ATLAS EXPERIMENT

大阪大学 OSAKA UNIVERSITY

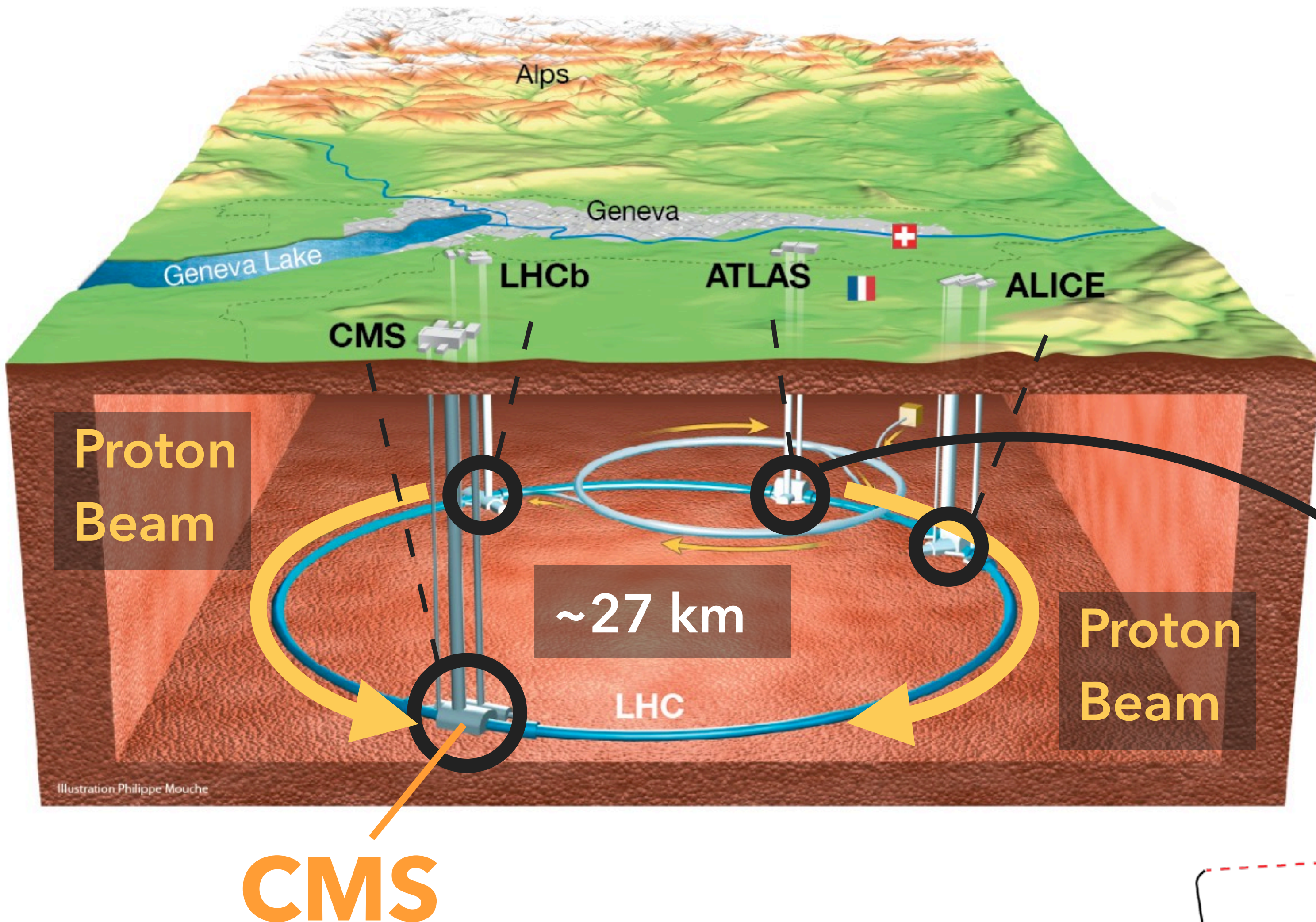
HIGH ENERGY PHYSICS YAMANAKA GROUP

Studies on Higgs to charm quark search using the LHC-ATLAS experiment

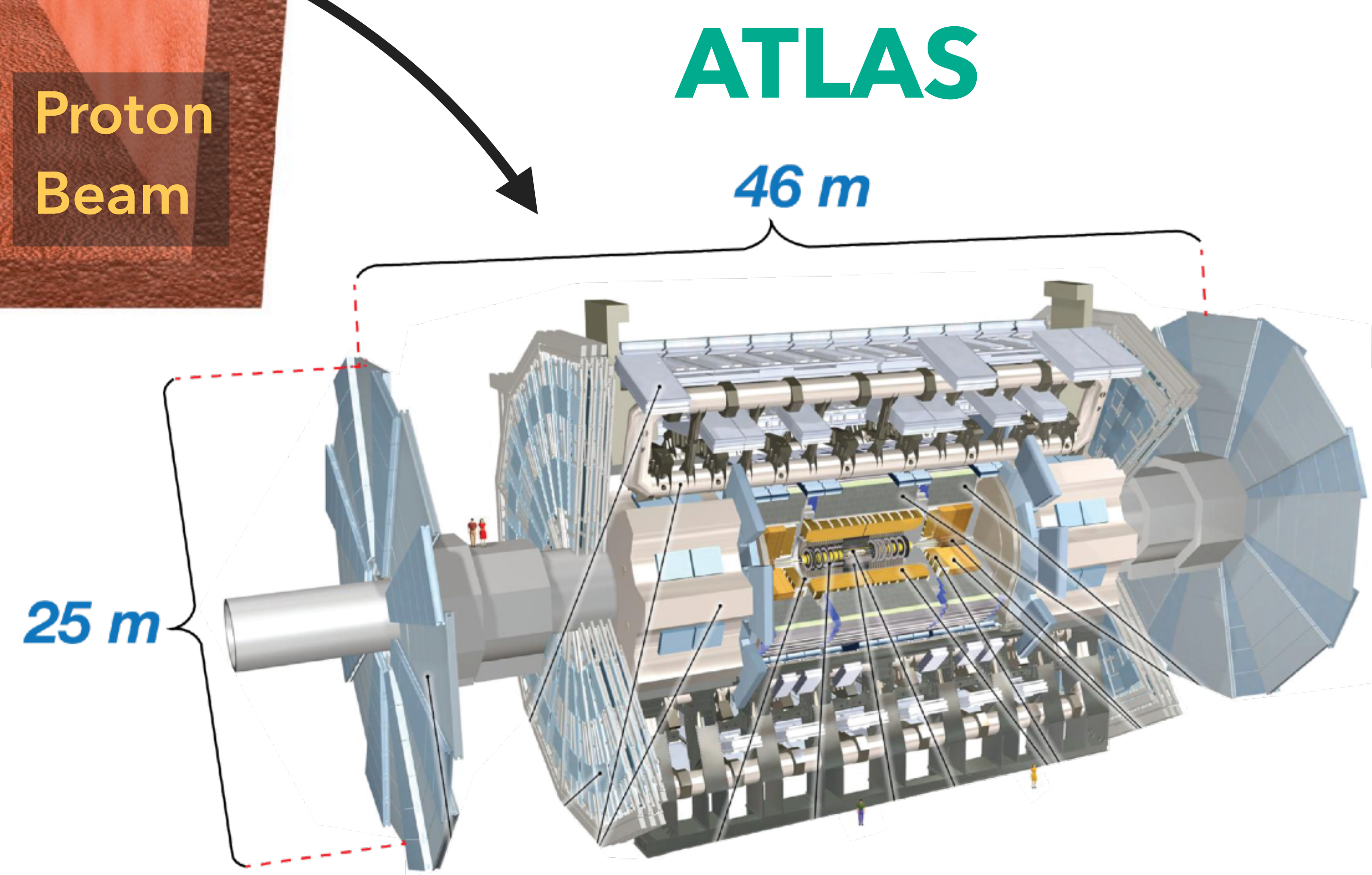
Year End Presentation - 22nd December 2022

Lakmin Wickremasinghe (D2)

ATLAS Experiment at the Large Hadron Collider



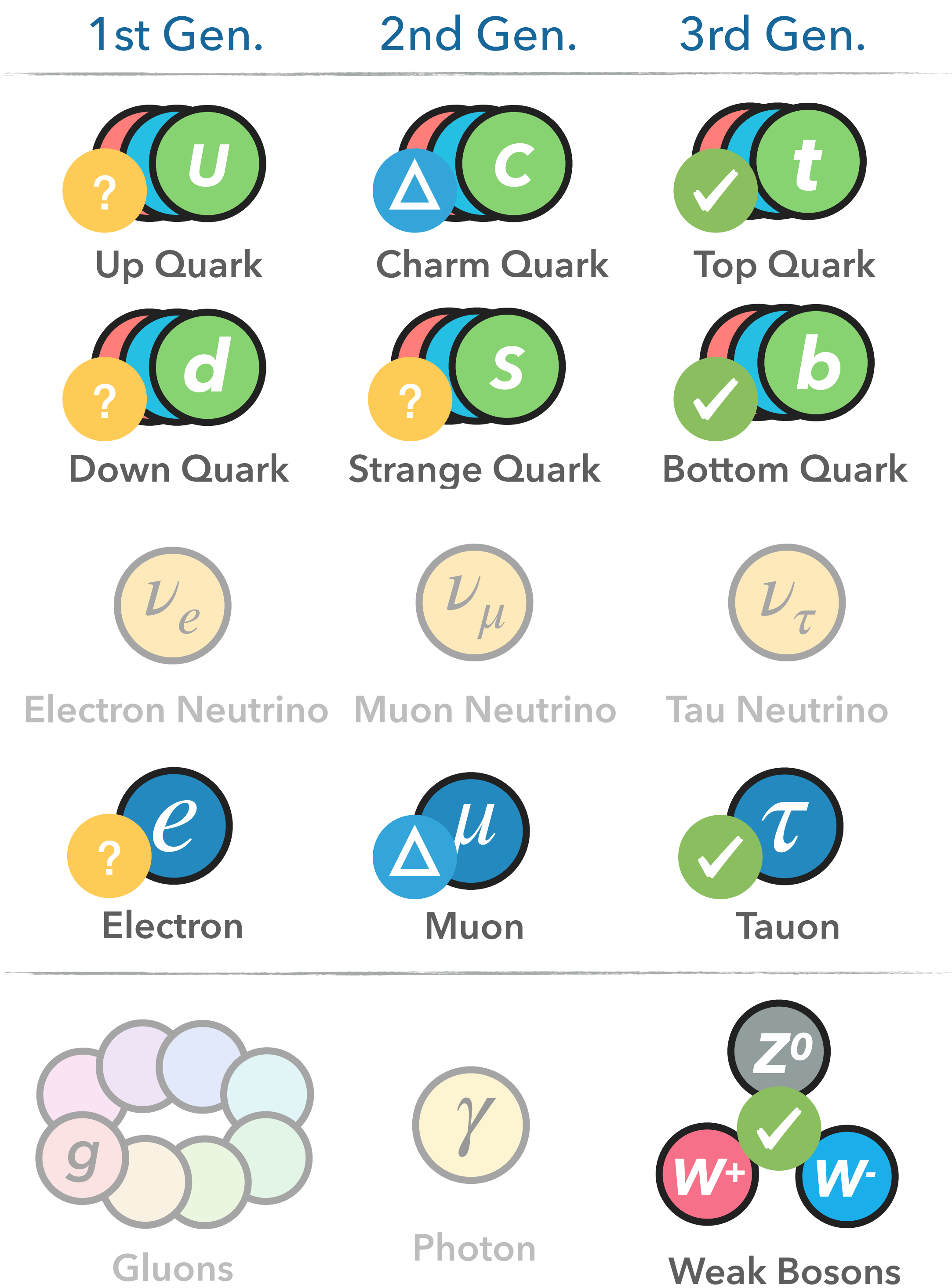
ATLAS started data taking this July (for *LHC Run 3*), after ~3 years of shutdown.



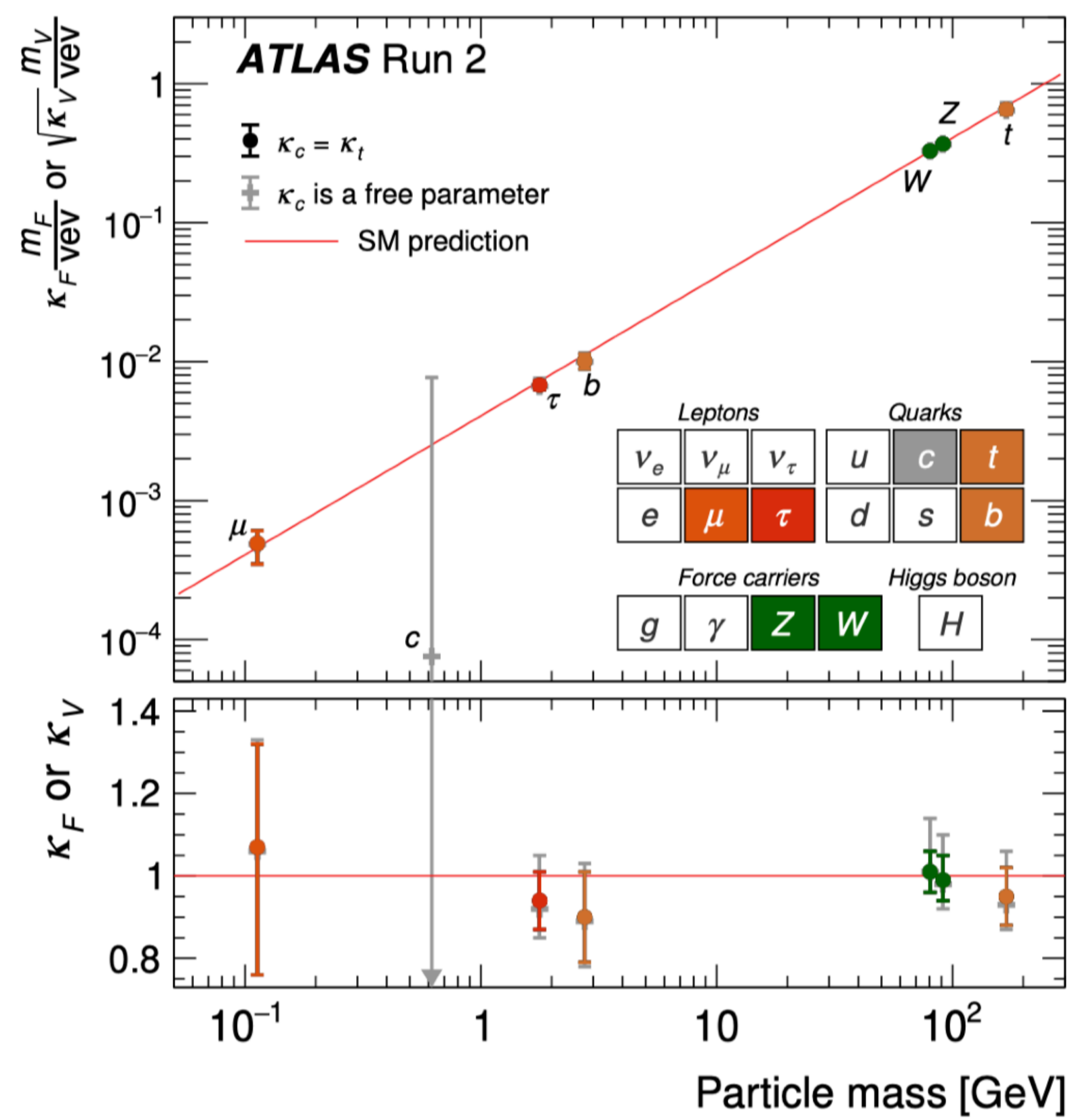
The *Higgs Boson* was discovered in 2012 by ATLAS and CMS, and this year marked the 10 year anniversary.

Higgs Boson Coupling Strength

Source- *ATL-COM-PHYS-2022-098, 10 years with the Higgs Boson: A detailed picture of it's interactions from the ATLAS experiment.*

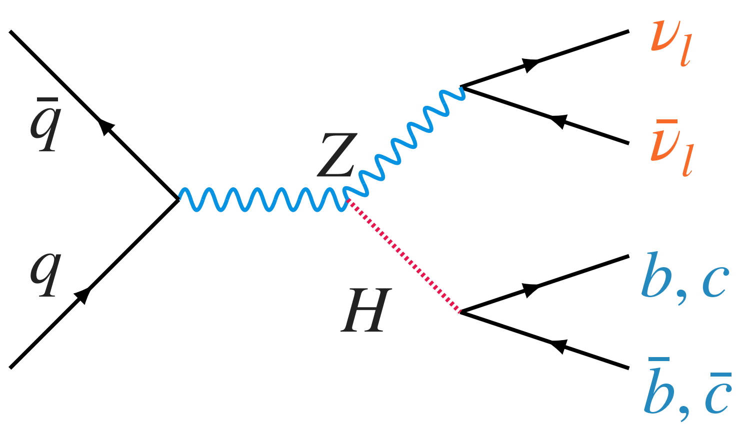


The **Higgs** to **Boson/Fermion** Coupling Strength

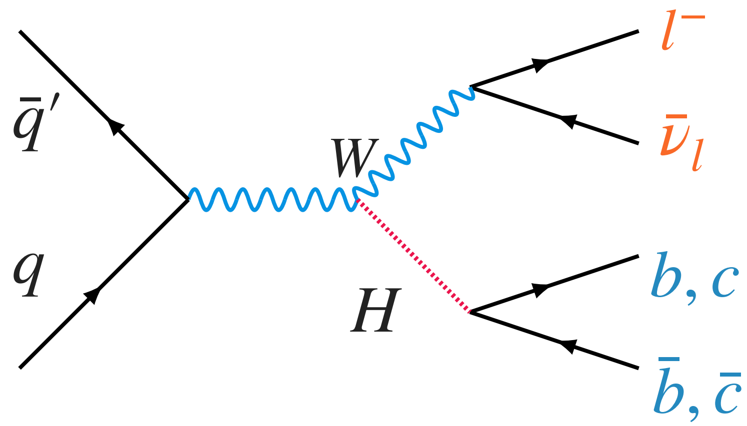


Probing the Higgs to b/c Quark coupling

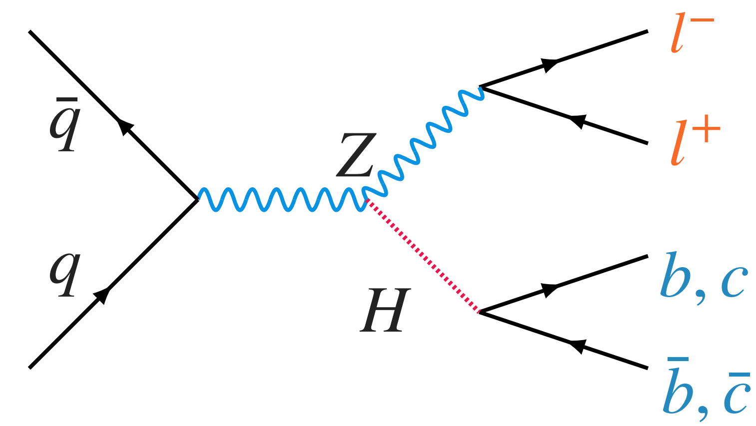
0 Charged Lepton Channel



1 Charged Lepton Channel



2 Charged Lepton Channel

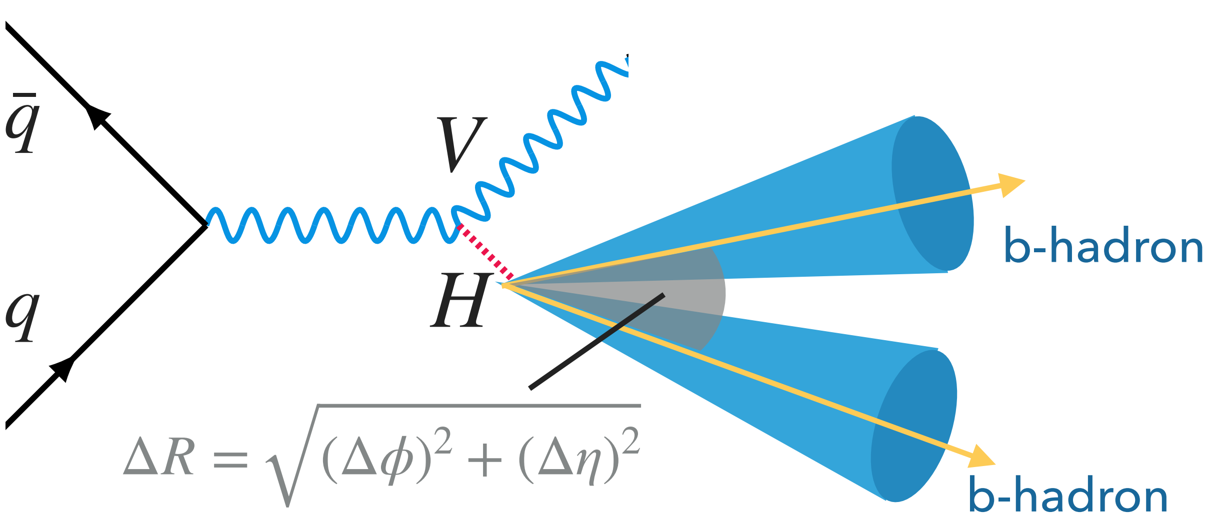


Using the Leptons as a trigger gives the best sensitivity

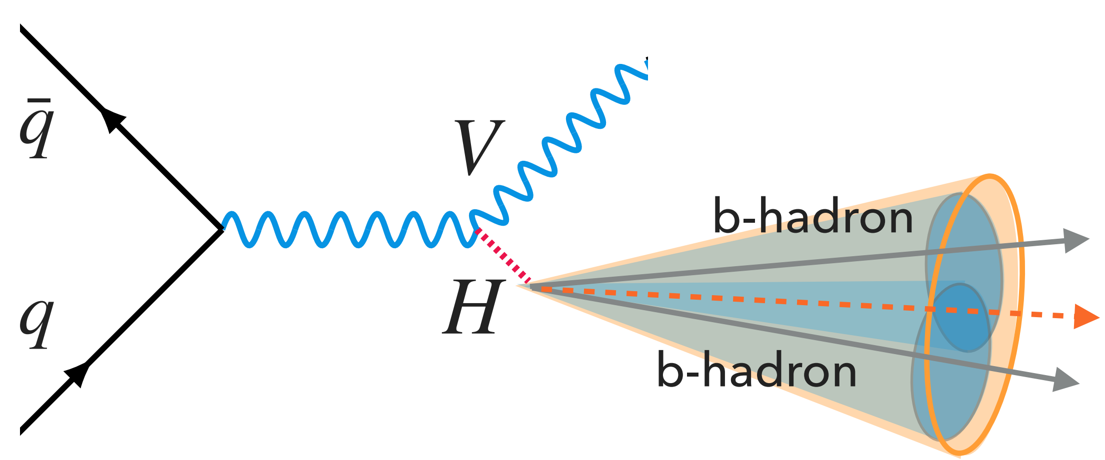
Two topologies based on the p_T of the Higgs

$$\Delta R(\overrightarrow{b}, \overrightarrow{b}) \approx \frac{2m_H}{p_T^H}$$

Resolved *(Low p_T^H)*



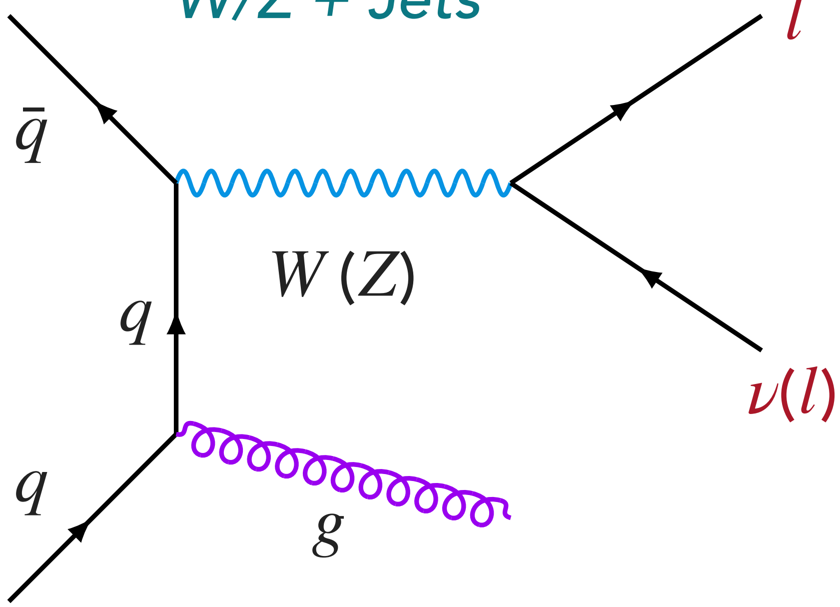
Boosted *(High p_T^H)*



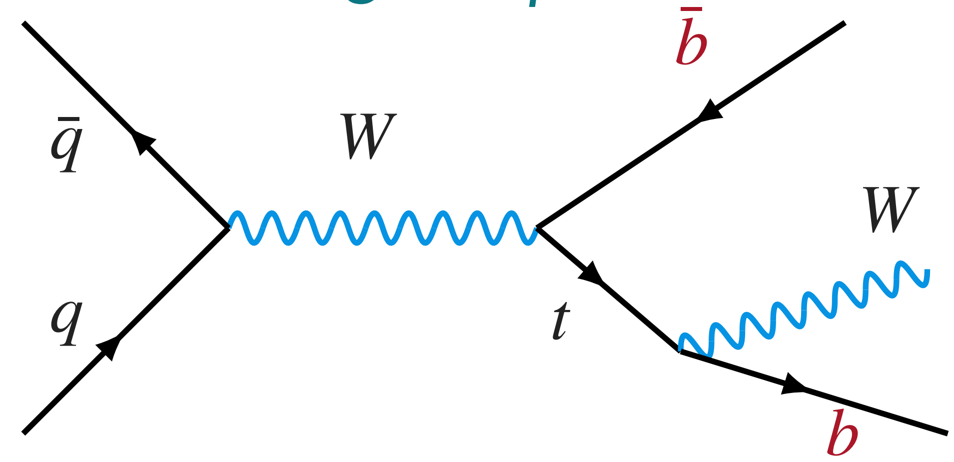
Backgrounds

There are 5 main backgrounds

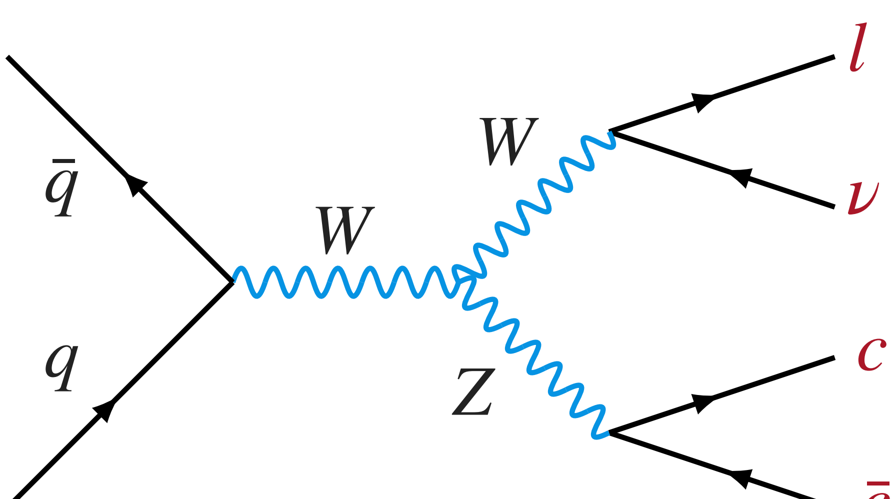
W/Z + Jets



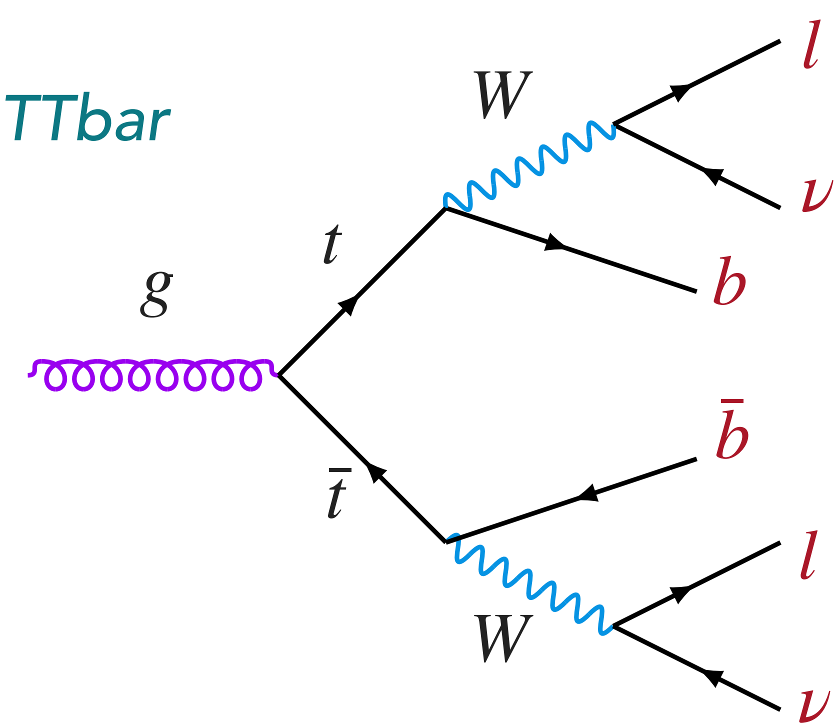
Single Top



DiBoson



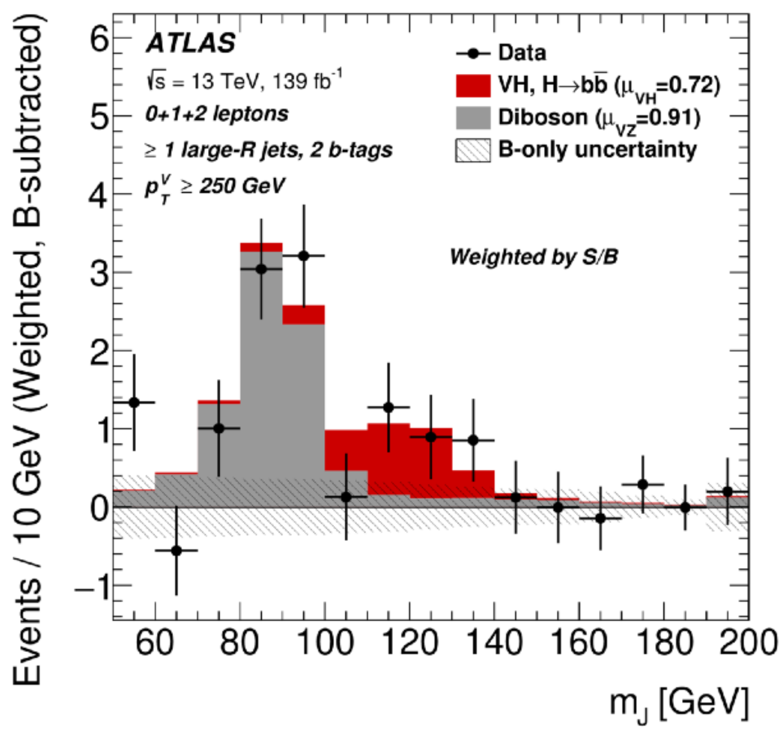
TTbar



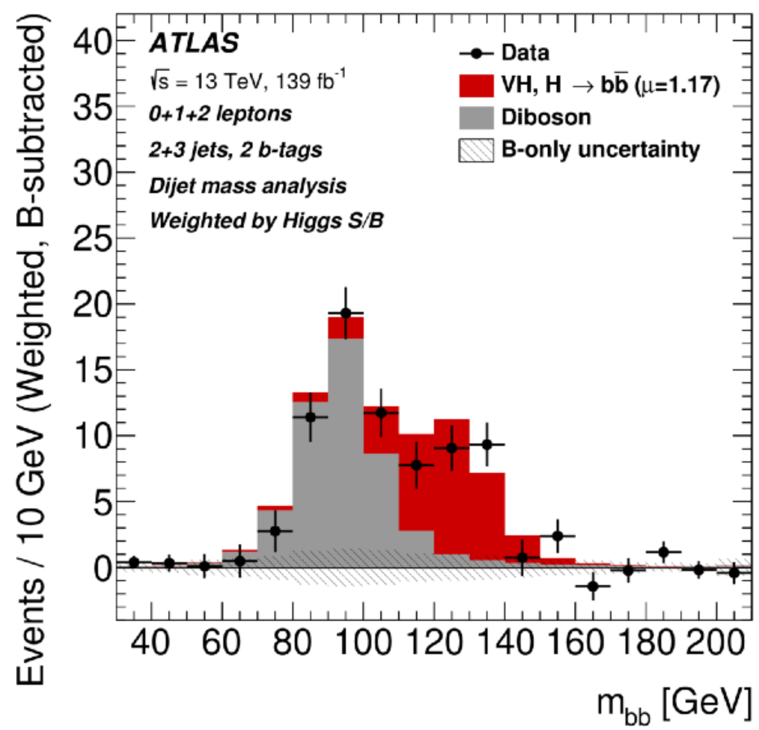
THE VH, H→bb AND VH, H→cc ANALYSES

So far we had 3 independent analysis using the *full Run-2 data set,*

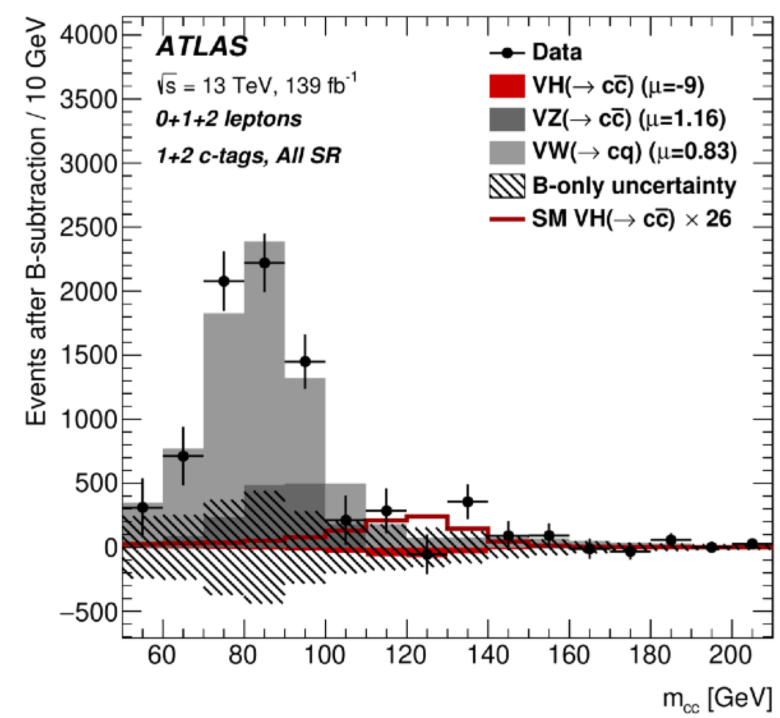
VHbb Boosted (paper)

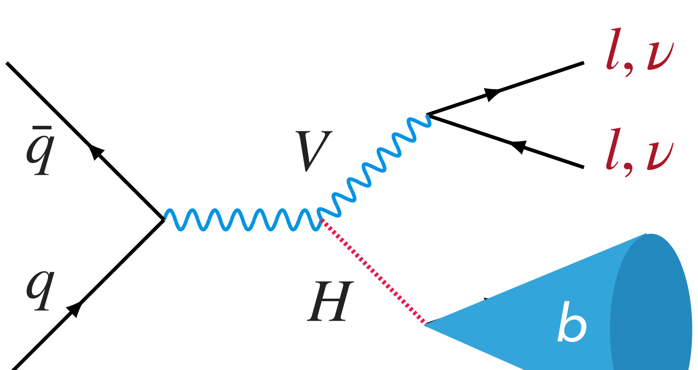


VHbb Resolved (paper)

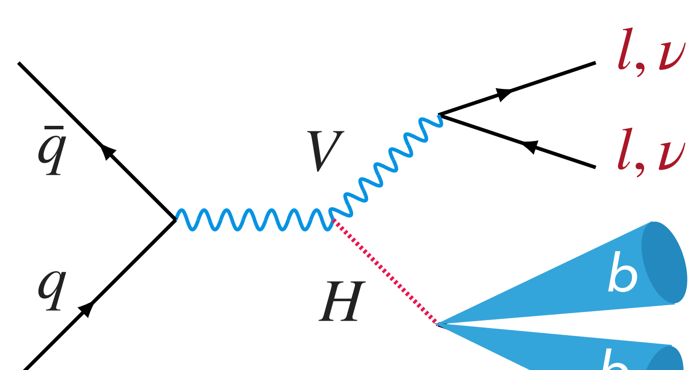


VHcc (paper)

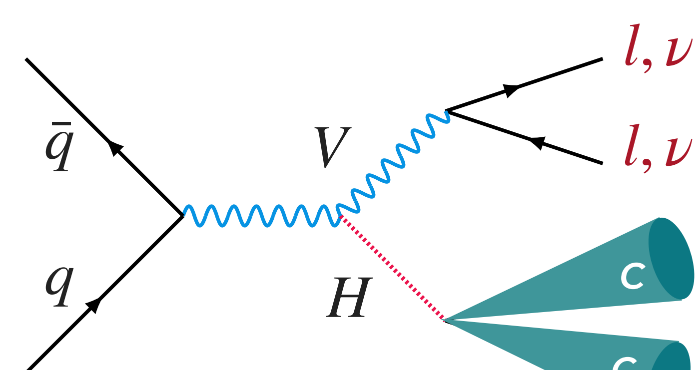




1 large radius b-jet



2 small radius b-jets

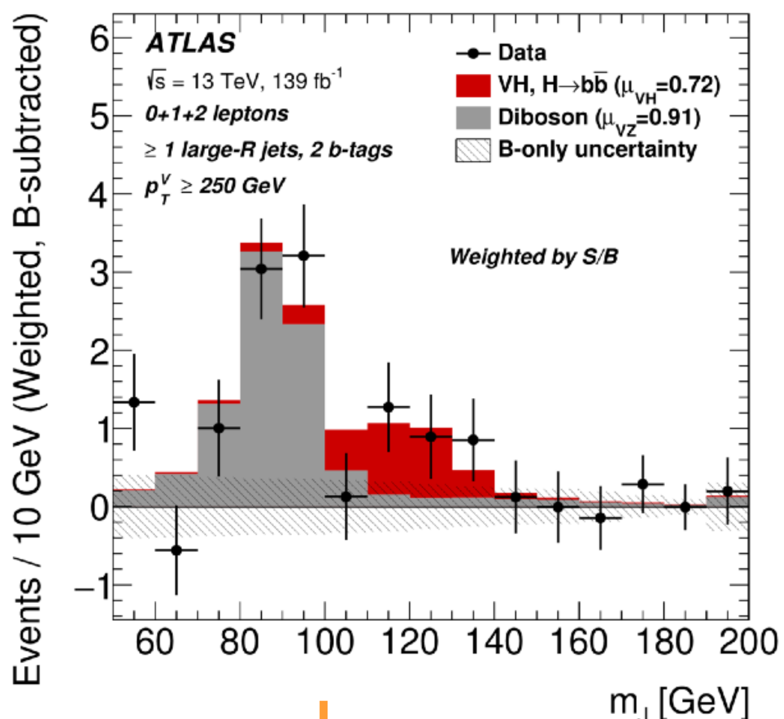


2 small radius c-jets

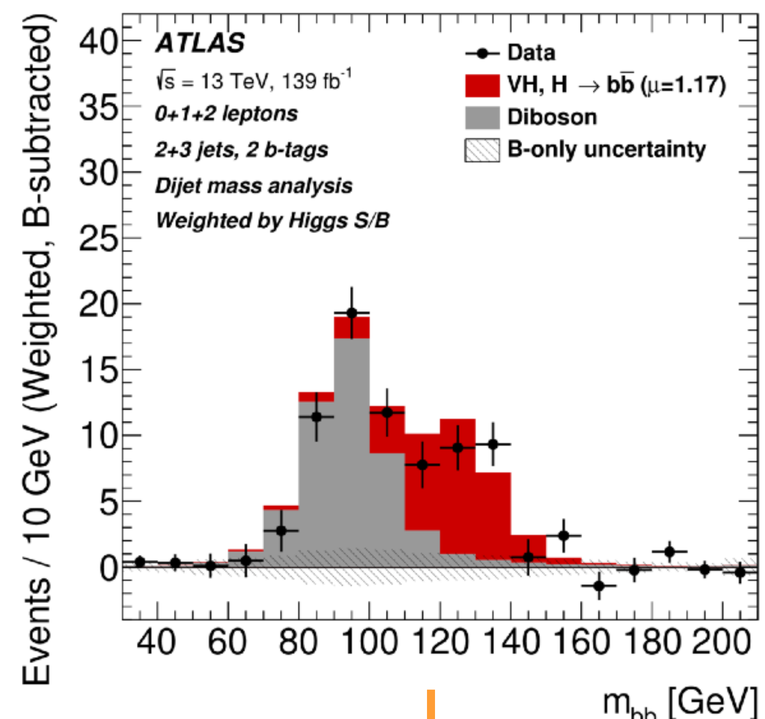
THE VH, H⟶bb AND VH, H⟶cc ANALYSES

And right now we're aiming for 3 ➡ 1,

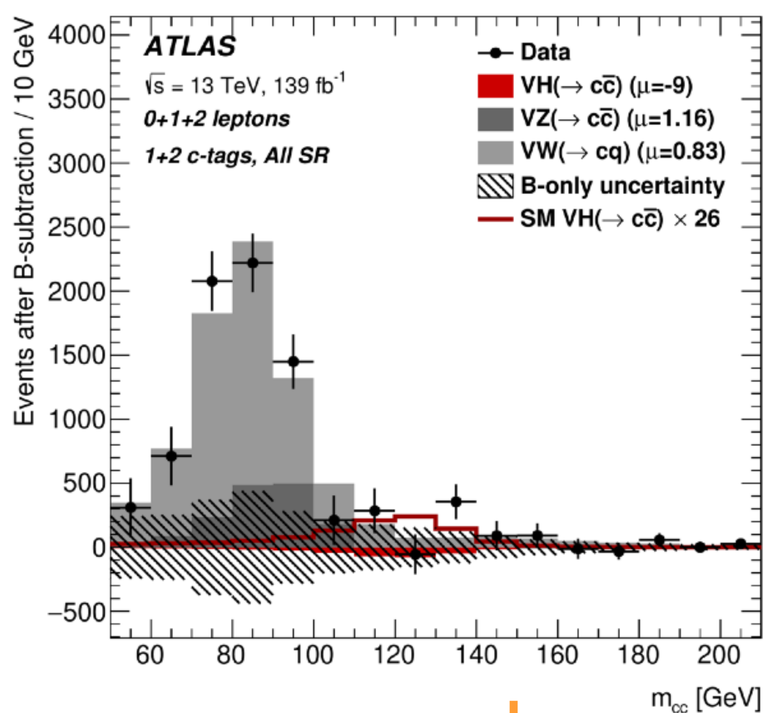
VHbb Boosted (paper)



VHbb Resolved (paper)



VHcc (paper)

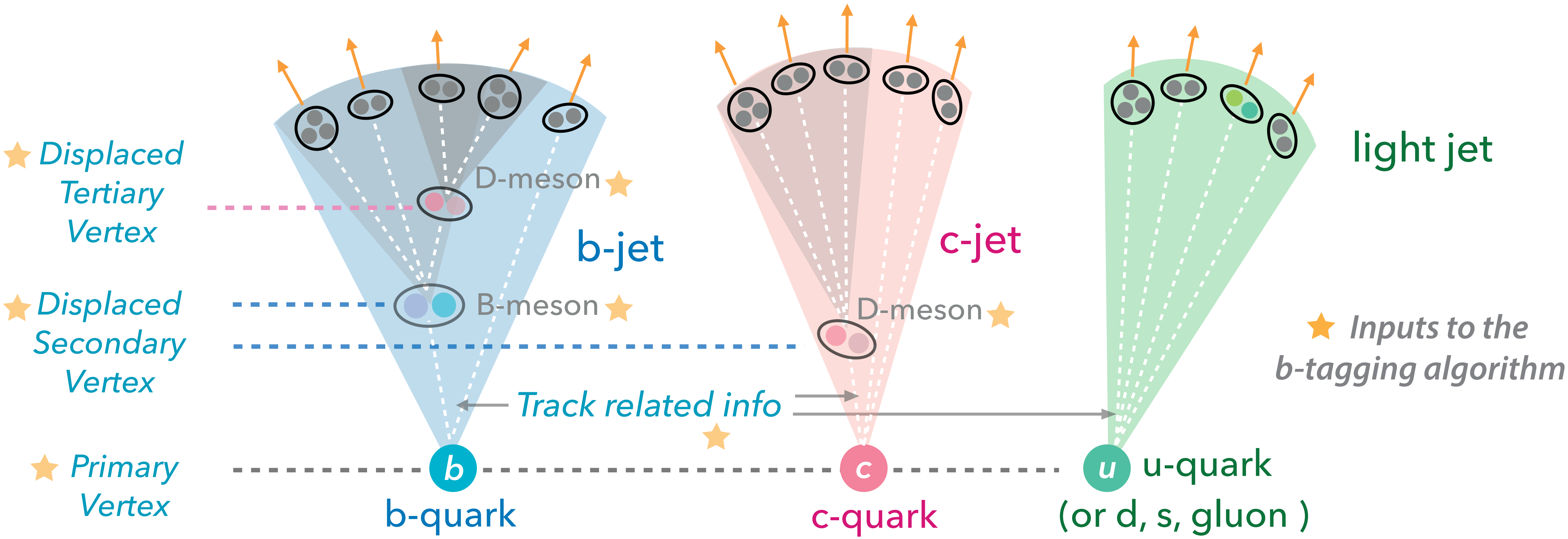


Combination *VH-Legacy* Analysis

- Simultaneous measurement of the signal strengths.
- *Harmonize* and improve of the "best practices" from all the 3 analysis.
  - One of them is the use of ***truth flavor tagging***, which I will be talking about today.

FLAVOR TAGGING

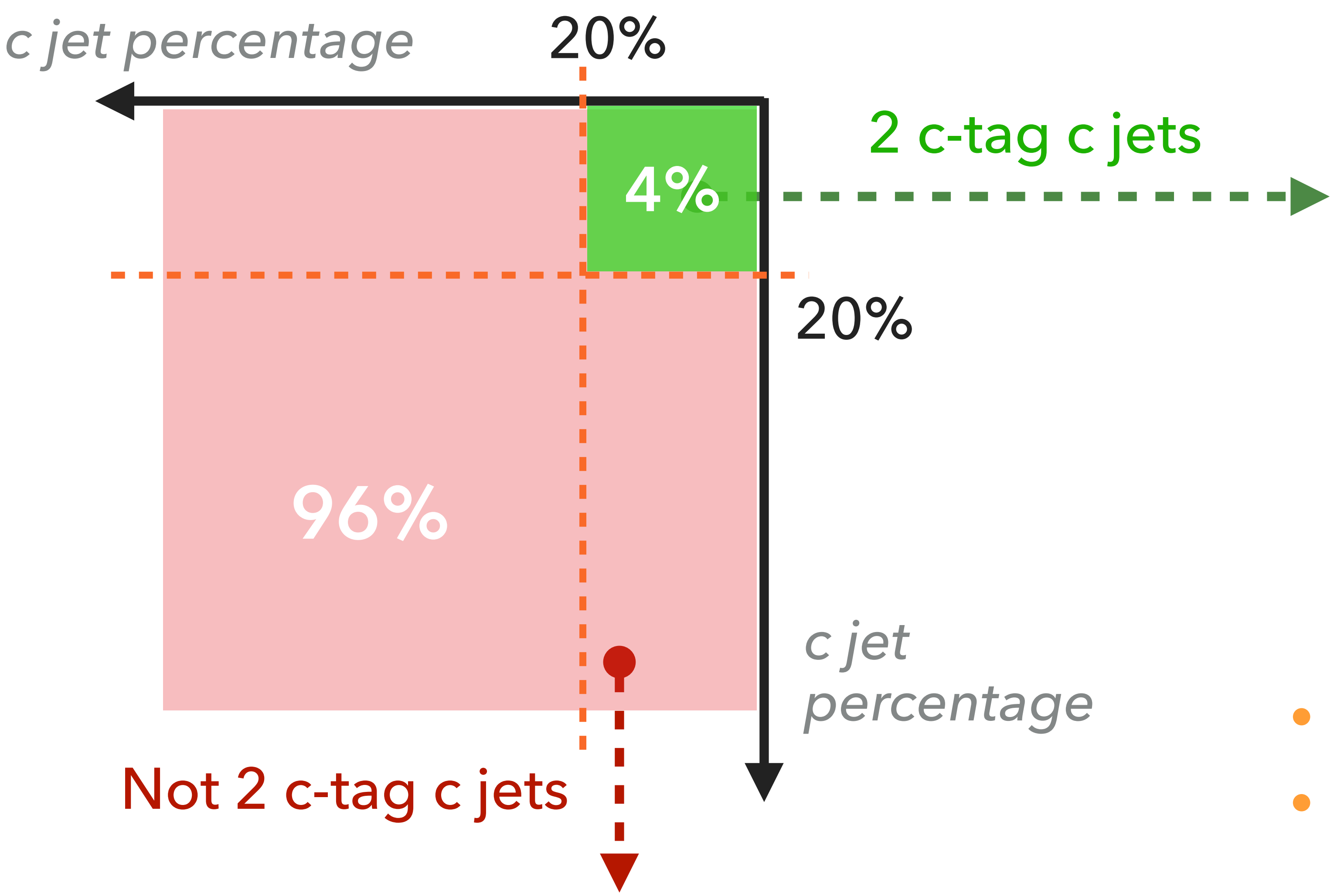
Flavor tagging is done using a set of machine learning based algorithms (called *b-tagging* algorithms) which exploit B-hadron decay features to identify jets.

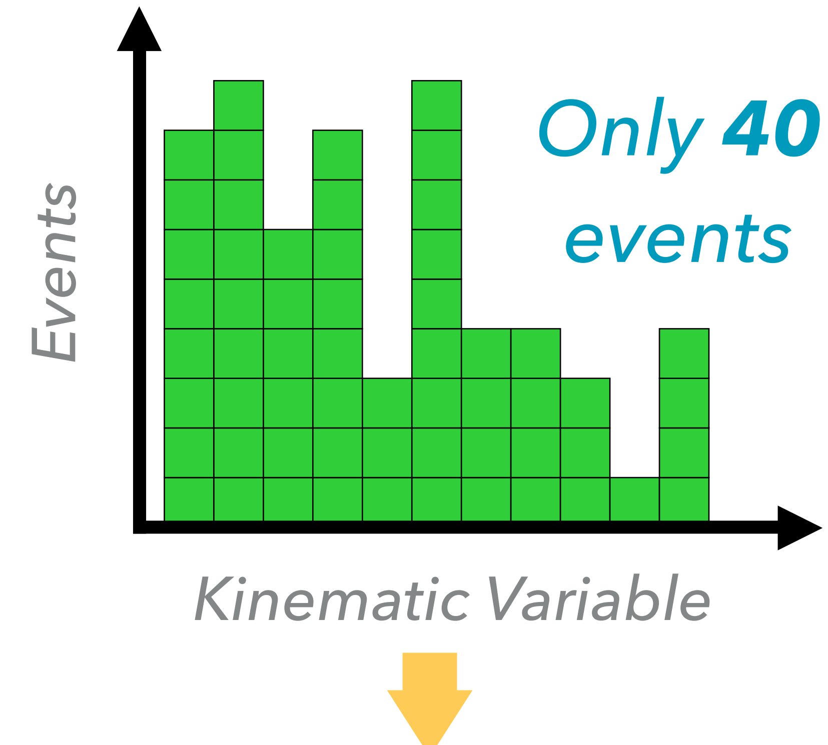


Jet Tagging Efficiency (ϵ_{jet}) = $\dfrac{\textit{Number of tagged jets of a flavor}}{\textit{Total number of jets of the same flavor}}$

DIRECTLY TAGGING THE JETS

*Let's say we have **1000** events with c-jets, and ϵ_{jet} is **20%*** (c-tight WP)





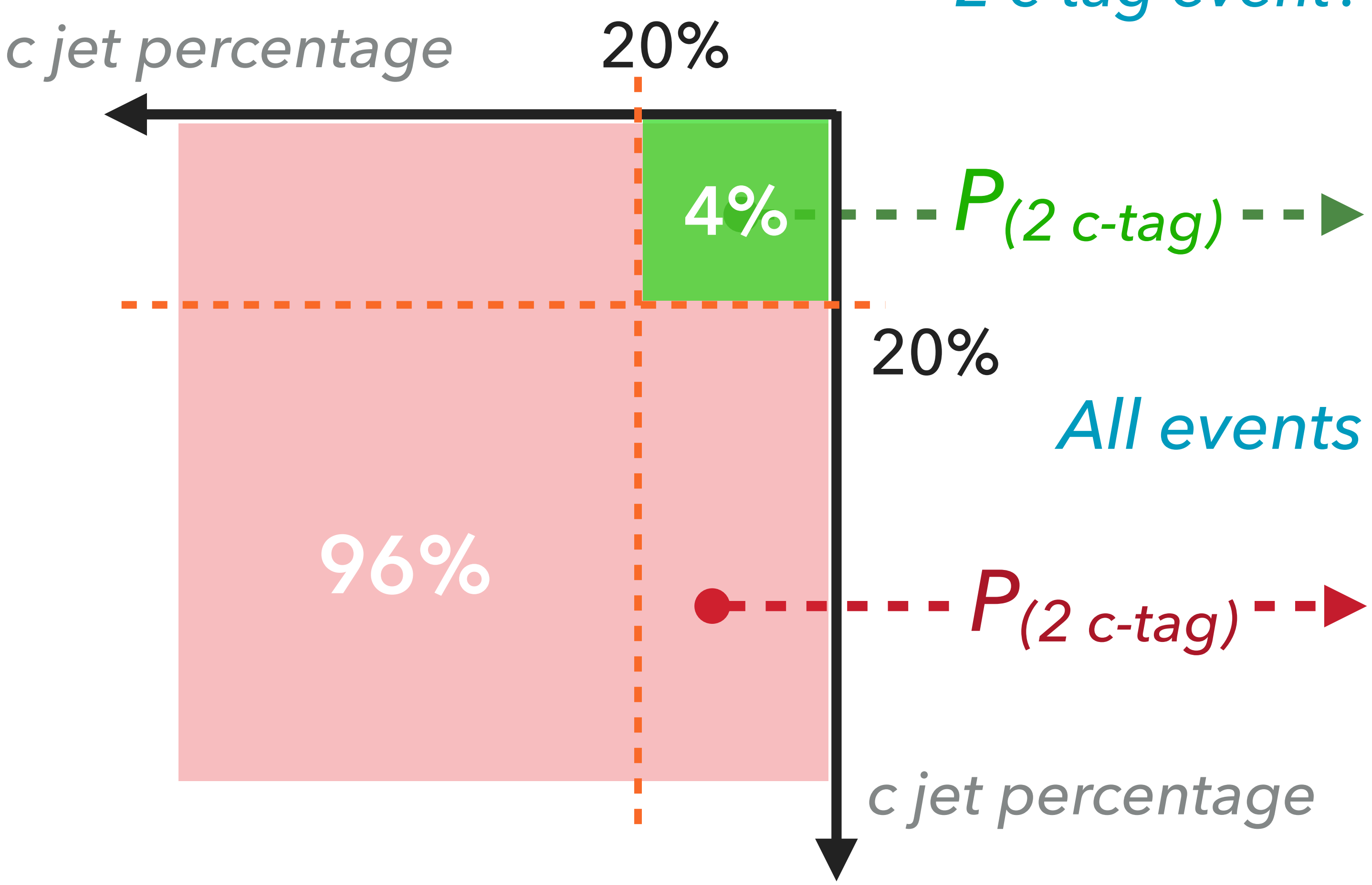
***960** "good" events are discarded*

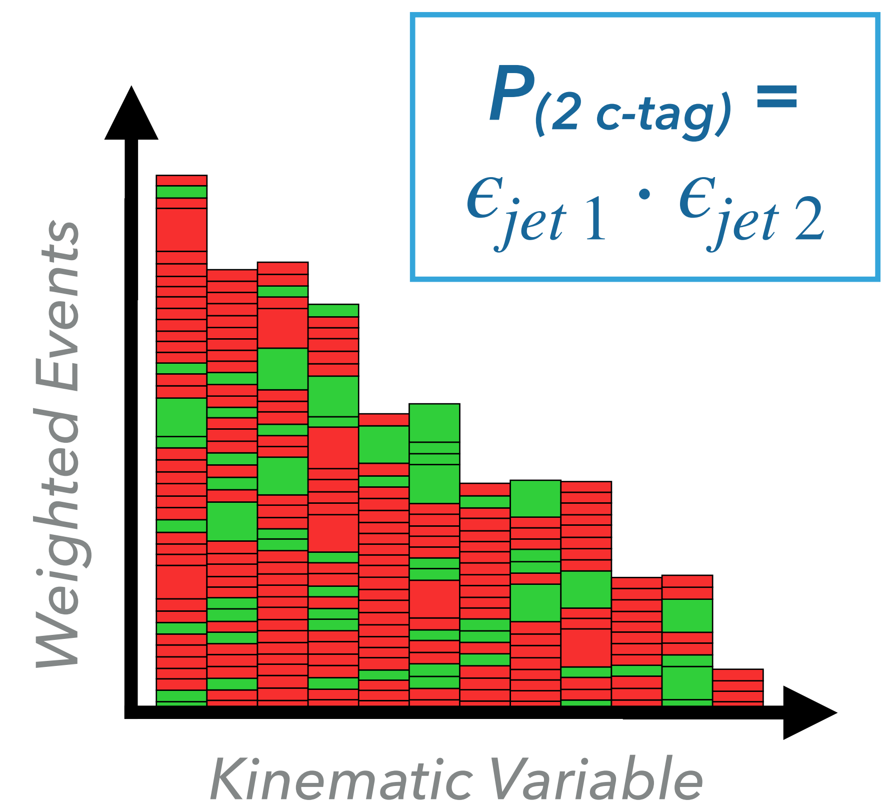
Good here means that these events model the physics processes well, but just didn't pass the tagging threshold.

- *Hard to see actual distribution*
- *Cannot obtain reliable modeling uncertainties*
- *Limited stat for MVA training leads to overtraining ([Johnny's talk])*
- *Not using MC samples effectively*

Event Weighting Method (Truth Tagging)

*Same problem, we look in a different way: What's the **probability** of getting a 2 c-tag event?*





Distributions are modeled much better

A more general equation is:

Tagging efficiency of each jet

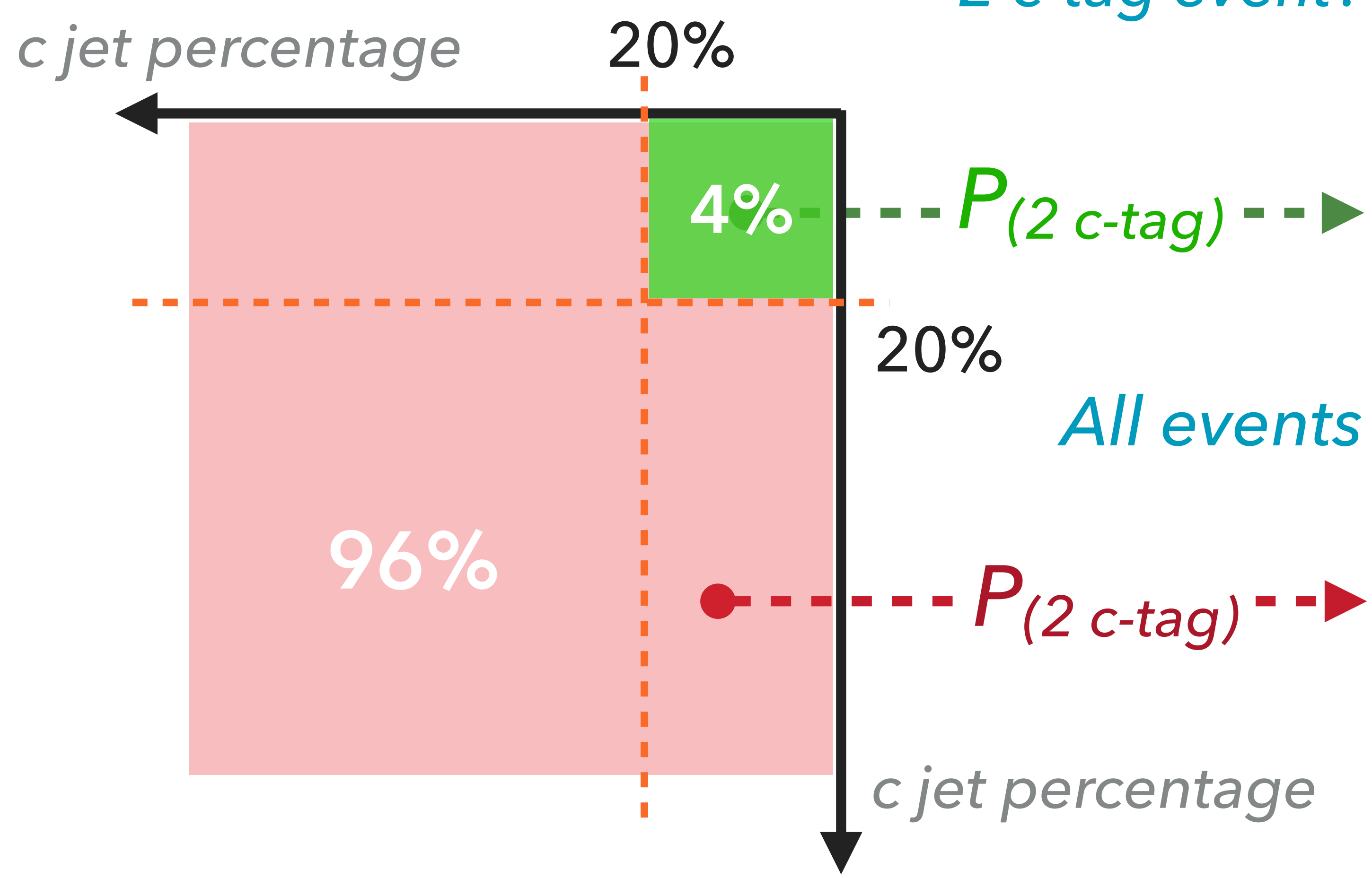
A set that samples all possible permutations of jets in the event, with the constraint that they are are b or c tagged.

$$P = \sum_{(k_1,\ldots,k_{N_{jet}})\in M} \left(\prod_{i=1}^{N_{jet}} \left(1 - k_i + (-1)^{1+k_i}\, \epsilon_i\right) \right) \quad \text{where} \quad M = \left\{ \left(k_1,\ldots,k_{N_{jet}}\right) \mid k_i \in \{0,1\},\ \sum_{i=1}^{N_{jet}} k_i = n_{b/c} \right\}$$

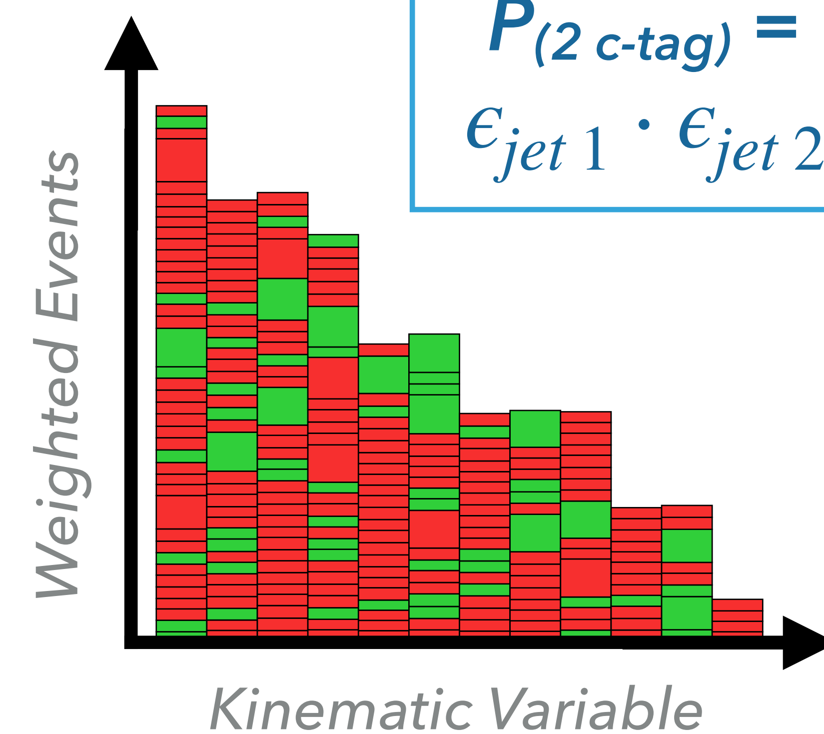
Tag or not

Event Weighting Method (Truth Tagging)

*Same problem, we look in a different way: What's the **probability** of getting a 2 c-tag event?*



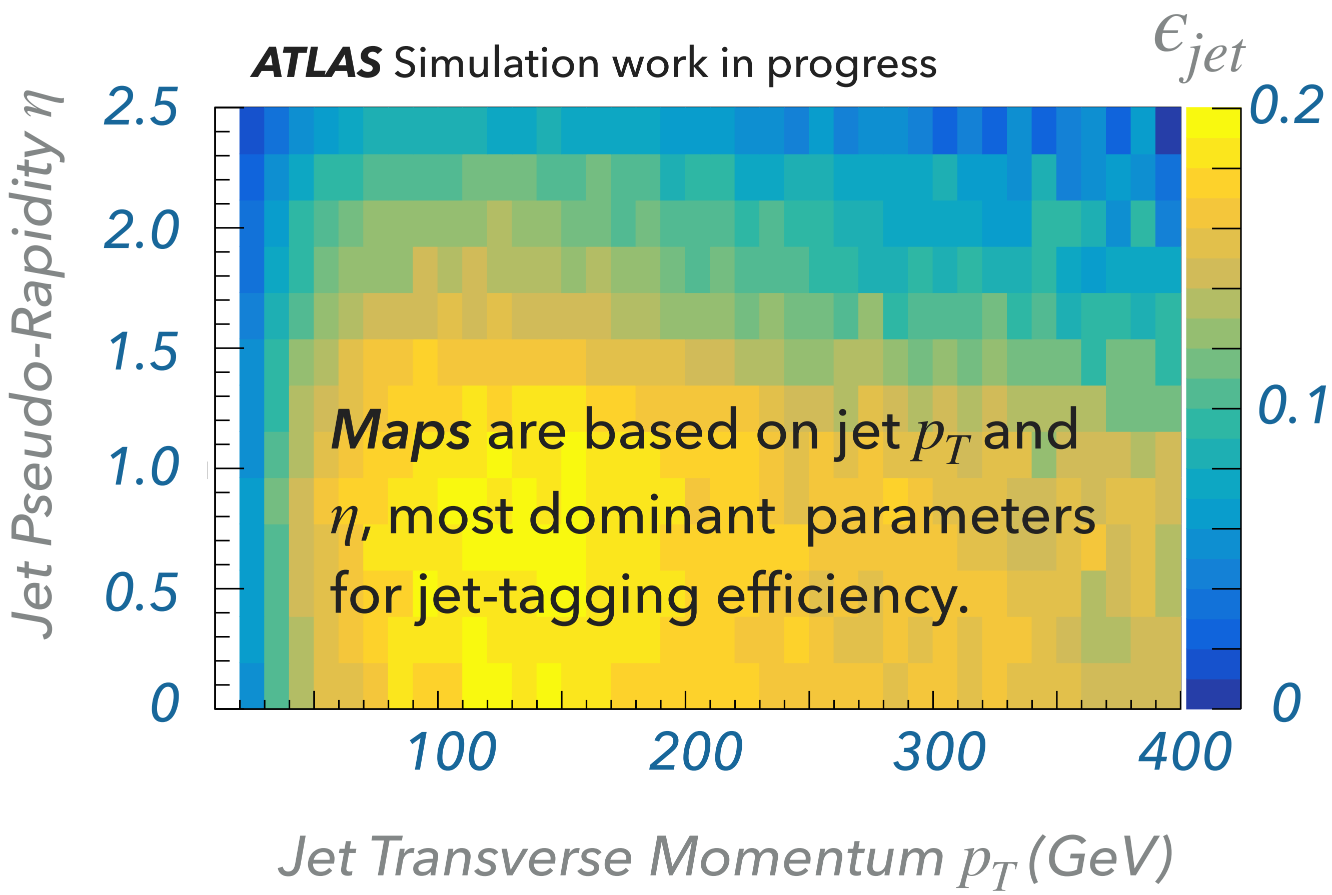
$$P_{(2\ c\text{-}tag)} = \epsilon_{jet\ 1} \cdot \epsilon_{jet\ 2}$$



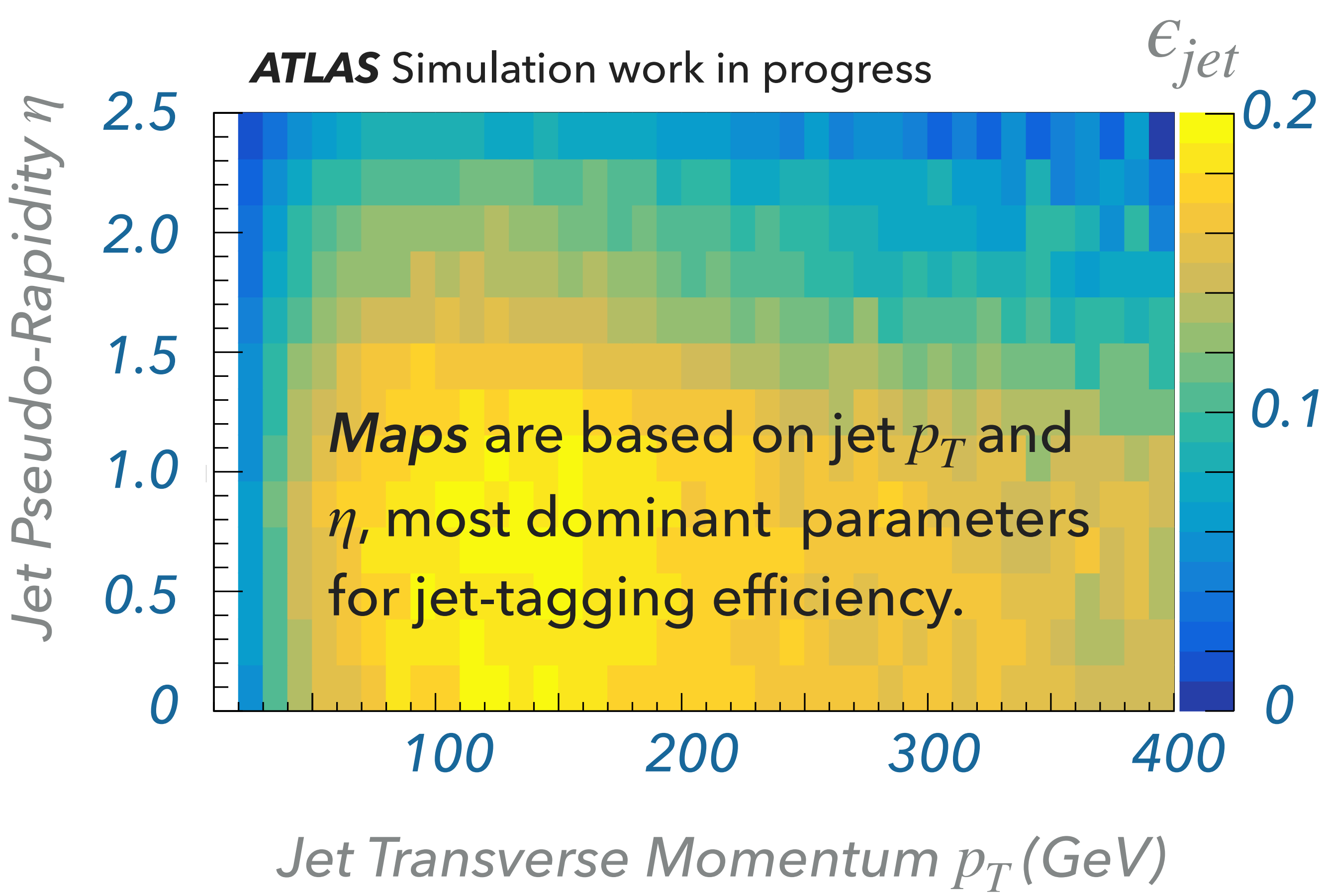
Distributions are modeled much better

*However, for this method to work, we need an **accurate parametrization of** ϵ_{jet}*

PARAMETRIZING ϵ_{jet} WITH 2D HISTOGRAMS (EFF.MAPS)

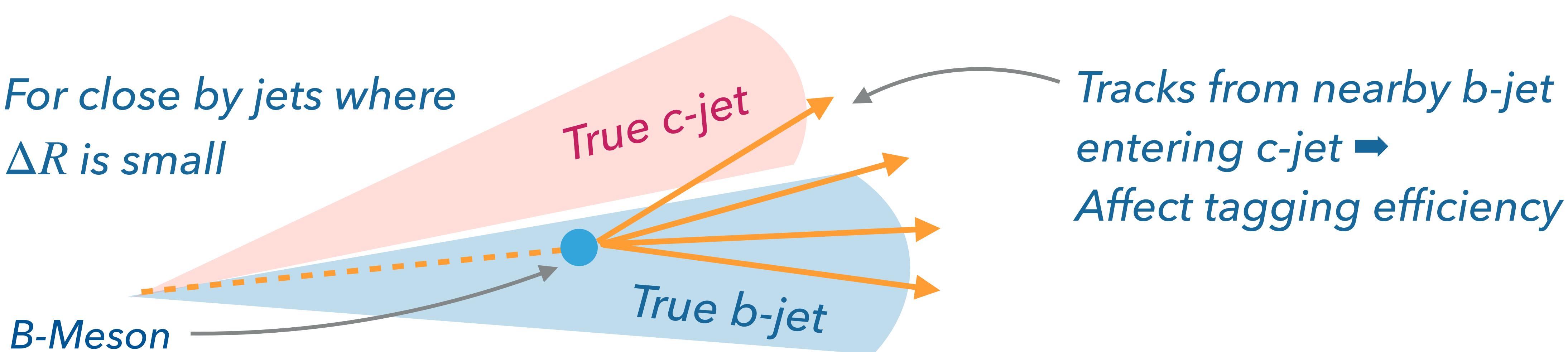


PARAMETRIZING ϵ_{jet} WITH 2D HISTOGRAMS (EFF.MAPS)



However, this method wasn't accurate enough

- *The ϵ_{jet} depends on **multiple parameters** ➡ but we cannot increase the dimensions (curse of dimensionality)*
- *Tagging efficiency is affected by **jet-jet dependencies** ➡ Needed a $\Delta R = \sqrt{\Delta\phi^2 + \Delta\eta^2}$ correction*



PARAMETRIZING ϵ_{jet} WITH 2D HISTOGRAMS (EFF.MAPS)

Source of uncertainty		$\mu_{VH(c\bar{c})}$	$\mu_{VW(cq)}$	$\mu_{VZ(c\bar{c})}$
Total		15.3	0.24	0.48
Statistical		10.0	0.11	0.32
Systematic		11.5	0.21	0.36
Statistical uncertainties				
Signal normalisation		7.8	0.05	0.23
Other normalisations		5.1	0.09	0.22
Theoretical and modelling uncertainties				
$VH(\to c\bar{c})$		2.1	< 0.01	0.01
$Z+$jets		7.0	0.05	0.17
Top quark		3.9	0.13	0.09
$W+$jets		3.0	0.05	0.11
Diboson		1.0	0.09	0.12
$VH(\to b\bar{b})$		0.8	< 0.01	0.01
Multi-jet		1.0	0.03	0.02
Simulation samples size		4.2	0.09	0.13
Experimental uncertainties				
Jets		2.8	0.06	0.13
Leptons		0.5	0.01	0.01
$E_{\mathrm{T}}^{\mathrm{miss}}$		0.2	0.01	0.01
Pile-up and luminosity		0.3	0.01	0.01
Flavour tagging	c-jets	1.6	0.05	0.16
	b-jets	1.1	0.01	0.03
	light-jets	0.4	0.01	0.06
	τ-jets	0.3	0.01	0.04
Truth-flavour tagging	ΔR correction	3.3	0.03	0.10
	Residual non-closure	1.7	0.03	0.10

Referred from the previous VHcc analysis [paper]

However, this method wasn't accurate enough

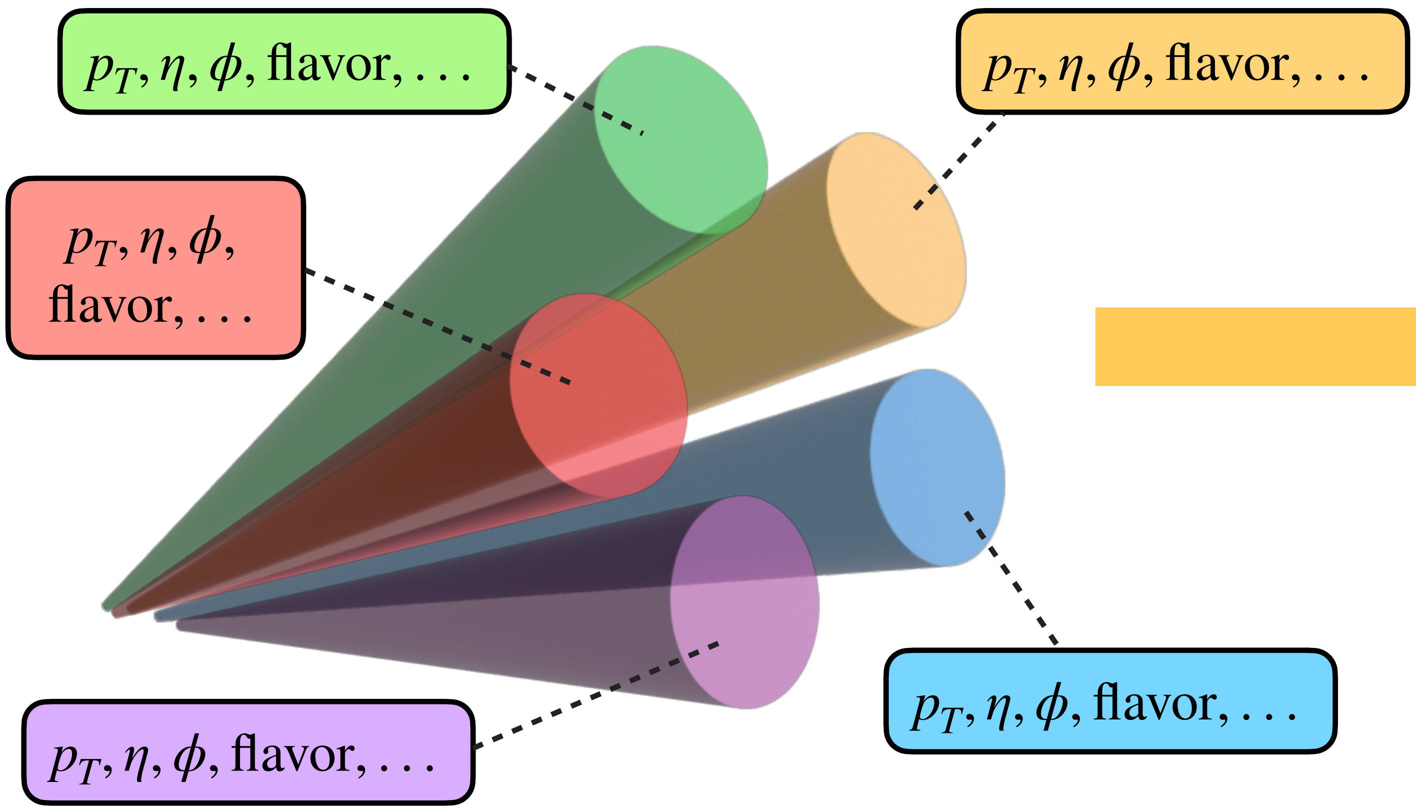
- *The ϵ_{jet} depends on **multiple parameters***
- *Tagging efficiency is affected by **jet-jet dependencies** ➡ Needed a $\Delta R = \sqrt{\Delta\phi^2 + \Delta\eta^2}$ correction*

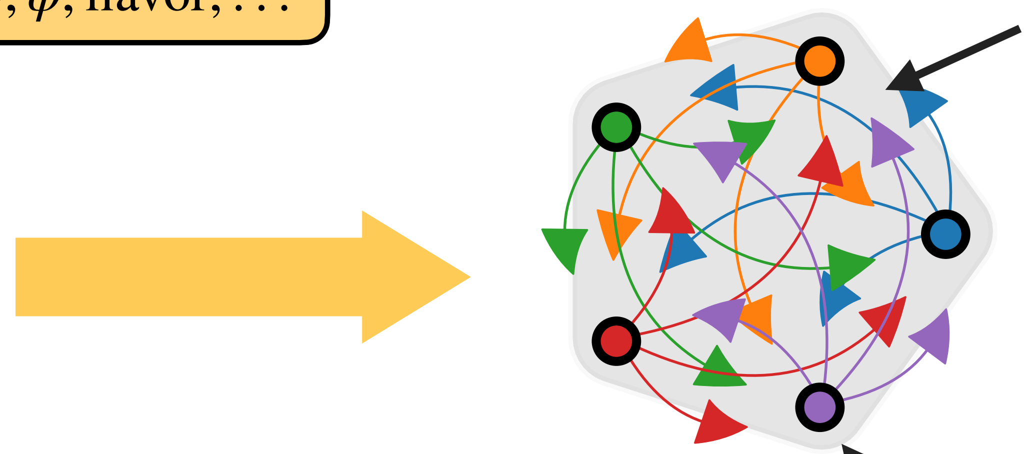
Had to attribute some systematics here.
As you can see, truth tagging had a large contribution to the experimental uncertainties.

Hence, we needed a new approach

USING GNN'S FOR PARAMETRIZING ϵ_{jet}

Graph Neural Networks (GNN)





Edges *set as ΔR*

- *Each **node** is set as a jet*
- *Parameters set as input **features***

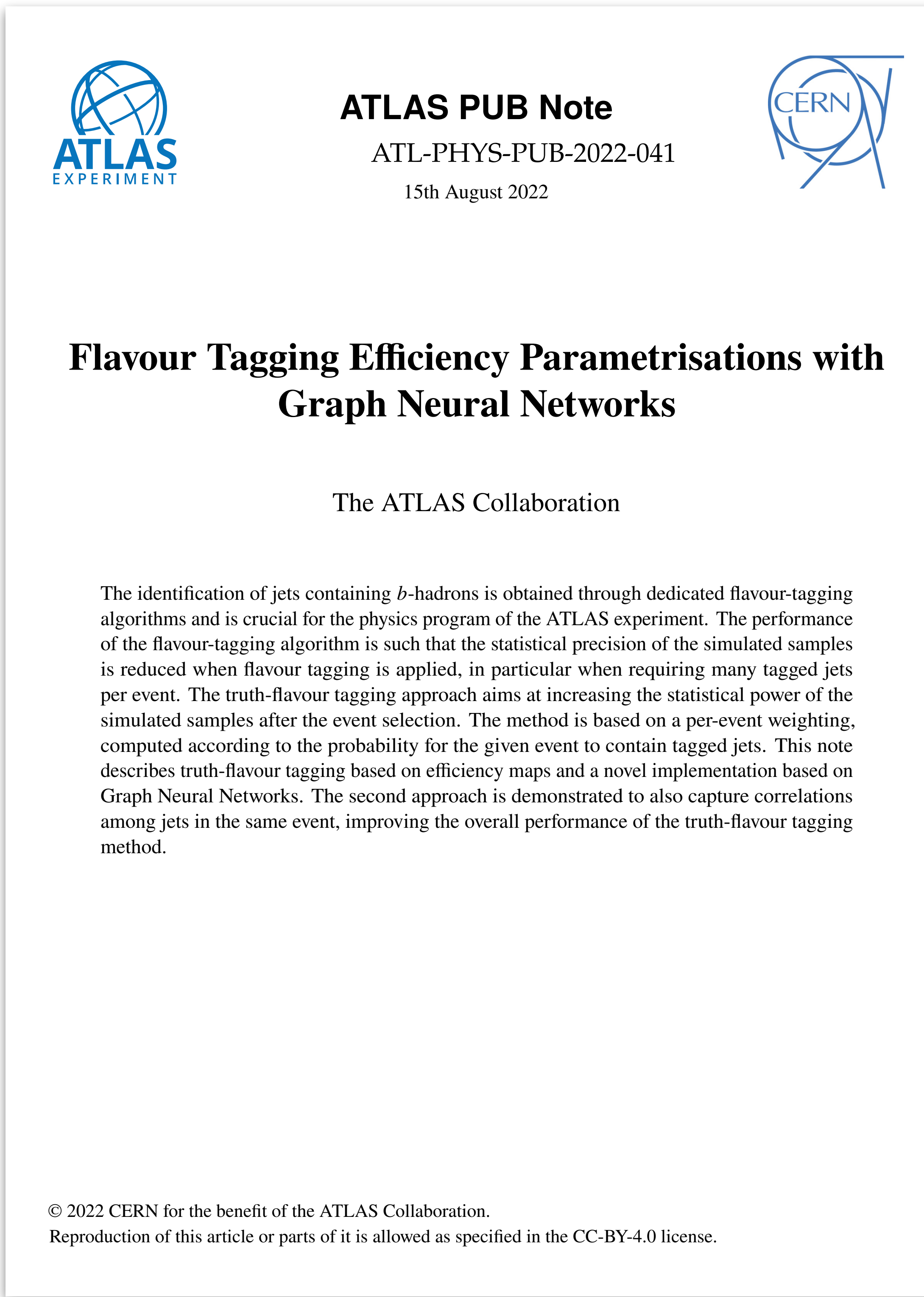
✓ *GNN's are able to handle multiple input parameters*

- *Currently we're using 13 parameters: p_T, η, ϕ, flavor, pile-up (Actual μ), bH-m, bH-p_T, bH-η, bH-ϕ, cH-m, cH-p_T, cH-η, cH-ϕ*

✓ *The model is trained for all jets ➡ Jet by jet dependencies are also included*

◉ *However, GNN's are not easy to interpret*

ATLAS Public Note



ATLAS PUB Note

ATL-PHYS-PUB-2022-041

15th August 2022

Flavour Tagging Efficiency Parametrisations with Graph Neural Networks

The ATLAS Collaboration

The identification of jets containing b-hadrons is obtained through dedicated flavour-tagging algorithms and is crucial for the physics program of the ATLAS experiment. The performance of the flavour-tagging algorithm is such that the statistical precision of the simulated samples is reduced when flavour tagging is applied, in particular when requiring many tagged jets per event. The truth-flavour tagging approach aims at increasing the statistical power of the simulated samples after the event selection. The method is based on a per-event weighting, computed according to the probability for the given event to contain tagged jets. This note describes truth-flavour tagging based on efficiency maps and a novel implementation based on Graph Neural Networks. The second approach is demonstrated to also capture correlations among jets in the same event, improving the overall performance of the truth-flavour tagging method.

If you're interested in learning about the concept in more depth, please check the public note here.

Small clarification: the public note shows the application to ***boosted topology $t\bar{t}$ background***, but it is the same for resolved topology as well.

In Summary

- Direct selection methods don't provide enough statistics to model restricted phase spaces due to low statistics ➡ <u>Using event weighting methods utilizes the whole sample set and model distributions better.</u>
- We need an accurate modeling of ϵ_{jet} for the event weighting method.
  - In previous analysis, we used 2-D Histograms to model ϵ_{jet} , but it couldn't model ϵ_{jet} accurately enough.
  - It was seen that GNN's (which can learn multiple parameters which affect ϵ_{jet}) manages to model the ϵ_{jet} well.
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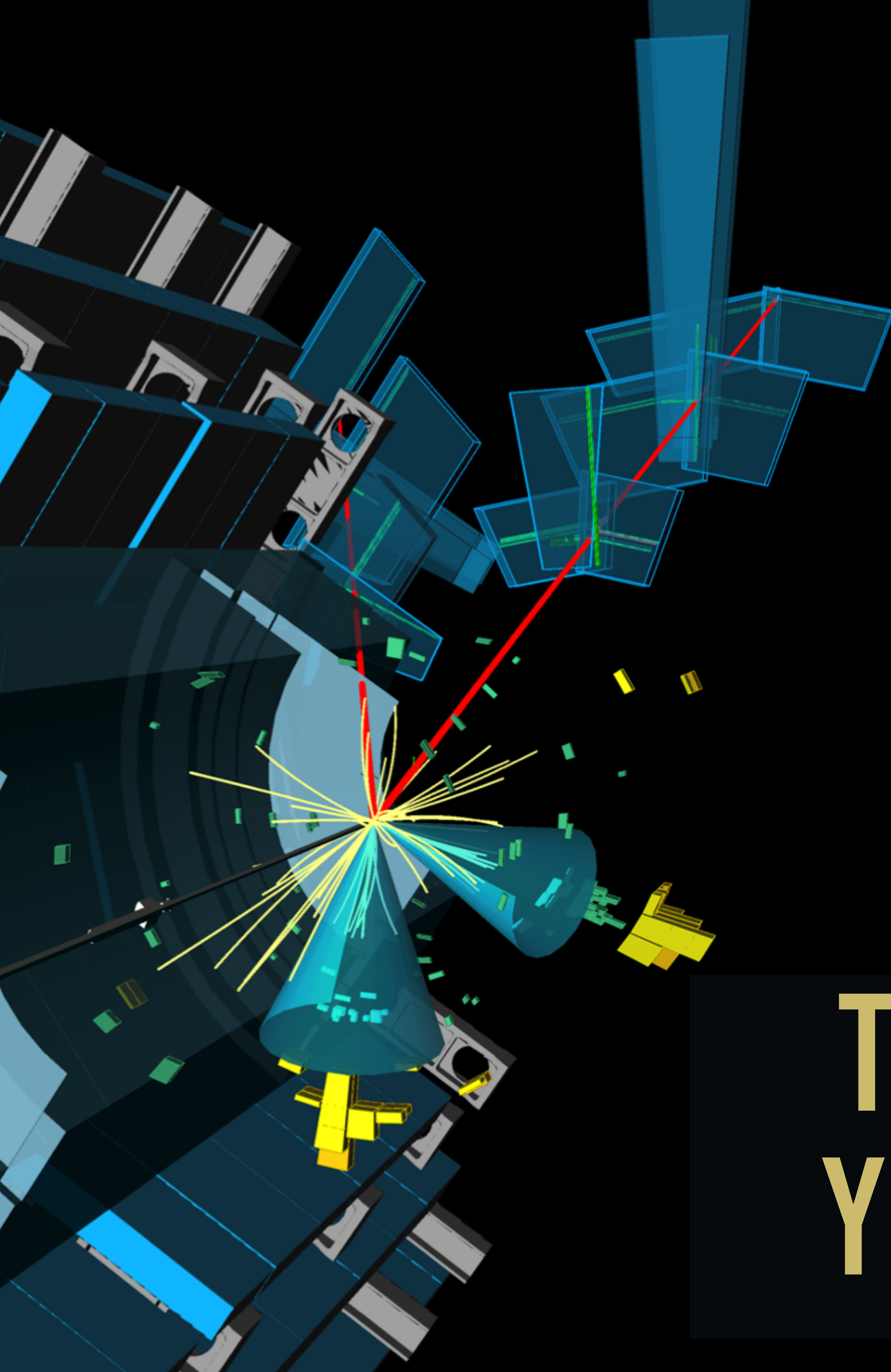

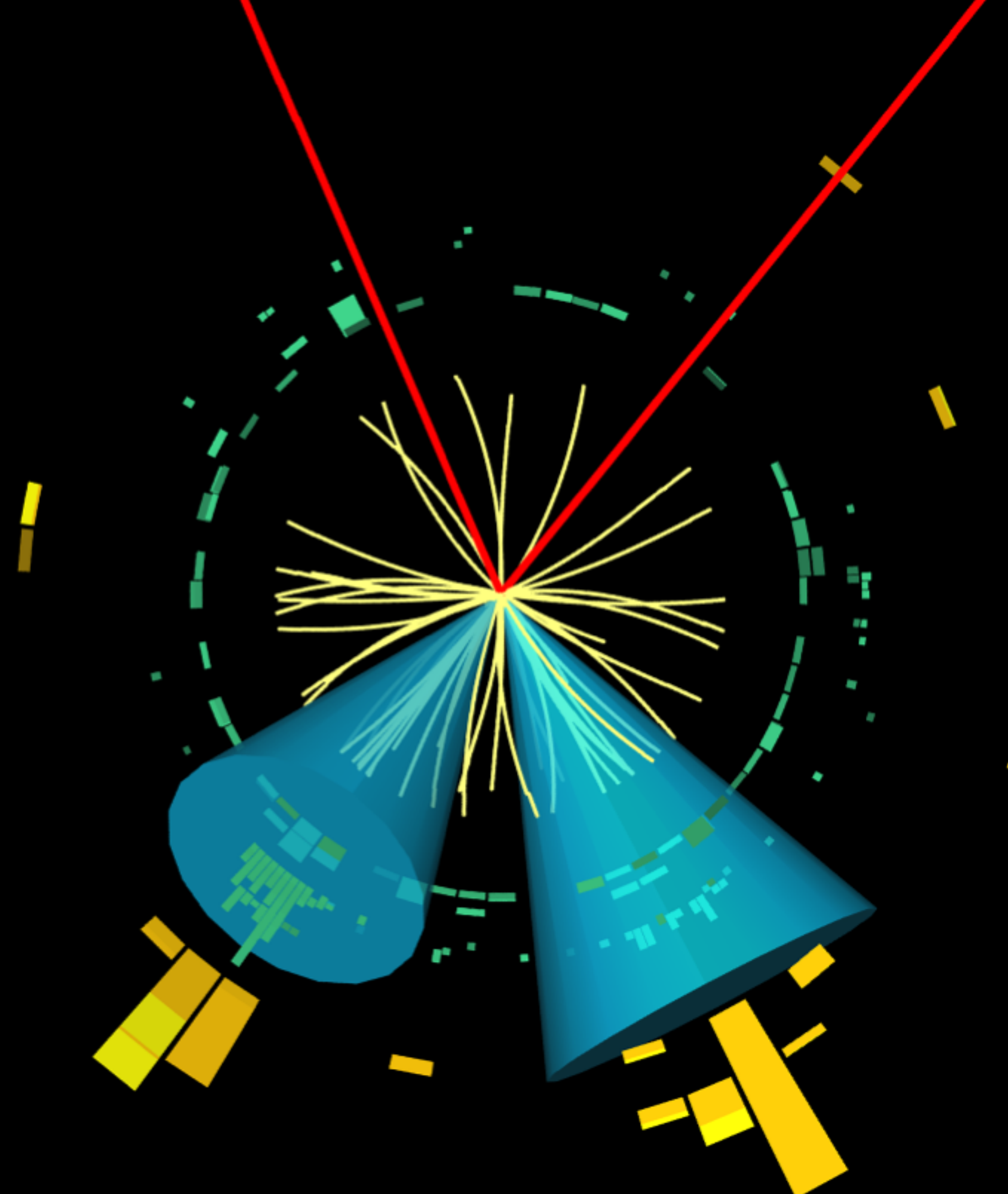

THANK YOU FOR YOUR ATTENTION