# Improving measurement on Higgs-gluon effective coupling Zhao Li

USTC Sep 12 2019

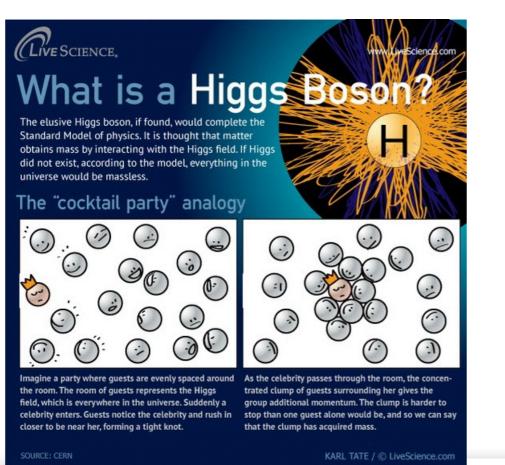
**IHEP-CAS** 



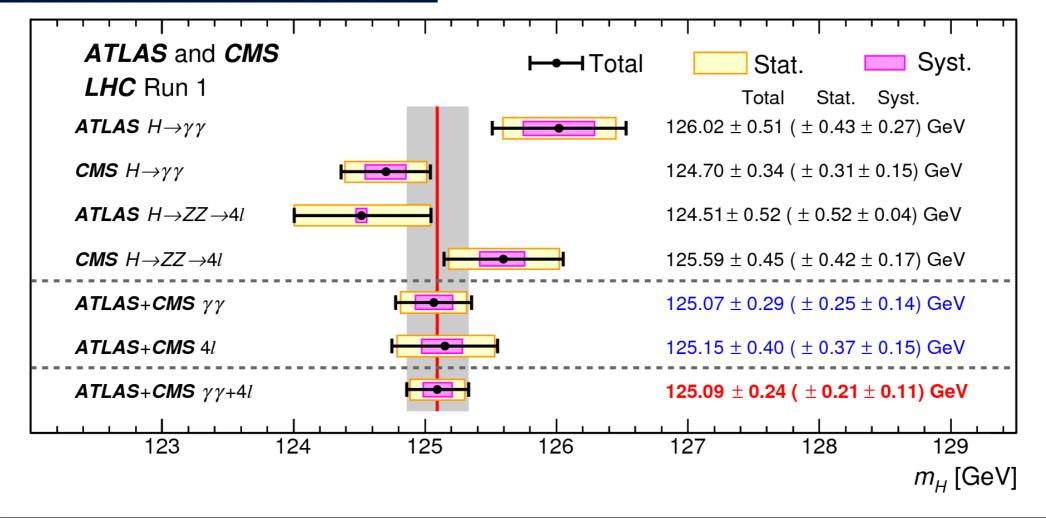


中國科學院為能物記酬完所 Institute of High Energy Physics Chinese Academy of Sciences

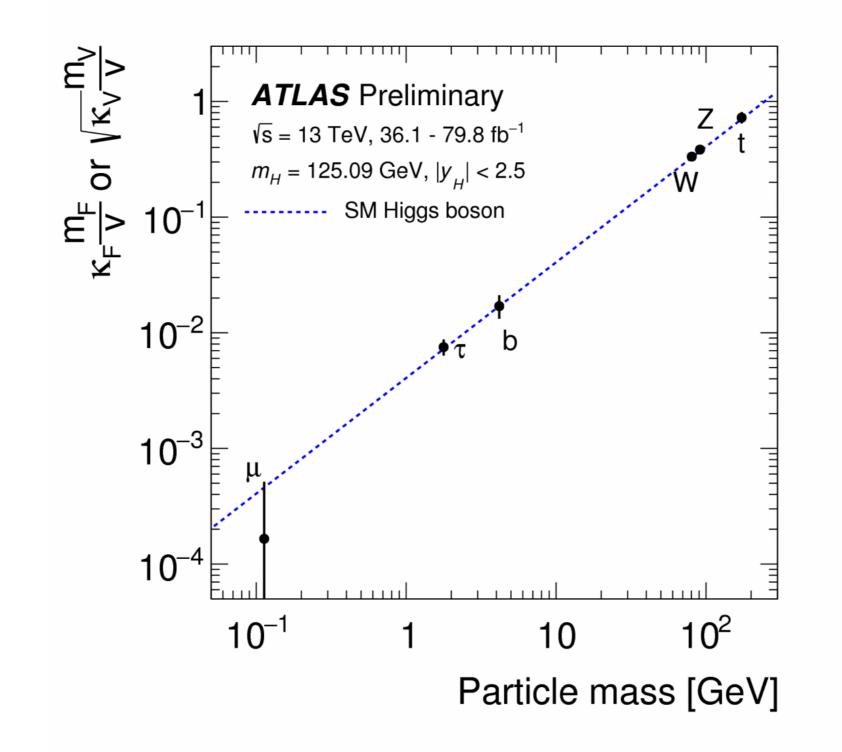
based on PRD98 (2018) no.7, 076010 & arXiv:1901.09391



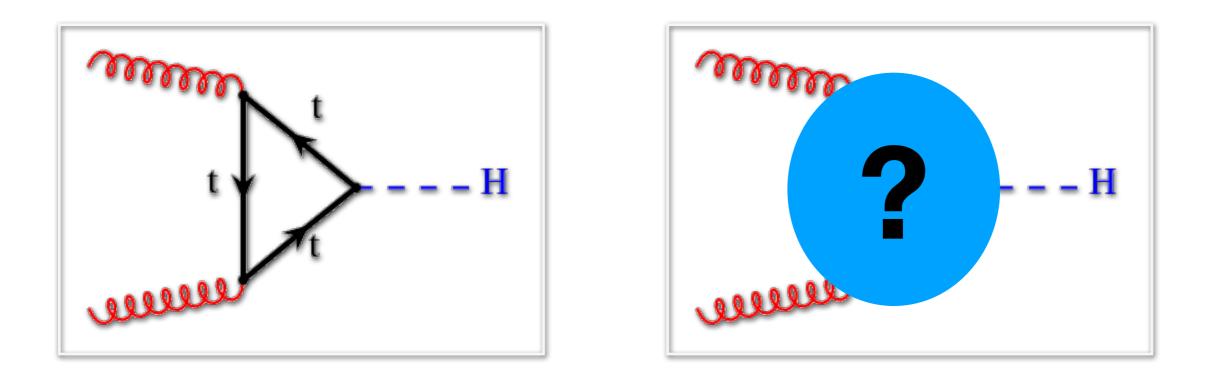




## Higgs Properties, i.e. couplings/interactions



### **Direct or Indirect modification**

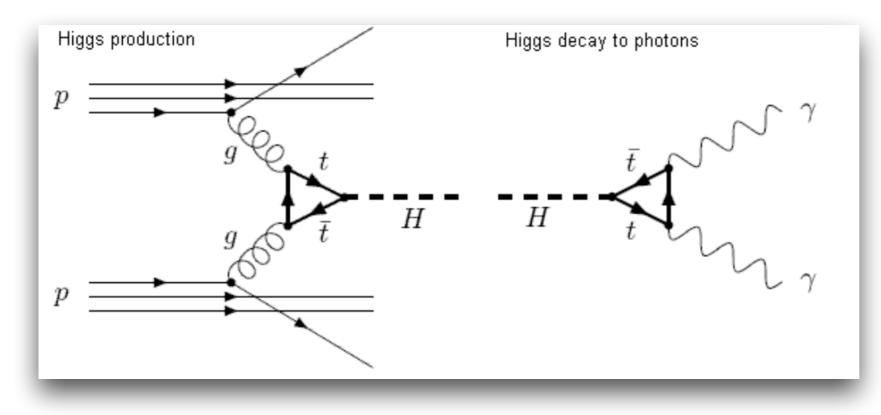


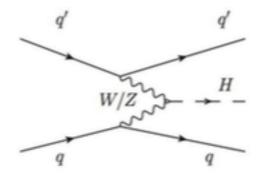
$$\mathcal{L}_{hgg} = \kappa_g c_{\rm SM}^g \frac{\alpha_s}{12\pi v} h G^a_{\mu\nu} G^{a\mu\nu},$$

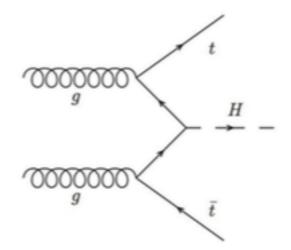
**SUSY?** Little Higgs? Extra Dimensions? etc.

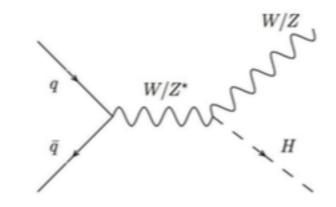
### Measurement @ LHC





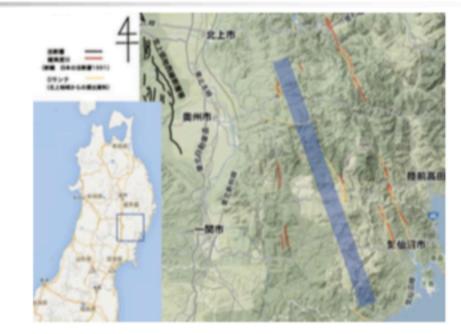






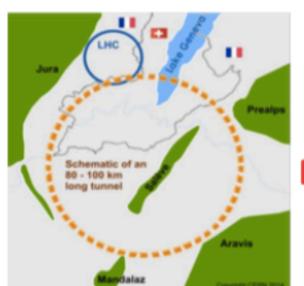
## Several Higgs factories under plan





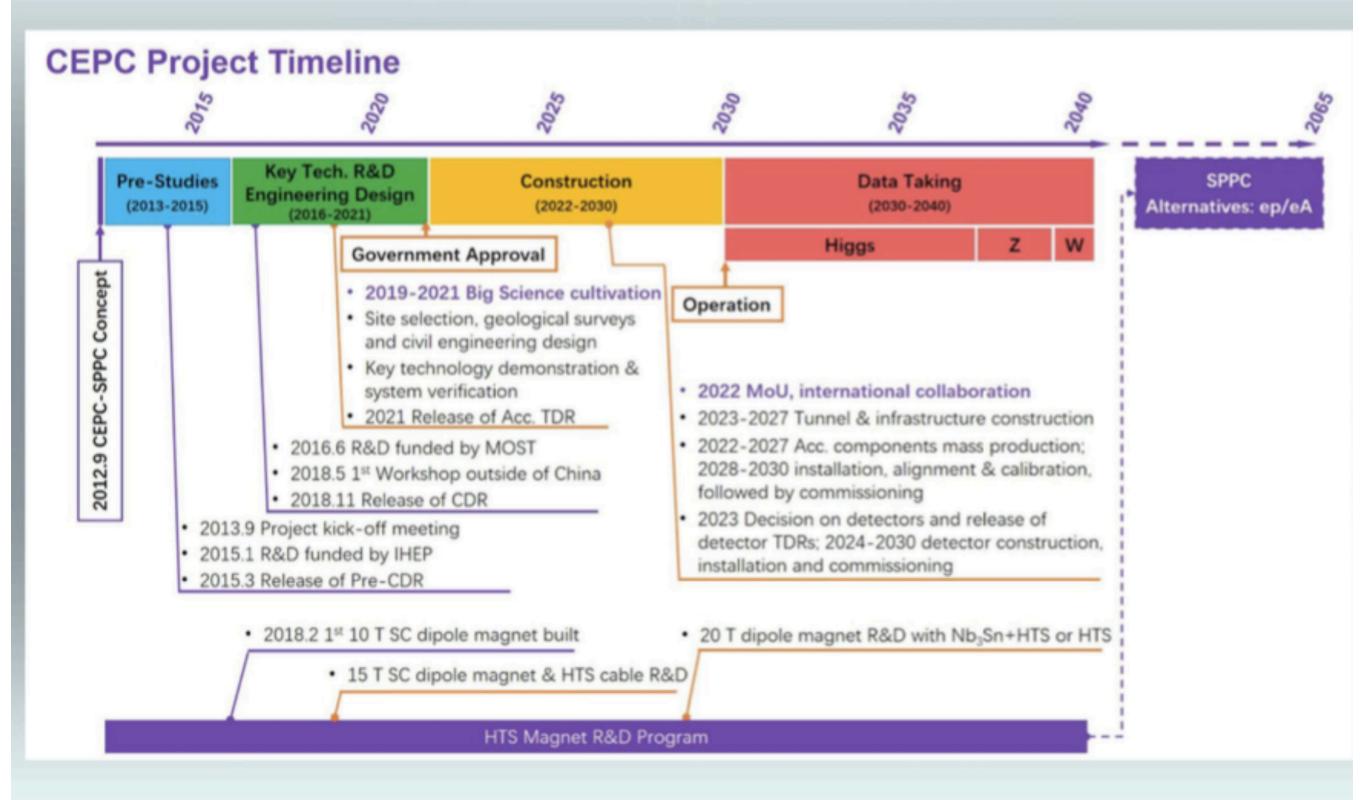
CEPC@90-240 GeV (China) 秦皇岛 or 雄安?

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



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

### **CEPC timeline**

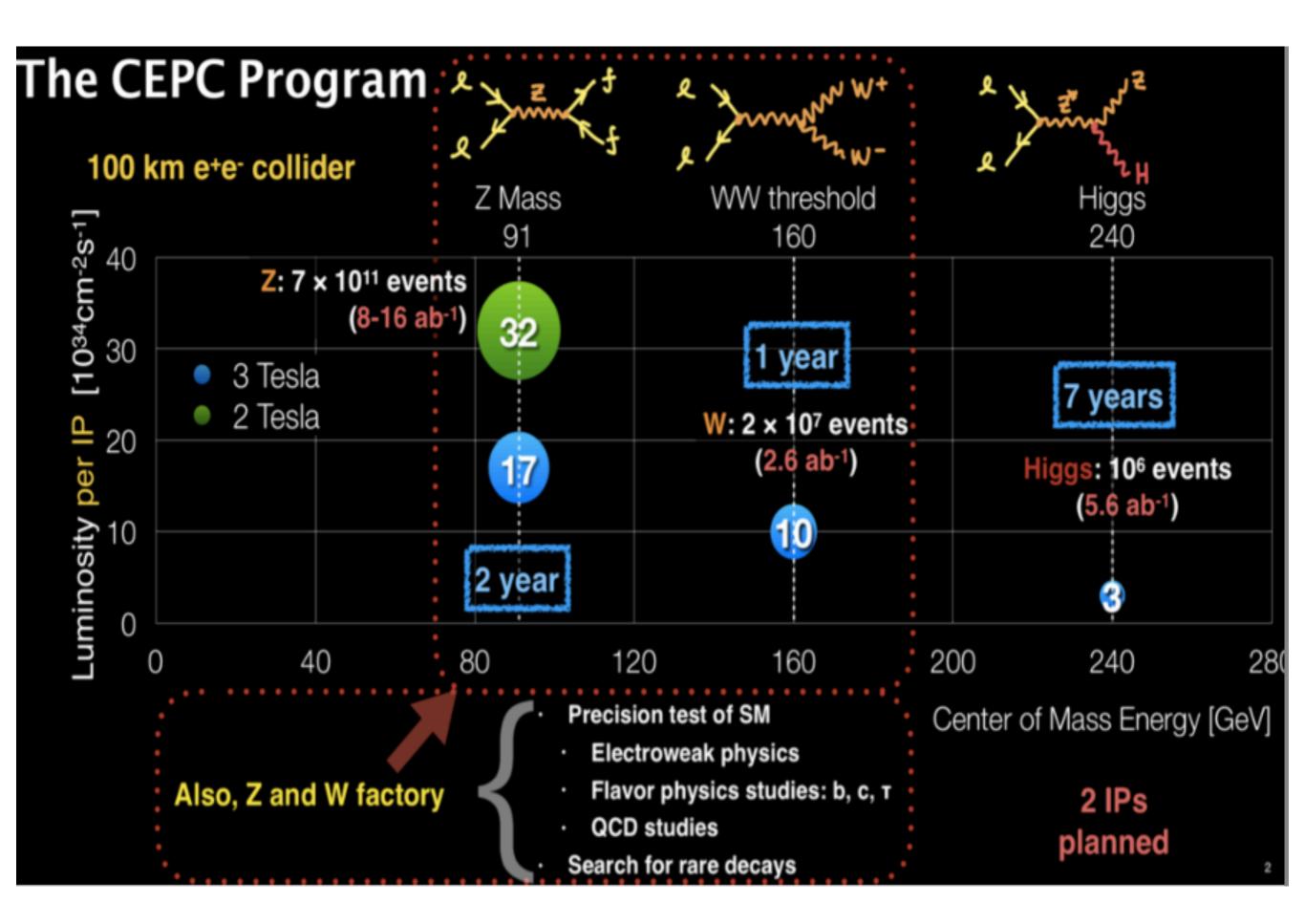


#### CEPC High Lumi Parameters@Higgs

D. Wang

	Higgs	W	Z (3T)	Z (2T)					
Number of IPs	2								
Beam energy (GeV)	120	80	45.5						
Circumference (km)	100								
Synchrotron radiation loss/turn (GeV)	1.68	0.33	0.035						
Crossing angle at IP (mrad)	16.5×2								
Piwinski angle	3.78	8.5	27.7						
Number of particles/bunch $N_e$ (10 <sup>10</sup> )	17.0	12.0	8.0						
Bunch number (bunch spacing)	218 (0.76µs)	////1568 (0.20µs)	12000 (25ns+10%gap)						
Beam current (mA)	17.8	90.4	461						
Synchrotron radiation power /beam (MW)	30	30	16	.5					
Bending radius (km)	10.7								
Momentum compact (10-5)	0.91								
$\beta$ function at IP $\beta_{c} * / \beta_{c} * (m)$	0.33/0.001	0.33/0.001	0.2/0	0.2/0.001					
Emittance $\varepsilon_x/\varepsilon_y$ (nm)	0.89/0.0018	0.395/0.0012	0.13/0.003	0.13/0.00115					
Beam size at IP $\sigma_x / \sigma_y$ (µm)	17.1/0.042	11.4/0.035	5.1/0.054	5.1/0.034					
Beam-beam parameters $\xi_y/\xi_y$	0.024/0.113	0.012/0.1	0.004/0.053	0.004/0.085					
RF voltage $V_{RF}$ (GV)	2.4	0.43	0.082						
RF frequency $f_{RF}$ (MHz) (harmonic)	650 (216816)								
Natural bunch length $\sigma_{e}$ (mm)	2.2	2.98	2.42						
Bunch length $\sigma_{z}$ (mm)	3.93	5.9	8.5						
HOM power/cavity (2 cell) (kw)	0.58	0.77	1.94						
Energy spread (%)	0.19	0.098	0.080						
Energy acceptance requirement (%)	1.7	0.90	0.49						
Energy acceptance by RF (%)	3.0	1.27	1.55						
Photon number due to beamstrahlung	0.104	0.050	0.023						
Beamstruhlung lifetime /quantum lifetime* (min)	30/50	>400							
Lifetime (hour)	0.22	1.2	3.2	2.0					
F (hour glass)	0.85	0.92	0.98						
Luminosity/IP L (10 <sup>34</sup> cm <sup>-2</sup> s <sup>-1</sup> )	5.2	14.5	23.6	37.7					

\*include beam-beam simulation and real lattice



# Results in CDR (2018.11)

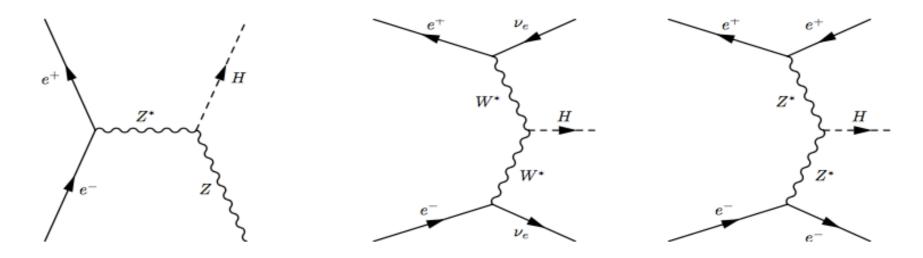


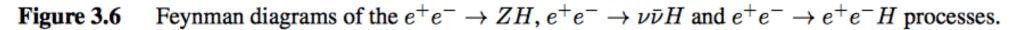
					_		Precisio	_					
Estimated Precision			S	Signal		Si	Signal Precisio		Signal		Precisio		
D	CIE			Cl	Z	н	n	Z	н	n	Z	н	n
Property		PC-v1		CEPC-v4		H->qq		H->WW		Η→γγ, Ζγ			
$m_H$		MeV		$5.9 { m MeV}$		bb	1.32%	ee	lvlv	9.52%	μμ+ττ		23.7%
$\Gamma_H$		.7%		2.8%		cc	13.5%		evqq	4.56%	vv		10.5%
$\sigma(ZH)$				0.5%		gg	7.22%	1	μvqq	3.93%	qq	1	9.84%
$\sigma(\nu\bar{\nu}H)$	3	.0%	3.3	2%		bb	0.99%		lvlv	7.29%	vv	Zγ(qqγ)	15.7%
					μμ	cc	9.54%	μμ	evqq	3.90%	vvH	(WW fus	Contraction and the second
Decay mode	$\sigma \!\times\! \mathrm{BR}$	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			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%	vv	μvqq	4.14%	ee	1	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	cc	3.83%	qq	qqqq	1.75%	vv	1	
$H \rightarrow \gamma \gamma$	6.2%	6.2%	6.8%	6.9%		gg			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	ZZ(VVVV)	370%		vvqq	7.32%	qq	ττ	0.95%
$\rm BR_{inv}^{\rm BSM}$	-	< 0.28%	-	< 0.30%	μμ			ZH bkg contribution		19.4%	vv	]	2.66%

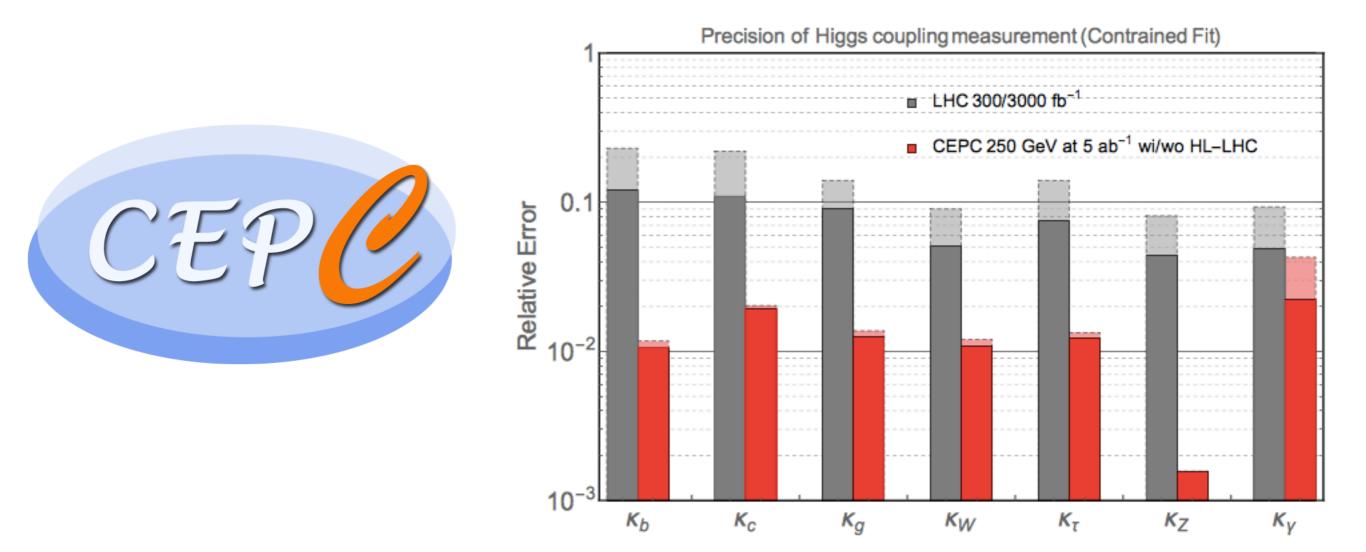
All scaled to 240 GeV, 5.6ab-1

### CEPC团队、国际顾问委员会部分委员和《CEPC概念设 计报告》国际评审委员会成员合影 -- 2018年11月14日





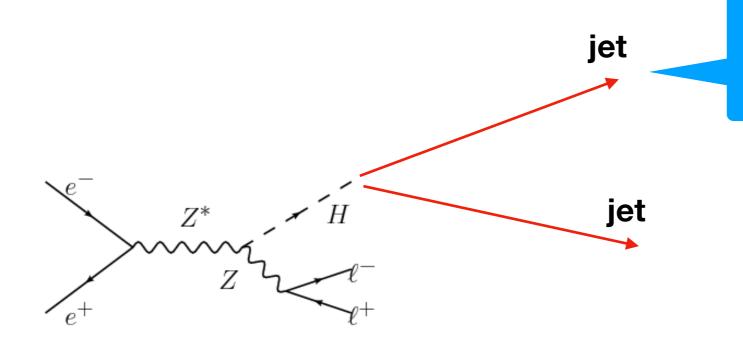




## ggH coupling from H->gg

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 gluonl
$$\sum_{r_i < R} \frac{1.2}{0.6}$$

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

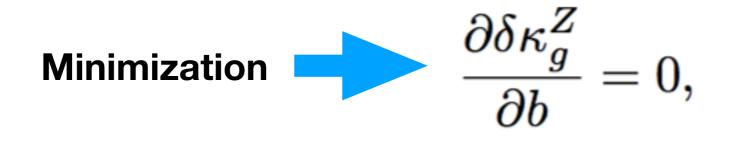
H->bb is well measured. & Assume Hbb Yukawa is true.

0.7

#### **Optimized uncertainty of effective coupling**

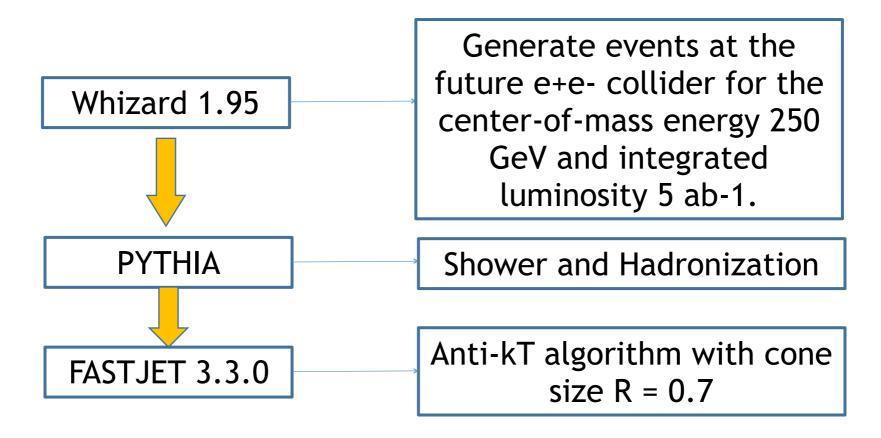
$$Z^{N}(r) = \frac{\sum_{j} (\psi_{j} + b)}{\sum_{j}^{SM} (\psi_{j} + b)},$$

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



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

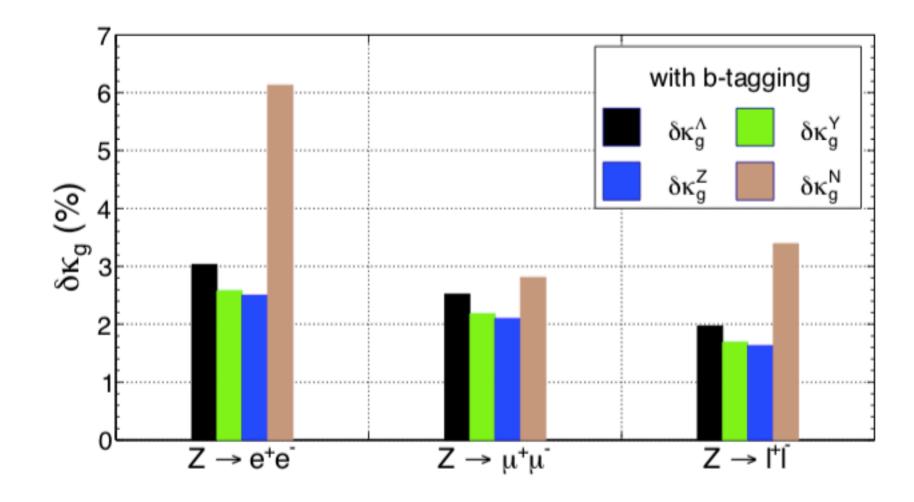
### **MC Simulation**



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



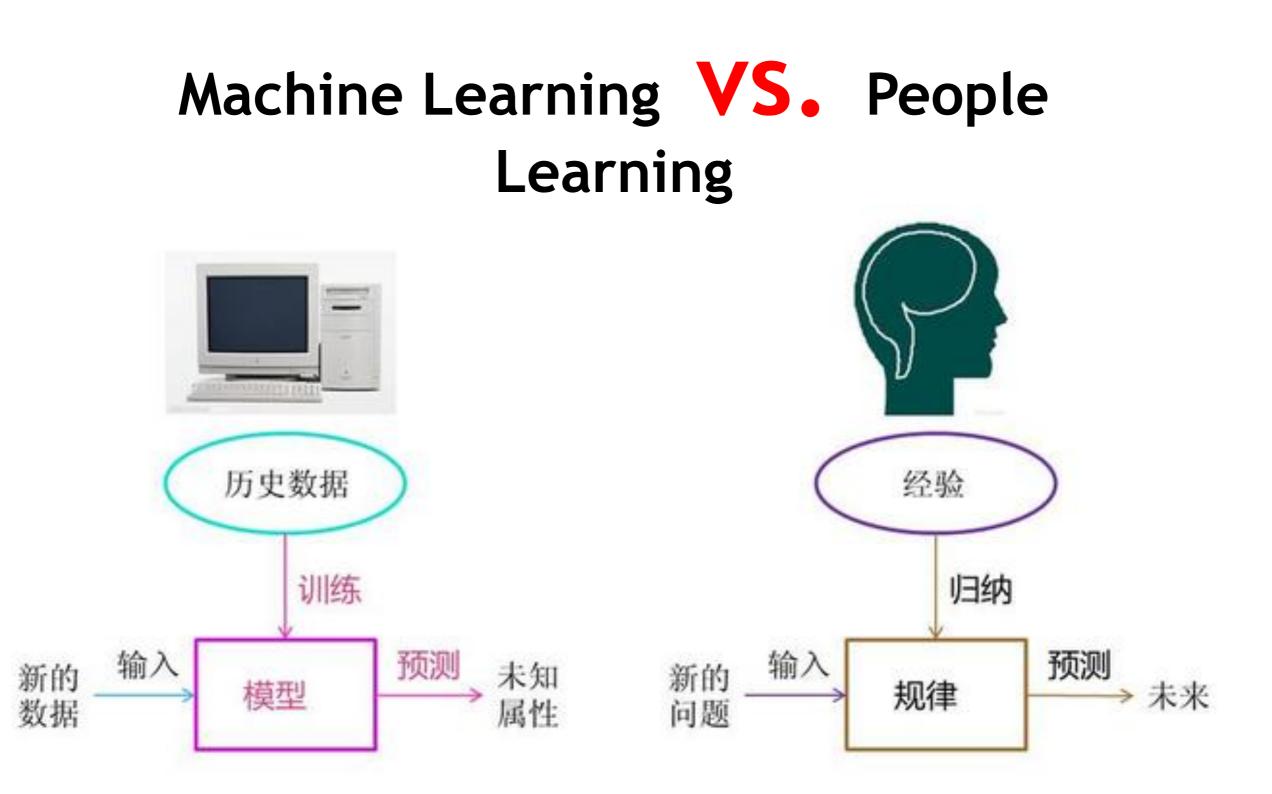




### ~50% improvement to reach ~1.6%

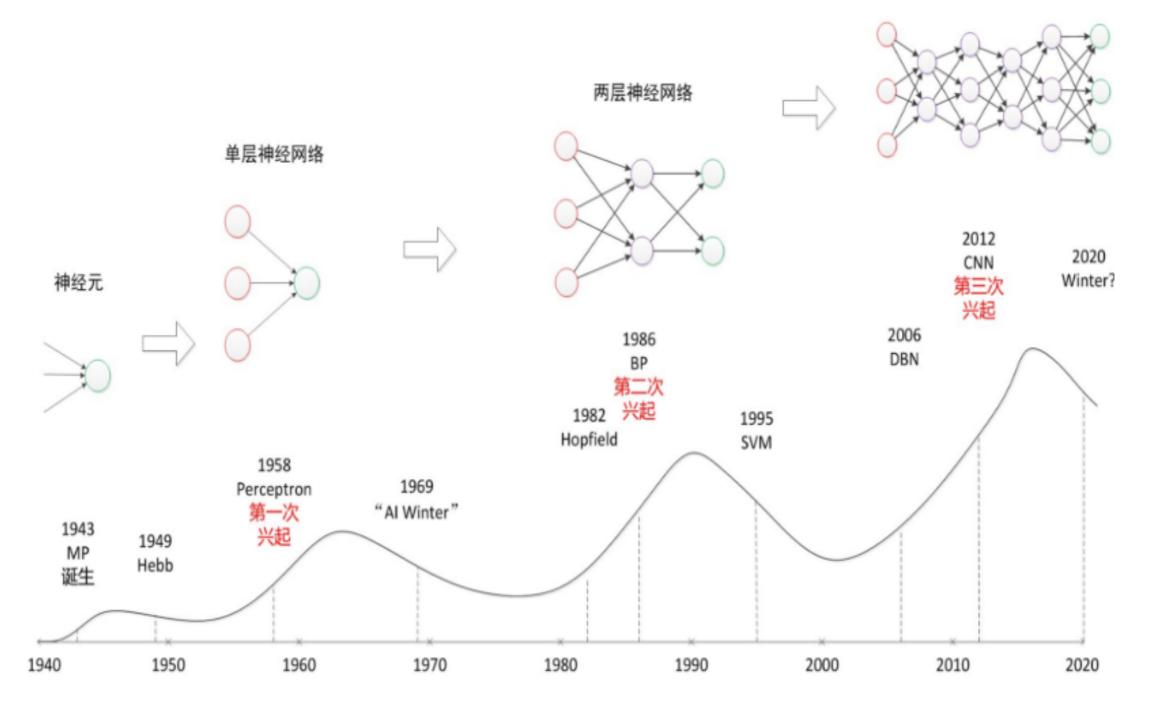
#### Machine Learning is widely used in many fields



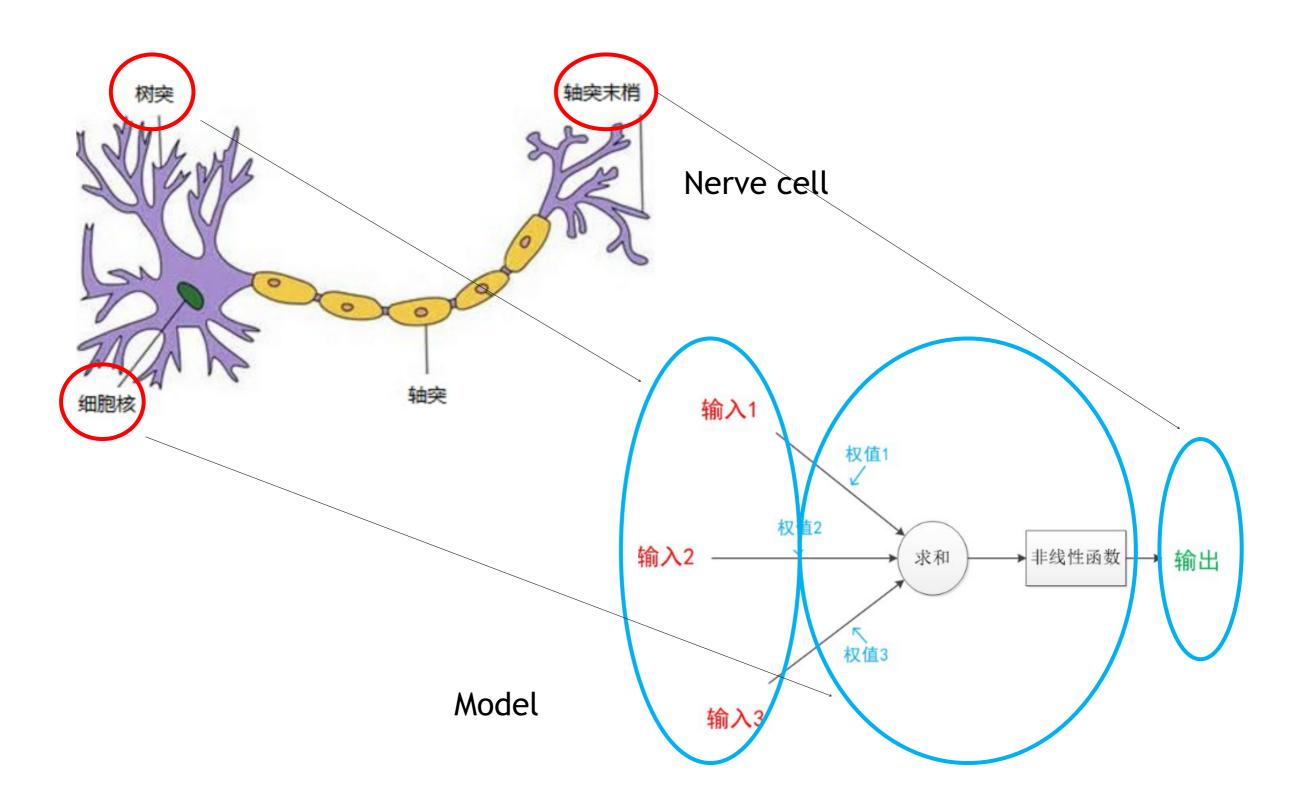


# History of Machine Learning

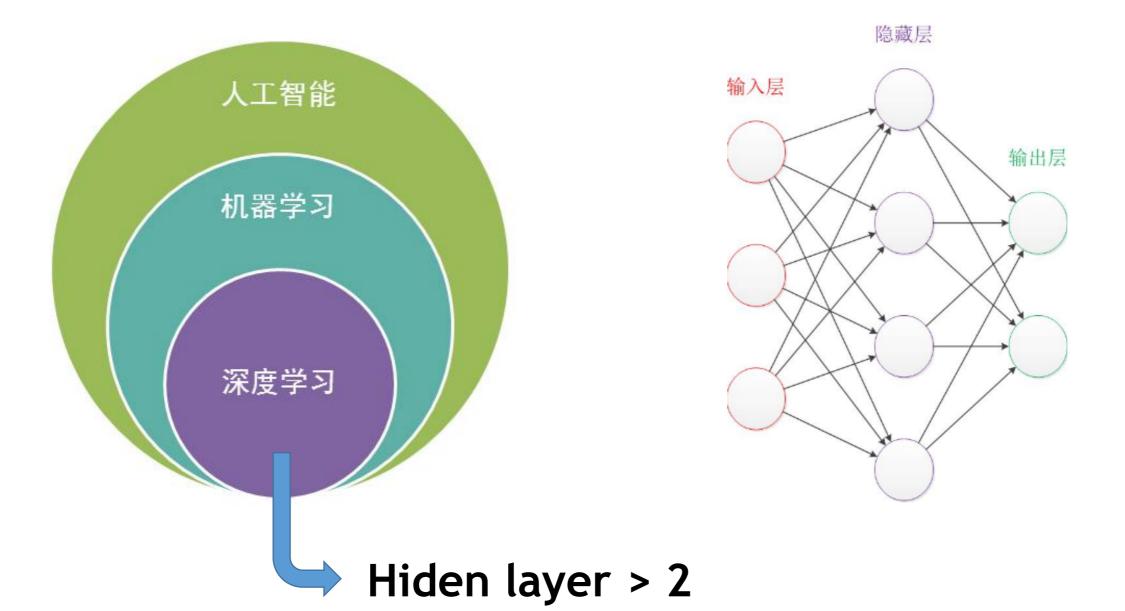
多层神经网络



# Nerve cell



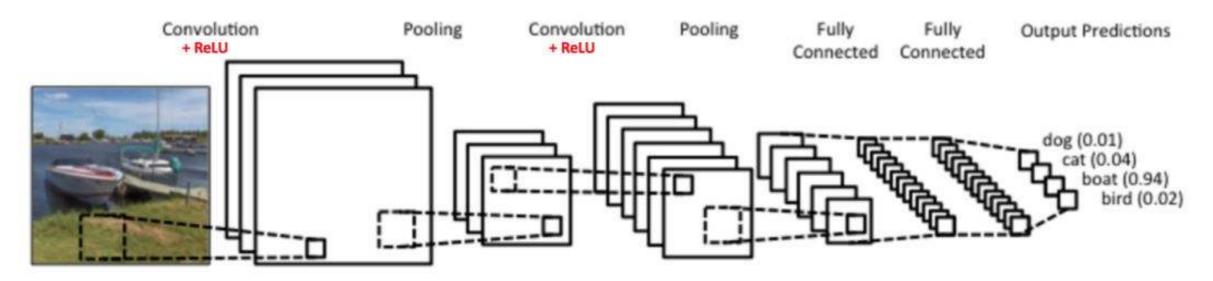
# Deep Learning

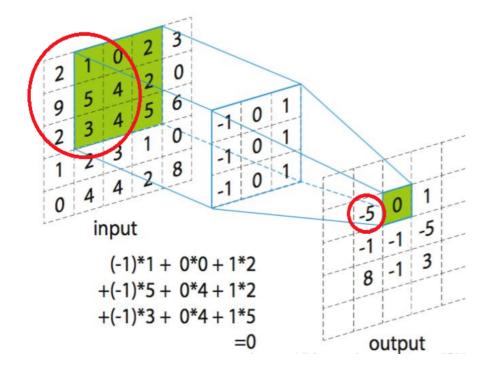


Deeper networks can achieve more complex linear classifications.

# Convolutional Neural Networks (CNNs)

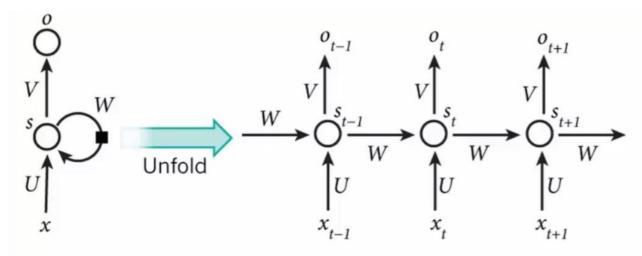
CNNs is one of the most popular algorithms in deep learning. It has powerful ability of image recognition.



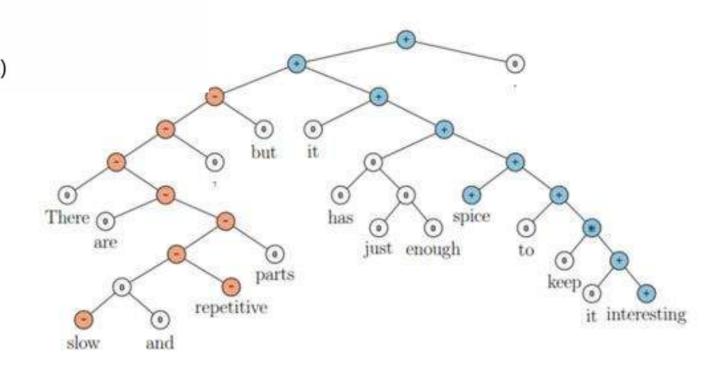


# CNNs extract the features form images by the convolutional layers.

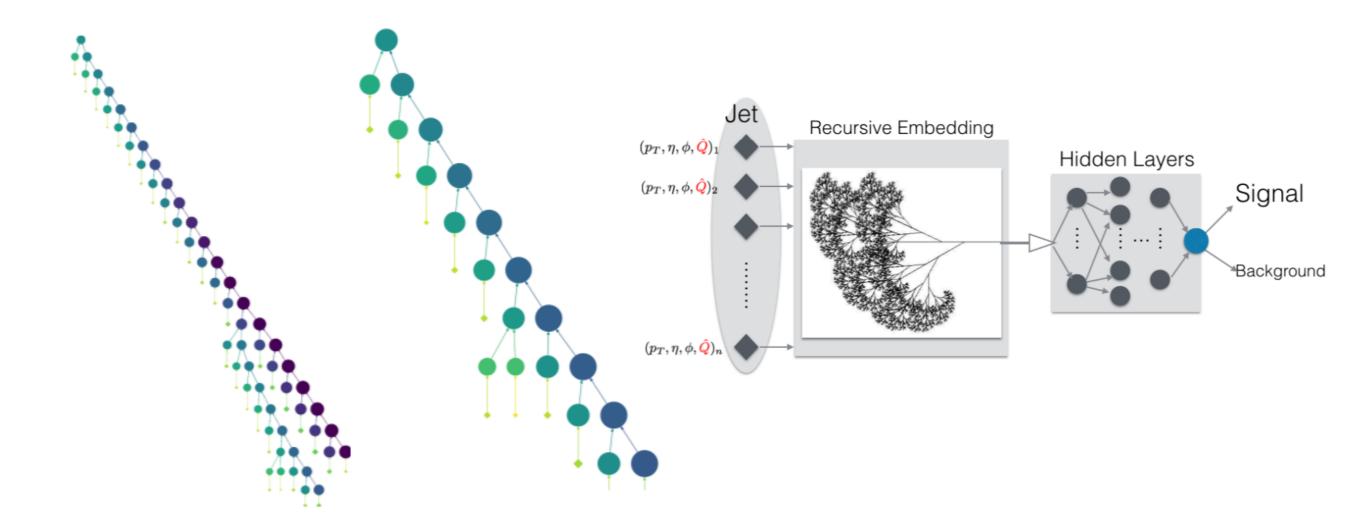
# Recursive neural networks (RecNN)



xt表示第t,t=1,2,3...步(step)的输入 st为隐藏层的第t步的状态,它是网络的记忆单元。 st=f(Uxt+Wst-1),其中f一般是非线性的激活函数 ot是第t步的输出,如下个单词的向量表示softmax(Vst)

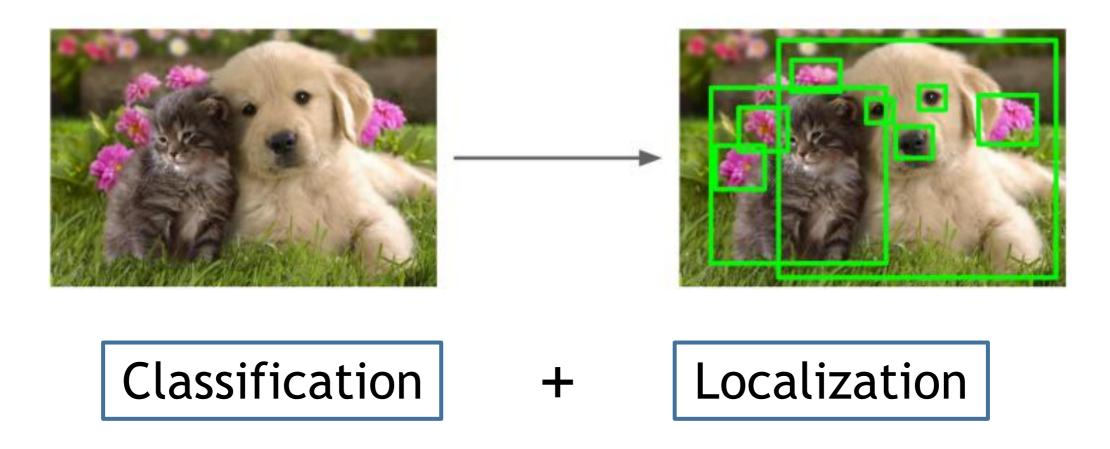


# Identification of quark/gluon jets by RecNN

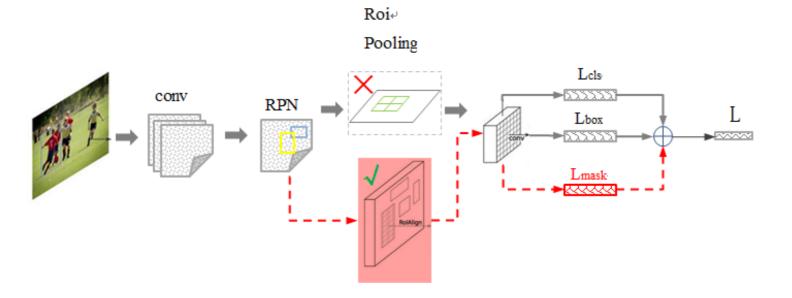


Typical tree structures for 1 TeV gluon jet (left) and quark jet (right)

#### Object detection: Region-based CNN (RCNN)



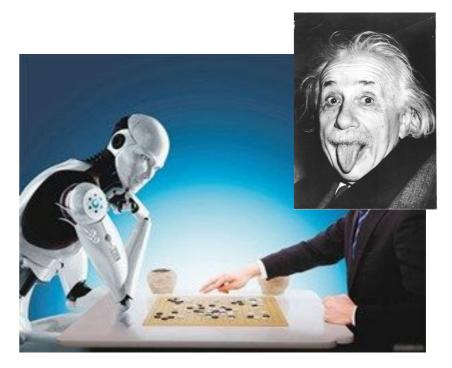
#### Evolution: RCNN -> Fast RCNN -> Faster RCNN -> Mask

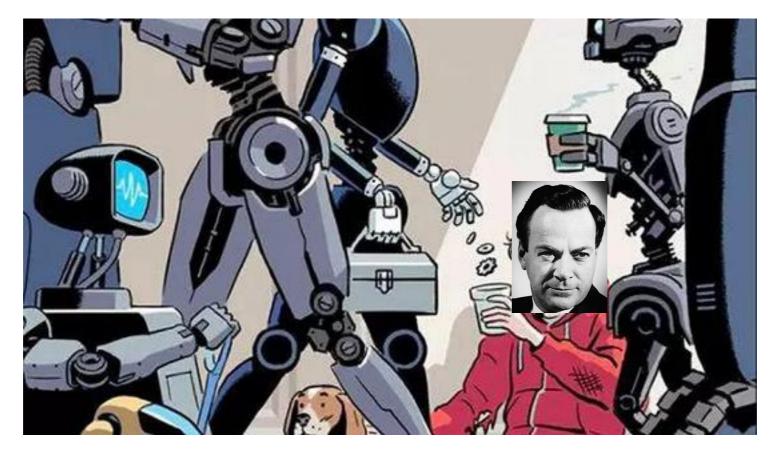


Automated jet construction and Classification

### Machine Learning @ HEP





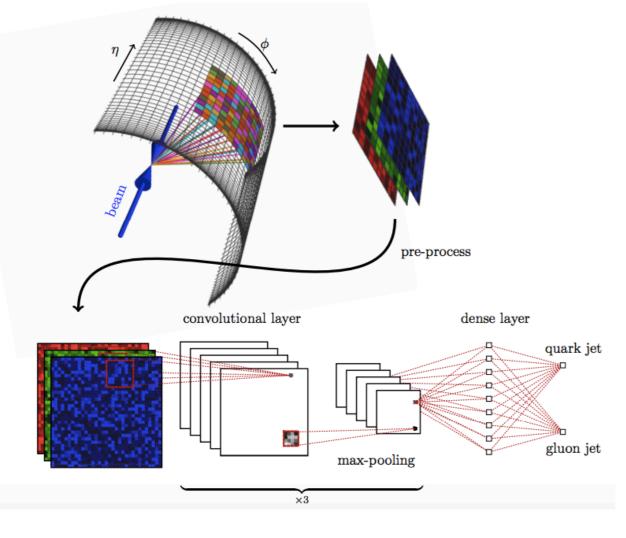


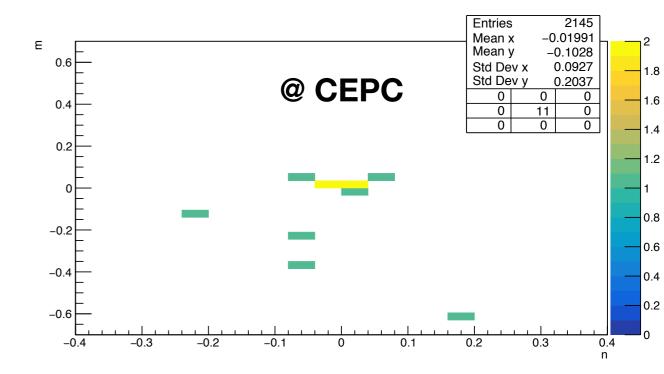
### Machine Learning @ HEP

- 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



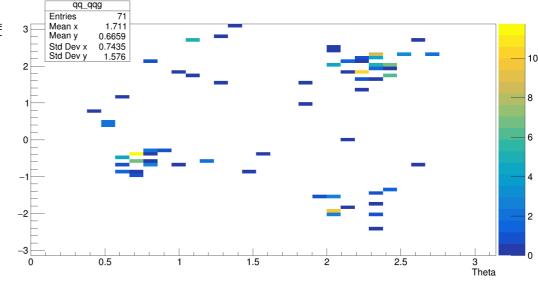


### **CNN Configuration**

```
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**



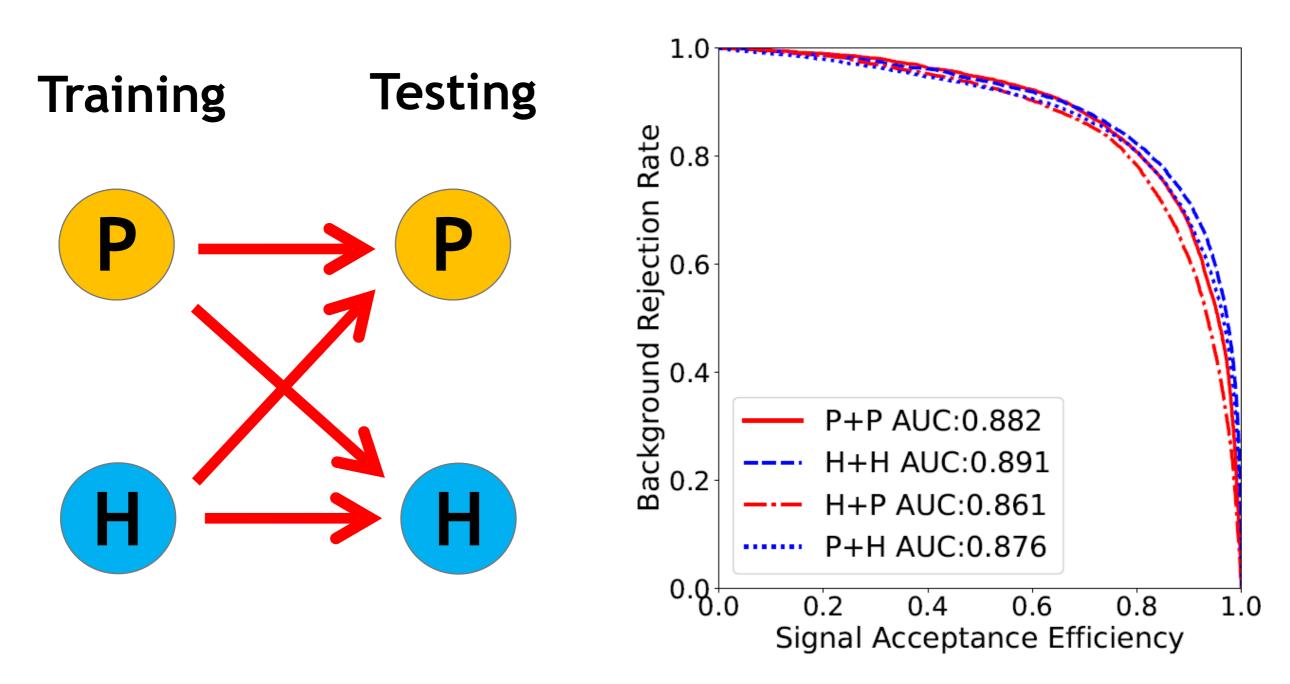


phi symmetry break

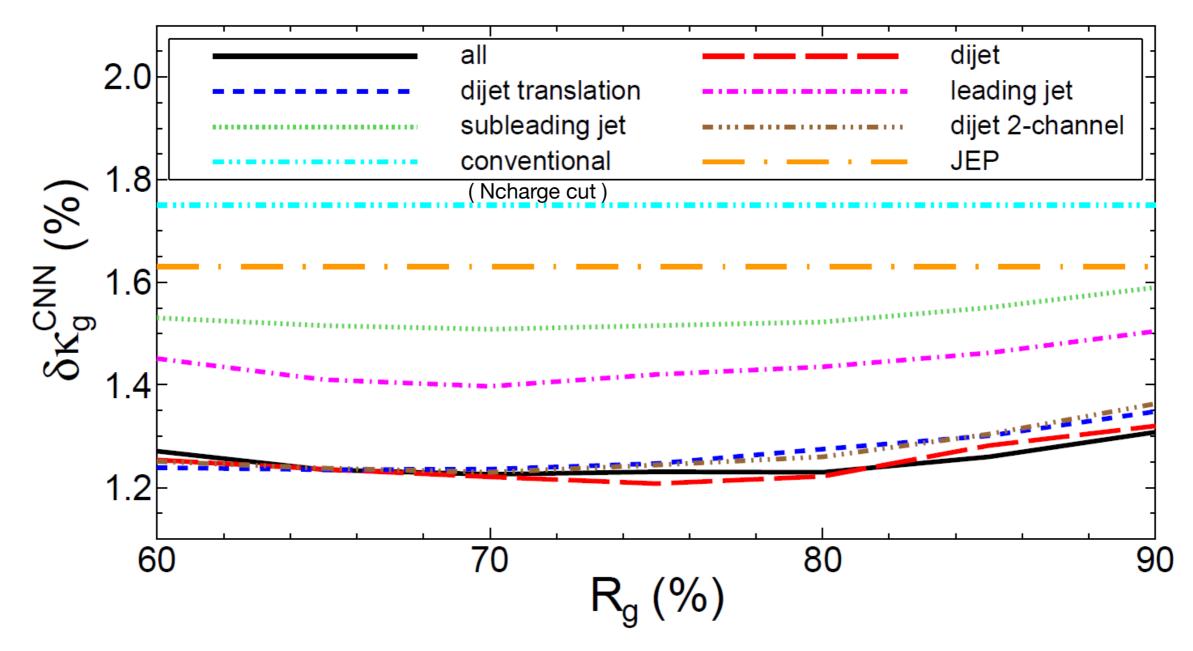
Rotate at phi direction

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

## Performance of CNNs

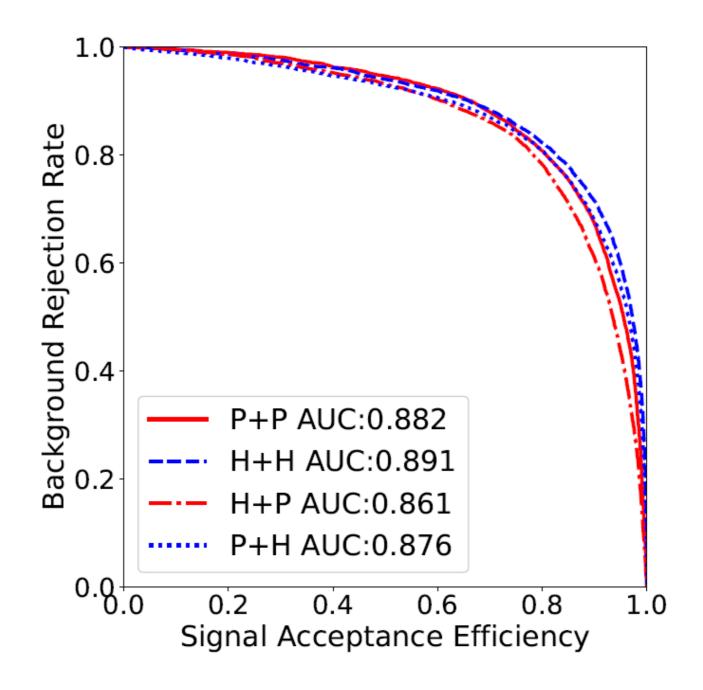


### Improvement of CNNs

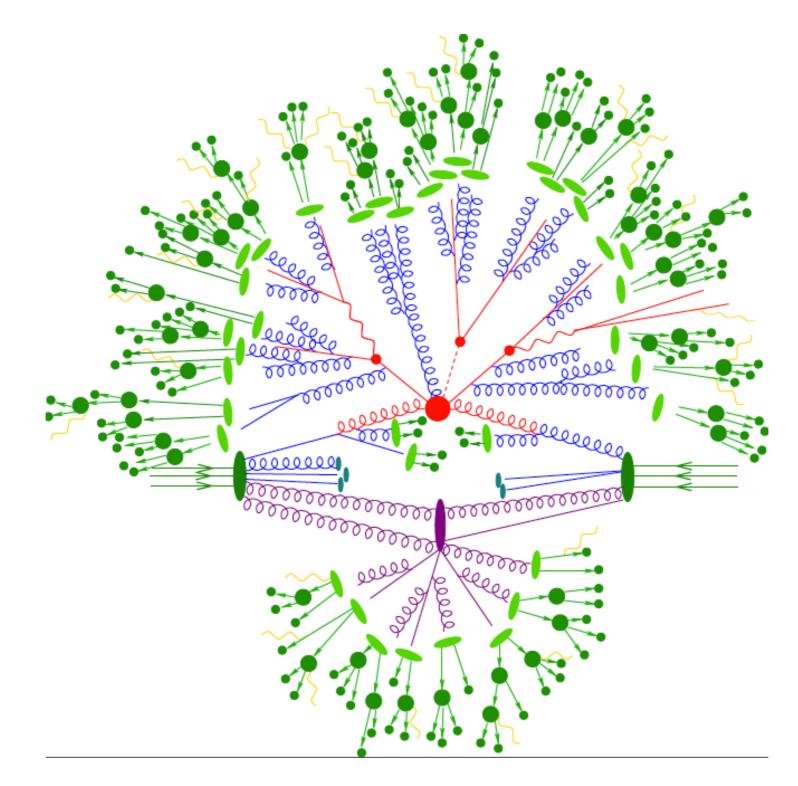


Further ~30% improvements to reach ~1,2%

### **Revisit AUC comparison between P & H**



### **Does simulation really simulate physics?**



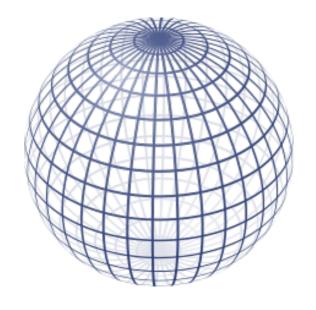
Parton Shower? Hadronization? Underlying events? etc.

# Conclusion

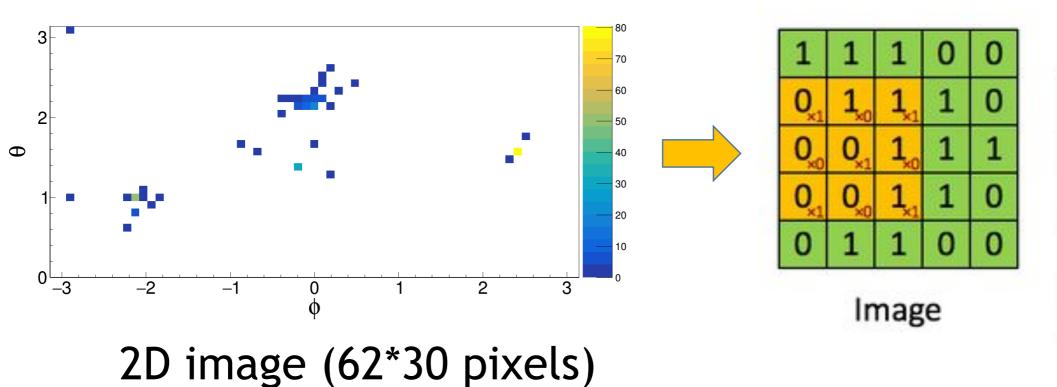
- CEPC can be very precise factory for Higgs investigation.
- Deep learning is full of potential for CEPC physics.
- Maybe deep learning can also help LHC physics.
- However, we should be careful about traps in simulations.

# Backup

# Convolutional Neural Networks (CNNs)

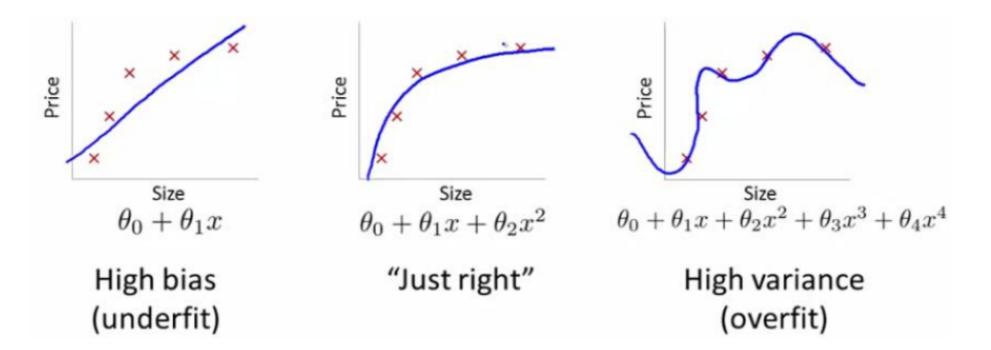


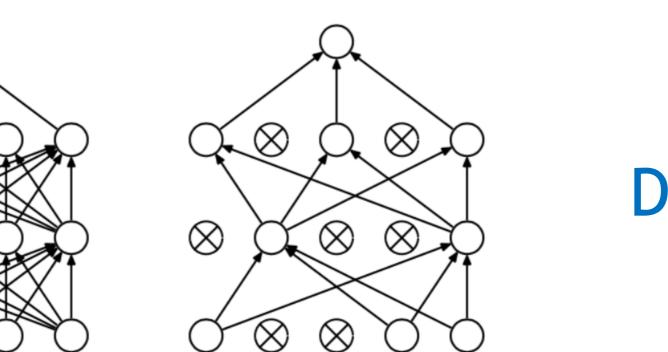
Energy of all the final state stable particles





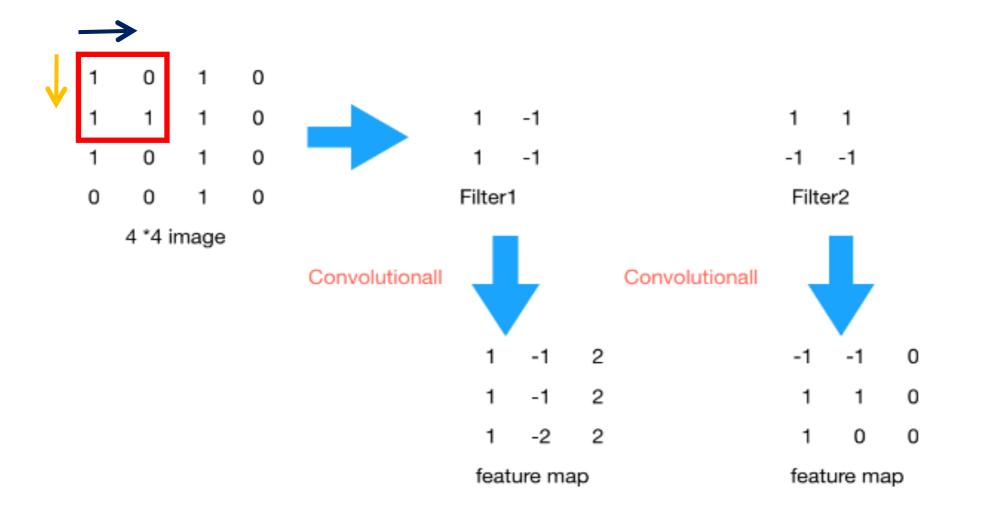
Convolved Feature

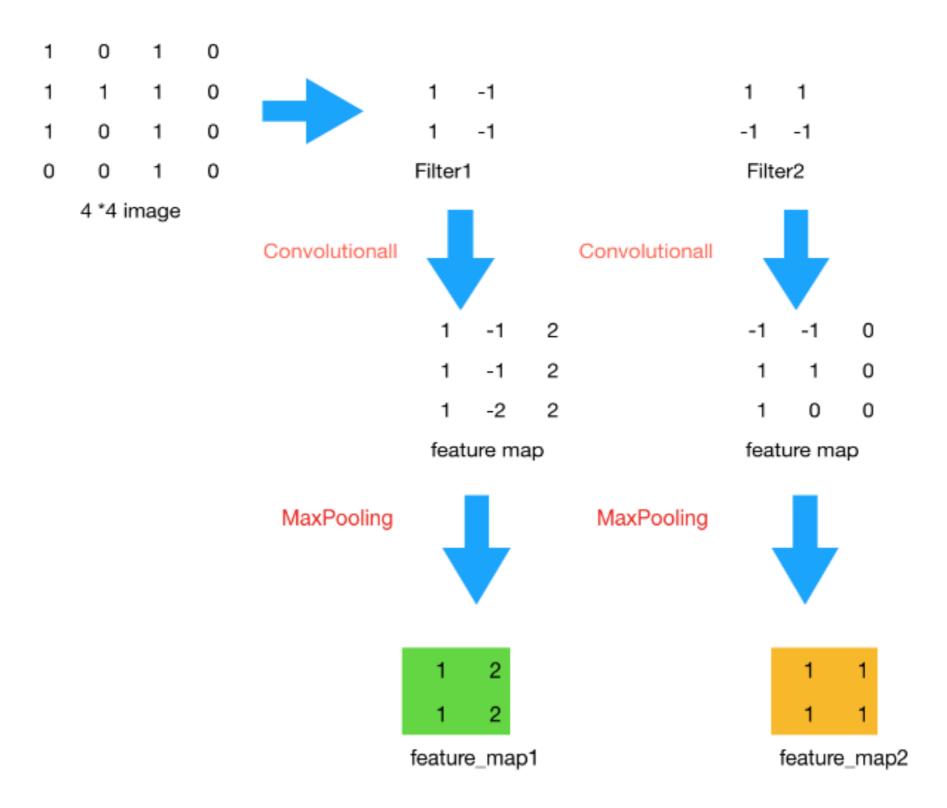


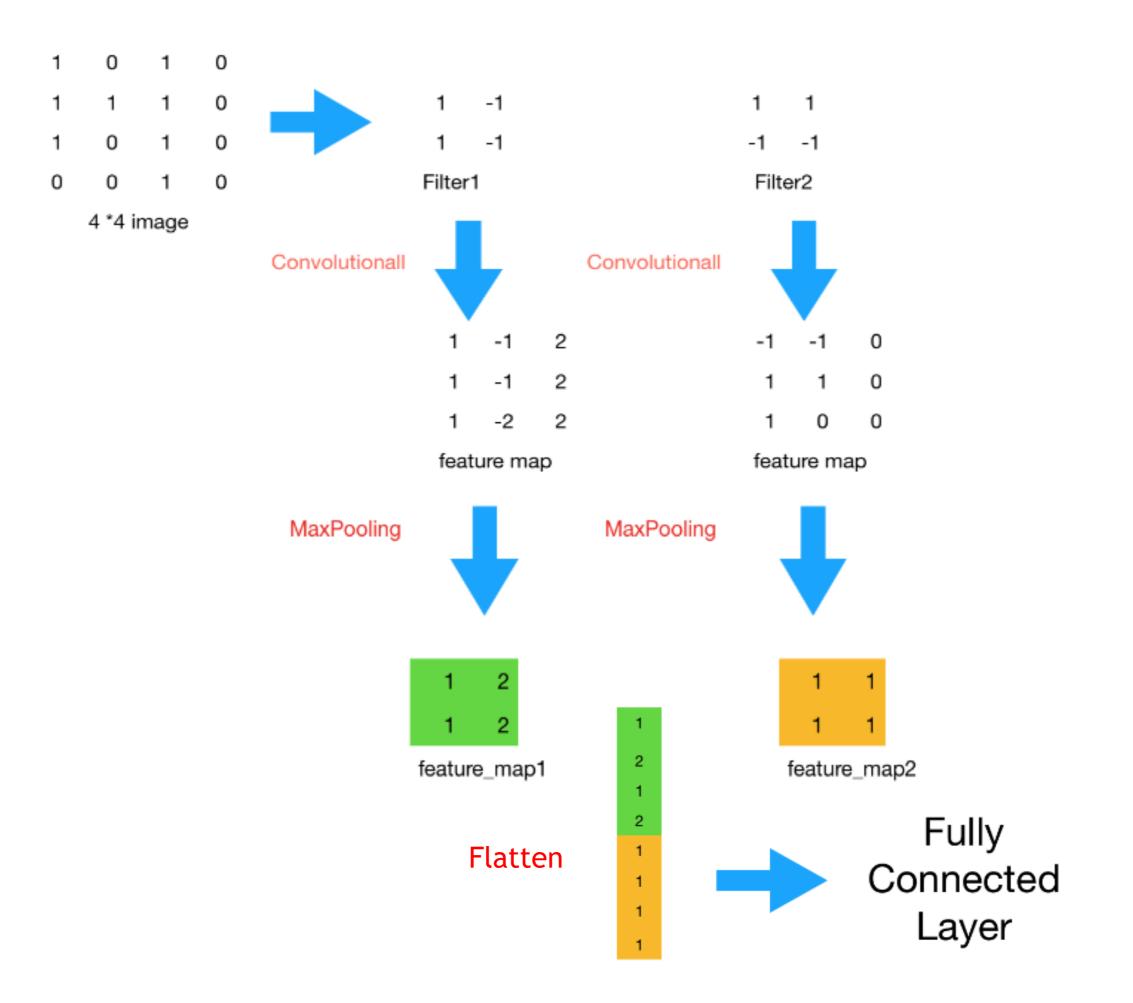


### Overfit

Dropout







### Max Pooling

