

Exercises

Introduction and practical details

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Enable internet connection

- 1) Go to session options
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Exercise 1 - Jet tagging with neural networks

+ Code

+ Markdown

A first look at training deep neural networks to classify jets in proton-proton collisions.

Learning objectives

- Understand what jet tagging is and how to frame it as a machine learning task
- Understand the main steps needed to train and evaluate a jet tagger
- Learn how to download and process data with the 🍌 Datasets library
- Gain an introduction to the fastai library and how to push models to the Hugging Face Hub

References

- Chapter 1 of [Deep Learning for Coders with fastai & PyTorch](#) by Jeremy Howard and Sylvain Gugger.
- [The Machine Learning Landscape of Top Taggers](#) by G. Kasieczka et al.
- [How Much Information is in a Jet?](#) by K. Datta and A. Larkowski.



Session options

ACCELERATOR

None

LANGUAGE

Python

PERSISTENCE

No persistence

ENVIRONMENT

Pin to original environment

You won't get new packages, but your code is less likely to break. [What is a notebook environment?](#)

INTERNET



Internet on

TAGS

Add Tags

(Optional) Weights and biases

1) Go to: <https://wandb.ai/site>

2) Login instructions: need to copy the API key when asked


Quickstart: Tracking your first run in Weights & Biases

Weights & Biases' tools make it easy for you to quickly track experiments, visualize results, spot regressions, and more. Simply put, Weights & Biases enables you to build better models faster and easily share findings with colleagues.

Visualize your model training with

 Python /  PyTorch ▼

or

 Open in Colab

1. Set up the wandb library

Install the CLI and Python library for interacting with the Weights and Biases API.

```
pip install wandb
```

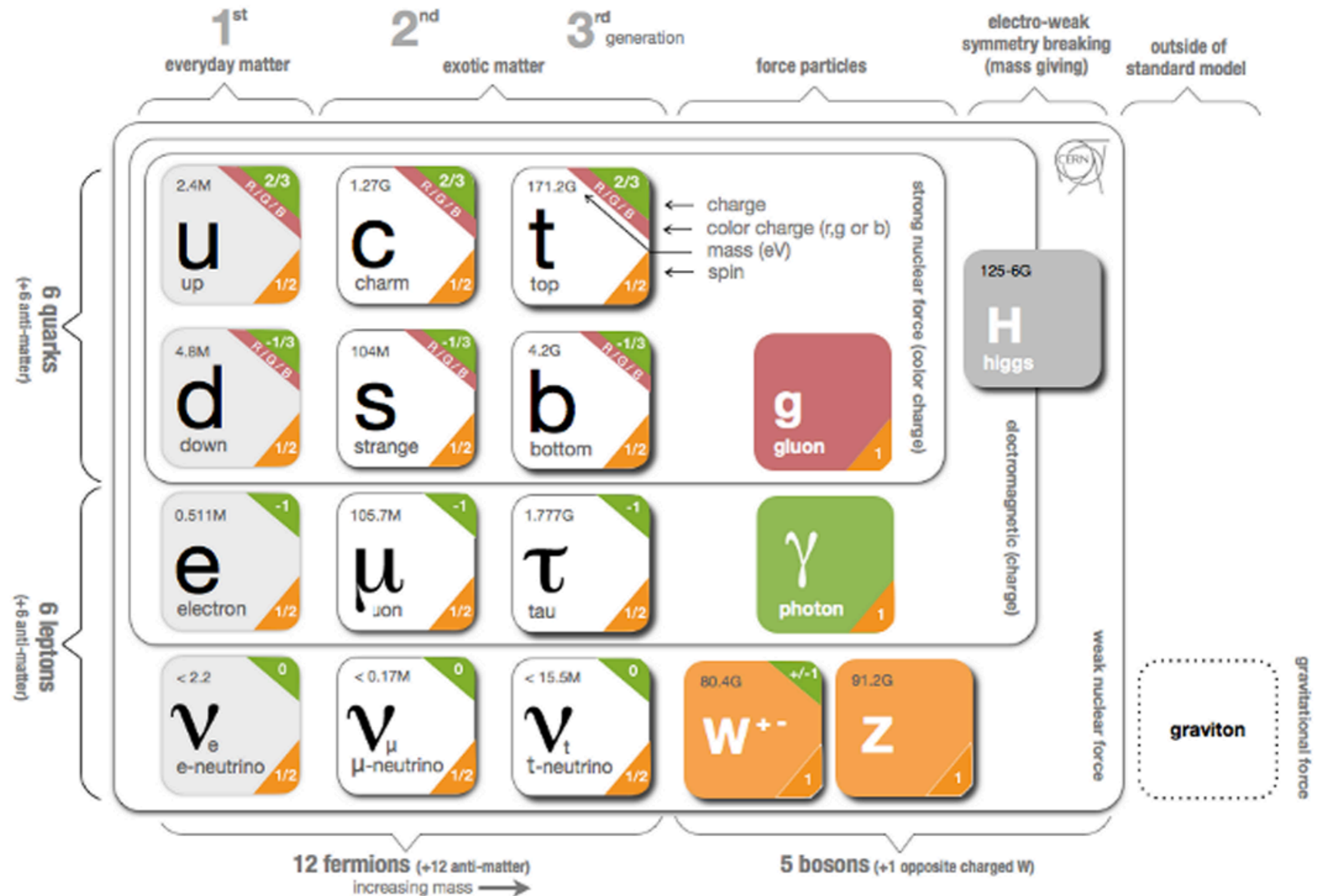
Next, log in and paste your API key when prompted.

```
wandb login
```

Particle Tagging

What is it and why is it important?

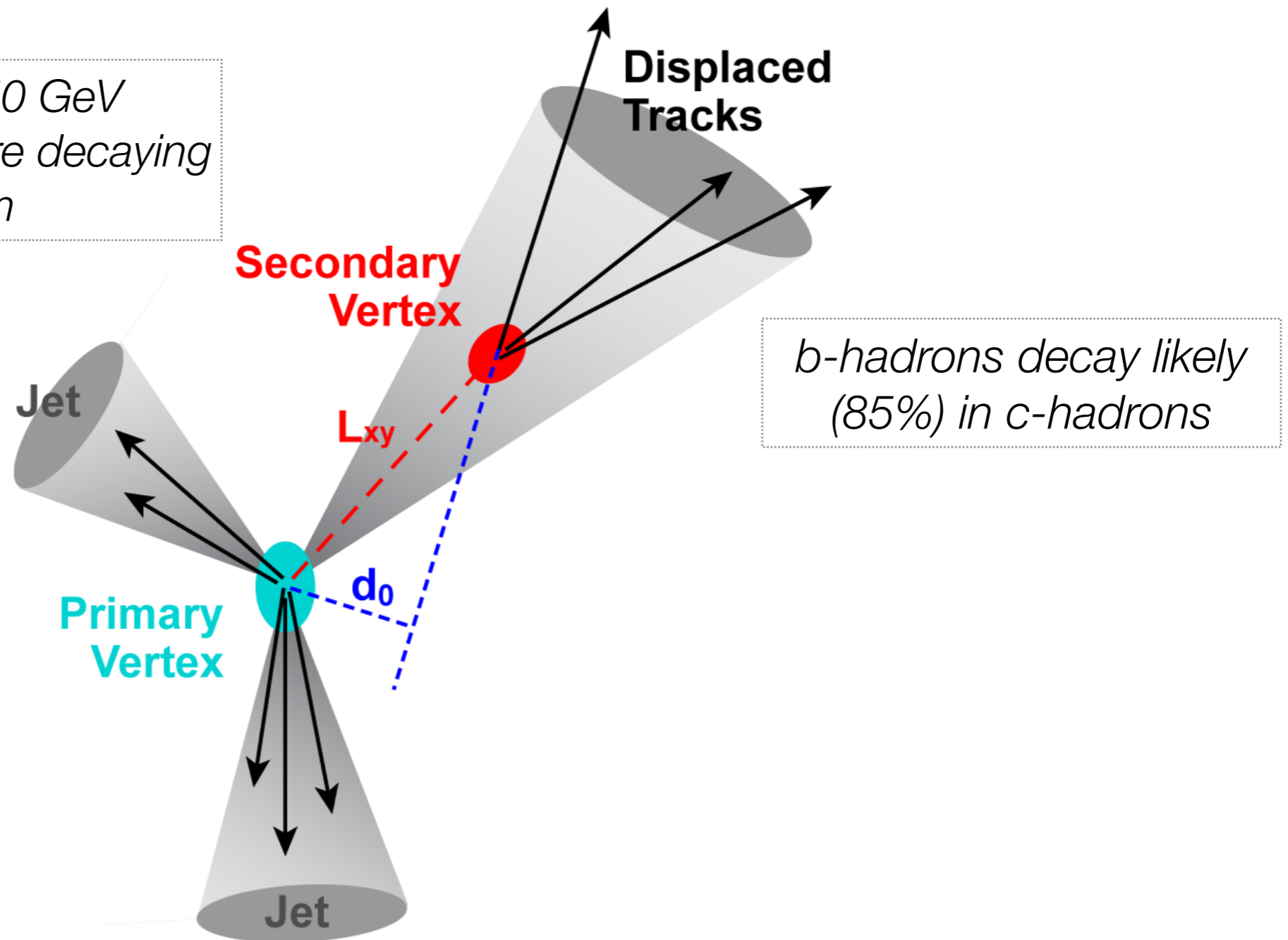
The standard model



Flavour tagging

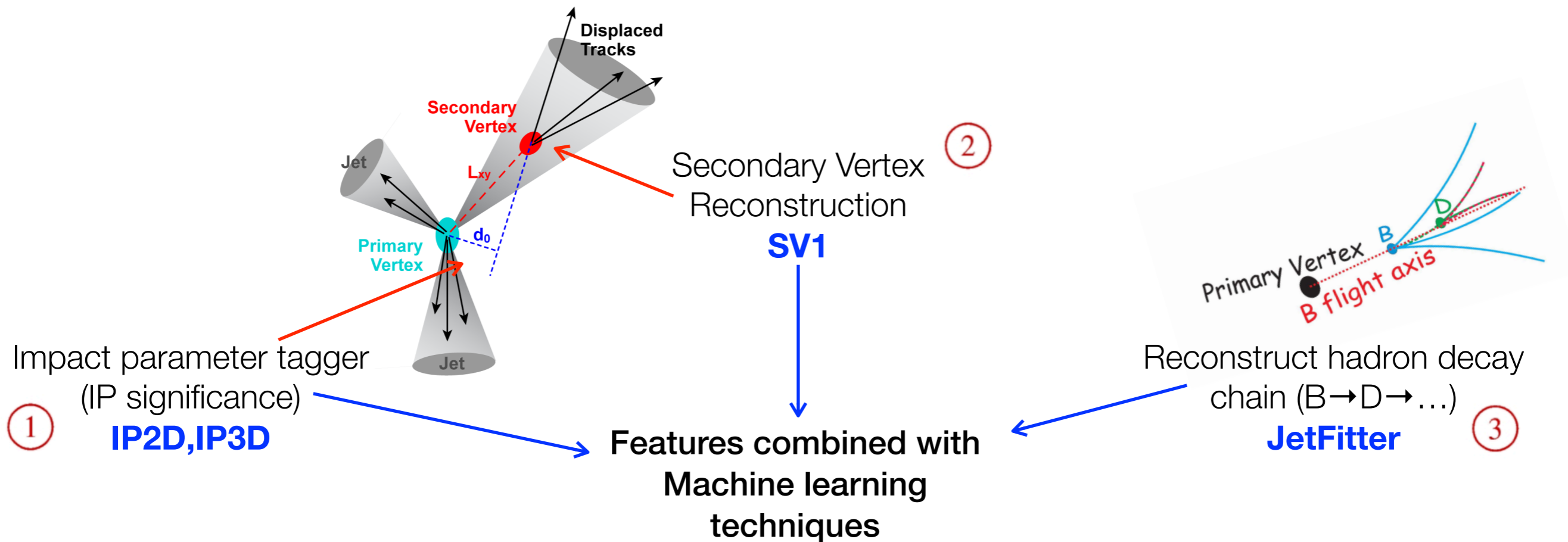
b-tagging: Separate b-jets from light (u,d,s,g) and c-jets using specific b-hadron properties

*b-hadron @ 50 GeV
flies few mm before decaying
 $c\tau \sim 3\text{mm}$*



Flavour tagging

b-tagging: Separate b-jets from light (u,d,s,g) and c-jets using specific b-hadron properties

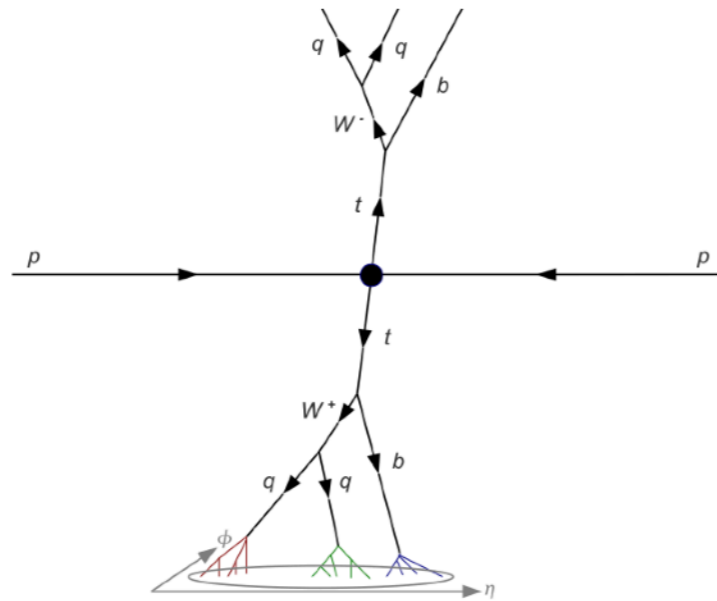


ParticleNet (CMS)

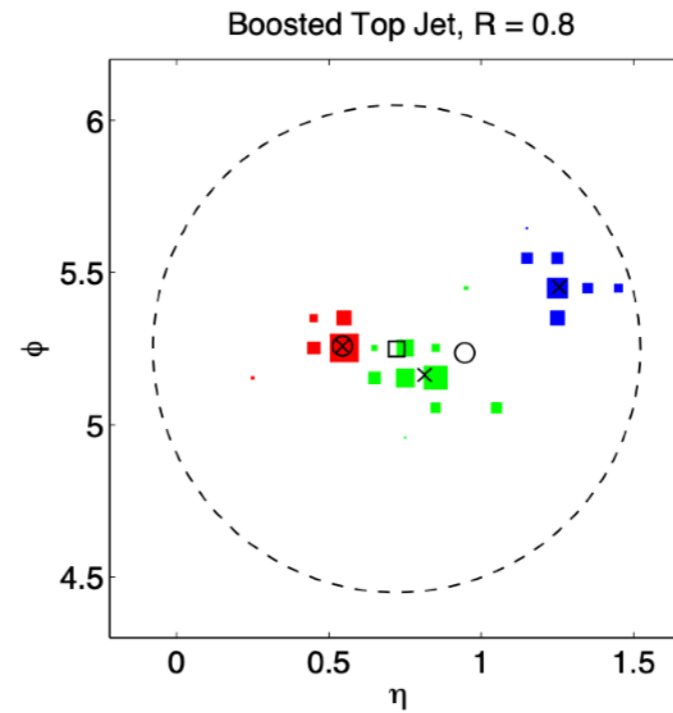
GN1 (single jet) - GN2X (boosted) (ATLAS)

Top tagging

top-tagging: identify boosted top-jets topologies

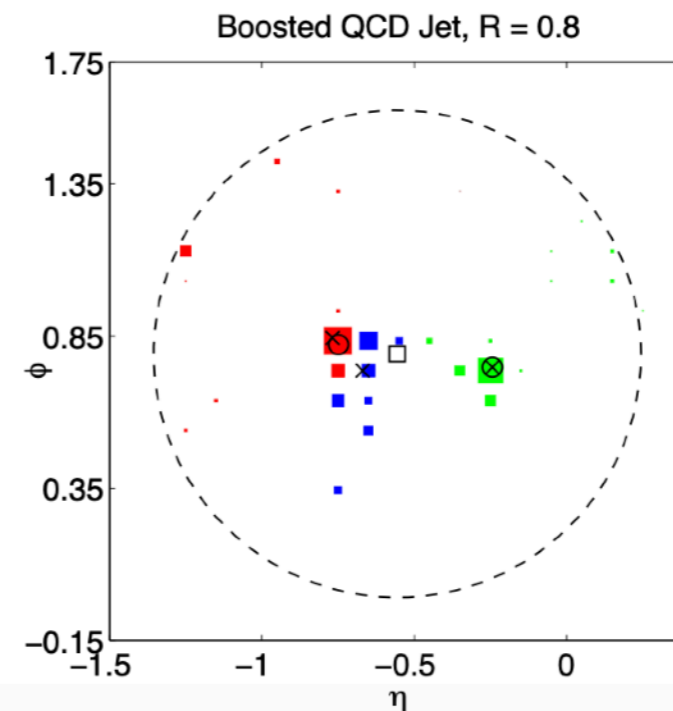
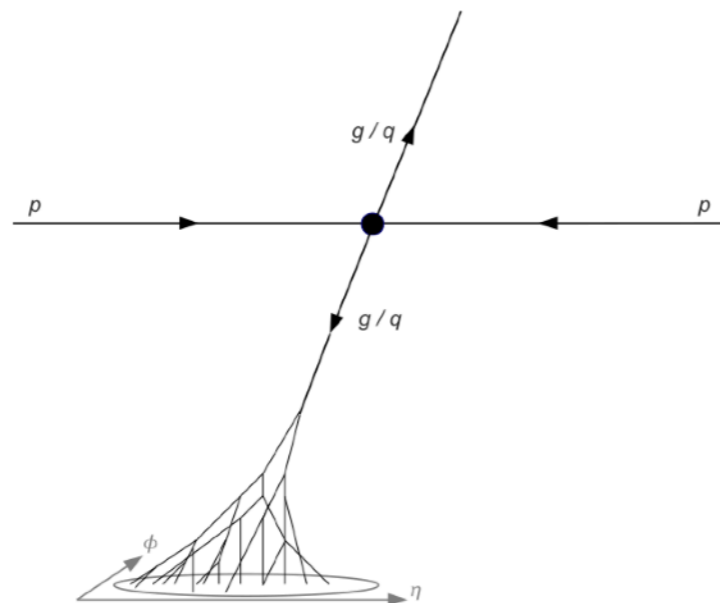


(a)



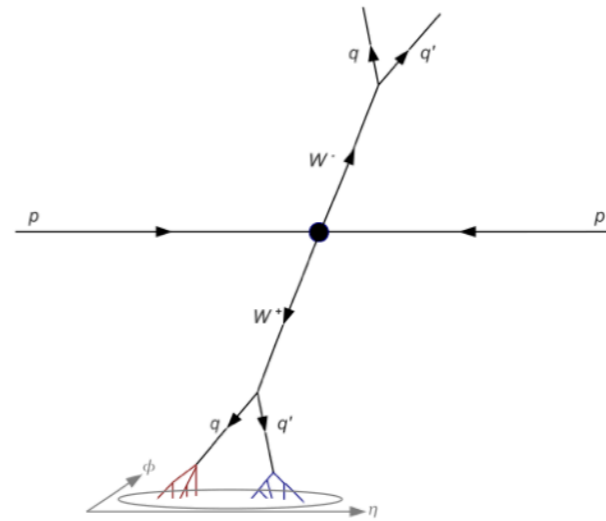
(b)

n-subjectiness

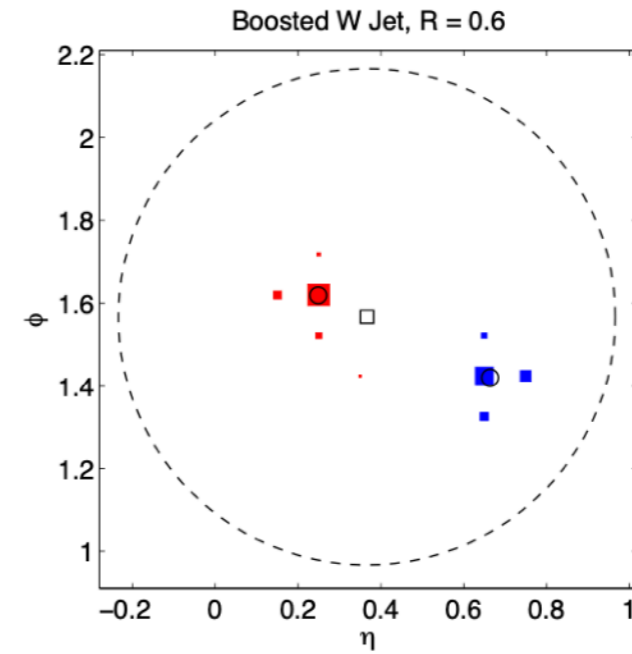


Top tagging

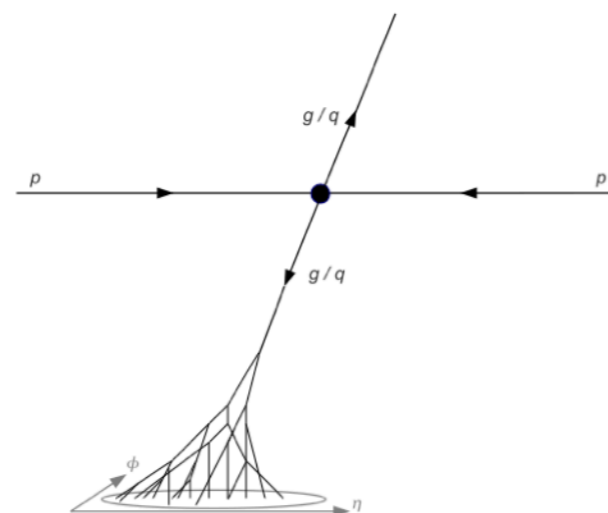
Other backgrounds



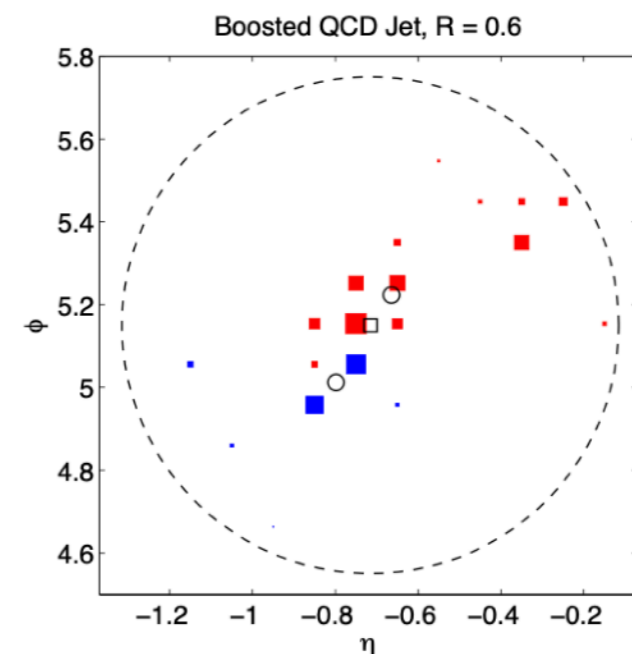
(a)



(b)



(c)



(d)

n-subjectiness

ATLAS: top taggers

Tagger	Number of parameters	Inference time
h1DNN	133,381	3 ms
DNN	876,641	3 ms
EFN	959,251	4 ms
PFN	754,501	3 ms
ResNet 50	1,499,585	20 ms
ParticleNet	764,887	143 ms

Accuracies

Tagger	AUC	ACC	ε_{bkg}^{-1} @ $\varepsilon_{sig} = 0.5$	ε_{bkg}^{-1} @ $\varepsilon_{sig} = 0.8$
ResNet 50	0.872 ± 0.006	0.787 ± 0.006	18.4 ± 1.1	4.63 ± 0.2
EFN	0.894 ± 0.001	0.810 ± 0.001	23.8 ± 0.5	5.74 ± 0.07
hIDNN	0.9374 ± 0.0001	0.8628 ± 0.0002	47.2 ± 0.4	10.36 ± 0.03
DNN	0.9447 ± 0.0004	0.8715 ± 0.0008	73.0 ± 1.3	12.5 ± 0.1
PFN	0.9502 ± 0.0004	0.878 ± 0.001	92.7 ± 1.8	14.6 ± 0.2
ParticleNet	0.9614 ± 0.0005	0.895 ± 0.001	155.8 ± 3.8	20.6 ± 0.4

Performance

	AUC	Acc	$1/\epsilon_B$ ($\epsilon_S = 0.3$)			#Param
			single	mean	median	
CNN [16]	0.981	0.930	914±14	995±15	975±18	610k
ResNeXt [31]	0.984	0.936	1122±47	1270±28	1286±31	1.46M
TopoDNN [18]	0.972	0.916	295±5	382±5	378±8	59k
Multi-body N -subjettiness 6 [24]	0.979	0.922	792±18	798±12	808±13	57k
Multi-body N -subjettiness 8 [24]	0.981	0.929	867±15	918±20	926±18	58k
TreeNiN [43]	0.982	0.933	1025±11	1202±23	1188±24	34k
P-CNN	0.980	0.930	732±24	845±13	834±14	348k
ParticleNet [47]	0.985	0.938	1298±46	1412±45	1393±41	498k
LBN [19]	0.981	0.931	836±17	859±67	966±20	705k
LoLa [22]	0.980	0.929	722±17	768±11	765±11	127k
LDA [54]	0.955	0.892	151±0.4	151.5±0.5	151.7±0.4	184k
Energy Flow Polynomials [21]	0.980	0.932	384			1k
Energy Flow Network [23]	0.979	0.927	633±31	729±13	726±11	82k
Particle Flow Network [23]	0.982	0.932	891±18	1063±21	1052±29	82k
GoaT	0.985	0.939	1368±140		1549±208	35k

You are going to train your own CNN based tagger:
How does it compare to these ones?

Let's get started:

<https://iluisse.github.io/dl4phys/intro.html>