# Improving measurement on Higgs-gluon effective coupling

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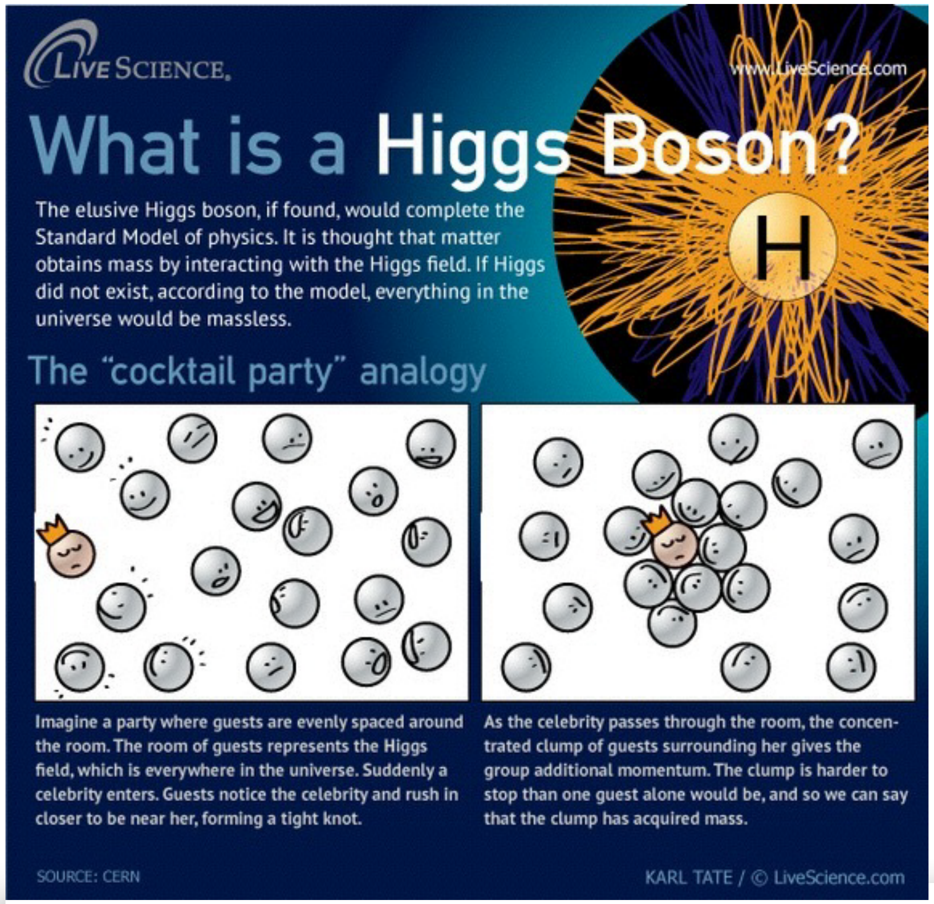
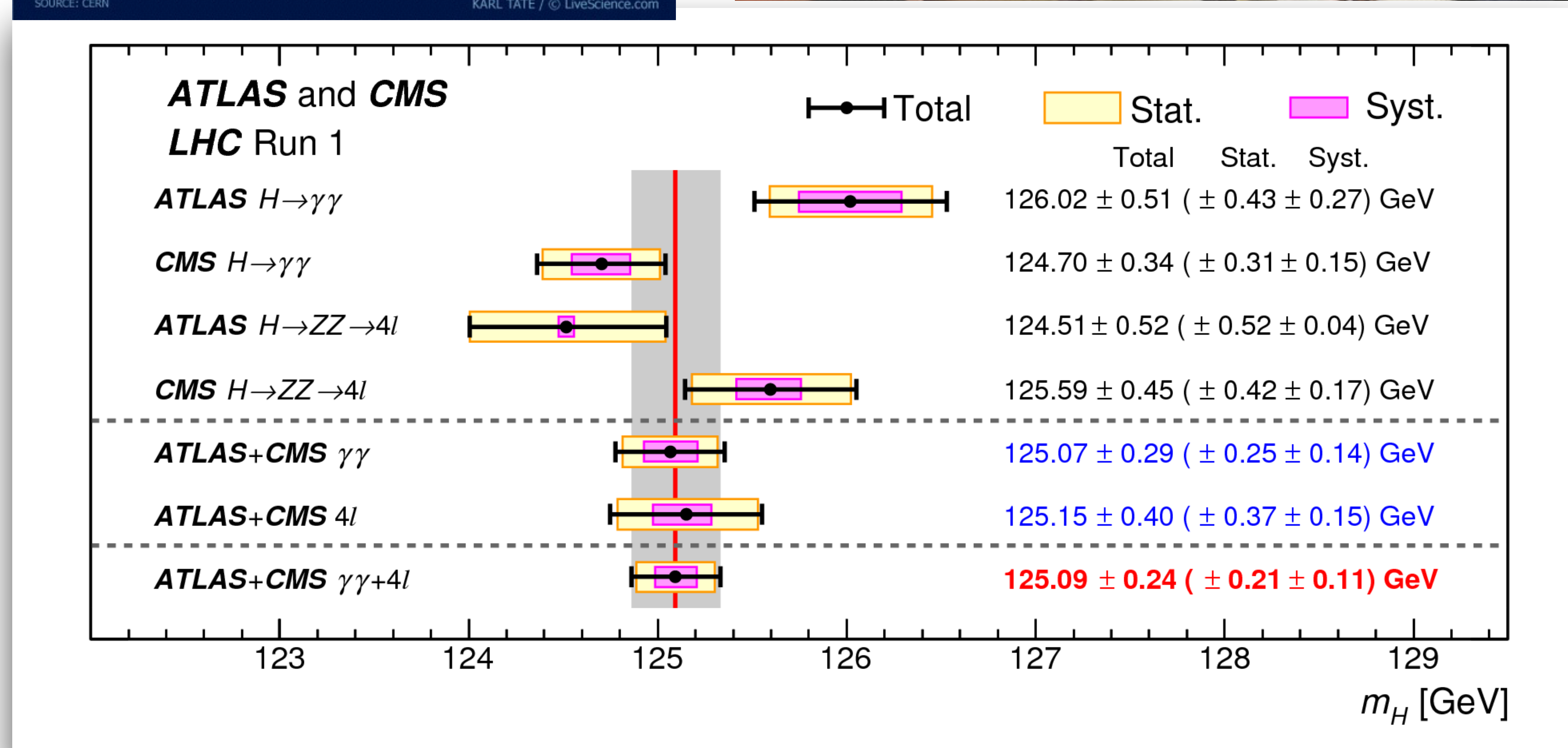
THEORETICAL PHYSICS DIVISION
物理理論

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

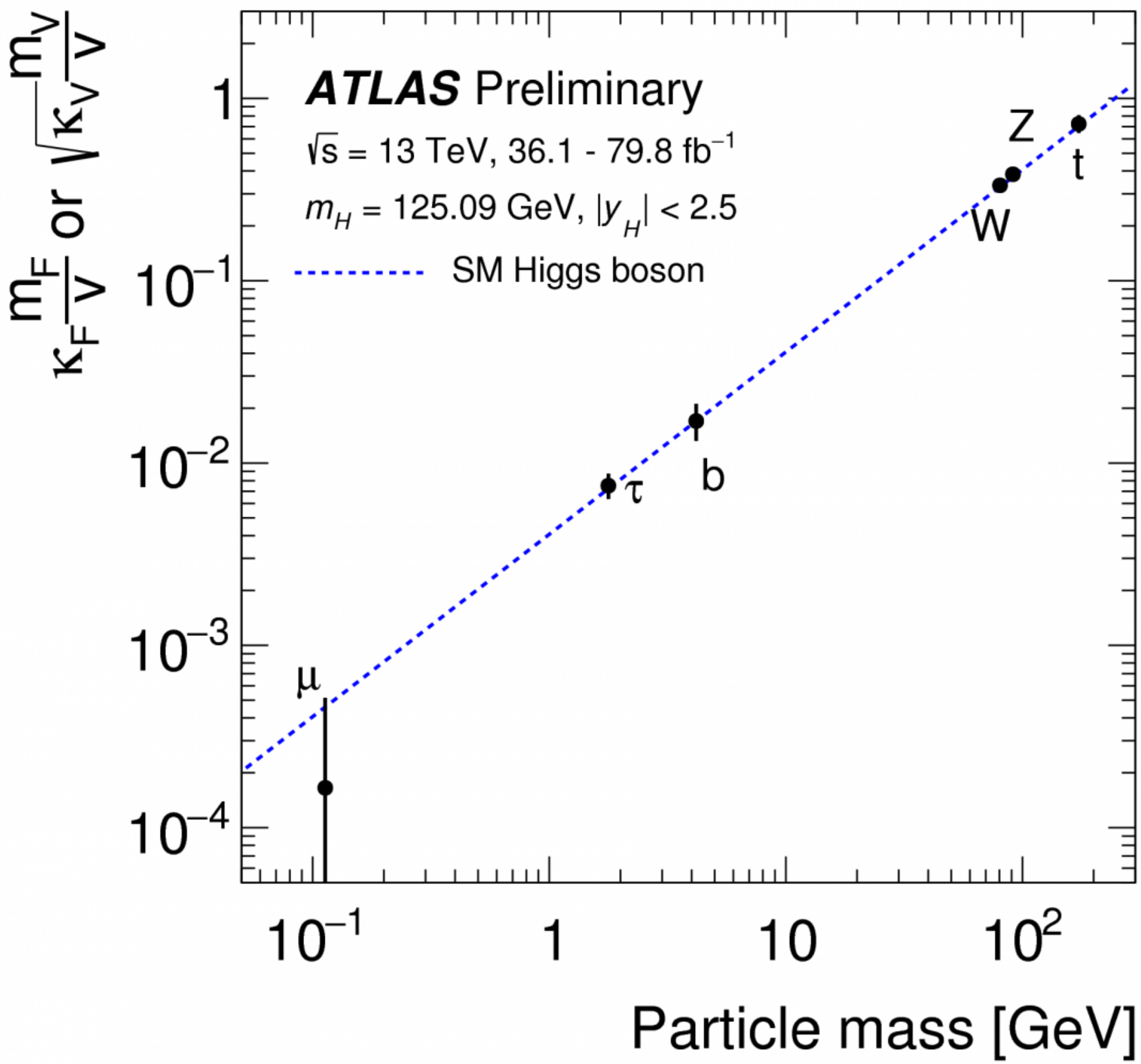


LIVE SCIENCE.
www.LiveScience.com
What is a Higgs Boson?
The elusive Higgs boson, if found, would complete the Standard Model of physics. It is thought that matter obtains mass by interacting with the Higgs field. If Higgs did not exist, according to the model, everything in the universe would be massless.
H
The "cocktail party" analogy
Imagine a party where guests are evenly spaced around the room. The room of guests represents the Higgs field, which is everywhere in the universe. Suddenly a celebrity enters. Guests notice the celebrity and rush in closer to be near her, forming a tight knot.
As the celebrity passes through the room, the concentrated clump of guests surrounding her gives the group additional momentum. The clump is harder to stop than one guest alone would be, and so we can say that the clump has acquired mass.
SOURCE: CERN
KARL TATE / © LiveScience.com

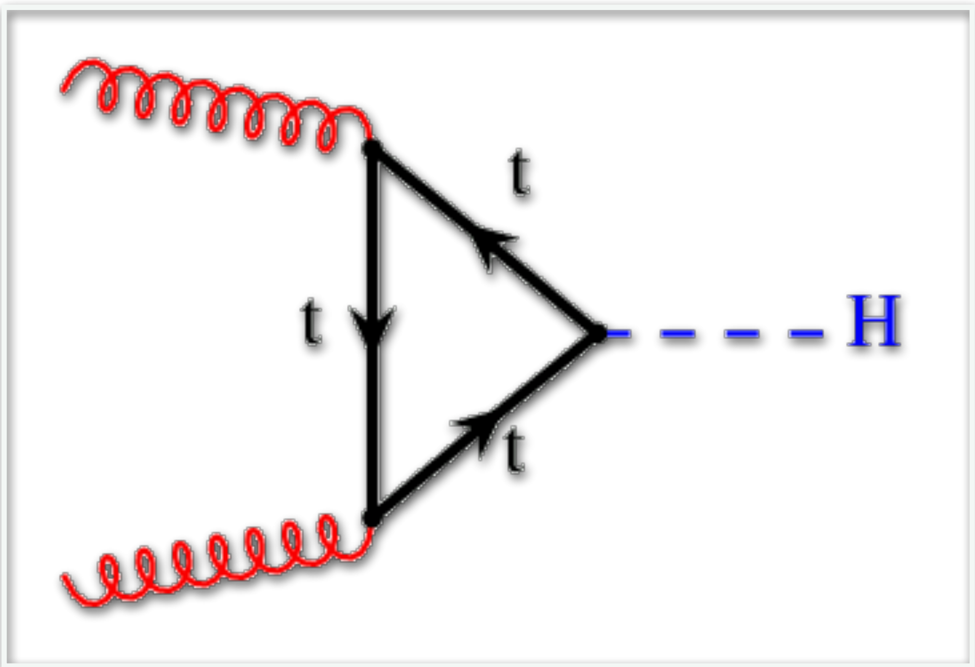



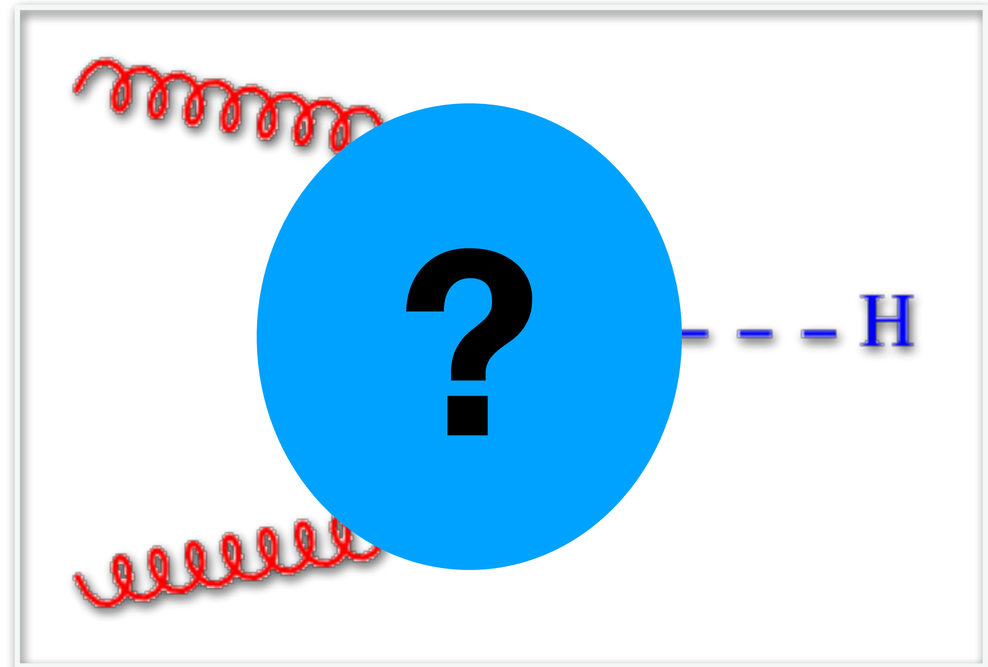
ATLAS and CMS
LHC Run 1
Total
Stat.
Syst.
Total Stat. Syst.
ATLAS $H\to\gamma\gamma$
126.02 ± 0.51 ( ± 0.43 ± 0.27) GeV
CMS $H\to\gamma\gamma$
124.70 ± 0.34 ( ± 0.31 ± 0.15) GeV
ATLAS $H\to ZZ\to 4l$
124.51 ± 0.52 ( ± 0.52 ± 0.04) GeV
CMS $H\to ZZ\to 4l$
125.59 ± 0.45 ( ± 0.42 ± 0.17) GeV
ATLAS+CMS $\gamma\gamma$
125.07 ± 0.29 ( ± 0.25 ± 0.14) GeV
ATLAS+CMS $4l$
125.15 ± 0.40 ( ± 0.37 ± 0.15) GeV
ATLAS+CMS $\gamma\gamma+4l$
125.09 ± 0.24 ( ± 0.21 ± 0.11) GeV
123
124
125
126
127
128
129
$m_H$ [GeV]

# Higgs Properties, i.e. couplings/interactions



# Direct or Indirect modification



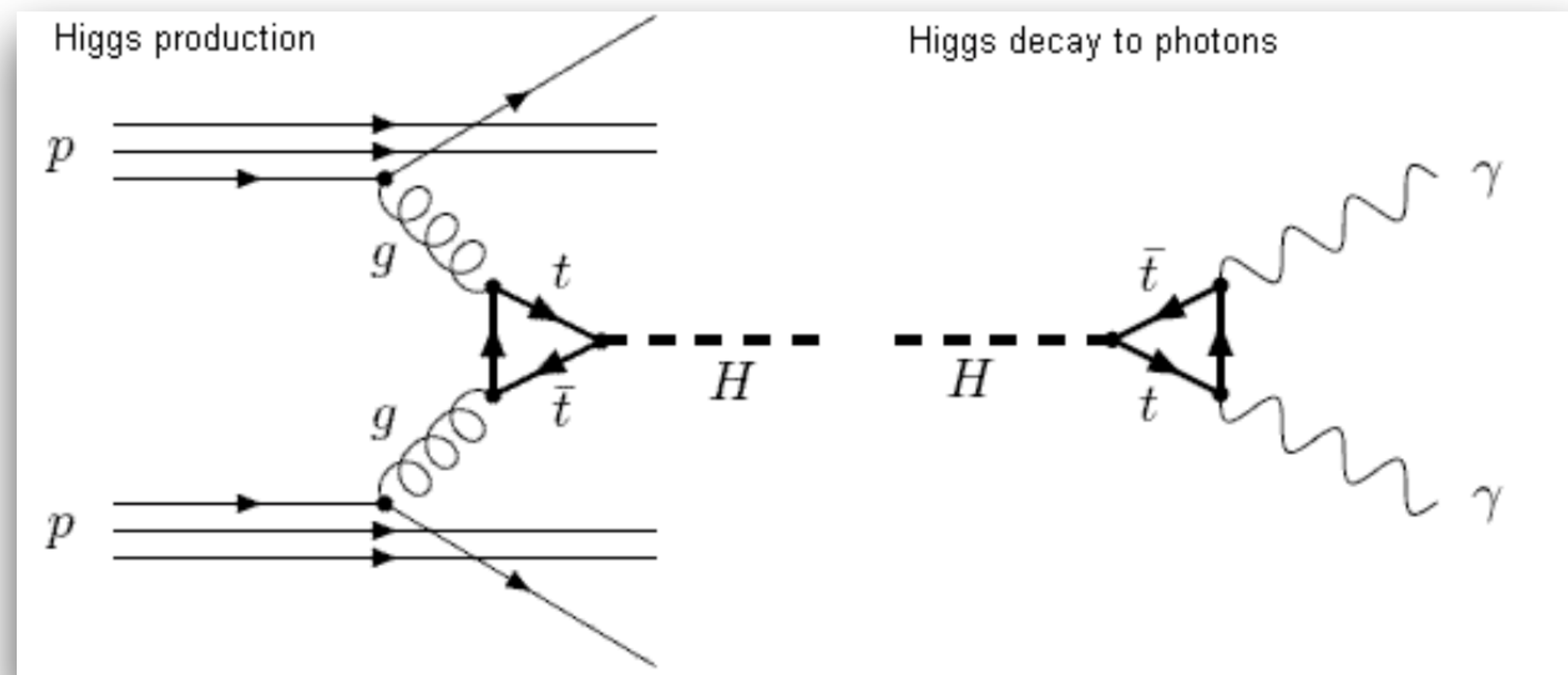



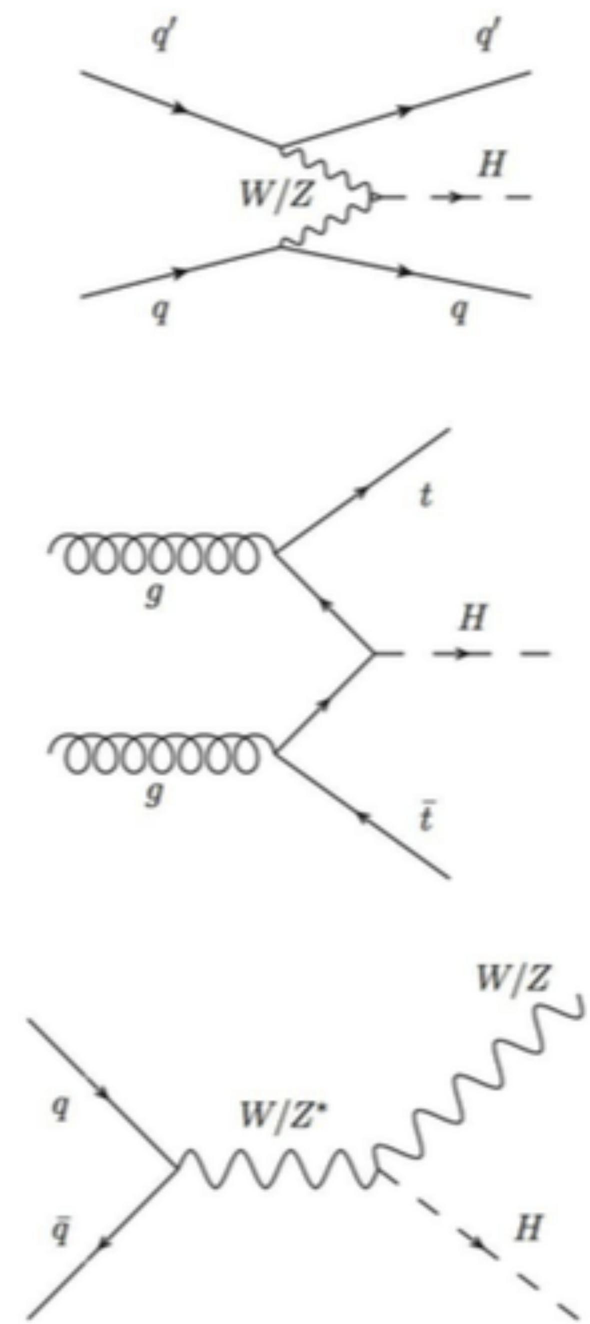

$$\mathcal{L}_{hgg} = \kappa_g c^g_{\rm SM} \frac{\alpha_s}{12\pi v} h G^a_{\mu\nu} G^{a\mu\nu},$$

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

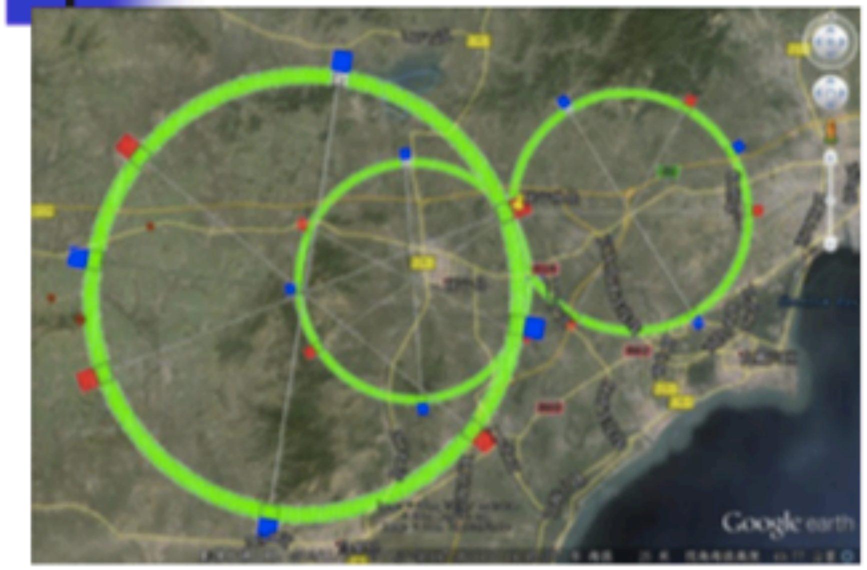
# Measurement @ LHC

**Different production rate**
**Different decay BR**

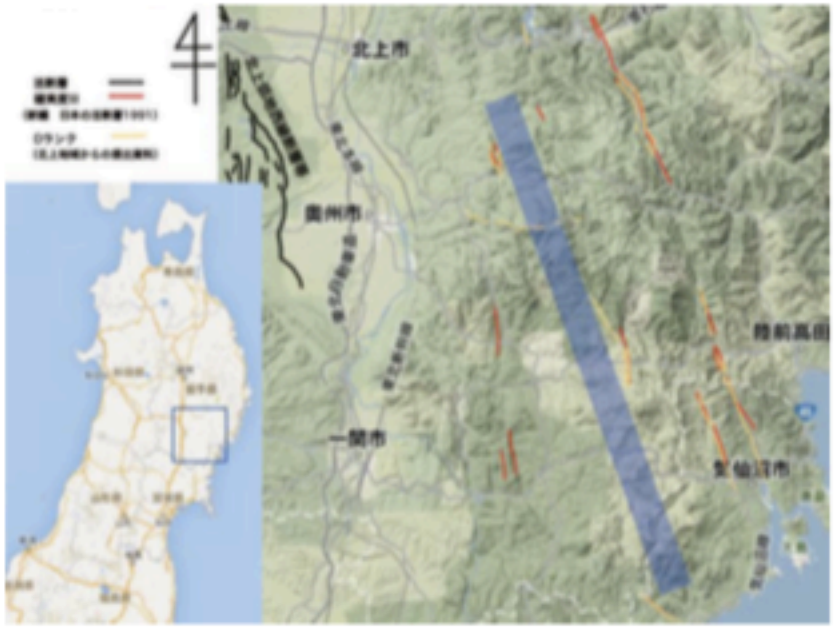


# Several Higgs factories under plan



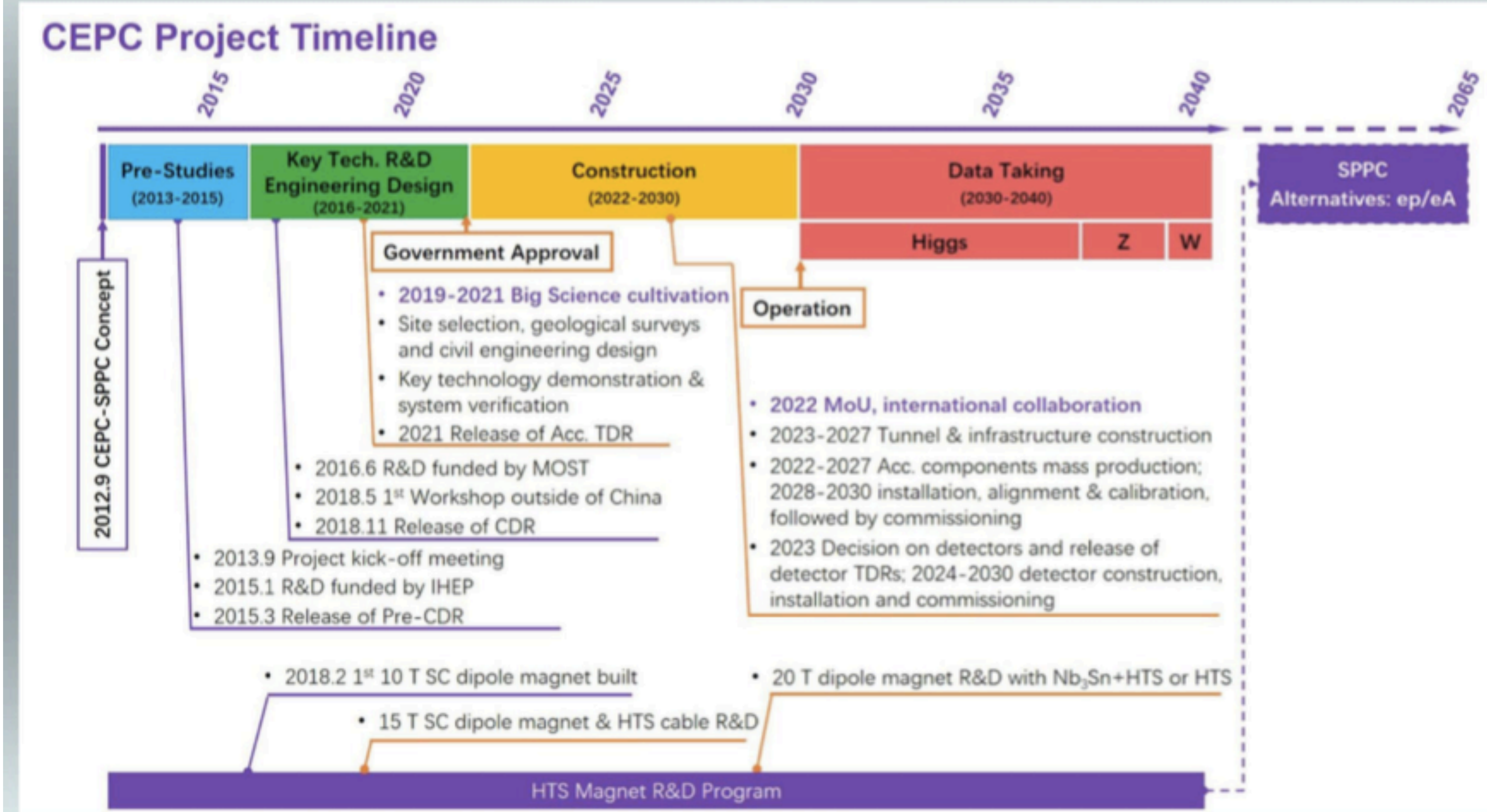

CEPC@90-240 GeV (China)
秦皇岛 or 雄安?




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


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

# CEPC timeline

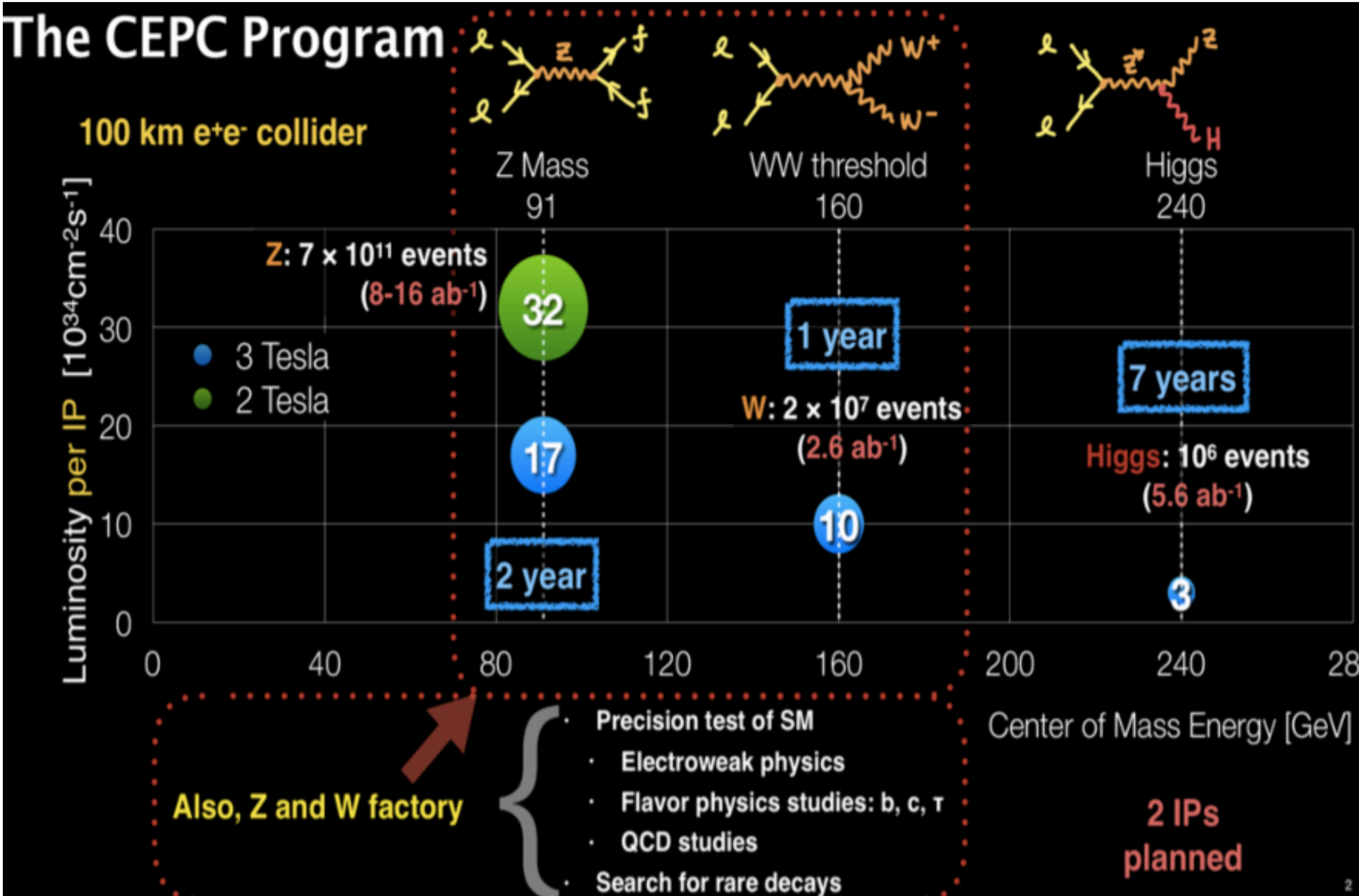


# CEPC High Lumi Parameters@Higgs

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 $N_e$ ($10^{10}$) | 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 | 461.0 | |
| Synchrotron radiation power /beam (MW) | 30 | 30 | 16.5 | |
| Bending radius (km) | 10.7 | | | |
| Momentum compact ($10^{-5}$) | 0.91 | | | |
| β function at IP $\beta_x^*$ / $\beta_y^*$ (m) | 0.33/0.001 | 0.33/0.001 | 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 $\xi_x/\xi_y$ | 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 $\sigma_z$ (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* ($10^{34}cm^{-2}s^{-1}$) | 5.2 | 14.5 | 23.6 | 37.7 |

*include beam-beam simulation and real lattice


The CEPC Program
100 km e+e- collider
Z Mass
91
WW threshold
160
Higgs
240
Luminosity per IP [10^34 cm^-2 s^-1]
Z: 7 × 10^11 events
(8-16 ab^-1)
32
3 Tesla
2 Tesla
17
2 year
1 year
W: 2 × 10^7 events
(2.6 ab^-1)
10
7 years
Higgs: 10^6 events
(5.6 ab^-1)
3
Center of Mass Energy [GeV]
Also, Z and W factory
Precision test of SM
Electroweak physics
Flavor physics studies: b, c, τ
QCD studies
Search for rare decays
2 IPs
planned
2

# Results in CDR (2018.11)

CEPC

All scaled to 240 GeV， 5.6$ab^{-1}$

| Property | Estimated Precision CEPC-v1 | | Estimated Precision CEPC-v4 | |
|---|---|---|---|---|
| $m_H$ | 5.9 MeV | | 5.9 MeV | |
| $\Gamma_H$ | 2.7% | | 2.8% | |
| $\sigma(ZH)$ | 0.5% | | 0.5% | |
| $\sigma(\nu\bar{\nu}H)$ | 3.0% | | 3.2% | |
| **Decay mode** | $\sigma\times$BR | BR | $\sigma\times$BR | BR |
| $H\to b\bar{b}$ | 0.26% | 0.56% | 0.27% | 0.56% |
| $H\to c\bar{c}$ | 3.1% | 3.1% | 3.3% | 3.3% |
| $H\to gg$ | 1.2% | 1.3% | 1.3% | 1.4% |
| $H\to WW^*$ | 0.9% | 1.1% | 1.0% | 1.1% |
| $H\to ZZ^*$ | 4.9% | 5.0% | 5.1% | 5.1% |
| $H\to\gamma\gamma$ | 6.2% | 6.2% | 6.8% | 6.9% |
| $H\to Z\gamma$ | 13% | 13% | 16% | 16% |
| $H\to\tau^+\tau^-$ | 0.8% | 0.9% | 0.8% | 1.0% |
| $H\to\mu^+\mu^-$ | 16% | 16% | 17% | 17% |
| $\mathrm{BR}^{\mathrm{BSM}}_{\mathrm{inv}}$ | – | $<0.28\%$ | – | $<0.30\%$ |

| Signal Z | Signal H | Precision | Signal Z | Signal H | Precision | Signal Z | Signal H | Precision |
|---|---|---|---|---|---|---|---|---|
| H->qq | | | H->WW | | | H→γγ, Zγ | | |
| ee | bb | 1.32% | ee | lvlv | 9.52% | μμ+ττ | γγ | 23.7% |
| | cc | 13.5% | | evqq | 4.56% | vv | | 10.5% |
| | gg | 7.22% | | μvqq | 3.93% | qq | | 9.84% |
| μμ | bb | 0.99% | μμ | lvlv | 7.29% | vv | Zγ(qqγ) | 15.7% |
| | cc | 9.54% | | evqq | 3.90% | vvH(WW fusion) | | |
| | gg | 5.01% | | μvqq | 3.90% | vv | bb | 3.00% |
| qq | bb | 0.46% | vv | qqqq | 1.90% | H→μμ | | |
| | cc | 11.1% | | evqq | 4.65% | qq | μμ | 17.1% |
| | gg | 3.64% | | μvqq | 4.14% | ee | | |
| vv | bb | 0.39% | | lvlv | 11.5% | μμ | | |
| | cc | 3.83% | qq | qqqq | 1.75% | vv | | |
| | gg | 1.47% | H->ZZ | | | H→ττ | | |
| H->Invisible | | | vv | μμqq | 8.26% | ee | ττ | 2.75% |
| qq | ZZ(vvvv) | 232% | vv | eeqq | 40% | μμ | | 2.61% |
| ee | | 370% | μμ | vvqq | 7.32% | qq | | 0.95% |
| μμ | | 245% | ZH bkg contribution | | 19.4% | vv | | 2.66% |

# 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

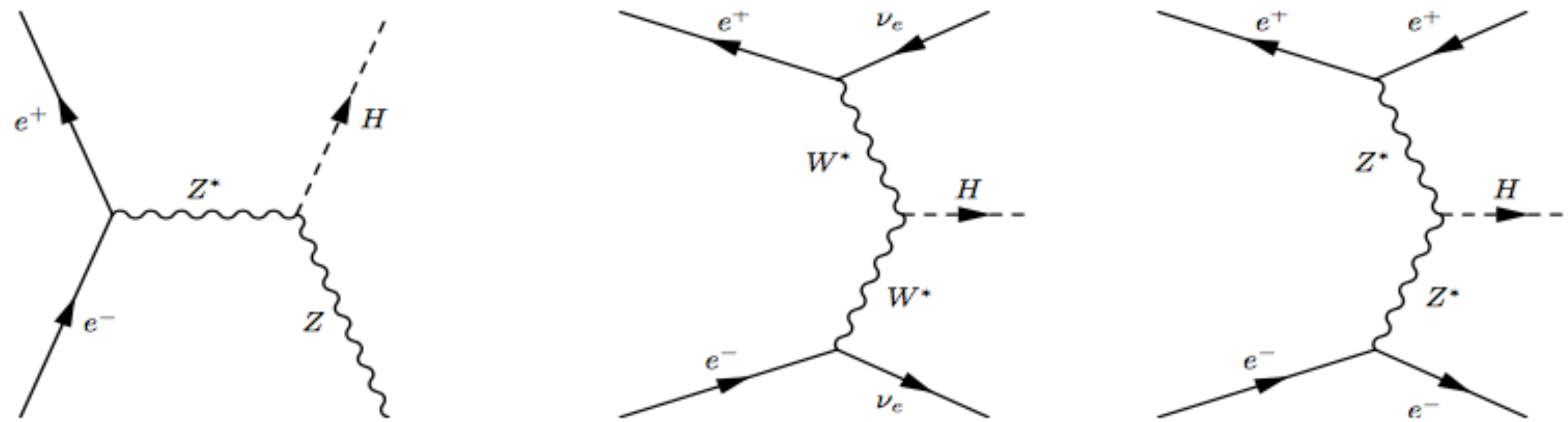
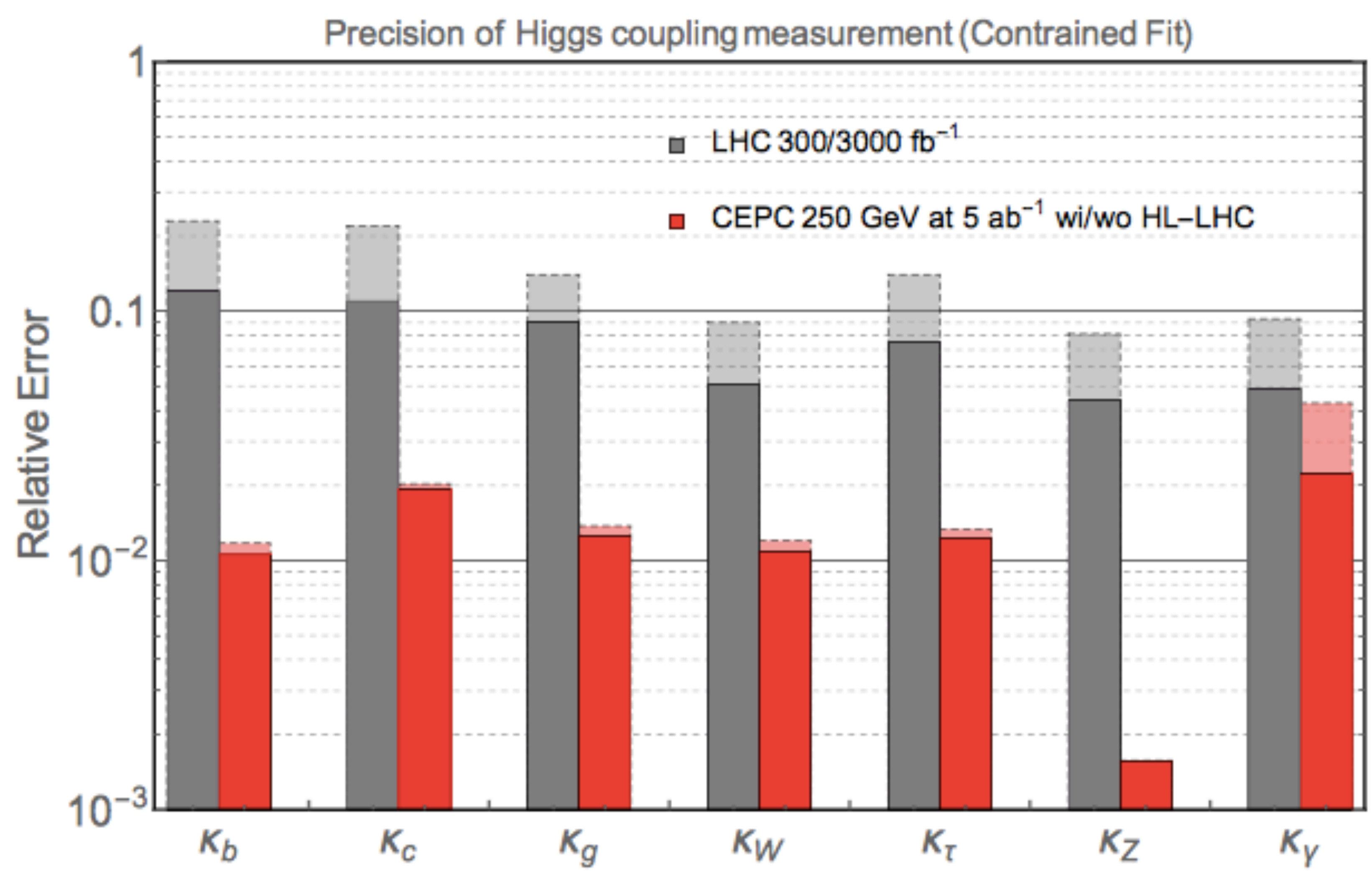


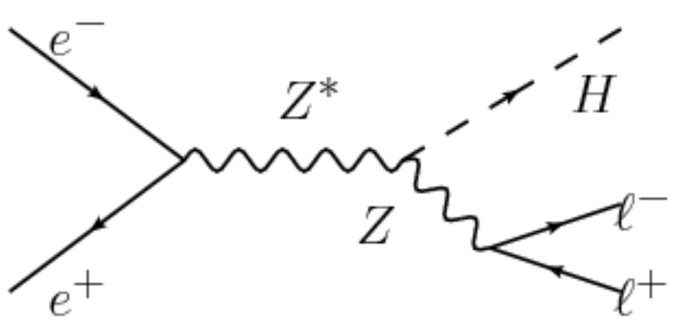

**Figure 3.6** Feynman diagrams of the $e^+e^- \to ZH$, $e^+e^- \to \nu\bar{\nu}H$ and $e^+e^- \to e^+e^-H$ processes.



# ggH coupling from H->gg

**H->gg decay rate is proportional to ggH coupling**

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



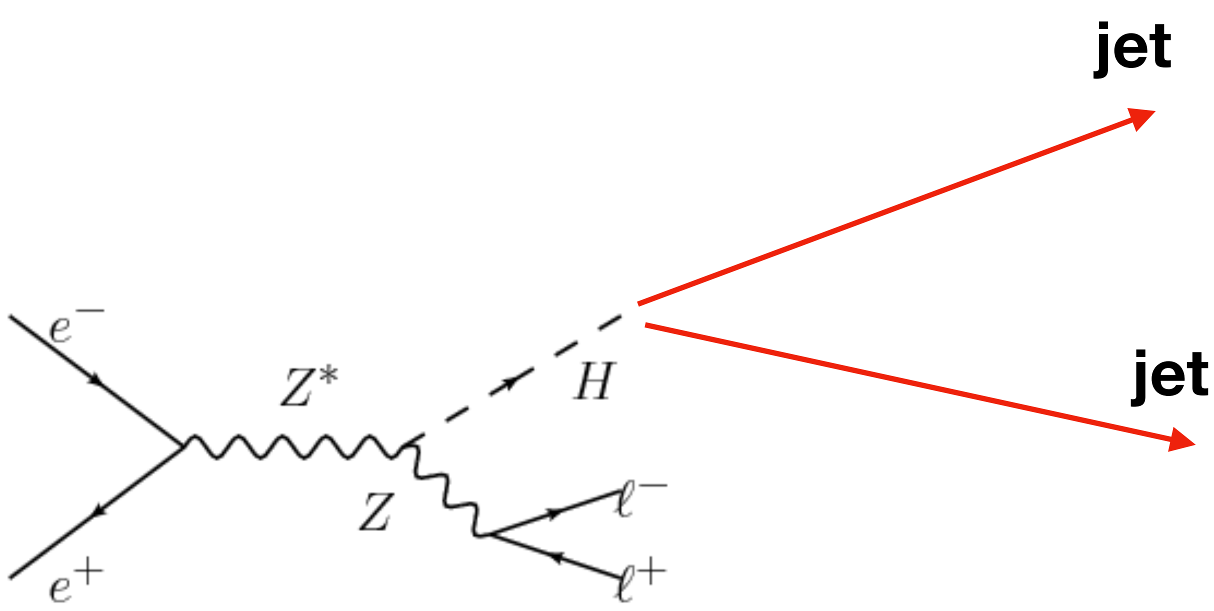

$$gg(8.18\%),\ \ c\bar{c}(2.884\%)\ \ \text{and}\ \ b\bar{b}(58.09\%)$$

# ggH coupling from H->gg

**H->gg decay rate is proportional to ggH coupling**

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

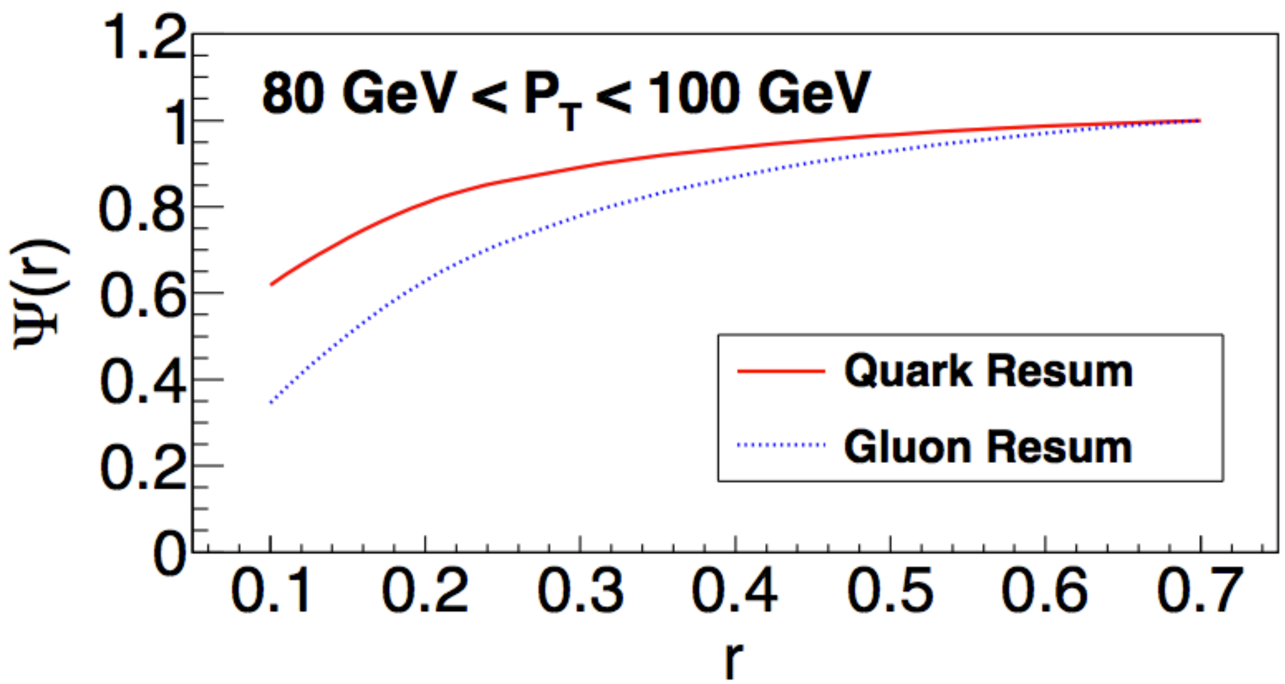
dijet including bb, cc and gg




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

# Jet Energy Profile

$$\psi(r) = \frac{1}{N_j}\sum_j \psi_j(r) = \frac{1}{N_j}\sum_j \frac{\sum_{r_i<r} p_{\mathrm{T},i}(r_i)}{\sum_{r_i<R} p_{\mathrm{T},i}(r_i)},$$




**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.**

# Optimized uncertainty of effective coupling

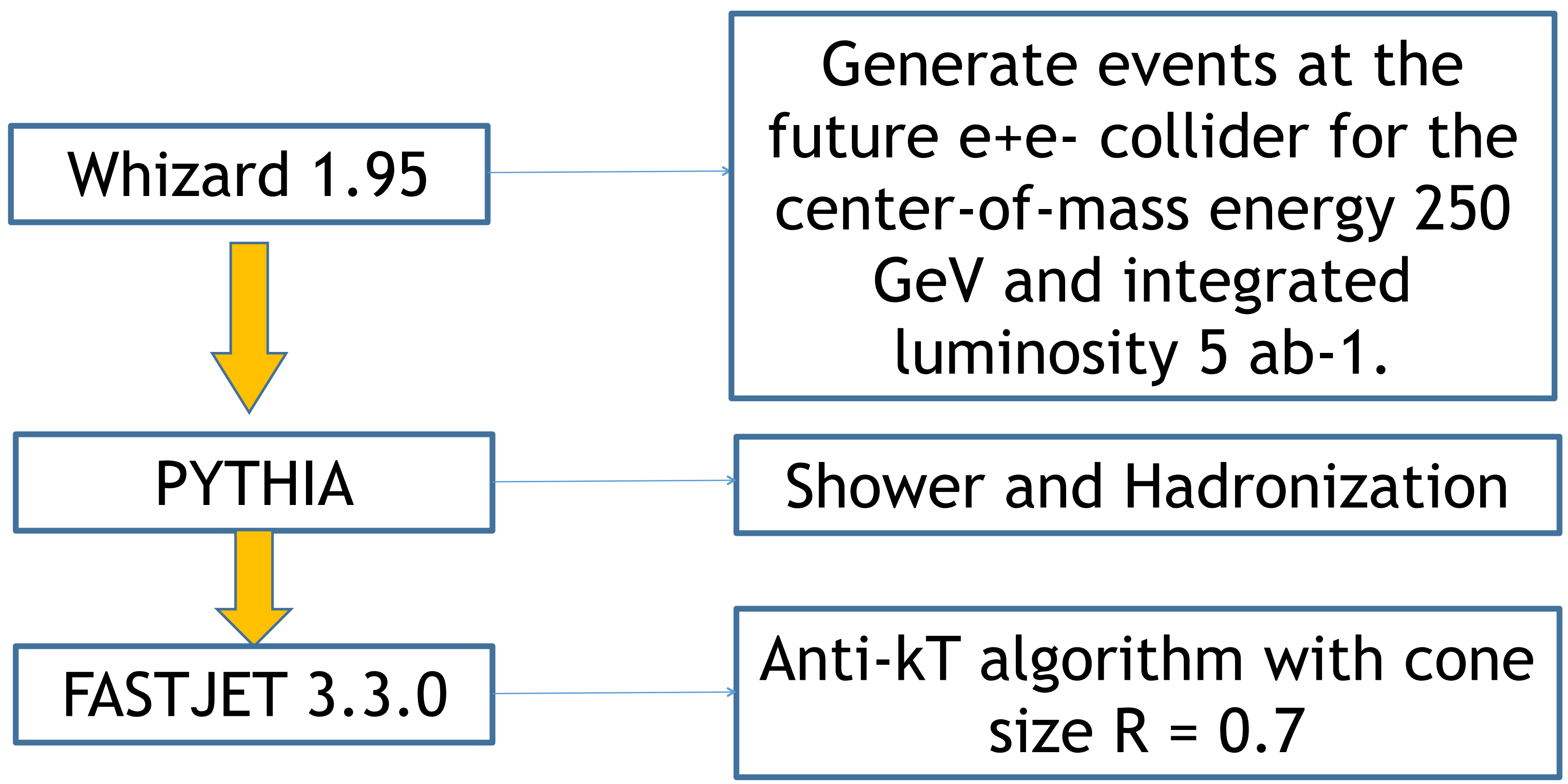
$$Z^N(r) = \frac{\sum_j (\psi_j + b)}{\sum_j^{\mathrm{SM}} (\psi_j + b)},$$

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

**Minimization** $\rightarrow$ $\dfrac{\partial \delta\kappa_g^Z}{\partial b} = 0,$

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

# MC Simulation

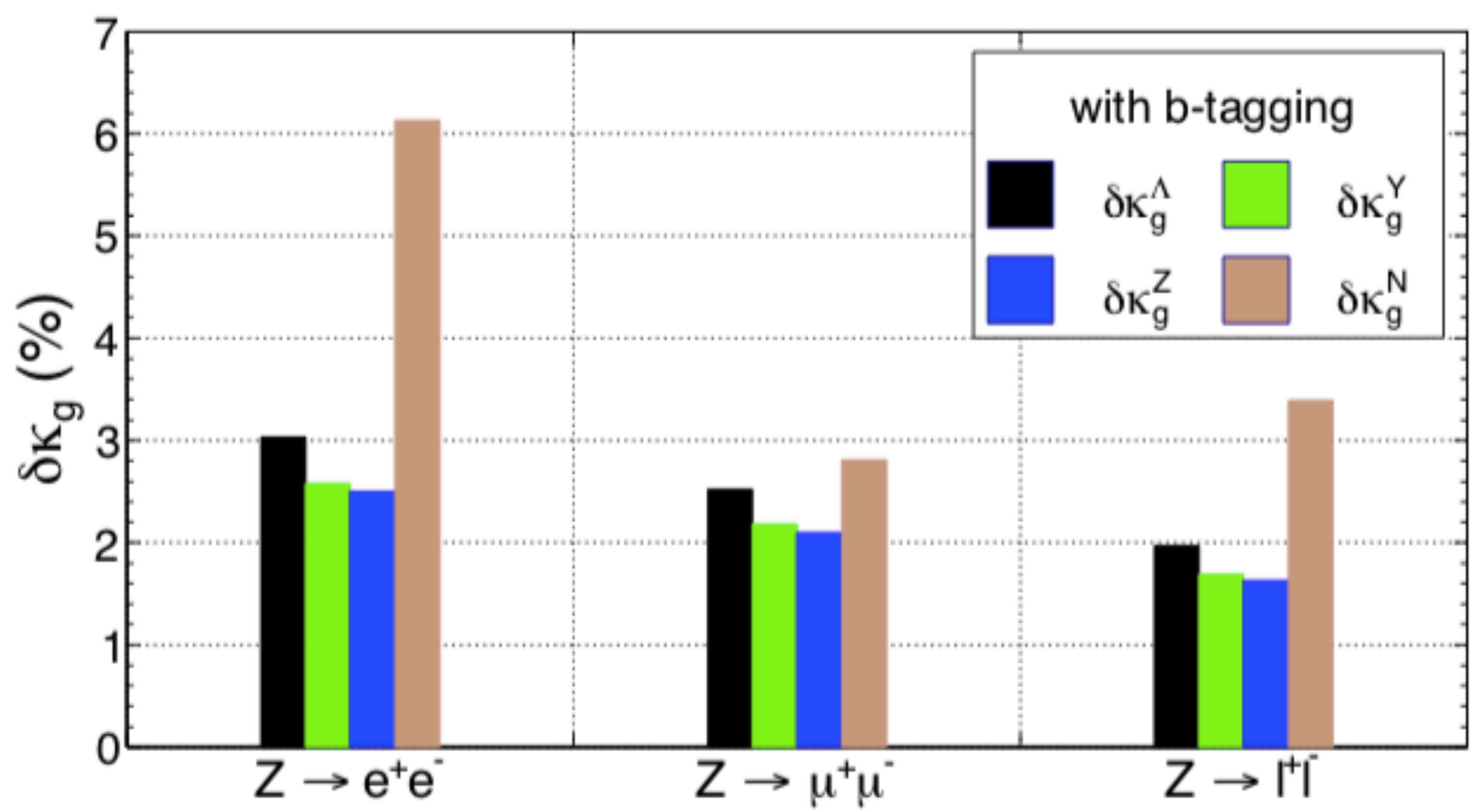



JEPs are obtained by analyzing
the jet substructure according to the formula.

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

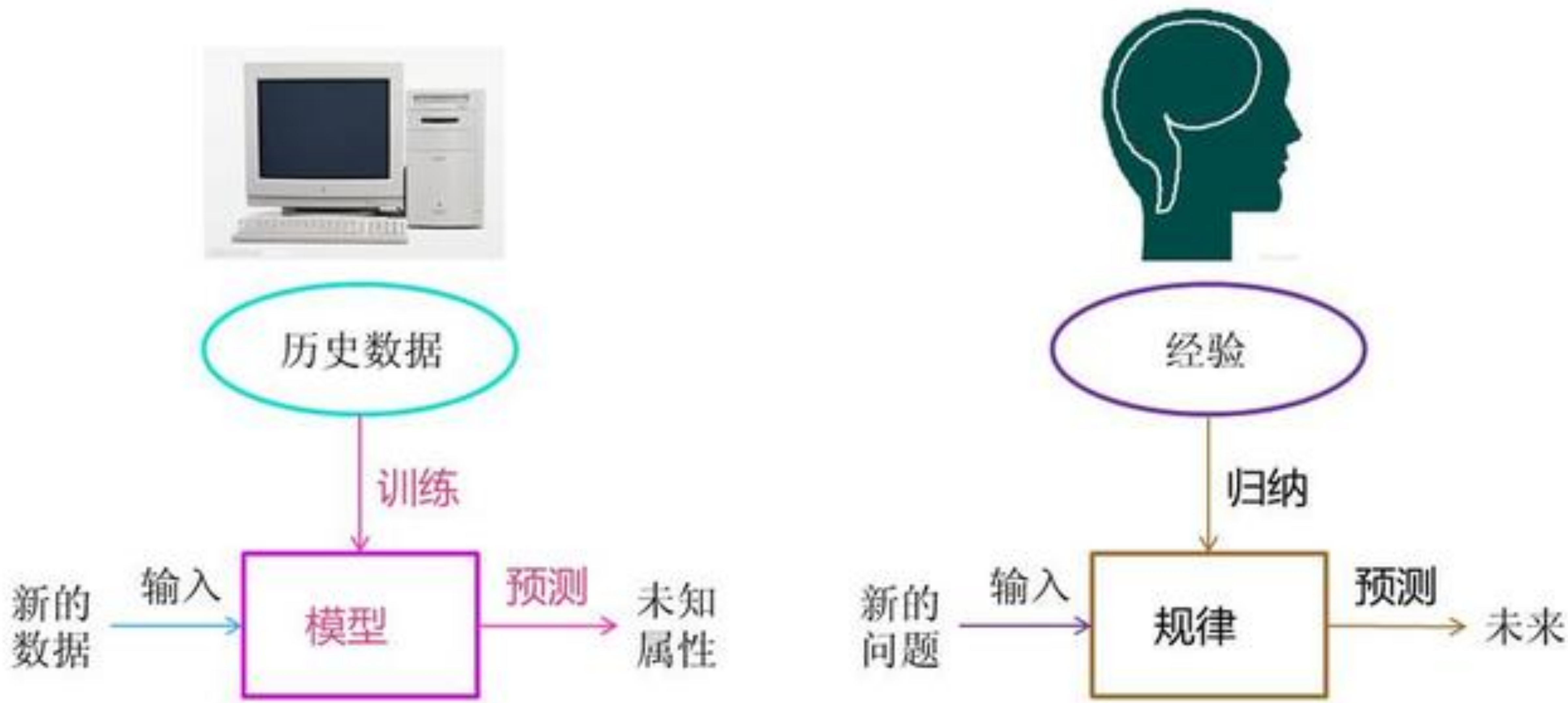
Phys. Rev. D **98**, 076010 – Published 17 October 2018



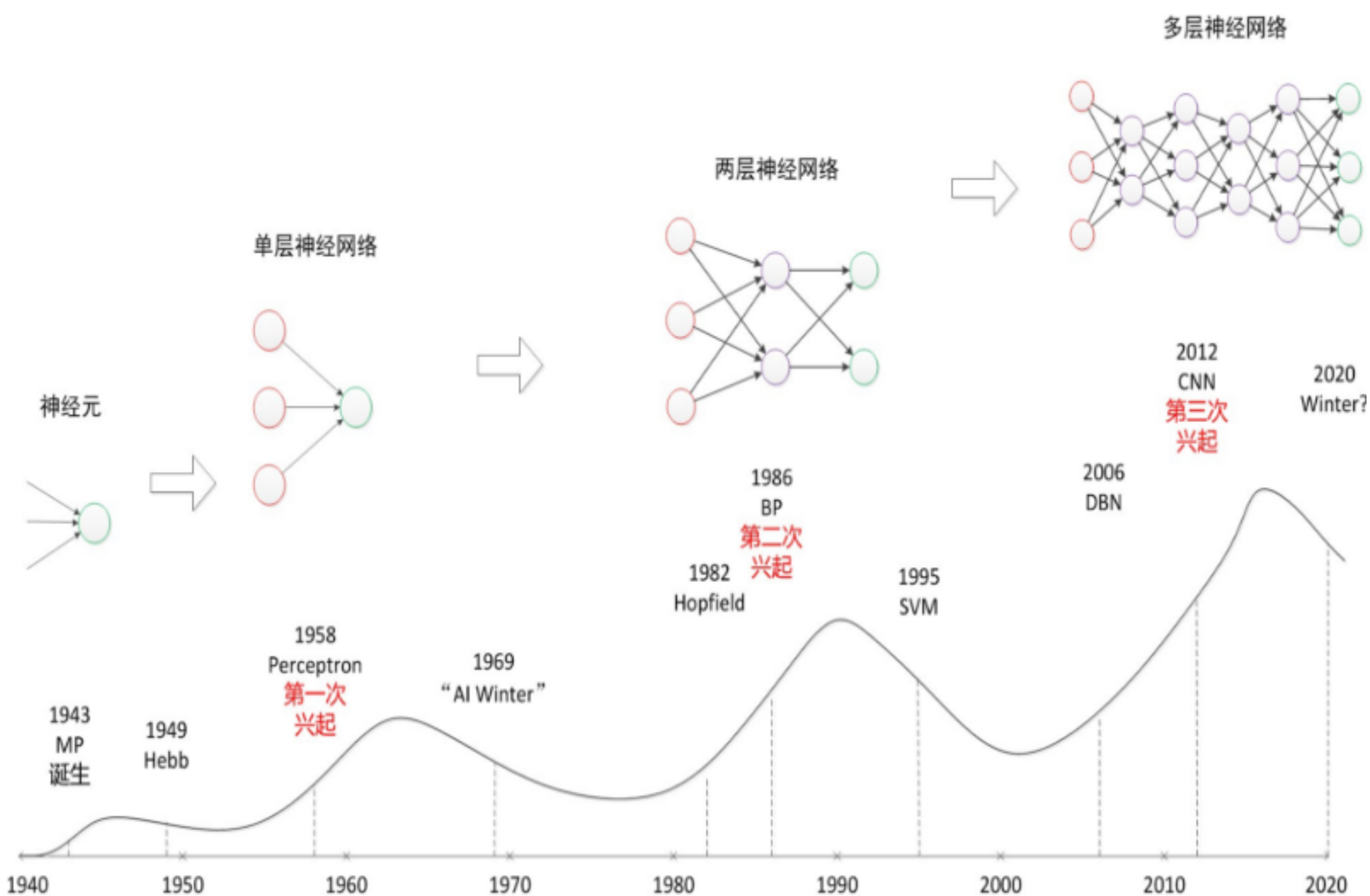

# ~50% improvement to reach ~1.6%

# Machine Learning is widely used in many fields

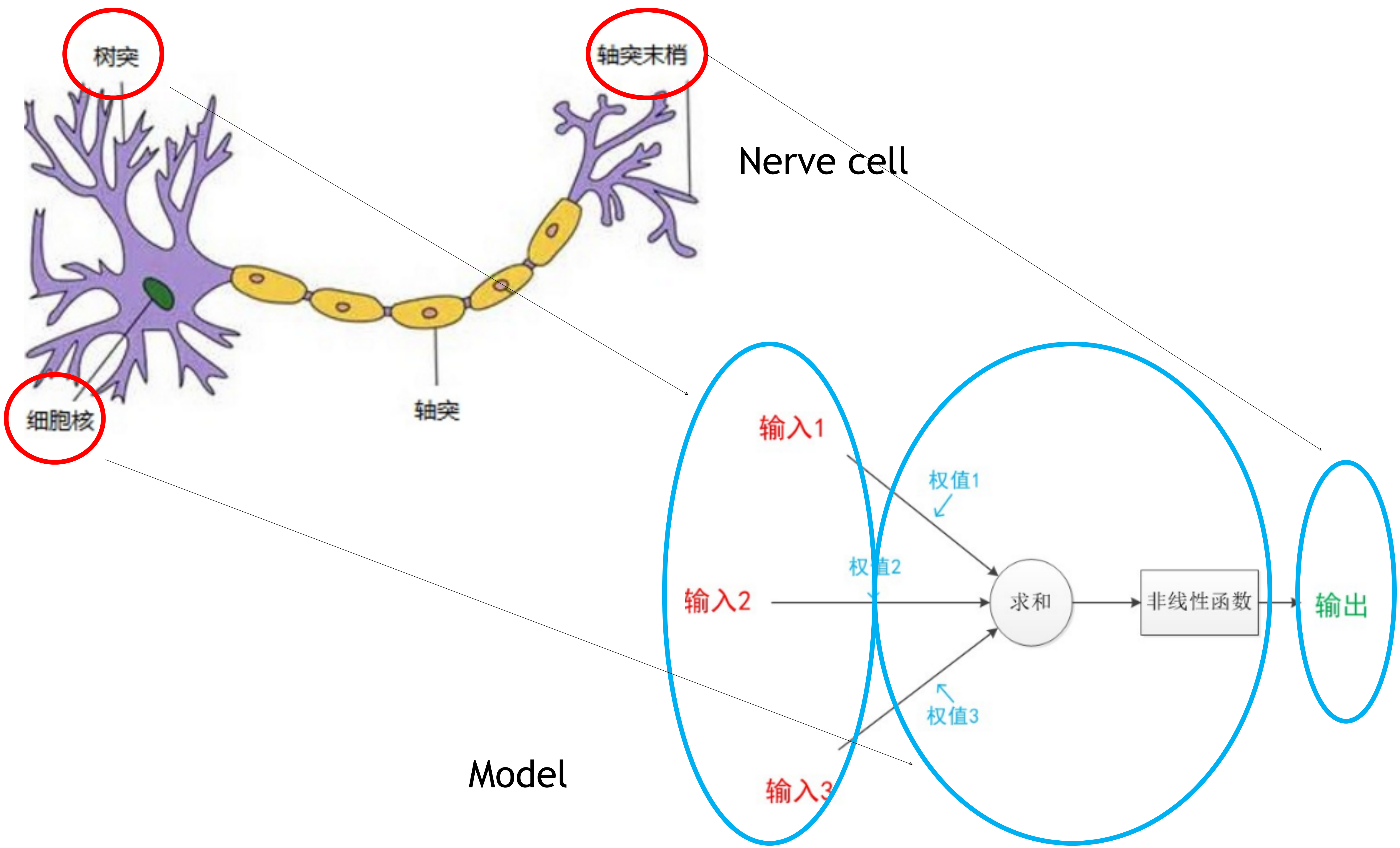
# Machine Learning VS. People Learning



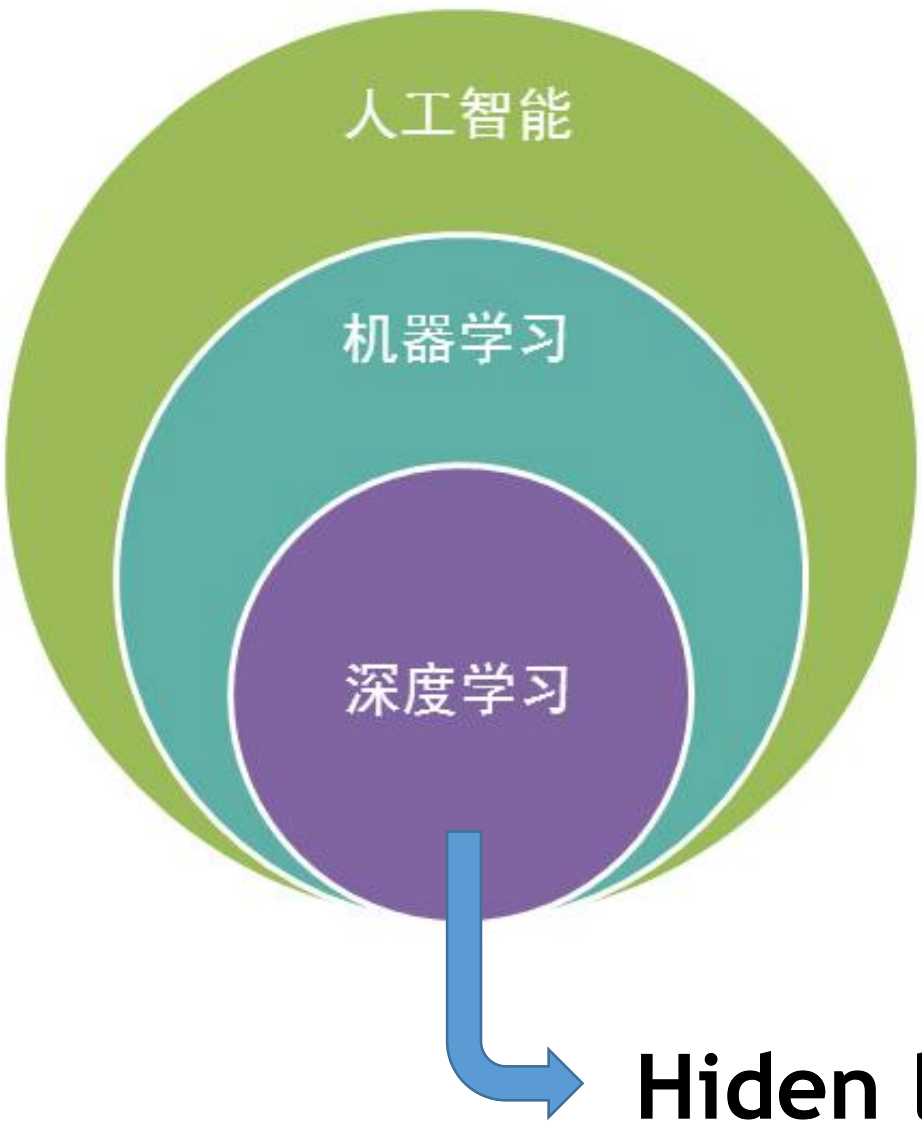
# History of Machine Learning

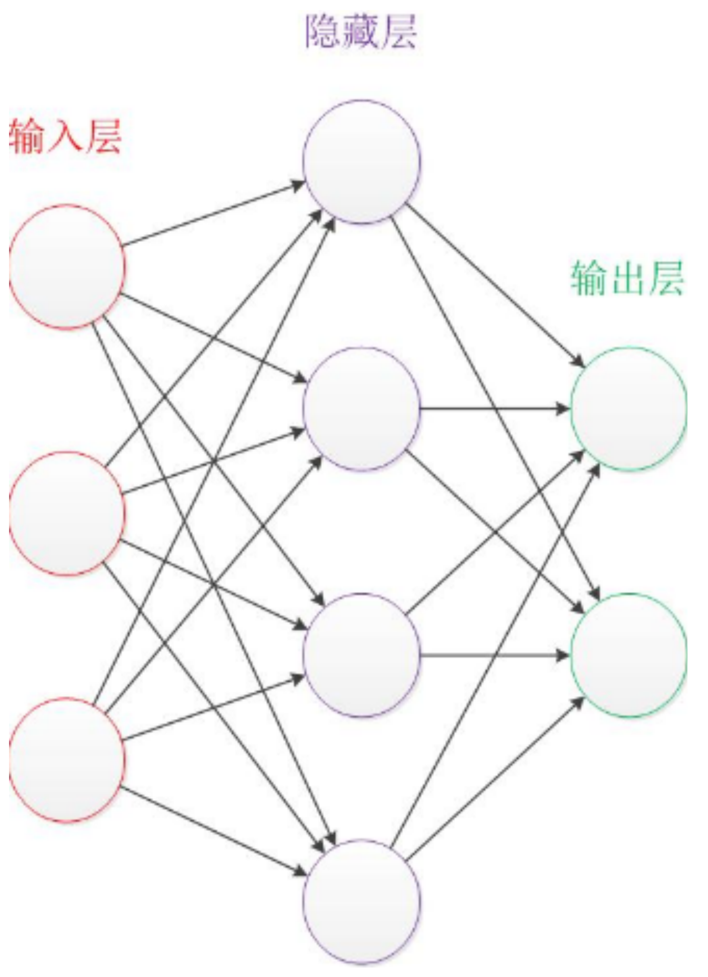


# Nerve cell


树突
轴突末梢
细胞核
轴突
Nerve cell
输入1
输入2
输入3
权值1
权值2
权值3
求和
非线性函数
输出
Model

# Deep Learning



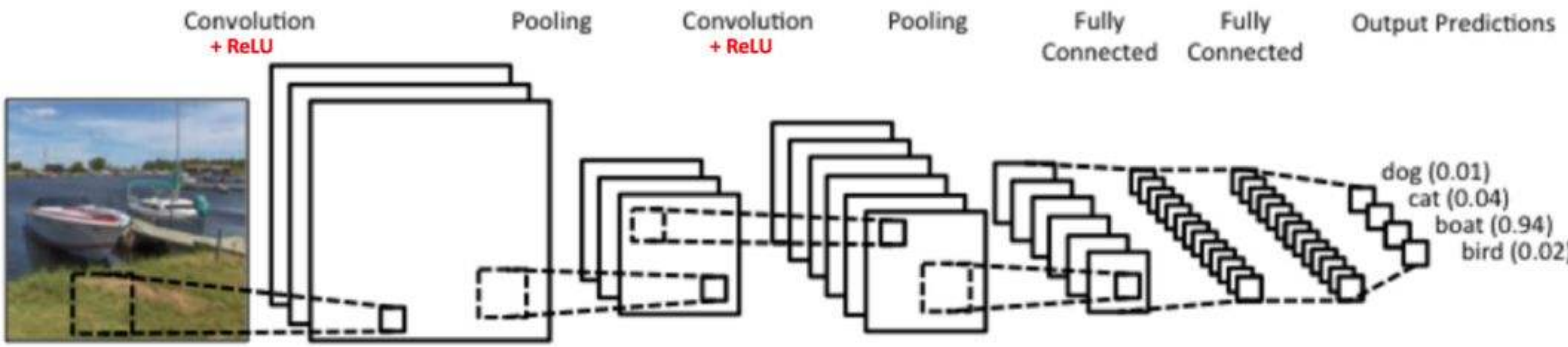



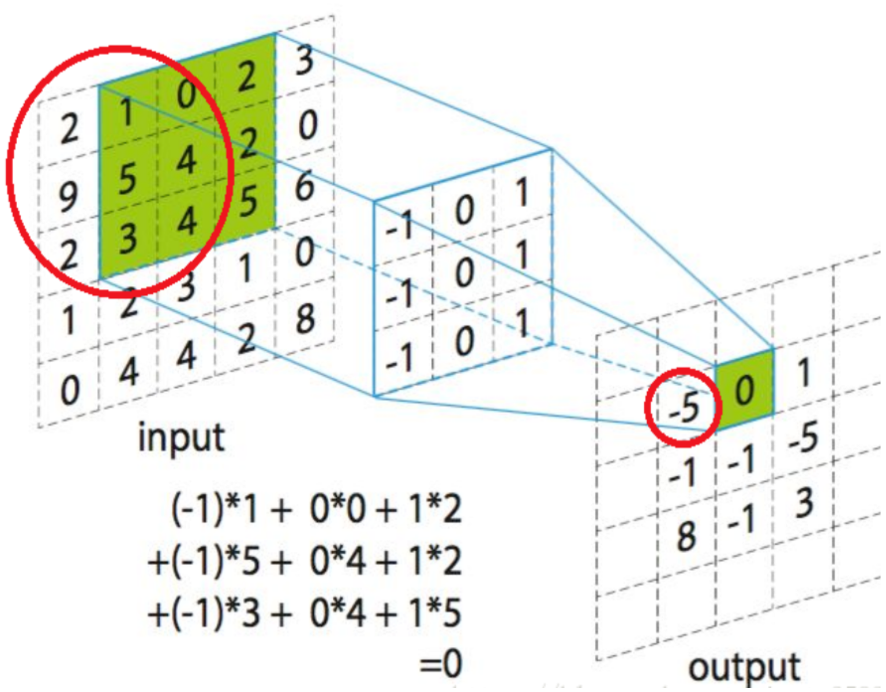

**Hiden layer > 2**

Deeper networks can achieve more complex linear classifications.

# Convolutional Neural Networks (CNNs)

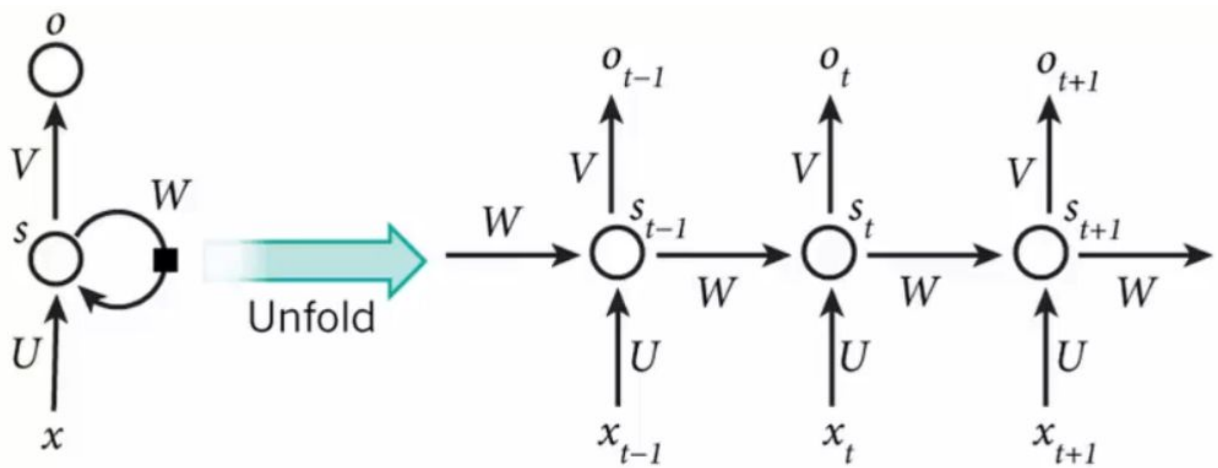
CNNs is one of the most popular algorithms in deep learning. It has powerful ability of image recognition.




CNNs extract the features form images by the convolutional layers.

# Recursive neural networks (RecNN)

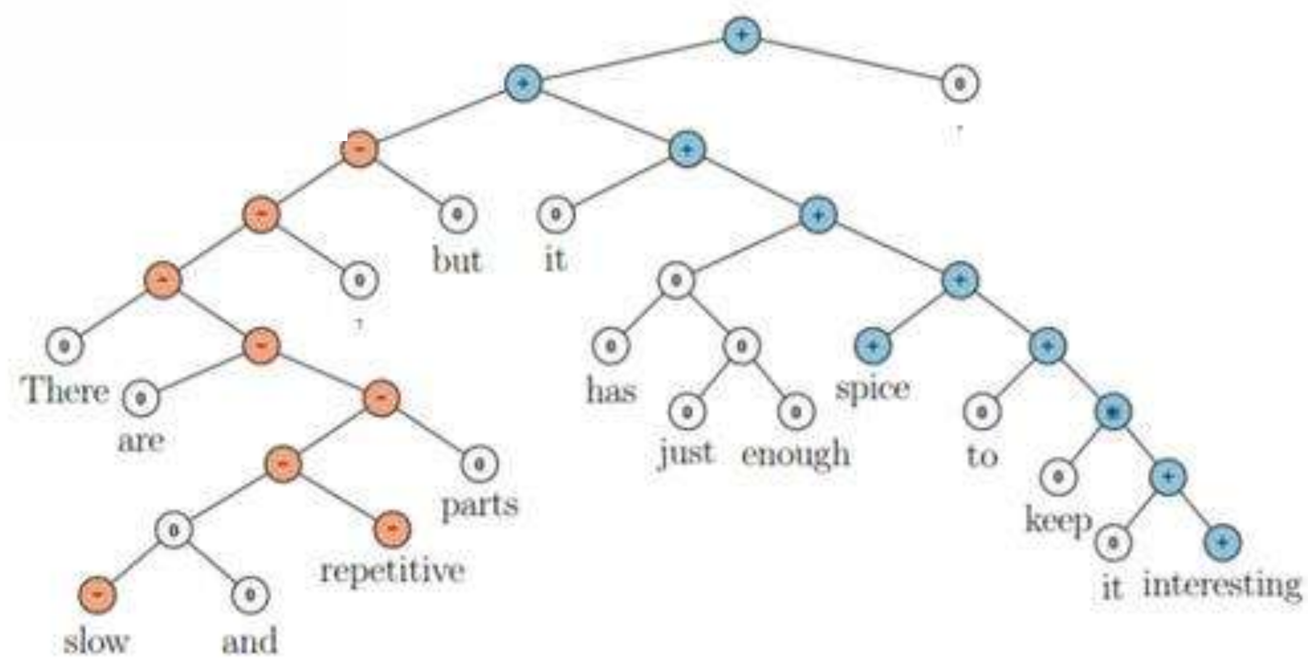



xt表示第t,t=1,2,3...步(step)的输入

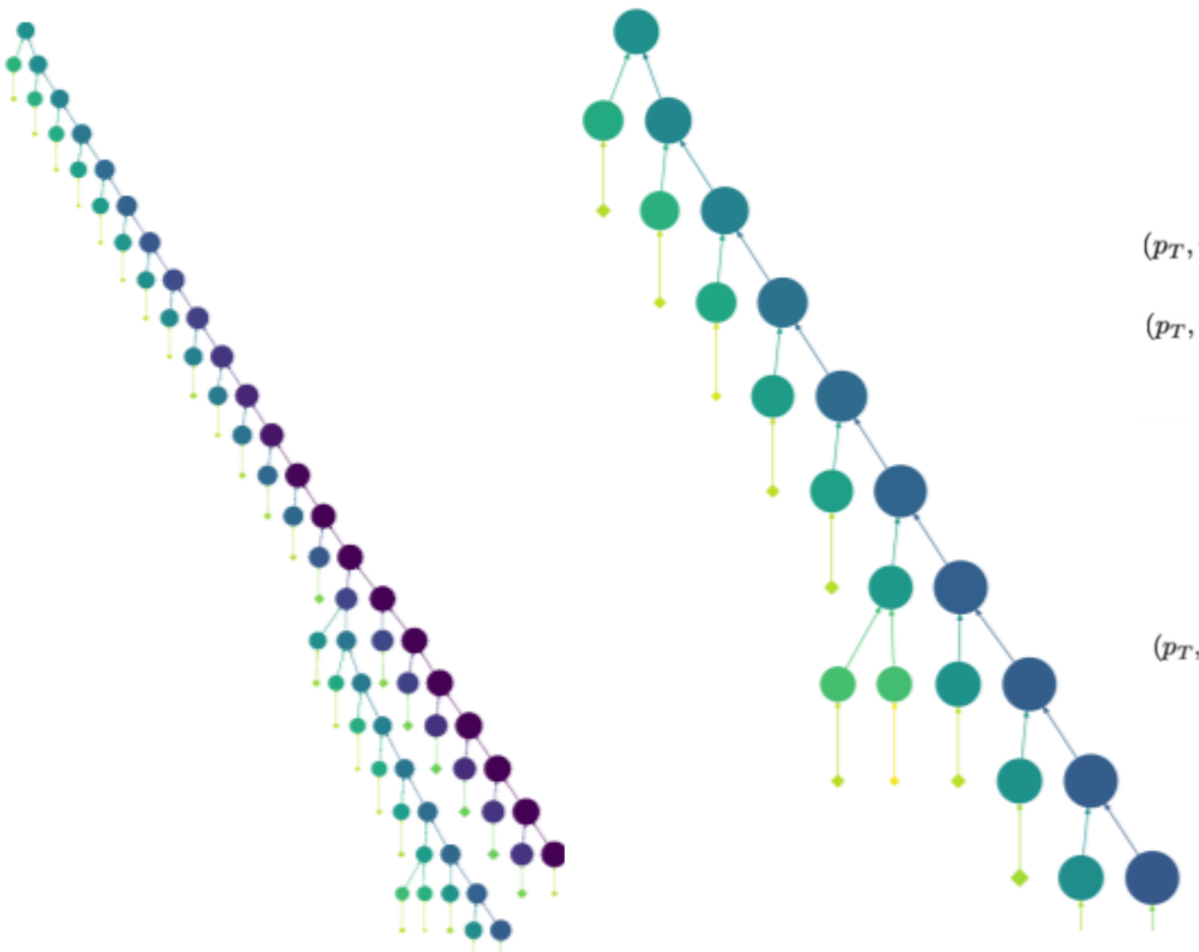
st为隐藏层的第t步的状态，它是网络的记忆单元。

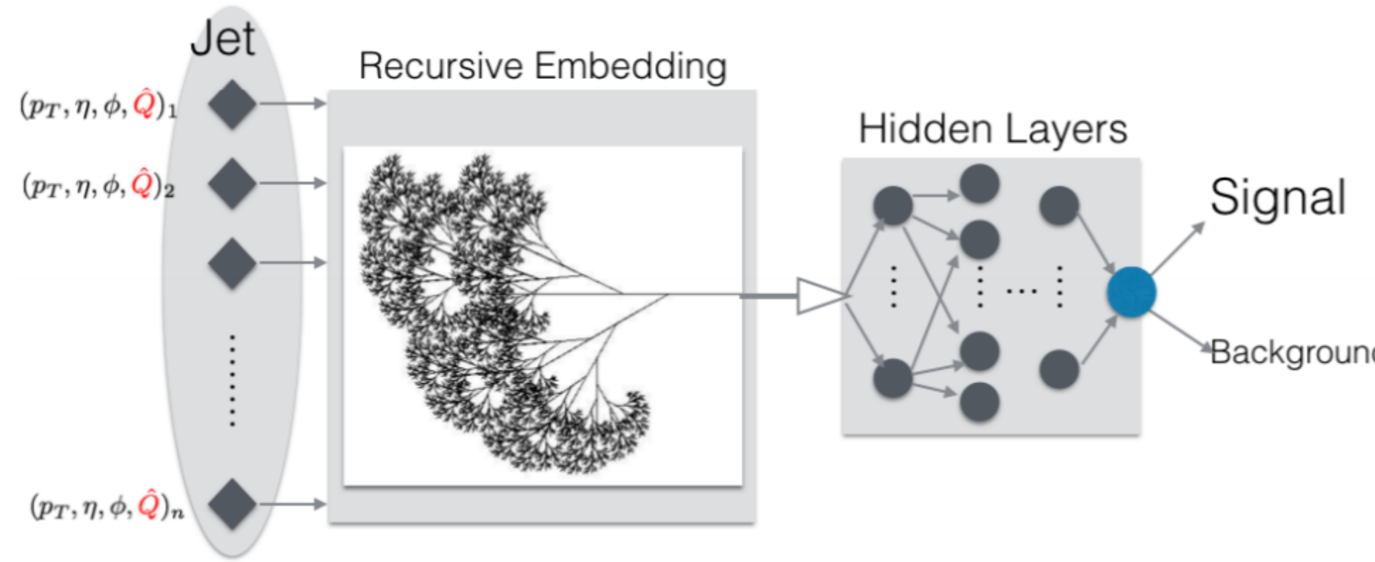
st=f(Uxt+Wst−1)，其中f一般是非线性的激活函数

ot是第t步的输出，如下个单词的向量表示softmax(Vst)



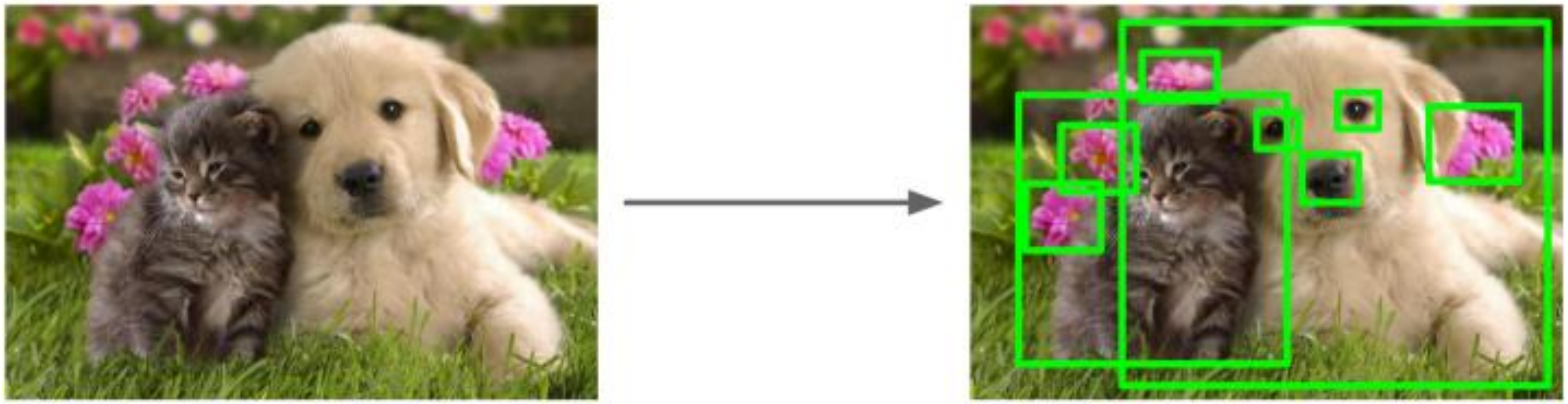
# Identification of quark/gluon jets by RecNN





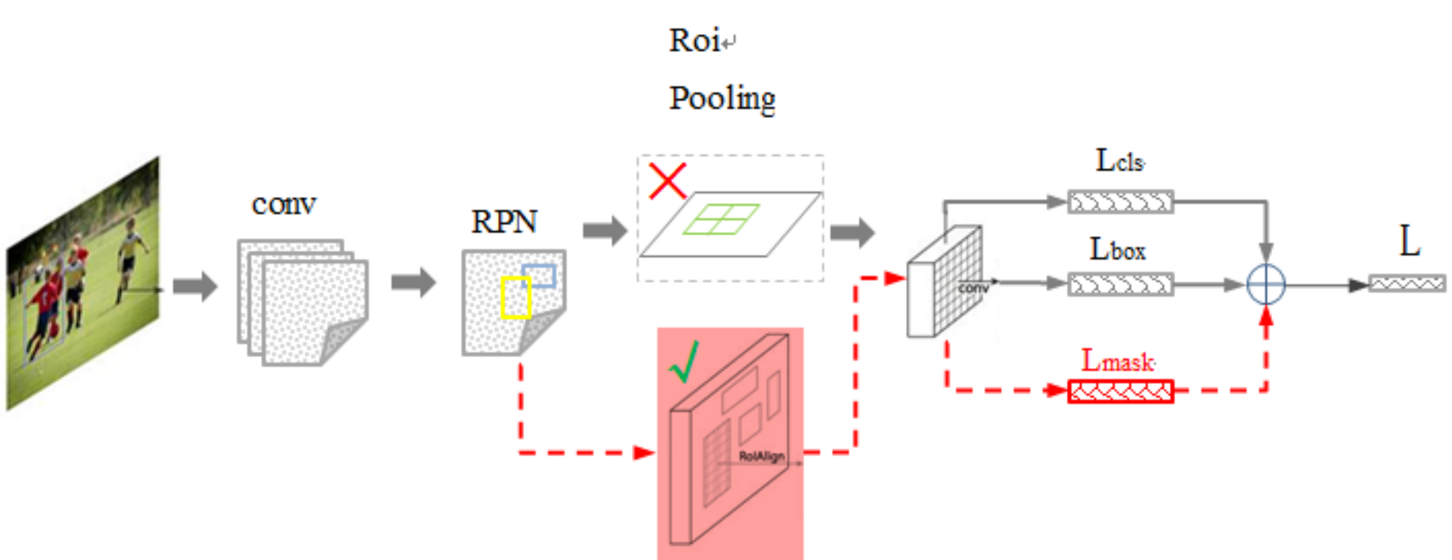

Typical tree structures for 1 TeV gluon jet (left) and quark jet (right)

# Object detection: Region-based CNN (RCNN)



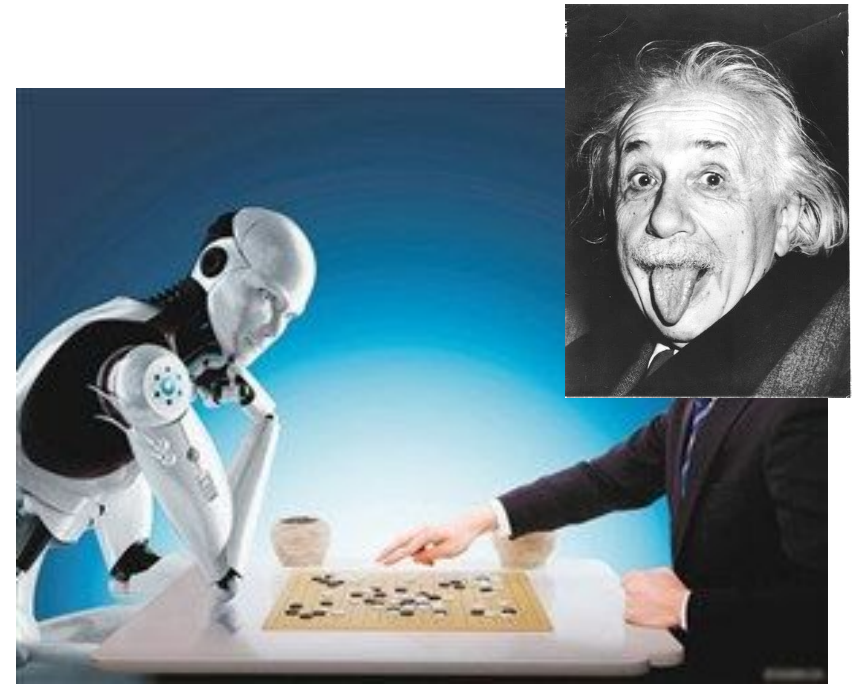
Classification + Localization

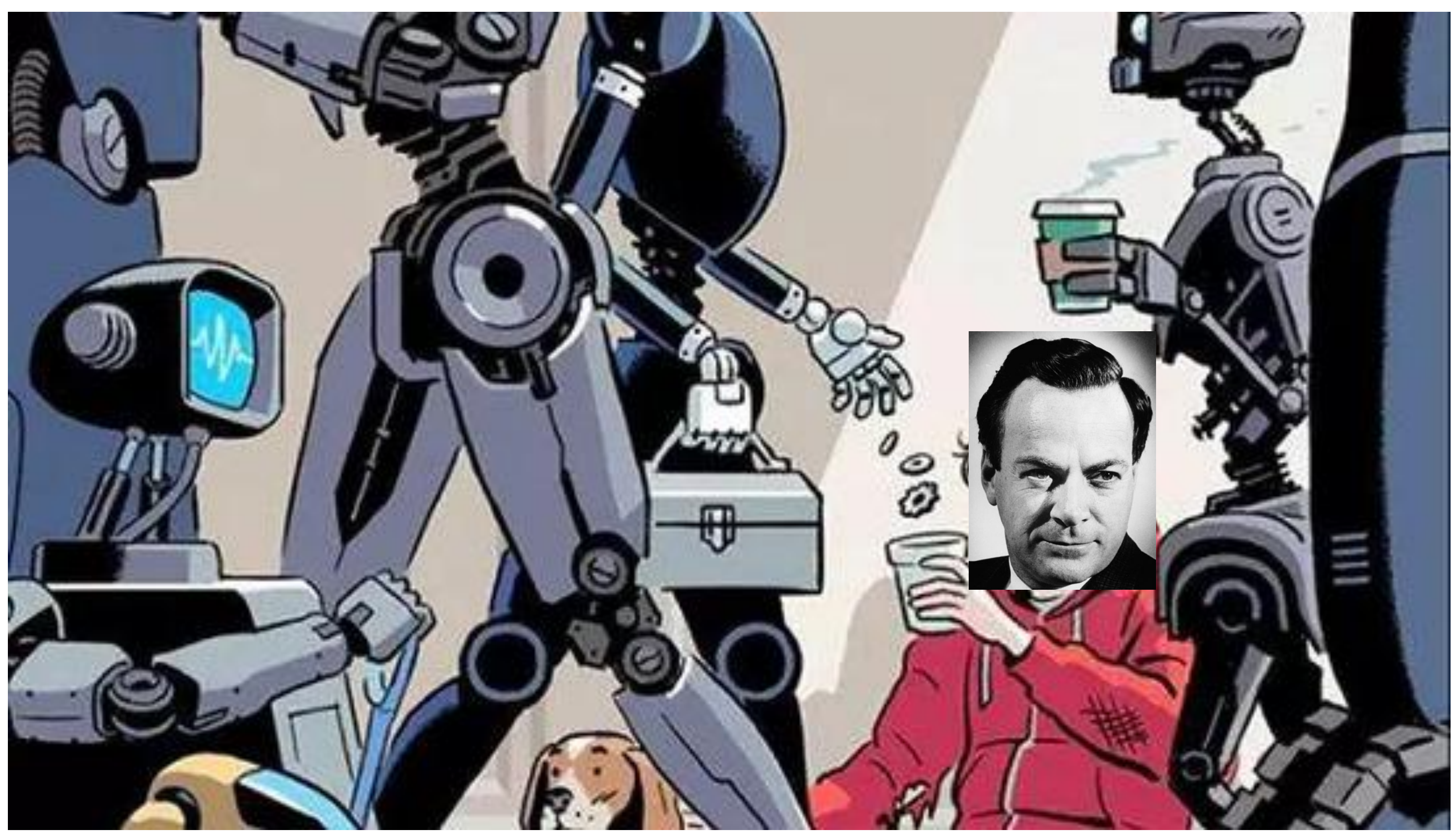
Evolution: **RCNN -> Fast RCNN -> Faster RCNN -> Mask**




**Automated jet construction and Classification**

# Machine Learning @ HEP

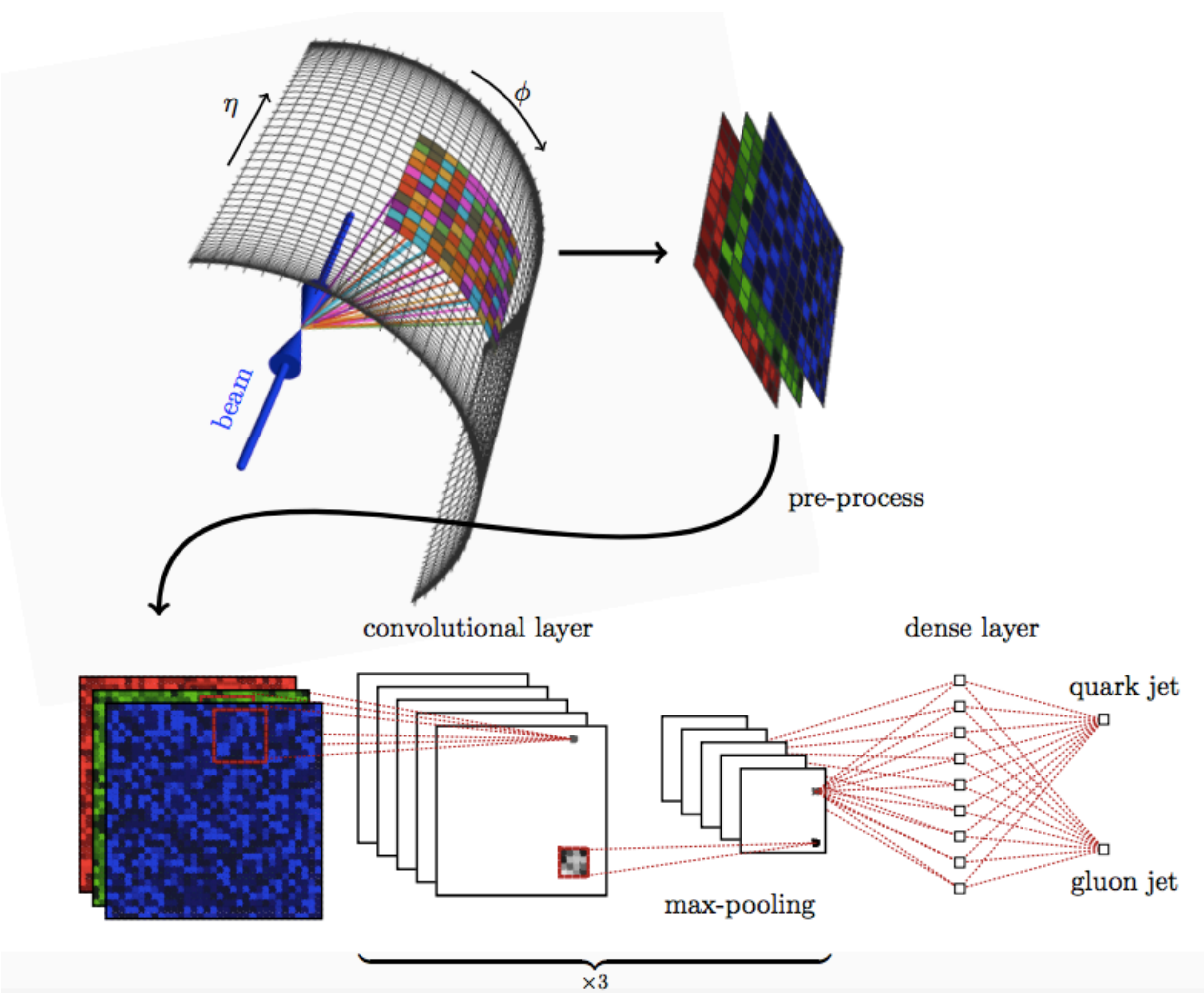





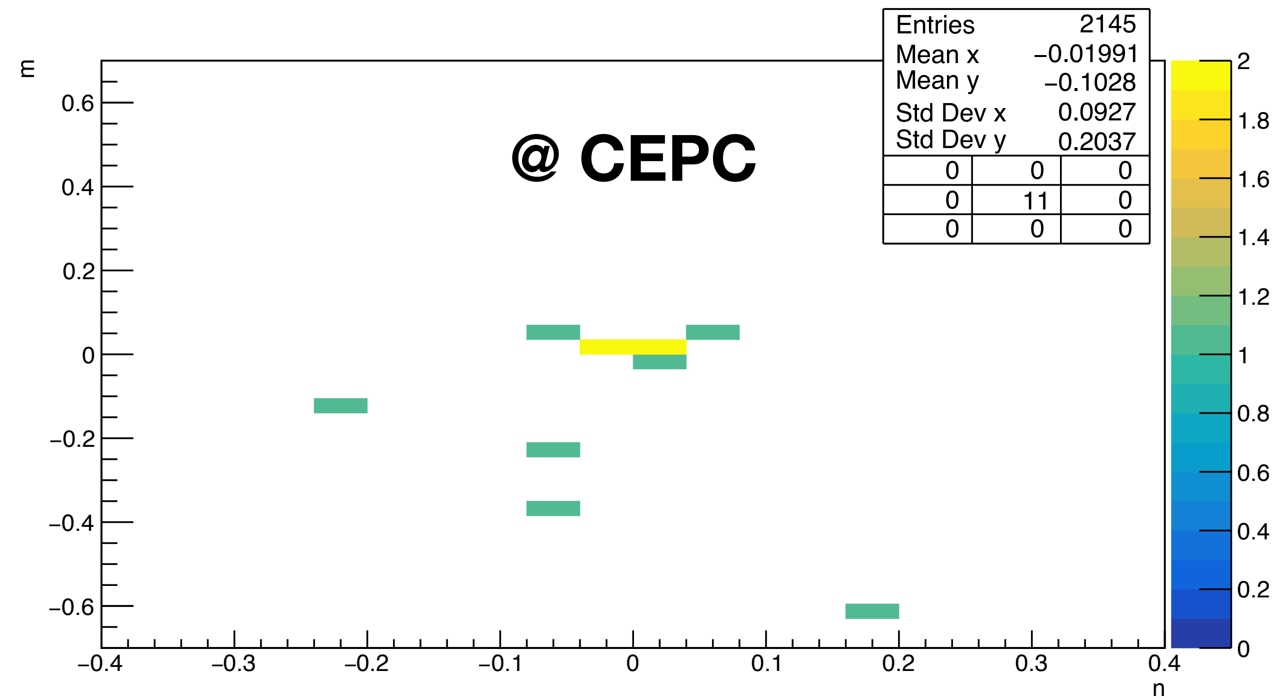
# Machine Learning @ HEP

- **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

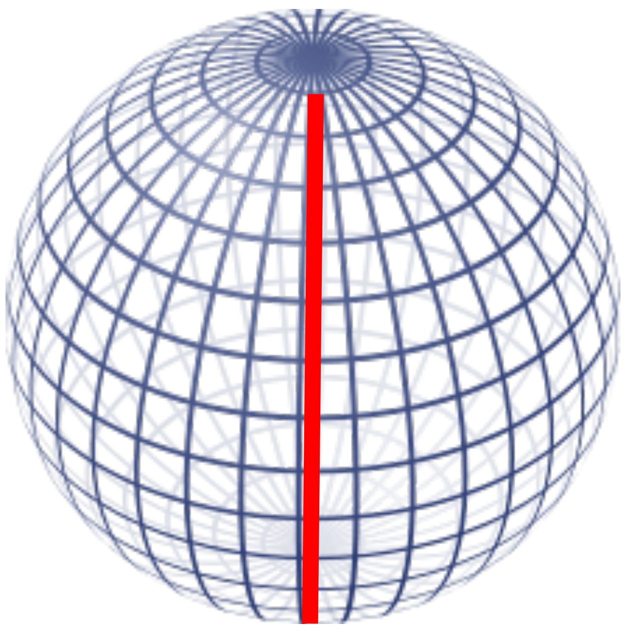


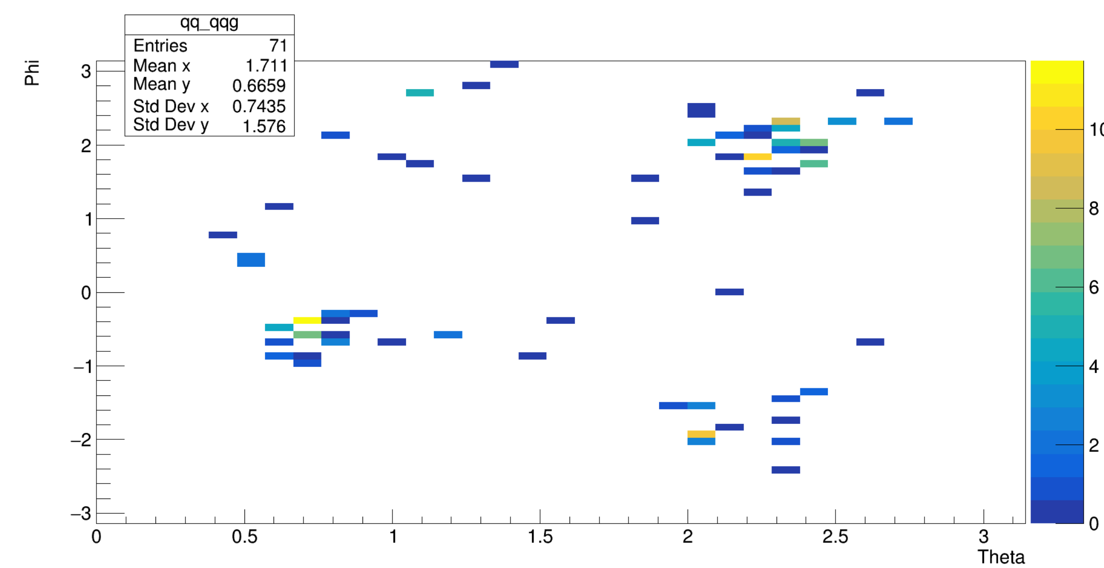
# CNN Configuration

```
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')
```

**https://github.com/zhaoli-IHEP/Higgs-ML**

# Recover symmetry via rotation



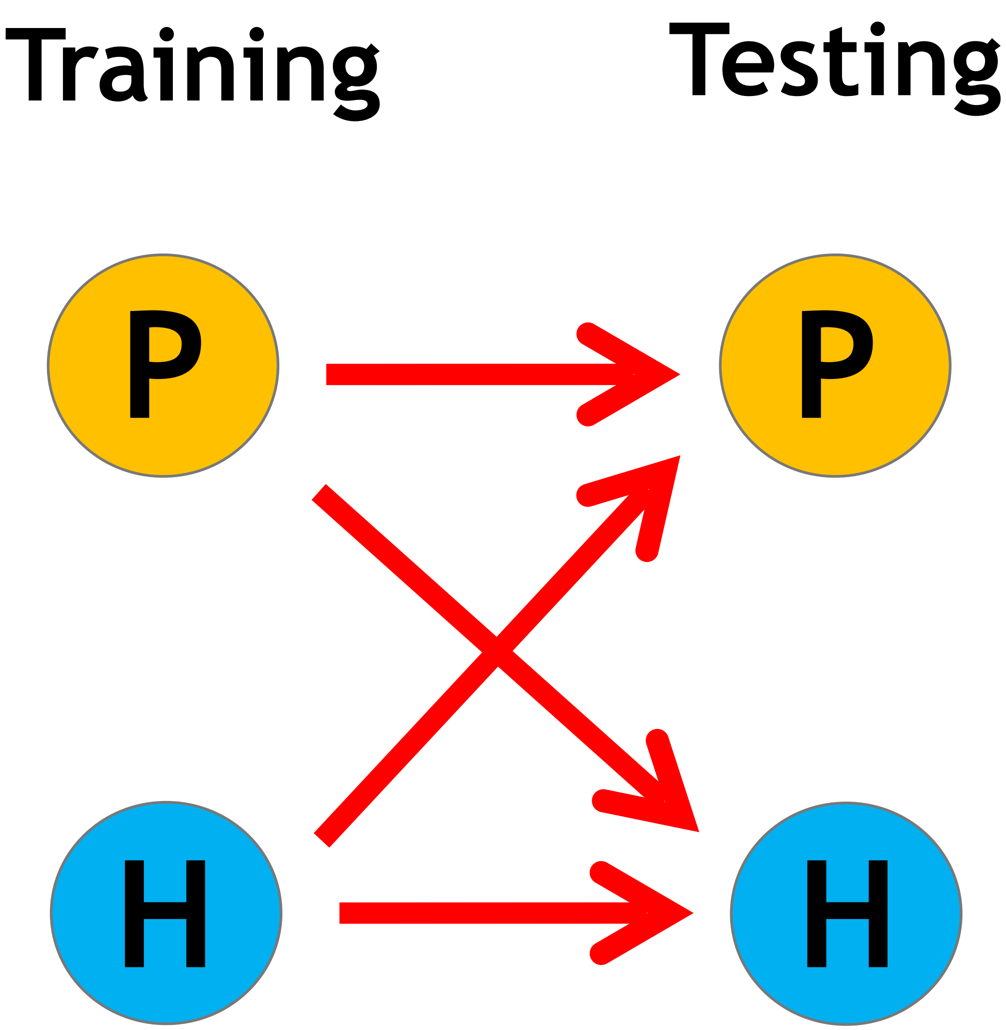


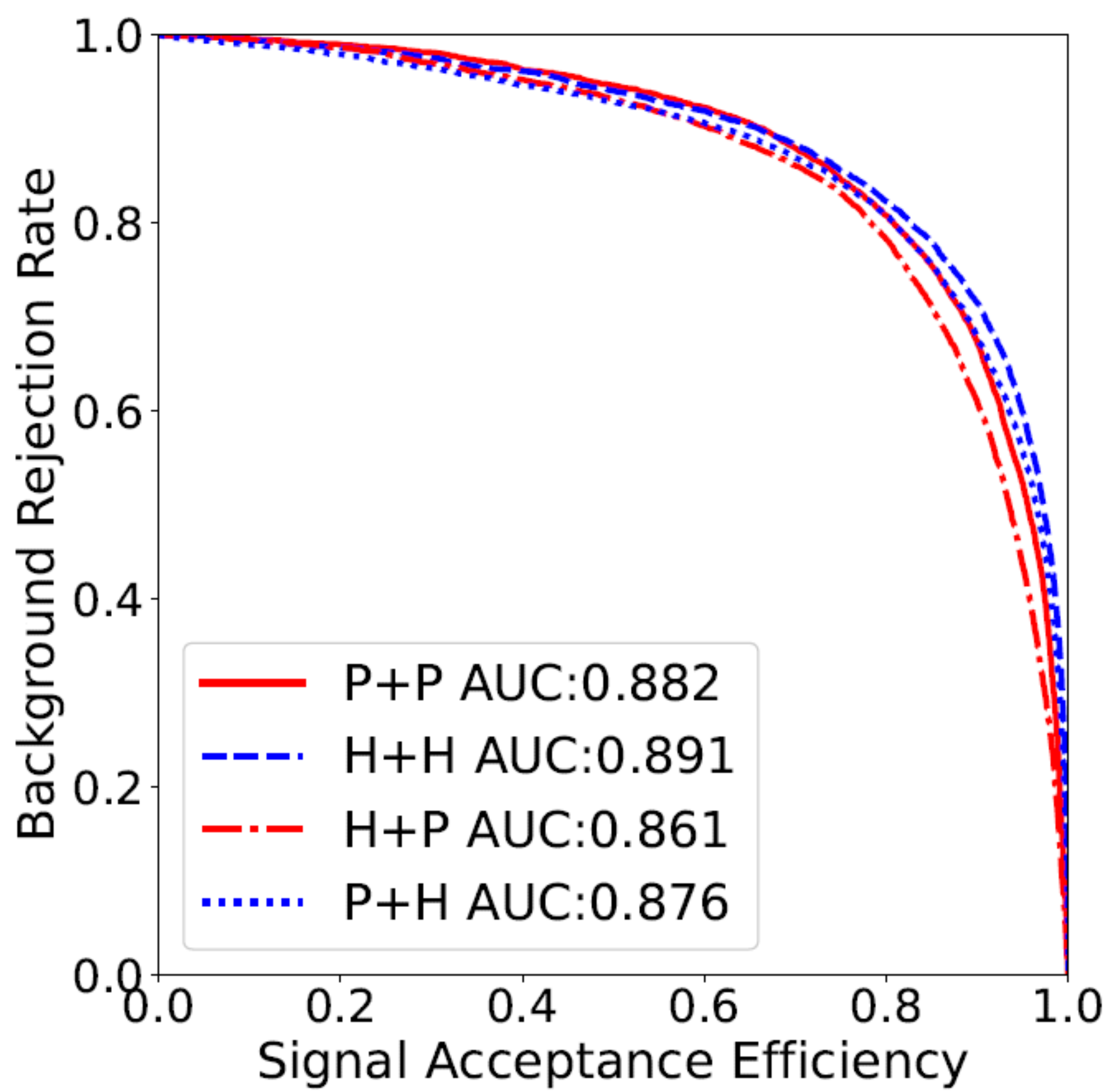

phi symmetry break

Rotate at phi direction

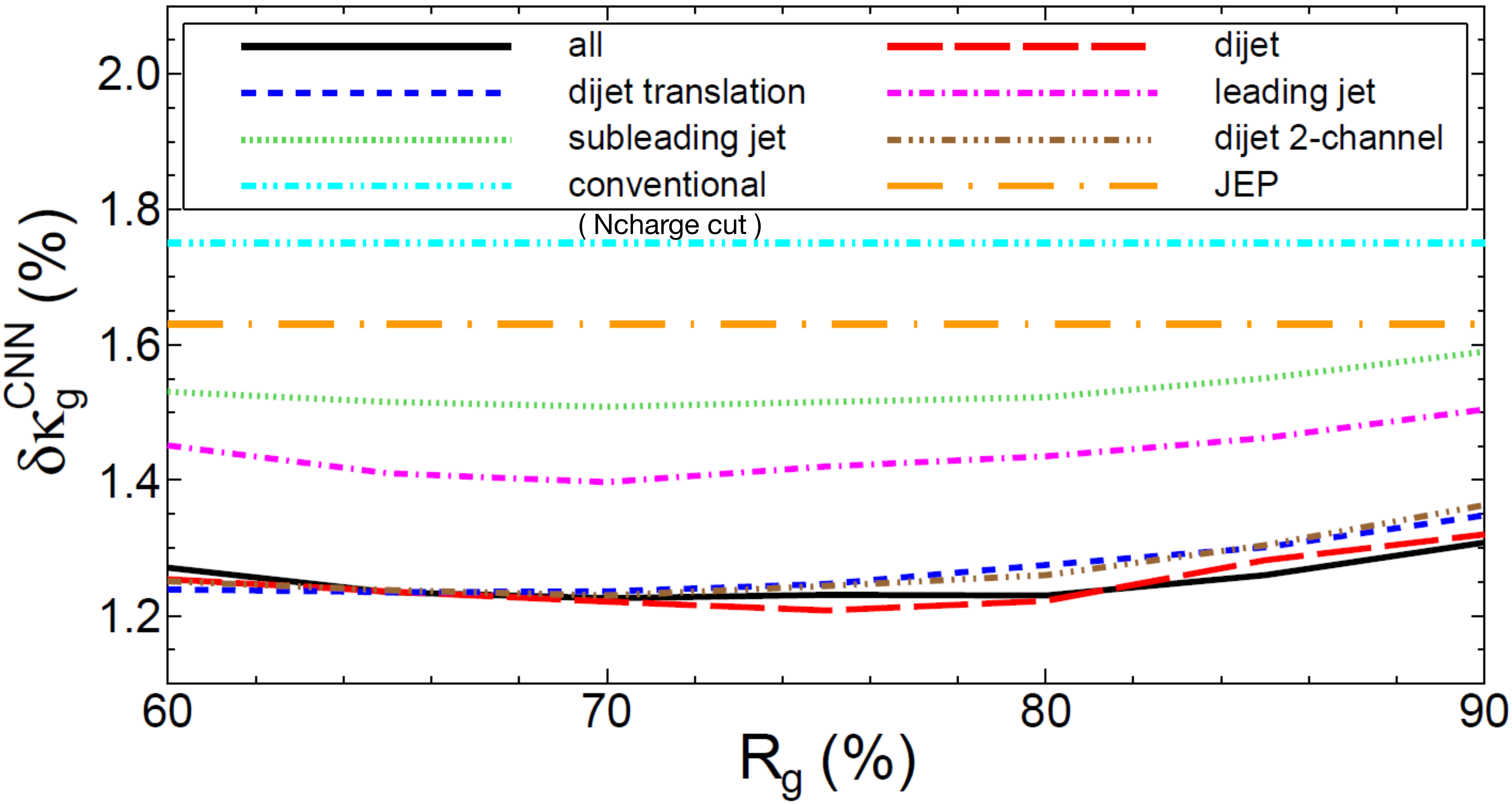
Each rotation turns 13 pixels.
Each image becomes 5 different images.

# Performance of CNNs



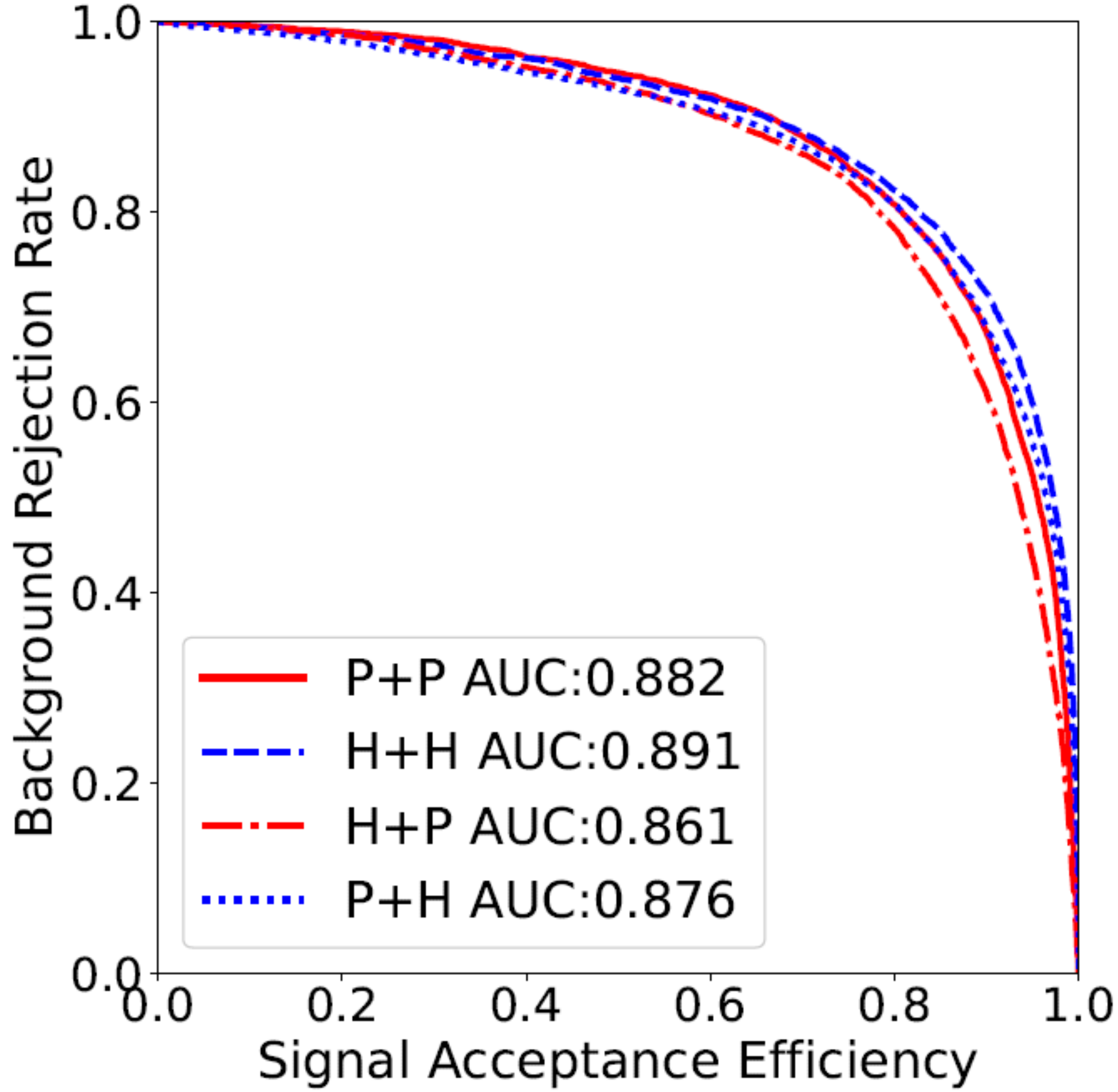



# Improvement of CNNs

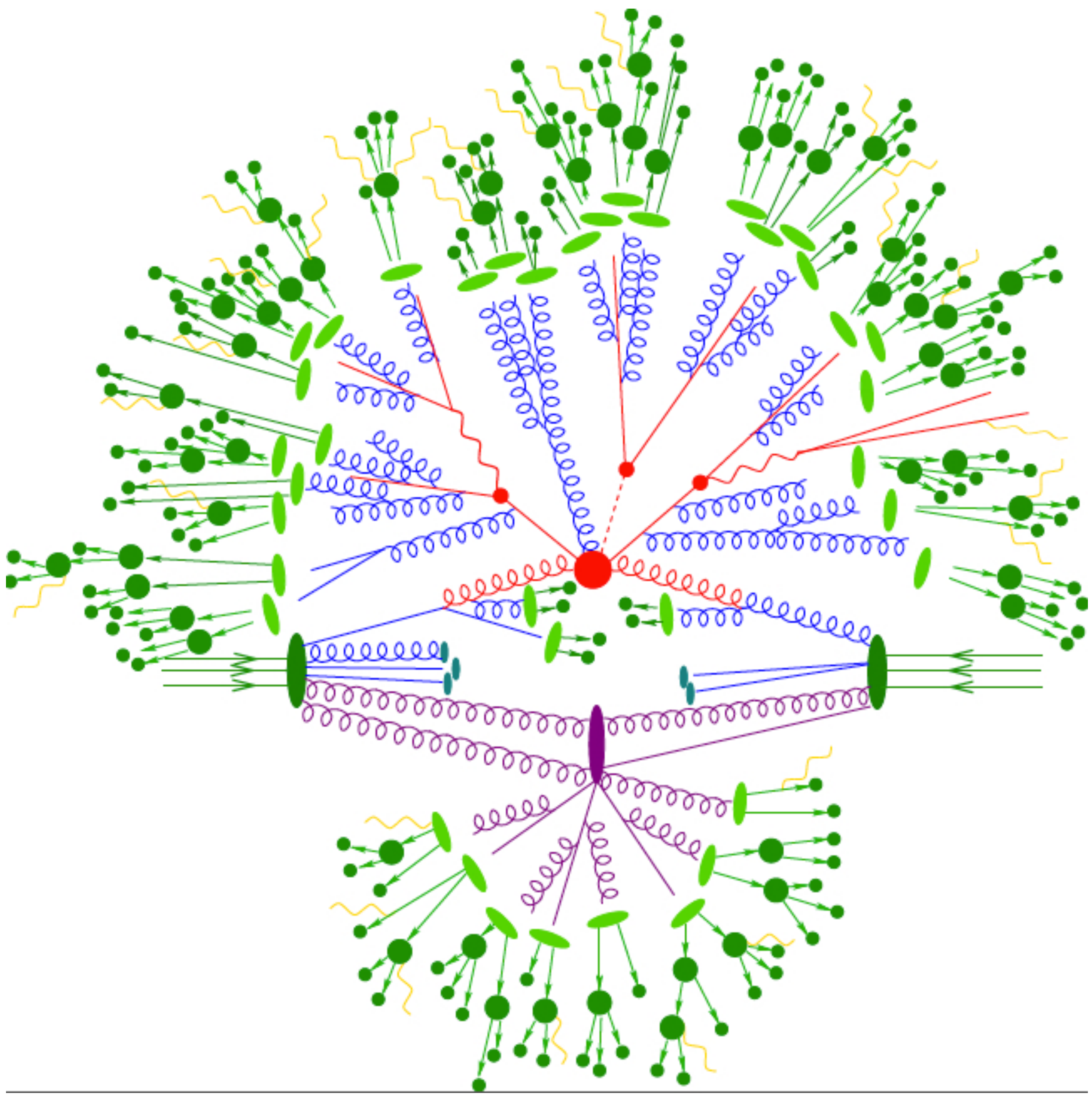



**Further ~30% improvements to reach ~1.2%**

# Revisit AUC comparison between P & H



# Does simulation really simulate physics?



Parton Shower? Hadronization? Underlying events? etc.

# Beyond $M_{t\bar{t}}$: learning to search for a broad $t\bar{t}$ resonance at the LHC

Sunghoon Jung,[1,*] Dongsub Lee,[1,†] and Ke-Pan Xie[1,‡]
[1] *Center for Theoretical Physics, Department of Physics and Astronomy, Seoul National University, Seoul 08826, Korea*

We have found that, in an attempt to develop methods to discover broad $t\bar{t}$ resonances, $M_{t\bar{t}}$ is still one of the most important observables, but additional information from both on- and off-resonance regions can significantly enhance discovery capability. As a result, the cross section upper limits can be improved by $\sim 60\%$ for $\Gamma_\rho/M_\rho \sim 40\%$, and the improved LHC sensitivities do not strongly depend on the width of a resonance. As resonances in new physics beyond the SM are easily broad, our learnings and technique can be used to efficiently search for them.

# Extending the Bump Hunt with Machine Learning

**Jack H. Collins**[1,2] **Kiel Howe**[3] **and Benjamin Nachman**[4,5]

We have presented a new anomaly detection technique for finding BSM physics signals directly from data. The central assumption is that the signal is localized as a bump in one variable in which the background is smooth, and that other features are available for additional discrimination power. This allows us to identify potential signal-enhanced and signal-depleted event samples with almost identical background characteristics on which a classifier can be trained using the Classification Without Labels approach. In the case that a distinctive signal is present, the trained classifier output becomes an effective discriminant between signal events and background events, while in the case that no signal is present the classifier output shows no clear pattern. An event selection based on a threshold cut on the classifier output produces a smooth distribution if no signal is present and produces a bump if a signal is present, and so standard bump hunting techniques can be used on the selected distribution.

# Jet-Images – Deep Learning Edition

**Luke de Oliveira,**[a] **Michael Kagan,**[b] **Lester Mackey,**[c] **Benjamin Nachman,**[b] **and Ariel Schwartzman**[b]

ABSTRACT: Building on the notion of a particle physics detector as a camera and the collimated streams of high energy particles, or jets, it measures as an image, we investigate the potential of machine learning techniques based on deep learning architectures to identify highly boosted $W$ bosons. Modern deep learning algorithms trained on *jet images* can out-perform standard physically-motivated feature driven approaches to jet tagging. We develop techniques for visualizing how these features are learned by the network and what additional information is used to improve performance. This interplay between physically-motivated feature driven tools and supervised learning algorithms is general and can be used to significantly increase the sensitivity to discover new particles and new forces, and gain a deeper understanding of the physics within jets.

# Jet Constituents for Deep Neural Network Based Top Quark Tagging

**J. Pearkes,[a] W. Fedorko,[a,1] A. Lister[a] C. Gay[a]**

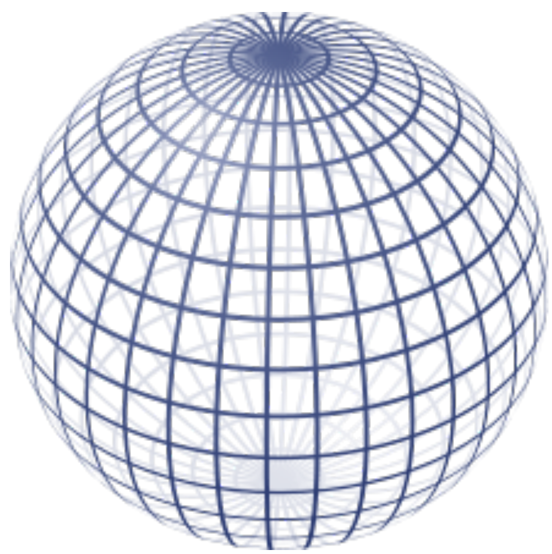
Abstract: Recent literature on deep neural networks for tagging of highly energetic jets resulting from top quark decays has focused on image based techniques or multivariate approaches using high-level jet substructure variables. Here, a sequential approach to this task is taken by using an ordered sequence of jet constituents as training inputs. Unlike the majority of previous approaches, this strategy does not result in a loss of information during pixelisation or the calculation of high level features. The jet classification method achieves a background rejection of 45 at a 50% efficiency operating point for reconstruction level jets with transverse momentum range of 600 to 2500 GeV and is insensitive to multiple proton-proton interactions at the levels expected throughout Run 2 of the LHC.

# Conclusion

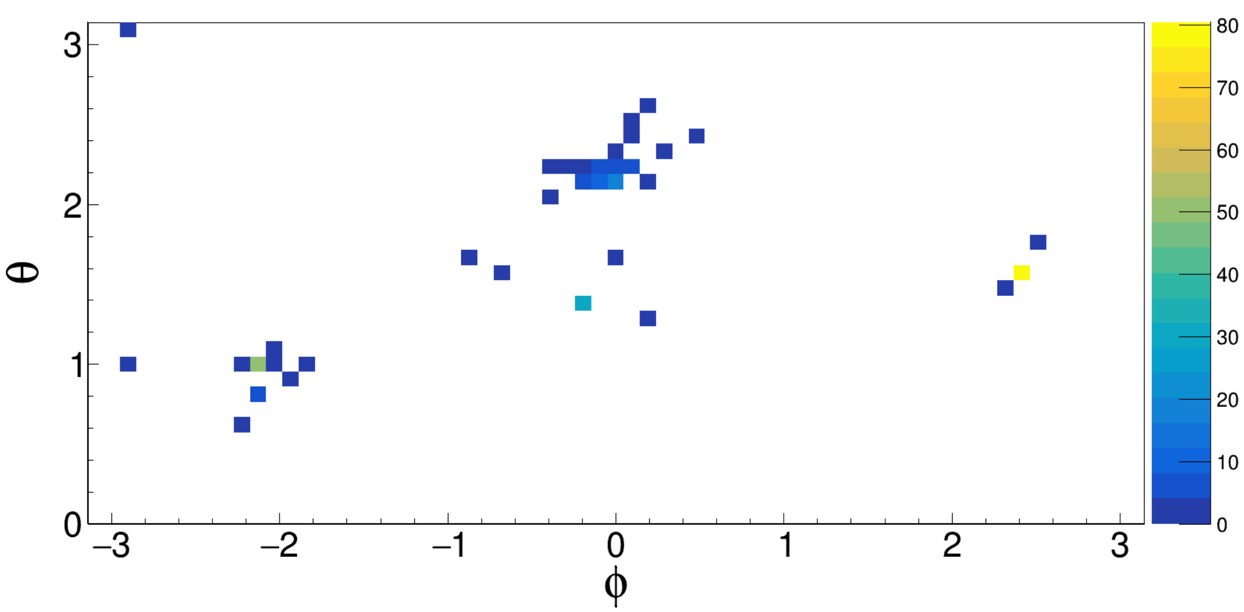
- CEPC can be very precise factory for Higgs investigation.
- Deep learning is full of potential for CEPC physics.
- Maybe deep learning can also help LHC physics.
- However, we should be careful about traps in simulations.

# Backup

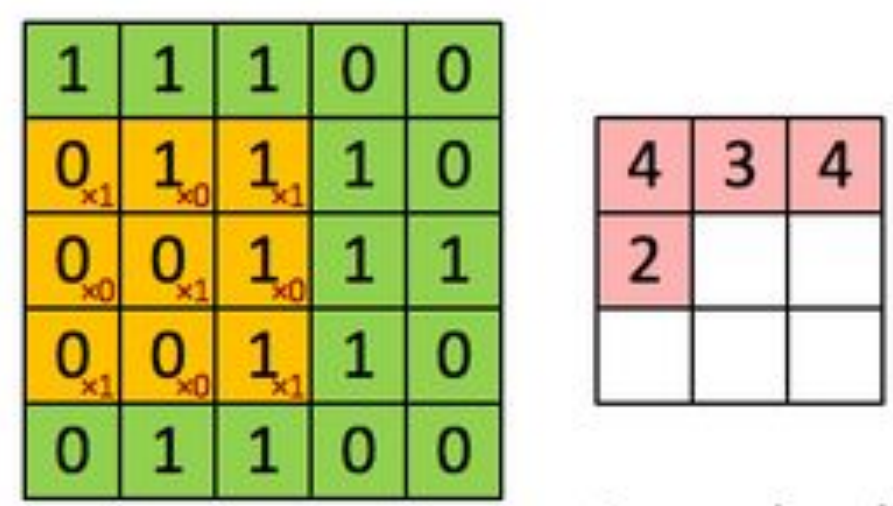
# Convolutional Neural Networks (CNNs)



Energy of all the final state stable particles

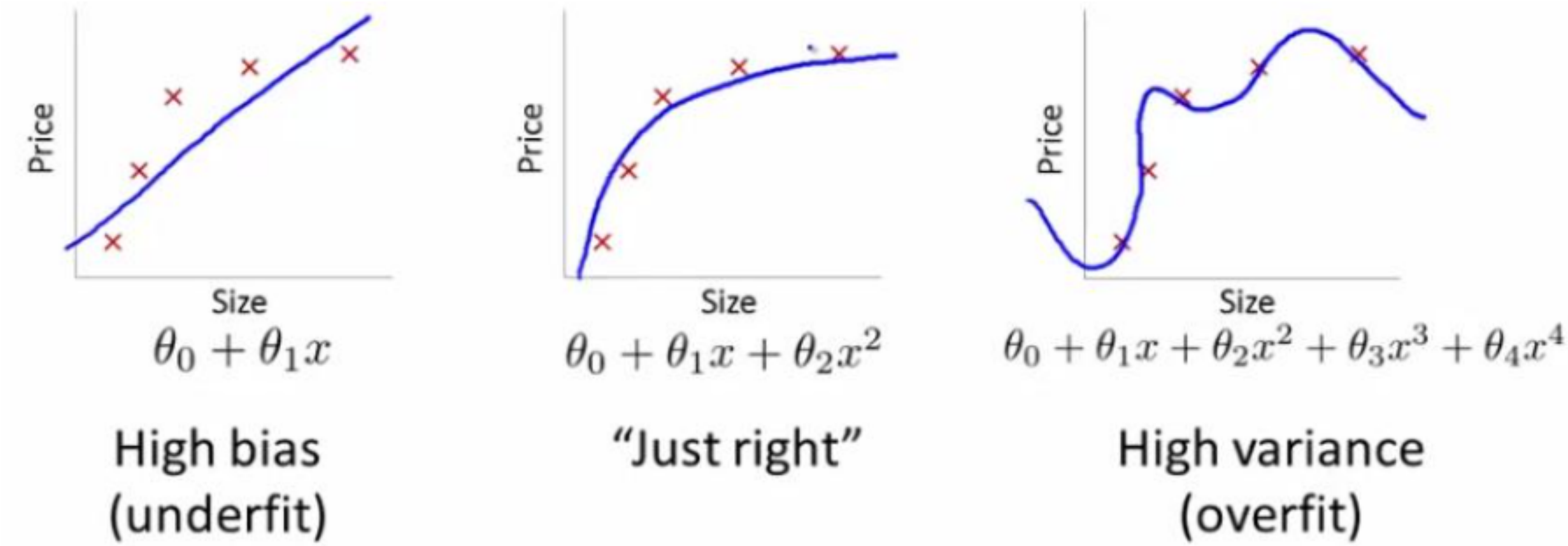



2D image (62*30 pixels)

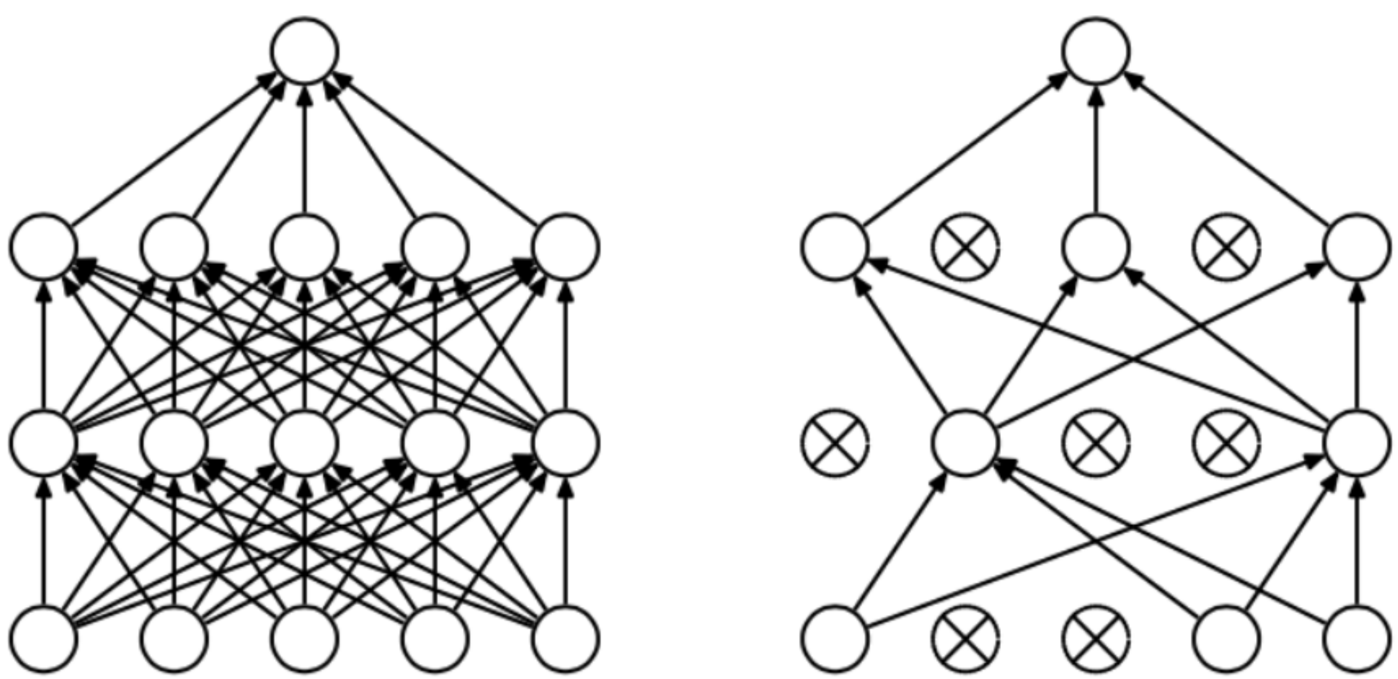



Image

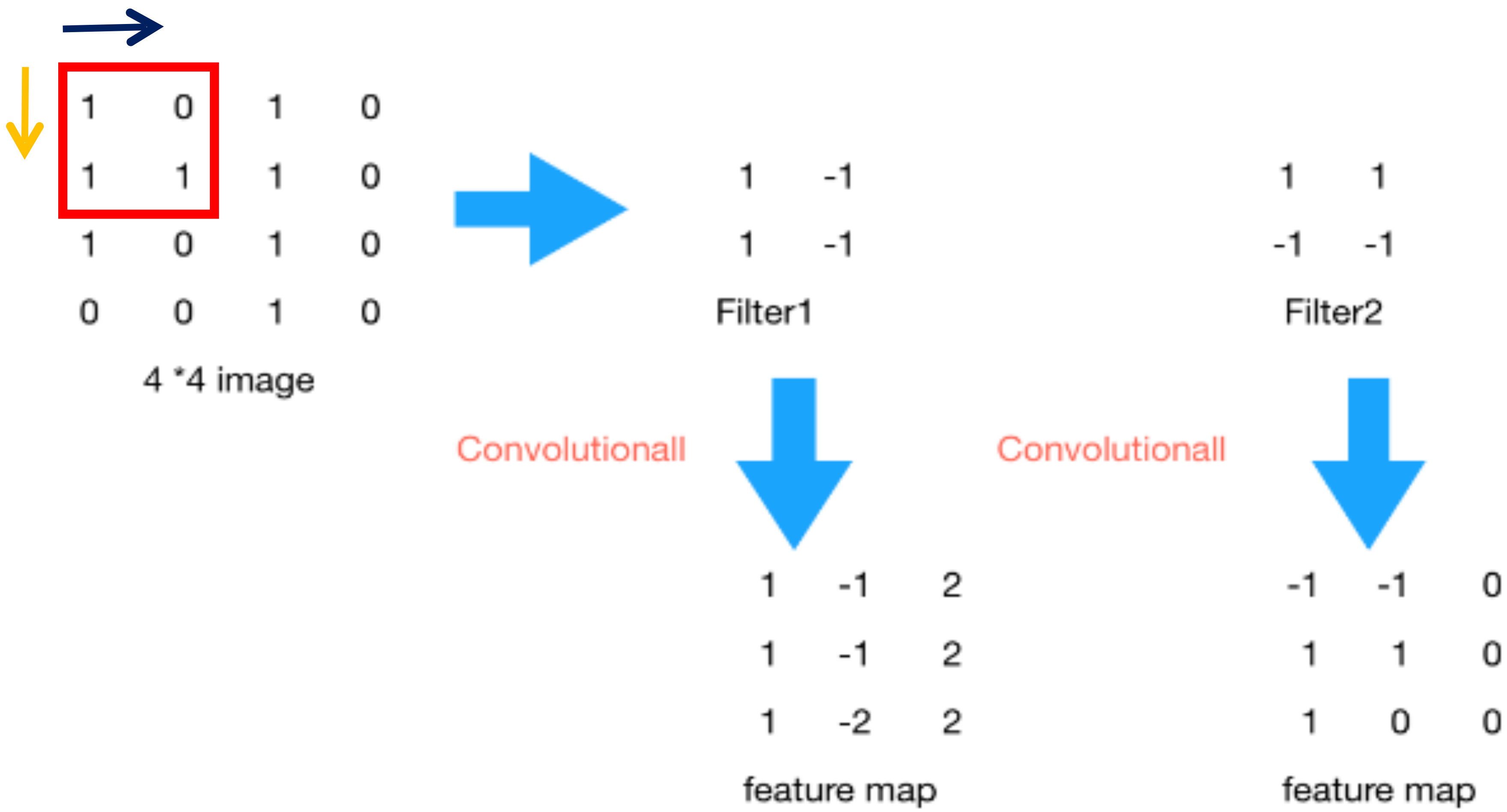
Convolved Feature

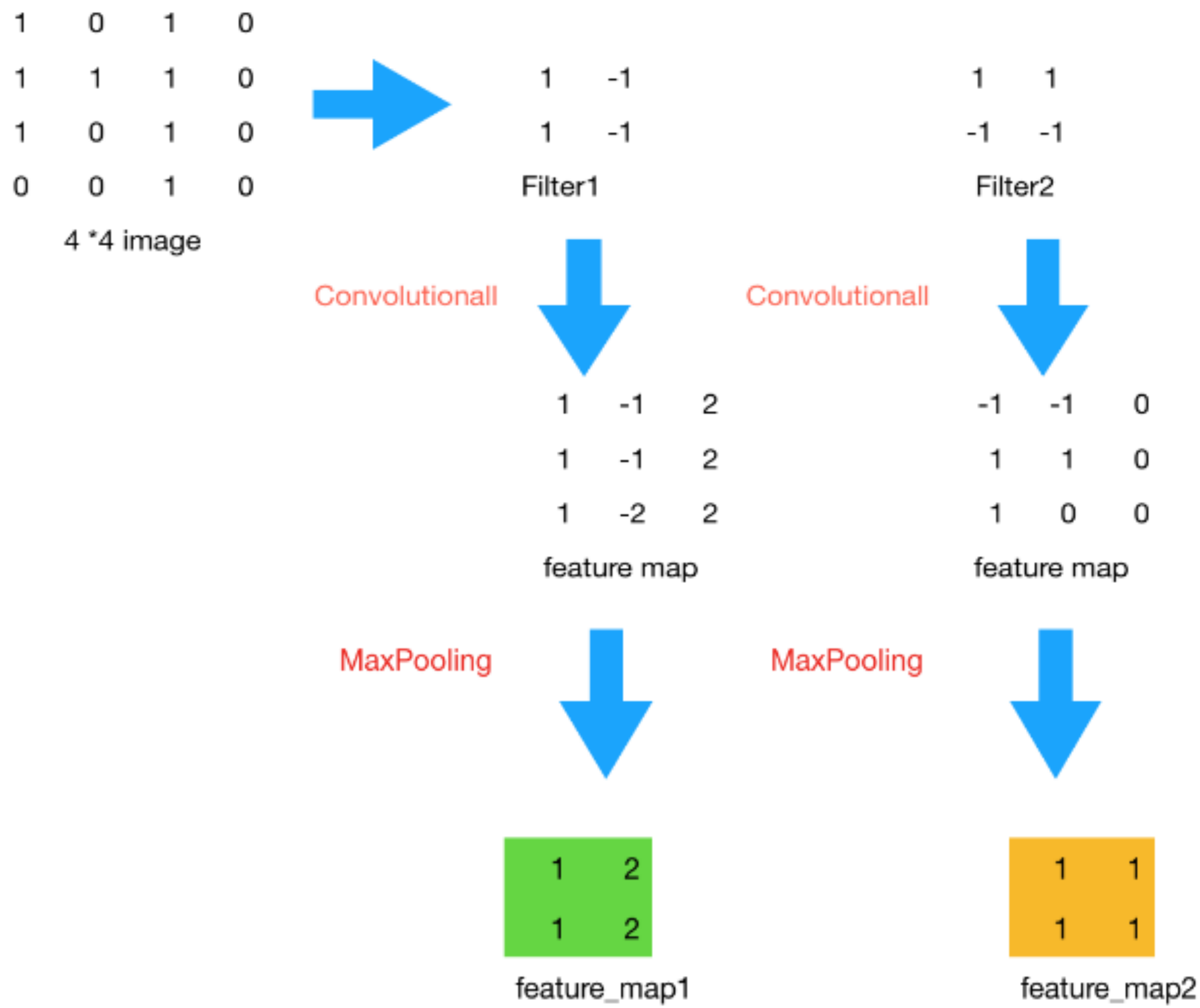


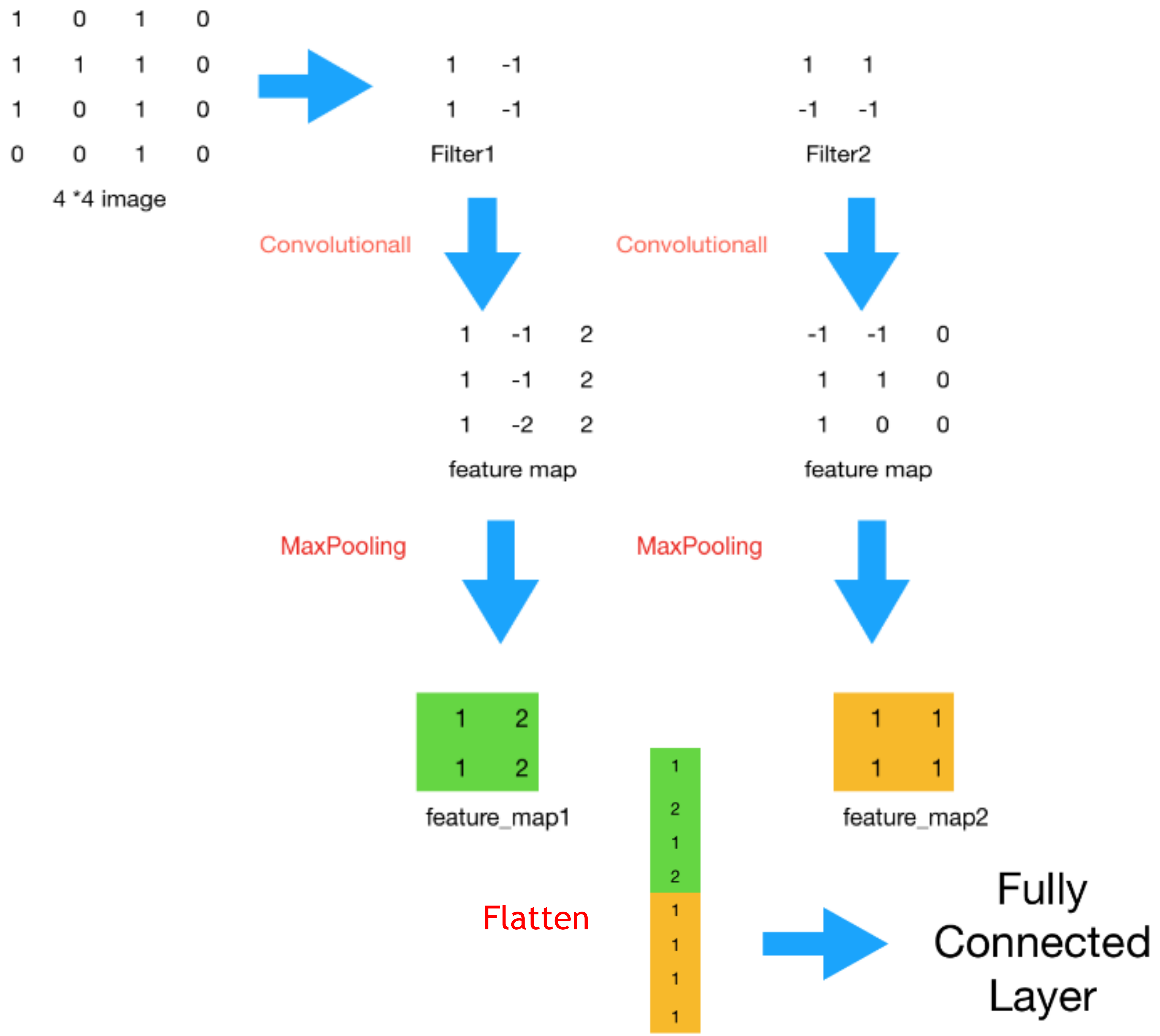

Overfit



Dropout


1 0 1 0
1 1 1 0
1 0 1 0
0 0 1 0
4 *4 image
1 -1
1 -1
Filter1
1 1
-1 -1
Filter2
Convolutionall
Convolutionall
1 -1 2
1 -1 2
1 -2 2
feature map
-1 -1 0
1 1 0
1 0 0
feature map


1 0 1 0
1 1 1 0
1 0 1 0
0 0 1 0
4 *4 image
1 -1
1 -1
Filter1
1 1
-1 -1
Filter2
Convolutionall
Convolutionall
1 -1 2
1 -1 2
1 -2 2
feature map
-1 -1 0
1 1 0
1 0 0
feature map
MaxPooling
MaxPooling
1 2
1 2
feature_map1
1 1
1 1
feature_map2


1 0 1 0
1 1 1 0
1 0 1 0
0 0 1 0
4 *4 image
1 -1
1 -1
Filter1
1 1
-1 -1
Filter2
Convolutionall
Convolutionall
1 -1 2
1 -1 2
1 -2 2
feature map
-1 -1 0
1 1 0
1 0 0
feature map
MaxPooling
MaxPooling
1 2
1 2
feature_map1
1 1
1 1
feature_map2
1
2
1
2
1
1
1
1
Flatten
Fully Connected Layer

# Max Pooling