

Di-Higgs day @ Konkuk University 2019. 06. 27. Thursday



Probing the trilinear Higgs boson coupling in the di-Higgs production at the LHC and its performance improvement using machine learning

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Collaborators : Prof. Kingman Cheung, Prof. Jae Sik Lee, Dr. Chih-Ting Lu, Dr. Jung Chang





- Ref : 1. An exploratory study of Higgs-boson pair production (JHEP 1508(2015) 133)
 - 2. Higgs-boson-pair production $H(\rightarrow b\overline{b})H(\rightarrow \gamma\gamma)$ from gluon fusion at the HL-LHC and HL-100 TeV hadron collider **(Arxiv :1804.07130)**
 - 3. <u>Higgs-boson-pair production $H(\rightarrow b\overline{b})H(\rightarrow \gamma\gamma)$ from gluon fusion with multivariate techenique</u> (Work in Progress)
 - 4. Introduction to Machine Learning with Python (Andreas Muller)

Contents

- Higgs in the SM (Prof. Song's presentation)
- How to probe it ? : Higgs pair production (From the experimental view, Dr. Yu's presentation)
 (From the intermediate(?), this talk
 (From the theoretical view, Prof. M. Park's and Prof. S. Park's talks
- Simulation
- Analysis (TMVA, BDT) BDTL1 scenario
- Expected yields and significance(Z)
- Conclusion
- Recent updates

Preliminary

Recent updates

- HH NLO generator POWHEG BOX V2 Use of NLO kinematic distributions (or variables)
- Improved yields and significance(Z)
- Improved Likelihood fit using the M_{HH} kinematic distribution

Higgs In the SM

- Higgs field (h) : responsible for
 1) the spontaneous EW symmetry breaking
 2) the generation of masses of all the SM particle
- The potential is characterized by only two parameters : ① vacuum expectation value v② the Higgs mass m_H

$$v = \frac{1}{\sqrt{\sqrt{2} G_F}} \approx 246 \text{ GeV} \qquad V_{SM}(h) = \frac{1}{2} m_H^2 h^2 + \lambda_3 v h^3 + \frac{1}{4} \lambda_4 h^4$$

Trilinear and Quartic Higgs boson coupling in the SM

$$\lambda_3^{SM} = \lambda_4^{SM} = \frac{m_H^2}{2\nu^2}$$

New Physics can affect the Higgs potential form



$$\lambda_3 = \lambda_3^{SM} + \delta \lambda_3^{SM} , \qquad \lambda_4 = \lambda_4^{SM} + \delta \lambda_4^{SM}$$

Trilinear Higgs boson coupling

 $\lambda_3 = \lambda_3^{SM} + \delta \lambda_3^{SM}$



How to probe it ?



We now focus on

Higgs pair production at the Hadron collider

Why Higgs pair production so interesting ?

Allows accessing crucial components of the Higgs sector !!!

can help to reconstruct the electroweak symmetry breaking potential

can probe the Higgs self-coupling

may reveal the doublet nature of the Higgs by means of the hhVV coupling



Higgs pair productions at the LHC Production modes



Vector Boson Fusion $V = V^*$ V^* V^*

Top associated productions







Why Higgs pair production so difficult ?





In the leading gluon fusion production mode, the cross section at 14 TeV is only 45 fb (in the SM), further suppressed by each decay branching fractions.

45 fb ↔ NNLO accuracy including NNLL gluon resummation in the infinite top quark mass approximation.

Why Higgs pair production so difficult ?

Full top-quark mass effect at the NLO

45.05 fb -----> 36.69 fb

Recently, the NLO corrections considering full top-quark mass dependence have been available. We observe that **20 % reduction** at 14 TeV compared to the cross sections used.

Strong QCD backgrounds

Which search mode would be better to use?

Search channels for Higgs pair production

at Collider

Our Channel reconstruct τ / W

b-tagging, QCD BG

Decay channels	$HH ightarrow bb \gamma \gamma$	HH ightarrow bb au au	HH ightarrow bbWW	HH ightarrow bbbb	
Branching ratios	0.263%	7.29%	24.8%	33.3%	

small BRHuge $t\bar{t}$ BGHuge hadronic BGrelatively clean channeldominate BGs comes fromfake photon or b-jet

Decay channels	$HH \rightarrow bb\gamma\gamma$	$HH \rightarrow bb\tau\tau$	$HH \rightarrow bbWW$	$HH \rightarrow bbbb$	•••
Expected events with 3 ab^{-1}	290	8000	27000	37000	•••

Simulation

Outline of Simulations



2015 MadGraph school on Collider Phenomenology November 23-27 @ Shanghai

(1) Updated Signal Cross Section (about 20% reduction) $\sigma \cdot Br(H \rightarrow \gamma\gamma)Br(H \rightarrow b\overline{b})=0.119 \text{ fb} \longrightarrow 0.096 \text{ fb}$

		Signal			
Signal process		Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
				in QCD	
$gg \to HH \to b\bar{b}\gamma\gamma$		$MG5_aMC@NLO/PYTHIA8$	0.096	NNLO	NNPDF2.3LO
		Backgrounds			
Background(BG)	Process	Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
				in QCD	
	$ggH(\rightarrow\gamma\gamma)$	POWHEG-BOX/PYTHIA6	1.20×10^2	NNNLO	CT10
Single-Higgs	$t\bar{t}H(\rightarrow\gamma\gamma)$	PYTHIA8/PYTHIA8	1.37	NLO	
associated BG	$ZH(\rightarrow \gamma\gamma)$	PYTHIA8/PYTHIA8	2.24	NLO	
	$bbH(\rightarrow \gamma\gamma)$	PYTHIA8/PYTHIA8	1.26	NLO	
	$bb\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.12×10^2	LO	CT14LO
	$c\bar{c}\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.08×10^{3}	LO	
	$jj\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.40×10^4	LO	
Non-resonant BG	$bbj\gamma$	$MG5_aMC@NLO/PYTHIA8$	$2.72 imes 10^5$	LO	
	$car{c}j\gamma$	$MG5_aMC@NLO/PYTHIA8$	$9.17 imes10^5$	LO	
	bbjj	$MG5_aMC@NLO/PYTHIA8$	3.00×10^8	LO	
	$Z(\rightarrow bb)\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	5.03	LO	
$t\bar{t}$ and $t\bar{t}$ BC	$tar{t}$	t POWHEG - BOX/PYTHIA8	$5.30 imes 10^5$	NNLO	CT10
ii and iii DG				+NNLL	
$(\geq 1 \text{ lepton})$	$- t \bar{t} \gamma$	$MG5_aMC@NLO/PYTHIA8$	1.60×10^{3}	NLO	CTEQ6L1

② Updated non-resonant BG with the recent PDF

CTEQ6L1 PDF CT14LO PDF

(+ about 20% reduction)

		Signal			
Signal process		Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
				in QCD	
$gg ightarrow HH ightarrow b ar{b} \gamma \gamma$		$MG5_aMC@NLO/PYTHIA8$	0.096	NNLO	NNPDF2.3LO
	Backgrounds				
Background(BG)	Process	Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
				in QCD	
	$ggH(\rightarrow\gamma\gamma)$	POWHEG-BOX/PYTHIA6	1.20×10^2	NNNLO	CT10
Single-Higgs	$t\bar{t}H(\rightarrow\gamma\gamma)$	PYTHIA8/PYTHIA8	1.37	NLO	
associated BG	$ZH(\rightarrow \gamma\gamma)$	PYTHIA8/PYTHIA8	2.24	NLO	
	$b\bar{b}H(\rightarrow\gamma\gamma)$	PYTHIA8/PYTHIA8	1.26	NLO	
	$b\overline{b}\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.12×10^2	LO	CT14L0
	$c \overline{c} \gamma \gamma$	$MG5_aMC@NLO/PYTHIA8$	1.08×10^3	LO	
	$jj\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.40×10^4	LO	
Non-resonant BG	$bbj\gamma$	$MG5_aMC@NLO/PYTHIA8$	$2.72 imes 10^5$	LO	
	$car{c}j\gamma$	$MG5_aMC@NLO/PYTHIA8$	$9.17 imes 10^5$	LO	
	bbjj	$MG5_aMC@NLO/PYTHIA8$	3.00×10^8	LO	
	$Z(\rightarrow bb)\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	5.03	LO	·
$t\bar{t}$ and $t\bar{t}\gamma$ BG	$tar{t}$	t POWHEG-BOX/PYTHIA8	$5.30 imes10^5$	NNLO	CT10
				+NNLL	
$(\geq 1 \text{ lepton})$	$t ar{t} \gamma$	MG5_aMC@NLO/PYTHIA8	1.60×10^{3}	NLO	CTEQ6L1

Cuts at the generator level on the non-resonant BGs

$$\begin{split} P_{T_j} > 20 \quad \text{GeV}, \ P_{T_b} > 20 \quad \text{GeV}, \ P_{T_{\gamma}} > 25 \quad \text{GeV}, \ P_{T_l} > 10 \quad \text{GeV}, \\ & |\eta_j| < 5, \ |\eta_{\gamma}| < 2.7, \ |\eta_l| < 2.5, \ \Delta R_{jj,ll,\gamma\gamma,\gamma j,jl,\gamma l} > 0.4, \\ & M_{jj} > 25 \text{ GeV}, \ M_{bb} > 45 \text{ GeV}, \ 60 < M_{\gamma\gamma} < 200 \text{ GeV}. \end{split}$$

CTEQ6L1 v.s. CT14LO CT14LO contains the LHC RUN I results

They show similar kinematic distributions.



Analysis

Analysis Methods

Cut Based Analysis

 Machine Learning Multi-Variate Analysis : BDT (Boosted Decision Tree) (work in progress)

TMVA (Toolkit for Multivariate Data Analysis with ROOT)

A. Hoecker, P. Speckmayer, J. Stelzer, J. Therhaag, E. von Toerne, and H. Voss, *TMVA - Toolkit for Multivariate Data Analysis*, PoS ACAT 040 (2007), arXiv:physics/0703039

Machine Learning TMVA package

Pre-selection cuts for TMVA study

Sequence	Event Selection Criteria at the HL-LHC
1	Di-photon trigger condition, ≥ 2 isolated photons with $P_T > 25$ GeV, $ \eta < 2.5$
2	≥ 2 isolated photons with $P_T > 30$ GeV, $ \eta < 1.37$ or $1.52 < \eta < 2.37$, $\Delta R_{j\gamma} > 0.4$
3	≥ 2 jets identified as b-jets with leading(subleading) $P_T > 40(30)$ GeV, $ \eta < 2.4$
4	Events are required to contain ≤ 5 jets with $P_T > 30$ GeV within $ \eta < 2.5$
5	No isolated leptons with $P_T > 25$ GeV, $ \eta < 2.5$

We use TMVA analysis to improve our previous result

TMVA Inputs : 8 (kinematic) variables

 $P_{T_{YY}}$, $P_{T_{bb}}$, $M_{\gamma\gamma}$, M_{bb} , $M_{\gamma\gamma bb}$, $\Delta R_{\gamma\gamma}$, ΔR_{bb} , $\Delta R_{\gamma b}$



Correlation Matrix among variables

Linear correlation coefficients in % 100 21 21 M aabb 8 100 80 DR ab -19 -34 -16 100 8 60 40 -52 _ DR aa -21 6 100 20 DR bb -50 -24 100 -34 2 4 0 PT aa -24 -52 24 100 -20 5 18 M aa 100 7 -40 -60 PT bb 100 5 -50 -21 21 -80 M bb 100 -19 6 -100 DR_ab PT aa DR bb DR aa M_aabb Mbb PT_bb M_aa

Correlation Matrix (background)

Correlation Matrix (signal)



Various ML methods in TMVA

Background rejection versus Signal efficiency

Background rejection **MVA Method:** BDT BDTG **RuleFit** Likelihood KNN A better direction LikelihoodPCA PDERS MLPBNN SVM Cuts. LD CutsD FDA MC 0.2 0.9 0.1 0.3 0.4 0.5 0.6 0.7 0.8 0 Signal efficiency

ROC = Receiver Operating Characteristic curve

Ideal line of ROC curve

: a good way to illustrate the performance of given classifier

> AUC = Area under the ROC curve

Background rejection versus Signal efficiency



Boosted Decision Tree)

DT (Decision Tree)



?2. A decision tree to distinguish among several animals

Decision Trees

Introduction to Machine Learning with Python (Andreas Muller)

- Decision trees are widely used models for classification and regression tasks. Essentially, they learn a hierarchy of if/else questions, leading to a decision.
- This series of questions can be expressed as a decision tree, as shown in



Figure 2-22. A decision tree to distinguish among several animals

<One example>

How to classify this set ?



Figure 2-23. Two-moons dataset on which the decision tree will be built



Figure 2-25. Decision boundary of tree with depth 2 (left) and corresponding decision tree (right)

Finally.....





Figure 2-26. Decision boundary of tree with depth 9 (left) and part of the corresponding tree (right); the full tree is quite large and hard to visualize

However,

If we don't restrict the depth of a decision tree, the tree can become arbitrarily deep and complex.

Easily Overfitting !!

Supervised Learning

- Classification and Regression
- Generalization, Overfitting, and Underfitting



To avoid the overfitting,

Ensembles of Decision Trees

• There are two ensemble models that have proven to be effective on a wide range of datasets for classification and regression, both of which use decision trees as their building blocks: **random forests** and **gradient boosted decision trees**.

Use the ensemble average !



Use the strong pre-pruning !

Gradient boosted trees often use very shallow trees, of depth one to five,

Shallow tree + Shallow tree + Shallow tree +

Other methods (algorithms)

- k-Nearest Neighbors
- Linear Models (Linear Fitting)
- Decision Trees
- Support Vector Machines
- Neural Networks (Deep Learning)



Decision boundaries created by the nearest neighbors model for different values of n_neighbors
Neural Network (Briefly.....)



Decision functions for different numbers of hidden units and different settings of the alpha parameter

BDT setup in TMVA

- Pre-Selection Cuts $(1) (5) \longrightarrow TMVA$ inputs
- NTrees=800
- MinNodeSize=2.5%
- MaxDepth=4
- BoostType=AdaBoost
- AdaBoostBeta=0.5
- UseBaggedBoost
- BaggedSampleFraction=0.5
- SeparationType=GiniIndex
- nCuts=20

BDT machine optimized with $\lambda_{3H} = 1$

AUC = 0.996 : Area under ROC (receiver operating characteristic curve) curve





Expected Yields and

Significance(Z)

	Expectd yields (3000 fb^{-1})			
Signal and Backgrounds	Pre-BDT Cuts	Cut based	BDT, Z_{Max}	
$H(b\overline{b})H(\gamma\gamma),\lambda_{3H}=0$	34.31	16.14	12.86	
$H(b\overline{b})H(\gamma\gamma),\lambda_{3H}=1$	17.71	$\left(\begin{array}{c}9.15\end{array}\right)$	$\left[\begin{array}{c}7.64\end{array}\right]$	
$H(b\overline{b})H(\gamma\gamma),\lambda_{3H}=2$	8.93	4.79	4.17	
$ggH(\gamma\gamma)$	68.76	6.60	4.86	
$tar{t}H(\gamma\gamma)$	158.14	13.21	7.97	
$ZH(\gamma\gamma)$	23.89	3.62	2.67	
$bar{b}H(\gamma\gamma)$	2.52	0.15	0.11	
$b\overline{b}\gamma\gamma$	7055.47	15.28	5.72	
$car{c}\gamma\gamma$	7058.43	7.14	2.27	
$jj\gamma\gamma$	1113.20	3.17	0.58	
$bar{b}j\gamma$	10607.63	14.73	2.85	
$car{c}j\gamma$	4716.52	4.82	1.51	
$bar{b}jj$	2606.49	3.53	0.74	
$Z(bar{b})\gamma\gamma$	179.33	0.86	0.35	
$t \bar{t} \ (\geq 1 \text{ leptons})$	5433.74	4.98	0.61	
$t \bar{t} \gamma \ (\geq 1 \text{ leptons})$	1916.50	3.61	1.04	
Total Background		81.70	31.27	
Significance $Z, \lambda_{3H} = 0$		1.73	2.16	
Significance $Z, \lambda_{3H} = 1$		0.99	1.32	
Significance $Z, \lambda_{3H} = 2$		0.52	0.73	

C&C

- # of signal = 9.15 # of bg = 81.70
- •• significance Z = 0.99

BDT λ_1 # of signal = 7.64

- # of bg = 31.27
- **BDT-improved Z = 1.32**

33% enhancement on Z

Significance of the signal over the background versus λ_{3H} at the HL-LHC



Significance of the signal over the background versus λ_{3H} at the HL-LHC



Z v.s. λ_{3H} = 1 in the cases of C&C and BDTL1



: It may be possible to measure at the LH-LHC with $6 ab^{-1}$.

If we can measure(?) the signal and bg. numbers for the case of $\lambda_{3H} = 1$ at the LH-LHC with 6 ab^{-1}



M_{hh} kinematic distributions



Log-Likelihood Ratios with the $\lambda_{3H} = 1$ nominal data set and the different λ_{3H} template sets



Impact of NLO

Preliminary

Recent updates

- HH NLO generator POWHEG BOX V2 Use of NLO kinematic distributions (or variables)
- Improved (NLO) yields and significance(Z)
- Improved Likelihood fit using the (NLO) M_{HH} kinematic distribution

Preliminary

HH NLO generator – POWHEG BOX V2

Signal process	Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
			in QCD	
$gg \to HH \to b \bar{b} \gamma \gamma$	POWHEG-BOX-V2/PYTHIA8	0.096	NNLO	PDF4LHC15_nlo

Validation of the NLO sample

At the parton level



After the decay of the Higgs boson



Validation of the NLO sample

At the detector level



TMVA (NLO) input variables



BDTL1 scenario



Improved (NLO) yields and significance(Z)



Improved Likelihood fit using the (NLO) M_{HH} kinematic distribution



Scenario	1σ CI	2σ CI	
$\lambda_{3H} = 1$ nominal set	$-0.1 < \lambda_{3H} < 2.6$ and $5.0 < \lambda_{3H} < 7.0$	$-1.1 < \lambda_{3H} < 7.9$	
$\lambda_{3H} = 0$ nominal set	$-0.9 < \lambda_{3H} < 1.1$ and $6.4 < \lambda_{3H} < 7.5$	$-1.8 < \lambda_{3H} < 2.8$ and $4.6 < \lambda_{3H} < 8.5$	

Conclusion

- 1. We examine the impact of the full NLO corrections considering full top-quark mass dependence, and the recent CT14LO PDF.
- 2. (CT14LO) At 14 TeV with 3000 fb⁻¹, the trilinear coupling is constrained to be -1.1 < λ_{3H} < 7.0 at 95% CL taking account of the uncertainties associated with the top-Yukawa coupling and the estimation of backgrounds.
- 3. (CT14LO) Taking the central line, the 95% CL sensitivity region for λ_{3H} is -0.3 < λ_{3H} < 6.7
- 4. (BDTL1) The trilinear coupling is constrained to be $-0.7 < \lambda_{3H} < 7.5$ at 95% CL taking account of the uncertainties associated with the top-Yukawa coupling and the estimation of backgrounds.
- 5. (BDTL1) Taking the central line, the 95% CL sensitivity region for λ_{3H} is 0.2 < λ_{3H} < 7.1
- 6. (BDTL1 + NLO) Taking the central line, the 95% CL sensitivity region for λ_{3H} is 0.6 < λ_{3H} < 6.7

• HL-LHC : constraint the λ_{3H}

1. Cut-Based Analysis : $-1.1 < \lambda_{3H} < 7.0$ at 95% CL,



Z v.s. λ_{3H} = 1 in the cases of C&C and BDTL1



Last, but not least

. . . .

- **Combined analysis** : $b\overline{b}b\overline{b} + b\overline{b}\gamma\gamma + b\overline{b}\tau\tau \rightarrow Z (\geq 3\sigma)$ ATL-PHYS-PUB-2018-053
- Advanced technology in the future ... Increased luminosity, improved tagging efficiency, improved resolution and so on....
- More precise simulation, higher order QCD correction .. Improved MC Event generators (at the NLO, NNLO QCD order), QCD NLO, NNLO, NNNLO corrections ...

• HL-LHC : constraint the λ_{3H} 1. Cut-Based Analysis : $-1.1 < \lambda_{3H} < 7.0$ at 95% CL, Thank 0.9 ($\lambda_{3H} < 0.9$) ($\lambda_{$ 23% 3. BDT Analysis + NLO : 0.6 < λ_{3H} < 6.7 at 95% CL, enhancement on Z $Z = 1.63 (\lambda_{3H} = 1)$

END

Backup Slides I

Further improvements to be made

- New low and high-level kinematic variables : ex. 8 var. -> 22 var.
- Finding the optimized pre-selection cuts (Hyperopt)

Impurity

Purity :
$$p=S/(S+B)$$

$$p \cdot (1-p)$$

Cross entropy :

$$-p \cdot ln(p) - (1-p) \cdot ln(1-p)$$

Misclassification error :

$$1 - max(p, 1 - p)$$

Statistical significance :

$$S/\sqrt{S+B}$$

Boost and Bagging

- A way of enhancing the classification performance
- Increasing the stability with respect to statistical fluctuations in the training sample
- TMVA Provides :

TMVA Users Guide

Adaptive Boost

- Starting with the original event weights when training the first decision tree
- Subsequent tree is trained using a modified event sample (previous misclassified events multiplied by a boost weight α)

$$\label{eq:alpha} \alpha = \frac{1 - \mathrm{err}}{\mathrm{err}} \ \, \text{err} = \text{misclassified / tot.}$$

 The boosted event classification : (small – background-like; large – signal-like event)

$$y_{\text{Boost}}(\mathbf{x}) = \frac{1}{N_{\text{collection}}} \cdot \sum_{i}^{N_{\text{collection}}} \ln(\alpha_i) \cdot h_i(\mathbf{x}) \qquad h(x) = \pm 1 \quad \begin{array}{c} \text{signal} \\ \mathbf{Bkg} \end{array}$$

• The learning rate $\alpha \to \alpha^{\beta}$

M_hh distributions II



Log-Likelihood Ratios v.s Lambda_3H



(NLO-) Correlation Matrix

Correlation Matrix (signal)



Correlation Matrix (background)


Event selection on Cut-and-Count Analysis

Sequence	Event Selection Criteria at the HL-LHC
1	Di-photon trigger condition, ≥ 2 isolated photons with $P_T > 25$ GeV, $ \eta < 2.5$
2	≥ 2 isolated photons with $P_T > 30$ GeV, $ \eta < 1.37$ or $1.52 < \eta < 2.37$, $\Delta R_{j\gamma} > 0.4$
3	≥ 2 jets identified as b-jets with leading (subleading) $P_T > 40(30)$ GeV, $ \eta < 2.4$
4	Events are required to contain ≤ 5 jets with $P_T > 30$ GeV within $ \eta < 2.5$
5	No isolated leptons with $P_T > 25$ GeV, $ \eta < 2.5$
6	$0.4 < \Delta R_{b\bar{b}} < 2.0, \ 0.4 < \Delta R_{\gamma\gamma} < 2.0$
7	$122 < M_{\gamma\gamma}/{\rm GeV} < 128$ and $100 < M_{b\bar{b}}/{\rm GeV} < 150$
8	$P_T^{\gamma\gamma}>80~{\rm GeV},P_T^{b\bar{b}}>80~{\rm GeV}$

These red conditions of cuts were very important to distinguish signal and background on the Cut-and-Count Analysis !

		 	L-L	Signal	4	Te	
Cignal		Signal pro	cess	Generator/Parton Shower	$\sigma \cdot BR$ [fb]	Order	PDF used
Signal						in QCD	
		$gg \to HH \to b$	$\bar{b}\gamma\gamma$ [15]	MG5_aMC@NLO/PYTHIA8	0.119	NNLO	NNPDF2.3LO
						+NNLL	
				Backgrounds			
(Background(BG)	Process	Generator/Parton Shower	$\sigma \cdot BR \; [{\rm fb}]$	Order	PDF used
						in QCD	
	inds	Single-Higgs associated BG [15]	$ggH(\to\gamma\gamma)$	POWHEG - BOX/PYTHIA6	1.20×10^2	NNNLO	CT10
			$t\bar{t}H(\rightarrow\gamma\gamma)$	PYTHIA8/PYTHIA8	1.37	NLO	
			$ZH(\to\gamma\gamma)$	PYTHIA8/PYTHIA8	2.24	NLO	
			$b\bar{b}H(\to\gamma\gamma)$	PYTHIA8/PYTHIA8	1.26	NLO	
			$b\bar{b}\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	1.40×10^2	LO	CTEQ6L1
Backarou			$c\bar{c}\gamma\gamma$	MG5_aMC@NLO/PYTHIA8	1.14×10^3	LO	
			$jj\gamma\gamma$	MG5_aMC@NLO/PYTHIA8	1.62×10^4	LO	
			Non-resonant BG	$bar{b}j\gamma$	MG5_aMC@NLO/PYTHIA8	3.67×10^5	LO
			$c\bar{c}j\gamma$	MG5_aMC@NLO/PYTHIA8	1.05×10^6	LO	
			$b\bar{b}jj$	$MG5_aMC@NLO/PYTHIA8$	4.34×10^8	LO	
			$Z(\to b\bar{b})\gamma\gamma$	$MG5_aMC@NLO/PYTHIA8$	5.17	LO	
		$t\bar{t}$ and $t\bar{t}\sim BG$	$t\bar{t}$ [18]	POWHEG - BOX/PYTHIA8	5.30×10^5	NNLO	CT10
						+NNLL	
		$(\geq 1 \text{ lepton})$	$t\bar{t}\gamma$ [19]	MG5_aMC@NL0/PYTHIA8	1.60×10^3	NLO	CTEQ6L1

		1				_	-
Expected yields (3000 fb^{-1})	Total	Barrel-barrel	Other	Ratio (O/B)	GeV	50	-
Samples			(End-cap)		"(1/3	-	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=-4$	77.14	57.03	20.11	0.35	ه/dM	40	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=0$	19.50	14.33	5.17	0.36	0	-	
$H(bar{b})H(\gamma\gamma),\lambda_{3H}=1$	11.42	8.53	2.89	0.34		30	
$H(b\overline{b})H(\gamma\gamma),\lambda_{3H}=2$	6.82	5.14	1.68	0.33		E	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=6$	11.03	7.91	3.12	0.39		20	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=10$	57.46	41.94	15.52	0.37			Ľ
$ggH(\gamma\gamma)$	6.60	4.50	2.10	0.47		10	
$tar{t}H(\gamma\gamma)$	13.21	9.82	3.39	0.35			
$Z H(\gamma \gamma)$	3.62	2.44	1.18	0.48		0	1
$bar{b}H(\gamma\gamma)$	0.15	0.11	0.04	0.40			
$bar{b}\gamma\gamma$	18.86	11.15	7.71	0.69			
$c \overline{c} \gamma \gamma$	7.53	4.79	2.74	0.57	ieV)		
$j j \gamma \gamma$	3.34	1.59	1.75	1.10	1/10C	30	
$bar{b}j\gamma$	18.77	10.40	8.37	0.80) ^{dd} Mb	25	
$car{c}j\gamma$	5.52	3.94	1.58	0.40	da/c		
$b \overline{b} j j$	5.54	3.81	1.73	0.45		20	
$Z(bar{b})\gamma\gamma$	0.90	0.54	0.36	0.67		15	
$t \bar{t} \ (\geq 1 \text{ leptons})$	4.98	3.04	1.94	0.64			
$t \bar{t} \gamma \ (\geq 1 \text{ leptons})$	3.61	2.29	1.32	0.58		10	-
Total Background	92.63	58.42	34.21	0.59		5	-
Significance Z	1.163	1.090	0.487	Combine	d significan	ce	
Combined significance		1.19	94	_	1,194	0	60 80

M_{bb}(GeV)

Result at the HL-LHC



Timeline of LHC



LHC RUN II



Machine Learning



From Wikipedia

- **Machine learning** (ML) is a field of <u>artificial intelligence</u> that uses statistical techniques to give <u>computer systems</u> the ability to "learn" (e.g., progressively improve performance on a specific task) from <u>data</u>, without being explicitly programmed.^[2]
- The name *machine learning* was coined in 1959 by <u>Arthur Samuel</u>.^[1] Machine learning explores the study and construction of <u>algorithms</u> that can learn from and make predictions on <u>data^[3]</u> such algorithms overcome following strictly static <u>program instructions</u> by making data-driven predictions or decisions,^{[4],2} through building a <u>model</u> from sample inputs. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or infeasible; example applications include <u>email filtering</u>, detection of network intruders, and <u>computer vision</u>.



[Ian Goodfellow, Yoshua Bengio a nd Aaron Courville] 'Deep Learning'

(In machine learning language) "machine" = 'model (from data)'

Learning = Improving performance at a task (ex) with experience

(In machine learning language)

"Learning" = Optimization of (machine's/model's) parameters of a proper error function which represents performance at a task.

Therefore, "I am training a machine

= I am building a new model (from data)



- No labels
- No feedback
- "Find hidden structure"

- Decision process
- · Reward system
- · Learn series of actions

<u>http://solarisailab.com/archives/1785</u>, 솔라리스의 인공지능 연구실

Supervised Learning

Supervised Learning

- Classification and Regression
- Generalization, Overfitting, and Underfitting

This figure is really important !!!



Each λ_{3H} optimized BDT machine







• •

Each λ_{3H} optimized BDT machine

AUC = 0.992-0.996



•
$$\lambda_{3h} = 1$$
 Optimized

• λ_{3h} Optimized



		1				_	-
Expected yields (3000 fb^{-1})	Total	Barrel-barrel	Other	Ratio (O/B)	GeV	50	-
Samples			(End-cap)		"(1/3	-	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=-4$	77.14	57.03	20.11	0.35	ه/dM	40	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=0$	19.50	14.33	5.17	0.36	0	-	
$H(bar{b})H(\gamma\gamma),\lambda_{3H}=1$	11.42	8.53	2.89	0.34		30	
$H(b\overline{b})H(\gamma\gamma),\lambda_{3H}=2$	6.82	5.14	1.68	0.33		E	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=6$	11.03	7.91	3.12	0.39		20	
$H(b\bar{b})H(\gamma\gamma),\lambda_{3H}=10$	57.46	41.94	15.52	0.37			Ľ
$ggH(\gamma\gamma)$	6.60	4.50	2.10	0.47		10	
$tar{t}H(\gamma\gamma)$	13.21	9.82	3.39	0.35			
$Z H(\gamma \gamma)$	3.62	2.44	1.18	0.48		0	1
$bar{b}H(\gamma\gamma)$	0.15	0.11	0.04	0.40			
$bar{b}\gamma\gamma$	18.86	11.15	7.71	0.69			
$c \overline{c} \gamma \gamma$	7.53	4.79	2.74	0.57	ieV)		
$j j \gamma \gamma$	3.34	1.59	1.75	1.10	1/10C	30	
$bar{b}j\gamma$	18.77	10.40	8.37	0.80) ^{dd} Mb	25	
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Significance Z	1.163	1.090	0.487	Combine	d significan	ce	
Combined significance		1.19	94	_	1,194	0	60 80

M_{bb}(GeV)

Recent Update I (on the signal)



• 1. We examine the impact of the NLO corrections considering full top-quark mass dependence.

Previously, (gg -> HH) = 45.05 fb (14 TeV), (gg -> HH) = 1749 fb (100 TeV)

NNLO accuracy including NNLL gluon resummation in the infinite top quark mass approximation.

Full top-quark mass effect at the NLO

 Recently, the NLO corrections considering full top-quark mass dependence have been available.
 We observe that 20 (30) % reduction at 14 (100) TeV compared to the cross sections used.

(gg -> HH) = 36.69 fb (14 TeV), (gg -> HH) = 1224 fb (100 TeV)

Double counting problem and their cross sections

- We have also checked the double counting problems between ME and PS on the non-resonant backgrounds.
- The final merged cross sections are reduced by about 20~30% (bbaa, zaa), about 30~40% (ccaa), about 50~60% (bbja, ccja), about 50~60% (jjaa).
- However, the merged cross section of the "bbjj" is not reliable.

Faking Processes and rates

Background(BG)	Process	Fake Process	Fake rate	
	$bar{b}\gamma\gamma$	N/A	N/A	
	$car{c}\gamma\gamma$	$c ightarrow b, ar{c} ightarrow ar{b}$	$(P_{c \rightarrow b})^2$	
	$jj\gamma\gamma$	$c_s \to b, \bar{c_s} \to \bar{b}$	$1/8 \qquad (P_{c_s \to b})^2$	
Non-resonant	$bar{b}j\gamma$	$j ightarrow \gamma$	$5 imes 10^{-4}$	
BG	$car{c}j\gamma$	$c ightarrow b, ar{c} ightarrow ar{b}, j ightarrow \gamma$	$(P_{c ightarrow b})^2 \cdot (5 imes 10^{-4})$	
	$bar{b}jj$	$j \rightarrow \gamma, j \rightarrow \gamma$	$(5 imes 10^{-4})^2$	
	$Z(ightarrow bar{b})\gamma\gamma$	N/A	N/A	
47	Leptonic decay	$e \to \gamma, e \to \gamma$	$(0.02)^2/0.02 \cdot 0.05/(0.05)^2$	
	Semi-leptonic decay	$e ightarrow \gamma, j ightarrow \gamma$	$(0.02) \cdot 5 \times 10^{-4} / (0.05) \cdot 5 \times 10^{-4}$	
47.	Leptonic decay	$e ightarrow \gamma$	0.02/0.05	
$tt\gamma$	Semi-leptonic	$e \to \gamma$	0.02/0.05	

	ainary								
alin	PDF	Cross Section [fb]	$b\bar{b}\gamma\gamma$	$c\bar{c}\gamma\gamma$	$jj\gamma\gamma$	$b \overline{b} j \gamma$	$car{c}j\gamma$	$bar{b}jj$	$z(b\overline{b})\gamma\gamma$
PIC	CTEQ6L1	σ	140	1140	1.62×10^4	$3.67 imes 10^5$	$1.05 imes 10^6$	4.34×10^8	5.17
	CT14LO	σ	112	1081	1.40×10^4	2.72×10^5	0.91×10^6	3.00×10^8	5.03
	CT14LO	$\sigma_{ m XQCUT}$	113	1082	1.54×10^4	2.88×10^5	0.92×10^6	$3.10 imes 10^8$	4.89
			82.5	647	0.59×10^4	1.22×10^5	0.35×10^{6}	0.67×10^{8}	3.65
	CT14LO	σ_{merged}	82.3	662	0.44×10^4	0.96×10^5	0.25×10^6	0.28×10^8	3.68
			81.5	662	$0.34 imes 10^4$	0.78×10^5	0.18×10^6	0.13×10^8	3.68

Preliminary



Preliminary



Understanding the process in the effective Lagrangian

$$-\mathcal{L} = \frac{1}{3!} \left(\frac{3M_H^2}{v} \right) \lambda_{3H} H^3 + \frac{m_t}{v} \bar{t} \left(g_t^S + i\gamma_5 g_t^P \right) t H + \frac{1}{2} \frac{m_t}{v^2} \bar{t} \left(g_{tt}^S + i\gamma_5 g_{tt}^P \right) t H^2$$

★ In the SM, $\lambda_{3H} = g_t^s = 1$ and $g_{tt}^s = g_{tt}^P = 0$

SM Higgs colf couplings

$$\mathcal{L} = -\frac{1}{2}m_H^2 H^2 - \frac{g_{HHH}}{3!}H^3 - \frac{g_{HHHH}}{4!}H^4$$

In the gluon fusion process at the hadron collide $g(p_1)g(p_2) \rightarrow H(p_3)H(p_4)$

 $g_{HHH}=rac{3m_{H}^{2}}{v}$, $g_{HHHH}=rac{3m_{H}^{2}}{v^{2}}$

The differential cross section is given by

$$\frac{d\hat{\sigma}(gg \to HH)}{d\hat{t}} = \frac{G_F^2 \alpha_s^2}{512(2\pi)^3} \left[\left| \lambda_{3H} g_t^S D(\hat{s}) F_{\Delta}^S + (g_t^S)^2 F_{\Box}^{SS} \right|^2 + \left| (g_t^S)^2 G_{\Box}^{SS} \right|^2 \right]$$

Feynman diagrams

Only QCD Leading Order (LO) ---h 9000 g_{00000} 1 h Propagator of Higgs hgoood 9.000 $D(\hat{s}) = \frac{3M_H^2}{\hat{s} - M_H^2 + iM_H\Gamma_H}$ $\frac{d\hat{\sigma}(gg \to HH)}{d\hat{t}} = \frac{G_F^2 \alpha_s^2}{512(2\pi)^3} \left[\left| \lambda_{3H} g_t^S D(\hat{s}) F_{\Delta}^S + (g_t^S)^2 F_{\Box}^{SS} \right|^2 + \left| (g_t^S)^2 G_{\Box}^{SS} \right|^2 \right]$ Important Interference term $!!! \leftrightarrow \lambda_{3H}^{Non-SM}$

$$\frac{d\hat{\sigma}(gg \to HH)}{d\hat{t}} = \frac{G_F^2 \alpha_s^2}{512(2\pi)^3} \left[\left| \lambda_{3H} g_t^S D(\hat{s}) F_{\Delta}^S + (g_t^S)^2 F_{\Box}^{SS} \right|^2 + \left| (g_t^S)^2 G_{\Box}^{SS} \right|^2 \right]$$

In the heavy quark limit

$$F^S_{\triangle} = +\frac{2}{3} + \mathcal{O}(\hat{s}/m_Q^2) \,, \qquad \qquad F^{SS}_{\Box} = -\frac{2}{3} + \mathcal{O}(\hat{s}/m_Q^2) \,, \quad F^{PP}_{\Box} = +\frac{2}{3} + \mathcal{O}(\hat{s}/m_Q^2) \,,$$

There is large cancellation between the triangle and box diagrams

The production cross section normalized to the corresponding SM cross section :

$$\frac{\sigma^{\text{LO}}(gg \to HH)}{\sigma^{\text{LO}}_{\text{SM}}(gg \to HH)} = \underbrace{c_1(s)}_{0.263} \lambda_{3H}^2 (g_t^S)^2 + \underbrace{c_2(s)}_{2(s)} \lambda_{3H} (g_t^S)^3 + \underbrace{c_3(s)}_{2.047} (g_t^S)^4 \\ -1.310 \\ 0.208 \\ -1.108 \\ 1.900 \\ 100 \text{ TeV}$$

JHEP 1508(2015) 133

For the reference, there are various production modes



The gluon fusion production mode is dominant one !

(gg -> HH) = 45.05 fb,

 $(qq_0 \rightarrow HHqq_0) = 1.94 \text{ fb},$ $(qq(_0) \rightarrow V HH = 0.567(V = W) = 0.415(V = Z) \text{ fb},$ $(gg/qq \rightarrow ttHH) = 0.949 \text{ fb}$ are calculated at NNLO+NNLL, NLO, NNLO, and NLO, respectively

 $0.4 < \Delta R_{\gamma\gamma} < 2.0$

 $0.4 < \Delta R_{b \, \overline{b}} < 2.0$



 $P_{\tau}^{\gamma\gamma} > 80 \text{ GeV}$



450

p_{_{T}}^{bb}(GeV)

500



Machine Learning approaches to the Higgs boson self coupling

(1) BDT(Boosted Decision Tree) : bbYY

1. Phys.Rev. D96 (2017) no.3, 035022 (Alves, Alexandre et al.) arXiv:1704.07395 [hep-ph]

BDT + kinematic cuts \longrightarrow 5 σ (4.6 σ) significance with 10 %(20%) systematics and 3 ab^-1

2 (Supervising) Deep Neural Networks (DNN) : bbWW + bbττ

1. "Supervising Deep Neural Networks with topological augmentation in search for di-Higgs production at the LHC (Dr. Won Sang Cho)

5 classes by the number of leptonic taus

Optimass & its compatibility distance with dim. Of vars ~ 40

AUC of ROC = 0.991

@(Background purity=0.01) = 0.84

Eff(sig)

Machine Learning approaches to the Higgs boson self coupling

③ DNN (ANN: a multi-layer feed-forward artificial neural network): bbbb 1. Eur. Phys. J. C (2016) 76:386 (Katharina Behr, Bortoletto et al.) arXiv:1512.08928 [hep-ph]

DNN + kinematic cuts $\longrightarrow \frac{S}{\sqrt{B}} \sim 3 \sigma$ significance with 3 ab^-1



Summary Table

Channel	Achievable Significance (σ)	Methods	Papers	Remarks
bbbb	~ 3	Kinematic Cuts+ DNN	Eur. Phys. J. C (2016) 76:386	HL-LHC (3 ab^-1)
	~ (3.1 ~ 5.7) DI	NN	Arxiv: 1609.002541	HQLHEV(3Faba-1) ab^-1)
bbWW			Dr. Won Sang Cho's work	
bbττ				
WWWW				
bbYY	~ 5 (4.6)	Kinematic Cuts + BDT	Phys.Rev. D96 (2017) no.3, 035022	HL-LHC (3 ab^-1),
	~ 2.1	Kinematic Cuts + BDT	Preliminary	With full BGs.
bbZZ(eemm)				

Summary Table

Channel	Achievable Significance (σ)	Methods	Papers	Remarks
bbbb	~ 3	Kinematic Cuts+	Eur. Phys. J. C (2016) 76:386	HL-LHC (3 ab^-1)
bbWW	~ (3.1 ~ 5.7) DI	NNPNN	Prof. Park's Work Arxiv: 1609.002541 Dr. Won Sang Cho's Work	HPLINE (3Faba-(1) ab^-1)
bbττ				
WWWW				
bbYY	~ 5 (4.6)	Kinematic Cuts + BDT	Phys.Rev. D96 (2017) no.3, 035022	HL-LHC (3 ab^-1),
	~ 2.1	Kinematic Cuts + BDT	Preriminary	With full BGs.
bbZZ(eemm)				

Summary Table

Channel	Achievable Significance (σ)	Methods	Papers	Remarks
bbbb	~ 3	Kinematic Cuts+ DNN	Eur. Phys. J. C (2016) 76:386	HL-LHC (3 ab^-1)
	~ (3.1 ~ 5.7) DI	NN	Arxiv: 1609.002541	HLOLHEV3Fabra-(1) ab^-1)
bbWW			Next Dr. Won Sang Cho talk	
bbττ				
WWWW				
bbYY	~ 5 (4.6)	Kinematic Cuts +	Phys.Rev. D96 (2017) no.3,	HL-LHC (3 ab^-1),
		BDT	035022	
	~ 2.1	Kinematic Cuts + BDT	Preriminary	With full BGs.
bbZZ(eemm)				



The ratio increases by about 10 (35) % at $\lambda_{3H} = -1$ (5) !

It is clear that the QCD corrections are less significant than the uncertainties associated with the top-Yukawa coupling.

About top Yukawa uncertainty !



Ratio of cross sections (gg -> HH)=(gg -> HH)_{SM} versus $_{3H}$ taking account of 10% uncertainty of the top-Yukawa coupling: $g_{st} = 1:1$ (black), 1 (blue), and 0:9 (red) for sqrt(s) = 14 TeV (left) and sqrt(s) = 100 TeV (right).

Y_t precision measurement



At the HL-LHC, the expected precision of measurement of the top-quark Yukawa coupling (Yt) is 10%.








- Rectangular cut optimisation (binary splits, Sec. 8.1).
- Projective likelihood estimation (Sec. 8.2).
- Multi-dimensional likelihood estimation (PDE range-search Sec. 8.3, PDE-Foam Sec. 8.4, and k-NN Sec. 8.5).
- Linear and nonlinear discriminant analysis (H-Matrix Sec. 8.6, Fisher Sec. 8.7, LD Sec. 8.8, FDA Sec. 8.9).
- Artificial neural networks (three different multilayer perceptron implementations Sec. 8.10).
- Support vector machine (Sec. 8.12). Boosted/bagged decision trees (Sec. 8.13).
- Predictive learning via rule ensembles (RuleFit, Sec. 8.14).
- A generic boost classifier allowing one to boost any of the above classifiers (Sec. 10).
- A generic category classifier allowing one to split the training data into disjoint categories with independent MVAs.