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CEPC

Improve Bs of the Higgs hadronic decays and probe the Higgs CP

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CEPC day @ 2021.12.22

Outline

- Part I
  - Improve the branch ratios of $H \rightarrow b\bar{b}/c\bar{c}/gg$ and other hadonic decays in e+e- → μμ H --- full simulation
- Part II
  - Differential study in the same process: lepton pair of Z used for Higgs CP study --- fast simulation
- Summary

Introduction

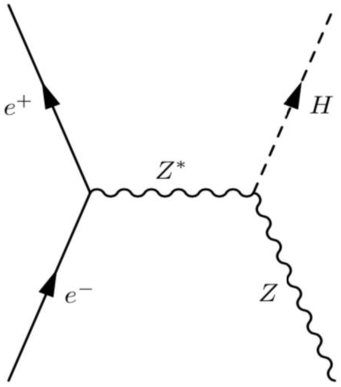
- At CDR stage, the branch ratios of $H \rightarrow b\bar{b}/c\bar{c}/gg$ measured with a 3D-fit method.
- To improve the measurement
  - ✓ Machine learning technique and
  - ✓ Including more decay modes : $H \rightarrow b\bar{b}/c\bar{c}/gg/ww^*/zz^*$
  - ✓ Matrix method to use more information
- Based on counting analysis, differential study is important extensions
  - ✓ The lepton pair of Z used for Higgs CP study

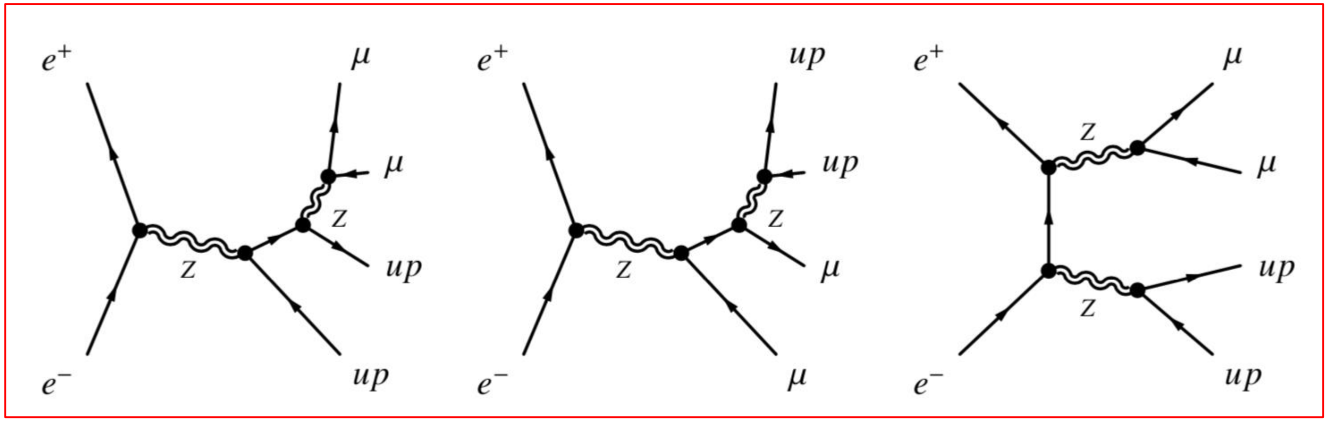
Part I

Brs of $H \to b\bar{b}/c\bar{c}/gg/ww^*/zz^*$

Physics processes

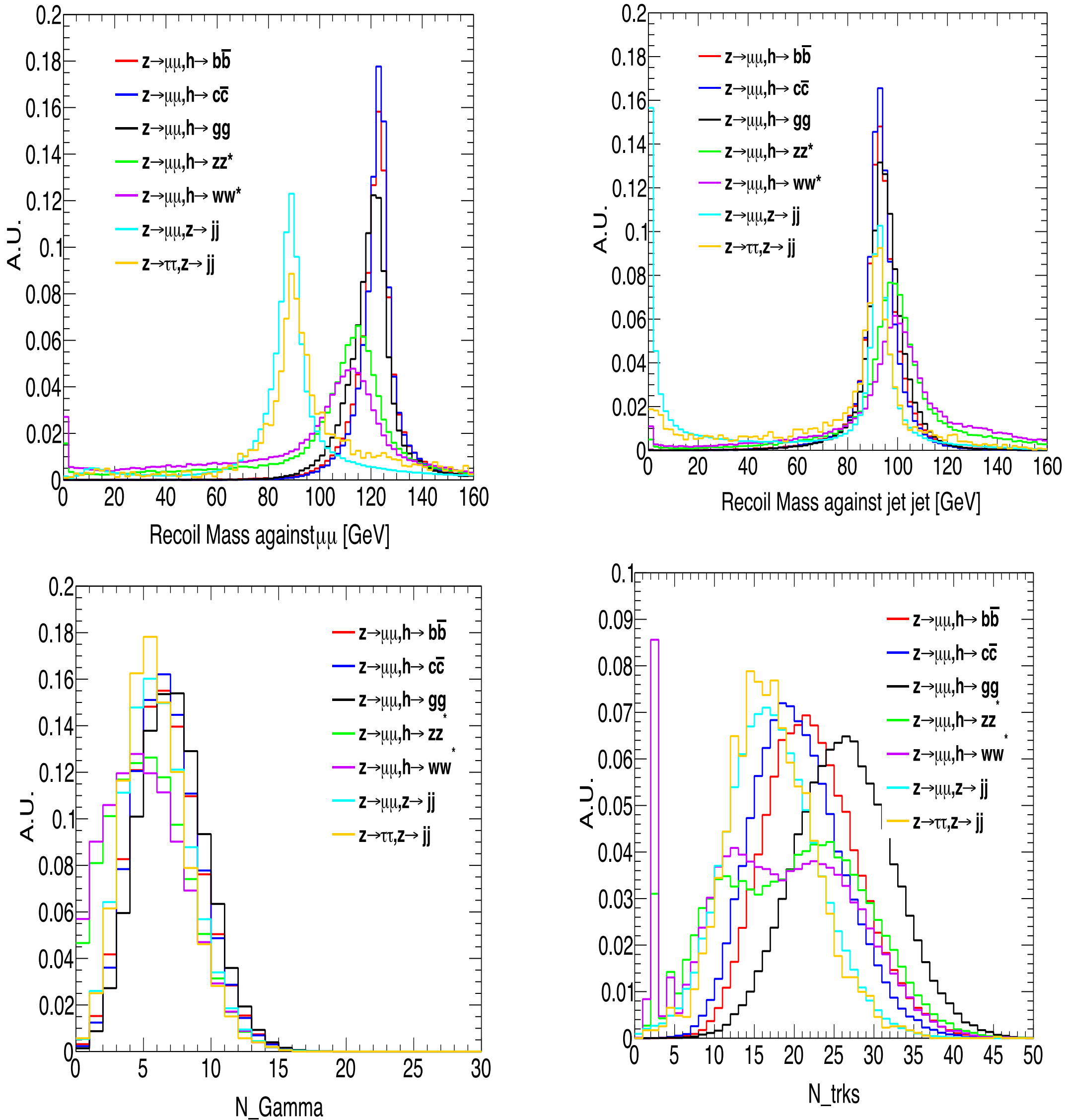
- Bs of $H \to b\bar{b}/c\bar{c}/gg/ww^*/zz^*$ with $\mathrm{Z} \to \mu^+\mu^-$
- Processes
  - Signals: Z($\mu^+\mu^-$) H(bb, cc, gg, WW*, ZZ*)
  - Irreducible Bkgs: $\mu^+\mu^-$qq (e+e- → ZZ)
  - Samples simulated with CEPC_v4 with L = 5.6/ab





Pre-selection

- Cut-based method including several variables cannot separate the different channels very well.
- Machine learning technique could help to improve the performance and make analysis more efficient



Particle Flow Network

➢ PFN : Particle Flow Networks is an architectures designed for learning from collider events.

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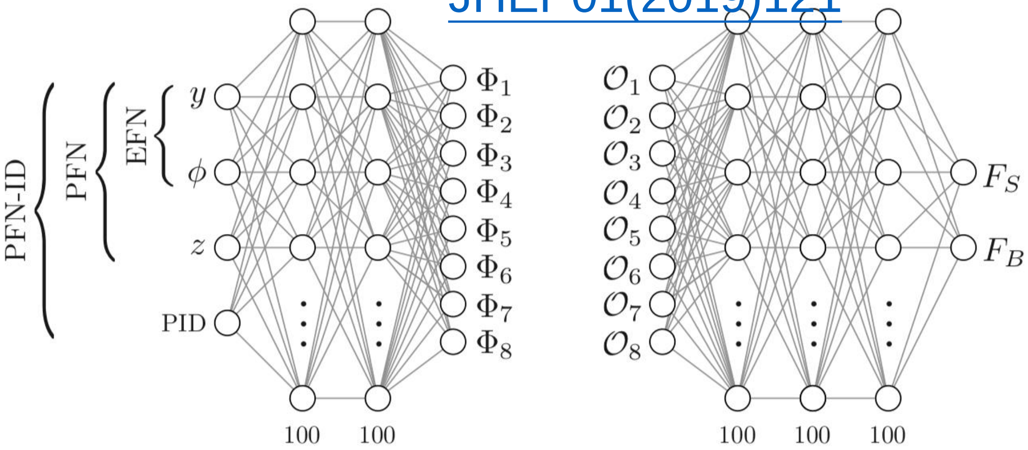
$$PFN = F\left(\sum_{i=1}^{M} \Phi(p_i)\right)$$

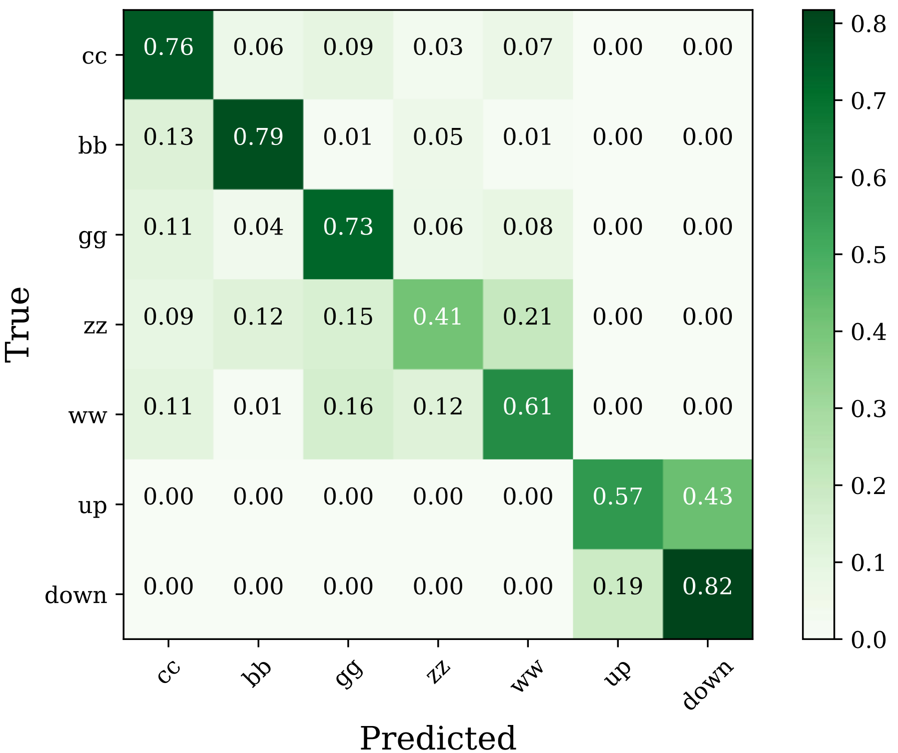


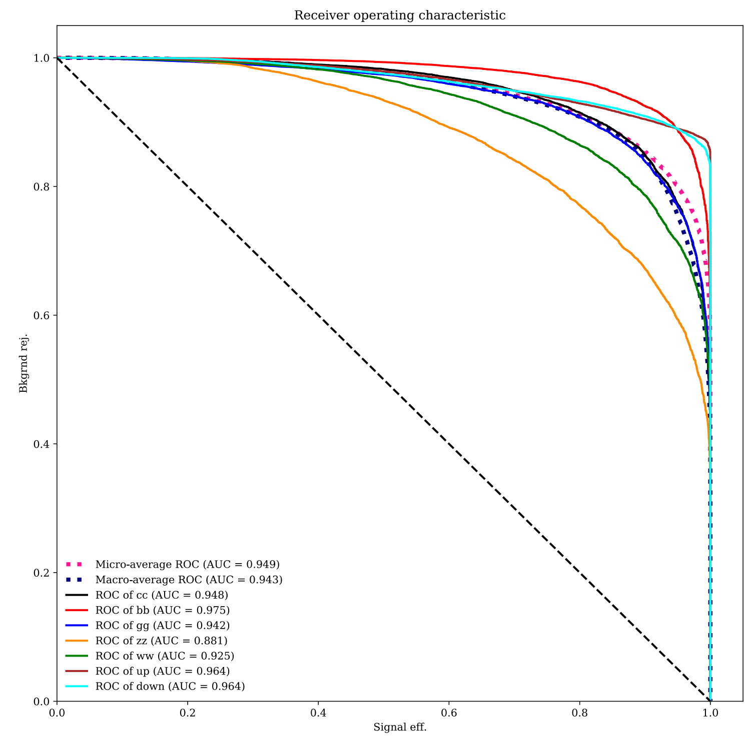
- p_i : the information of particle i, such as four-momentum, charge, or Pid, impact parameter, etc

➢ **Advantage**
  - Use all info at particle level,
  - W/o impacts of jet clustering and e/γ isolation,
  - Multi-classification is possible

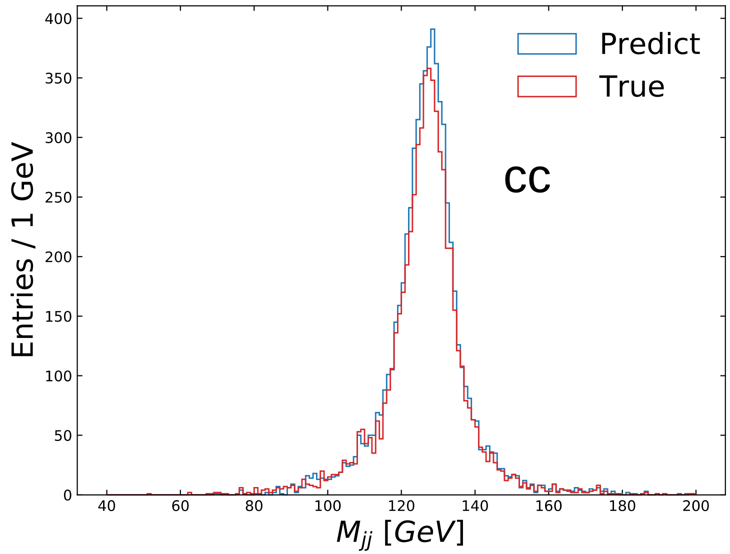
Results of full simulation

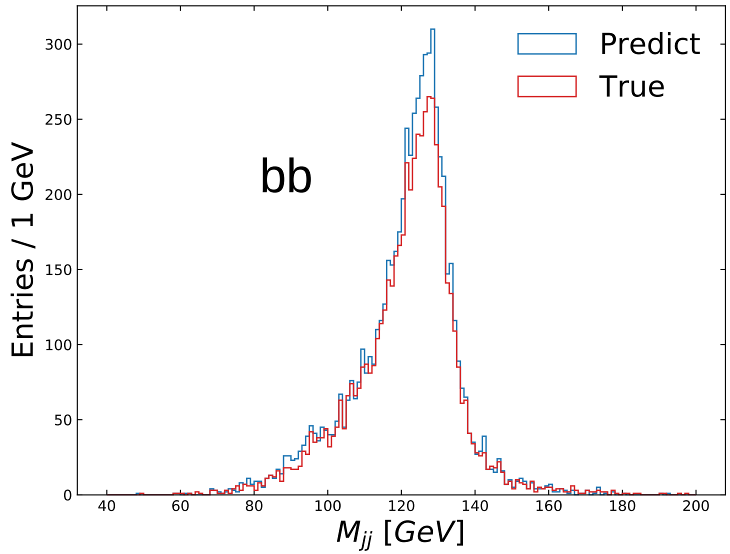
- 5 signals: $b\bar{b}/c\bar{c}/gg/ww^{*}/zz^{*}$
- 2 bkgs: zz_sl0mu_down(down) and zz_sl0mu_up(up).
- Train and validation got consistent losses and accuracies: successful training
- The separation power of $b\bar{b}$ is the best, ZZ* not good as bb

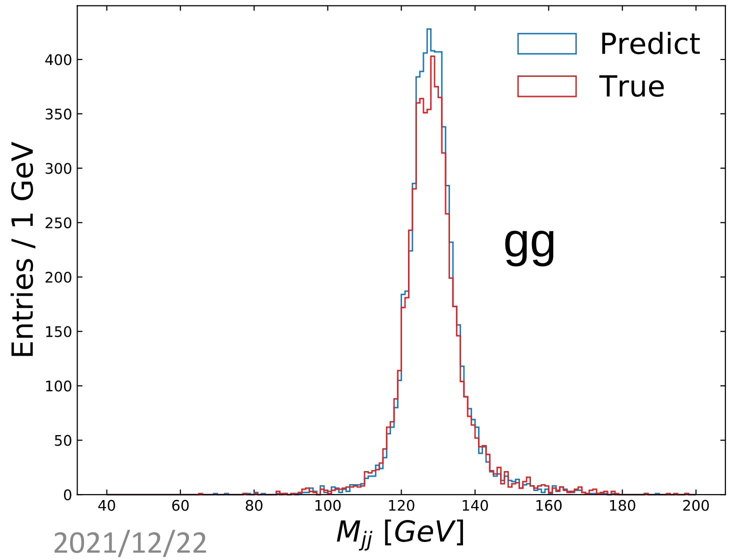




Performance of PFN

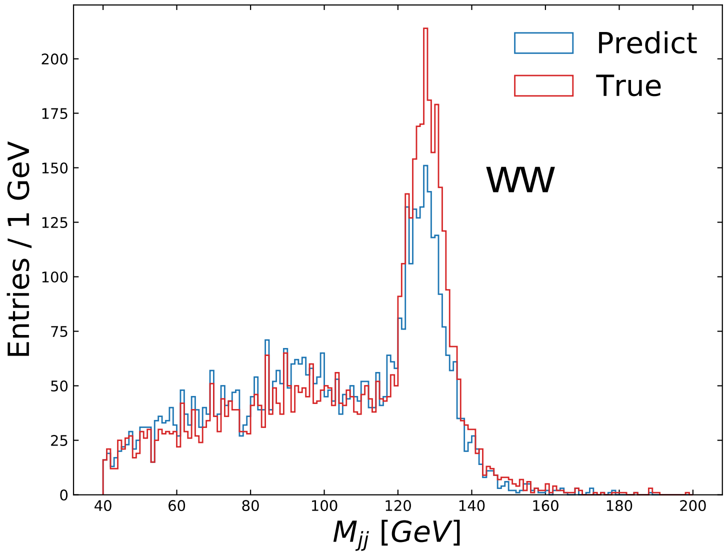


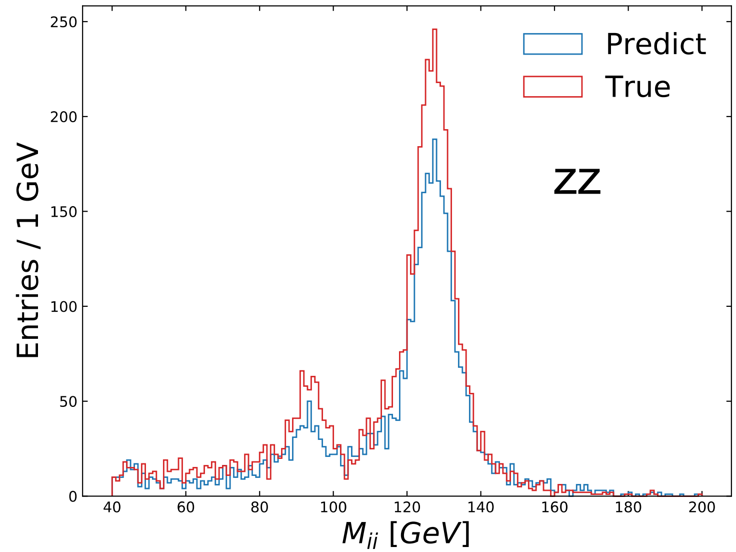


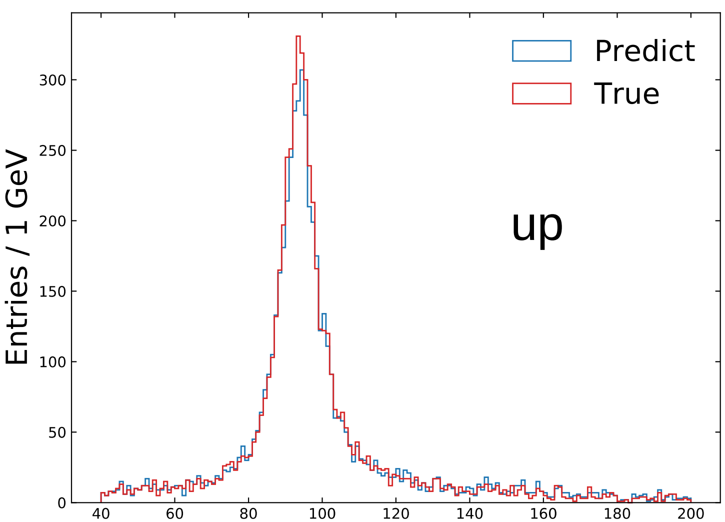


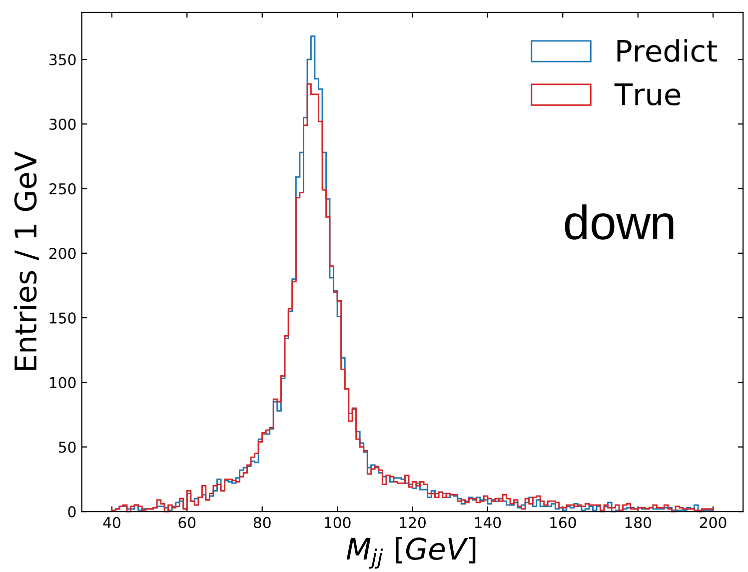
- The comparison between true and prediction on the test sample(10% of the total).
- The predictions of cc, bb and gg are quite good, the differences between predict and true are small.

Performance of PFN









Results

- Use test samples(10% of MC events) to perform the study.
- Scale the MC events according to the cross-section × integrated lumi (5.6 ab^{-1})

	$c\bar{c}$	$b\bar{b}$	gg	zz	ww	up	down
n	1272±36	21435±146	3689±61	8822±94	11709±334	66245±257	105853±325
$\hat{N}$	1079±33	21389±146	3177±56	14189±119	107436±328	72711±270	97784±313
N	1089±33	21539±147	3079±55	14430±119	108045±329	72729±270	98448±314

n : observed number of events of each channel,

$\hat{N}$: the true number of events of each channel,

N : the number of events of each channel, calculated from observed number.

Next to do

- More backgrounds and more statistics
- Optimize the performance of ML model
- Extract the branch ratios with more sophisticated statistical method
- The systematic uncertainties

Part II

Probe the Higgs CP

Introduction

- The SM Higgs: $m_H = 125.10\ GeV,\ \ J^{PC} = 0^{++}$
- Related experiments in LHC:

  Eur. Phys. J. C75 (2015) 476

  - Spin is well determined
  - Study of the CP of the Higgs boson interactions with gauge bosons by the ATLAS and CMS shows no deviations from the SM predictions.
  - Sensitivity need to be improved
- CP could be the mixture of even and odd
- **Any observation of CP odd components of Higgs would be New Physics!**

Theory of H→ZZ*

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The $H \to Zll$ matrix element:

$$\mathcal{M}^{\mu}_{HZ\ell\ell} = \frac{1}{m_H}\bar{u}(p_3,s_3)\left[\gamma^{\mu}(H_{1,V}+H_{1,A}\gamma_5)+\frac{q^{\mu}\not{p}}{m_H^2}(H_{2,V}+H_{2,A}\gamma_5)+\frac{\epsilon^{\mu\nu\sigma\rho}p_\nu q_\sigma}{m_H^2}\gamma_\rho(H_{3,V}+H_{3,A}\gamma_5)\right]v(p_4,s_4)$$

- Where $\epsilon_{0123} = +1$ and $q = p_3 + p_4$.

And the parameters in the function are following:

$$H_{1,V} = -\frac{2m_H(\sqrt{2}G_F)^{1/2}r}{r-s}g_V\left(1+\hat{\alpha}_1^{\rm eff}-\frac{\kappa}{r}\hat{\alpha}_{ZZ}-\frac{\kappa}{2r}\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{AZ}\right)$$

$$H_{1,A} = \frac{2m_H(\sqrt{2}G_F)^{1/2}r}{r-s}g_A\left(1+\hat{\alpha}_2^{\rm eff}-\frac{\kappa}{r}\hat{\alpha}_{ZZ}\right),$$

$$H_{2,V} = -\frac{2m_H(\sqrt{2}G_F)^{1/2}}{r-s}g_V\left[2\hat{\alpha}_{ZZ}+\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{AZ}\right]$$

$$H_{2,A} = \frac{4m_H(\sqrt{2}G_F)^{1/2}}{r-s}g_A\hat{\alpha}_{ZZ}$$

$$H_{3,V} = -\frac{2m_H(\sqrt{2}G_F)^{1/2}}{r-s}g_V\left[2\hat{\alpha}_{Z\tilde{Z}}+\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{A\tilde{Z}}\right]$$

$$H_{3,A} = \frac{4m_H(\sqrt{2}G_F)^{1/2}}{r-s}g_A\hat{\alpha}_{Z\tilde{Z}}$$

$$\hat{\alpha}_1^{\rm eff} \equiv \hat{\alpha}_{ZZ}^{(1)} - \frac{m_H(\sqrt{2}G_F)^{1/2}(r-s)}{2\sqrt{r}}\frac{\hat{\alpha}_{\Phi l}^V}{g_V}$$

$$\hat{\alpha}_2^{\rm eff} \equiv \hat{\alpha}_{ZZ}^{(1)} + \frac{m_H(\sqrt{2}G_F)^{1/2}(r-s)}{2\sqrt{r}}\frac{\hat{\alpha}_{\Phi l}^A}{g_A}$$

(red box) **: SM term**

Others : EFT contribution

This process limited by statistics

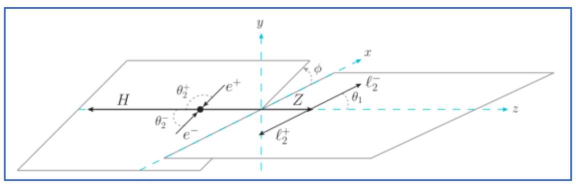
cross symmetry: Z* →ZH:

JHEP 03(2016) 050　　JHEP 11(2014) 028

Differential cross section for $e^+e^- \to Z^* \to ZH \to llH$:

$$\frac{d\sigma}{d\cos\theta_1 d\cos\theta_2 d\phi} = \frac{\mathcal{N}_\sigma(q^2)}{m_H^2}\mathcal{J}(q^2,\theta_1,\theta_2,\phi),$$

$$\mathcal{N}_\sigma(q^2) = \frac{1}{2^{10}(2\pi)^3}\cdot\frac{1}{\sqrt{r}\gamma_Z}\cdot\frac{\sqrt{\lambda(1,s,r)}}{s^2}$$



$$\begin{aligned}\mathcal{J}(q^2,\theta_1,\theta_2,\phi) = {} & J_1(1+\cos^2\theta_1\cos^2\theta_2+\cos^2\theta_1+\cos^2\theta_2) \\ & + J_2\sin^2\theta_1\sin^2\theta_2 + J_3\cos\theta_1\cos\theta_2 \\ & + (J_4\sin\theta_1\sin\theta_2 + J_5\sin 2\theta_1\sin 2\theta_2)\sin\phi \\ & + (J_6\sin\theta_1\sin\theta_2 + J_7\sin 2\theta_1\sin 2\theta_2)\cos\phi \\ & + J_8\sin^2\theta_1\sin^2\theta_2\sin 2\phi + J_9\sin^2\theta_1\sin^2\theta_2\cos 2\phi.\end{aligned}$$

Variables for studying distribution: θ_1, θ_2, ϕ

Assumption for simplification:

- $\delta_{G_F} = \hat{\alpha}_{\phi l}^V = \hat{\alpha}_{\phi l}^A = \hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3}$, others are set to 0, so $H_{2,V/A} = 0$.
- $\hat{\alpha}_{A\tilde{Z}}$ and $\hat{\alpha}_{Z\tilde{Z}}$ have the most contribution for cp-odd.

$$J_1 = 2rs\,(g_A^2+g_V^2)\,(|H_{1,V}|^2+|H_{1,A}|^2),$$

$$J_2 = \kappa\,(g_A^2+g_V^2)\,[\kappa\,(|H_{1,V}|^2+|H_{1,A}|^2)+\lambda\,\mathrm{Re}\,(H_{1,V}H_{2,V}^*+H_{1,A}H_{2,A}^*)],$$

$$J_3 = 32\,r\,s\,g_A\,g_V\,\mathrm{Re}\,(H_{1,V}\,H_{1,A}^*),$$

$$J_4 = 4\kappa\sqrt{rs\lambda}\,g_A\,g_V\,\mathrm{Re}\,(H_{1,V}H_{3,A}^*+H_{1,A}H_{3,V}^*),$$

$$J_5 = \frac{1}{2}\kappa\sqrt{rs\lambda}\,(g_A^2+g_V^2)\,\mathrm{Re}\,(H_{1,V}H_{3,V}^*+H_{1,A}H_{3,A}^*),$$

$$J_6 = 4\sqrt{rs}\,g_A\,g_V\,[4\kappa\,\mathrm{Re}\,(H_{1,V}H_{1,A}^*)+\lambda\,\mathrm{Re}\,(H_{1,V}H_{2,A}^*+H_{1,A}H_{2,V}^*)],$$

$$J_7 = \frac{1}{2}\sqrt{rs}\,(g_A^2+g_V^2)\,[2\kappa\,(|H_{1,V}|^2+|H_{1,A}|^2)+\lambda\,\mathrm{Re}\,(H_{1,V}H_{2,V}^*+H_{1,A}H_{2,A}^*)],$$

$$J_8 = 2rs\sqrt{\lambda}\,(g_A^2+g_V^2)\,\mathrm{Re}\,(H_{1,V}H_{3,V}^*+H_{1,A}H_{3,A}^*),$$

$$J_9 = 2rs\,(g_A^2+g_V^2)\,(|H_{1,V}|^2+|H_{1,A}|^2).$$

6 of these 9 functions are independent

0 in assumption
EFT CP-odd term
Others CP-even contribution

More statistics & negligible backgrounds: μμH has ~36k signals at CEPC

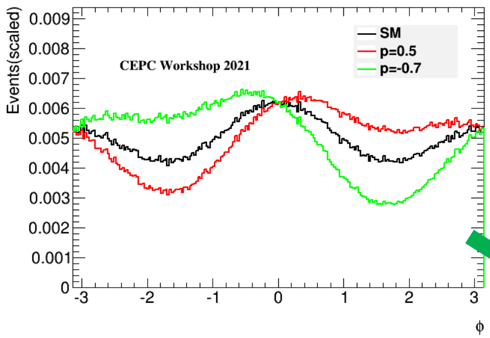
Dimension reduction: an optimal variable approach

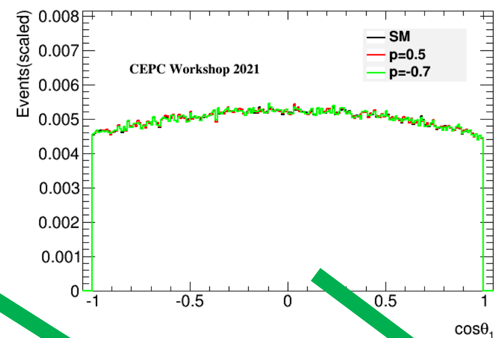
- Differential cross section could be expressed as:

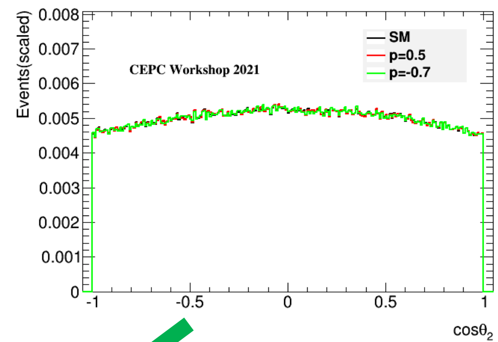
PLB 306（1993）411-417 By M. Davier

$$\frac{d\sigma}{dcos\theta_1 dcos\theta_2 d\phi} = N \times (J_{CP-even}(\theta_1,\theta_2,\phi) + p \times J_{CP-odd}(\theta_1,\theta_2,\phi)).$$

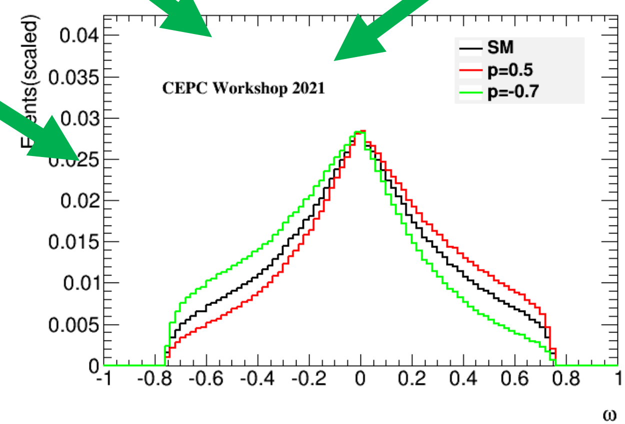
p is an additional global CP-mixing parameter.







Define : $\omega = \frac{J_{CP-odd}(\theta_1,\theta_2,\phi)}{J_{CP-even}(\theta_1,\theta_2,\phi)}$



- 3D fit → 1D problem
- 1D fit is much easier

Event selection

- **Signal**: $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^- H(\rightarrow jj\,)$ channel
- **Background**: Irreducible background which contains the same final states.

- Muon pair selection:

$|cos\theta_{\mu^+\mu^-}| < 0.81$; $Mass_{\mu\mu} \epsilon\ (77.5GeV, 104.5GeV)$; $M_{recoil\_\mu\mu} \epsilon\ (124GeV, 140GeV)$.

- Jets pair selection:

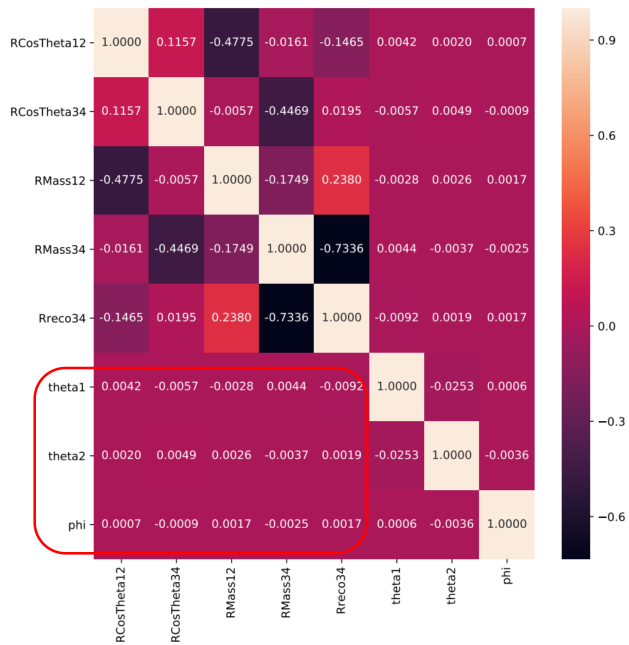
$|cos\theta_{jet}| < 0.96$; $Mass_{jj}\ \epsilon\ (100GeV, 150GeV)$.

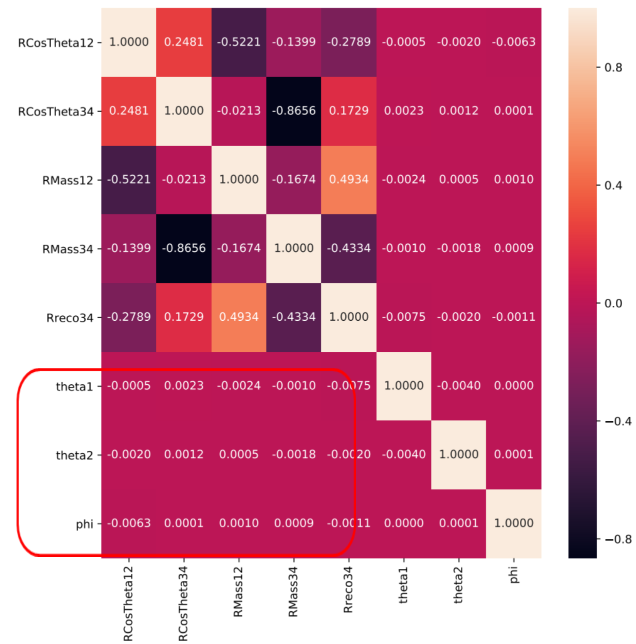
Results of event selection

$ZH \rightarrow \mu^+\mu^- + b\bar{b}/c\bar{c}/\mathrm{gg}$ **channel**		
	Signal	Irreducible Bkg
Original	28627	1251768
Muon pair selection	18555 (efficiency:64.8%)	11198 (efficiency:0.9%)
All selection	13405 (efficiency:46.8%)	3610 (efficiency:0.3%)

Higgs CP-mixing measurement

- **Correlation check**
  - We can see that $\theta_1,\ \theta_2, \phi$ have negligible correlation with $cos\theta_{\mu^+\mu^-}$, $\text{Mass}_{\mu\mu}$, $M_{recoil\_\mu\mu}$, $cos\theta_{jet}$, Mass_{jj}.

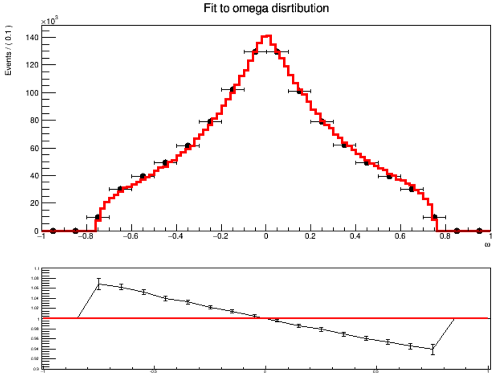




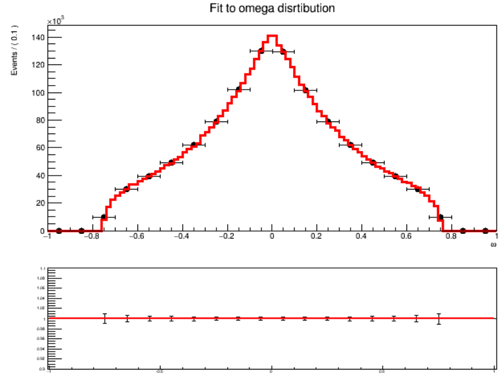
- Impacts of event selections on $\theta_1,\ \theta_2, and\ \phi$ neglected next

Fitting strategy and result

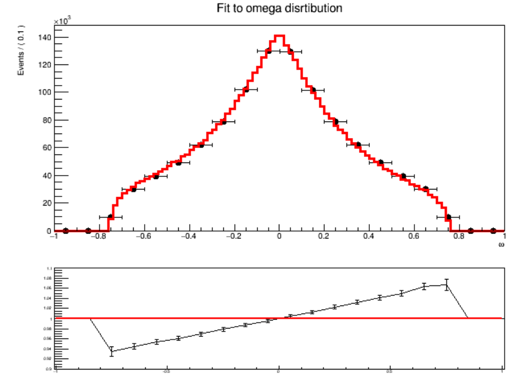
- Fit strategy:
  - Maximum-likelihood $of\ f^{p}(\omega) = N_{sig} * f^{p}_{sig}(\omega) + N_{bkg} * f^{p}_{bkg}(\omega)$
  - **Fit to ω for signal and bkg shape, $f^{p}_{sig}(\omega)$ and $f^{p}_{bkg}(\omega)$**
  - **Fit to $M_{recoil\_\mu\mu}$ for N_{sig} and N_{bkg}**
  - Evaluate likelihood function for each p value hypothesis, and construct a ΔNLL as a function of p.



P= 0.09 vs p= 0



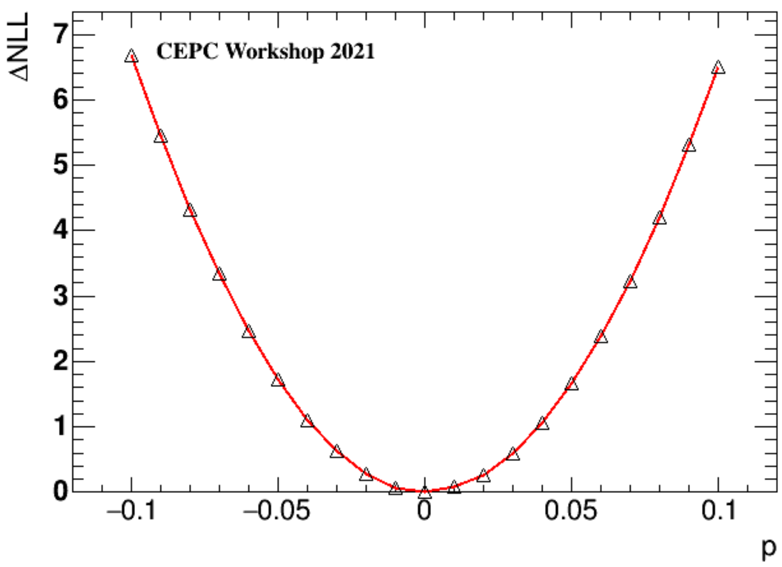
P= 0 vs p= 0



P= -0.09 vs p= 0

Fitting strategy and result

- Extract maximum-likelihood fit p-value and interval
  - Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
  - 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
  - Assumption: $\hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3}$.



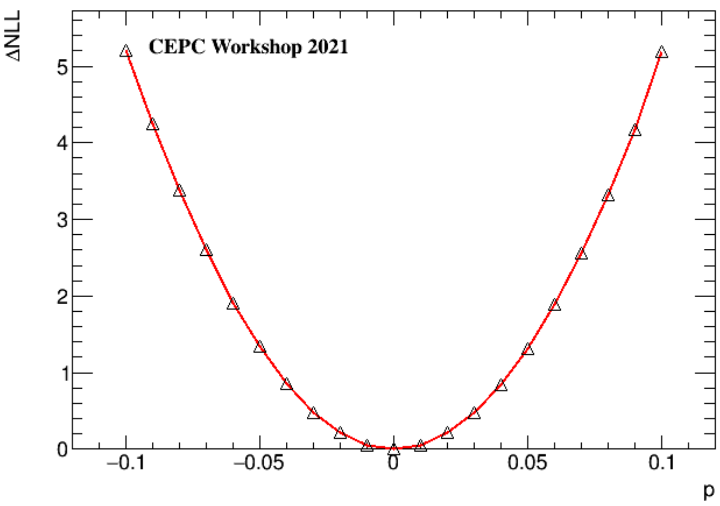
$\boldsymbol{\Delta NLL(p|\omega) = 659.6(p - 5.6 \times 10^{-4})^2}$

For p:
68% CL: $[-2.79 \times 10^{-2}, 2.70 \times 10^{-2}]$
95% CL: $[-5.52 \times 10^{-2}, 5.40 \times 10^{-2}]$

$\hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3} \times \mathrm{p}$

Fitting strategy and result

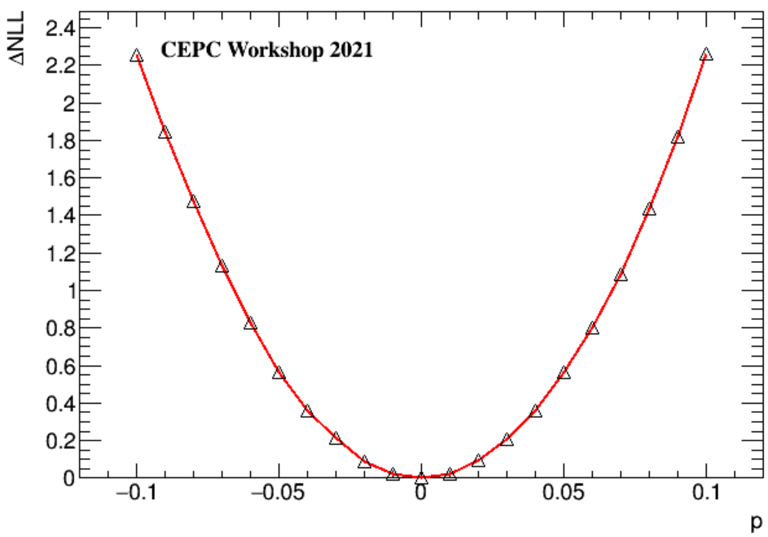
- Extract maximum-likelihood fit p-value and interval
  - Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
  - 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
  - Assumption: $\hat{\alpha}_{A\tilde{Z}} = 10^{-3},\ \hat{\alpha}_{Z\tilde{Z}} = 0.$



$\boldsymbol{\Delta NLL(p|\omega)} =$
$\mathbf{519.53(p - 2.32 \times 10^{-4})^2}$
For p:
68% CL:
$[-3.13 \times 10^{-2}, 3.08 \times 10^{-2}]$
95% CL:
$[-6.17 \times 10^{-2}, 6.12 \times 10^{-2}]$
$\hat{\alpha}_{A\tilde{Z}} = 10^{-3} \times \mathrm{p}$

Fitting strategy and result

- Extract maximum-likelihood fit p-value and interval
  - Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
  - 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
  - Assumption: $\hat{\alpha}_{A\tilde{Z}} = 0,\ \hat{\alpha}_{Z\tilde{Z}} = 5 \cdot 10^{-3}$.



$\boldsymbol{\Delta NLL(p|\omega) = 226.22(p - 2.73 \times 10^{-4})^2}$

For p:

68% CL:

$[-4.73 \times 10^{-2}, 4.67 \times 10^{-2}]$

95% CL:

$[-9.34 \times 10^{-2}, 9.28 \times 10^{-2}]$

$\hat{\alpha}_{Z\tilde{Z}} = 5 \cdot 10^{-3} \times p$

Result compare

- HL-LHC: (1σ) arXiv:1902.00134

Analysis \ Parameter	$\tilde{c}_{Z\gamma}$	$\tilde{c}_{ZZ}$	Case
HL-LHC (4ℓ, incl.)	[-0.22,0.22]	[-0.33,0.33]	1P
	[-0.25,0.25]	[-0.27,0.27]	$1P_{marg.}$
HL-LHC (4ℓ, diff.)	[-0.10,0.10]	[-0.31,0.31]	1P
	[-0.13,0.13]	[-0.22,0.22]	$1P_{marg.}$
HE-LHC (4ℓ, incl.)	[-0.18,0.18]	[-0.17,0.17]	1P
	[-0.23,0.23]	[-0.20,0.20]	$1P_{marg.}$
HE-LHC (4ℓ, diff.)	[-0.05,0.05]	[-0.13,0.13]	1P
	[-0.06,0.06]	[-0.10,0.10]	$1P_{marg.}$

This study:

	$\tilde{c}_{Z\gamma}$	$\tilde{c}_{ZZ}$
68% CL(1σ)	$[-2.70 \times 10^{-4}, 2.66 \times 10^{-4}]$	$[-1.73 \times 10^{-4}, 1.70 \times 10^{-4}]$
95% CL(2σ)	$[-5.32 \times 10^{-4}, 5.28 \times 10^{-4}]$	$[-3.41 \times 10^{-4}, 3.39 \times 10^{-4}]$

Summary

- A Higgs hadronic decay study is ongoing with ML method and full simulation shows promising performance.
- An EFT based Higgs CP-mixing test is performed.
  - Using ML-fit to optimal variable ω and extract p.
  - Result: 95% CL $p \in [-5.5 \times 10^{-2}, 5.4 \times 10^{-2}]$,
    - Sensitivity : $\delta G_F, \hat{\alpha}_{\phi l}^{V}, \hat{\alpha}_{\phi l}^{A}, \hat{\alpha}_{A\tilde{Z}}, \hat{\alpha}_{Z\tilde{Z}} < 10^{-4}$, much better than LHC
- Both two studies need more validations and to be finalized in near future

Backup

Method to extract production numbers

- A simple example, only $H \to b\bar{b}$ and $H \to c\bar{c}$.

$$\begin{pmatrix} n_b \\ n_c \end{pmatrix} = \begin{pmatrix} \epsilon_{bb} & \epsilon_{bc} \\ \epsilon_{cb} & \epsilon_{cc} \end{pmatrix} \begin{pmatrix} N_b \\ N_c \end{pmatrix} \qquad n = EN$$

- n_i : the observed number of events of i class,
- N_i : the production number of events of i class,
- ϵ_{ij} : the rate of state i reconstructed to be state j.

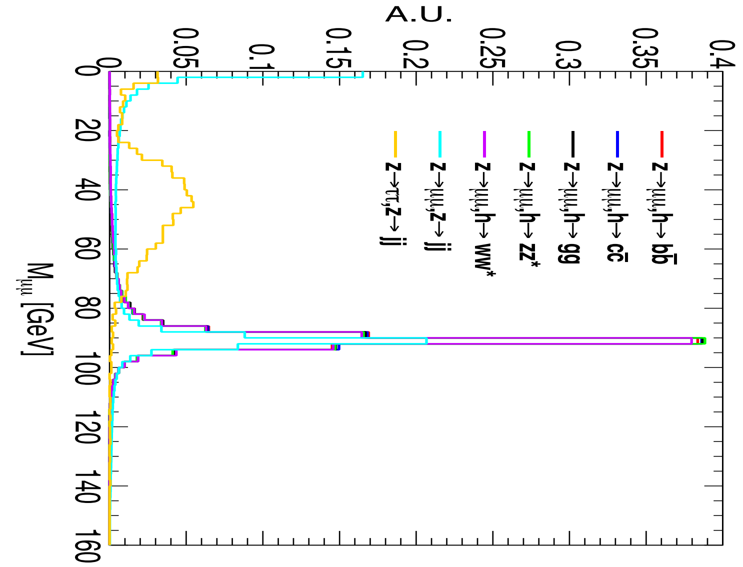
- If we can measure the matrix E, then $N = E^{-1}n$
- The PFN is used to extract the matrix.

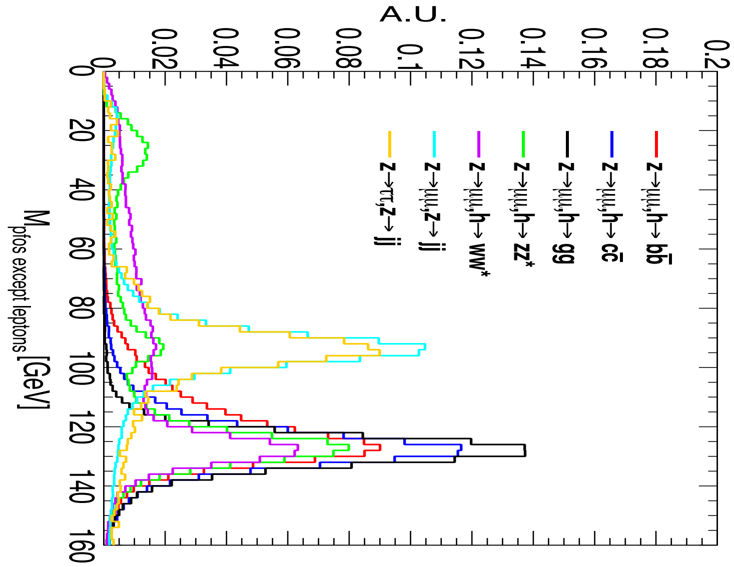
Backup

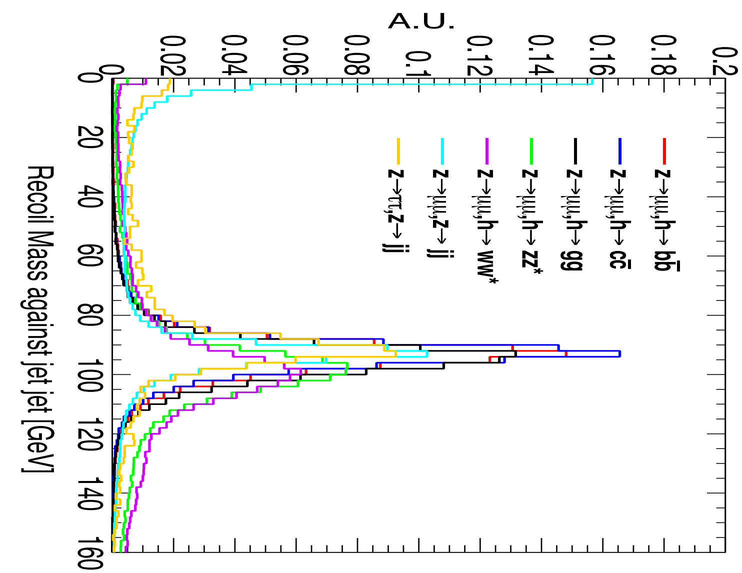
Table 2. Uncertainties on $\sigma^{b\bar{b}}_{l^+l^-H}$, $\sigma^{c\bar{c}}_{l^+l^-H}$ and $\sigma^{gg}_{l^+l^-H}$.

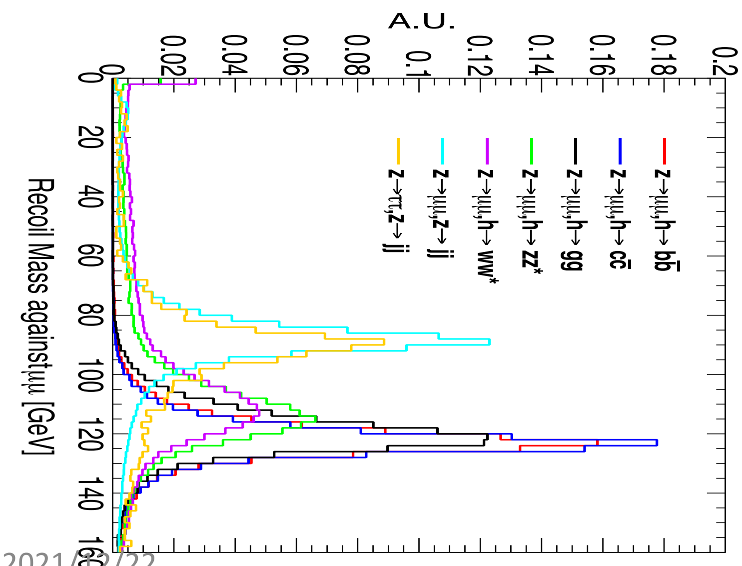
Higgs boson production	$\mu^+\mu^-H$			e^+e^-H		
Higgs boson decay	$H \to b\bar{b}$	$H \to c\bar{c}$	$H \to gg$	$H \to b\bar{b}$	$H \to c\bar{c}$	$H \to gg$
statistic uncertainty	1.1%	10.5%	5.4%	1.6%	14.7%	10.5%
fixed background	−0.2% +0.1%	+4.1% −4.2%	7.6%	−0.2% +0.1%	+4.1% −4.2%	7.6%
event selection	+0.7% −0.2%	+0.4% −1.1%	+0.7% −1.7%	+0.7% −0.2%	+0.4% −1.1%	+0.7% −1.7%
flavor tagging	−0.4% +0.2%	+3.7% −5.0%	+0.2% −0.7%	−0.4% +0.2%	+3.7% −5.0%	+0.2% −0.7%
combined systematic uncertainty	+0.7% −0.5%	+5.5% −6.6%	+7.6% −7.8%	+0.7% −0.5%	+5.5% −6.6%	+7.6% −7.8%

Pre-selection





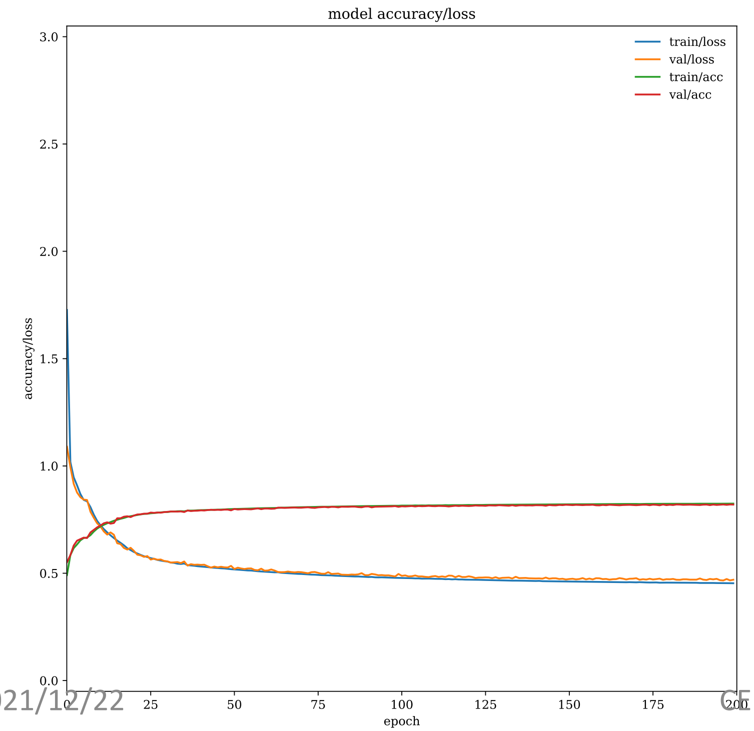


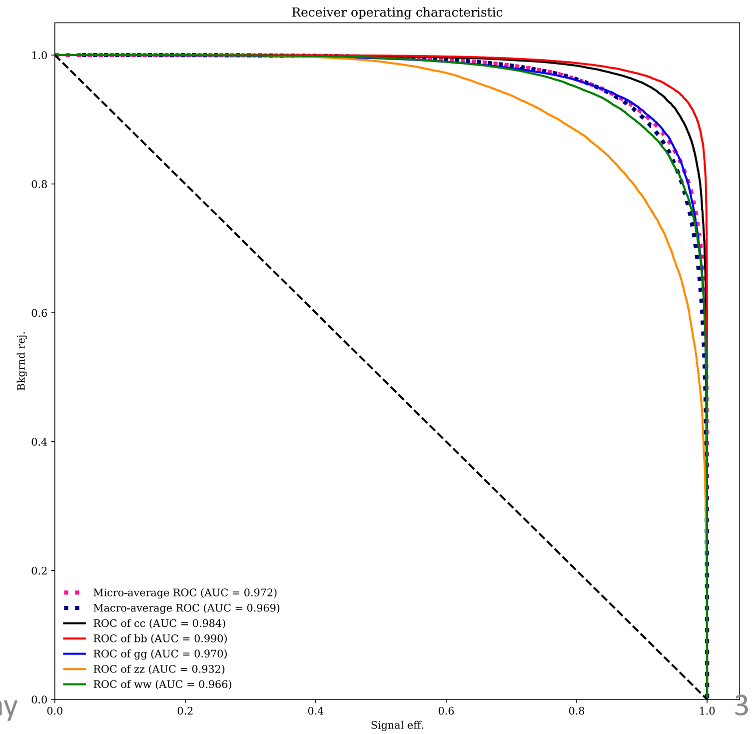


Results of fast simulation

- Fast simulation sample : only has $b\bar{b}/c\bar{c}/gg/ww^*/zz^*$.
- Tiny difference at loss between train and validation.
- From the ROC curve, the separation power of $b\bar{b}$ is highest, zz^* is lowest.

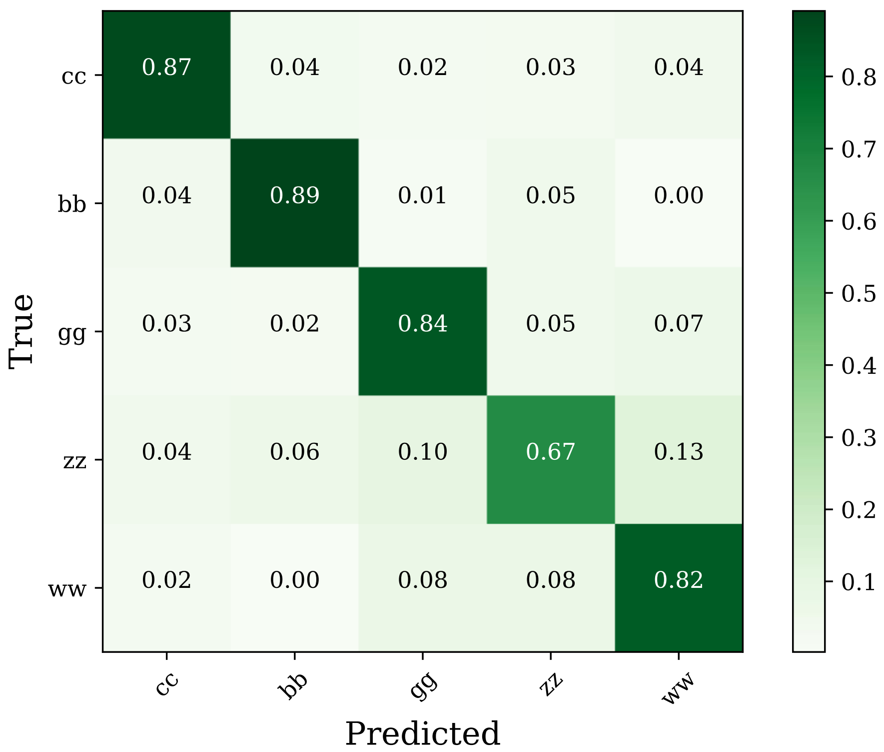
https://github.com/Wujinfei/HiggsHadron-PFNs-gpu.git

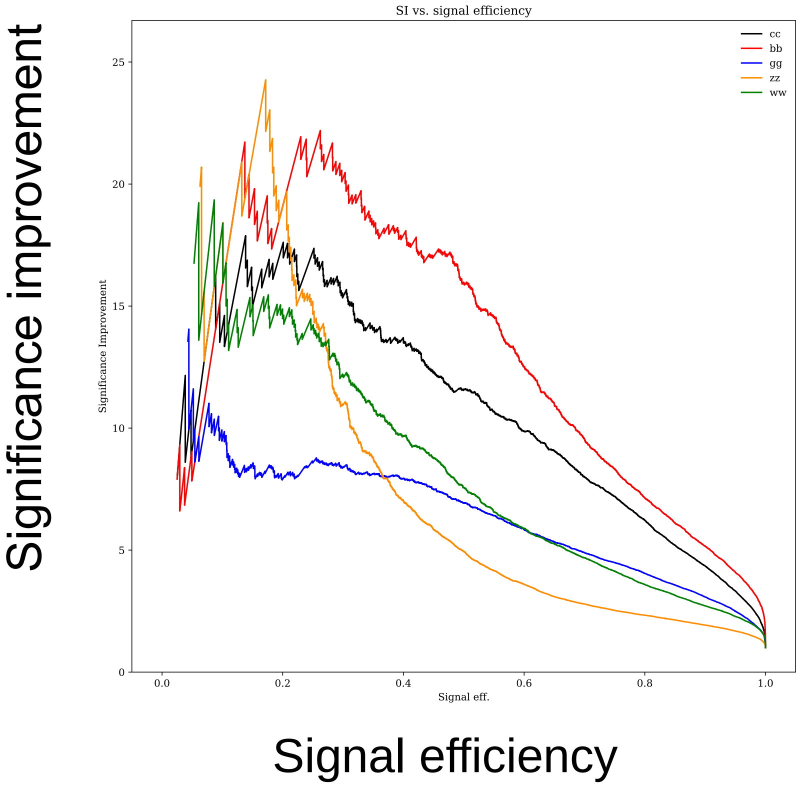




Results of fast simulation

- The performance of PFN on fast simulation is good, except the zz^* calss.





Comparison between fast and full simulation

- Why is the performance of full simulation worse than fast simulation:
  - Fast simulation has larger statistic than full simulation.
  - Maybe due to the reconstruction is not perfect.
  - Fewer training epochs of full simulation.

- Possible ways to improve the training performance
  - Include more input variables,
  - Generate more full simulation samples.

Theory of H→ZZ*

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In a 6-dimension EFT model: $\mathcal{L}_{eff} = \mathcal{L}_{SM}^{(4)} + \frac{1}{\Lambda^2}\sum_{k=1}^{59} \alpha_k \mathcal{O}_k \; (\mathcal{L}_{BSM})$

- $\mathcal{L}_{eff} \supset c_{ZZ}^{(1)} H Z_\mu Z^\mu + c_{ZZ}^{(2)} H Z_{\mu\nu} Z^{\mu\nu} + c_{Z\tilde{Z}} H Z_{\mu\nu} \tilde{Z}^{\mu\nu} + c_{AZ} H Z_{\mu\nu} A^{\mu\nu} + c_{A\tilde{Z}}^{HZ_{\mu\nu}} \tilde{A}^{\mu\nu}$
  $+ H Z_\mu \bar{\ell} \gamma^\mu (c_V + c_A \gamma_5) \ell + Z_\mu \bar{\ell} \gamma^\mu (g_V - g_A \gamma_5) \ell - g_{em} Q_\ell A_\mu \bar{\ell} \gamma^\mu \ell$

Where: $c_{ZZ}^{(1)} = m_Z^2 \left(\sqrt{2} G_F\right)^{1/2} \left(1 + \hat{\alpha}_{ZZ}^{(1)}\right), c_{ZZ}^{(2)} \& = \left(\sqrt{2} G_F\right)^{1/2} \hat{\alpha}_{ZZ}, c_{Z\tilde{Z}} \& = \left(\sqrt{2} G_F\right)^{1/2} \hat{\alpha}_{Z\tilde{Z}},$

$$c_{AZ} = \left(\sqrt{2} G_F\right)^{1/2} \hat{\alpha}_{AZ}, \; c_{A\tilde{Z}} = \left(\sqrt{2} G_F\right)^{1/2} \hat{\alpha}_{A\tilde{Z}}.$$

- In this base, the G_F, m_z, α_{em} could be expressed

  $m_z = m_{Z0}(1 + \delta_Z), \; G_F = G_{F0}\left(1 + \delta_{G_F}\right), \; \alpha_{em} = \alpha_{em0}(1 + \delta_A)$

  where: $\delta_Z = \hat{\alpha}_{ZZ} + \frac{1}{4}\hat{\alpha}_{\Phi D}, \; \delta_{G_F} = -\hat{\alpha}_{4l} + 2\hat{\alpha}_{\Phi l}^{(3)}, \; \delta_A = 2\hat{\alpha}_{AA}.$

Compared with HL-LHC

- In HL-LHC: arXiv:1902.00134

$$\mathcal{L}_{\mathrm{CPV}} = \frac{H}{v}\left[\tilde{c}_{\gamma\gamma}\frac{e^2}{4}A_{\mu\nu}\tilde{A}^{\mu\nu} + \tilde{c}_{Z\gamma}\frac{e\sqrt{g_1^2+g_2^2}}{2}Z_{\mu\nu}\tilde{A}^{\mu\nu} + \tilde{c}_{ZZ}\frac{g_1^2+g_2^2}{4}Z_{\mu\nu}\tilde{Z}^{\mu\nu} + \tilde{c}_{WW}\frac{g_2^2}{2}W^+_{\mu\nu}\tilde{W}^{\mu\nu}\right]$$

Compare theory model in P5, we can get that the value in red frame are same:

(g1=0.358, g2=0.648, e=0.313, $v = 1/\sqrt{\sqrt{2}G_F^0} = 2M_W/g \approx 246.22\mathrm{GeV}$)

$$\left(\sqrt{2}G_F\right)^{1/2}\hat{\alpha}_{Z\tilde{Z}}HZ_{\mu\nu}\tilde{Z}^{\mu\nu} = \frac{H}{v}\tilde{c}_{ZZ}\frac{g_1^2+g_2^2}{4}Z_{\mu\nu}\tilde{Z}^{\mu\nu}$$

$$\frac{g_1^2+g_2^2}{4} = 0.137$$

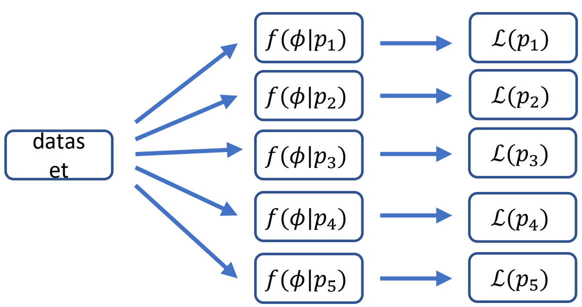
$$\left(\sqrt{2}G_F\right)^{1/2}\hat{\alpha}_{A\tilde{Z}}HZ_{\mu\nu}\tilde{A}^{\mu\nu} = \frac{H}{v}\tilde{c}_{Z\gamma}\frac{\mathrm{e}\sqrt{g_1^2+g_2^2}}{2}Z_{\mu\nu}\tilde{A}^{\mu\nu}$$

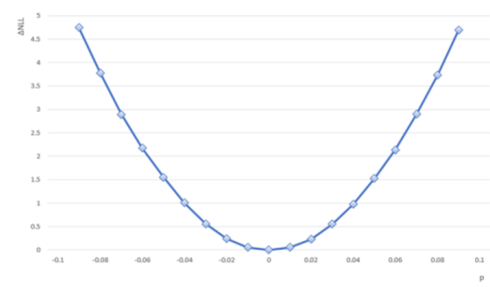
$$\frac{\mathrm{e}\sqrt{g_1^2+g_2^2}}{2} = 0.116$$

Maximum likelihood fit

- Construct a likelihood function
  - $\mathcal{L}(\vec{x}|p,\vec{\theta}) = \prod_{data} f(x_i\,|p,\vec{\theta})$

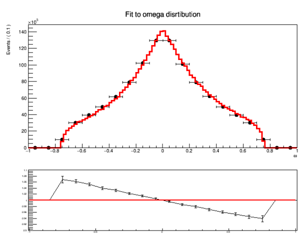
  $\vec{\theta}$: nuisance parameter. p: POI, CP-mixing parameter. x_i: dataset (ω).
  - When statistics is large enough, we suppose $\mathcal{L}\left(\vec{x}\middle|p,\vec{\theta}\right) \sim Gaus(\hat{p},\sigma_p^2)$, so $ln\mathcal{L}(p) = ln\mathcal{L}_{max} - \frac{1}{2}\left(\frac{p-\hat{p}}{\sigma_p}\right)^2$
  - From $\Delta NLL = NLL - NLL_{\mathrm{min}}$ (negative log likelihood) we can extract maximum likelihood estimate $\hat{p}$ and its CL interval.





Maximum likelihood fit

- Sample modelling
  - ω modelling: Histogram pdf. Highly depends on the sample statistics used to build histogram and HistPdf.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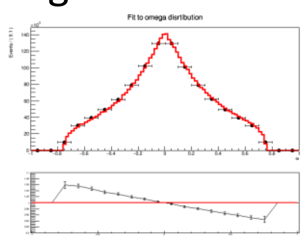
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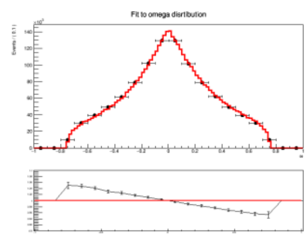
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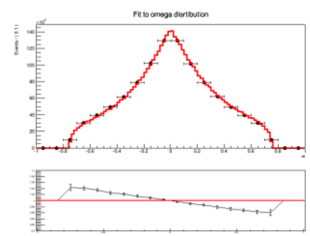
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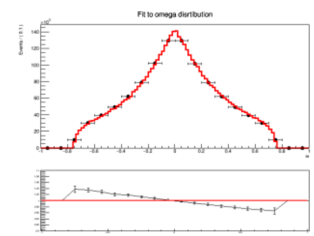
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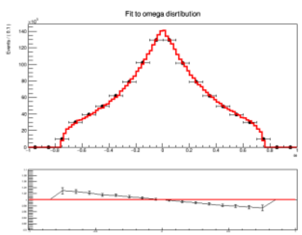
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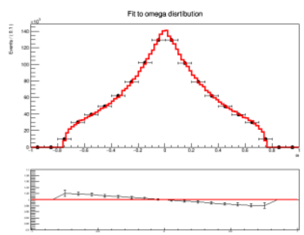
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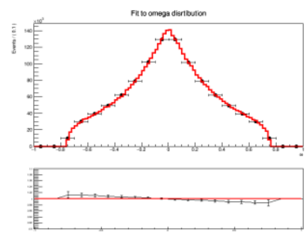
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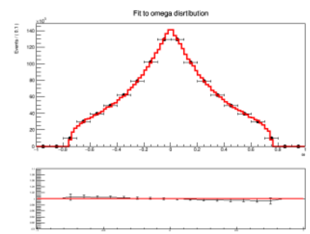
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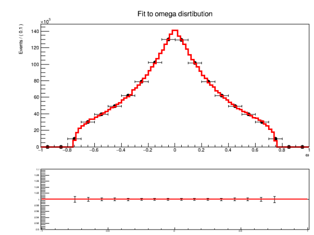
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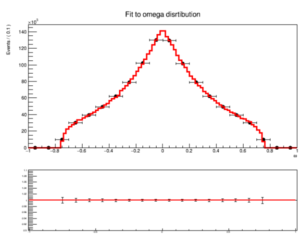
Maximum likelihood fit

- Sample modelling
  - ω modelling: Histogram pdf. Highly depends on the sample statistics used to build histogram and HistPdf.



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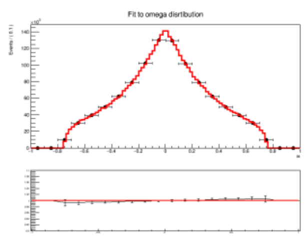

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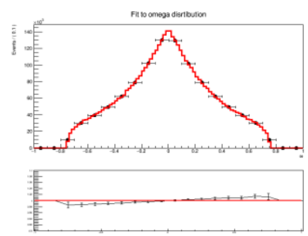

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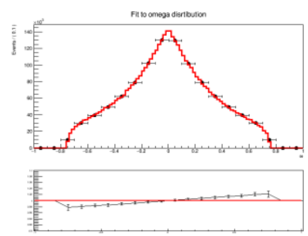

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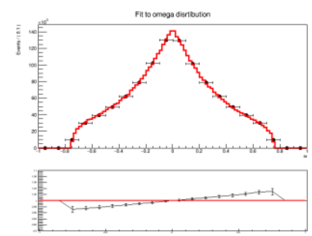

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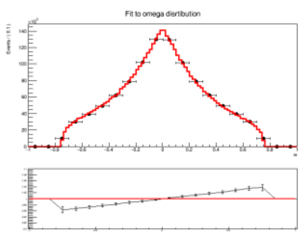

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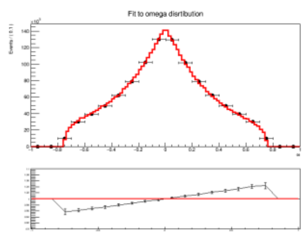

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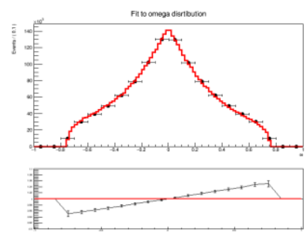

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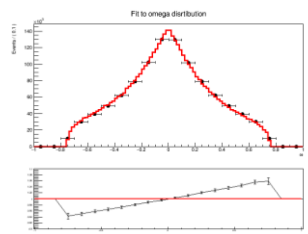

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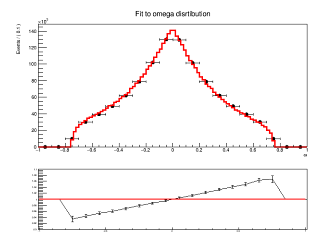

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