Deeply Learned Preselection of Dijet Higgs Decays at Future Lepton Colliders

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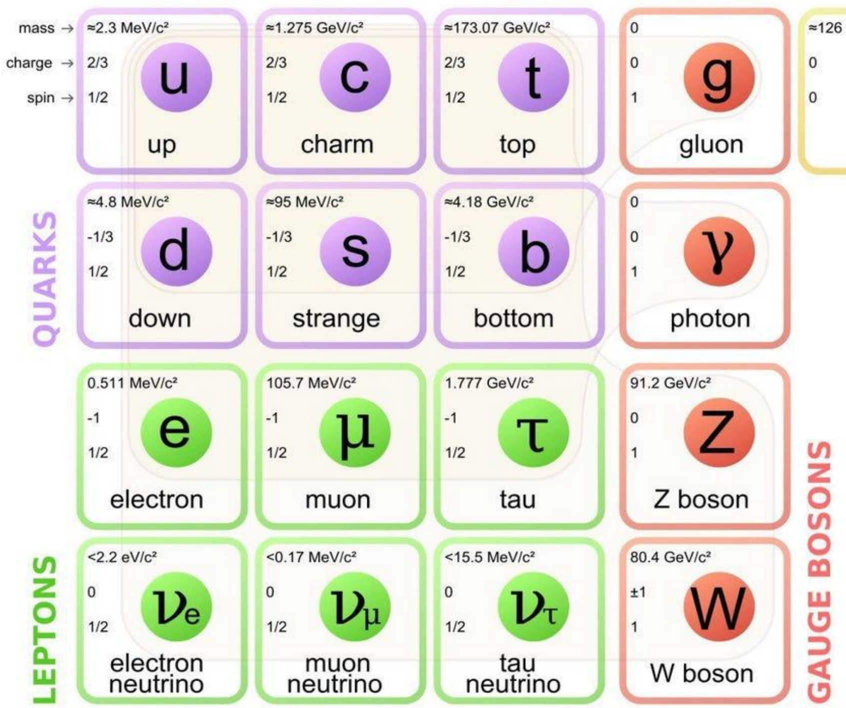
Outline

- Precise measurement of light Yukawa coupling in standard model.

- CEPC in Higgs coupling measurement.

- Preselection at CEPC.
  - Cut-based selection
  - Boosted Decision Tree algorithm
  - Fully-connected neural network algorithm

Yukawa couplings in SM



Why should we test yukawa coupling?

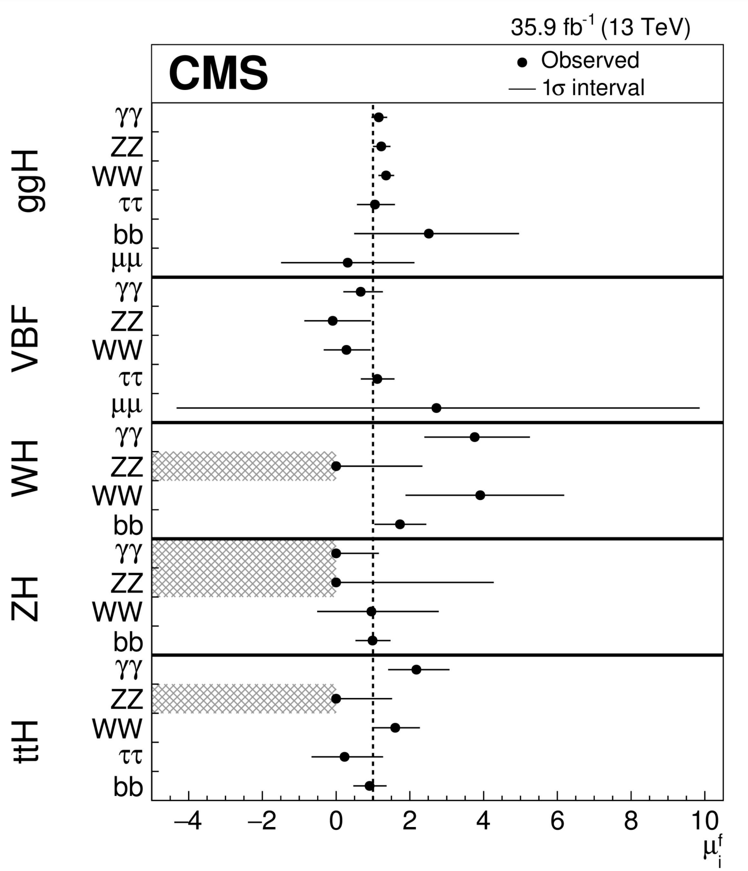
- $m_f \propto y_f v$.
- Potential for new scalar/physics.
- New physics contributions to light fermions can easily dominate over the SM predictions.

- Higgs rare decay: BR($h \to V\gamma$)$\sim 10^{-6}$.
- Flavor violation (eg.$h \to \tau\mu$).
- Jet flavor tagging with ML method

For process $i \to H \to f$, the signal strength is

$$\mu_i^f = \frac{\sigma_i \times BR^f}{(\sigma_i \times BR^f)_{SM}} = \mu_i \times \mu_f$$

Signal Strength

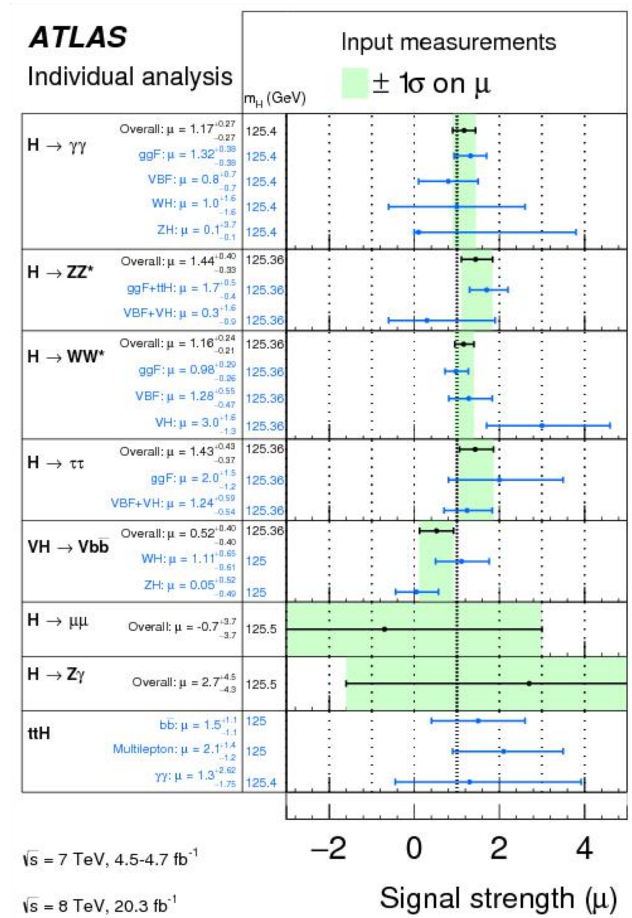


arXiv: 1809.10773

The light fermion signal strength are[1]

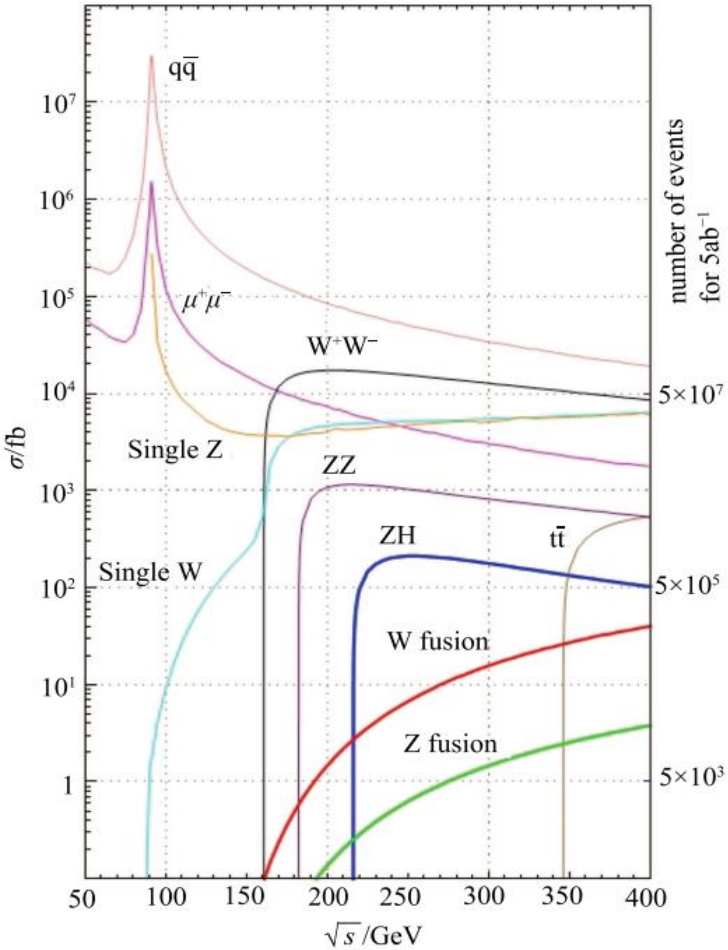
$$\mu_{cc} \lesssim 110, \quad \mu_{ss} \lesssim 7.2 \times 10^8$$

[1] arXiv:1811.09636

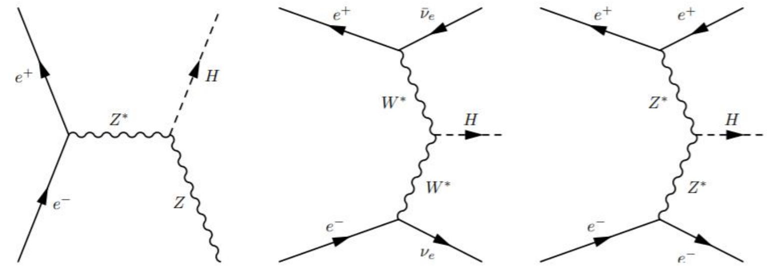


arXiv:1507.04548

CEPC



arXiv:1810.09037



Process	Cross section	Events in 5.6 ab^{-1}
Higgs boson production, cross section in fb		
$e^+e^- \to ZH$	204.7	1.15×10^6
$e^+e^- \to \nu_e\bar{\nu}_e H$	6.85	3.84×10^4
$e^+e^- \to e^+e^- H$	0.63	3.53×10^3
Total	212.1	1.19×10^6
Background processes, cross section in pb		
$e^+e^- \to e^+e^-(\gamma)$ (Bhabha)	850	4.5×10^9
$e^+e^- \to q\bar{q}(\gamma)$	50.2	2.8×10^8
$e^+e^- \to \mu^+\mu^-(\gamma)$ [or $\tau^+\tau^-(\gamma)$]	4.40	2.5×10^7
$e^+e^- \to WW$	15.4	8.6×10^7
$e^+e^- \to ZZ$	1.03	5.8×10^6
$e^+e^- \to e^+e^- Z$	4.73	2.7×10^7
$e^+e^- \to e^+\nu W^- / e^-\bar{\nu} W^+$	5.14	2.9×10^7

Preselection

- Missing mass M_{miss}

$$m_h \leq M_{miss} = \sqrt{E^2 - p_T^2},$$

- p_T, p_L and N_{chd}
- Y_{ij}

  Y_{ij} is the threshold of y-value for clustering jets from $i \to j$.

$$y_{ij} = \frac{2min(E_i^2, E_j^2)(1 - cos\theta_{ij})}{E_{vis}^2}$$

- Di-jet mass M_{jj}

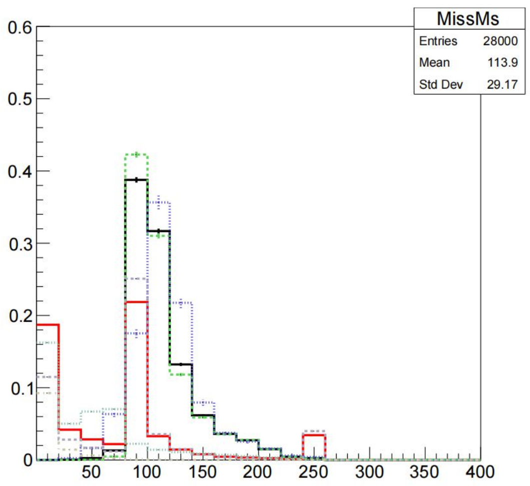
$$M_{jj} = \sqrt{(E_1 + E_2)^2 - (p_1 + p_2)^2},$$

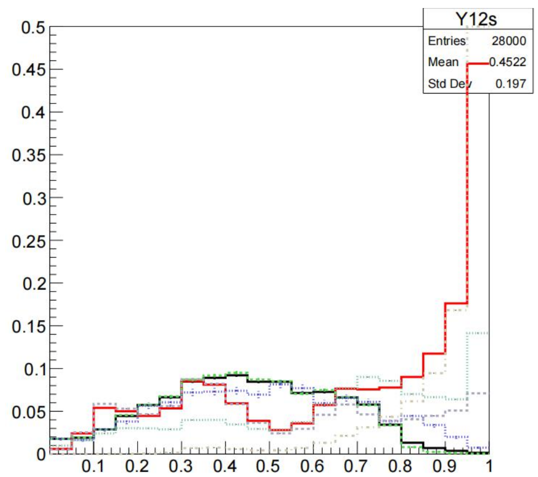
arXiv:1207.0300

CUT-Based Preselection

	$ee \to WW$	$ee \to q\bar{q}$	$ee \to ZZ$	$ee \to e\nu W$	$ee \to eeZ$	$ee \to ZH$	$ee \to WWH$
80GeV$\leq M_{miss} \leq$ 140GeV	452748	33876.3	83565.2	242224	241020	8854	1318
20GeV$\leq p_T \leq$ 70GeV	322171	4376.25	49099.1	169402	144559	8161	1069
$\lvert p_L \rvert \leq$ 60GeV	160461	4043.27	16086.3	83310.8	38178.3	7967	967
$N_{chd} \geq 10$	58722	4008.92	14072.8	4477.92	0	7772	943
$P_{max} \leq$ 30GeV	30168	2618.88	10951.1	446.69	0	6963	852
$Y_{23} \leq 0.02$	4807	2193.41	7545.75	108.919	0	4623	552
$0.2 \leq Y_{12} \leq 0.8$	3745	2008.42	4995.1	90.5619	0	4535	498
100GeV$\leq M_{jj} \leq$ 130GeV	1856	277.479	856.486	50.1762	0	4331	474

Table 1: The result is obtained with $\sqrt{s} = 250GeV$ and $\mathcal{L} = 250fb^{-1}$.

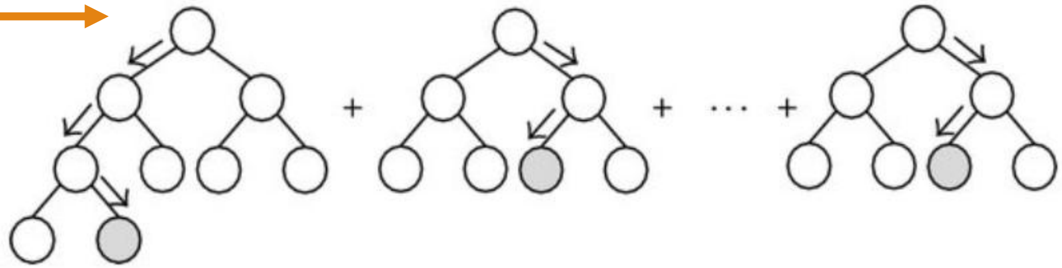




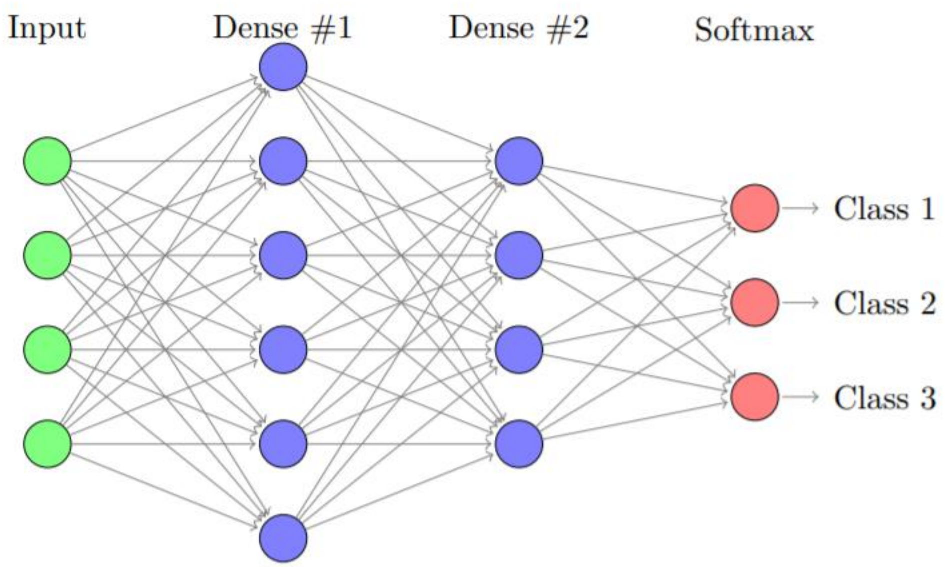
All the quantities are put into the BDT networks and fully-connected neural networks.

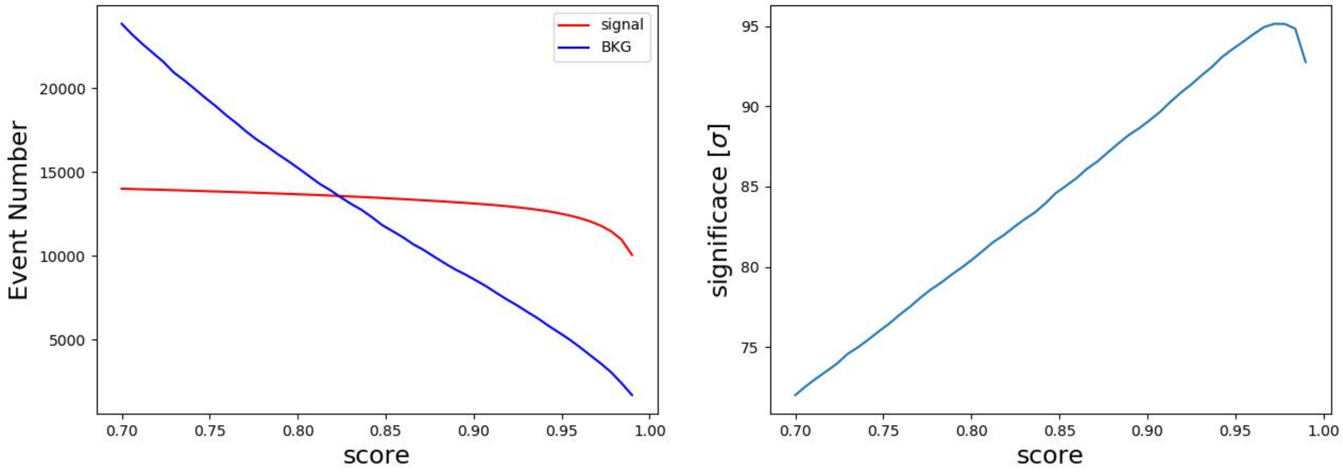
BDT & FCNN networks

BDT input, cut-based physics quantities…

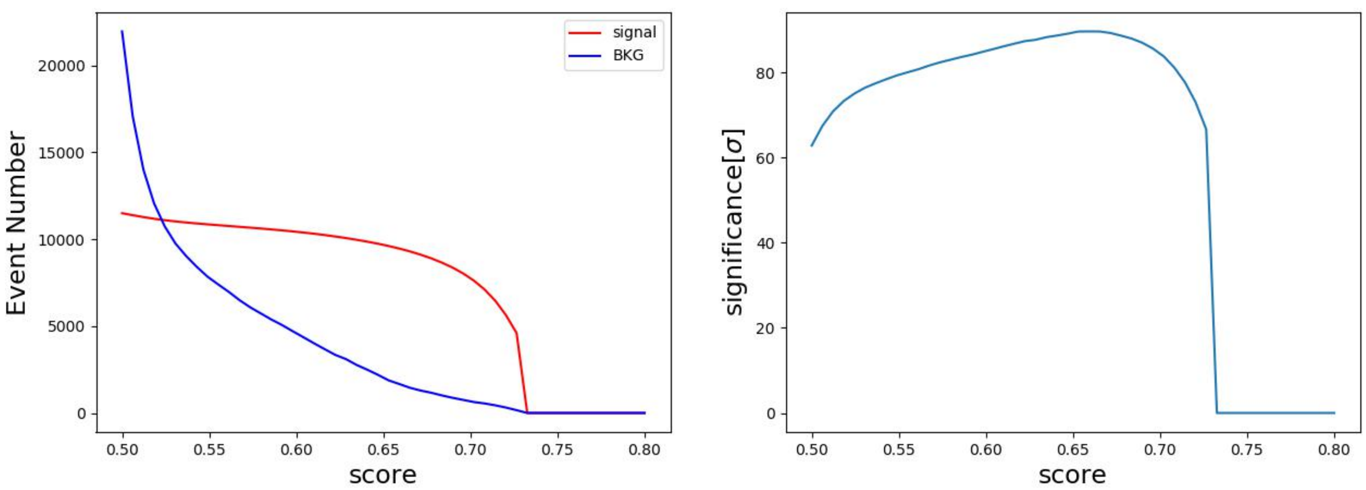


Input data is same with BDT

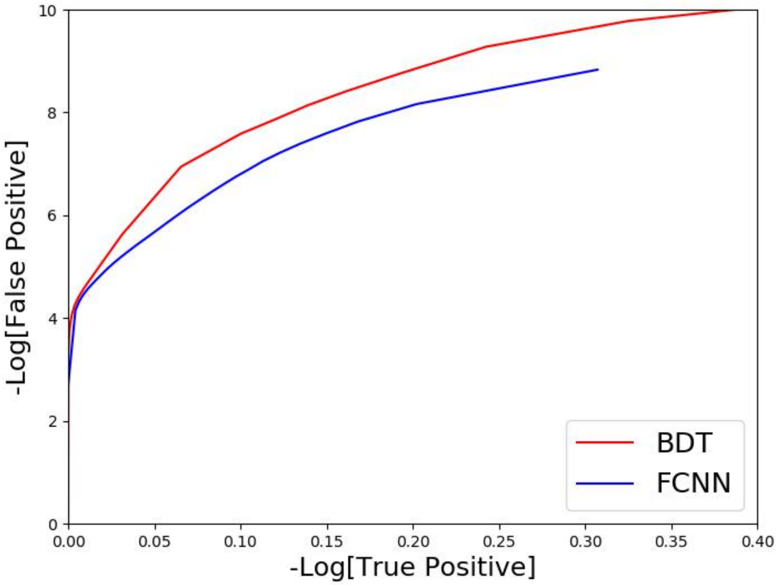




FCNN result



BDT result



	$ee \to WW$	$ee \to q\bar{q}$	$ee \to ZZ$	$ee \to e\nu W$	$ee \to eeZ$	$ee \to ZH$	$ee \to WWH$	Significance
BDT-only	67	195	399	9	0	6721	1044	84.6σ
FCNN-only	835	1101	419	109	1	9562	1423	94.7σ
CNN-only	7012	5407	432	1237	552	4776	747	38.9σ
Cut-based only	1856	277	856	50	0	4331	474	52.7σ
Cut+BDT	11	129	57	1	0	3744	402	62.9σ
Cut+FCNN	105	145	170	0	0	3941	408	63.0σ
Cut+CNN	320	219	486	0	0	3733	408	57.6σ

Table 1: Event number after cut-based selection. The result is obtained with $\sqrt{s} = 250GeV$ and $\mathcal{L} = 250fb^{-1}$.

Results

The deviation from SM predictions is defined as,

$$\sigma^2 \equiv \frac{(N_{\rm exp} - N_{\rm SM})^2}{N_{\rm SM}} \,,$$

The actural and SM branching ratio can be expressed as

$$\begin{aligned} N^{\rm exp} &= N_{jj}\left(\mathrm{Br}(h \to f\bar{f})\epsilon_{ff} + \mathrm{Br}(h \to \mathrm{else})\epsilon_{\rm bkg}^{h\to jj}\right) \\ &+ N_{\mathrm{non}-jj}\epsilon_{\rm bkg}^{\mathrm{non}\to jj} \,, \\ N^{SM} &= N_{jj}\left(\mathrm{Br}^{\rm SM}(h \to f\bar{f})\epsilon_{ff} + \mathrm{Br}^{\rm SM}(h \to \mathrm{else})\epsilon_{\rm bkg}^{h\to jj}\right) \\ &+ N_{\mathrm{non}-jj}\epsilon_{\rm bkg}^{\mathrm{non}\to jj} \,, \end{aligned}$$

where the the signal strength μ_{ff} is defined as

$$\mathrm{Br}(h \to s\bar{s}) = \mu_{ff}\mathrm{Br}^{\rm SM}(h \to s\bar{s}) \,,$$

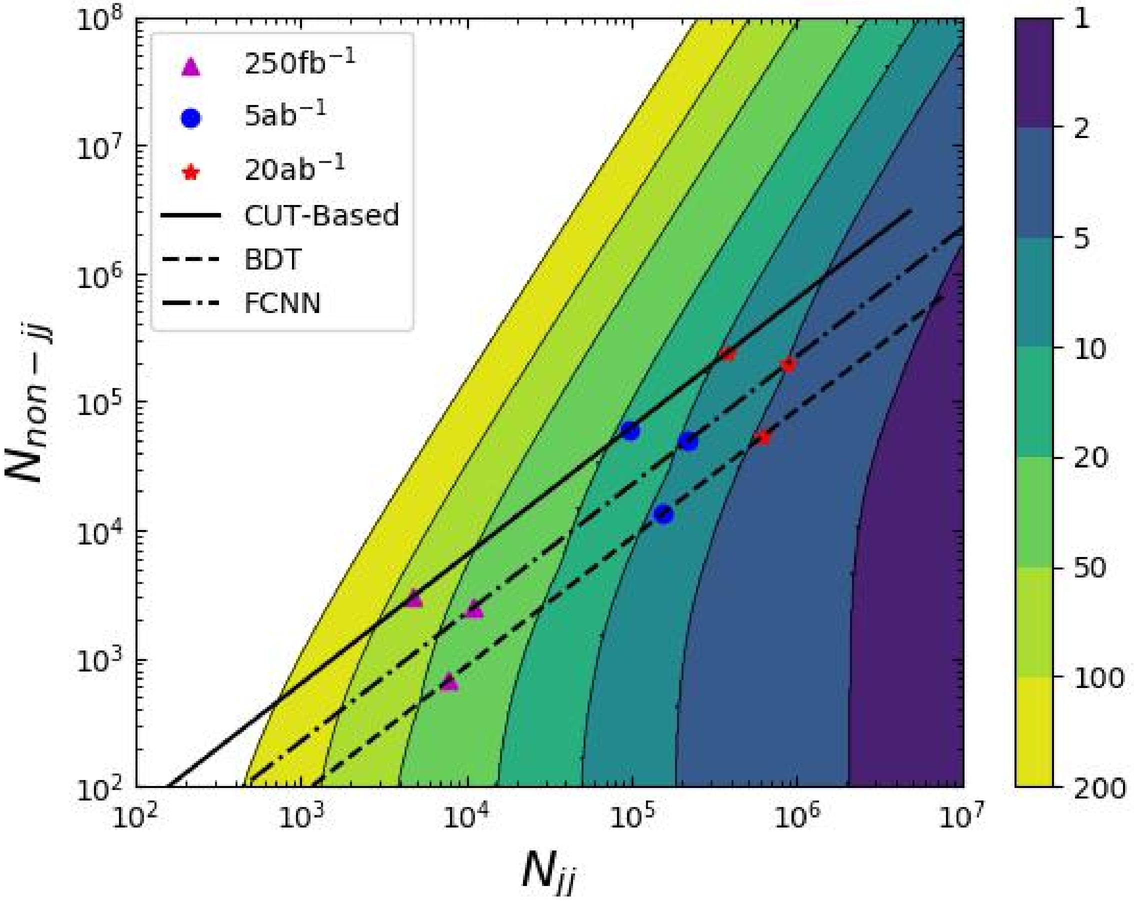
$$\mathrm{Br}(h \to else) = 1 - \mu_{ff}\mathrm{Br}^{\mathrm{SM}}(h \to f\bar{f})\,,$$
$$\mathrm{Br}^{\mathrm{SM}}(h \to else) = 1 - \mathrm{Br}^{\mathrm{SM}}(h \to f\bar{f})\,,$$

so that

$$N_{\exp} - N_{\mathrm{SM}} = N_{jj}\mathrm{Br}^{\mathrm{SM}}(h \to s\bar{s}) \cdot (\mu - 1)\left(\epsilon_{ss} - \epsilon_{\mathrm{bkg}}^{h\to jj}\right)\,.$$

Substitute the equation in the significance σ expression, we have

$$\sigma^2 \equiv \frac{N_{jj}\mathrm{Br}^{\mathrm{SM}}(h \to s\bar{s}) \cdot (\mu - 1)\left(\epsilon_{ss} - \epsilon_{\mathrm{bkg}}^{h\to jj}\right)}{N_{jj}\left(\mathrm{Br}^{\mathrm{SM}}(h \to f\bar{f})\epsilon_{ff} + \mathrm{Br}^{\mathrm{SM}}(h \to \mathrm{else})\epsilon_{\mathrm{bkg}}^{h\to jj}\right) + N_{\mathrm{non}-jj}\epsilon_{\mathrm{bkg}}^{\mathrm{non}\to jj}}$$
$$= F(N_{jj}, N_{\mathrm{non}-jj})$$



250fb^{-1}
5ab^{-1}
20ab^{-1}
CUT-Based
BDT
FCNN
N_{non-jj}
N_{jj}
10^2
10^3
10^4
10^5
10^6
10^7
10^8
1
2
5
10
20
50
100
200

μ_{ss} at CEPC

Summary

- We propose a method to improve the efficiency of preselection in Higgs signal searches at CEPC.
- For this propose we developed three machine learning algorithms including boosted decision tree algorithm, fully-connected neural networks and convolutional neural networks.
- Among all these algorithms, we found the fully-connected neural networks gives the best prediction on Higgs signals. Using such algorithms, we improve the signal strength of s-tagging events from cut-based result, $\mu_{ss} \sim 200$, to FCNN result $\mu_{ss} \sim 50$.