Improving measurement on Higgs-gluon effective coupling

Zhao Li IHEP-CAS

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「 (国 神 孝 茂 為 権 約 II 加 尻 所 Institute of High Energy Physics Chinese Academy of Sciences



based on PRD98 (2018) no.7, 076010 & arXiv:1901.09391







Higgs Properties, i.e. couplings/interactions



Direct or Indirect modification



$$\mathcal{L}_{hgg} = \kappa_g c_{\rm SM}^g \frac{\alpha_s}{12\pi v} h G^a_{\mu\nu} G^{a\mu\nu},$$

SUSY? Little Higgs? Extra Dimensions? etc.

Measurement @ LHC











Several Higgs factories under plan





CEPC@90-240 GeV (China) 秦皇岛 or 雄安?

ILC@500,350,250 GeV (Japan) Kitakami Candidate Site



FCC-ee @ 90-400 GeV (Geneva, EU)

Results in CDR (2018.11)



	Estimated Precision					Signal		Signal Precisio		Signal		Precisio	
D	CEDC1		CIER	CEDCard		н	n	Z	н	n	Z	н	n
Property	CEPC-VI		CEP	CEPC-v4		H->qq		H->WW		Η→γγ, Ζγ		13	
m_H	5.9 MeV		5.9	5.9 MeV 2.8% 0.5%		bb	1.32%	ee	lvlv	9.52%	μμ+ττ	77	23.7%
Γ_H	н 2.7%		2.			cc	13.5%		evqq	4.56%	vv		10.5%
$\sigma(ZH)$	(ZH) 0.5%		0.			gg	7.22%		μvqq	3.93%	qq		9.84%
$\sigma(\nu\bar{\nu}H)$	3.0%		3.	3.2%		bb	0.99%		lvlv	7.29%	vv	Zy(qqy)	15.7%
					μμ	сс	9.54%	μμ	evqq	3.90%	vvH	(WW fus	ion)
Decay mode	$\sigma \times BR$	BR	$\sigma \times BR$	BR		gg	5.01%		μvqq	3.90%	vv	bb	3.00%
$H \rightarrow b \bar{b}$	0.26%	0.56%	0.27%	0.56%		bb	0.46%		qqqq	1.90%	Н→µµ		
$H \rightarrow c\bar{c}$	3.1%	3.1%	3.3%	3.3%	qq	cc	11.1%		evqq	4.65%	qq		
$H \rightarrow gg$	1.2%	1.3%	1.3%	1.4%		gg	3.64%	~~	μvqq	4.14%	ee		17.10/
$H \mathop{\rightarrow} WW^*$	0.9%	1.1%	1.0%	1.1%		bb	0.39%		lvlv	11.5%	μμ	μμ	17.1%
$H \rightarrow ZZ^*$	4.9%	5.0%	5.1%	5.1%	vv	сс	3.83%	qq	qqqq	1.75%	vv		
$H \rightarrow \gamma \gamma$	6.2%	6.2%	6.8%	6.9%		gg	1.47%		H->ZZ		Η→ττ		
$H \rightarrow Z \gamma$	13%	13%	16%	16%	H->I	H->Invisible		vv	μμqq	8.26%	ee		2.75%
$H{\rightarrow}\tau^{+}\tau^{-}$	0.8%	0.9%	0.8%	1.0%	qq		232%	vv	eeqq	40%	μμ		2.61%
$H \rightarrow \mu^+ \mu^-$	16%	16%	17%	17%	ee	77(1000)	370%	μμ	vvqq	7.32%	qq	ττ	0.95%
$\rm BR_{inv}^{\rm BSM}$	-	< 0.28%	-	< 0.30%	μμ	22(000)	245%	ZH bkg		19.4%	vv]	2.66%

All scaled to 240 GeV, 5.6ab⁻¹







ggH coupling from H->gg

H->gg decay rate is proportional to ggH coupling

But H->gg is hidden inside H->jj



dijet including bb, cc and gg

 $gg(8.18\%), \ c\bar{c}(2.884\%) \text{ and } bb(58.09\%)$

Jet Energy Profile

$$\psi(r) = \frac{1}{N_j} \sum_{j} \psi_j(r) = \frac{1}{N_j} \sum_{j} \frac{\sum_{r_i < r} p_{T,i}(r_i)}{\sum_{r_i < R} p_{T,i}(r_i)},$$
Shape of JEP
reflects the relative
ratio between quark
and gluon!

$$\Psi(r) = \frac{N_q \Psi_q(r) + N_g \Psi_g(r)}{N_q + N_g}$$

H->bb is well measured. & Assume Hbb Yukawa is true.

0.7

Optimized uncertainty of effective coupling

$$Z^{N}(r) = \frac{\sum_{j} (\psi_{j} + b)}{\sum_{j}^{SM} (\psi_{j} + b)},$$

$$\delta \kappa_g^Z = \delta \kappa_g^N \Big[\left(\frac{\sigma(r)}{\psi_g + b} \right)^2 + f_g + f_q \left(\frac{\psi_q + b}{\psi_g + b} \right)^2 + f_{\rm BG} \left(\frac{\psi_{\rm BG} + b}{\psi_g + b} \right)^2 \Big]^{1/2}$$



$$b = \frac{\sigma^2(r) + f_{BG}(\psi_q - \psi_{BG})(\psi_g - \psi_{BG})}{f_q(\psi_g - \psi_q) + f_{BG}(\psi_g - \psi_{BG})} - \psi_q.$$

MC Simulation



JEPs are obtained by analyzing the jet substructure according to the formula.

Probing the Higgs boson-gluon coupling via the jet energy profile at $e^+ e^-$ colliders

Gexing Li, Zhao Li, Yandong Liu, Yan Wang, and Xiaoran Zhao Phys. Rev. D **98**, 076010 – Published 17 October 2018







~50% improvement to reach ~1.6%

Machine Learning is widely used in many fields



Convolutional Neural Networks (CNNs)

CNNs is one of the most popular algorithms in deep learning. It has powerful ability of image recognition.





CNNs extract the features form images by the convolutional layers.

Machine Learning @ HEP

- Higgs boson tagging *PLB 322 (1994) 219-223*
- boosted W boson tagging JHEP1502 (2015) 118
- **boosted top tagging** *JHEP 1507 (2015) 086*
- single merged jet tagging PRD 93 (2016) 094034
- heavy-light quark discrimination *PRD 94 (2016) 112002*
- quark-gluon discrimination PRL 65 (1990) 1321-1324
- scan parameter space in the BSM *arXiv:1708.06615*
- ...

CNN for effective coupling measurement

Images of not-only-jet-but-whole-event





CNN Configuration

```
nb filters=64
batch size=128
nb epoch=50
model=Sequential()
model.add(Conv2D(nb filters,(3,3),padding='valid',kernel initializer="random normal",input shape=(33,65,1)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool size=(2,2),strides=2))
model.add(Dropout(0.5))
model.add(Conv2D(nb filters,(3,3),padding='valid',kernel initializer="random normal"))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool size=(2,2),strides=2))
model.add(Dropout(0.5))
model.add(Conv2D(nb filters,(3,3),padding='valid',kernel initializer="random normal"))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool size=(2,2),strides=2))
model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))
adam = Adam(lr=0.0005, beta 1=0.9, beta 2=0.999, epsilon=1e-08)
model.compile(loss='binary crossentropy',optimizer = adam, metrics=['accuracy'])
early stopping = EarlyStopping(monitor='val loss', patience=3, verbose=0, mode='auto')
```

Recover symmetry via rotation



phi symmetry break

Rotate at phi direction

1.5

Each rotation turns 13 pixels. Each image becomes 5 different images. 3 Theta

Performance of CNNs



Improvement of CNNs



Further ~30% improvements to reach ~1,2%

Revisit AUC comparison between P & H



Does simulation really simulate physics?



Parton Shower? Hadronization? Underlying events? etc.

Conclusion

- CEPC can be very precise factory for Higgs investigation.
- Deep learning is full of potential for CEPC physics.
- Maybe deep learning can also help LHC physics.
- However, we should be careful about traps in simulations.

Backup

Convolutional Neural Networks (CNNs)



Energy of all the final state stable particles



3

4











Max Pooling

