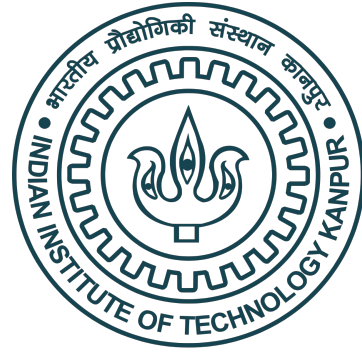


PHY654

Machine learning (ML) in particle physics



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26th September 2024

top-tagging using CNN

- Today we will run an example code of **CNN** which performs **top-tagging** using collider simulation.
- Signal: top-quark, Background: any other quark/gluons. Classification problem.
- We will start from basics and discuss several things needed to understand this problem. We will discuss in the context of proton-proton collision at LHC.

CNN code (jet images):

https://github.com/swagata87/IITKanpurPhy654/blob/main/jetImage_CNN.ipynb

Units

Our scale

Length m

Mass kg

Time s

Energy $\text{kg m}^2 \text{s}^{-2}$

Particle Physics

Length fm

Mass eV/c^2

Time s

Energy eV

Convert

$1 \text{ eV} = 1.6 \times 10^{-19} \text{ J}$

$1 \text{ GeV} = 10^9 \text{ eV}$

$1 \text{ TeV} = 10^3 \text{ GeV}$

$1 \text{ fm} = 10^{-15} \text{ m}$

Note: often set $\hbar = c = 1$

3 generations

Top (this is what we want to tag, i.e. find)

Mass →
Charge →
Spin →

2.4 MeV/c²
2/3
1/2
u
up

1.27 GeV/c²
2/3
1/2
c
charm

171.2 GeV/c²
2/3
1/2
t
top

quarks

4.8 MeV/c²
-1/3
1/2
d
down

104 MeV/c²
-1/3
1/2
s
strange

4.2 GeV/c²
-1/3
1/2
b
bottom

+ anti-particles

0.511 MeV/c²
-1
1/2
e
electron

105.7 MeV/c²
-1
1/2
μ
muon

1.777 GeV/c²
-1
1/2
τ
tau

leptons

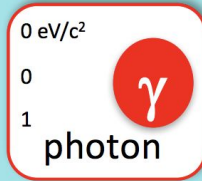
< 2.2 eV/c²
0
1/2
ν_e
e neutrino

< 0.17 MeV/c²
0
1/2
ν_μ
μ neutrino

< 15.5 MeV/c²
0
1/2
ν_τ
τ neutrino

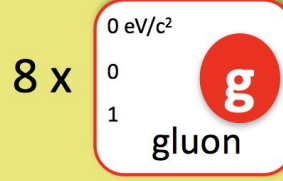
Matter is held together by forces. Mediated by force-carrying particles.

Electromagnetic



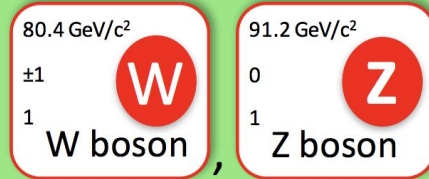
U(1)

Strong (QCD)



SU(3)

Weak



SU(2)

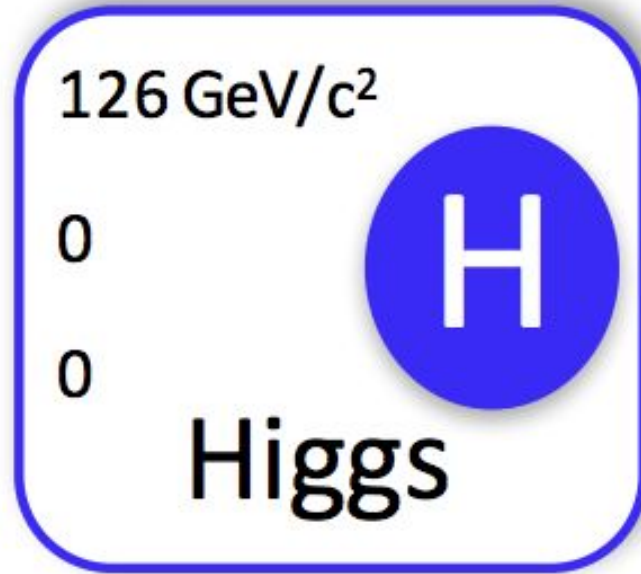
Strong: $\alpha_s \sim 1$
Electromagnetic: $\alpha_{em} \sim 1/137$
Weak: $\alpha_W \sim 10^{-6}$

Note: these are low energy / large distance values.
Coupling strength changes with energy.

Note:
No gravity!!

And, the Higgs boson.

This was needed to write down mass-terms of W and Z.



The Standard model of particle physics

Fermions

matter particles

Quarks



Leptons



Gauge bosons

force carriers



photon



gluon



Z boson



W boson

Higgs boson

origin of mass



The strength of strong force grows with distance.

Implication → Confinement

No free quarks or gluons can be detected in a detector.

Quarks emit gluons.

Gluons split to quarks or gluons.

Showering

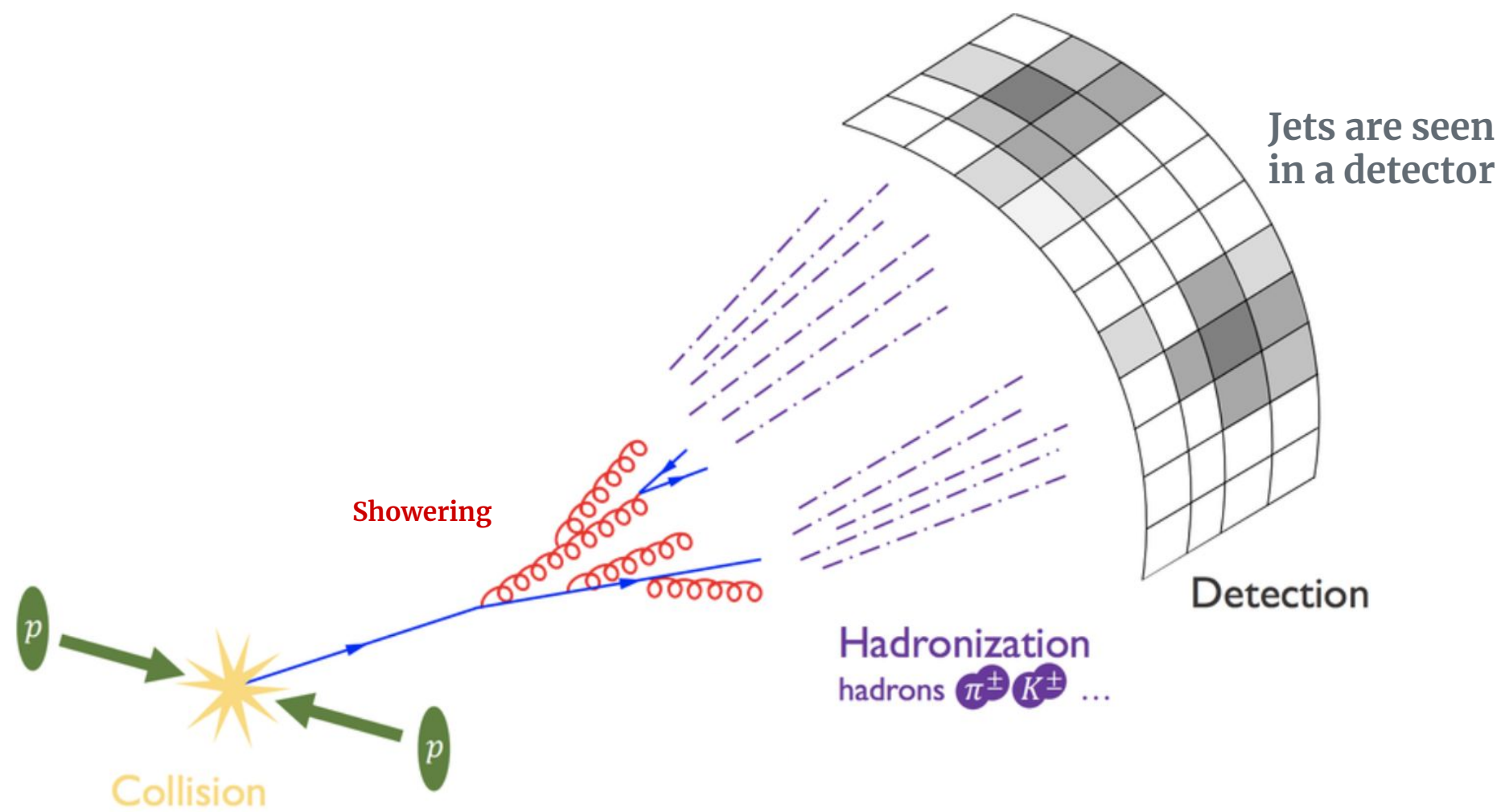
Finally, the quarks form colourless hadrons

Baryons (3 quarks)

Mesons (quark and anti-quark)

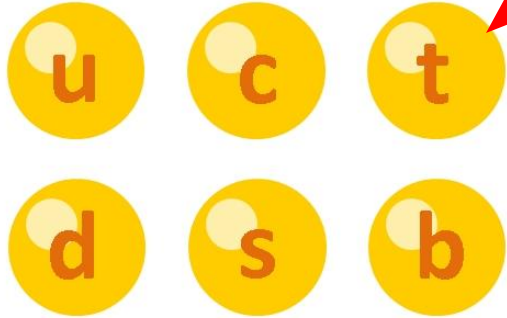
Hadronization

Spray of hadrons are detected in detectors as jets.

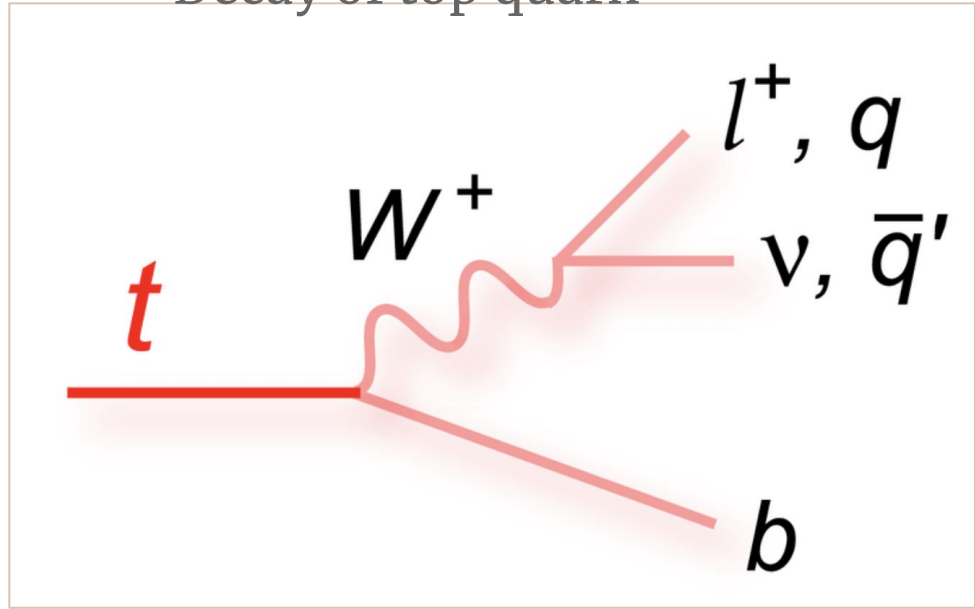


Top quark is special.
It is the heaviest elementary particle known to us.
It decays before hadronization can occur.

Quarks

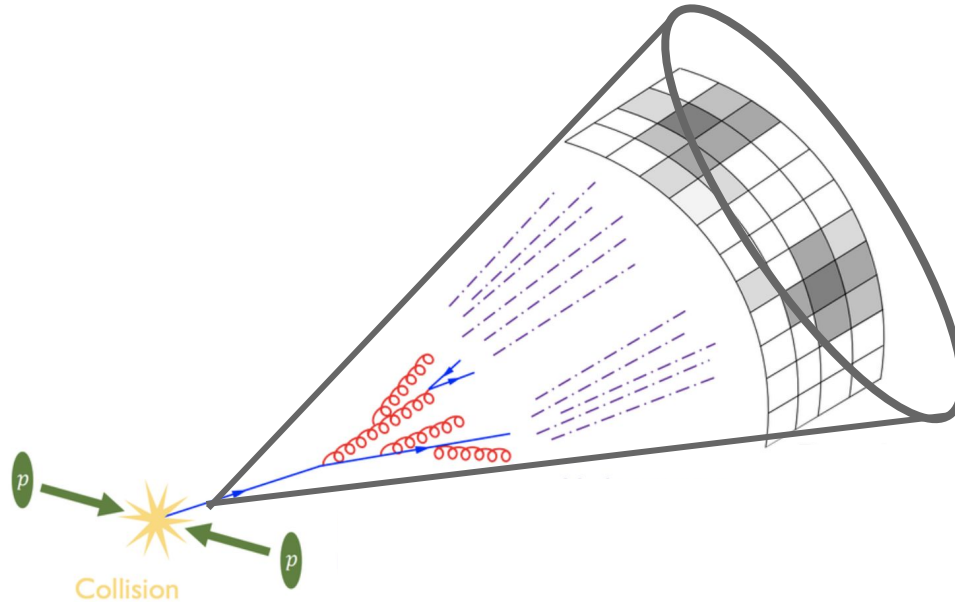


Decay of top quark



Jets

Jets: collimated spray of particles coming from showering and hadronization of quark/gluon
Basic idea: construct a cone which captures all the hadrons from the initial parton

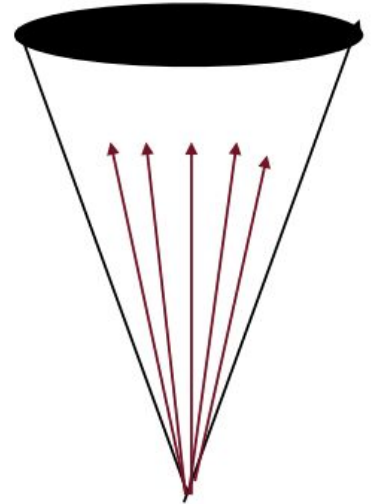


Jet: which cone size to choose?

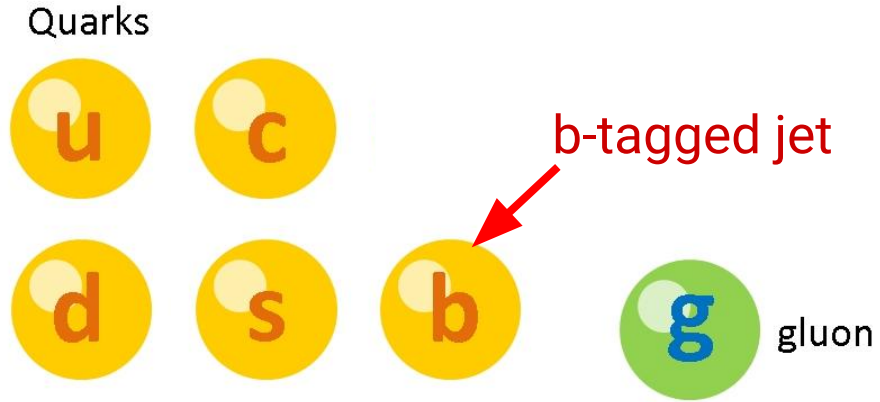
May not
Capture
All the
particles



Capture
All the
particles



These particles are detected as jets in the detector



Some of the quarks decay, but they decay after hadronization

These particles are detected as it is in a typical collider detector.



These particles have very short lifetime, so they decay to other (stable) particles as soon they are produced. They can be indirectly seen via their decay products.



Z boson



W boson

Neutrinos will escape collider detectors. They can be indirectly seen via missing transverse momentum \rightarrow an imbalance in momentum in transverse plane

Leptons



Particles that we directly see in detectors are...

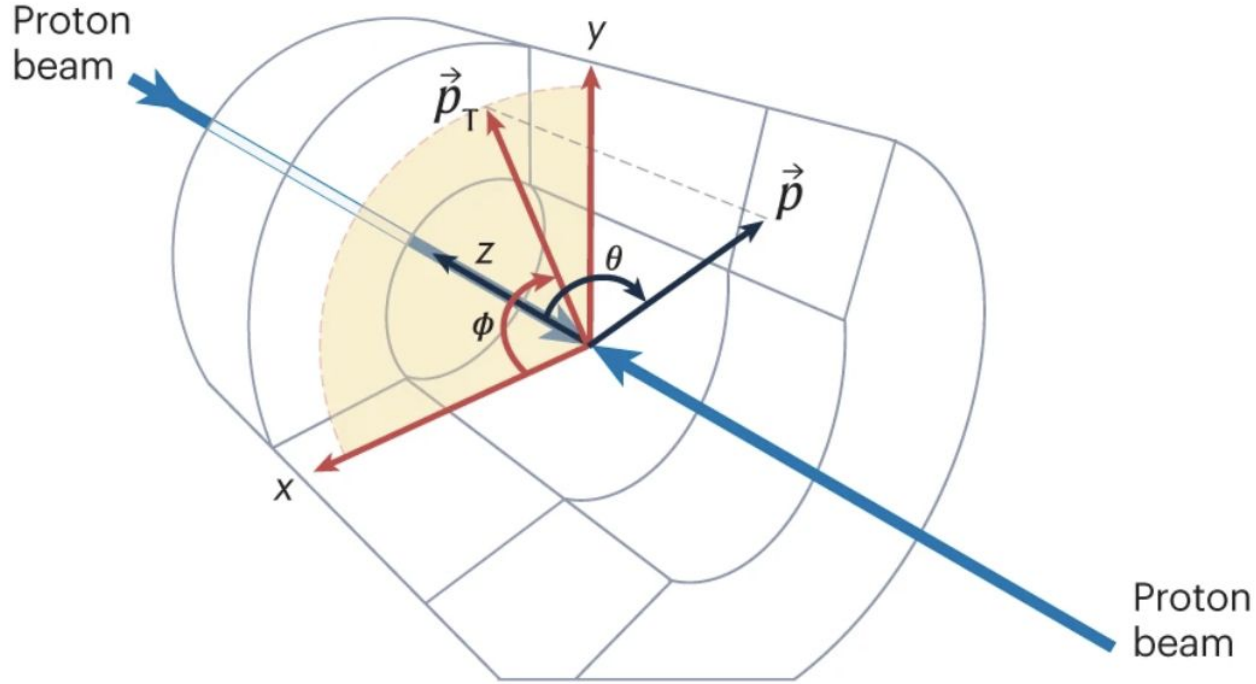
Electron, muon, photon, and some hadrons (mostly charged pion, charged kaon, neutral kaon, proton, neutron)

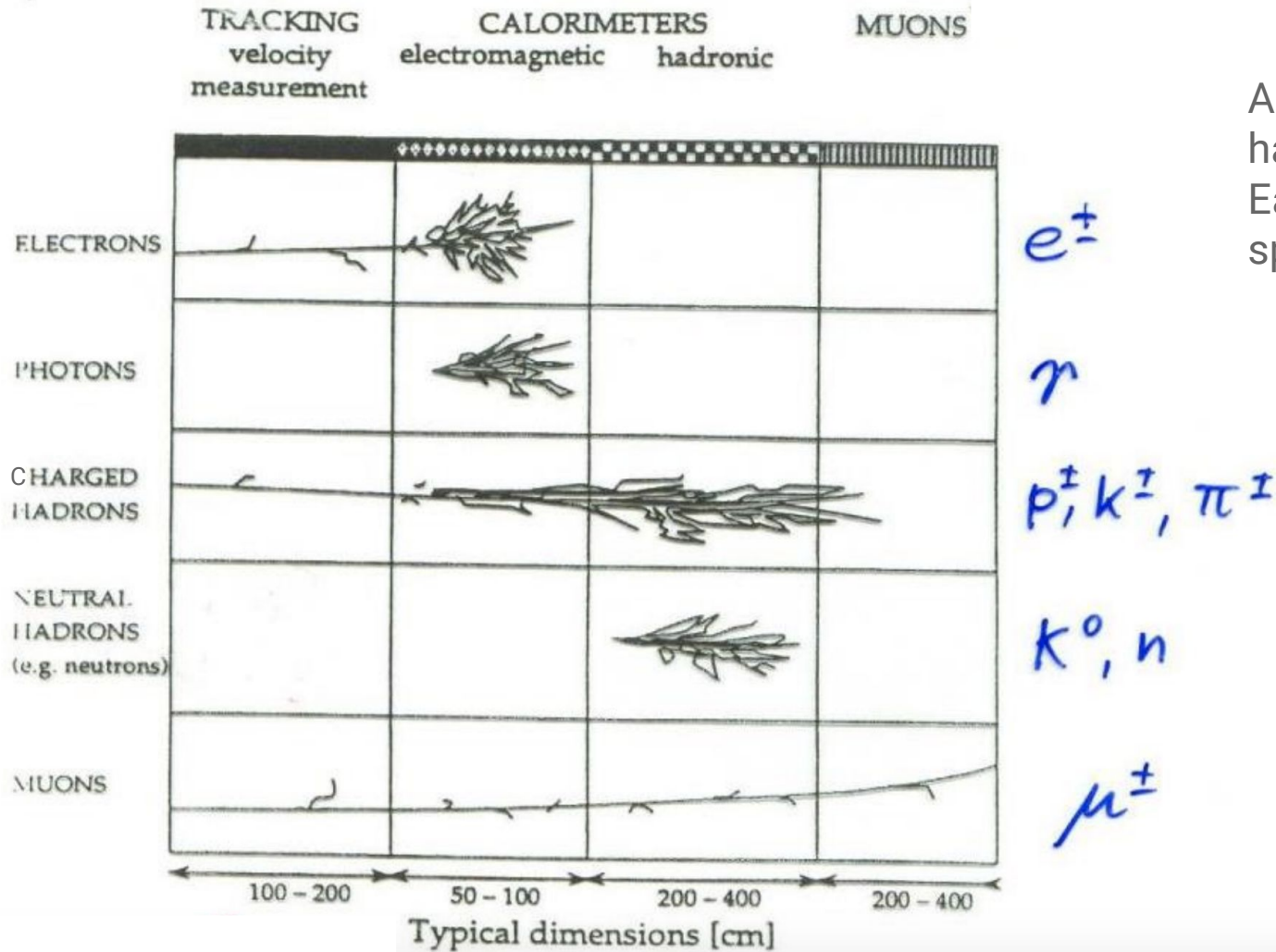
e^\pm	$m_e = 0.511 \text{ MeV}$	} EM
μ^\pm	$m_\mu = 105.7 \text{ MeV} \sim 200 m_e$	
γ	$m_\gamma = 0, Q = 0$	
π^\pm	$m_\pi = 139.6 \text{ MeV} \sim 270 m_e$	} EM, Strong $\sim 3.5 m_\pi$
K^\pm	$m_K = 493.7 \text{ MeV} \sim 1000 m_e$	
p^\pm	$m_p = 938.3 \text{ MeV} \sim 2000 m_e$	
K^0	$m_{K^0} = 497.7 \text{ MeV} \quad Q=0$	} Strong
n	$m_n = 939.6 \text{ MeV} \quad Q=0$	

A typical collider detector should be able to identify these particles, and measure the energy and momentum

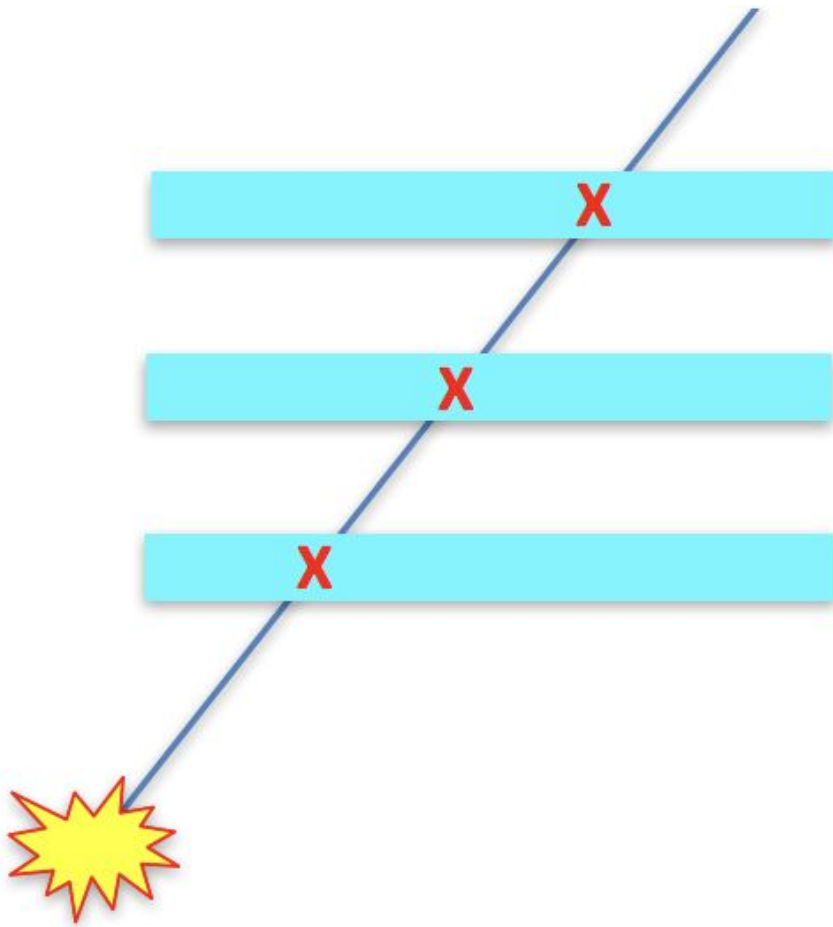
Their difference in mass, charge and interaction is the key to their identification.

Cylindrical detector. Almost 4π coverage around collision-point.

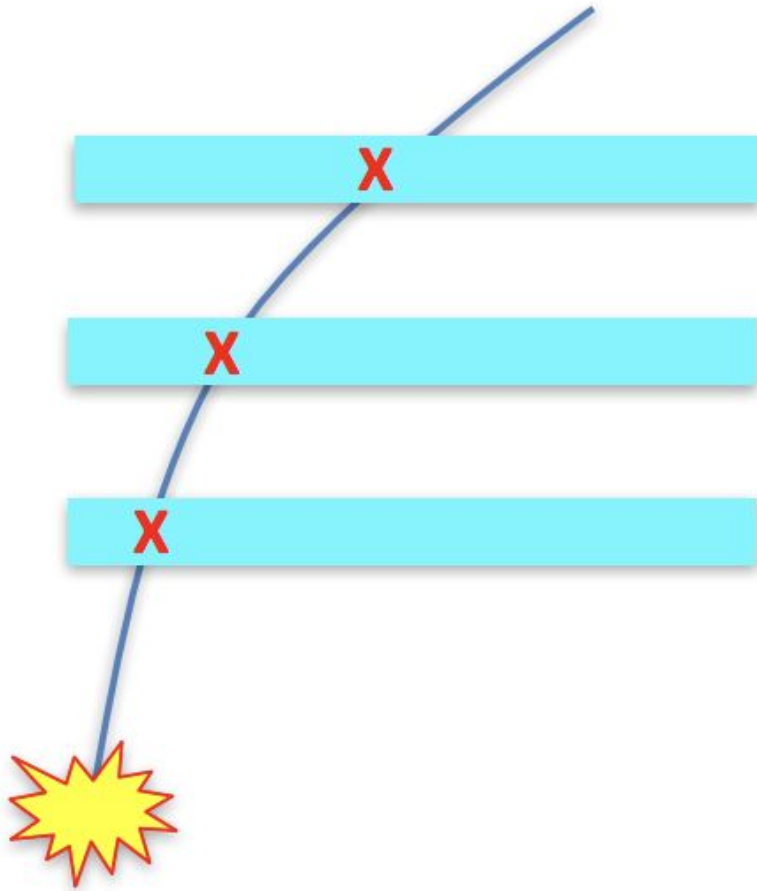




A typical detector has several layers, Each layer serve a specific purpose.



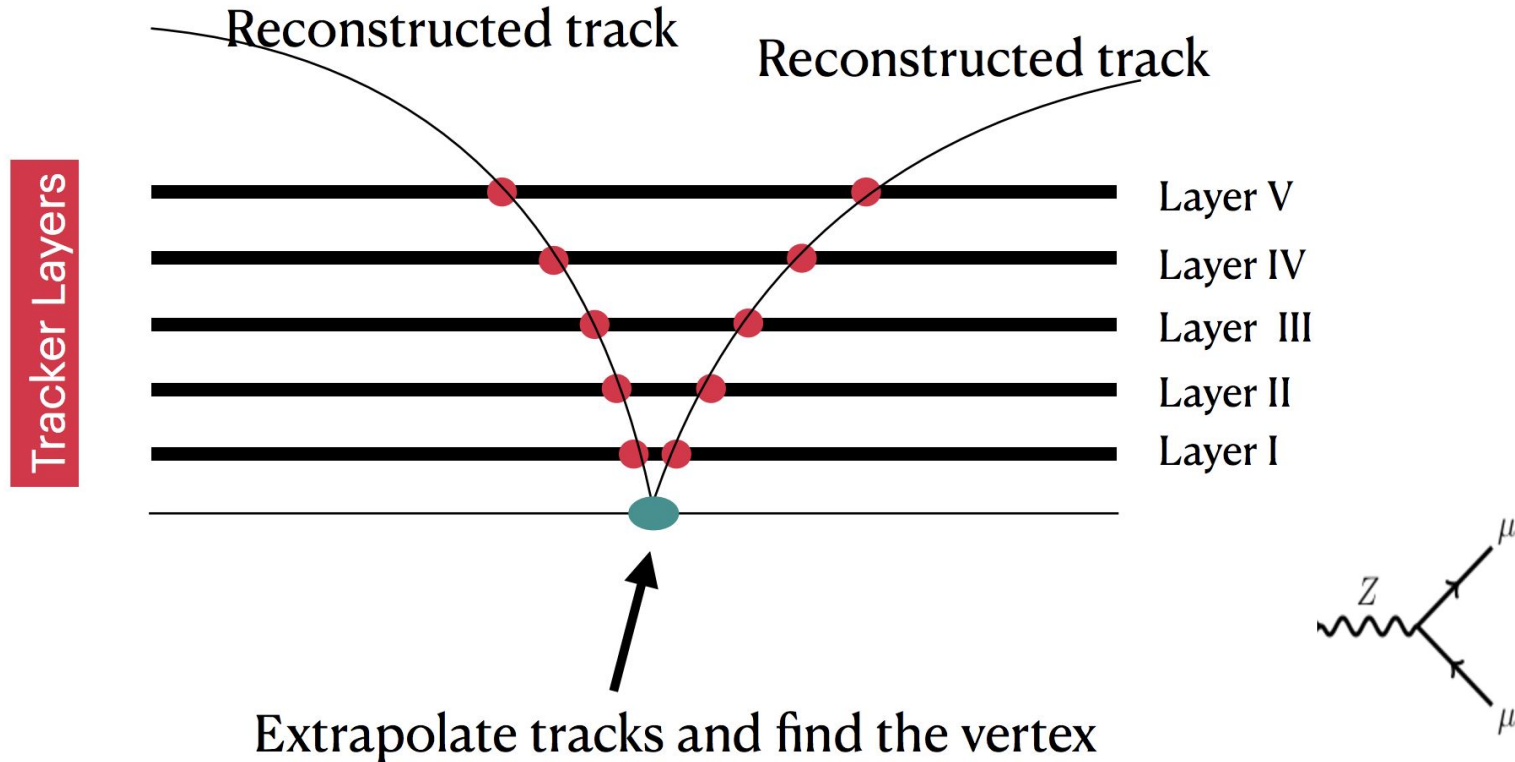
- Inner tracking detector.
- Detect charged particles.
- Determine location of charged particles.

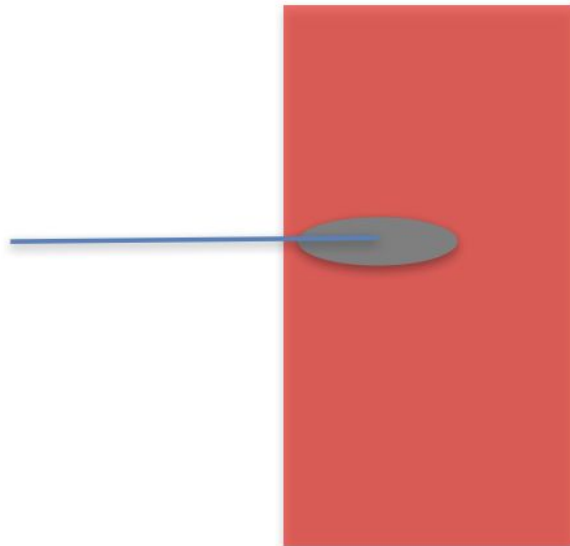


- Inner tracking detector placed inside a magnetic field (B).
- Measure momentum of charged particles.
- Track curvature, B and momentum are related.

$$\text{Radius of Curvature} = r = \frac{p_T}{0.3B}$$

Location of the collision vertex





Calorimeters

Charged + neutral particles

Two types:

- Electromagnetic

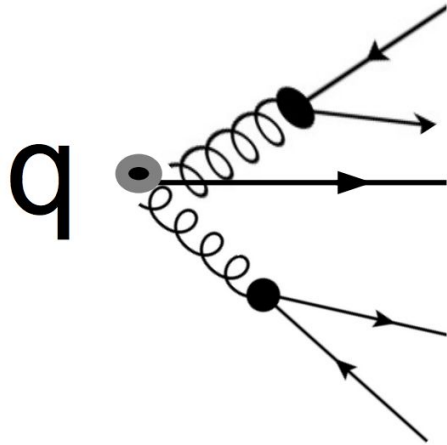
- Hadronic

Absorb + measure energy

Calorimeters are destructive detectors, unlike tracker.

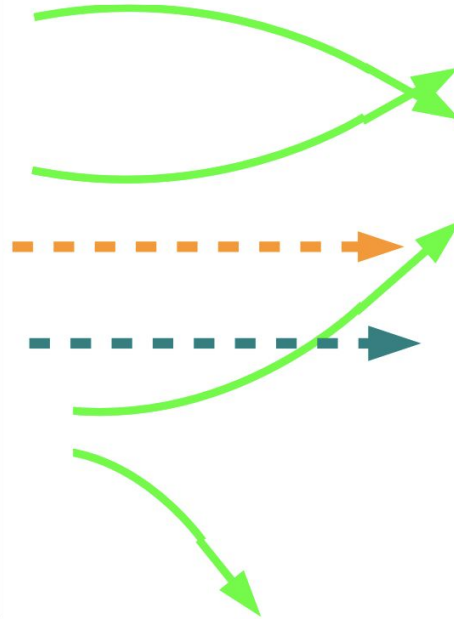
What is a jet?

Theory level



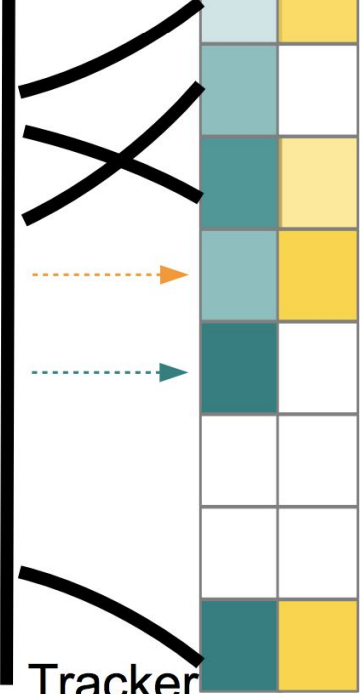
A composition of many particles originating from a quark or gluon

Particle level



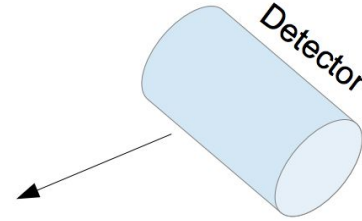
Charged Hadron
Neutral Hadron
Photon

Detector Level



Tracker

EcalHcal



Jet formation algorithm

Starts with N stable particles

$$R_{ij}^2 = (\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2$$

$$d_{ij} = \min(p_{Ti}^2, p_{Tj}^2) \frac{R_{ij}^2}{R^2}$$

$$d_{iB} = p_{Ti}^2$$

Kt algorithm

$$d_{ij} = \min\left(\frac{1}{p_{Ti}^2}, \frac{1}{p_{Tj}^2}\right) \frac{R_{ij}^2}{R^2}$$

$$d_{iB} = \frac{1}{p_{Ti}^2}$$

Anti-Kt algorithm

$$d_{ij} = \frac{R_{ij}^2}{R^2}$$

$$d_{iB} = 1$$

Cambridge Aachen algorithm

Find the minimum of $\{d_{ij}, d_{iB}\}$ for the entire set of N particles

If some d_{ij} is minimum \Rightarrow combine i and j particle into one particle (number of particle is reduced to N-1)

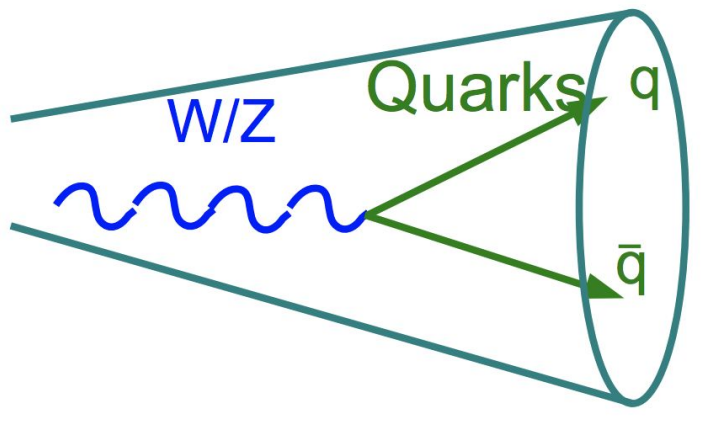
If some d_{iB} is minimum $\Rightarrow i^{th}$ particle is declared as a jet and removed from the list

AK4 is a popular choice. Anti-kT, with cone size=0.4

Jet substructure

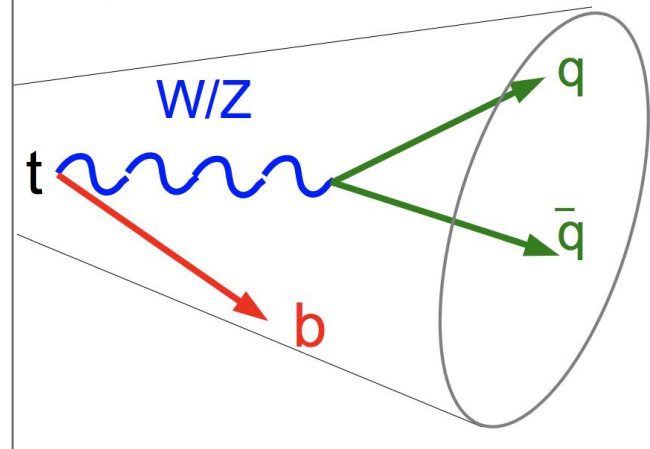
Large-radius jet (also called fat-jet).

V Boson Jet



2 sub-jets

Top Jet



3 sub-jets

The term **boosted** applies to particles with $p_T > 2 \cdot \text{mass}$.

The opening angle of the decay products is:

$$\Delta R = \frac{2m}{p_T}$$

For $H \rightarrow b\bar{b}$ to be captured in a AK8 jet (jet cone of radius 0.8)

$0.8 = 2 \cdot 125 / p_T$, where Higgs mass ~ 125 GeV

$\Rightarrow p_T = 2 \cdot 125 / 0.8 \sim 312$ GeV \rightarrow Higgs p_T have to be this high or more.

For top to be captured in a AK10 jet (jet cone of radius 1.0)

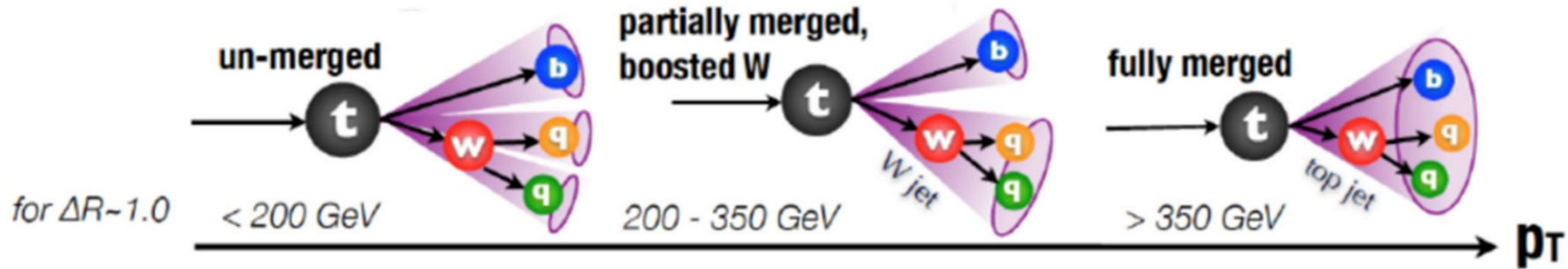
$1.0 = 2 \cdot 173 / p_T$, where top mass ~ 173 GeV

$\Rightarrow p_T = 2 \cdot 173 / 1.0 \sim 346$ GeV \rightarrow Top p_T have to be this high or more.

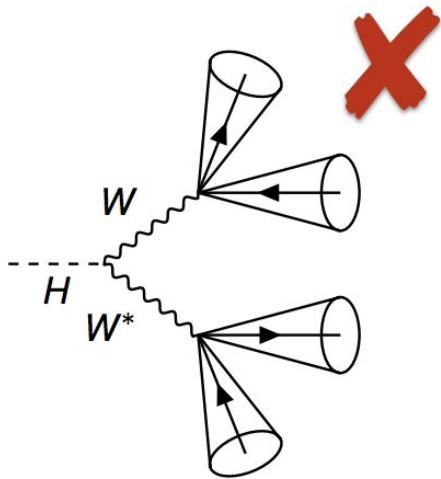
For top to be captured in a AK10 jet (jet cone of radius 1.0)

$1.0 = 2 \cdot 173 / p_T$, where top mass ~ 173 GeV

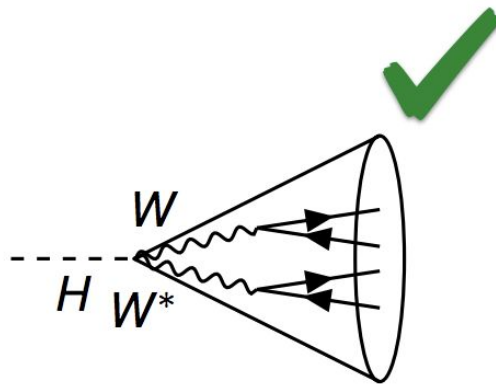
$\Rightarrow p_T = 2 \cdot 173 / 1.0 \sim 346$ GeV \rightarrow Top p_T have to be this high or more.



Another example: $H \rightarrow WW^* \rightarrow 4q$ tagging



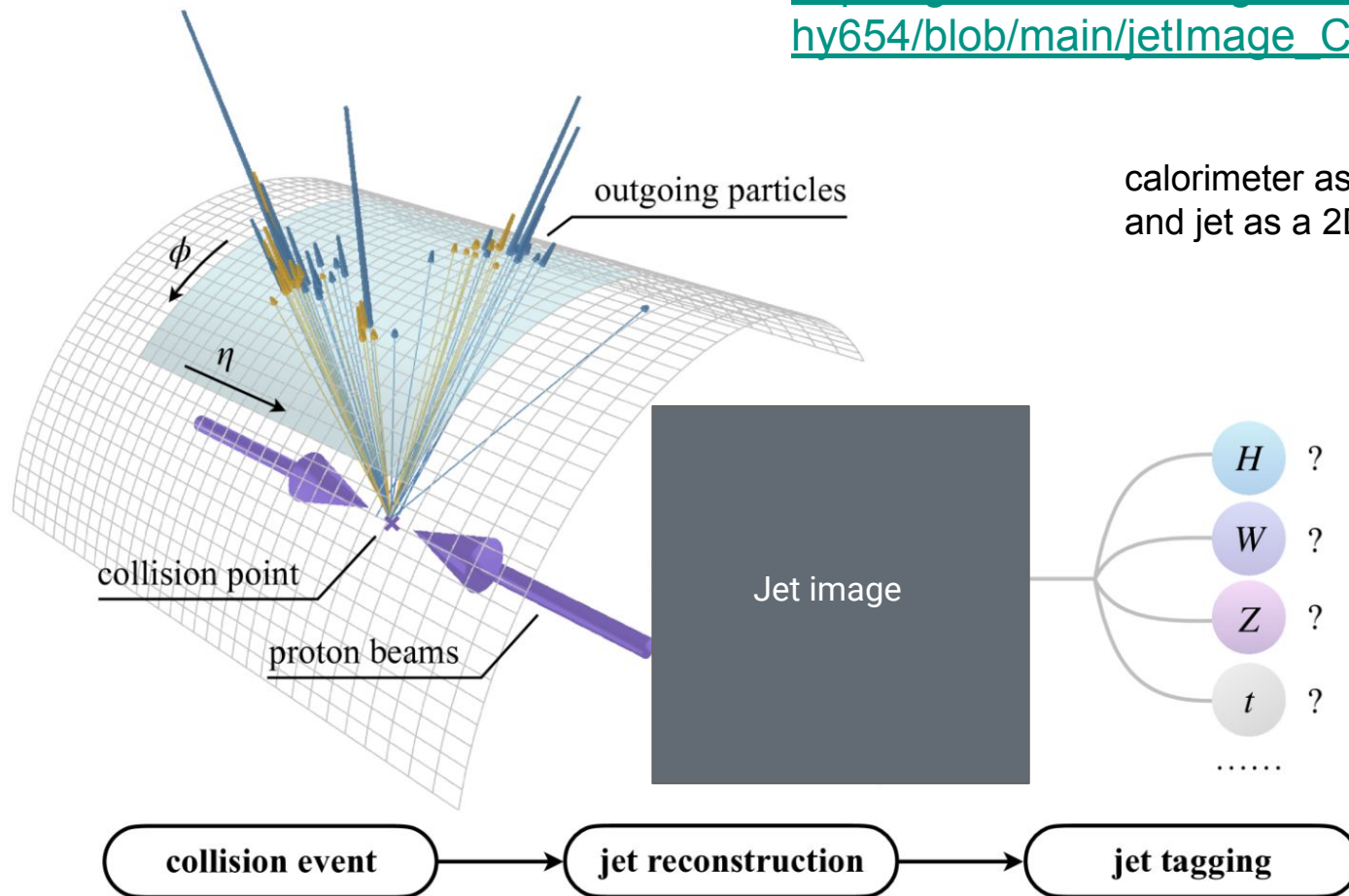
**Overwhelming
background**



Potentially useful

Jet as an image?

Coming back to the CNN code (jet images):
https://github.com/swagata87/IITKanpurPhy654/blob/main/jetImage_CNN.ipynb



References

- CERN summer school lectures
 - <https://indico.cern.ch/category/345/>
- Lectures on Collider Physics by Biplob Bhattacharjee (IISc Bengaluru) in Sangam school at HRI, 2024.
 - <https://www.hri.res.in/~sangam/sangam24/lectures/BB/collider1.pdf>
 - <https://www.hri.res.in/~sangam/sangam24/lectures/BB/collider2.pdf>
 - <https://www.hri.res.in/~sangam/sangam24/lectures/BB/collider3.pdf>

Where do we use ML in High energy physics?

<https://iml-wg.github.io/HEPML-LivingReview/>

Regression



Pileup



Calibration



Recasting



Matrix elements



Parameter estimation



Parton Distribution Functions (and related)



Lattice Gauge Theory



Function Approximation

Formal Theory and ML



Theory and physics for ML



ML for theory

Reviews



Modern reviews



Specialized reviews



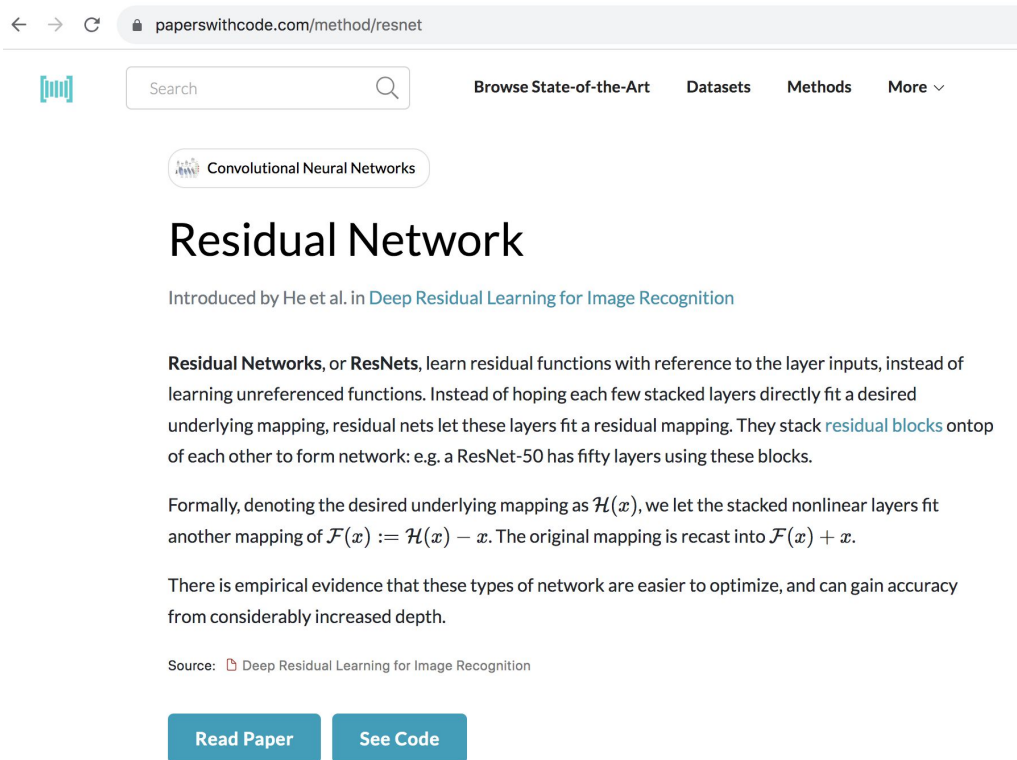
Classical papers



Datasets

Another useful website

<https://paperswithcode.com/>



The screenshot shows the website paperswithcode.com/method/resnet. The navigation bar includes a search bar, "Browse State-of-the-Art", "Datasets", "Methods", and a "More" dropdown. A category filter for "Convolutional Neural Networks" is active. The main heading is "Residual Network", followed by the text "Introduced by He et al. in [Deep Residual Learning for Image Recognition](#)". The body text explains that Residual Networks (ResNets) learn residual functions with reference to the layer inputs, instead of learning unreferenced functions. It states that residual nets let these layers fit a residual mapping by stacking residual blocks. A formal definition is provided: denoting the desired underlying mapping as $\mathcal{H}(x)$, the stacked nonlinear layers fit another mapping of $\mathcal{F}(x) := \mathcal{H}(x) - x$. The original mapping is recast into $\mathcal{F}(x) + x$. It concludes that there is empirical evidence that these types of network are easier to optimize and can gain accuracy from considerably increased depth. The source is cited as "Deep Residual Learning for Image Recognition". At the bottom, there are two buttons: "Read Paper" and "See Code".

paperswithcode.com/method/resnet

Search

Browse State-of-the-Art Datasets Methods More ▾

Convolutional Neural Networks

Residual Network

Introduced by He et al. in [Deep Residual Learning for Image Recognition](#)

Residual Networks, or **ResNets**, learn residual functions with reference to the layer inputs, instead of learning unreferenced functions. Instead of hoping each few stacked layers directly fit a desired underlying mapping, residual nets let these layers fit a residual mapping. They stack [residual blocks](#) on top of each other to form network: e.g. a ResNet-50 has fifty layers using these blocks.

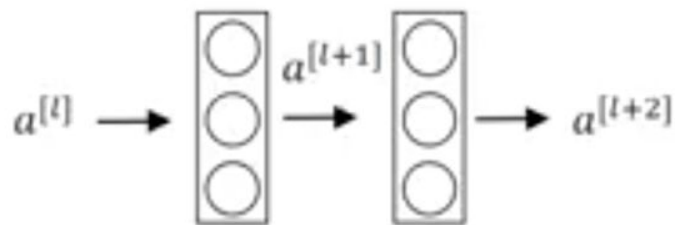
Formally, denoting the desired underlying mapping as $\mathcal{H}(x)$, we let the stacked nonlinear layers fit another mapping of $\mathcal{F}(x) := \mathcal{H}(x) - x$. The original mapping is recast into $\mathcal{F}(x) + x$.

There is empirical evidence that these types of network are easier to optimize, and can gain accuracy from considerably increased depth.

Source: [Deep Residual Learning for Image Recognition](#)

[Read Paper](#) [See Code](#)

Reminder of a neural net



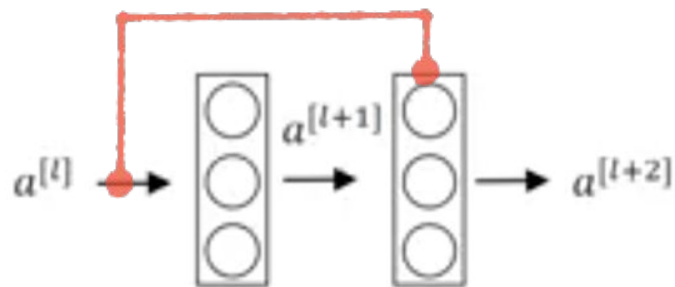
Example with 2 layers of
a neural network (NN)

$a^{[l]} \rightarrow \text{Linear} \rightarrow \text{ReLU} \rightarrow \text{Linear} \rightarrow \text{ReLU} \rightarrow a^{[l+2]}$

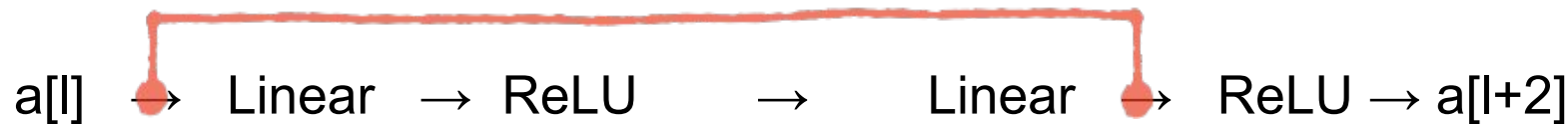
$$z^{[l+1]} = W^{[l+1]}a^{[l]} + b^{[l+1]} \quad a^{[l+1]} = g(z^{[l+1]}) \quad z^{[l+2]} = W^{[l+2]}a^{[l+1]} + b^{[l+2]} \quad a^{[l+2]} = g(z^{[l+2]})$$

For information to flow from $a^{[l]}$ to $a^{[l+2]}$ it needs to go through all of these steps in case of a usual NN.

ResNet



ResNets are built out of Residual blocks



$$z[l+1] = W[l+1]a[l] + b[l+1]$$

$$a[l+1] = g(z[l+1])$$

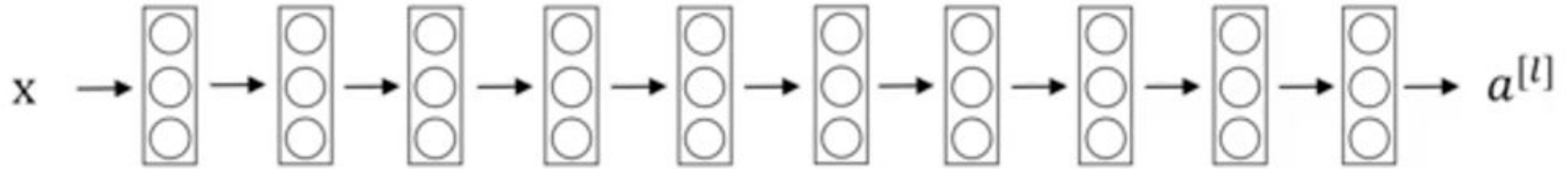
$$z[l+2] = W[l+2]a[l+1] + b[l+2]$$

~~$$a[l+2] = g(z[l+2])$$~~

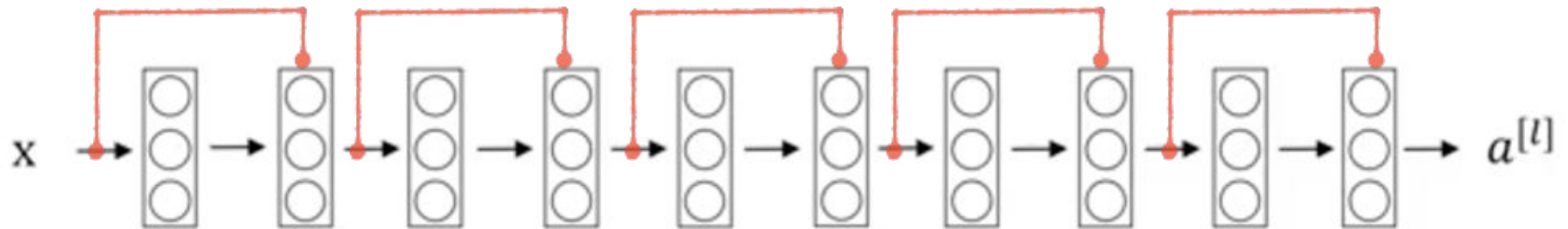
$$a[l+2] = g(z[l+2]) + a[l]$$

ResNet

Take many residual blocks and stack them together to build a ResNet.

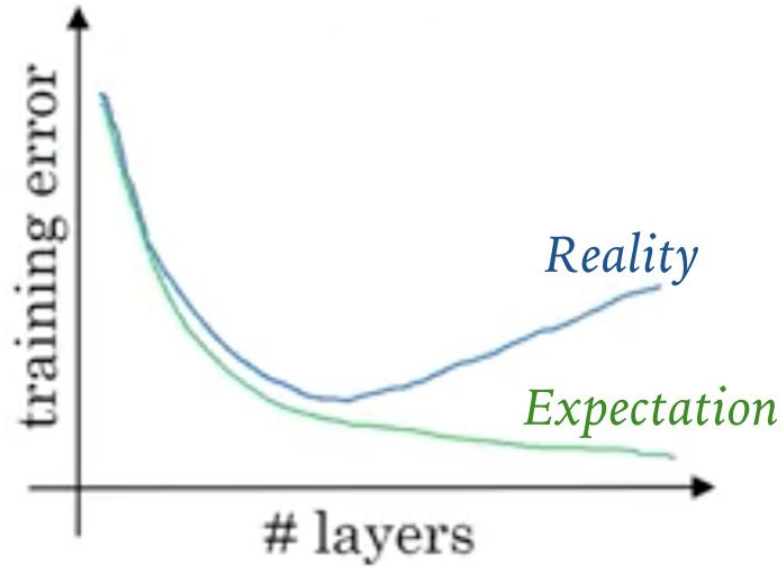


Plain Network

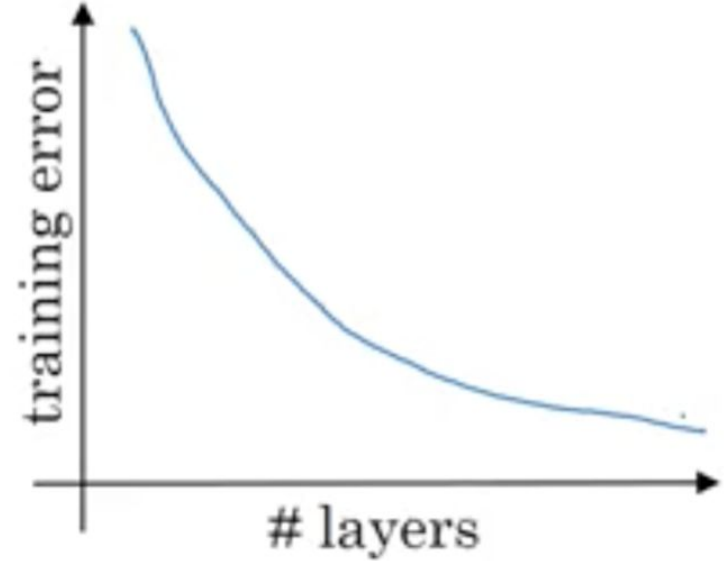


ResNet

Plain network



ResNet



Deep Residual Learning for Image Recognition, Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, <https://arxiv.org/pdf/1512.03385.pdf>