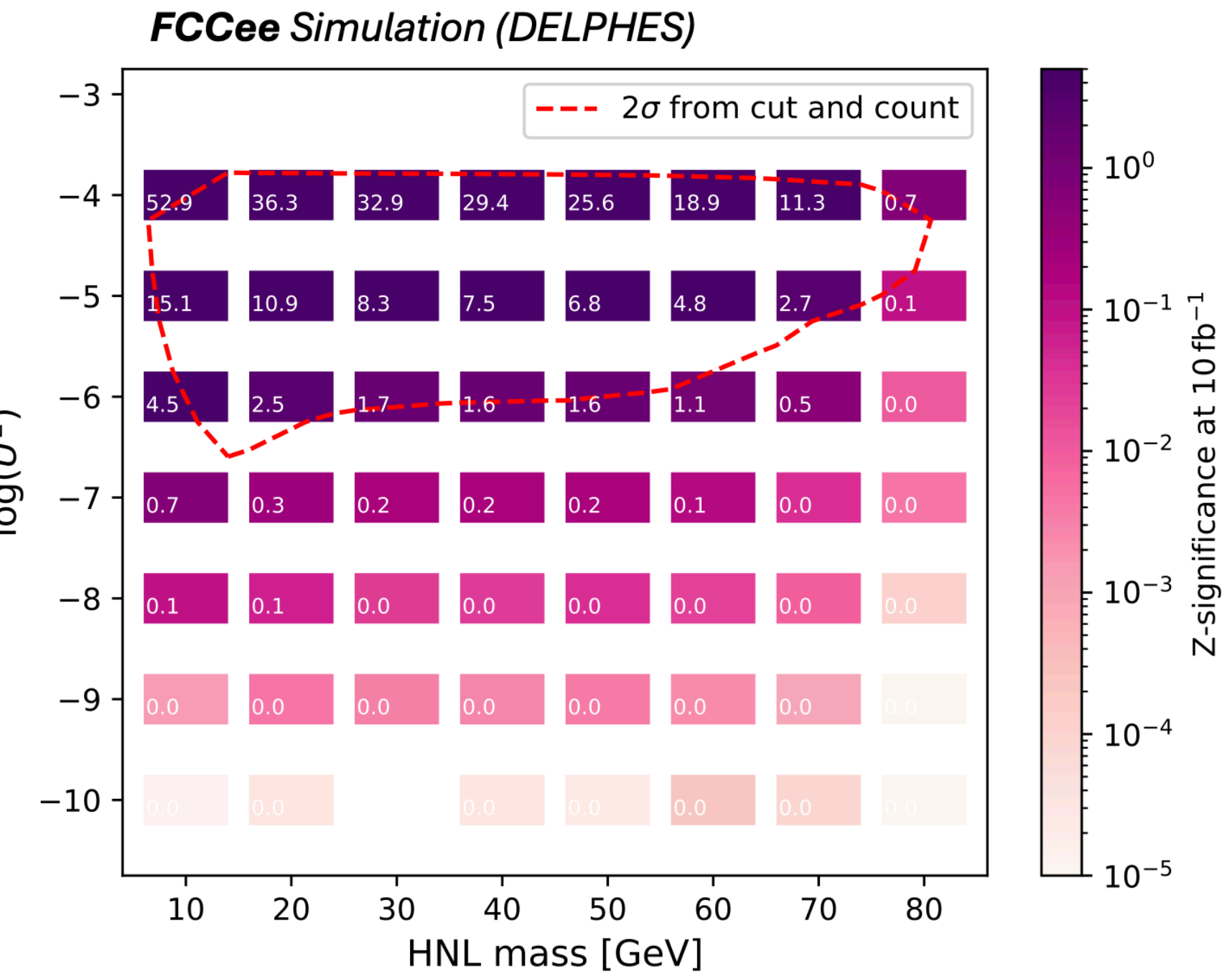
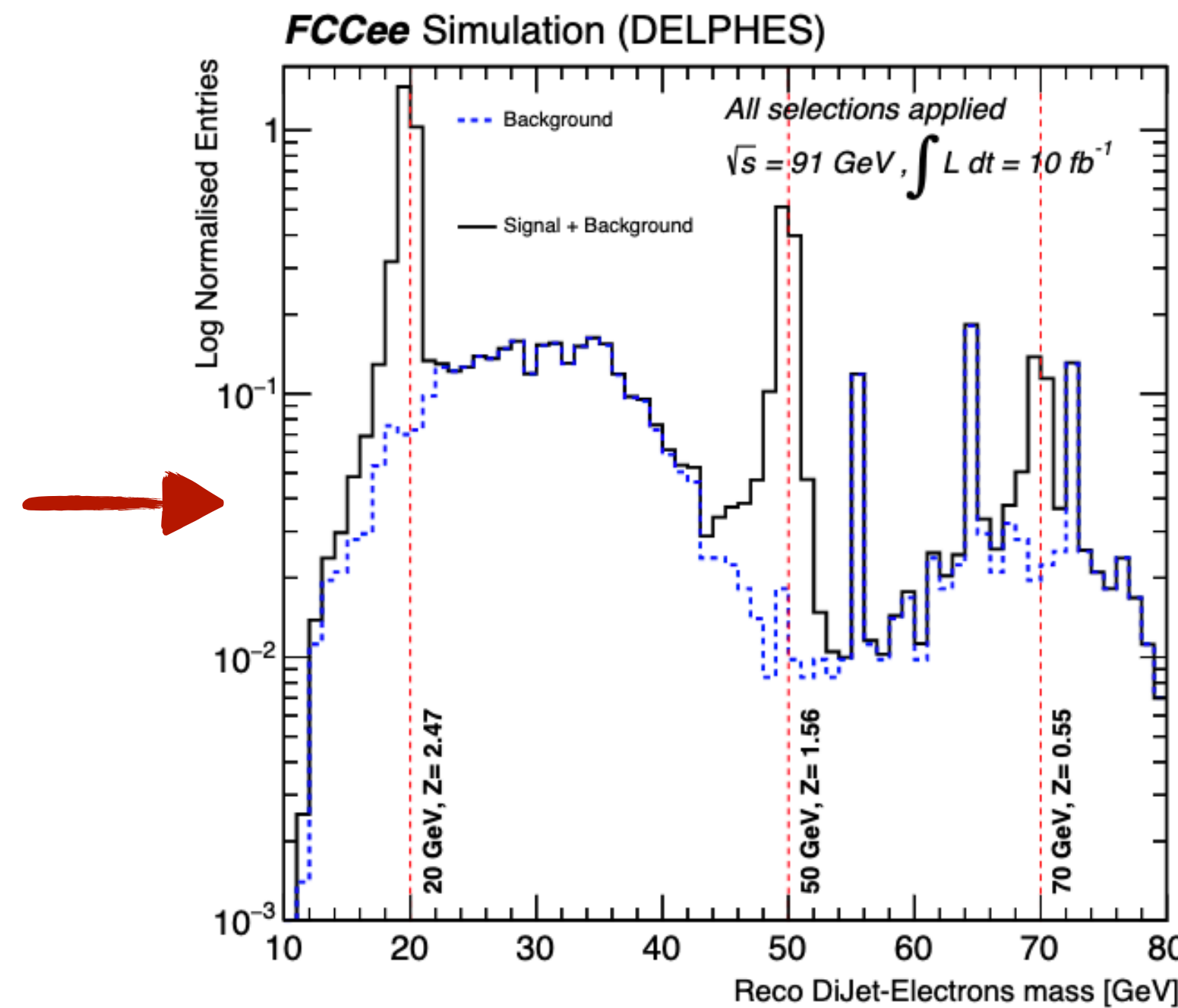
Limited MC statistics for central backgrounds; the analysis is conducted at 10 fb^{-1} and scaled to 150 ab^{-1} for the final result

Analysis Methods

● Cut and Count Method

- C&C studies made by D. Moulin ([master thesis, 2023](#)) and used as benchmark for optimization

Variable	Selection
Missing energy	> 12 GeV
Leading electron energy	> 35 GeV
3D di-jet Angle	< 2.4 rad
Di-jet – Electron ΔR	< 3



Significance: $Z = \sqrt{2 \left(n \cdot \ln \left[\frac{n(b + \sigma^2)}{b^2 + n\sigma^2} \right] - \frac{b^2}{\sigma^2} \ln \left[1 + \frac{\sigma^2(n - b)}{b(b + \sigma^2)} \right] \right)}$

Analysis Methods

● Machine Learning Method(s)

- Studies made by T. Critchley ([master thesis, 2024](#)) trying to increase the sensitivity from the C&C method

◆ **BDT Method:**

- XGBoost in conjunction with TMVA (binary classification)

◆ **DNN Method:**

- Keras in Tensorflow with hyperparameter optimization (binary classification)

❖ **For both methods:**

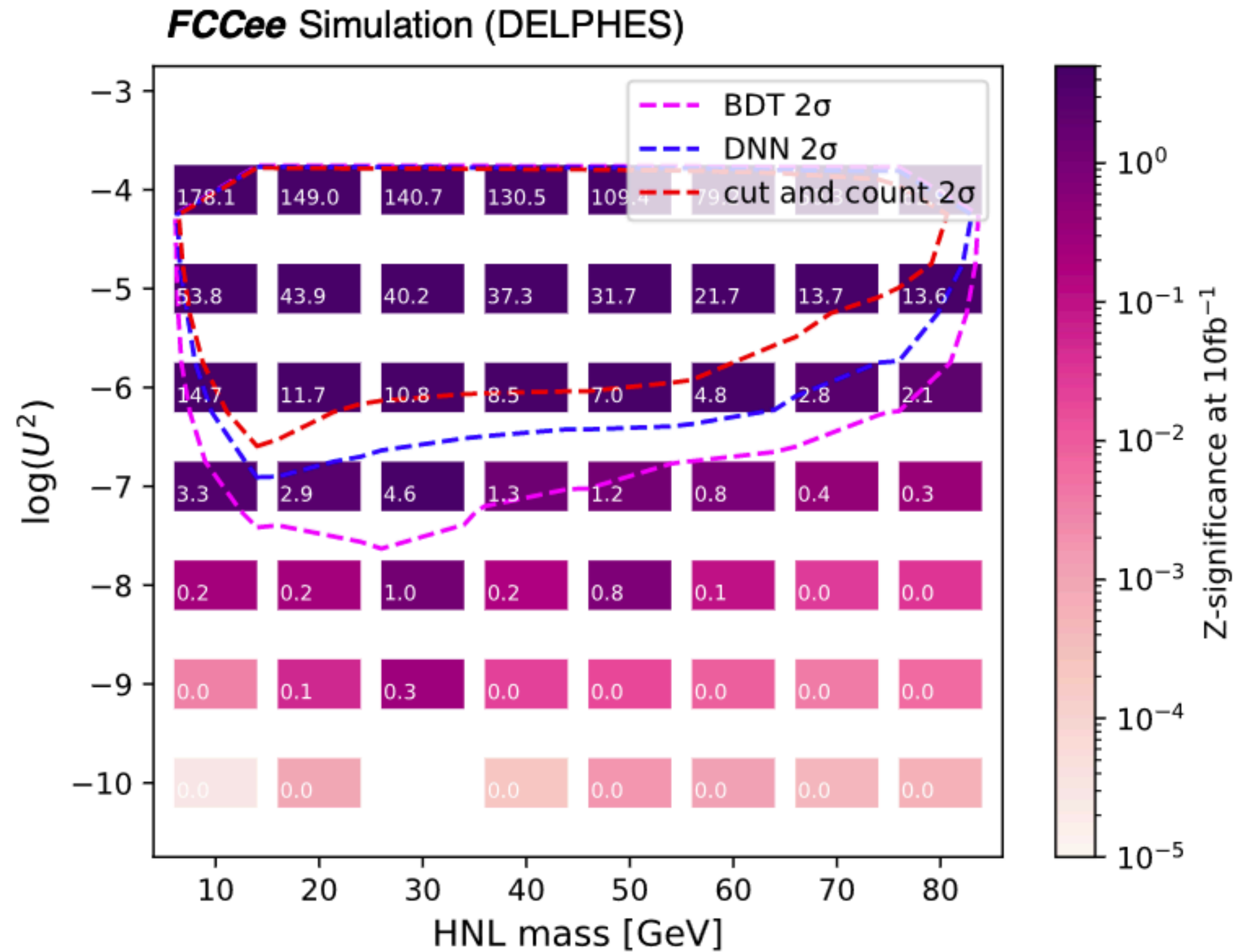
- Individual training for every mass point trying to reach the full sensitivity
- The following variables were used for the training



Object	Variables
Leading electron	$E, \phi, d_0, \sigma_{d_0}, \Delta R_{ejj}$
Neutrino	E_{miss}, θ
Di-jet system	$\Delta R_{jj}, \phi$
Vertex and tracks	$n_{\text{tracks}}, n_{\text{primary tracks}}, \chi_{\text{vertex}}^2$

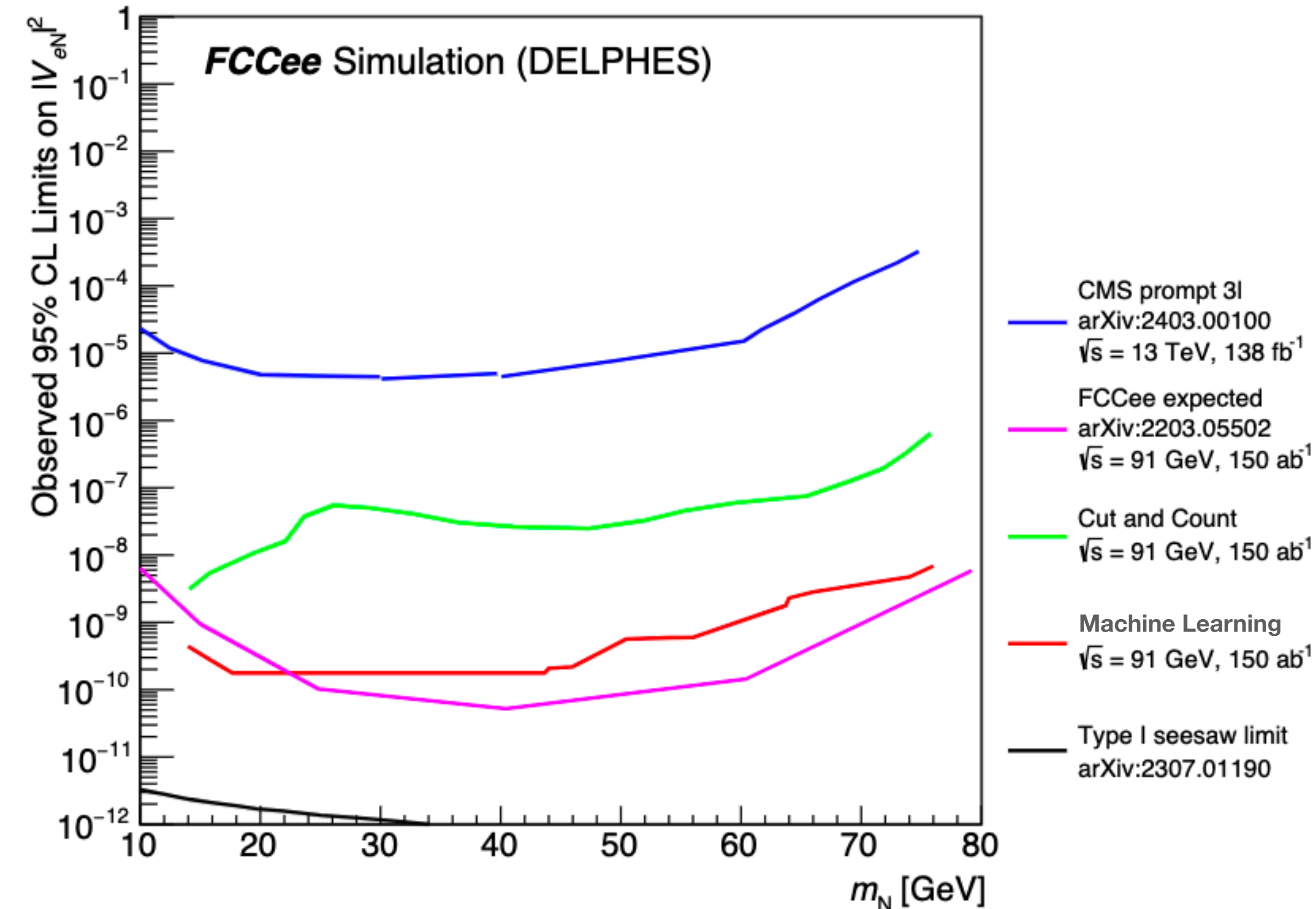
Sensitivity Comparison

- BDT model provides **~2 orders of magnitude** more sensitivity compared to the C&C method and outperforms DNN
- The (current) DNN approach offers **~1 order of magnitude** improvement
 - Hard to optimize but...
 - ...implementing more sophisticated DNN architectures and robust hyperparameter optimization could significantly improve the performance



Summary

*CMS result only for 138 fb⁻¹



- Scaled to 150 ab⁻¹ without accounting for uncertainties, the plot **shows broader phase space coverage compared to the C&C**
- Nearing FCC-ee limits with ~50% of the branching ratio; serves as a guide for improvement
- **ML shows strong potential to improve limits**
- **Increasing MC statistics** in the signal region is **essential** for robust analysis