Strange Jet Tagging

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Based on YN, D. Shih and S. Thomas, 2003.09517 [hep-ph].

Higgs and Flavor, EF02, Snowmass, August 2020

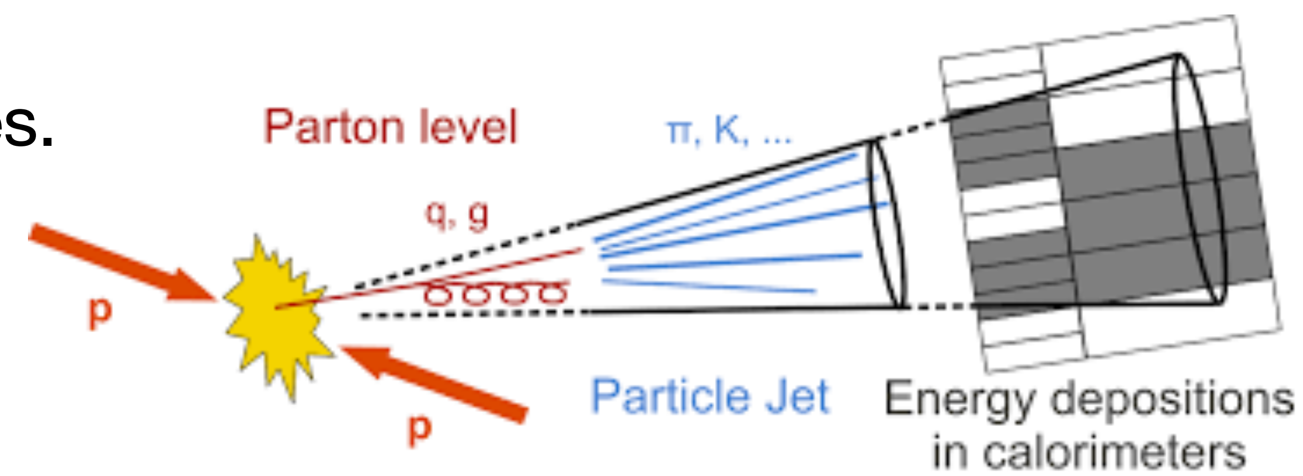
Jets at colliders

Jet : collimated bunch of hadrons as the signatures of quarks and gluons produced in high-energy collisions

✓ QCD partons are never observed isolated due to confinement.

✓ They give cascades of radiation (parton shower) by QCD processes.

✓ Hadrons are formed at $\sim \Lambda_{\rm QCD}$

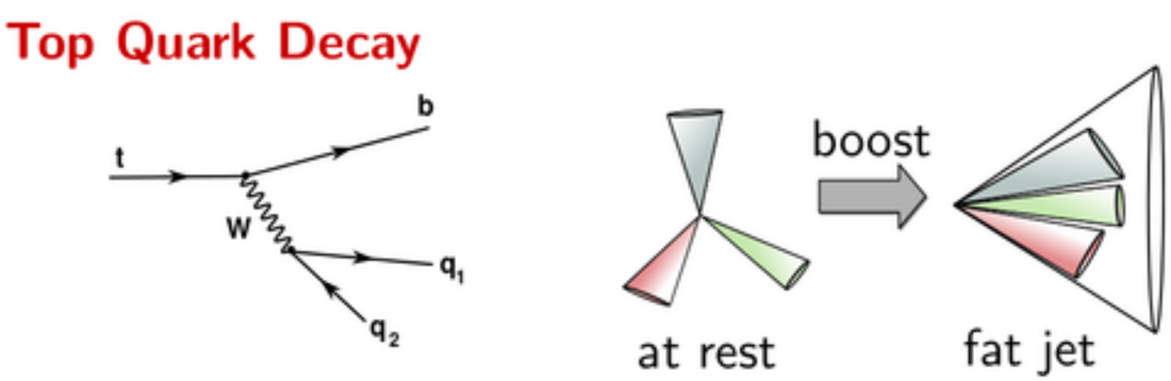


Understanding jets is a key ingredient of physics measurements and new physics searches at colliders.

What initial parton produces a jet ?

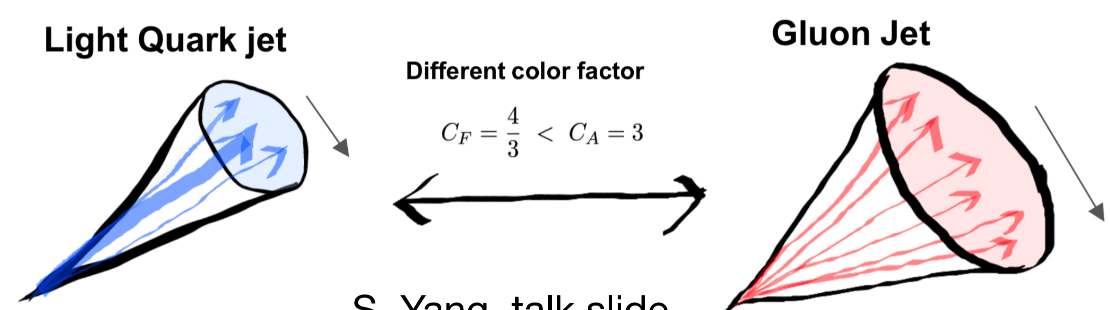
Quark and Gluon Tagging

☑ Top quark



Jet mass, N-subjettiness, …

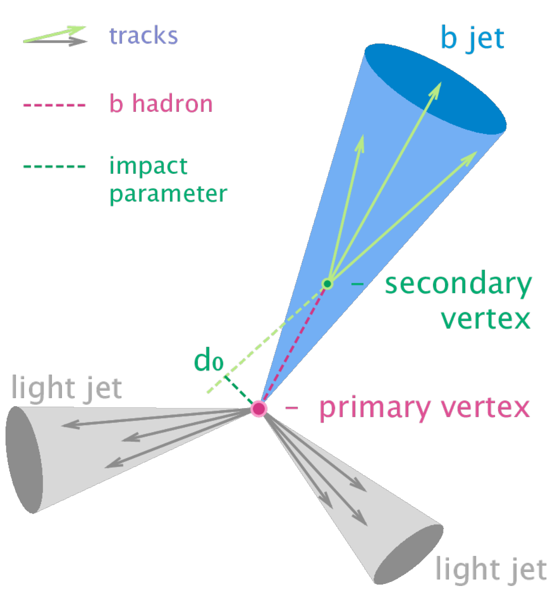
☑ Gluon



S. Yang, talk slide

More constituents with more uniform energy fragmentation and wider.

☑ Bottom/Charm



Look for a displaced (secondary) vertex.

Wikipedia

☑ Up-type vs Down-type

p_T-weighted jet charge

$$Q_\kappa^i = \frac{1}{(p_T^{\text{jet}})^\kappa} \sum_{j \in \text{jet}} Q_j (p_T^j)^\kappa$$

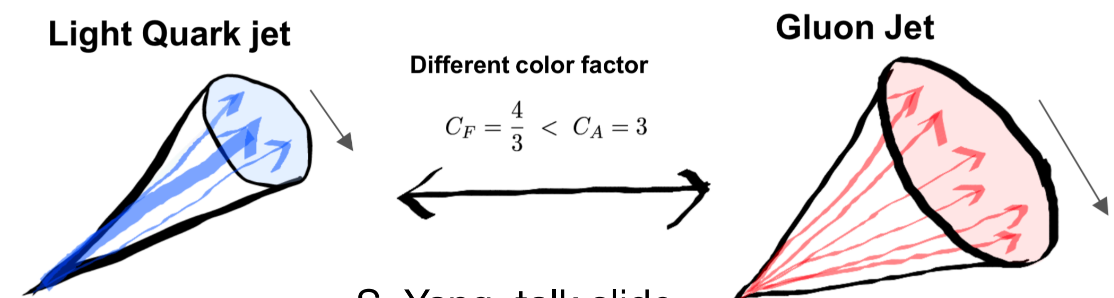
The last missing piece :

Strange quark tagging?

Tagging Strategy

- **Strange vs Gluon**

  We can expect the same thing as quark/gluon discrimination.



S. Yang, talk slide

More constituents with more uniform energy fragmentation and wider.

- **Strange vs Up**

  We can expect the same thing as up/down discrimination.

p_T-weighted jet charge

$$Q_\kappa^i = \frac{1}{(p_T^{\text{jet}})^\kappa} \sum_{j \in \text{jet}} Q_j (p_T^j)^\kappa$$

- **Strange vs Down**

Possible ??

Both are quarks with the same charge.

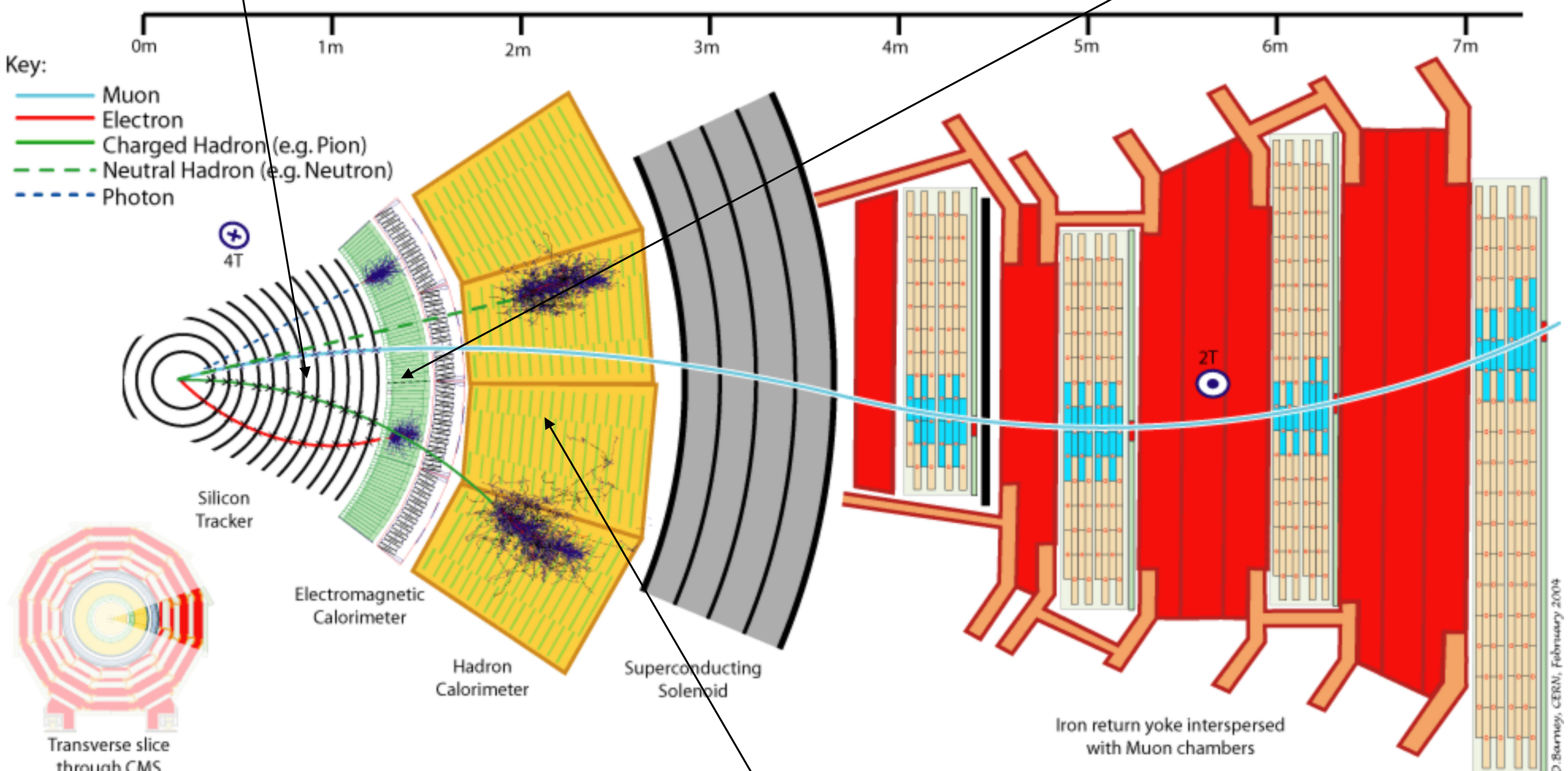
Main theme of this talk

Tagging Strategy

CMS experiment at the LHC

Tracker : trajectories of charged particles

ECAL : energy of electrons and photons



HCAL : energy deposits of hadrons

Tagging Strategy

After hadronization, strange quarks form Kaons :

$$K^- = s\bar{u}, \quad K^+ = \bar{s}u, \quad K_L \approx \frac{s\bar{d} - d\bar{s}}{\sqrt{2}}, \quad K_S \approx \frac{s\bar{d} + d\bar{s}}{\sqrt{2}}$$

$K_L, K^{\pm}$ $\quad \gamma c\tau \sim 3$ m

No decay inside detectors

K_S $\quad \gamma c\tau \sim 3$ cm

Decay inside detectors

$$K_S \to \pi^+\pi^- (\sim 70\%), \ \ \pi^0\pi^0 (\sim 30\%)$$

No difference

Detector responses to hadrons :

Down jets

	K_L	K_S	$K^{\pm}$	π^0	$\pi^{\pm}$
HN	○	△			
ECAL		△		○	
Tracker		△	○		○

Strange jets

Hadronic Neutral (HN) = HCAL - Tracker

K-long (and K-short) can be used for tagging !

Tagging Strategy

K-short behaves very differently in detectors depending on decay length and decay mode.

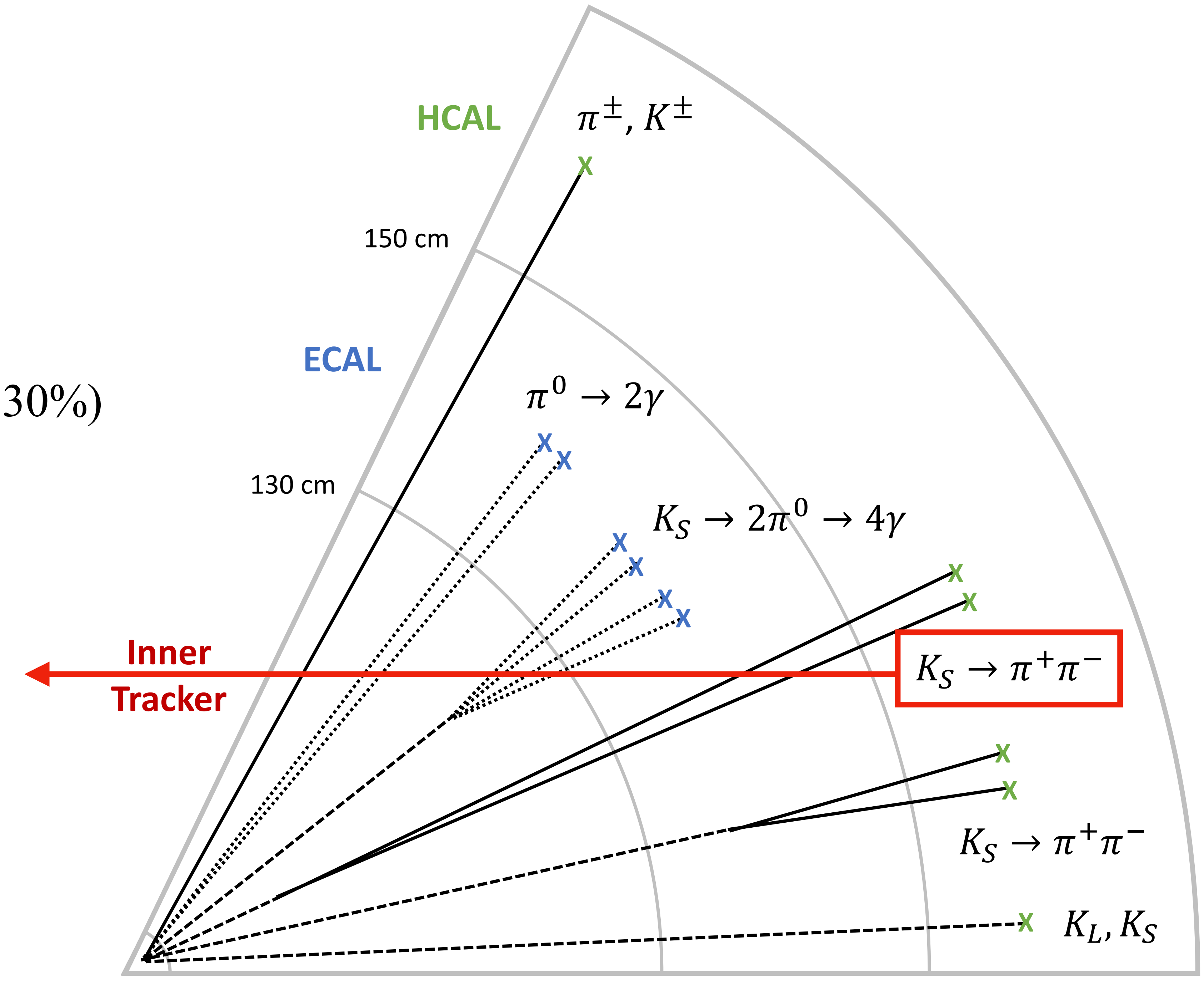
K_S $\gamma c\tau \sim 3$ cm

Decay inside detectors

$K_S \to \pi^+\pi^-(\sim 70\%),\ \ \pi^0\pi^0(\sim 30\%)$

Charged track pairs from the secondary vertex.

Reconstructable



Jet Samples

Generate strange/down jet samples by using MadGraph, PYTHIA and Delphes.

1M events for each case of :

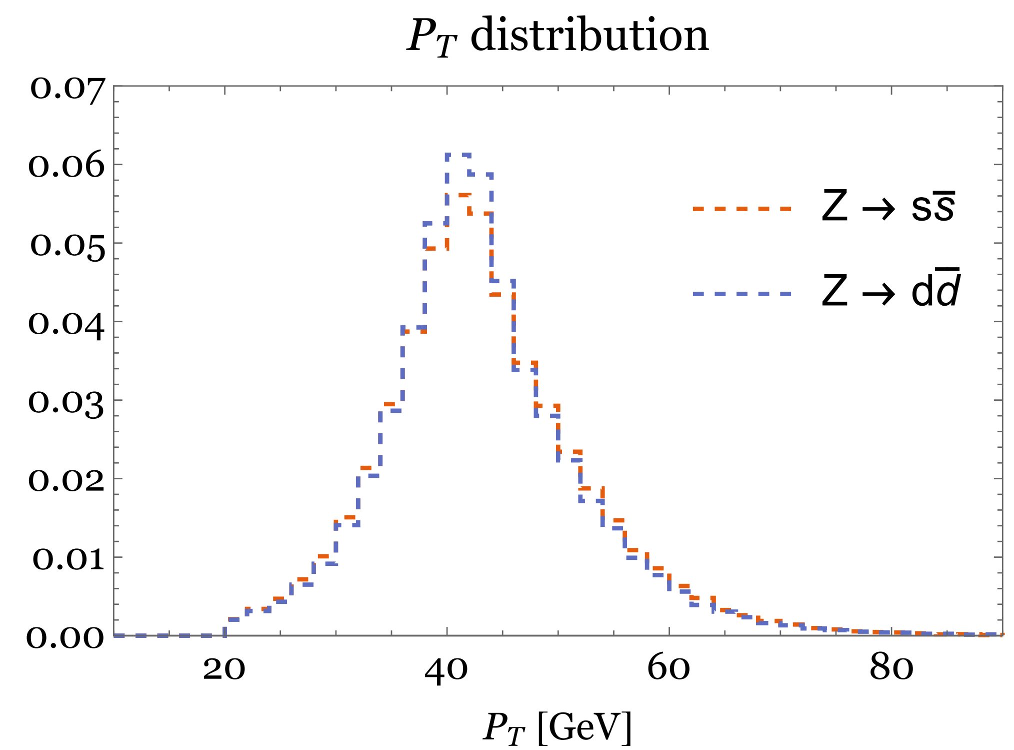
$$Z \rightarrow s\bar{s} \quad (p_T > 20 \text{ GeV})$$
$$Z \rightarrow d\bar{d} \quad (p_T > 20 \text{ GeV})$$

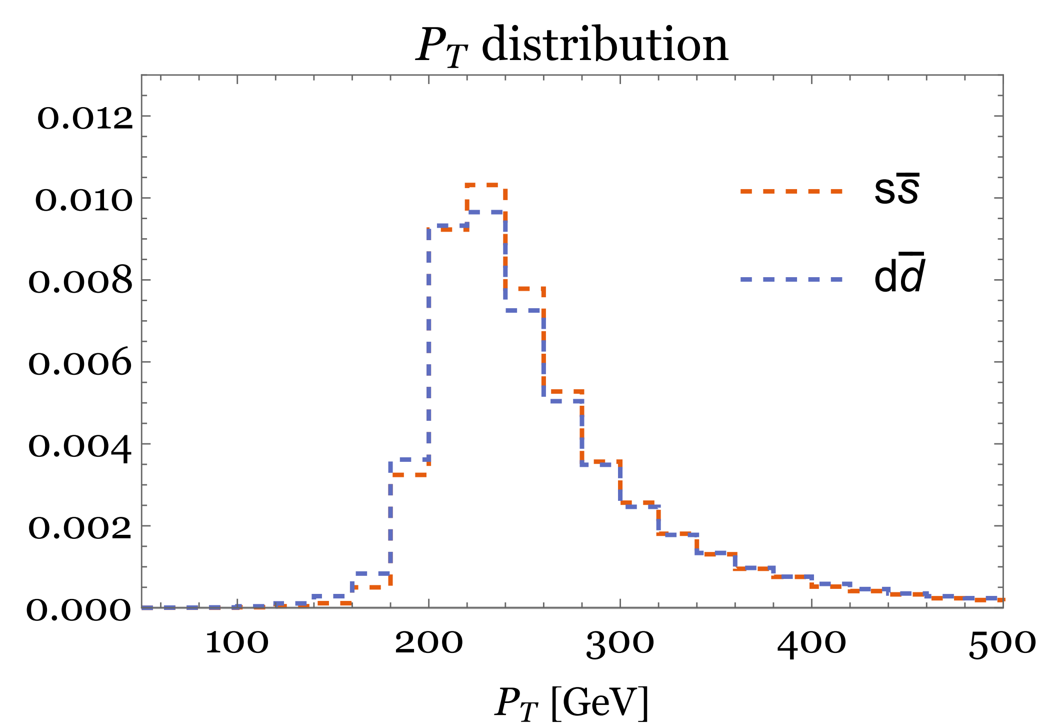
$$s\bar{s} \quad (p_T > 200 \text{ GeV})$$
$$d\bar{d} \quad (p_T > 200 \text{ GeV})$$

$$(|\eta| < 0.05)$$

Initial parton is required to be inside the leading jet : $\Delta R \equiv \sqrt{(\Delta\eta)^2 + (\Delta\phi)^2} < 0.4$

Herwig gives the similar results.

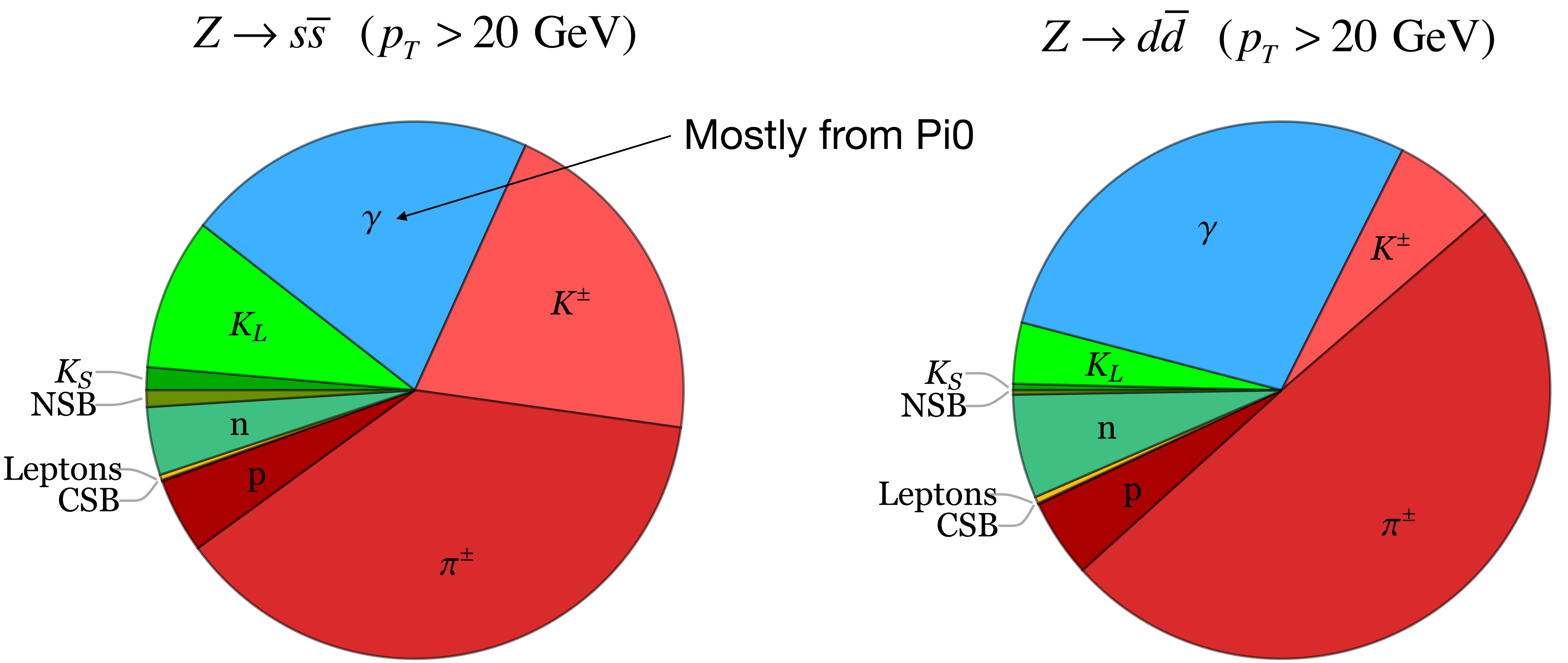




Ingredients of strange/down jets

Strange jets contain more energetic Kaons than down jets.

The pT fraction of a detector-stable particle averaged over jet samples :



NSB: neutral strange baryons, CSB: charged strange baryons

Cut-Based Tagging

Classify each jet into strange jet (signal) or down jet (background).

Put a cut in distribution of **HN − E**.

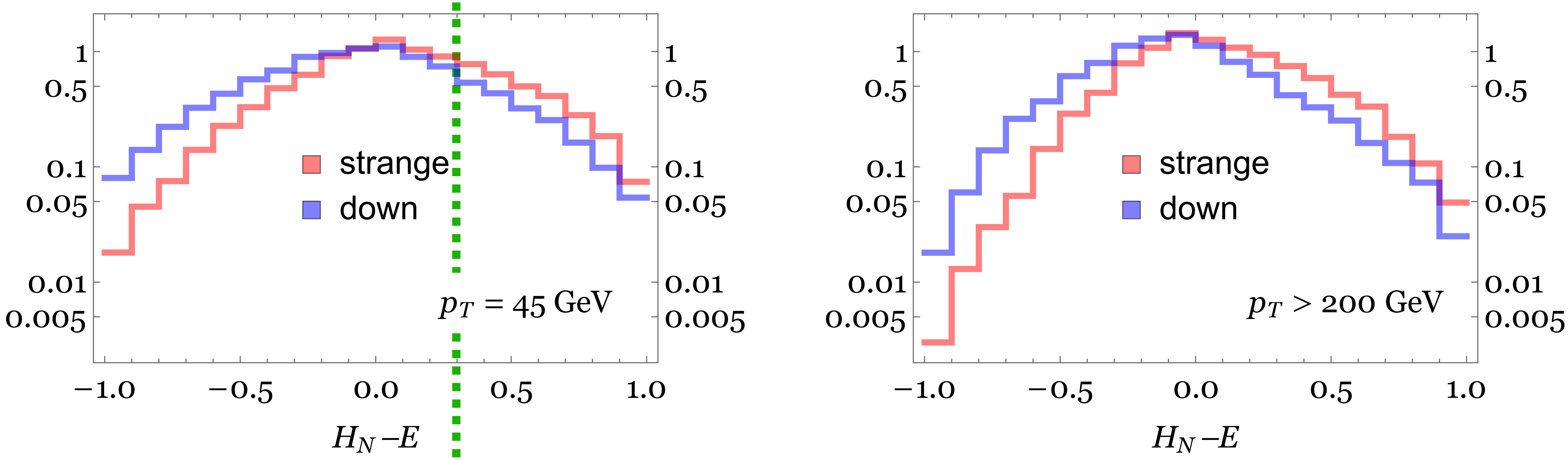
Measures to estimate efficiency and accuracy of taggers

$$\varepsilon_S = \frac{\text{(Correctly classified into signals)}}{\text{(Total number of signal jets)}}$$

$$\varepsilon_B = \frac{\text{(Misclassified into signals)}}{\text{(Total number of backgrounds)}}$$

Larger ε_S
Larger ε_B

Smaller ε_S
Smaller ε_B

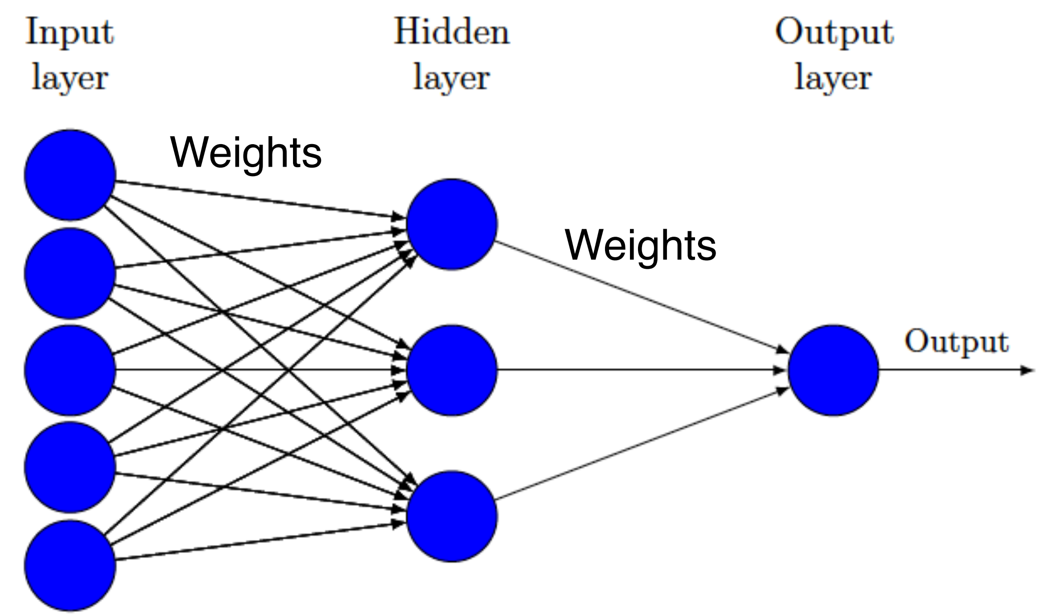


Neural Networks

✓ Powerful machine learning-based techniques used to solve many real-world problems

✓ Modeled loosely after the human brain and designed to recognize patterns

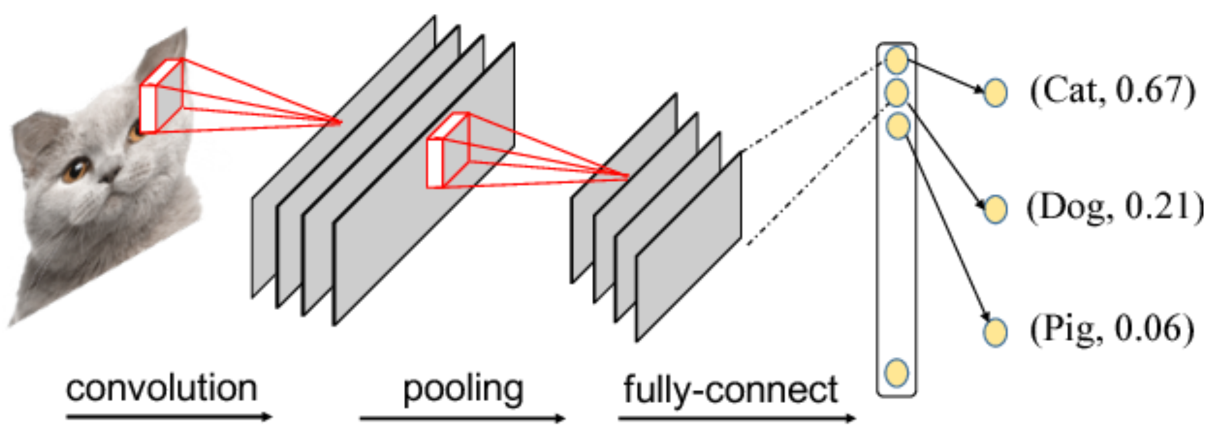
✓ Containing weights between neurons that are tuned by learning from data



Convolutional Neural Network (CNN)

✓ Show high performance for image recognitions

✓ Maintain the spacial information of images



arXiv:1712.01670

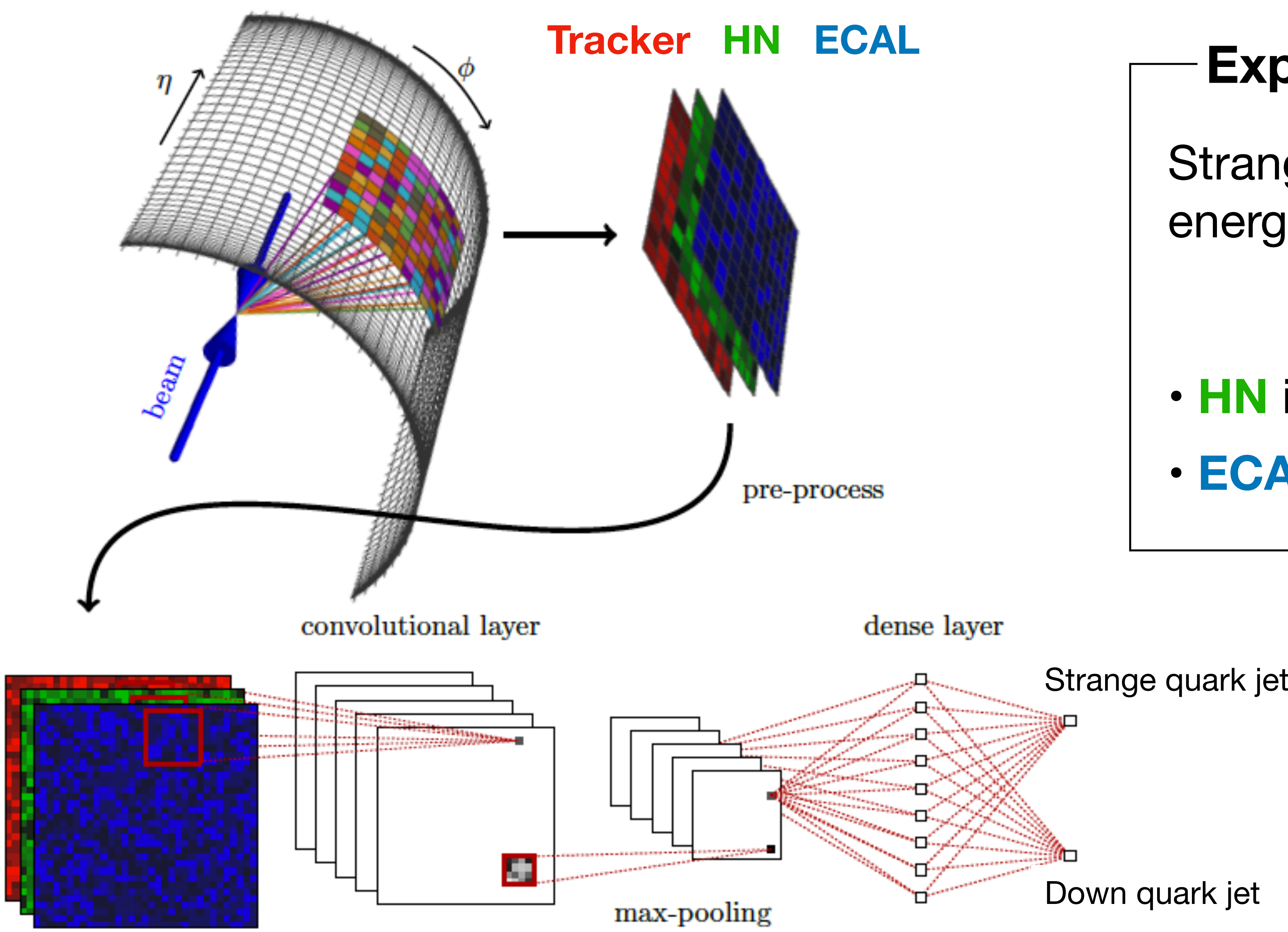
Apply a convolution operation to the input, passing the result to the next layer

Reduce the image size

Jet Images and CNN

Classification problem : **Strange jet** vs **Down jet**

Create jet images with colors (Tracker, HN, ECAL) and feed them into CNN.



Expectation

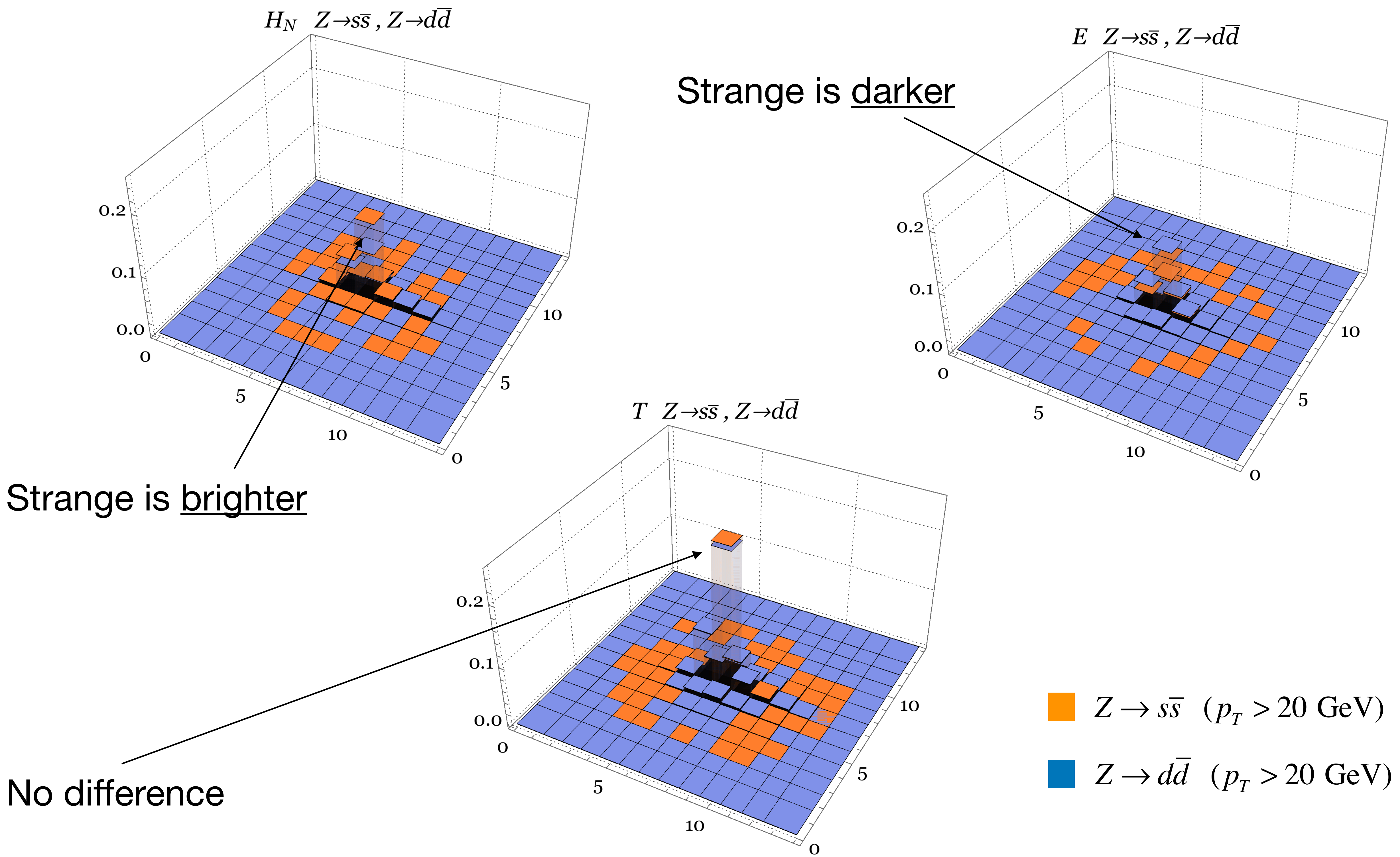
Strange jet contains more energetic neutral Kaons.

- **HN** image : brighter
- **ECAL** image : darker

Komiske, Metodiev, Schwartz (2016)

Average Images

Strange jet (average) image is brighter in HN and darker in ECAL.

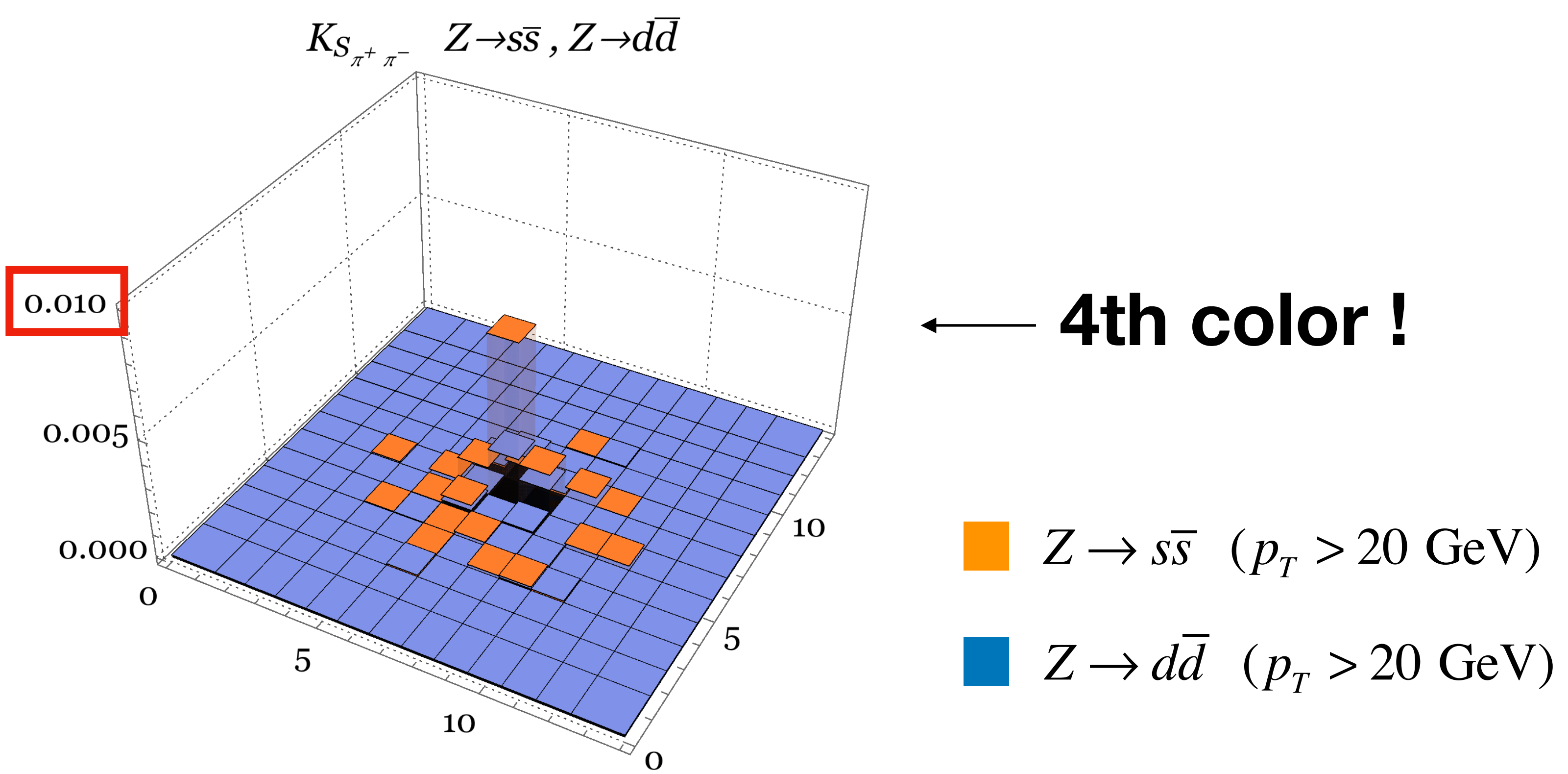


Average Images

We add **the 4th color of reconstructable KS pT**.

The intensity is normalized by the sum of the track pT , ECAL and HN in the whole image.

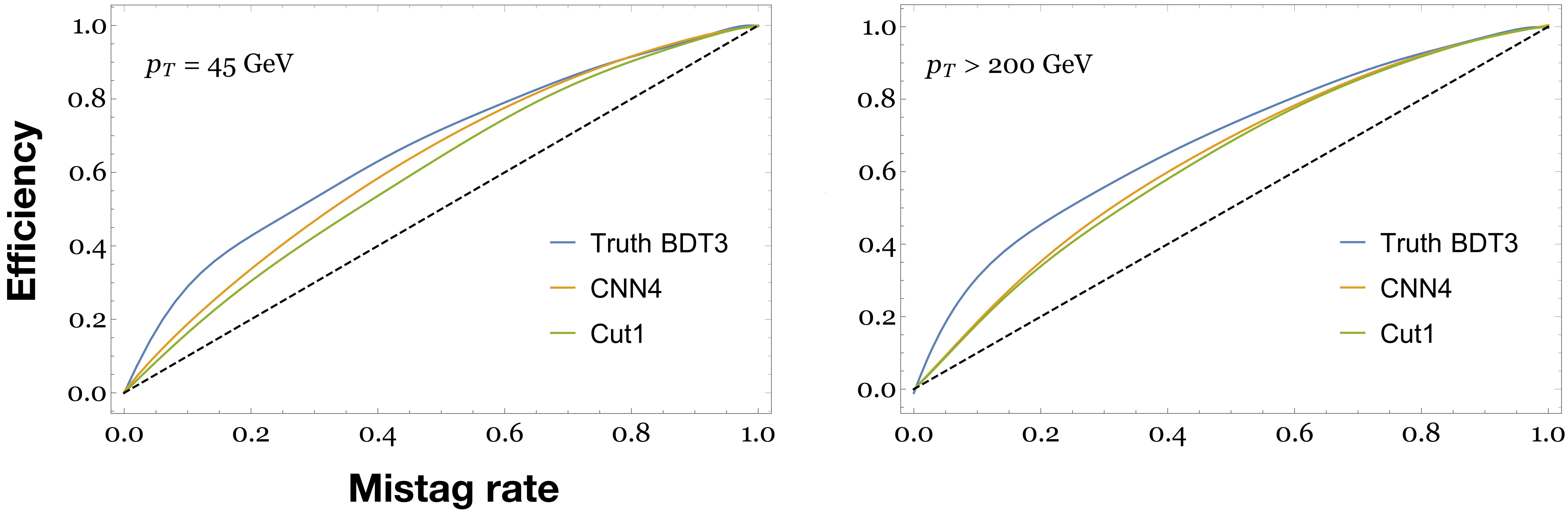
Strange jets contain more energetic K-shorts than down jets.



★ The intensity is much small compared to the other colors because the number of images including reconstructable KS is less than 8% (5%) of the total number of images for strange (down) jets.

Results

ROC curves :



The performance is worse than other classification problems. (quark vs. gluon, …)

Can we use such a weak classifier ??

Application

CKM mixings

The CKM matrix elements are fundamental parameters of the SM and their precise determination is important.

However… **The values for $|V_{cs}|$ and $|V_{cd}|$ are not measured very well.**

Because the charm quark mass is too heavy to be considered light but not heavy enough to treat in the heavy quark limit.

If strange/down jet classification is possible…

W boson decay W → cs, cd give the most direct measurement.

Measure the ratio of strange to down jets : $\frac{|V_{cs}|^2}{|V_{cd}|^2}$

In principle, any amount of discrimination power will make the measurement possible with enough data.

Summary

✓ Strange tagging is the last missing piece of quark/gluon tagging.

✓ Neutral Kaons can be used for strange tagging.

✓ We create jet images with colors (**Tracker**, **Hadronic Neutral**, **ECAL**, **Ks pT**).
(= HCAL - Tracker)

✓ Average images of strange jets can be distinguished from down images.

✓ Convolutional Neural Network outperforms cut-based tagger.

✓ Strange jet tagger may be important for measuring CKM mixings.

Thank you.

Backup Material

Applications of Strange Tagging

- **Top quark reconstruction**

✓ All-hadronic channel

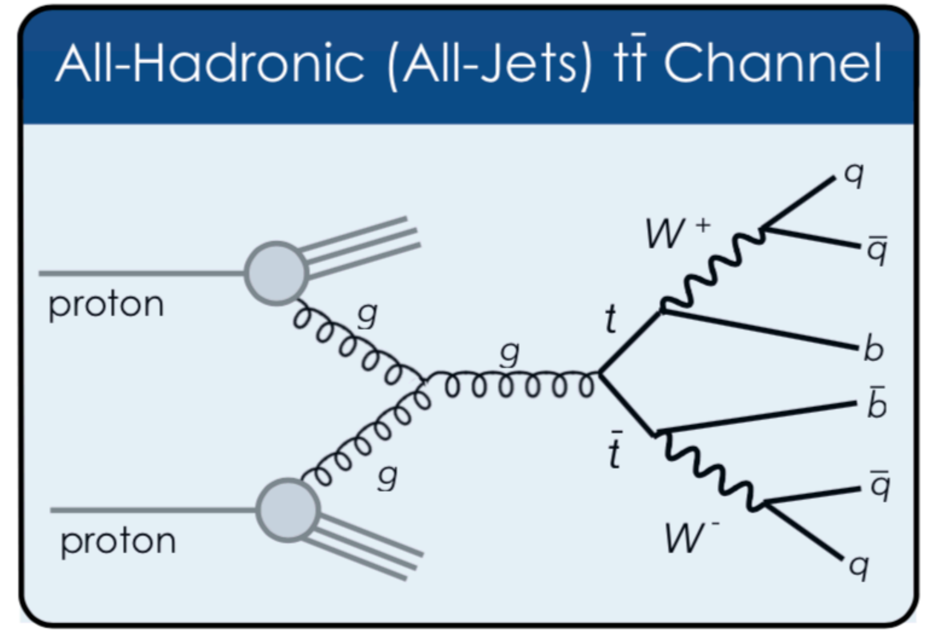
🙂 Full event reconstruction is possible.

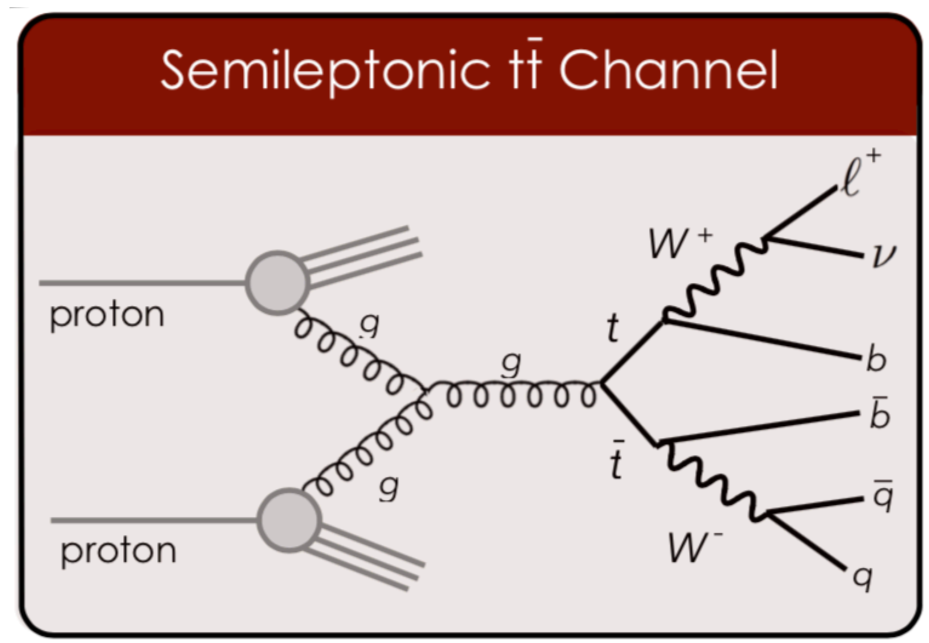
😱 Jet combinatorics and large multi-jet background are problematic.

✓ Semileptonic channel

😉 Leptonic top identifies event and hadronic top can be reconstructed.

😰 Jet combinatorics and multi-jet background are still issues.





Which jets are W → cs, us, cd, ud decay products?

T. McCarthy, talk slide

Identification of strange jet may give some help.

Applications of Strange Tagging

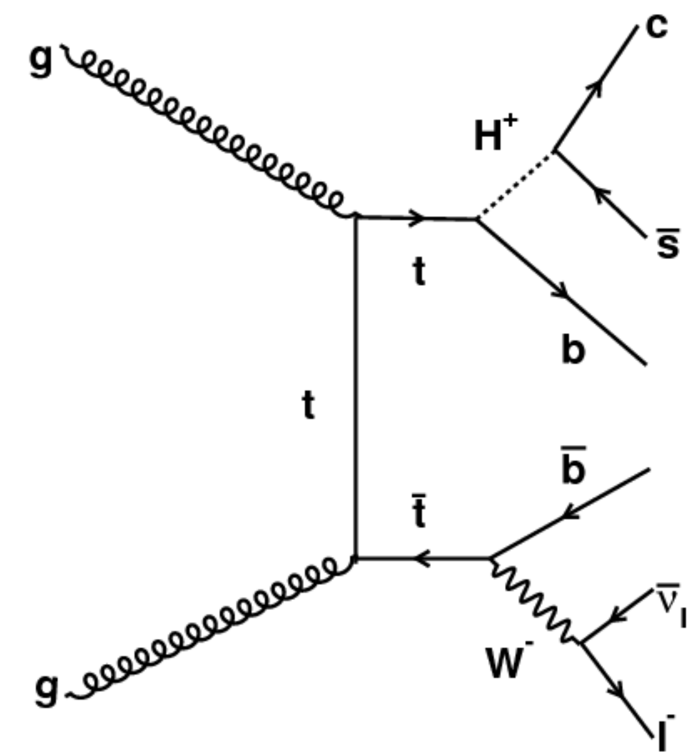
- **Light charged Higgs search**

Production : $t\bar{t} \to W^{\pm} b H^{\mp} \bar{b}$

Decay : $H^{+} \to c\bar{s}$

😰 The same issue as top quark reconstruction is applied.

😱 We do not know the charged Higgs mass!



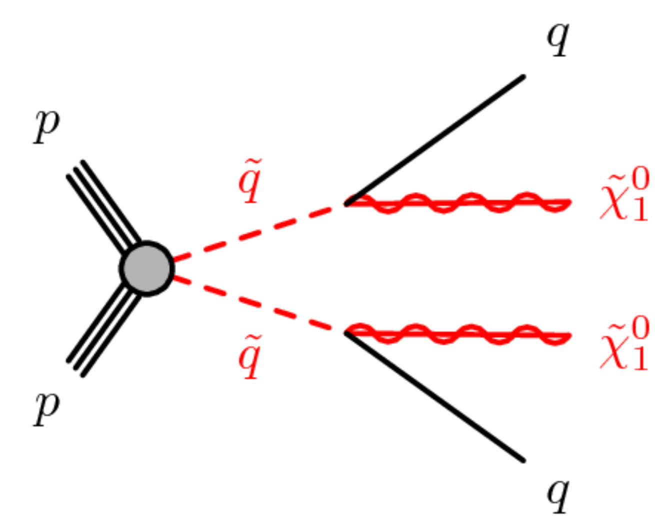
CMS

- **Squark search**

Identification of strange jet can …

✓ reduce the background $Z(\to \nu\nu) +$ jets

✓ identify squark flavor after the discovery



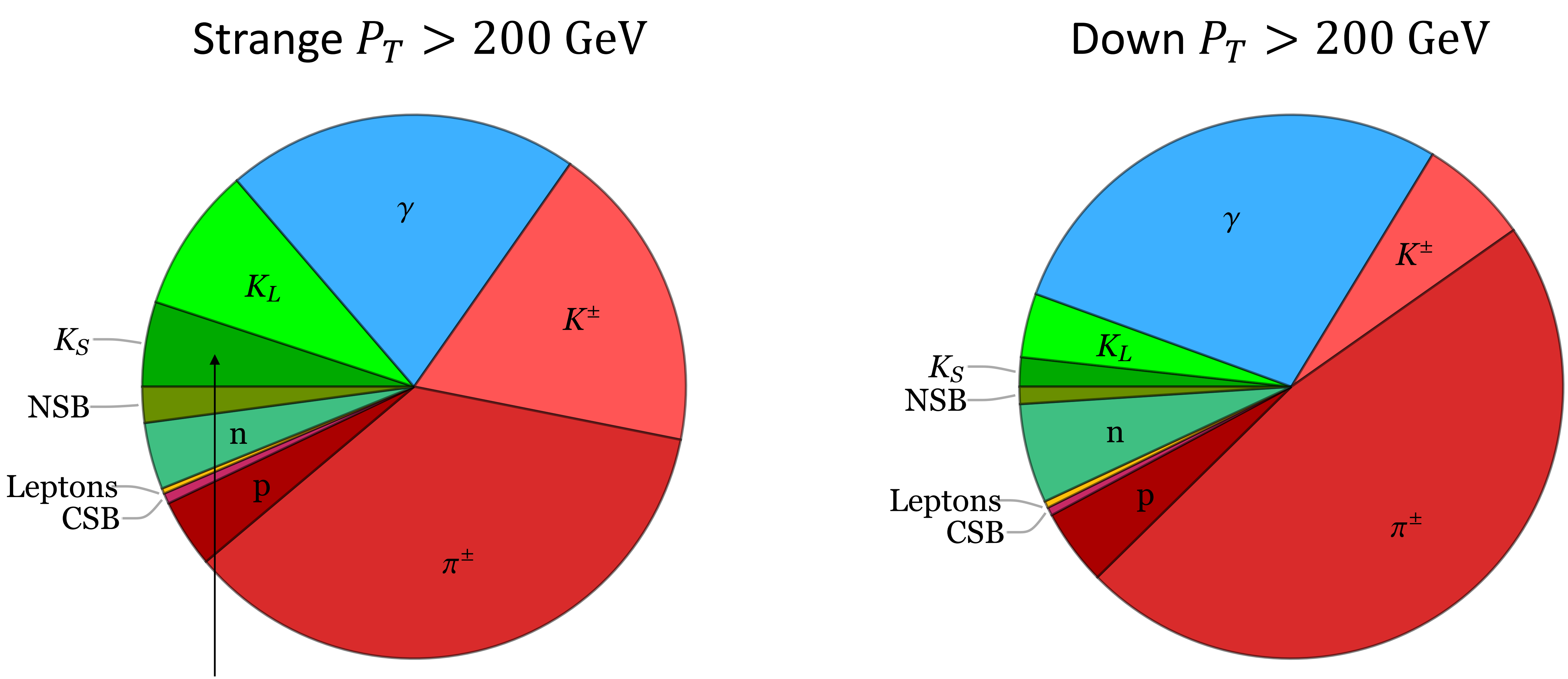
CMS

Strange tagging may be important !

Ingredients of strange/down jets

Strange jets contain more energetic Kaons than down jets.

The pT fraction of a detector-stable particle averaged over jet samples :

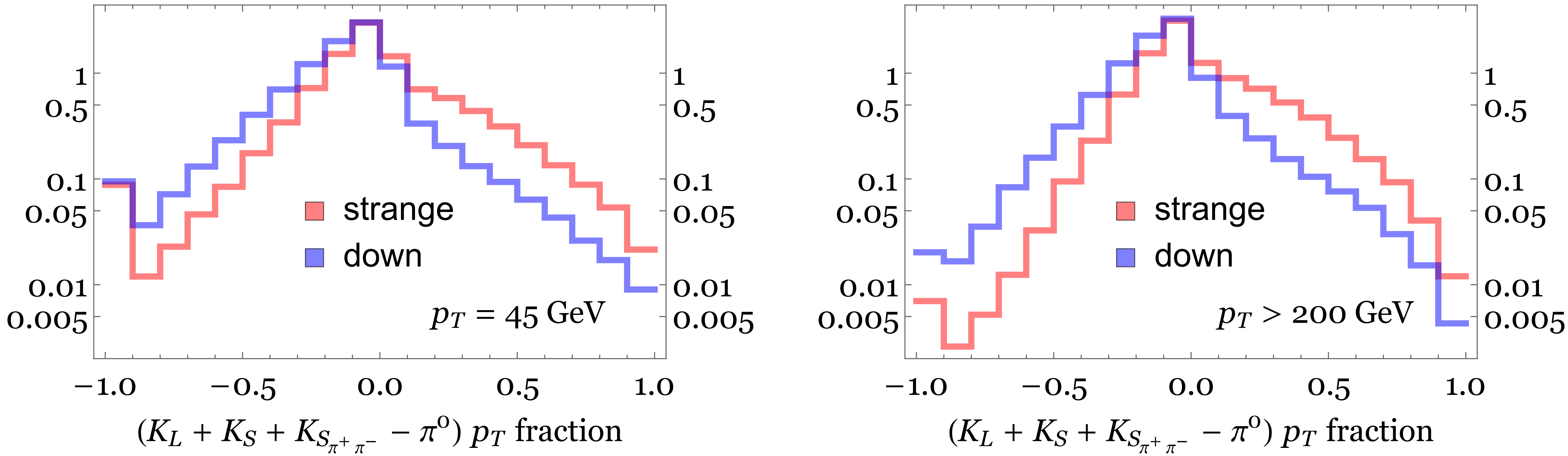


More K-shorts due to boost factor

NSB: neutral strange baryons, CSB: charged strange baryons

Truth-level classifier

Classification problem : **Strange jet** vs **Down jet**



Use **Boosted Decision Tree (BDT)** for classification.

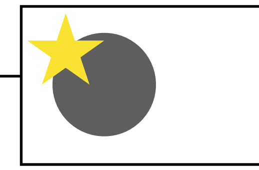
Inputs have 3 dimensions: K_L , K_S , π^0 p_T

Approximately set the maximal performance we can achieve.

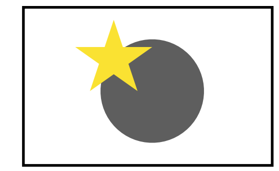
Jet Images

Create jet images with colors (Tracker, HN = HCAL - Tracker, ECAL).

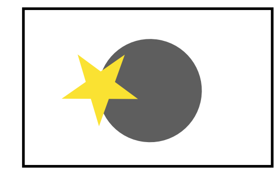
Image pre-processing



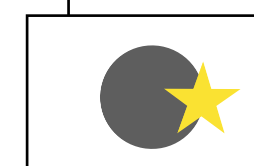
1. Shift an image so that the centroid is at the origin



2. Rotate the image so that the major principal axis is vertical



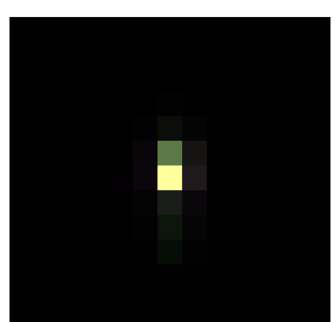
3. Flip the image so that the maximum intensity is in the upper right region



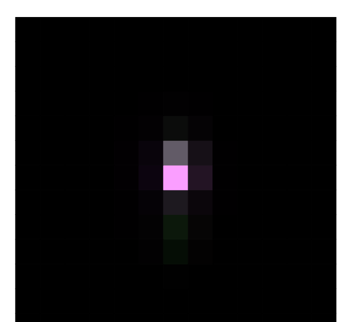
4. Normalize the image to unit total intensity : $\sum_{jet} (\hat{p}_T^{track} + \hat{E}_{had} + \hat{E}_{em}) = 1$

5. Pixelate the image : $\Delta\eta = \Delta\phi = 1.2$ 13 x 13 pixels

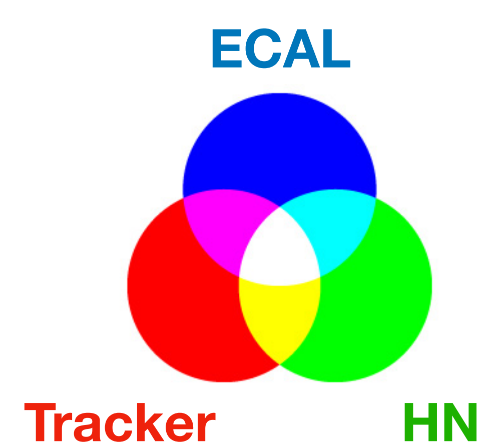
Average images :



$Z \to s\bar{s} \quad (p_T > 20 \text{ GeV})$

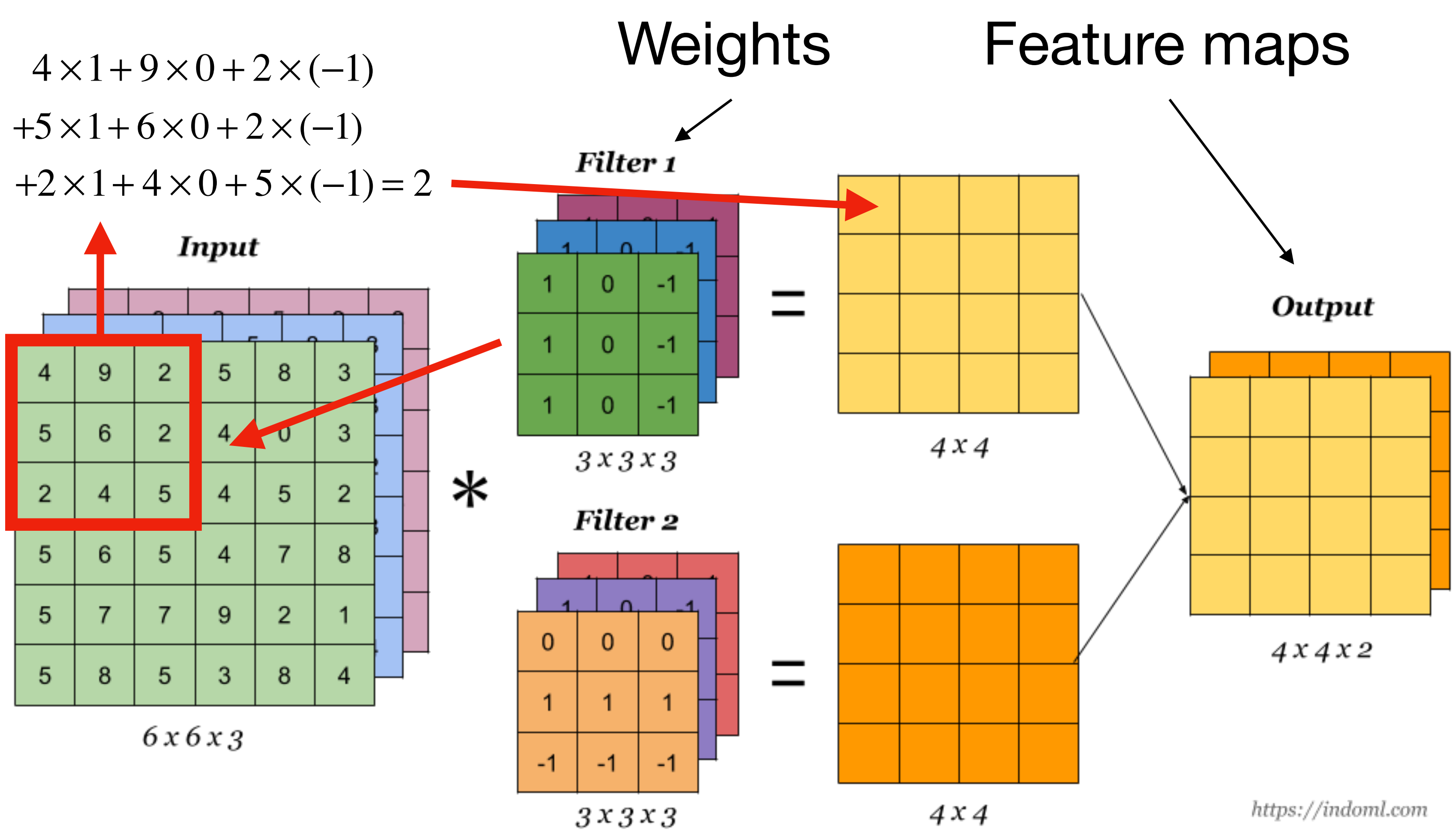


$Z \to d\bar{d} \quad (p_T > 20 \text{ GeV})$



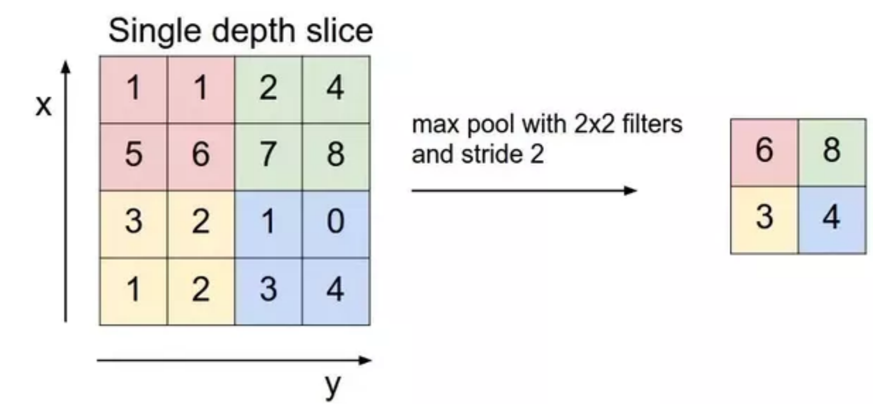
Network Architecture

Convolutional layer

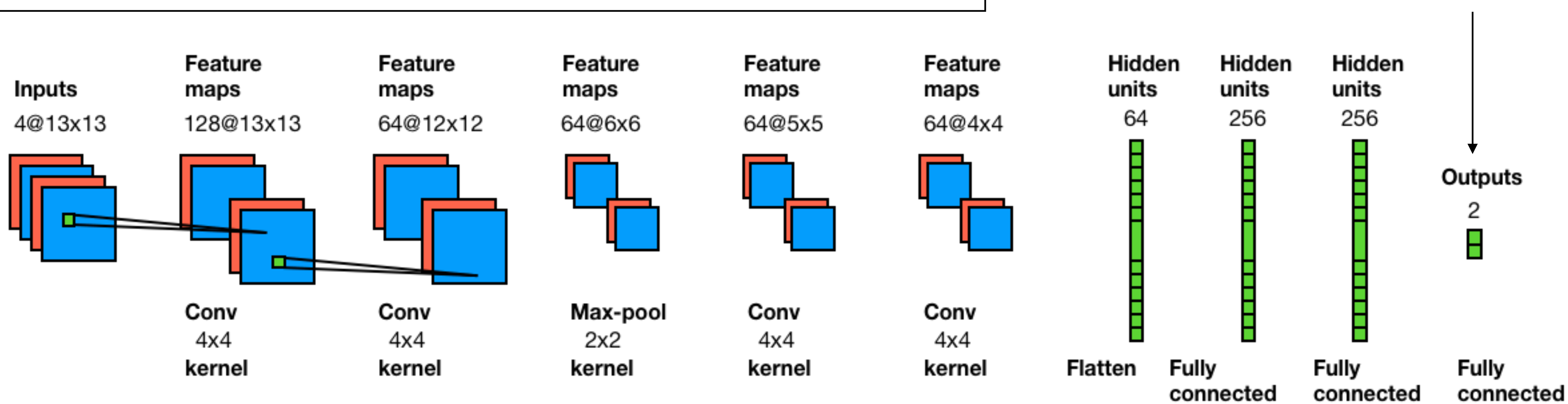


Max pooling

Reduce the image size



Probabilities of signal and background



Training

The goal of training is to minimize loss function :

Network prediction

$$L = \sum_i f(p(\theta, x_i), y_i)$$

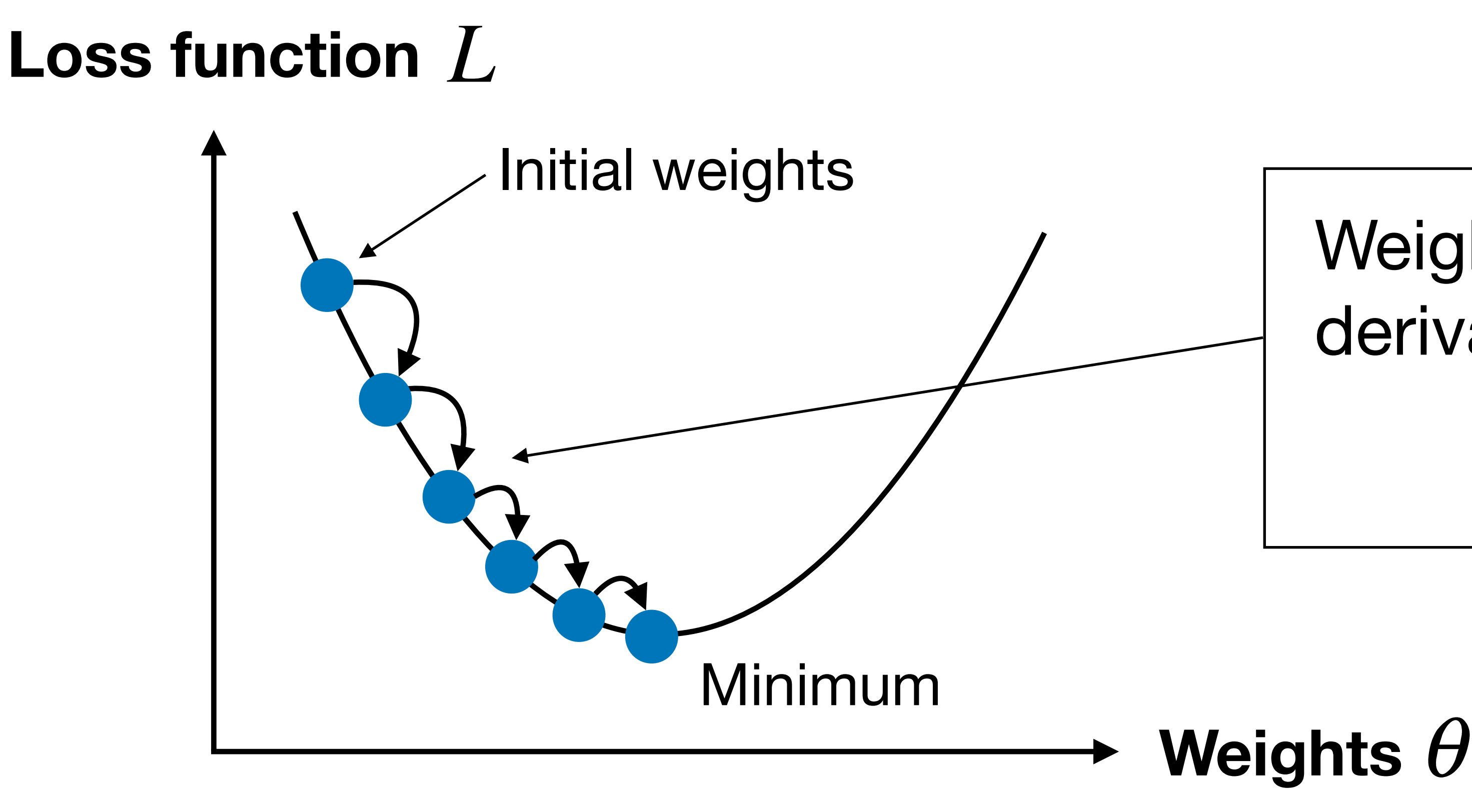
$p(\theta, x_i)$: Signal probability

θ : Weights

x_i : Input

y_i : Truth label of example i $\left(\begin{array}{l} y_i = 0 \text{ : Signal} \\ y_i = 1 \text{ : Background} \end{array} \right)$

We use cross entropy : $f(p, y) = -(y \log(1-p) + (1-y)\log p)$



Weights are updated according to derivative of loss function :

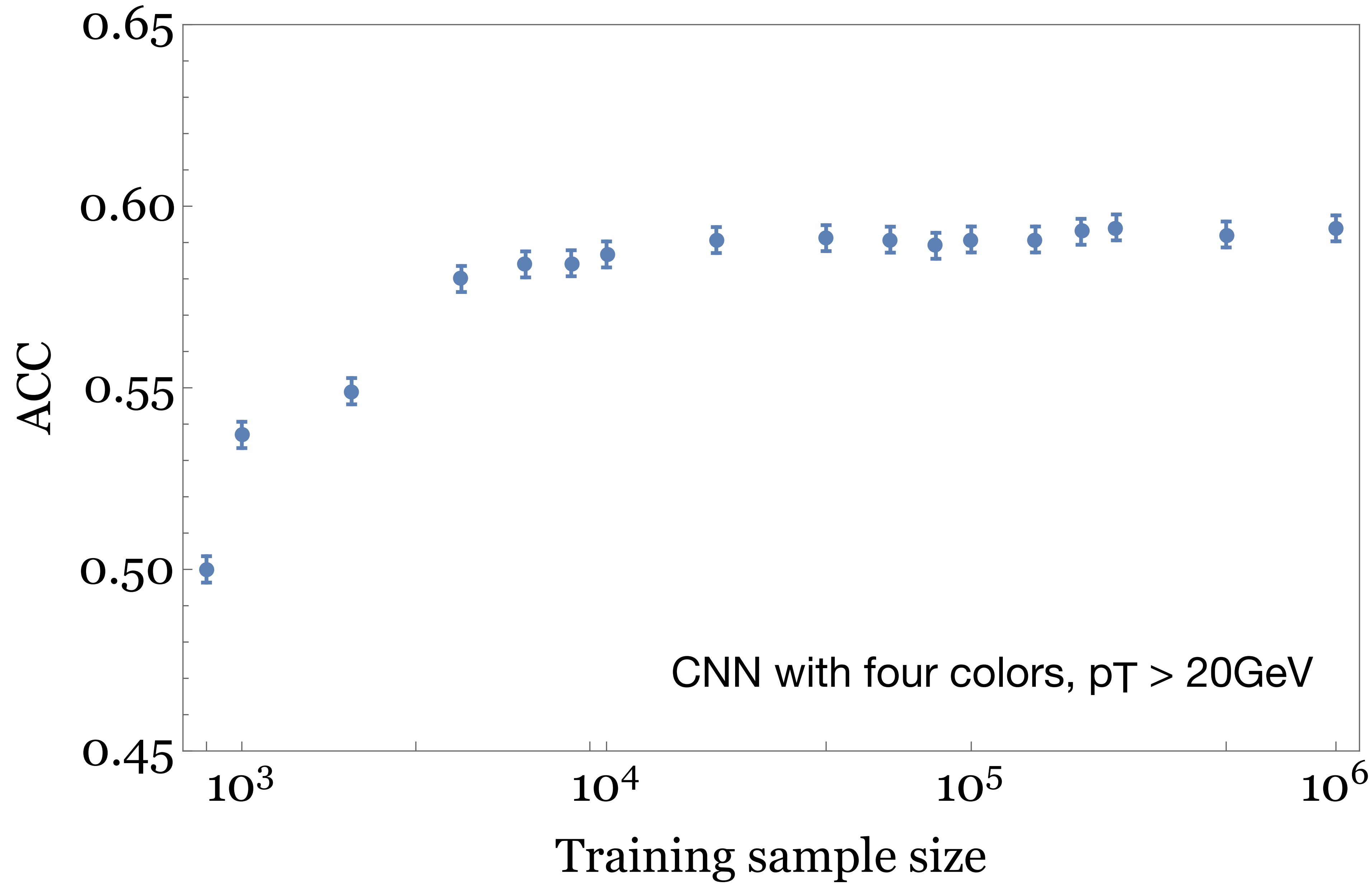
$$\Delta\theta = -\eta \nabla L$$

Learning rate

Training Curve

How the performance of the CNN is affected by the number of training samples.

The best accuracy



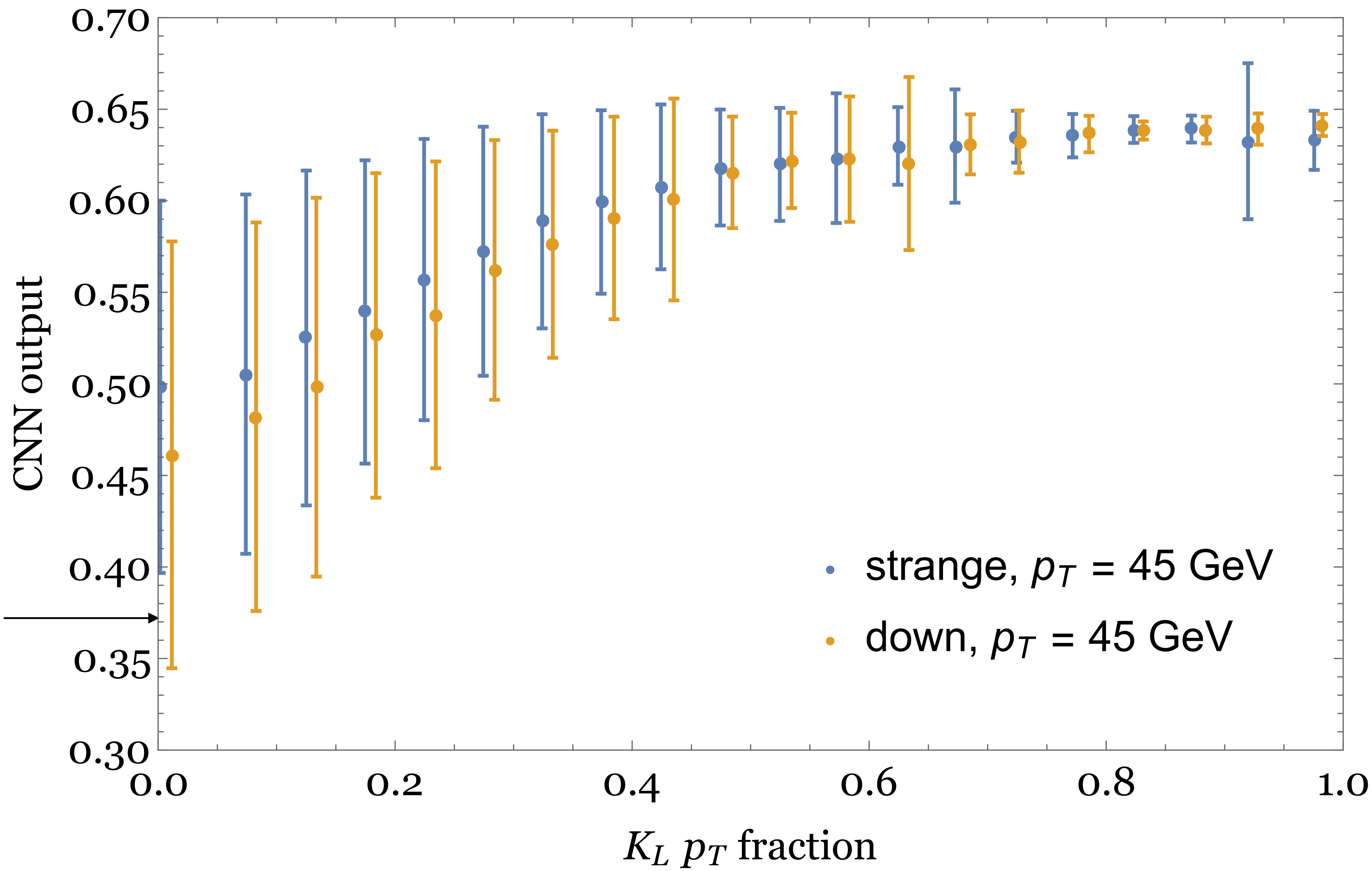
The performance saturates immediately for more than 10000 training samples.

Neural Network Output

The correlation between the K_L pT fraction of input images and CNN (with 3 colors of tracker, HN and ECAL) outputs.

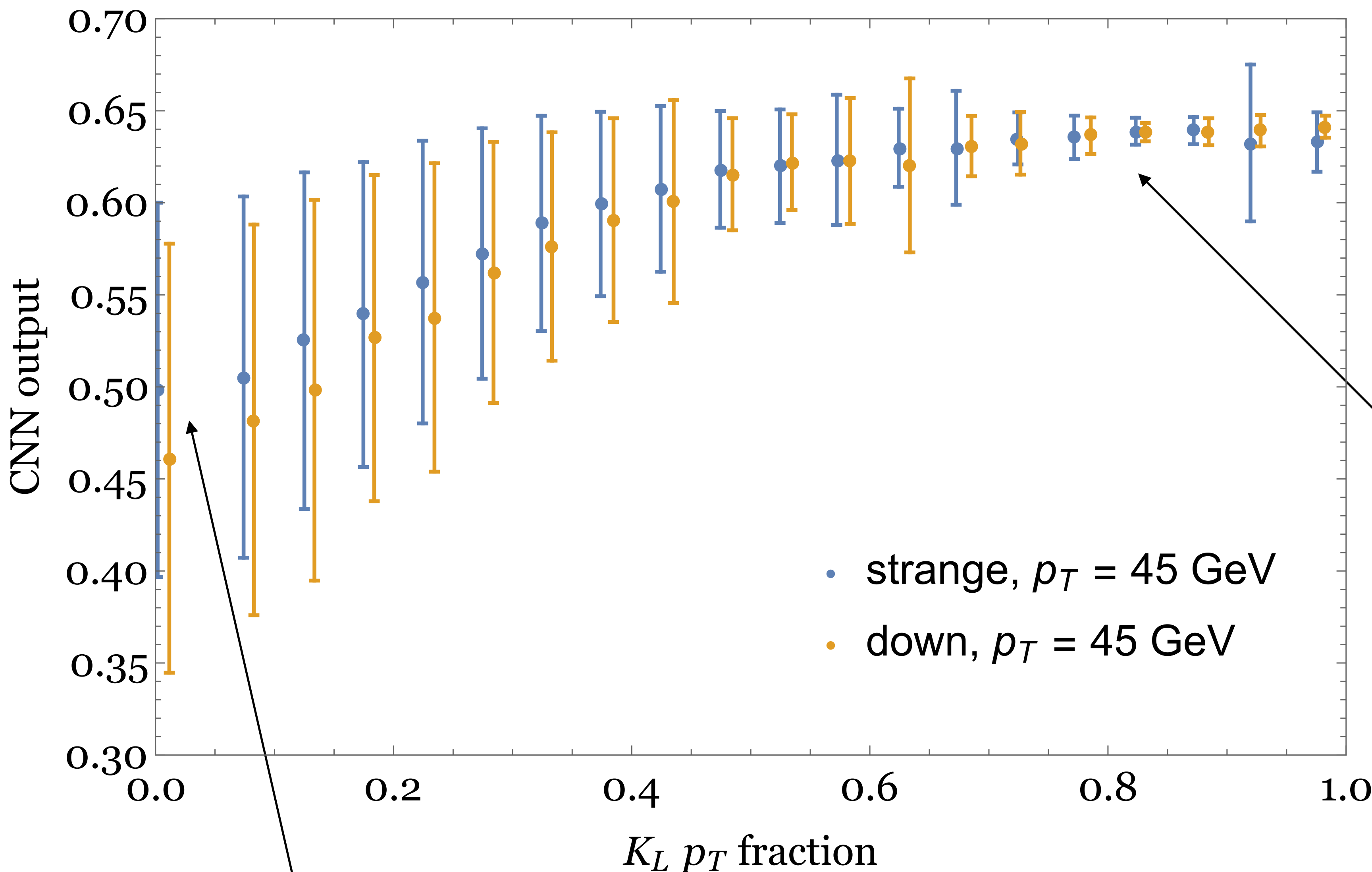
Take the average in each bin.

Standard deviation



Neural Network Output

A clear correlation: **Signal probability increases as K-long pT ratio increases**



Standard deviation decreases.

The signal probability of strange jets is larger than that of down jets due to the KS component.

Various taggers

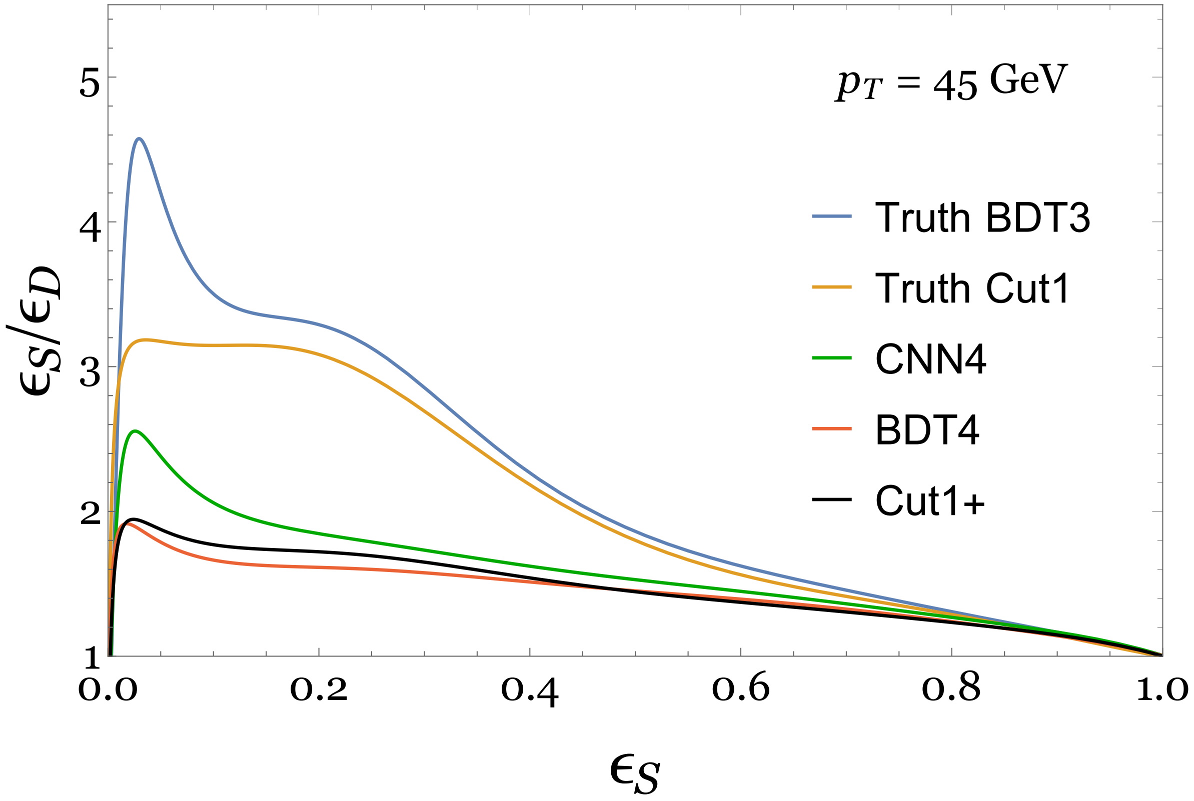
Algorithm	Input Source	Input Variable(s)	
Truth Cut1	Pythia 8	$-\pi^0 + K_L + K_S + K_{S_{\pi^+\pi^-}}$	
Truth BDT3	Pythia 8	$\pi^0\,,\ K_L\,,\ K_S + K_{S_{\pi^+\pi^-}}$	
Cut1	Delphes	$H_N - E$	
Cut1+	Delphes	$H_N - E + K_{S_{\pi^+\pi^-}}$	
BDT3	Delphes	$H_N\,,\ E\,,\ T$	
BDT4	Delphes	$H_N\,,\ E\,,\ T\,,\ K_{S_{\pi^+\pi^-}}$	
CNN3	Delphes	$H_N\,,\ E\,,\ T$	13×13 Jet Image
CNN4	Delphes	$H_N\,,\ E\,,\ T\,,\ K_{S_{\pi^+\pi^-}}$	13×13 Jet Image

Results

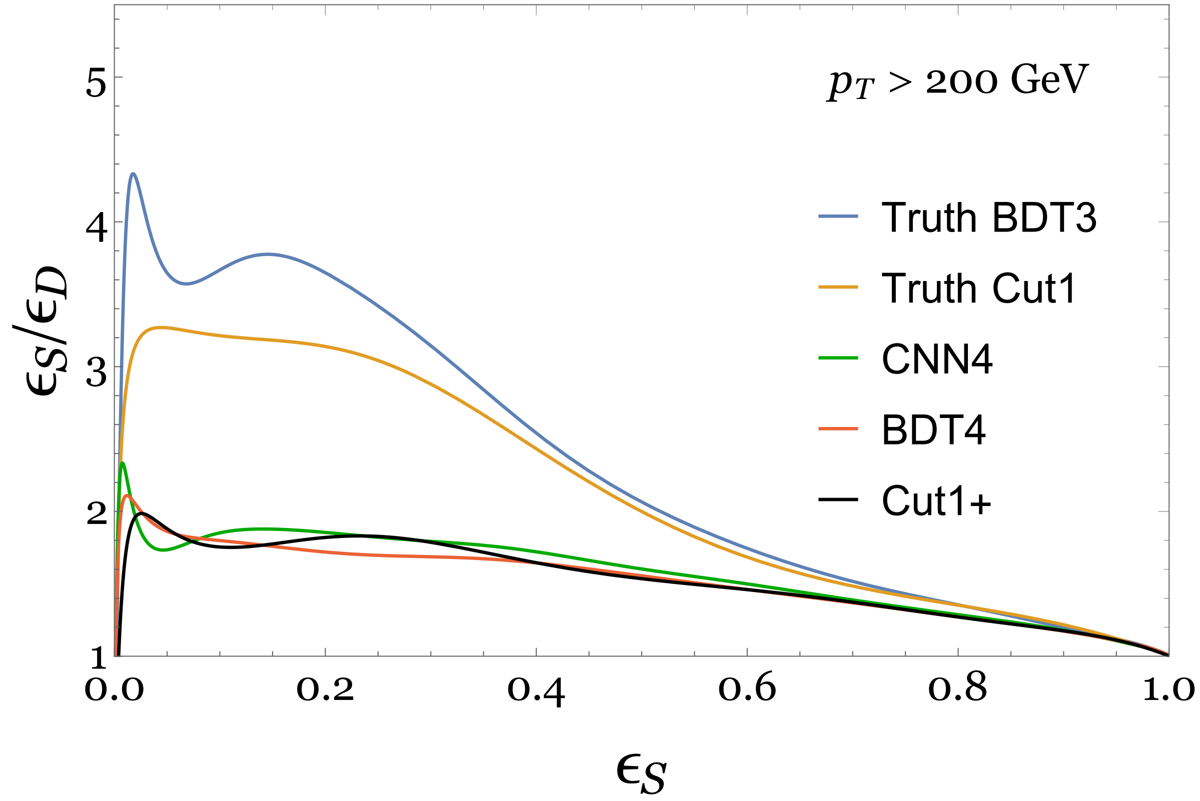
	AUC	ACC	R10	R50
Truth Cut1	0.65 (0.68)	0.61 (0.62)	31.9 (32.3)	3.6 (3.9)
Truth BDT3	0.66 (0.68)	0.62 (0.63)	36.4 (37.0)	3.7 (4.2)
Cut1	0.60 (0.63)	0.57 (0.59)	16.8 (17.9)	2.7 (3.0)
Cut1+	0.62 (0.63)	0.58 (0.60)	17.8 (17.8)	2.9 (3.1)
BDT3	0.61 (0.63)	0.58 (0.60)	16.0 (18.0)	2.8 (3.1)
BDT4	0.61 (0.63)	0.59 (0.60)	17.0 (18.0)	2.9 (3.1)
CNN3	0.62 (0.63)	0.59 (0.60)	17.7 (18.2)	3.0 (3.2)
CNN4	0.63 (0.64)	0.59 (0.60)	20.9 (18.3)	3.1 (3.2)

$\mathrm{R10} = 1/\epsilon_D$ for $\epsilon_S = 0.1$ $\mathrm{R50} = 1/\epsilon_D$ for $\epsilon_S = 0.5$

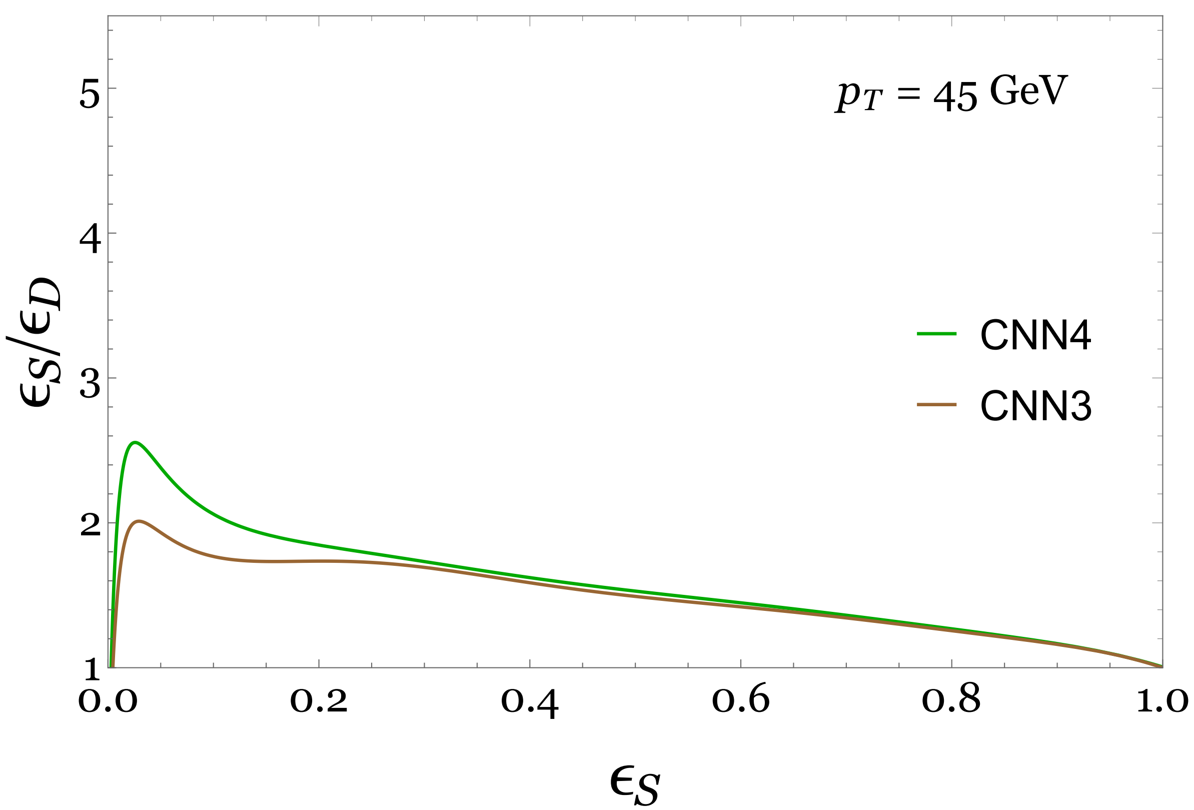
Results



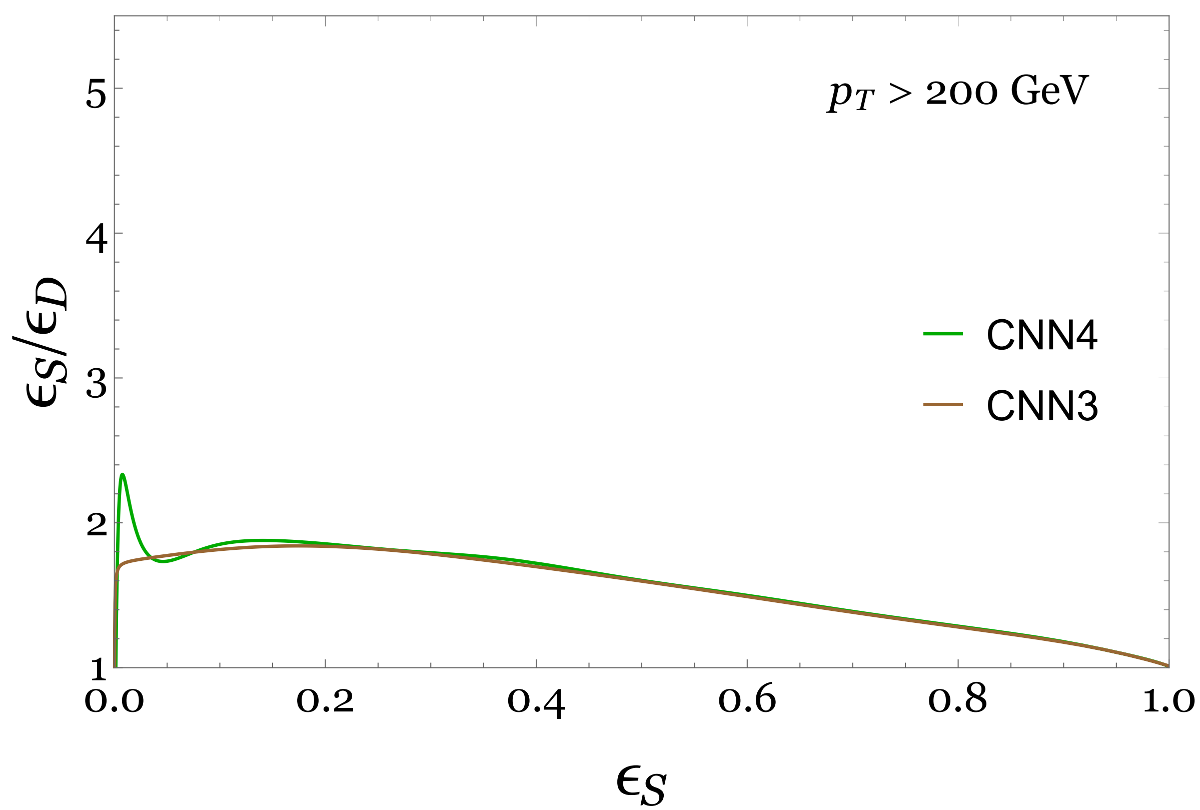
$p_T = 45$ GeV
Truth BDT3
Truth Cut1
CNN4
BDT4
Cut1+
ϵ_S/ϵ_D
ϵ_S



$p_T > 200$ GeV
Truth BDT3
Truth Cut1
CNN4
BDT4
Cut1+
ϵ_S/ϵ_D
ϵ_S



$p_T = 45$ GeV
CNN4
CNN3
ϵ_S/ϵ_D
ϵ_S



$p_T > 200$ GeV
CNN4
CNN3
ϵ_S/ϵ_D
ϵ_S

Significance Improvement

Consider a binary classifier with efficiency $\boldsymbol{\varepsilon_S}$ and mistag rate $\boldsymbol{\varepsilon_B}$.

Before a cut on the classifier…

Statistical significance of the signal : $S/\sqrt{B}$ (S « B)

After a cut on the classifier…

If we throw away the events that fail the cut…

Statistical significance of the signal : $$q = \boxed{\frac{\epsilon_S}{\sqrt{\epsilon_B}}} \frac{S}{\sqrt{B}}$$

Significance improvement factor

If a weak classifier gives a significance improvement factor smaller than 1, the classifier reduces our significance ??

Significance Improvement

If we view the classifier as defining two categories (pass vs. fail)…

Combined significance of two categories :

$$q = \sqrt{\left(\frac{\epsilon_S}{\sqrt{\epsilon_B}}\frac{S}{\sqrt{B}}\right)^2 + \left(\frac{(1-\epsilon_S)}{\sqrt{(1-\epsilon_B)}}\frac{S}{\sqrt{B}}\right)^2}$$

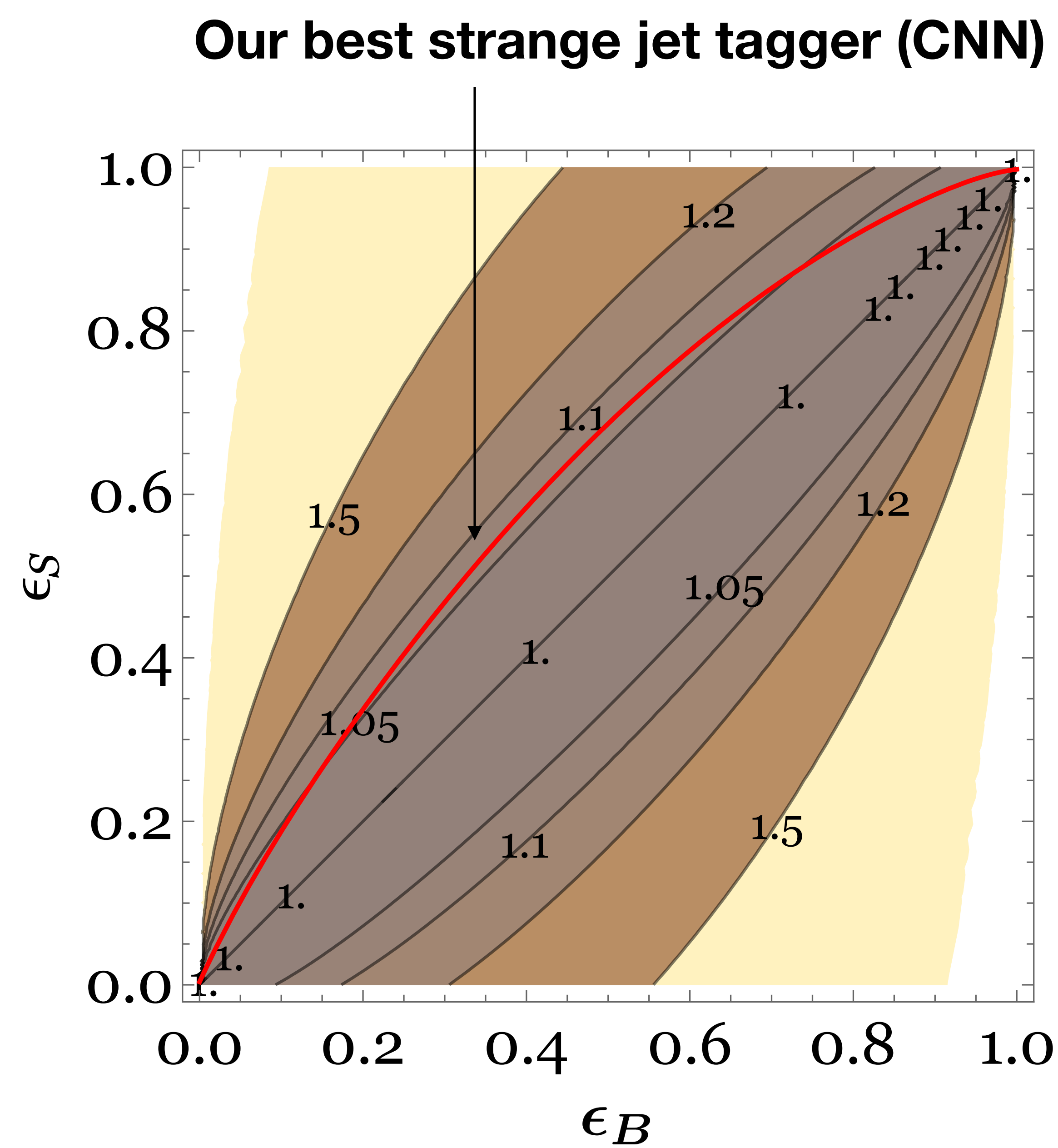
$$= \sqrt{1 + \frac{(\epsilon_S - \epsilon_B)^2}{\epsilon_B(1-\epsilon_B)}}\frac{S}{\sqrt{B}}$$

The significance can only increase.

Our best strange jet tagger (CNN)

Significance improvement is only 5-10%.

The importance of our strange tagger is limited…



Applications of Strange Tagging

• CKM mixings

The CKM matrix elements are fundamental parameters of the SM and their precise determination is important.

However… **The values for $|V_{cs}|$ and $|V_{cd}|$ are not measured very well.**

Because the charm quark mass is too heavy to be considered light but not heavy enough to treat in the heavy quark limit.

One process to probe $|V_{cs}|$ is through **semileptonic decays $D \to K e \nu$**.

Our best effort is to use lattice QCD :

$$V_{cs} = 0.98 \pm 0.01_{exp} \pm 0.10_{th}$$

The experimental error is small but the theoretical error is huge !

W boson decay $W \to cs$ gives the most direct measurement of $|V_{cs}|$ if strange tagging is possible.

CKM Mixings

A simple estimate

# of data → N

A fraction of strange to down → f_S

# of events passing the cut : $N_{pass}(f_S) = N(f_S\epsilon_S + (1-f_S)\epsilon_B)$

# of events failing the cut : $N_{fail}(f_S) = N(f_S(1-\epsilon_S) + (1-f_S)(1-\epsilon_B))$

$$\chi^2 = \frac{(N_{pass}(f_S) - N_{pass}(\hat{f}_S))^2}{N_{pass}(\hat{f}_S)} + \frac{(N_{fail}(f_S) - N_{fail}(\hat{f}_S))^2}{N_{fail}(\hat{f}_S)}$$

$$= \frac{N(\epsilon_B - \epsilon_S)^2}{f_{eff}(1-f_{eff})}(f_S - \hat{f}_S)^2$$

$$f_{eff} = \hat{f}_S\epsilon_S + (1-\hat{f}_S)\epsilon_B$$

True fraction → $\hat{f}_S$

$$f_S = \hat{f}_S \pm \delta f_S \qquad \delta f_S = \frac{1}{|\epsilon_B - \epsilon_S|}\sqrt{\frac{f_{eff}(1-f_{eff})}{N}}$$

As long as $\varepsilon_B \neq \varepsilon_S$, a sufficiently large N gives an accurate measurement.

CKM Mixings

W boson decay

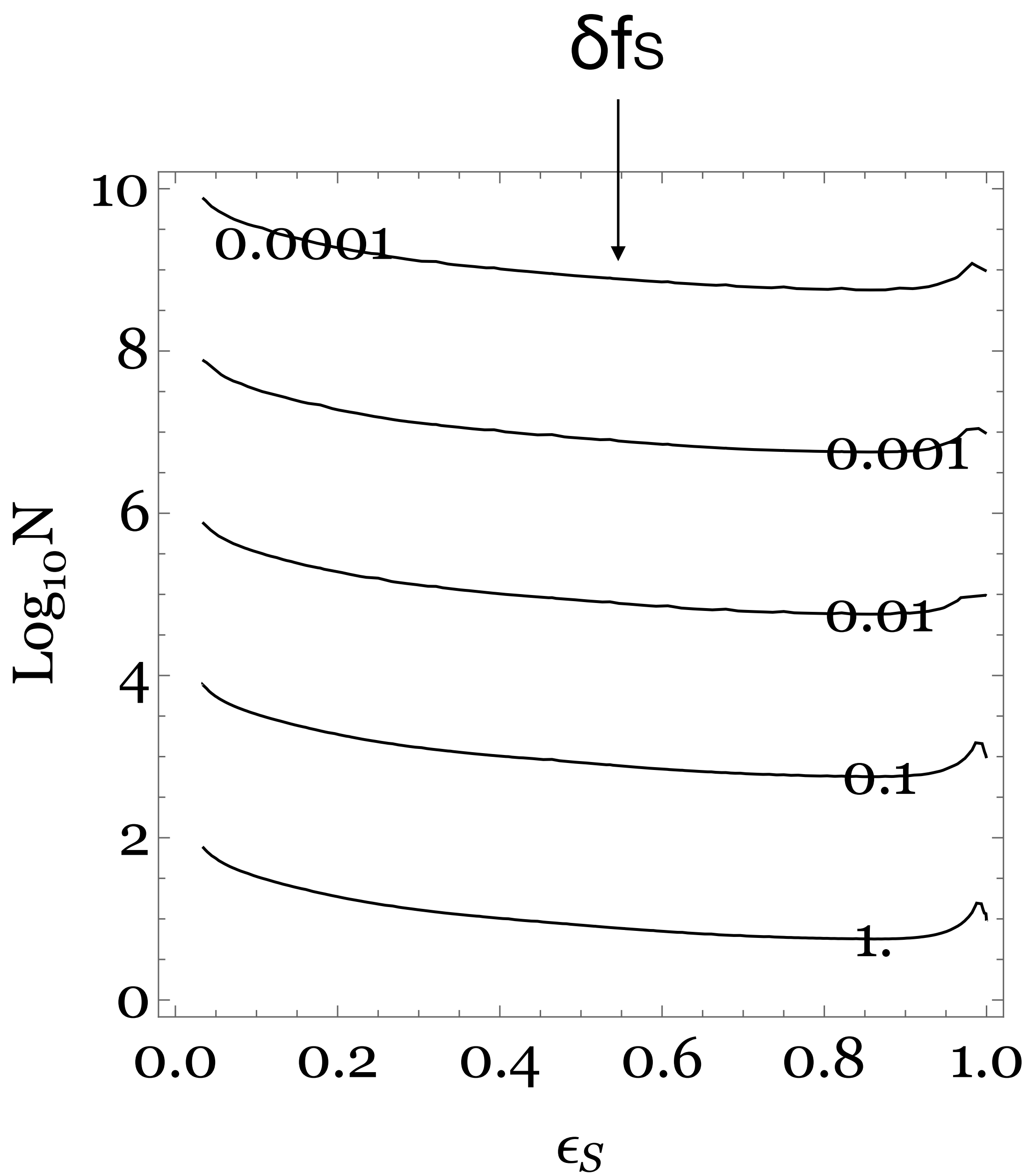
$$\Gamma(W^- \to s\bar{c}) = \Gamma(W^- \to e^-\bar{\nu}) \times 3|V_{cs}|^2$$
$$\Gamma(W^- \to d\bar{c}) = \Gamma(W^- \to e^-\bar{\nu}) \times 3|V_{cd}|^2$$

$$f_S = \hat{f}_S \pm \delta f_S$$

$$\delta f_S = \frac{1}{|\epsilon_B - \epsilon_S|}\sqrt{\frac{f_{eff}(1-f_{eff})}{N}}$$

$$f_{eff} = \hat{f}_S \epsilon_S + (1-\hat{f}_S)\epsilon_B$$

$$\boxed{\hat{f}_s = \frac{\frac{|V_{cs}|^2}{|V_{cd}|^2}}{1+\frac{|V_{cs}|^2}{|V_{cd}|^2}}} \qquad \frac{|V_{cs}|^2}{|V_{cd}|^2} \sim 20$$

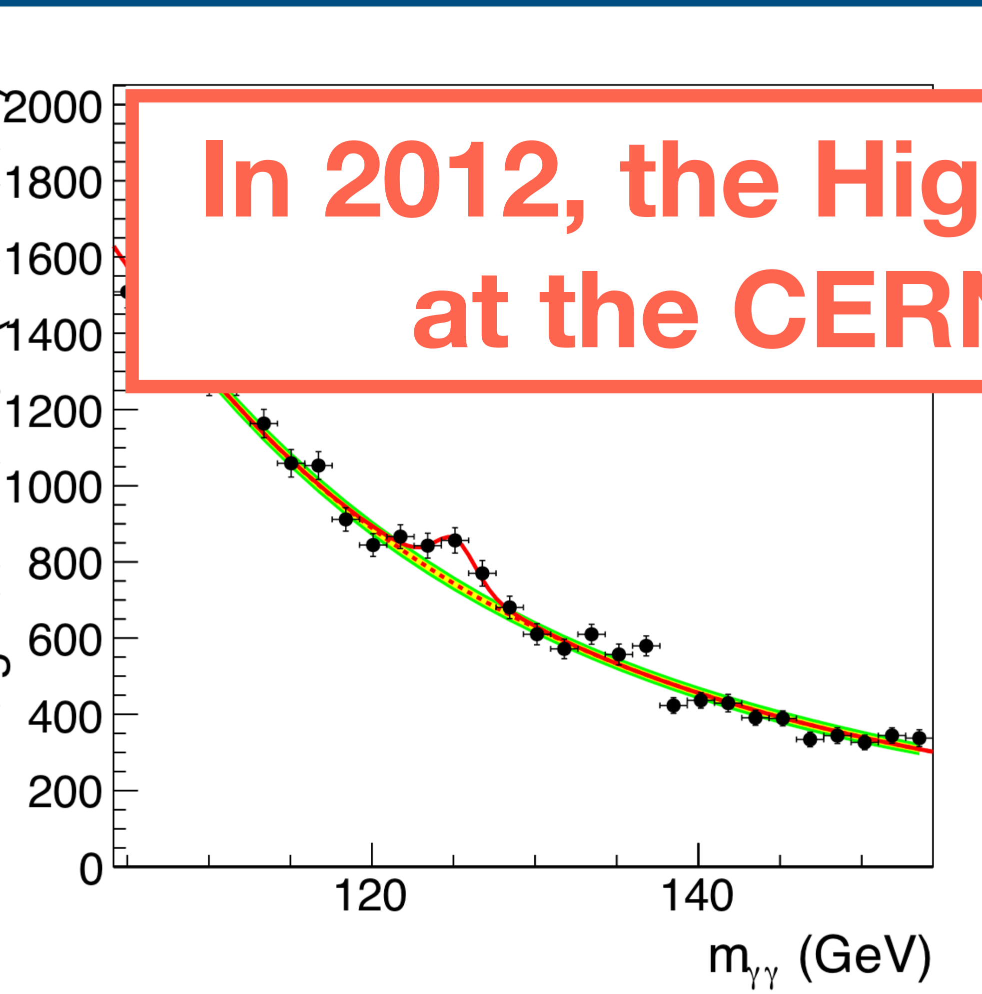


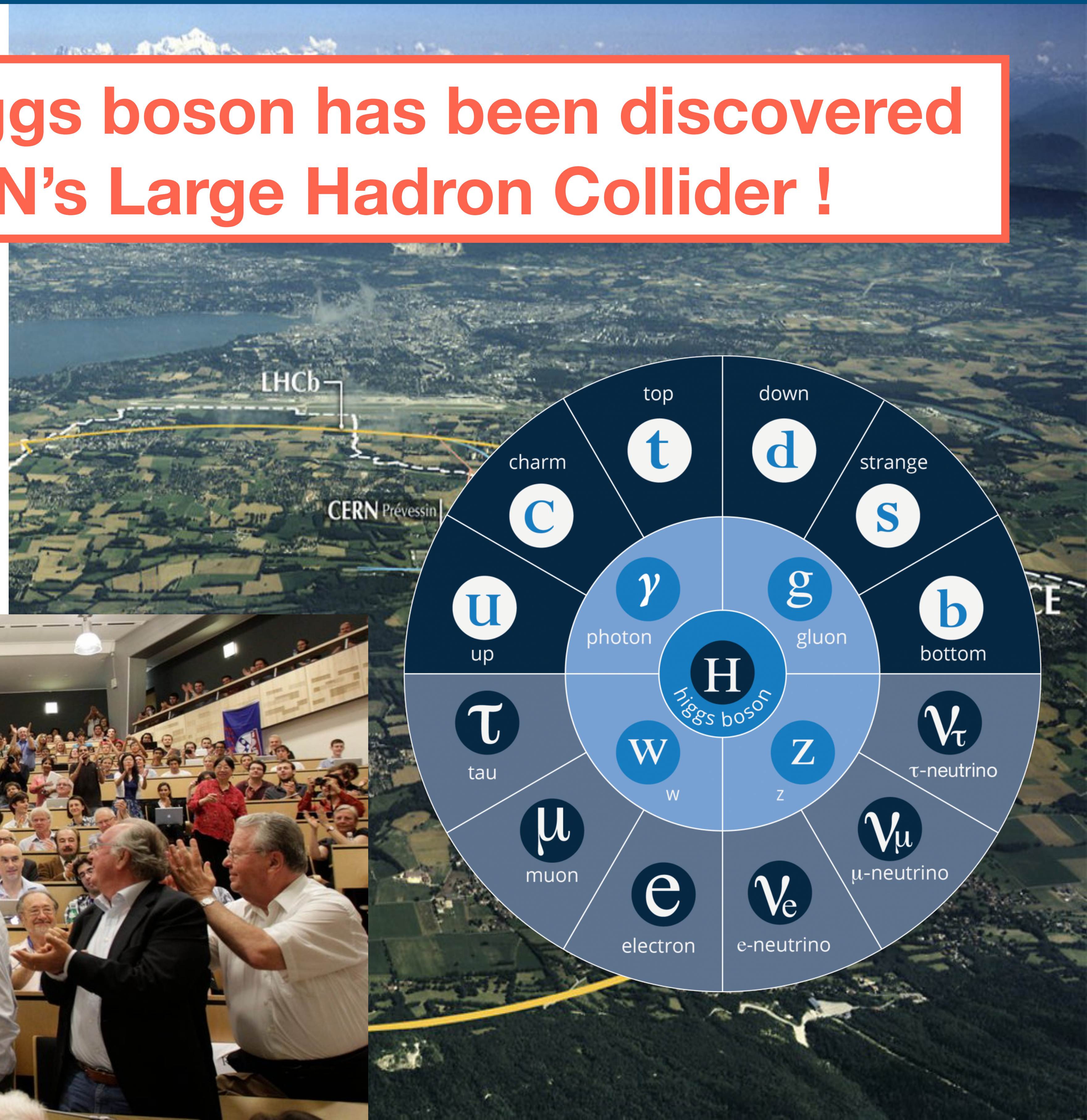
Our best strange jet tagger (CNN)

Since the LHC generates a lot of W bosons, a precise measurement is possible !

The Great Achievement

In 2012, the Higgs boson has been discovered at the CERN's Large Hadron Collider !





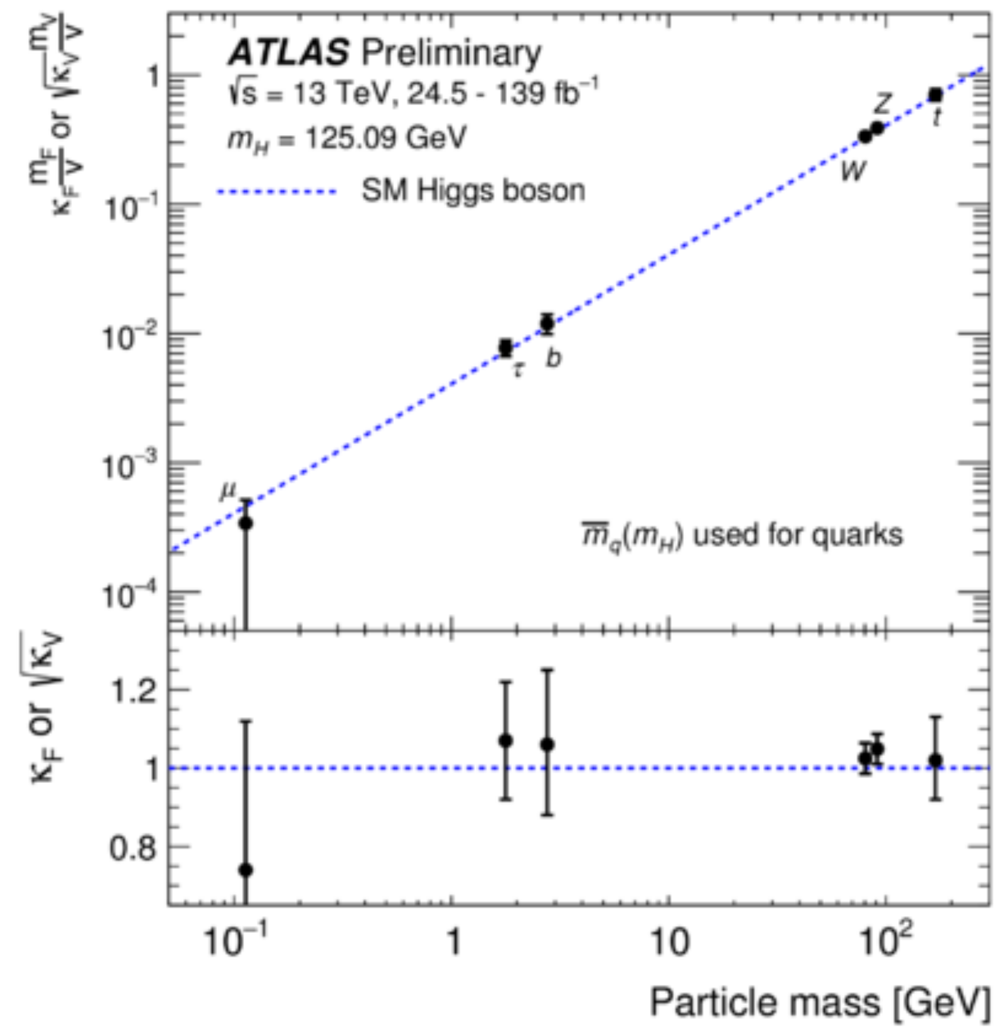
Higgs Precision Era

The SM predictions of the Higgs couplings to heavy gauge bosons and fermions, $2m^2_{W,Z}/v$ and m_f/v, have been confirmed for the W and Z bosons and for the third-generation fermions.

A key aspect of the experimental program of post-LHC colliders includes precision studies of…

- Higgs couplings
- Self-couplings (HH production)
- Total width
- Exotic / Invisible decays

…



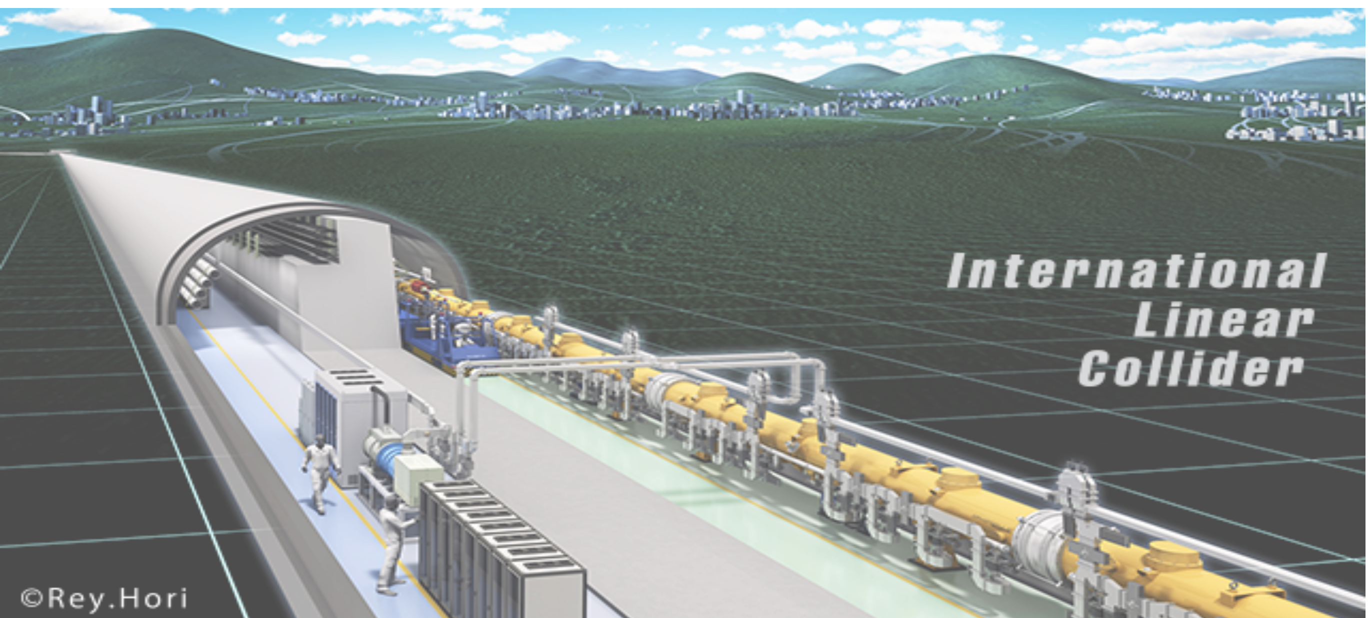
We really need further studies on the newly observed Higgs sector.

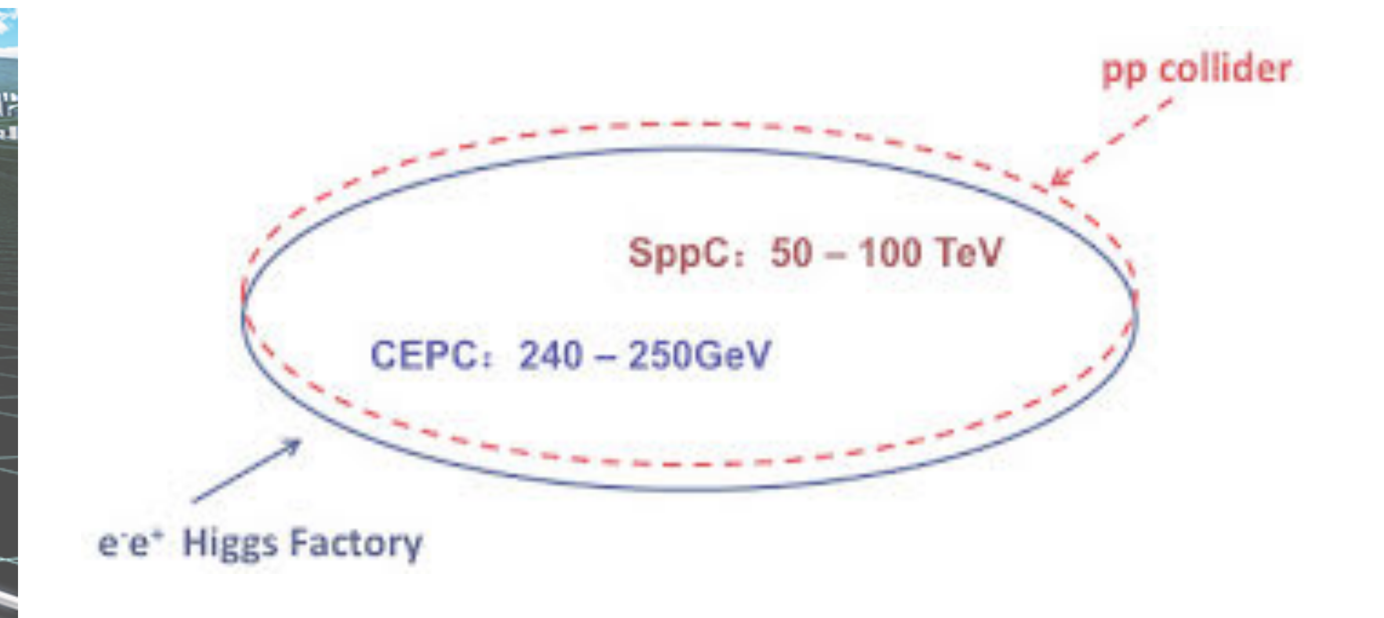
Any small deviations could be a sign of new physics !

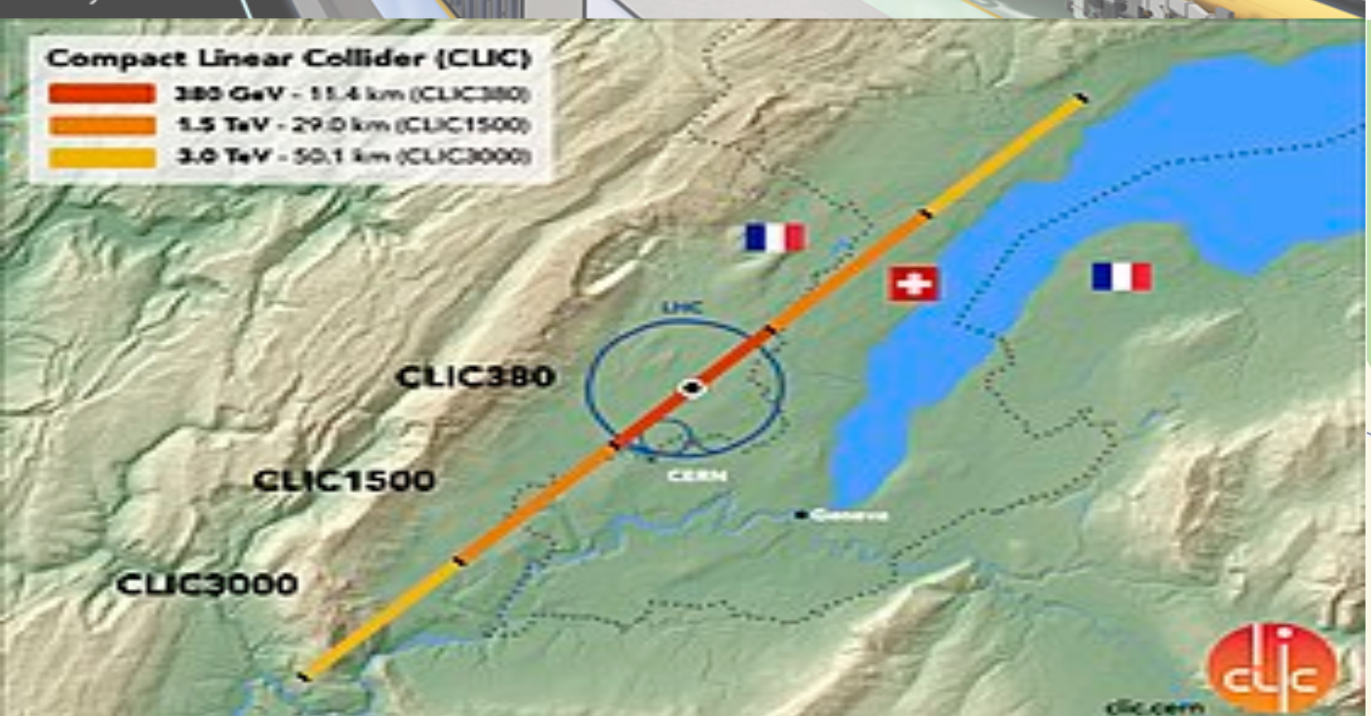
Higgs Precision Era

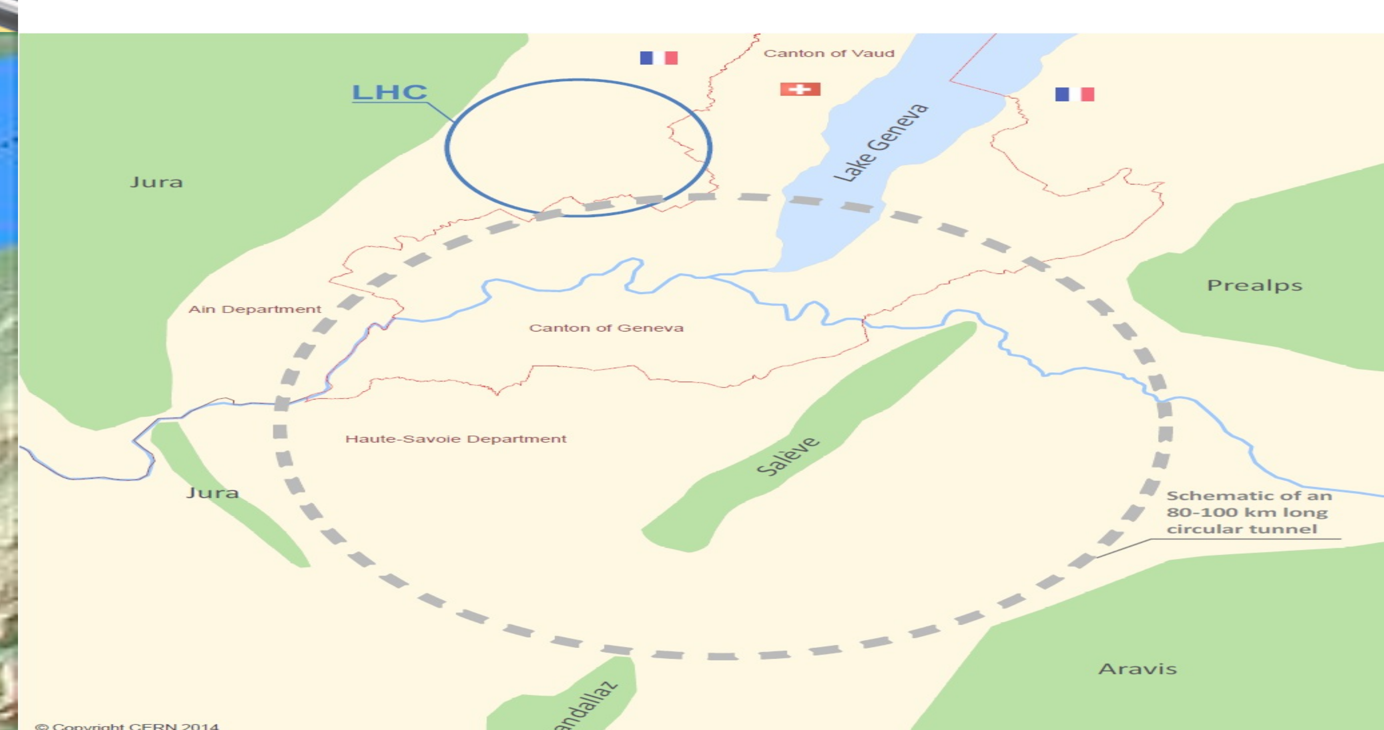
An upgrade of the LHC : **High Luminosity LHC**

Future lepton colliders : **ILC, FCC-ee, CEPC, CLIC**



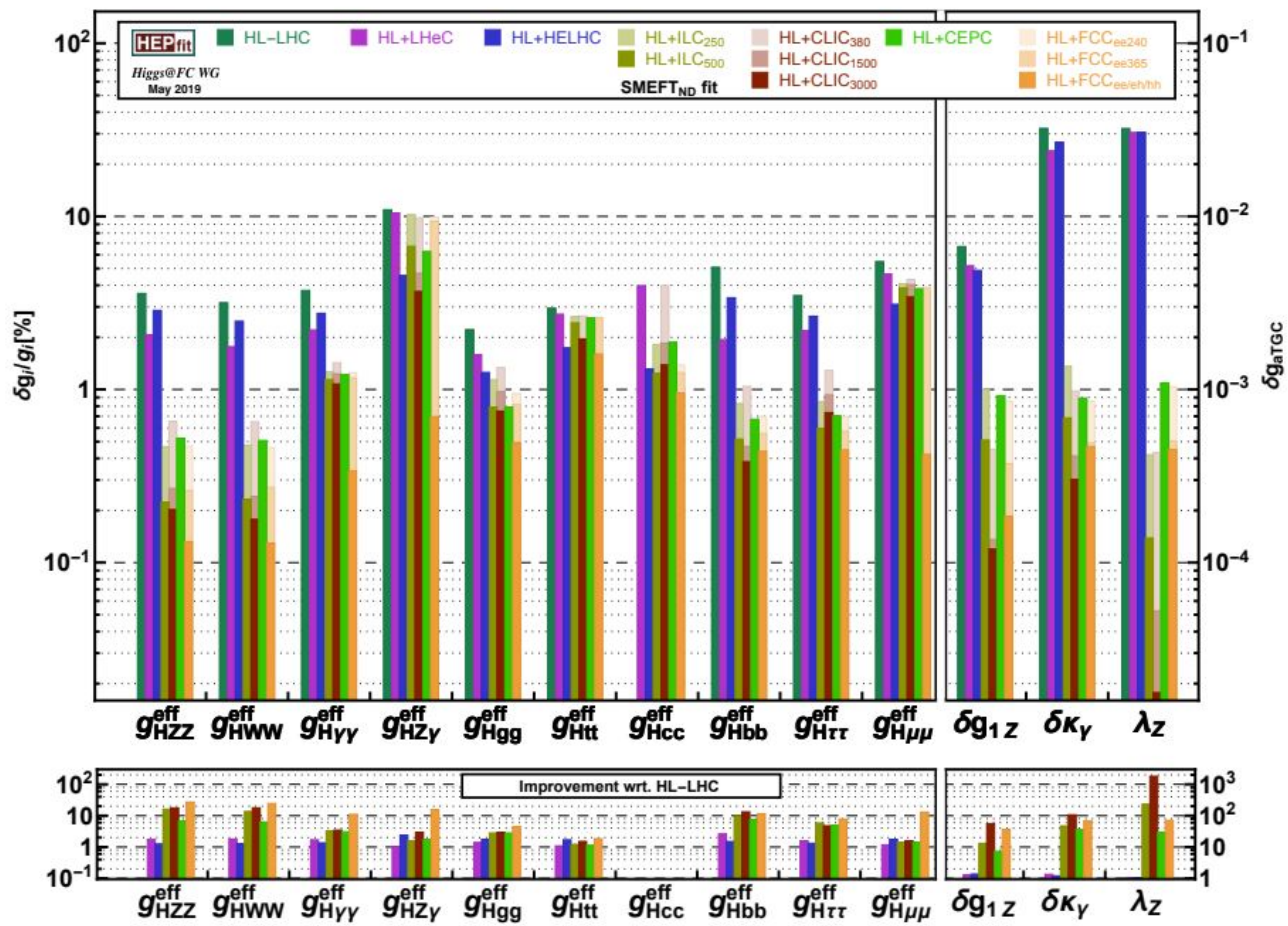






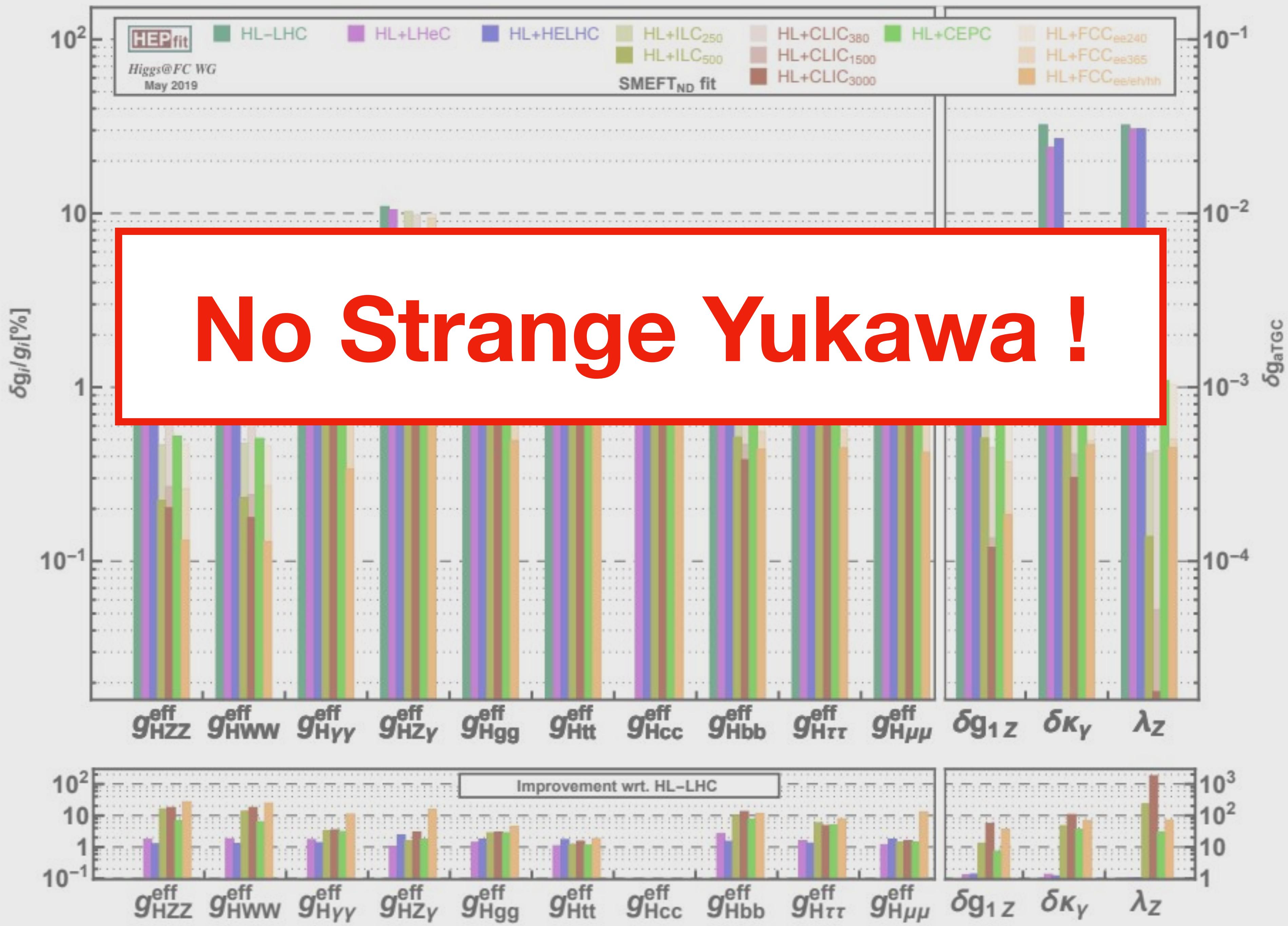
Higgs Precision Era

Sensitivity at 68% probability to deviations in the different effective Higgs couplings



Higgs Precision Era

Sensitivity at 68% probability to deviations in the different effective Higgs couplings



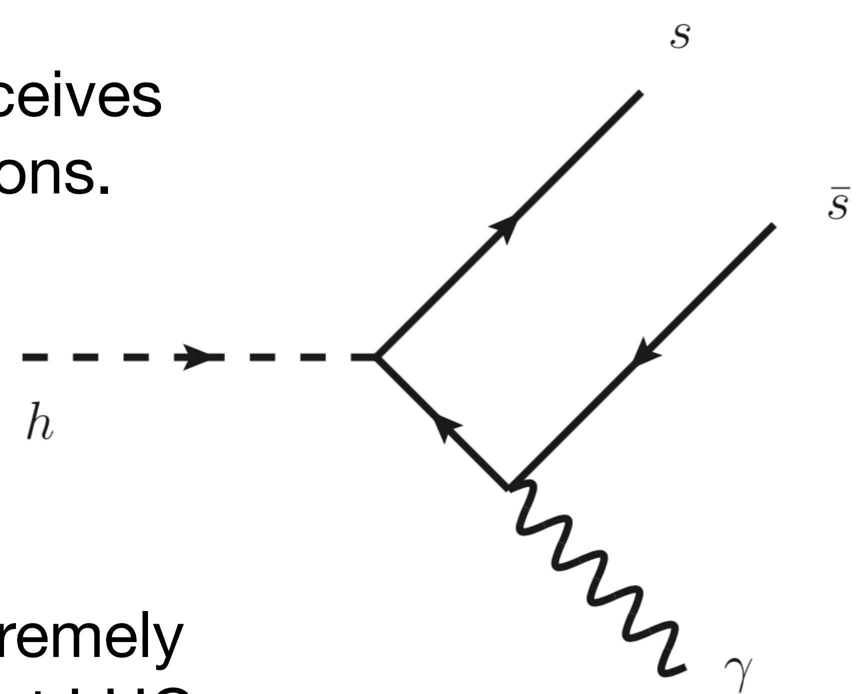
No Strange Yukawa !

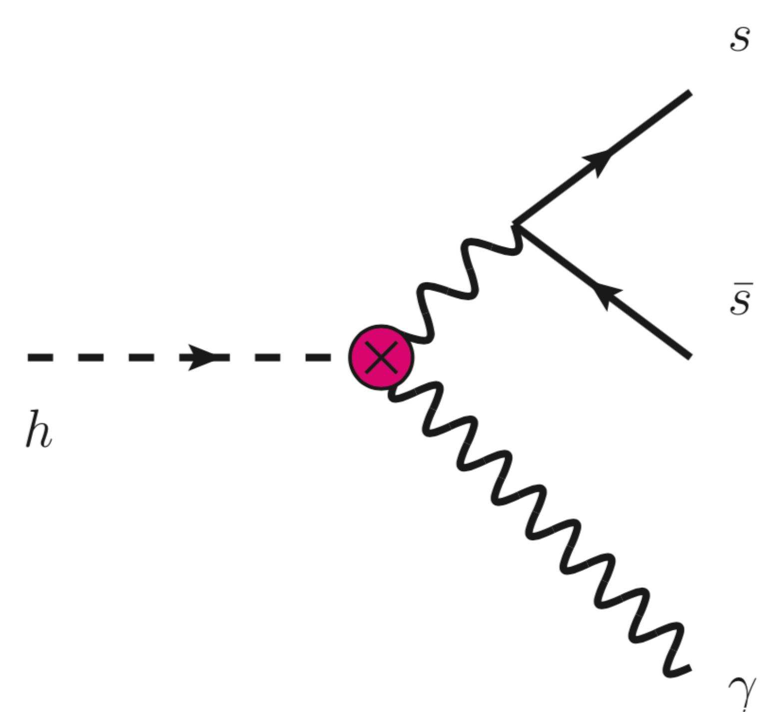
Rare Higgs decay

One way to get access to the strange Yukawa is to focus on the rare decay
h → ϕγ (ϕ: a vector meson).

Kagan, Perez, Petriello, Soreq, Stoynev, Zupan (2014)   Konig, Neubert (2015)

The decay amplitude receives two dominant contributions.





The measurement is extremely challenging at the present LHC.

(The branching fraction is in the range of few times 10^{-6}.)

How about HL-LHC ?

HL-LHC can probe O(30) modifications of the strange Yukawa.

Global χ^2 Fit

Another way is a global χ^2 fit to the measured Higgs rates.

Kagan, Perez, Petriello, Soreq, Stoynev, Zupan (2014)   Perez, Soreq, Stamou, Tobioka (2015)

The effective Lagrangian

$$\mathcal{L}_{\text{eff}}^{\text{Higgs}} = \kappa_W \frac{2m_W^2}{v} h W_\mu^+ W^{-\mu} + \kappa_Z \frac{m_Z^2}{v} h Z_\mu Z^\mu - \sum_f \frac{m_f}{v} h \bar{f} (\kappa_f + i\tilde{\kappa}_f \gamma_5) f + \frac{\alpha}{4\pi v}\left(\kappa_{\gamma\gamma} h F_{\mu\nu}F^{\mu\nu} - \tilde{\kappa}_{\gamma\gamma} h F_{\mu\nu}\tilde{F}^{\mu\nu} + \frac{2\kappa_{\gamma Z}}{s_W c_W} h F_{\mu\nu} Z^{\mu\nu} - \frac{2\tilde{\kappa}_{\gamma Z}}{s_W c_W} h F_{\mu\nu}\tilde{Z}^{\mu\nu}\right) + \ldots ,$$

All of the Higgs couplings are allowed to vary from their SM values…

$$\sqrt{|\kappa_u|^2 + |\tilde{\kappa}_u|^2} < 3000 \qquad \sqrt{|\kappa_d|^2 + |\tilde{\kappa}_d|^2} < 1500$$

$$\sqrt{|\kappa_c|^2 + |\tilde{\kappa}_c|^2} < 6.2 \qquad \sqrt{|\kappa_s|^2 + |\tilde{\kappa}_s|^2} < 75$$

(95% CL)

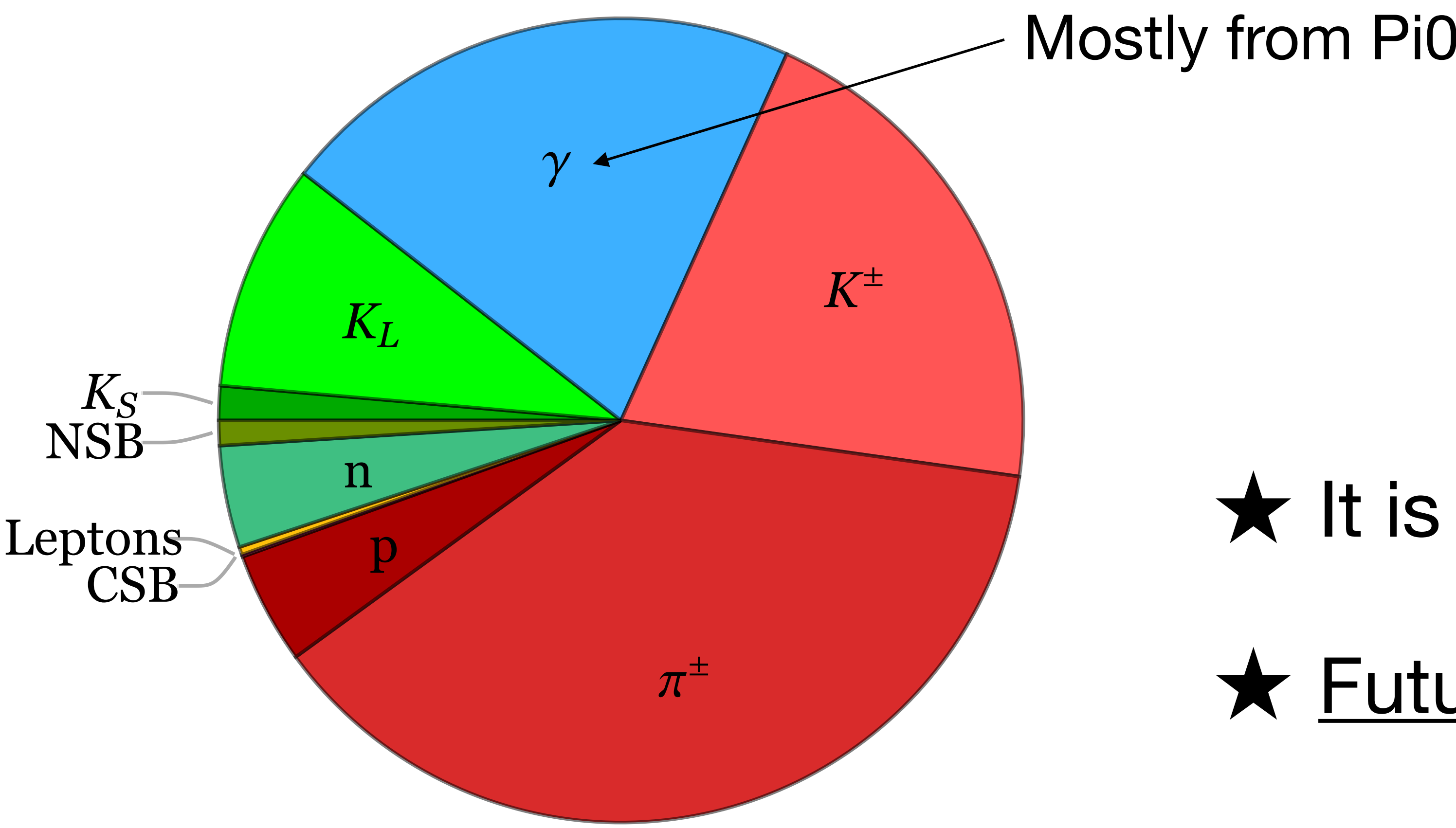
The present LHC data are largely insensitive to the light quark Yukawa.

Can we test the SM strange Yukawa?

Strange tagging is essential.

The pT fraction of a detector-stable particle averaged over jet samples :

$$Z \to s\bar{s} \quad (p_T > 20\ \mathrm{GeV})$$



★ It is unlikely at the LHC.

★ Future lepton colliders can do it?

NSB: neutral strange baryons, CSB: charged strange baryons

Can we test the SM strange Yukawa?

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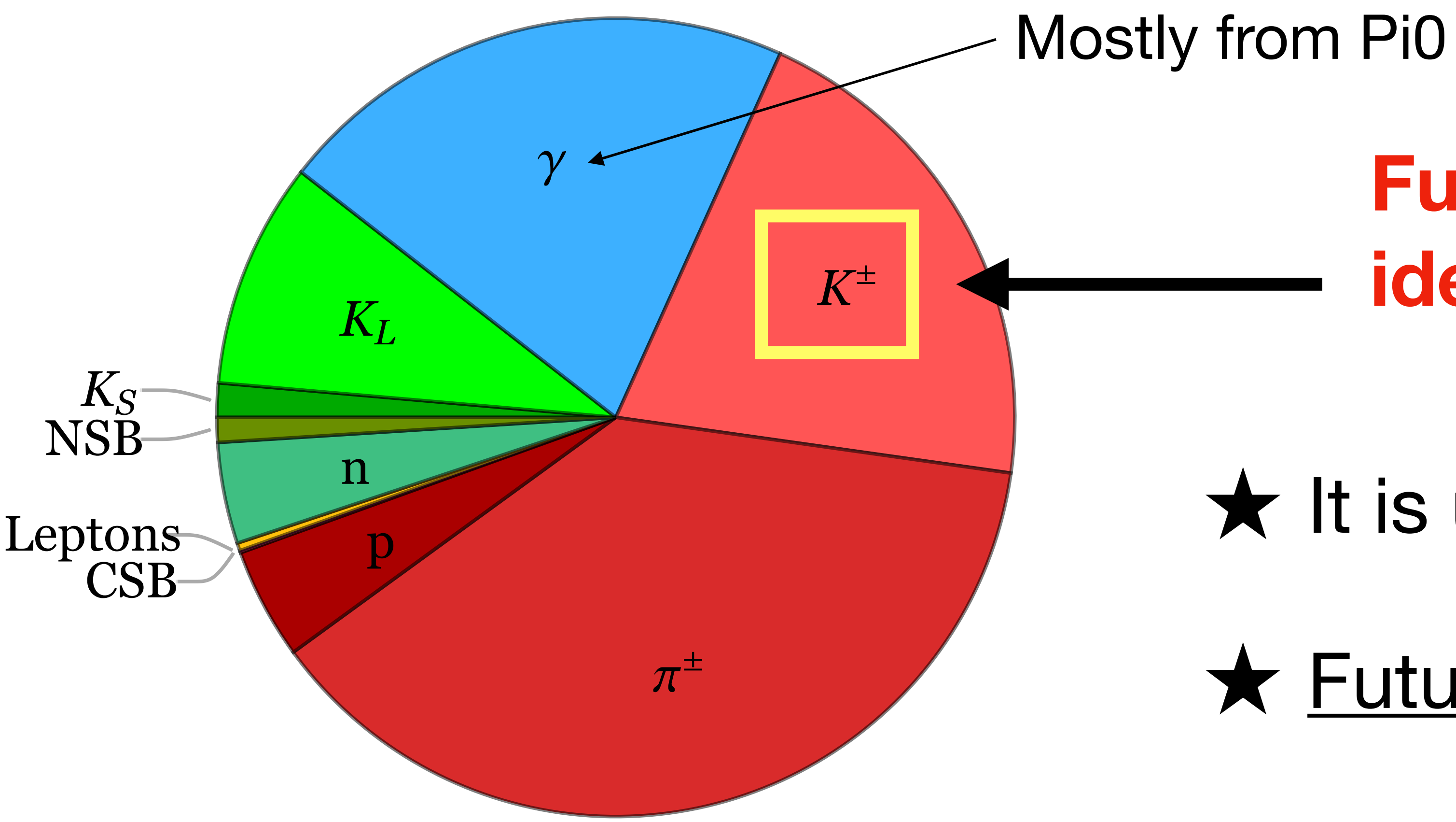


Future lepton colliders can identify charged Kaons !

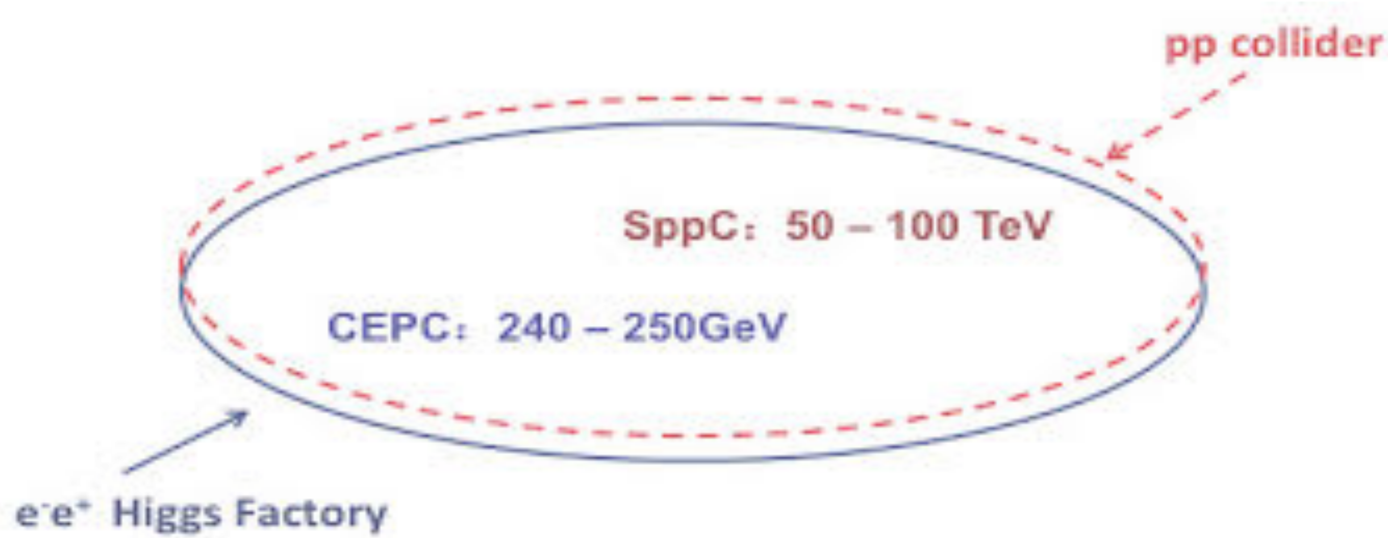
★ It is unlikely at the LHC.

★ Future lepton colliders can do it?

NSB: neutral strange baryons, CSB: charged strange baryons

CEPC

- ✓ Circular Electron-Positron Collider (CEPC) proposed to be built in China.
- ✓ CEPC will operate as a Higgs boson factory at center-of-mass energy of around 240 GeV.
- ✓ During its lifetime, one million Higgs bosons are expected to be produced, allowing precision measurements of the Higgs boson properties.



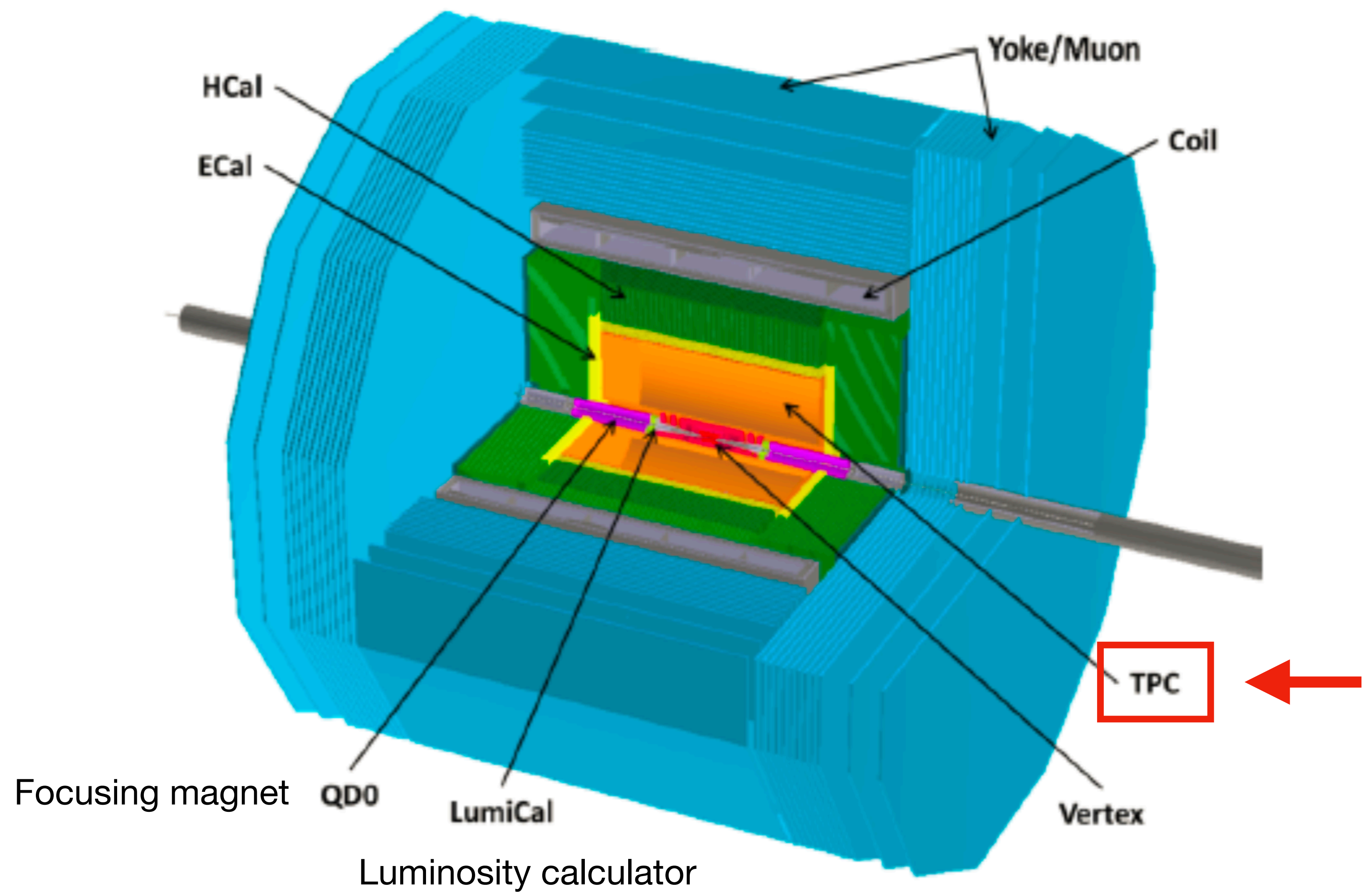
- ✓ The same tunnel could also host a Super Proton Proton Collider (SppC) to reach energies beyond the LHC.

CEPC Detector Design

✓ Time Projection Chamber (TPC) is proposed as a charged particle tracking device.

✓ TPC provides precise momentum and position measurements and a good particle identification (PID) over a wide range of momentum.

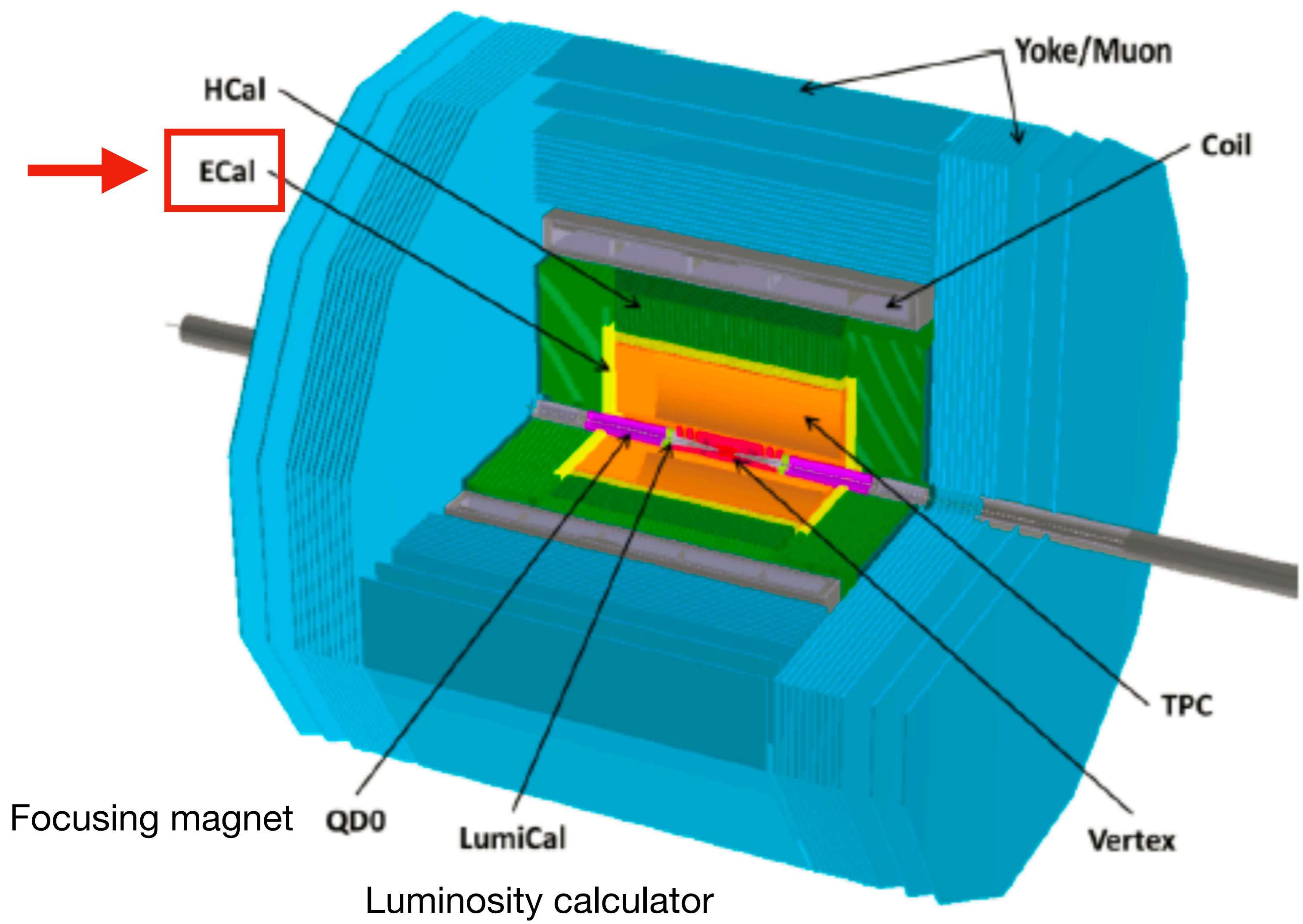
✓ PID is based on measurements of *dE/dx* (energy deposit per unit path length).



CEPC Detector Design

In addition…

✓ Electromagnetic Calorimeter (ECAL) provides time-of-flight (TOF) information.



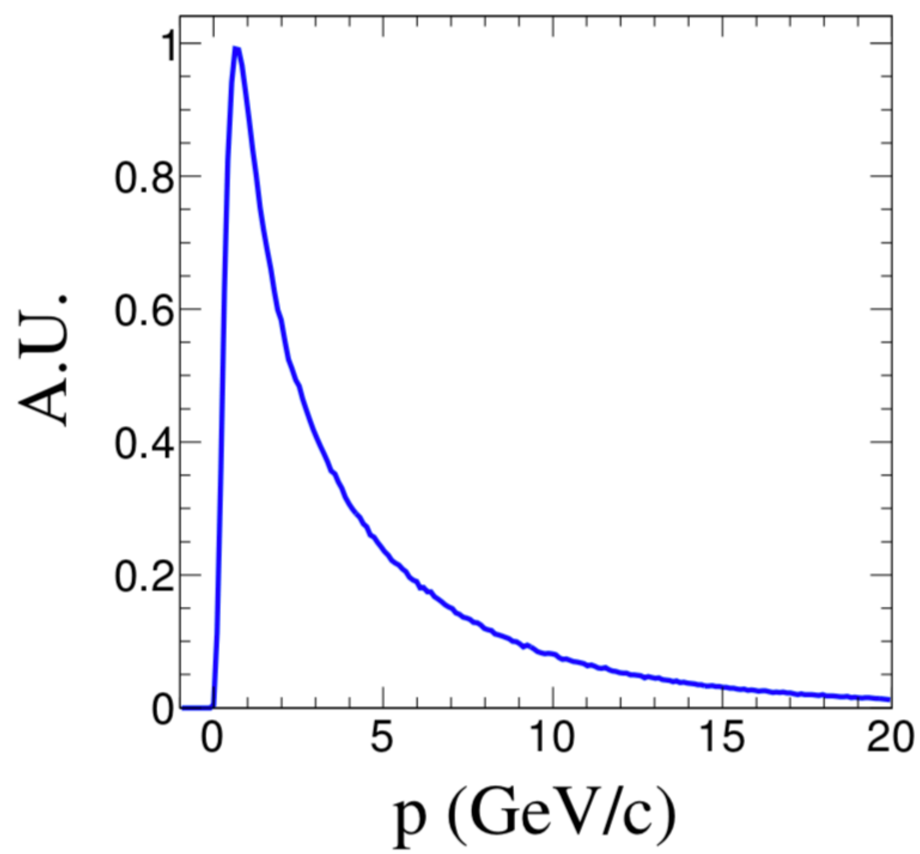
Charged Kaon ID

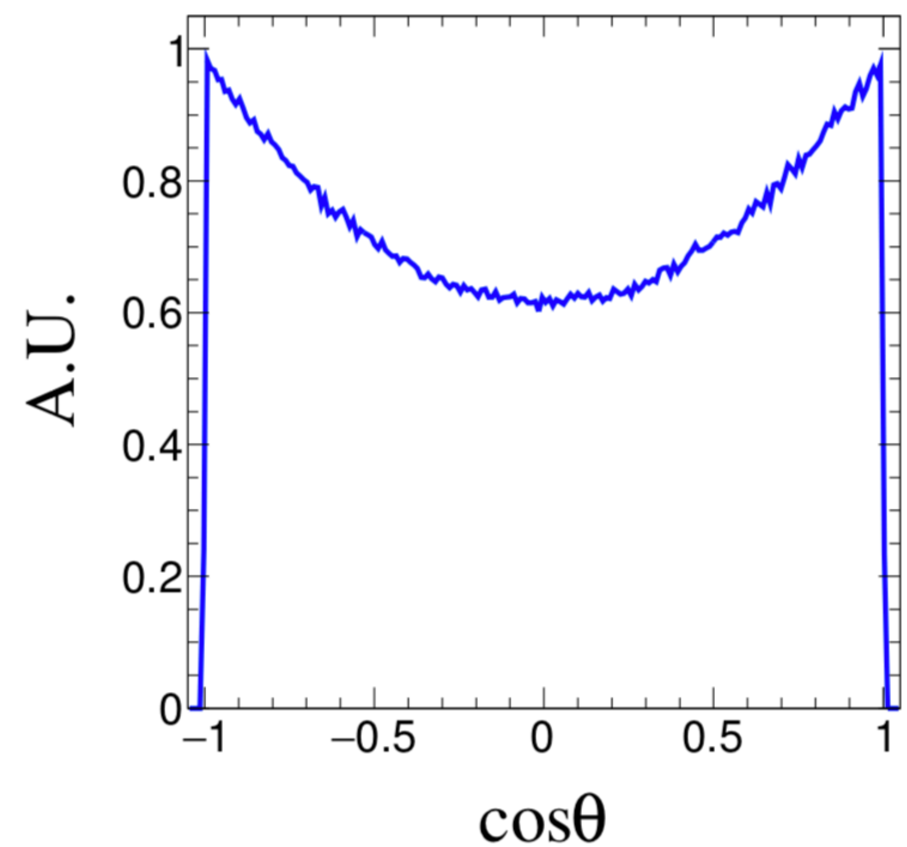
✓ **Charge kaons can be identified** by combining the information of TPC with TOF of ECAL.

✓ PID of kaons, pions and protons in hadronic decays at the *Z* pole has been studied.

An, Prell, Chen, Cochran, Lou, Ruan (2018)

Kinematic distribution of kaons in $e^+e^- \to Z \to qq$





Polar angle of the tracks with respect to the beam direction

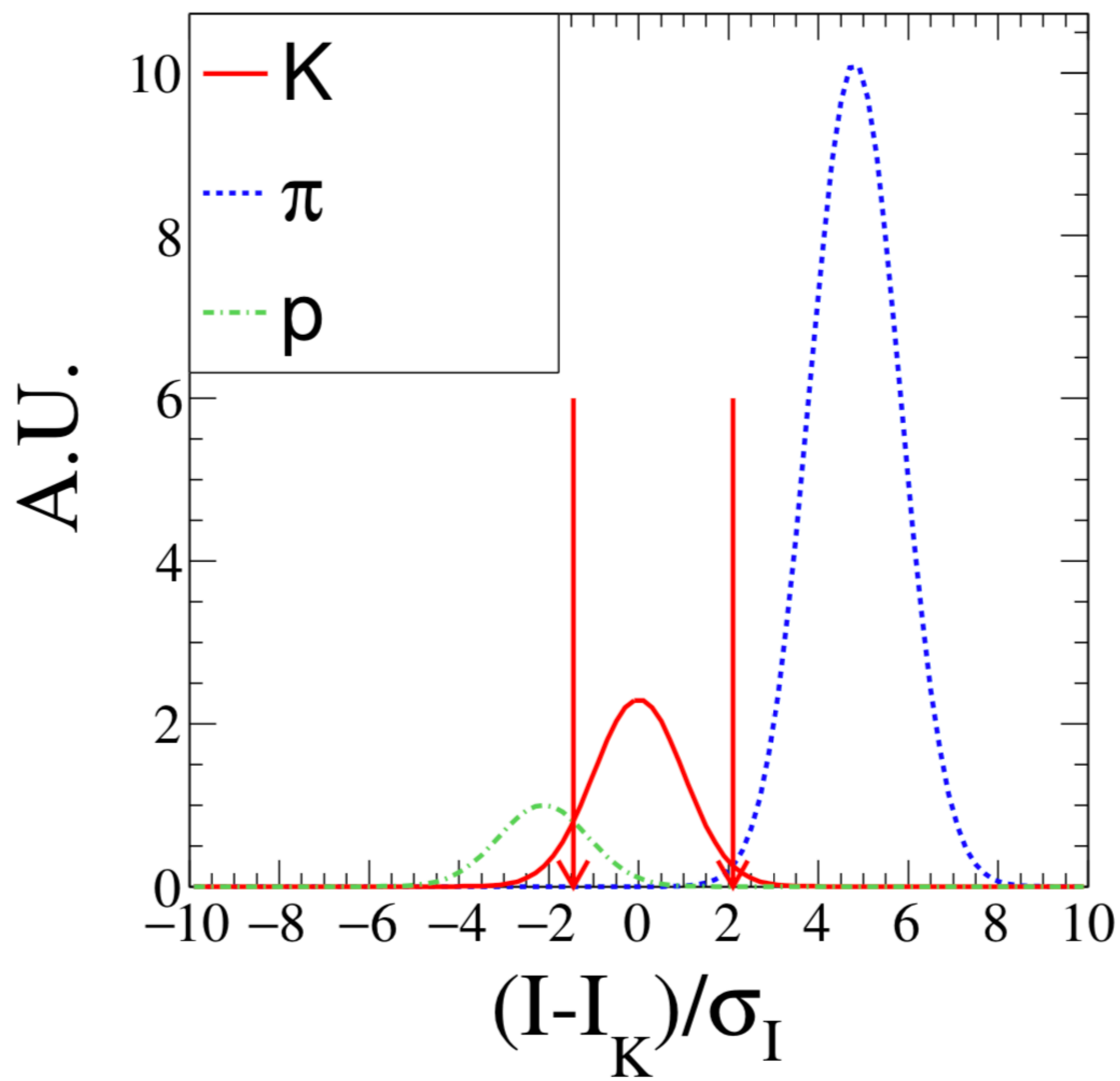
Charged Kaon ID

Measure of separation power between particles A and B :

$$S_{AB} = \frac{|I_A - I_B|}{\sqrt{\sigma_{I_A}^2 + \sigma_{I_B}^2}}$$

I_A (I_B) : average *dE/dx* measurement of particle A (B)

σI_A (σI_B) : the corresponding resolution



An, Prell, Chen, Cochran, Lou, Ruan (2018)

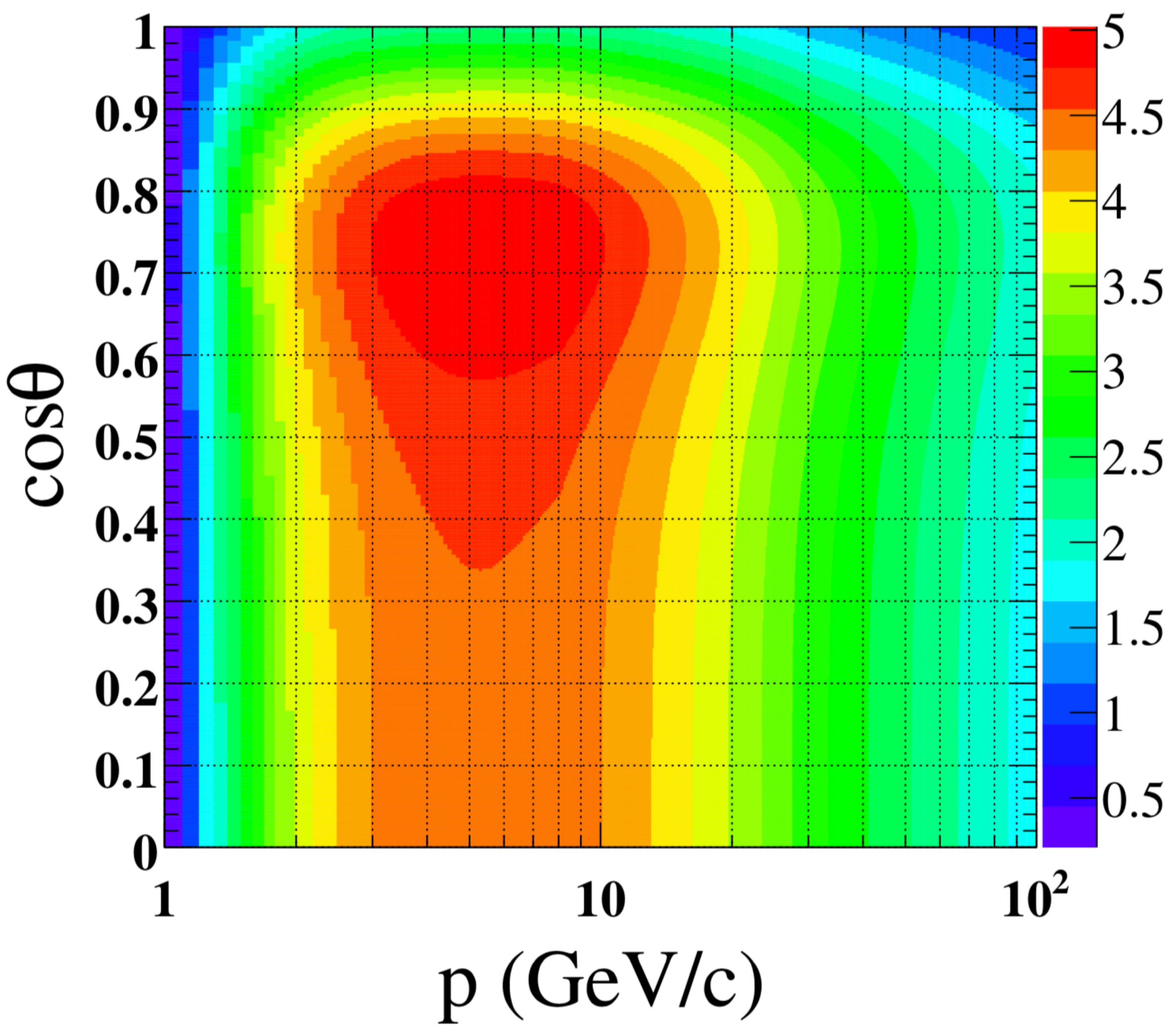
Particles with a momentum of 5 GeV

The relative populations :

$N_\pi = 4.4\, N_K, \quad N_K = 2.3\, N_p$

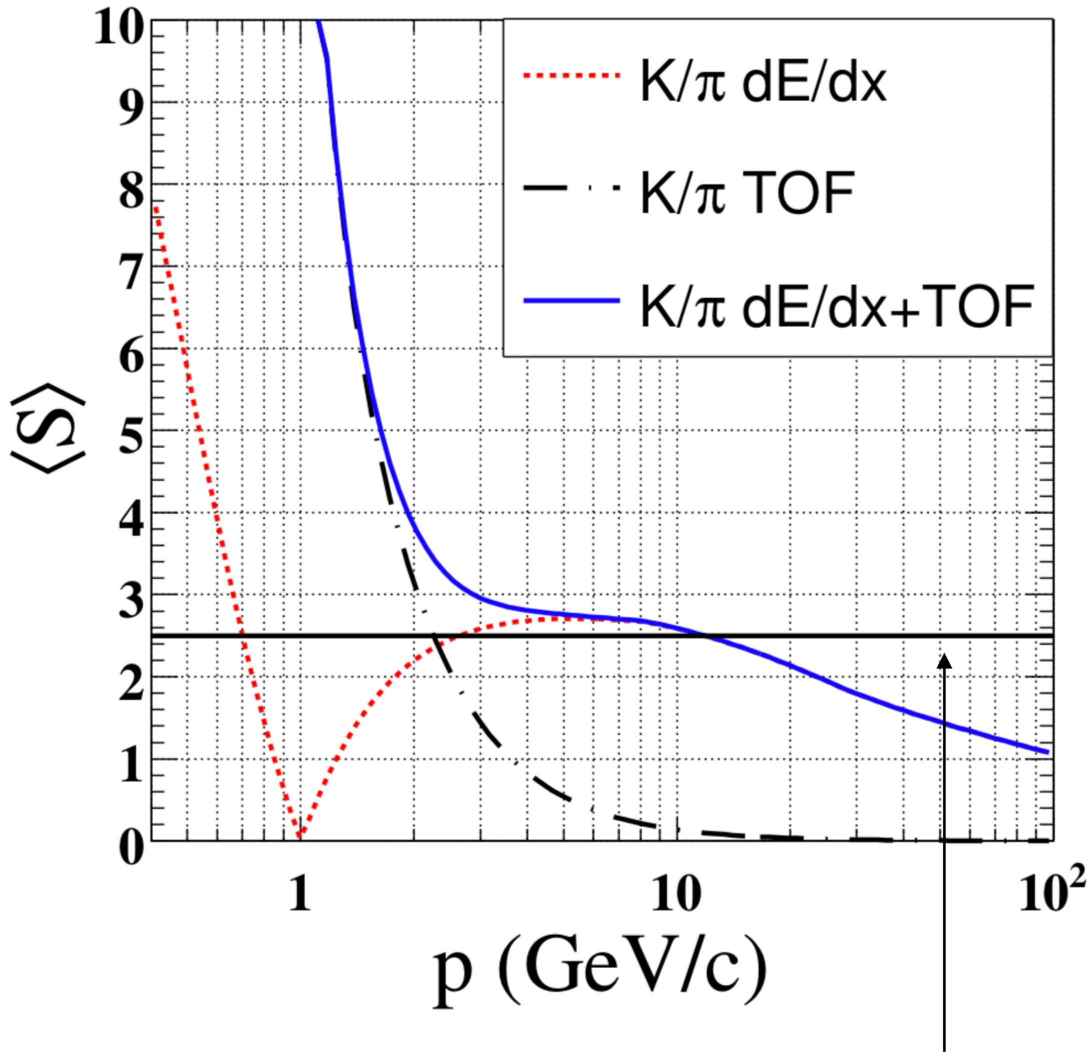
Charged Kaon ID

Separation power S between kaons and pions in the *p*-cosθ plane :



An, Prell, Chen, Cochran, Lou, Ruan (2018)

K/π separation using *dE/dx* and/or TOF :



CEPC can identify charged Kaons with momenta p < 20 GeV !

Prospect of Strange Yukawa

Probe the strange Yukawa by tagging strange jets in future lepton colliders.

Duarte-Campderros, Perez, Schlaffer, Soffer (2018)

$e^+ e^- \to Z h$

1. Separate h → jj from all non-h → jj events (preselection).

2. Apply a flavor tag on the selected signal-rich sample.

Z → νν has a large branching fraction of 20% and a clean, missing-energy signature that provides good rejection of non-Higgs background and Higgs decays into non-jj final states. (→ preselection)

Non-h → jj background events and their percentages after preselection :

$e^+e^- \to$ Final state	WW $(\tau\nu)(qq')$	$Z(Z+\gamma^*)$ $(\nu\nu)(dd,\ ss,\ bb)$	$Zh+\nu\nu h$ $(\nu\nu)(\text{non-}jj)$	$Z(Z+\gamma^*)$ $(\nu\nu)(uu,\ cc)$	Zh $(\tau\tau)(bb)$	Zh $(qq)(\text{non-}jj)$	WW $(\mu\nu)(qq')$
Fraction [%]	47.1	18.0	13.7	12.2	2.7	2.5	2.0

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Probe the strange Yukawa by tagging strange jets in future lepton colliders.

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$e^+ e^- \to Z h$

1. Separate h → jj from all non-h → jj events (preselection).

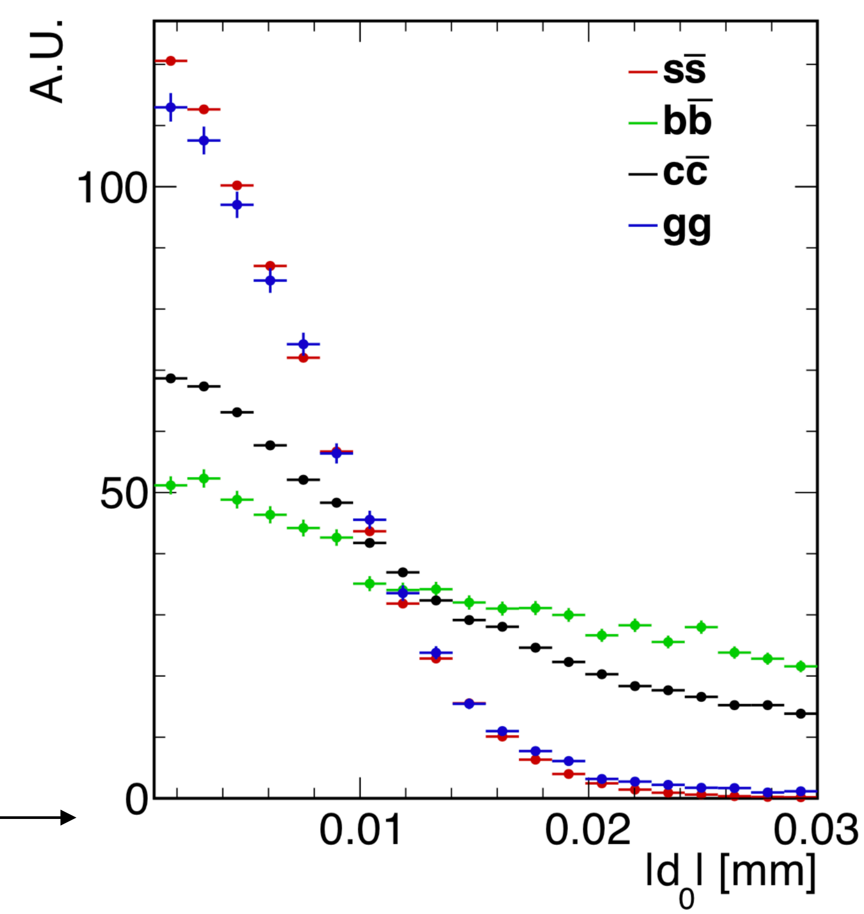
2. Apply a flavor tag on the selected signal-rich sample.

Relevant h → jj background decays :

h → bb, h → cc, h → gg

Look for a displaced (secondary) vertex.

d0 : impact parameter →



Prospect of Strange Yukawa

Duarte-Campderros, Perez, Schlaffer, Soffer (2018)

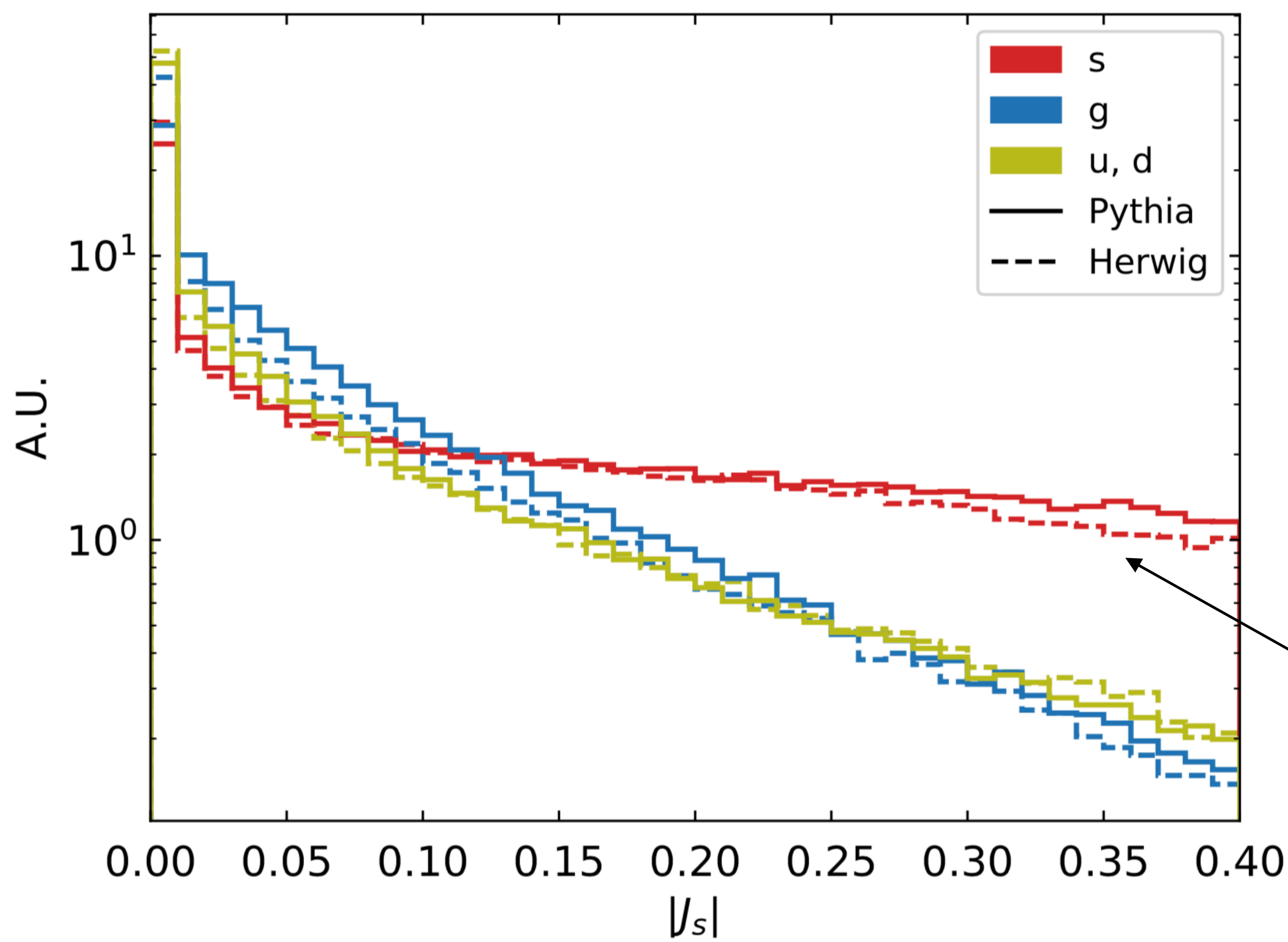
A new jet-flavor variable :

$$J_F = \frac{\sum_H \vec{p}_H \cdot \hat{s}\, R_H}{\sum_H \vec{p}_H \cdot \hat{s}}$$

$R_{K^\pm} = \mp 1$, $R_H = 0$ for $H = \pi^\pm, \pi^0$

Normalized jet axis

All hadrons inside the jet

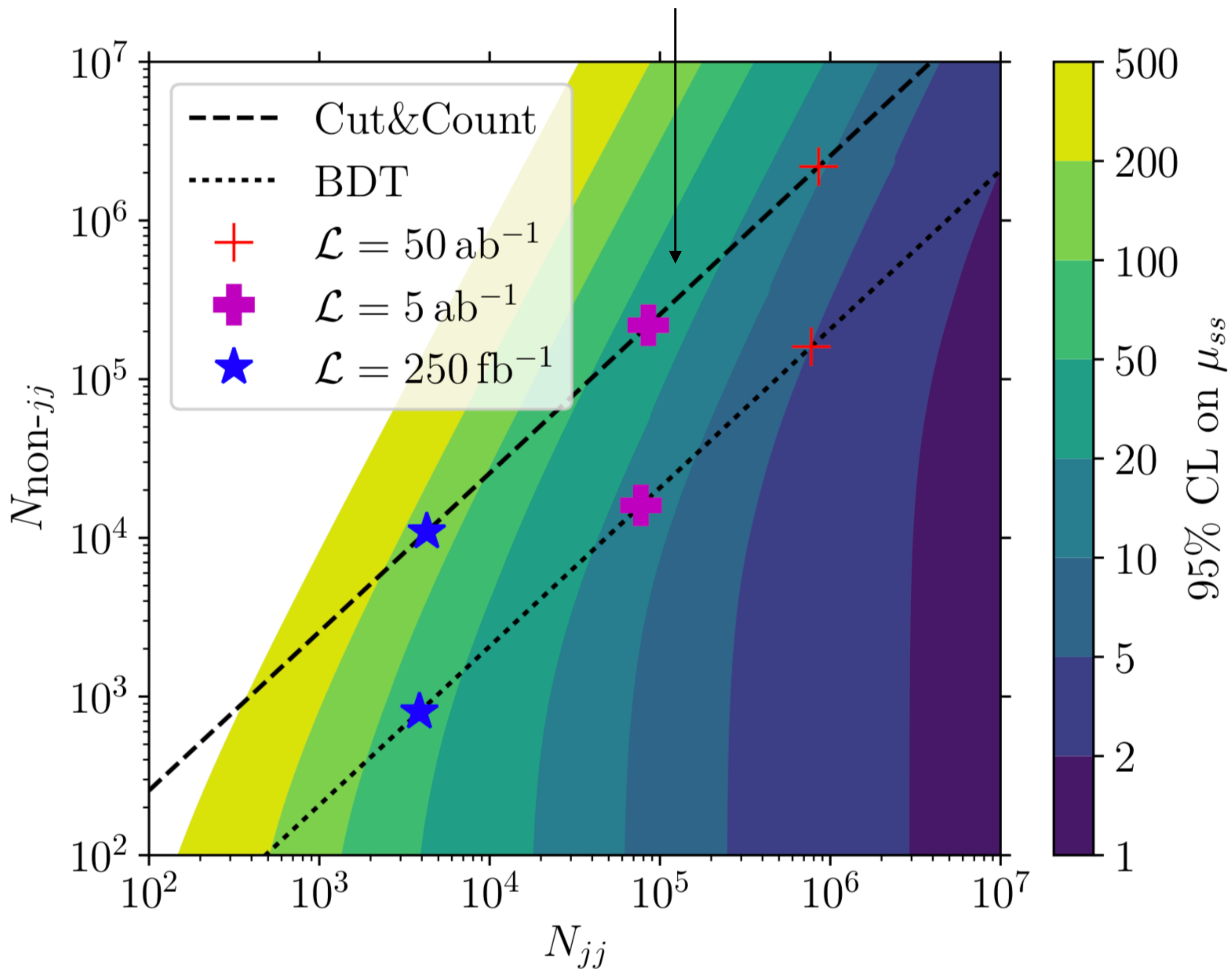


If a K^- (K^+) carries all of the momentum, the $K^\mp$ would have $J_s = \pm 1$.

Distribution of h → ssbar events is broad.

Prospect of Strange Yukawa

The number of non-h → jj events (N_{non-jj}) vs. h → jj events (N_{jj}) after preselection but before the s-tagger



Duarte-Campderros, Perez, Schlaffer, Soffer (2018)

The limit on the signal strength after the s-tagger

$$\mu_i \equiv (\sigma \times \mathrm{BR})_i / (\sigma \times \mathrm{BR})_i^{\mathrm{SM}}$$

μ_{ss} < O(15) and O(5) for integrated luminosities of 5 and 50 ab^{-1}

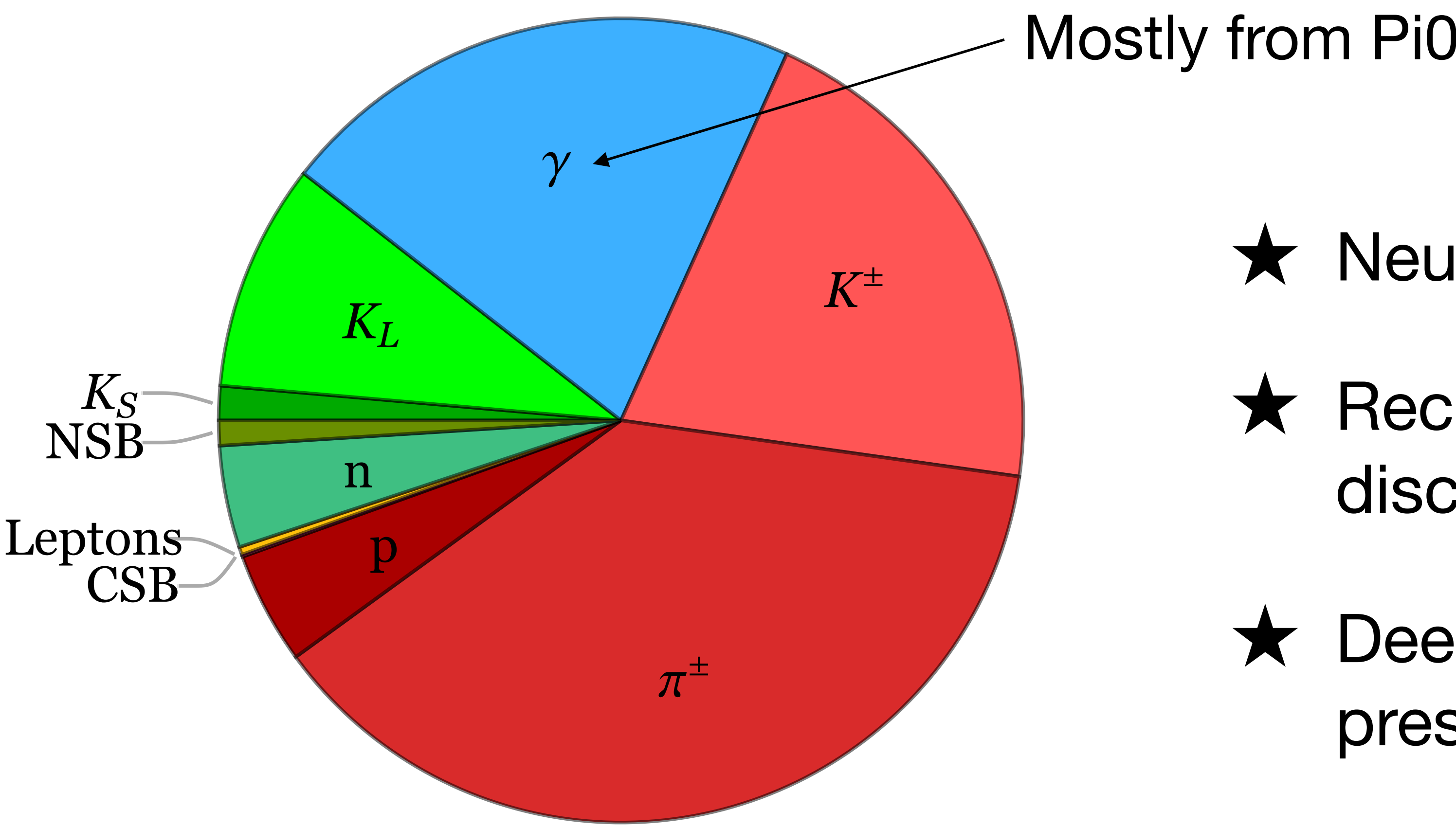
μ_{ss} < O(75) for an integrated luminosity of 250 fb^{-1}

Can we test the SM strange Yukawa?

Machine learning can help to improve the limit?

The pT fraction of a detector-stable particle averaged over jet samples :

$$Z \to s\bar{s} \quad (p_T > 20 \text{ GeV})$$



★ Neutral Kaon is useful?

★ Recent development of quark/gluon discrimination is useful?

★ Deep learning can improve preselection?

…

NSB: neutral strange baryons, CSB: charged strange baryons