A 3D visualization of a particle detector simulation. It shows a central collision point with a dense spray of yellow lines representing particle tracks. Two blue rectangular structures, likely calorimeters, are positioned on either side of the collision point. Green lines and dots represent specific particles or decay products. To the right, a series of red, overlapping rectangular planes represent a detector's internal structure or a specific region of interest. The background is dark, highlighting the complex geometry and particle paths.

JAVIER DUARTE
FERMILAB W&C
JUNE 3, 2022



ENABLING HIGGS COUPLING MEASUREMENTS WITH BOOSTED HH



WRIGLEYVILLE

LINCOLN PARK

OLD TOWN

GOLD COAST

WEST LOOP

THE LOOP

PILSEN

CHINATOWN

BRONZEVILLE

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- ▶ LHC+HL-LHC lifespan as the Chicago marathon
- ▶ 10 years since the Higgs discovery!

We are here!

Higgs discovery!



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▶ But mile 10 is not mile 26.2!

- ▶ *Plenty of time for twists & turns*

- ▶ Measuring Higgs self interaction necessary for establishing connection between the Higgs boson and *electroweak symmetry breaking*

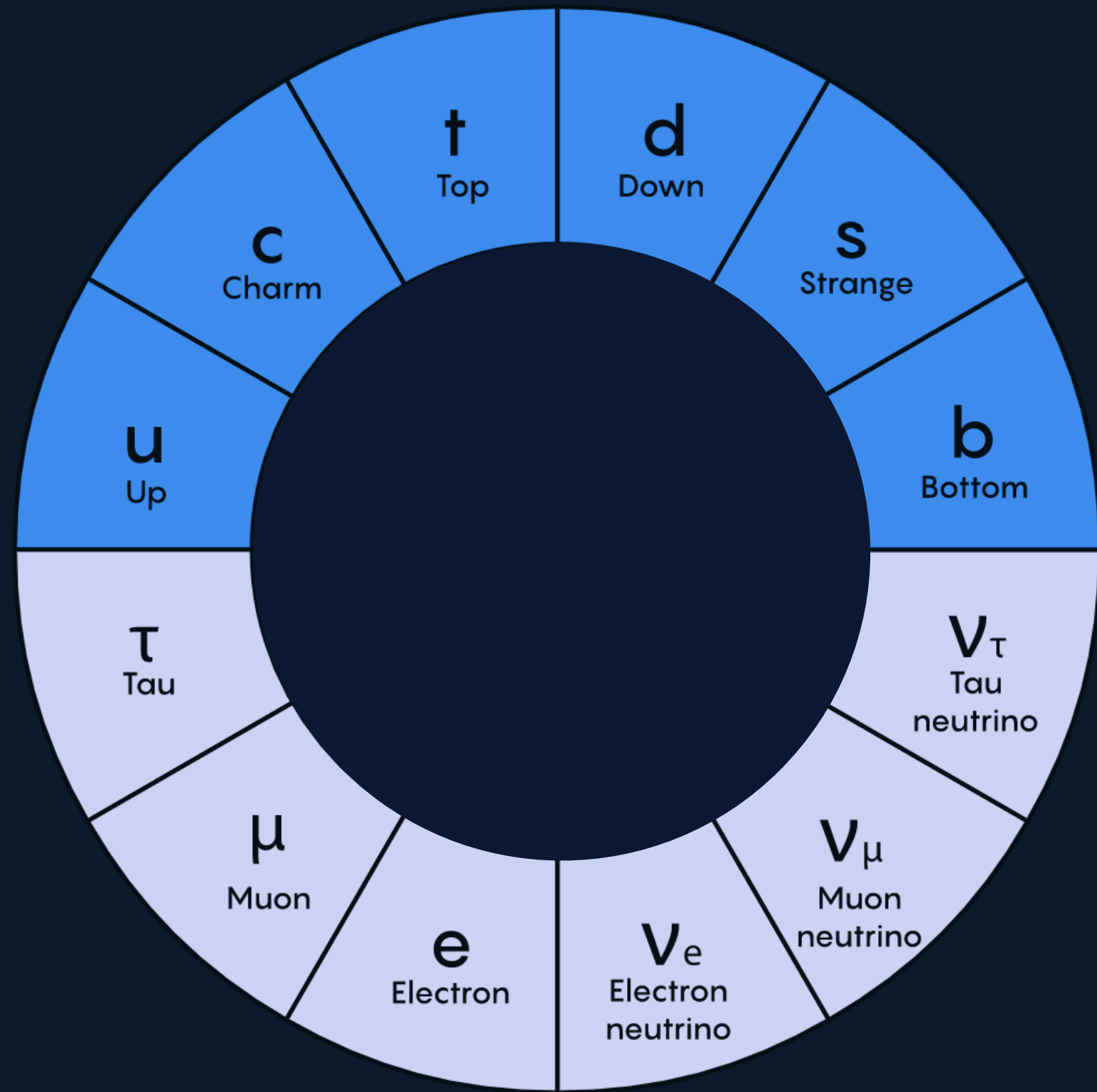
We are here!

Higgs discovery!

Higgs self-interaction?

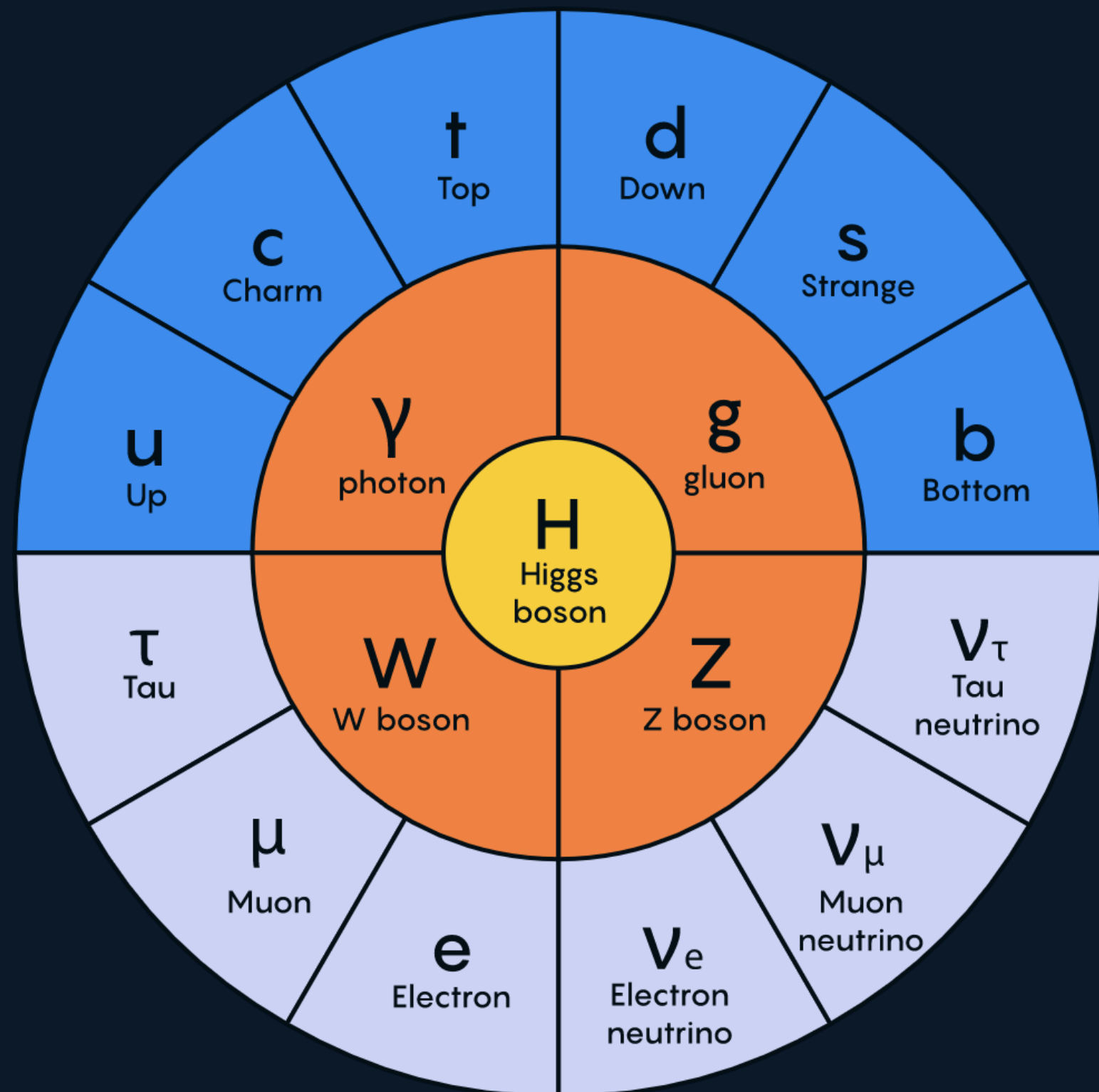


HIGGS BOSON IN THE STANDARD MODEL



FERMIONS (MATTER)
● QUARKS ● LEPTONS

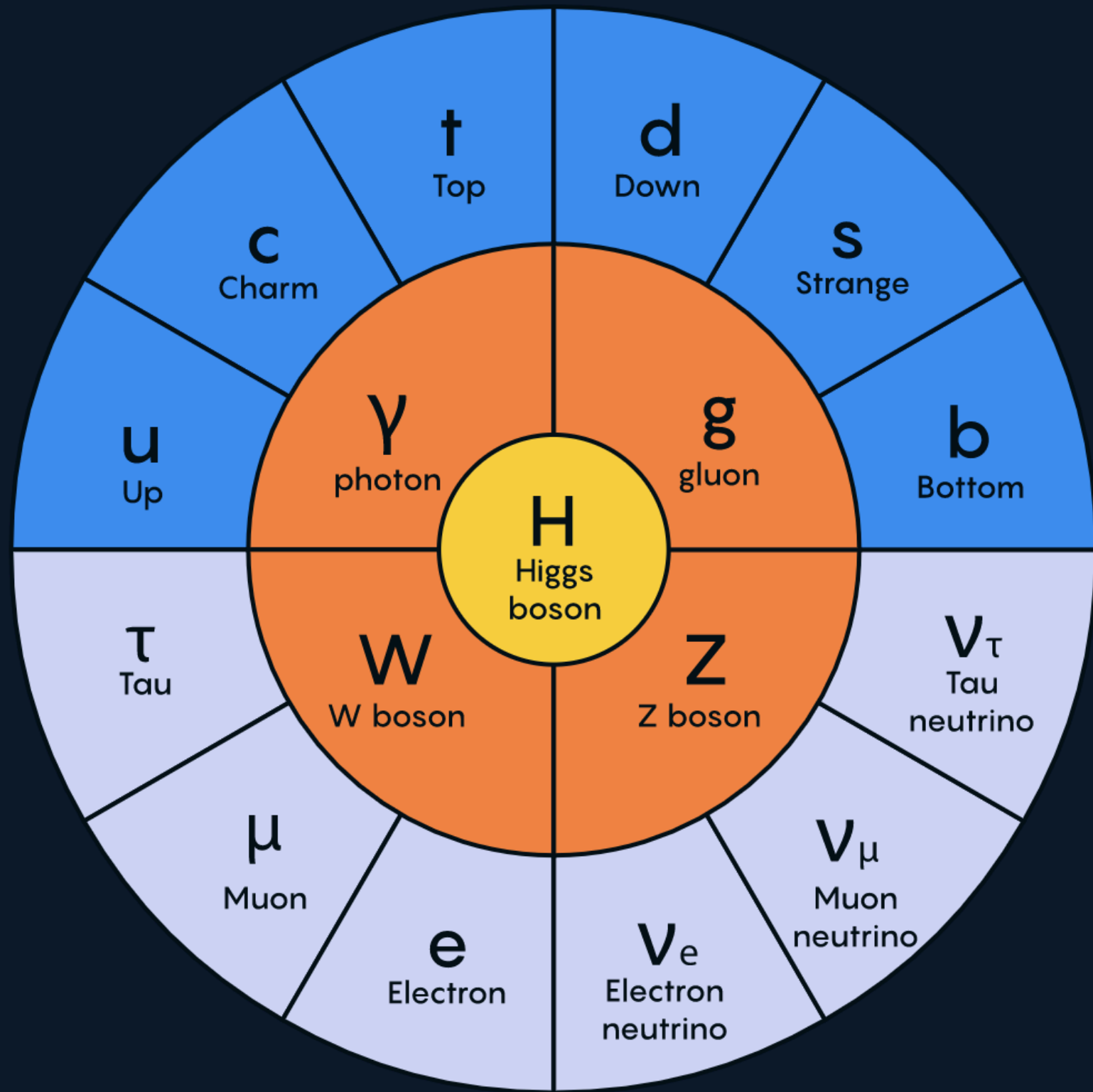
HIGGS BOSON IN THE STANDARD MODEL



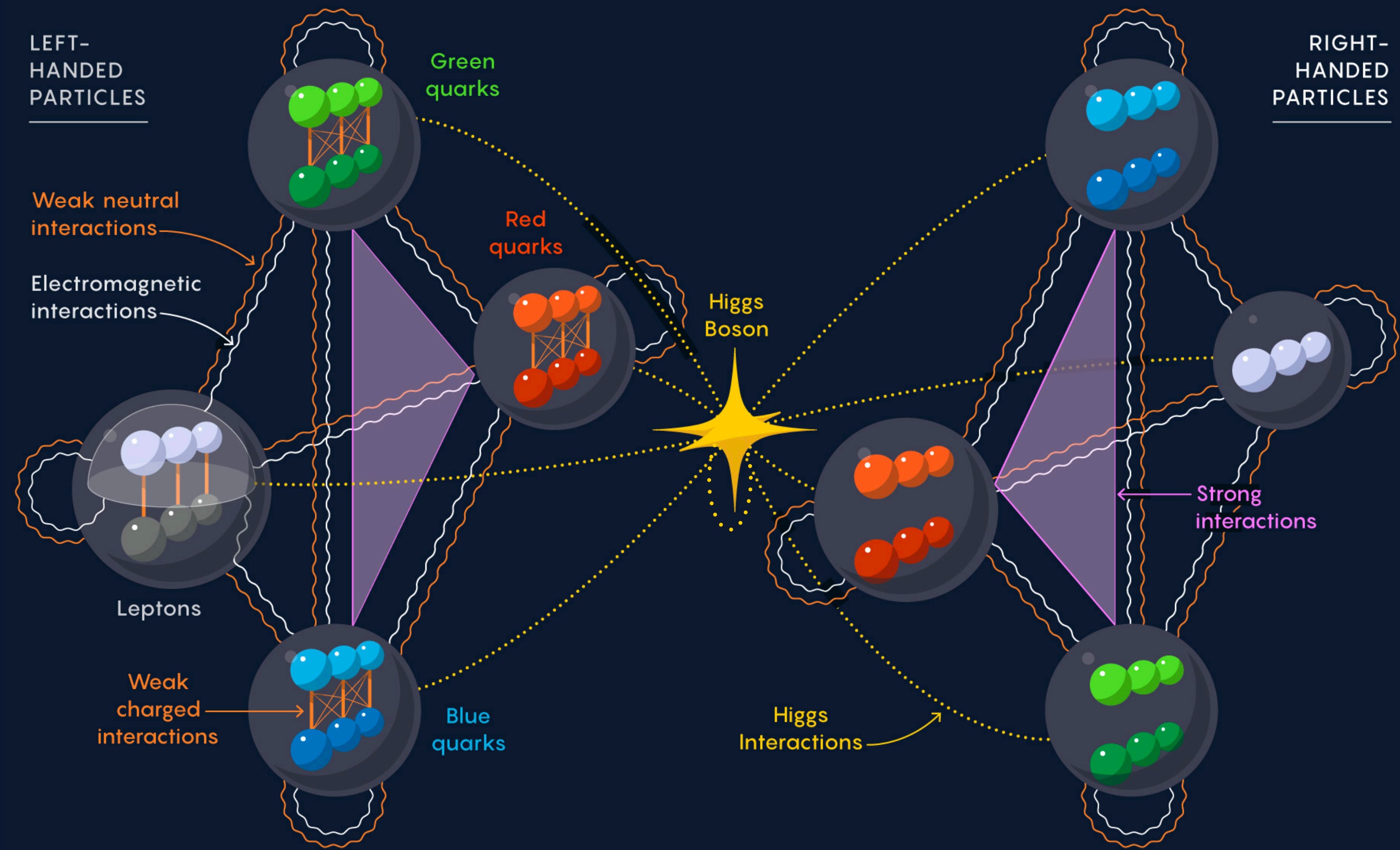
FERMIONS (MATTER) BOSONS (FORCE CARRIERS)

● QUARKS ● LEPTONS ● GAUGE BOSONS ● HIGGS BOSON

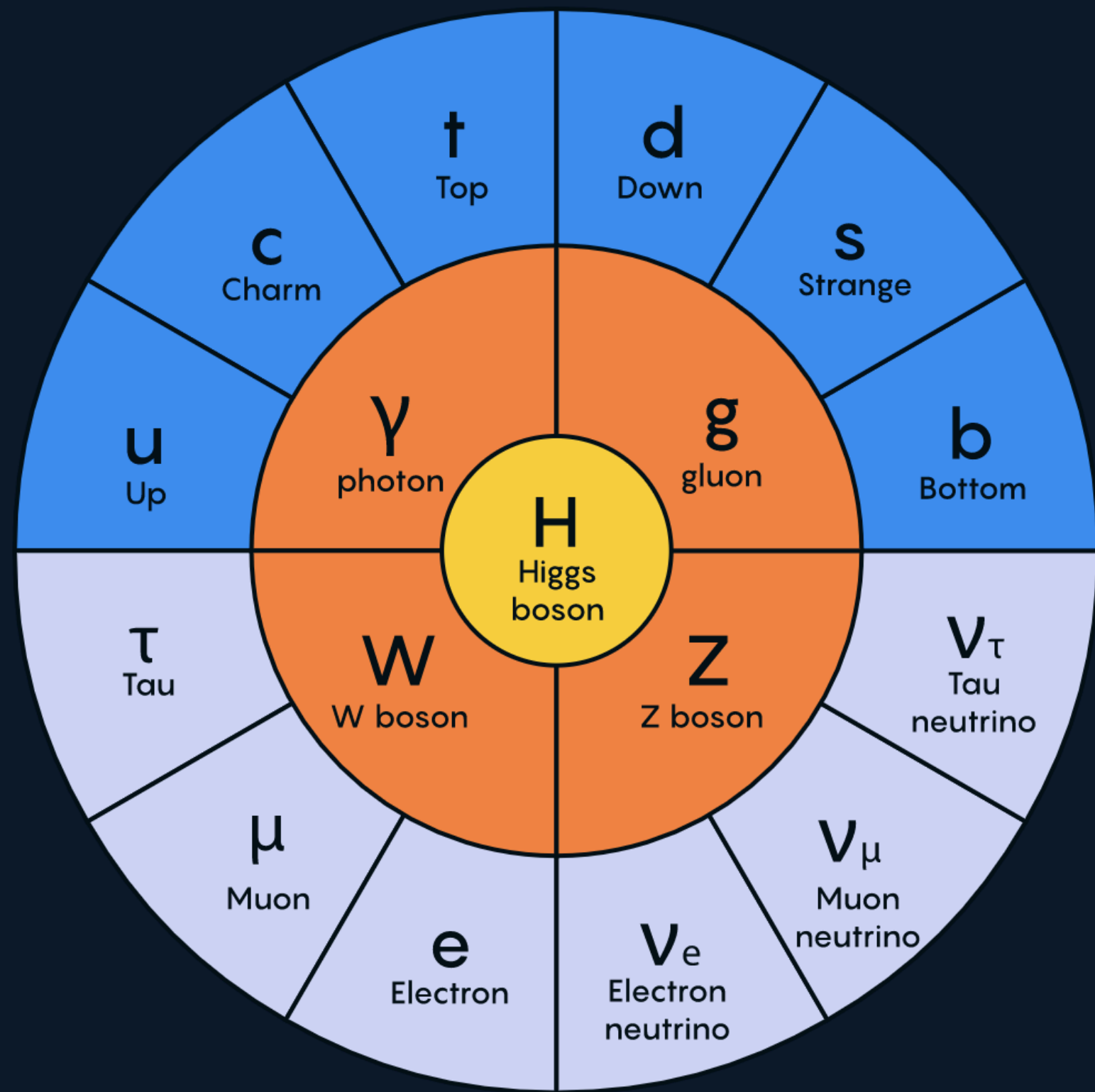
HIGGS BOSON IN THE STANDARD MODEL



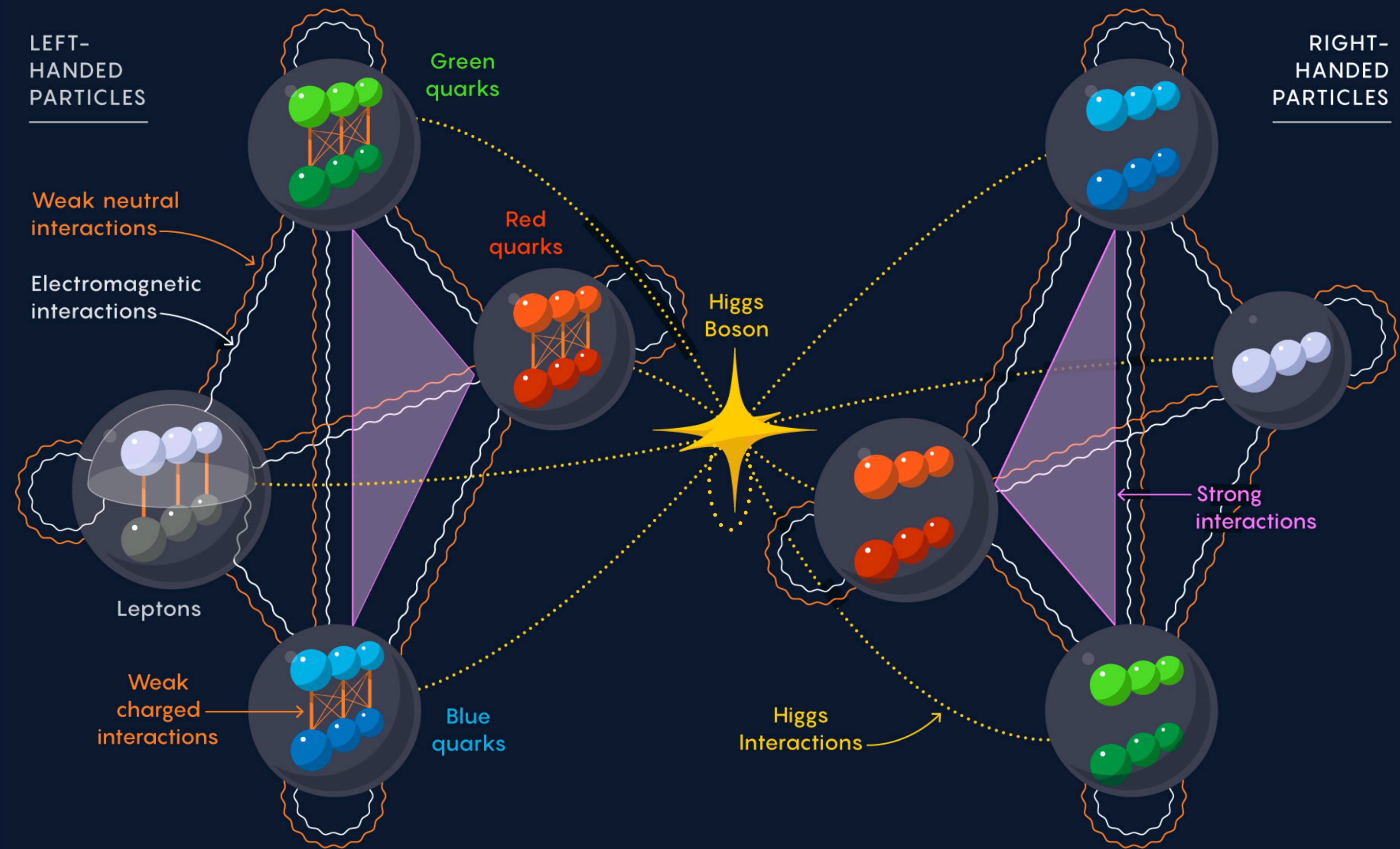
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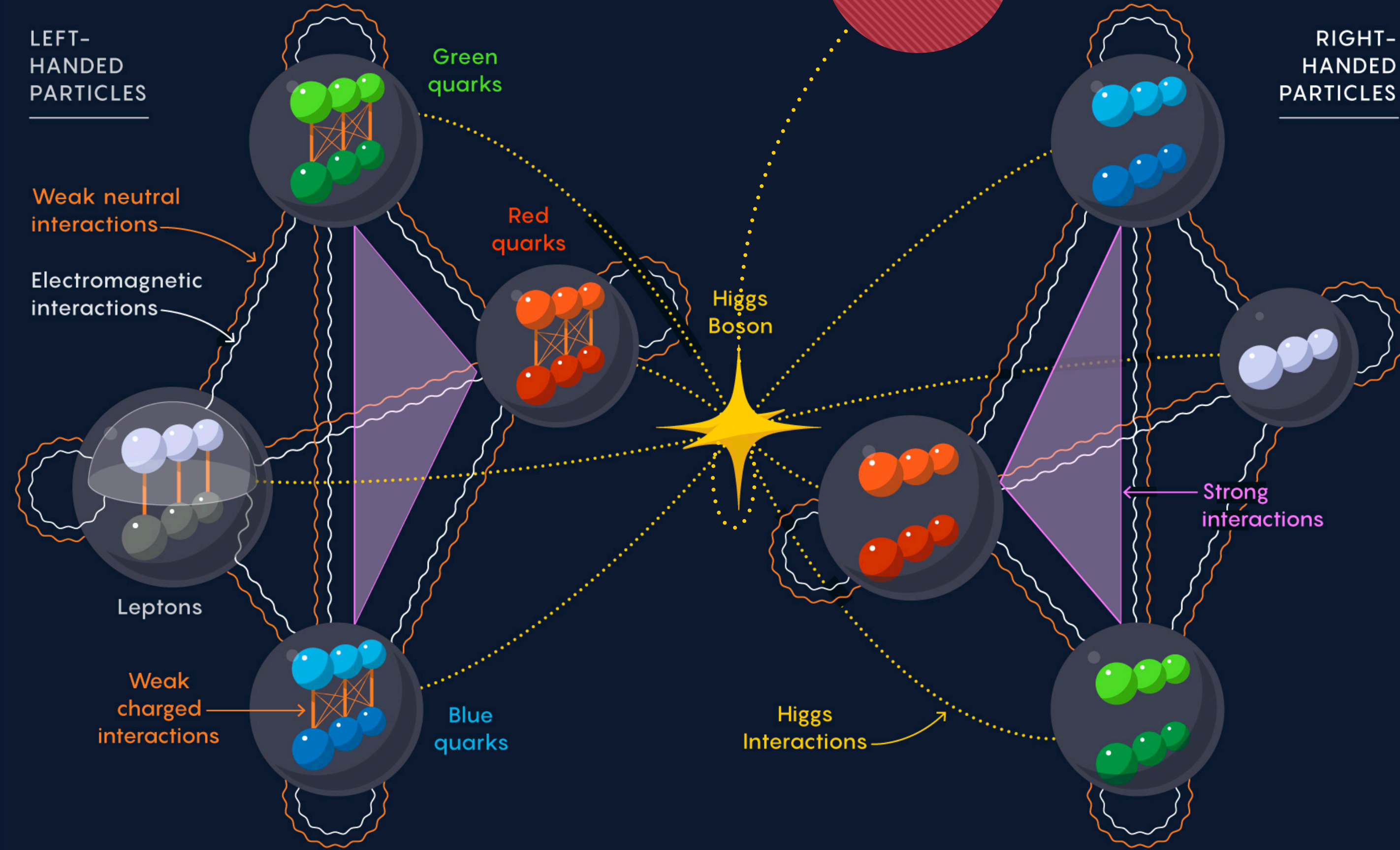
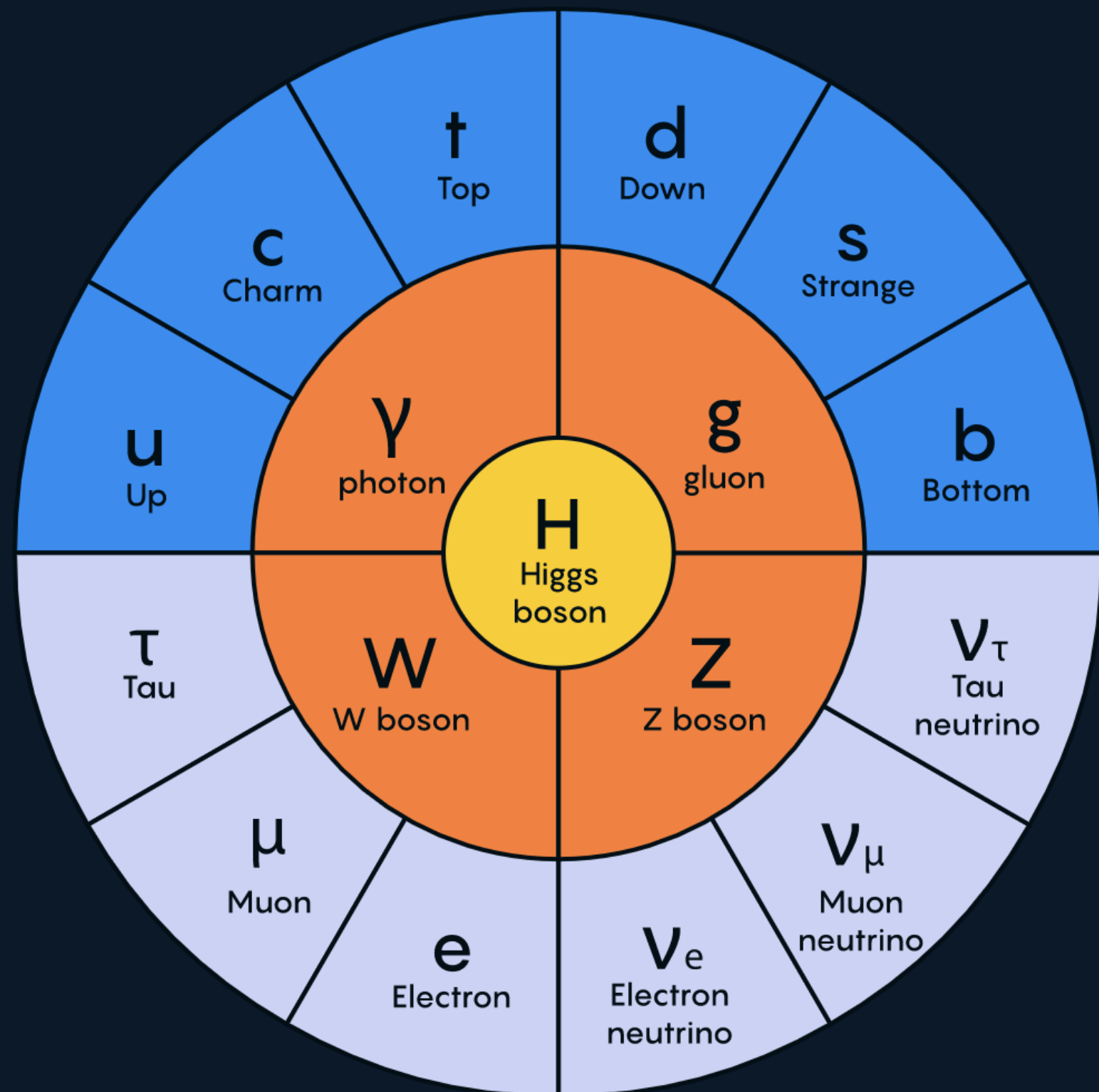


FERMIONS (MATTER) BOSONS (FORCE CARRIERS)
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- ▶ But there has to be more to it! SM does not explain **dark matter**, **neutrino masses**, and the **matter-antimatter asymmetry**...
- ▶ Higgs boson is the **centerpiece**: all particles interact with it

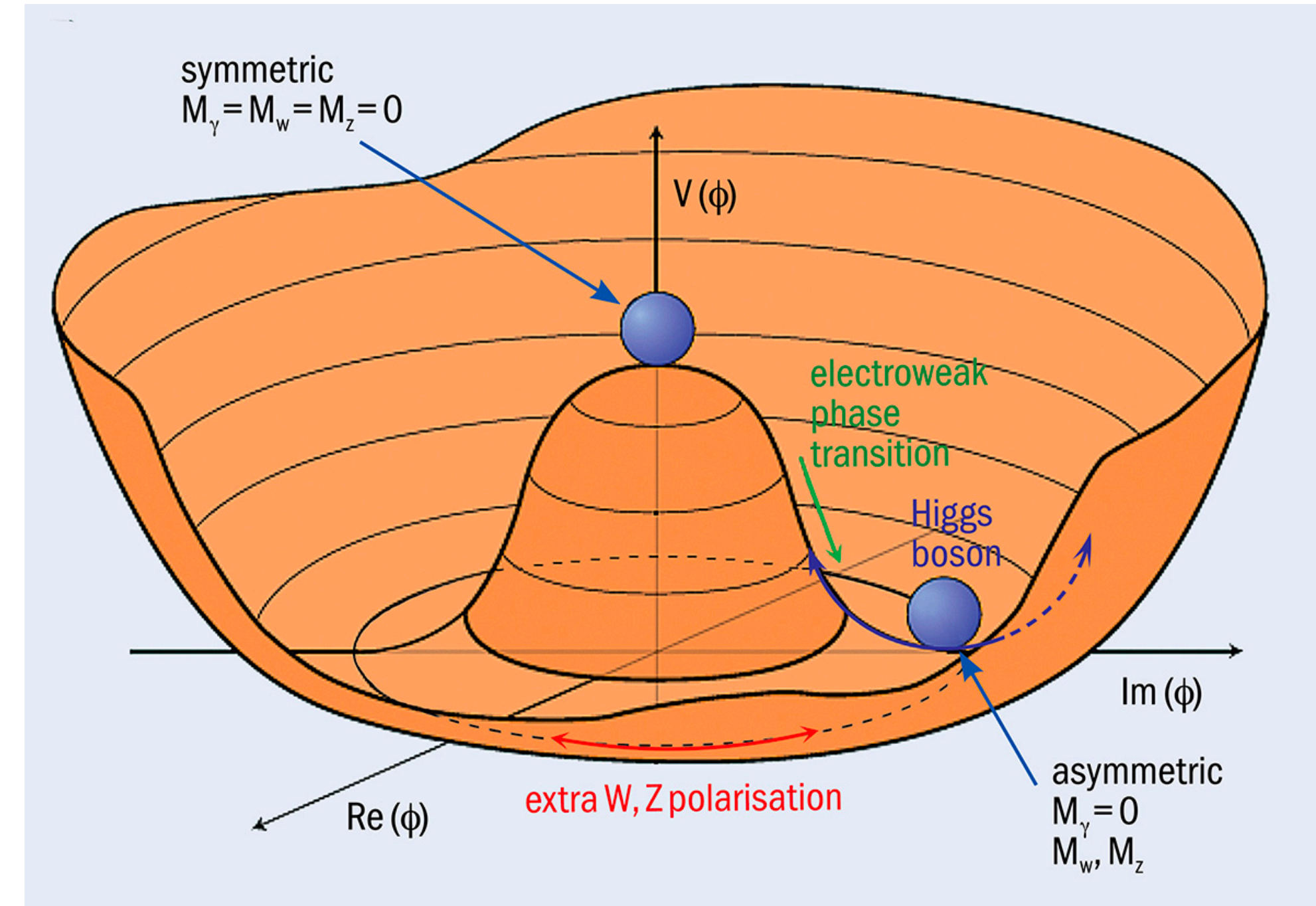
HIGGS BOSON IN THE STANDARD MODEL



- ▶ But there has to be more to it! SM does not explain **dark matter**, **neutrino masses**, and the **matter-antimatter asymmetry**...
- ▶ Higgs boson is the **centerpiece**: all particles interact with it
- ▶ Measuring its couplings to other particles (and to *itself*) may give insight into BSM physics

ELECTROWEAK SYMMETRY BREAKING & THE HIGGS POTENTIAL

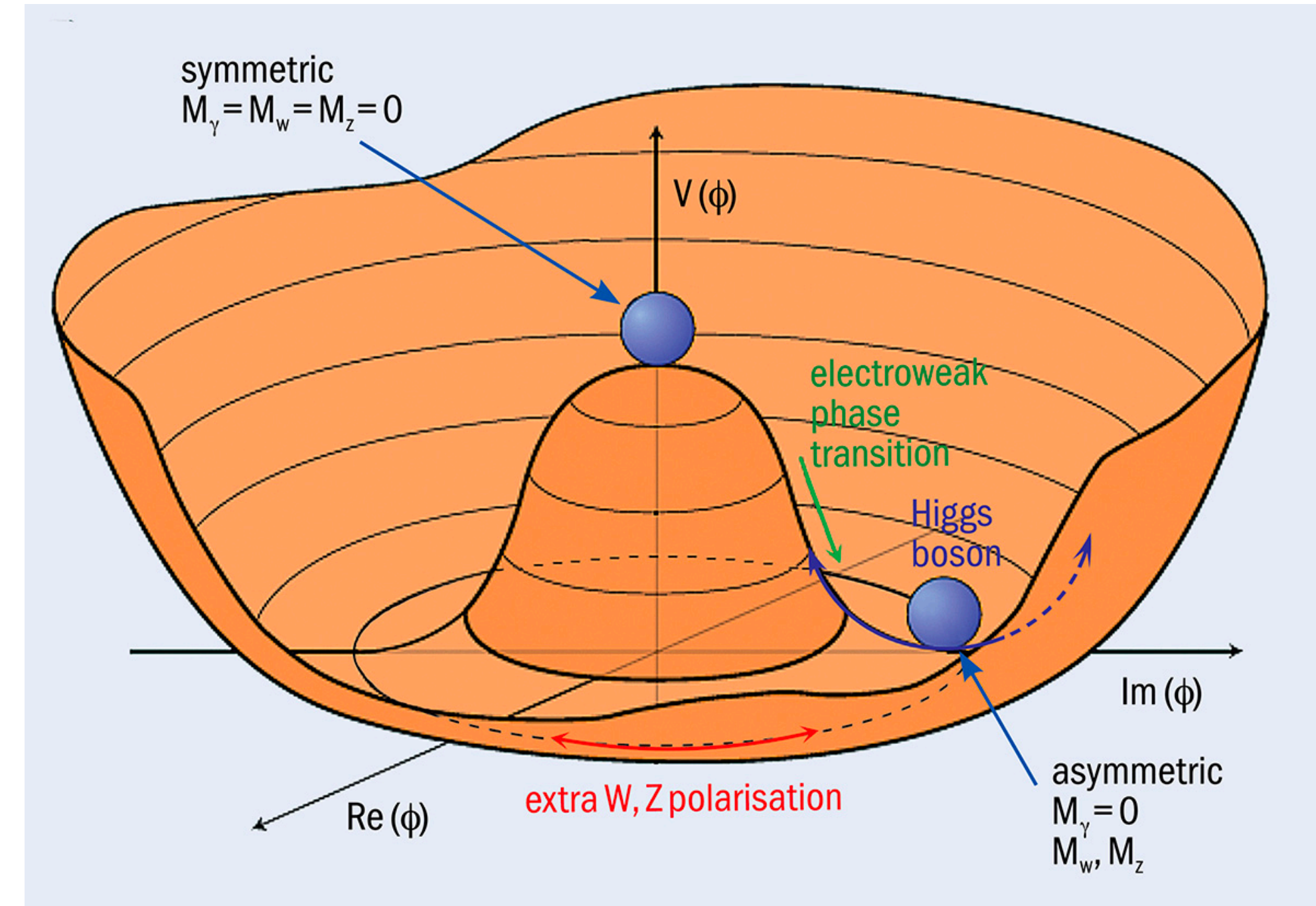
$$V(\phi) = \frac{1}{2}\mu^2\phi^2 + \frac{1}{4}\lambda\phi^4$$



ELECTROWEAK SYMMETRY BREAKING & THE HIGGS POTENTIAL

- ▶ The shape of the quartic Higgs potential determined by the self-coupling λ

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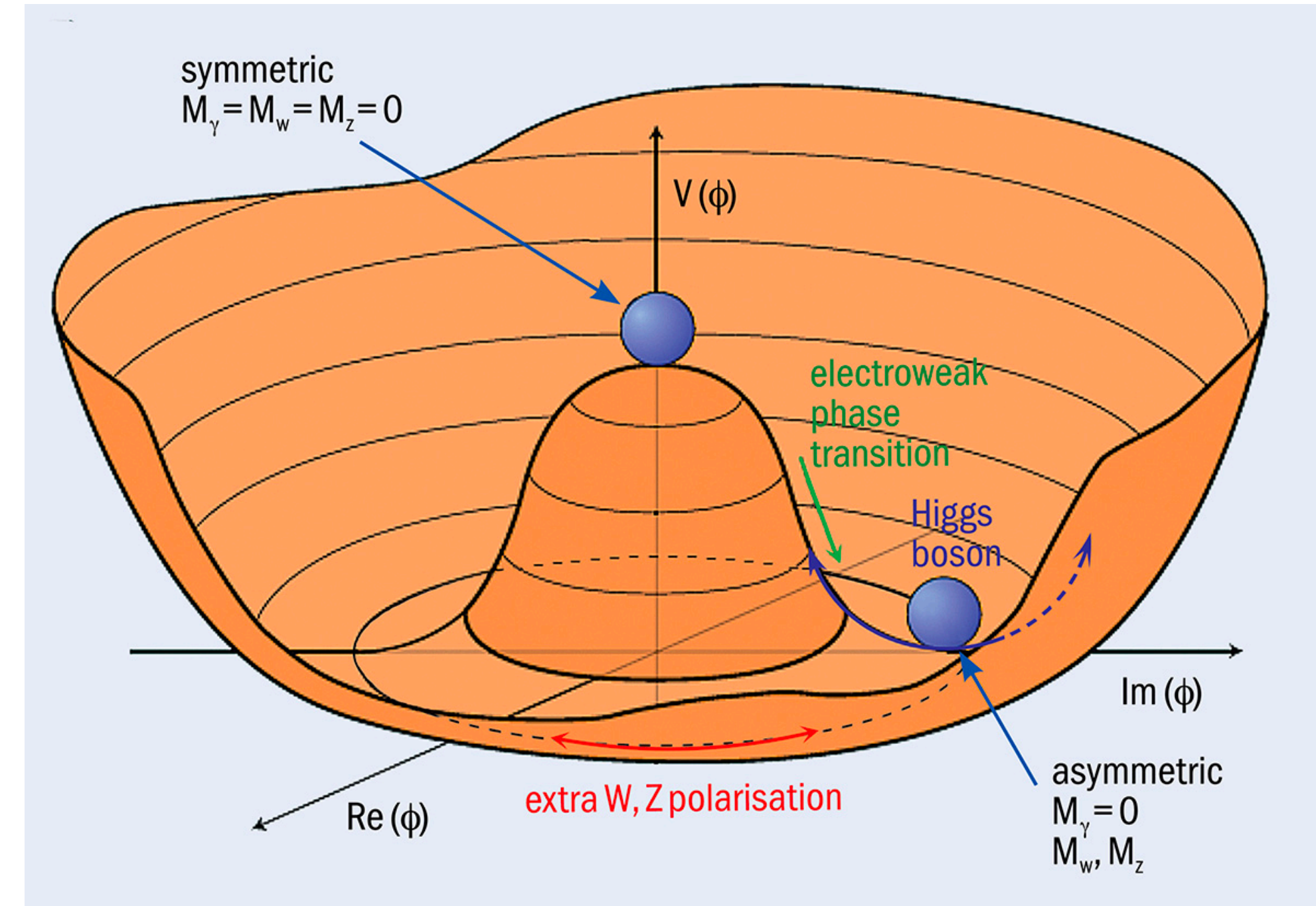


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- ▶ Sombrero shape means the Higgs field prefers a nonzero value (smaller energy)
 - ▶ W, Z bosons acquire mass; while γ remains massless \rightarrow symmetry of electroweak force is broken

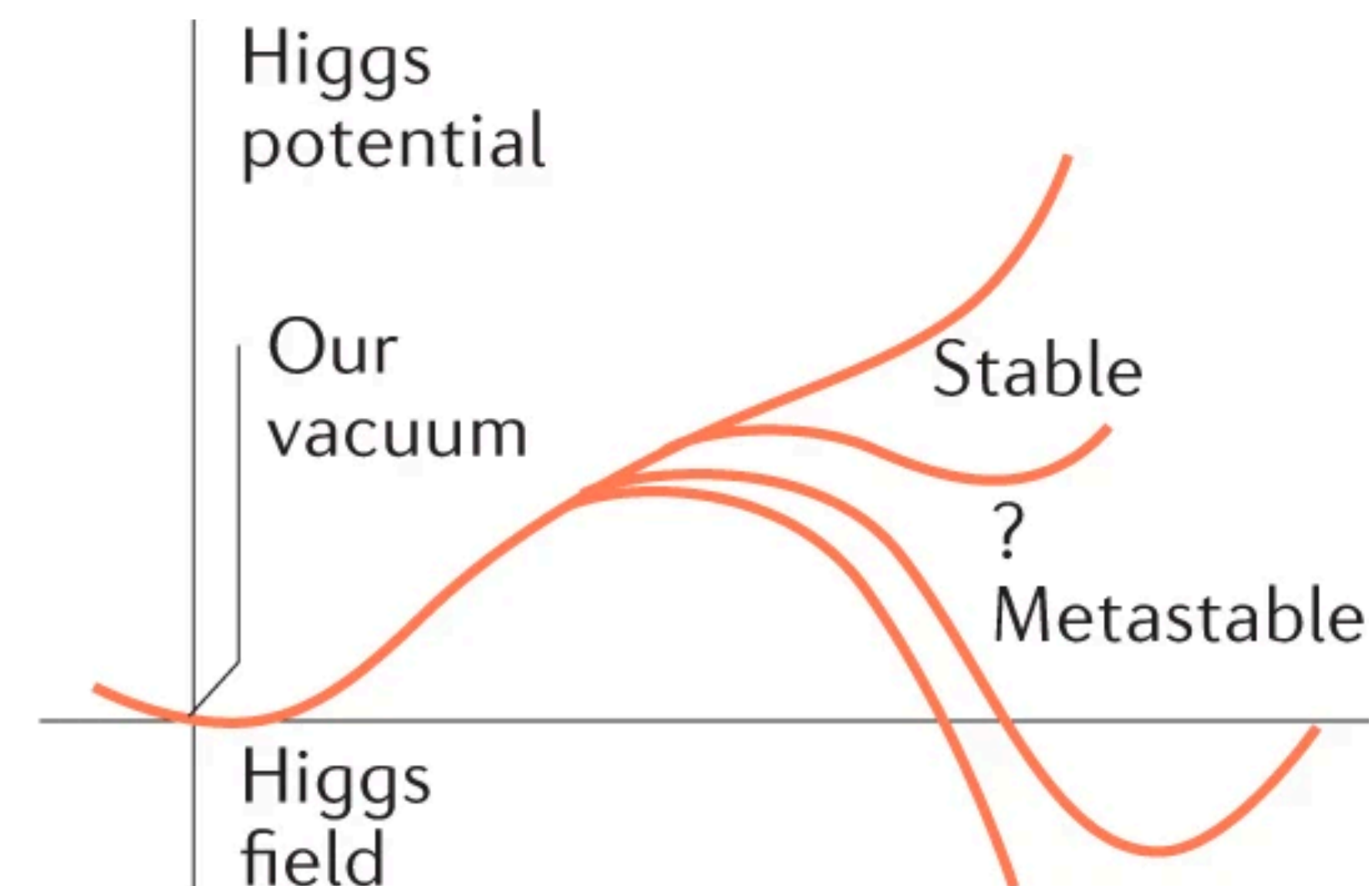
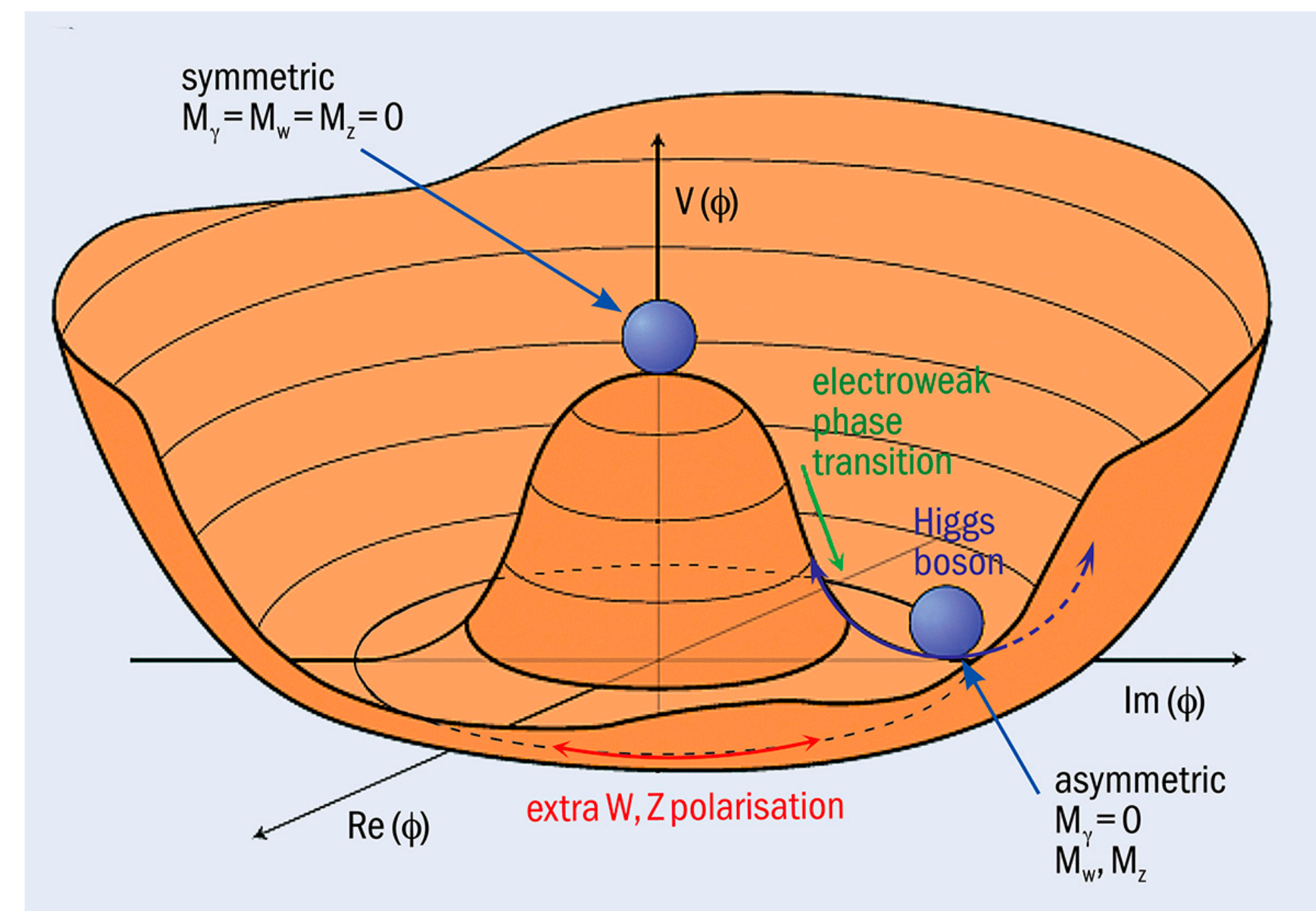


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- ▶ Sombrero shape means the Higgs field prefers a nonzero value (smaller energy)
 - ▶ W, Z bosons acquire mass; while γ remains massless \rightarrow symmetry of electroweak force is broken
- ▶ Measurement of λ crucial for confirming this story of how electroweak symmetry breaking is realized
 - ▶ And the (meta)stability of our vacuum



$$\mathcal{L} \supset -\frac{m_t}{v} \bar{t}tH + \frac{m_H^2}{2v} H^3 + \frac{m_H^2}{8v^2} H^4$$
$$+ \delta_V \frac{2m_V^2}{v} V_\mu V^\mu H + \delta_V \frac{m_V^2}{v^2} V_\mu V^\mu H^2 + \dots$$

► In the SM, relevant part of the Lagrangian is

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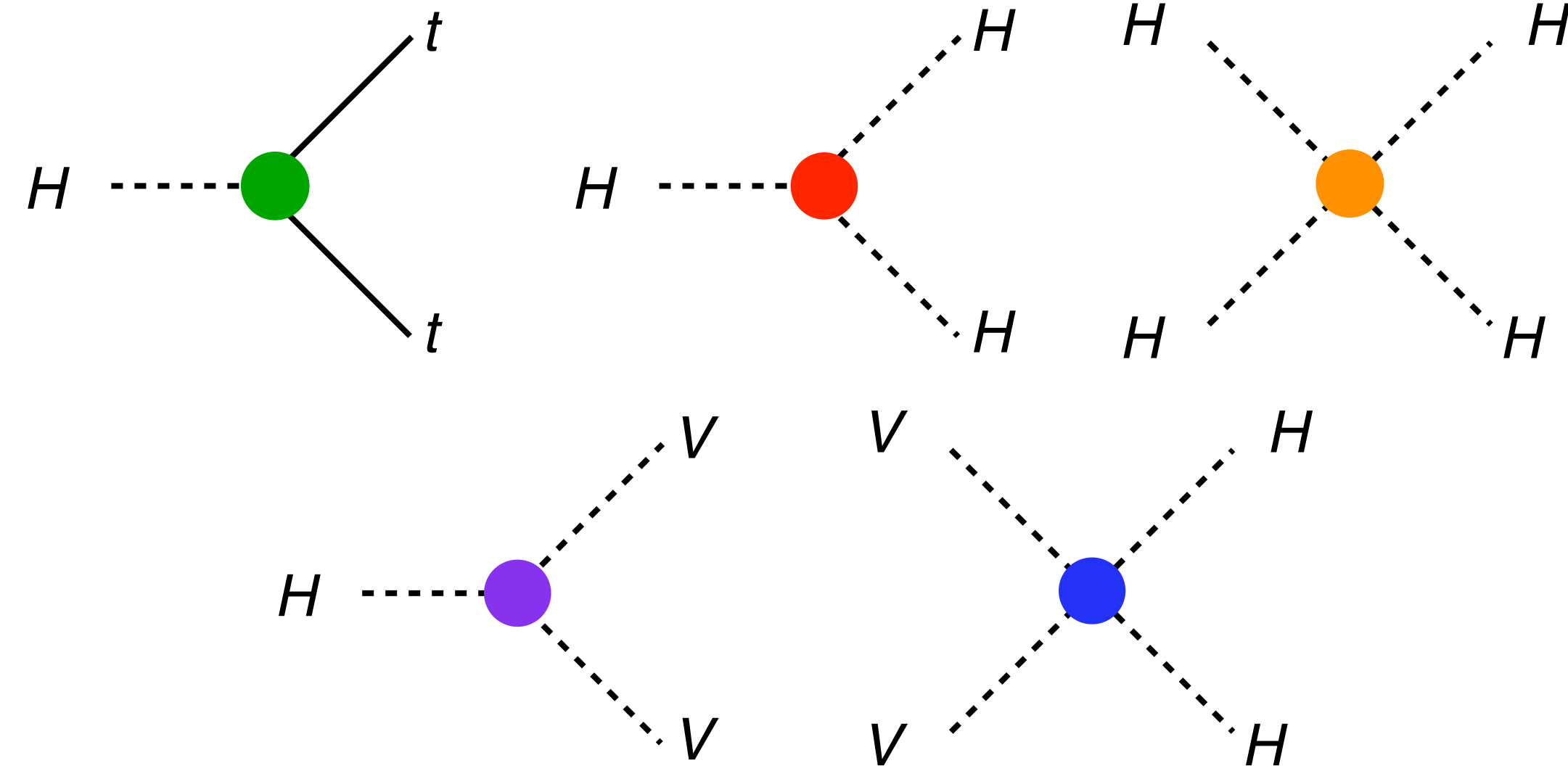
where $V = W^\pm$ or Z and $\delta_W = 1$, $\delta_Z = 1/2$

(B) SM HIGGS COUPLINGS

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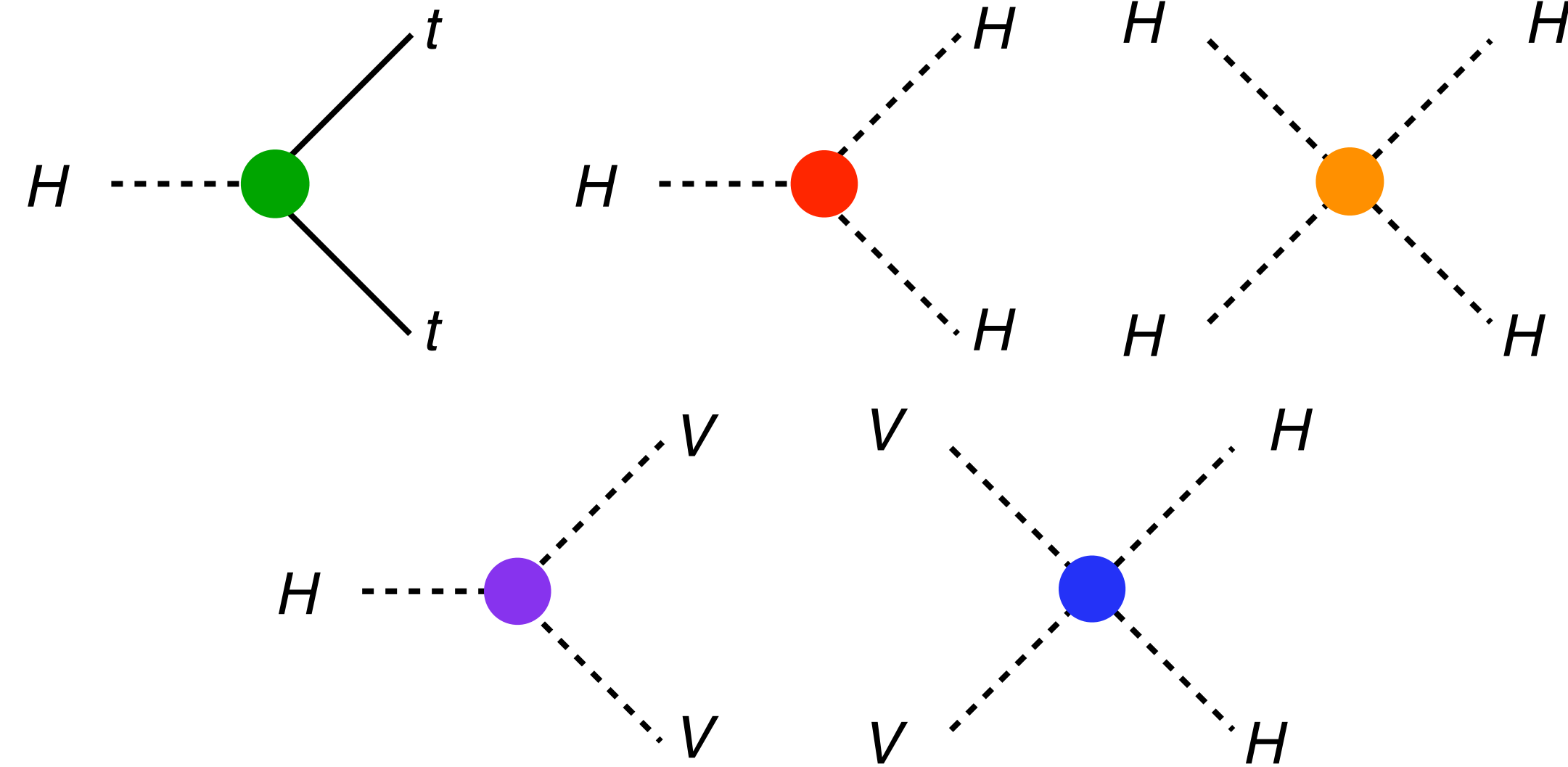
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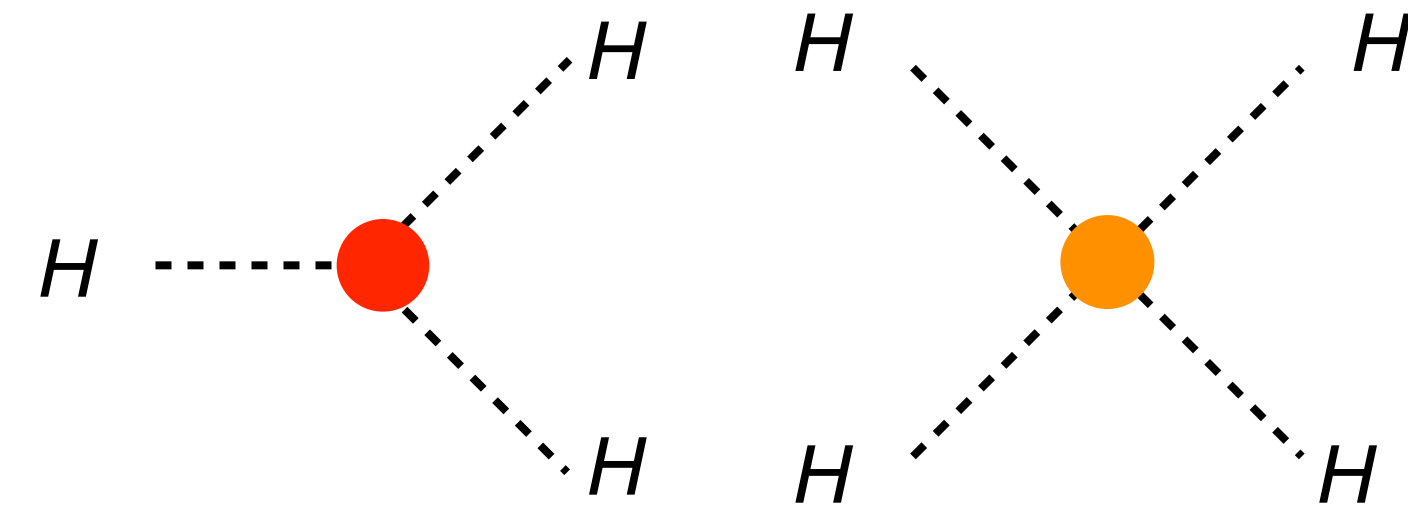
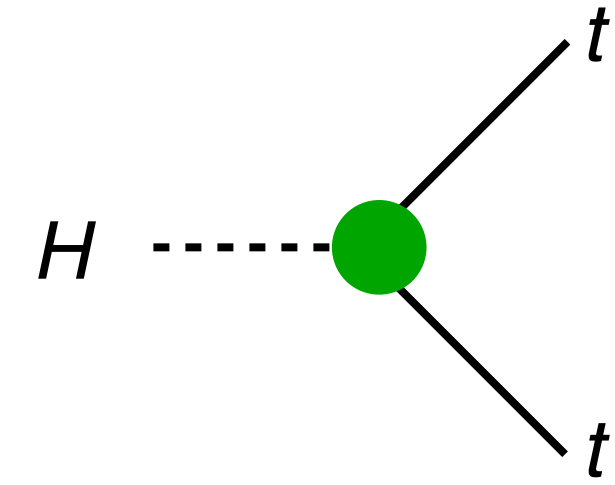
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- ▶ Many BSM scenarios conceivable for interpreting results

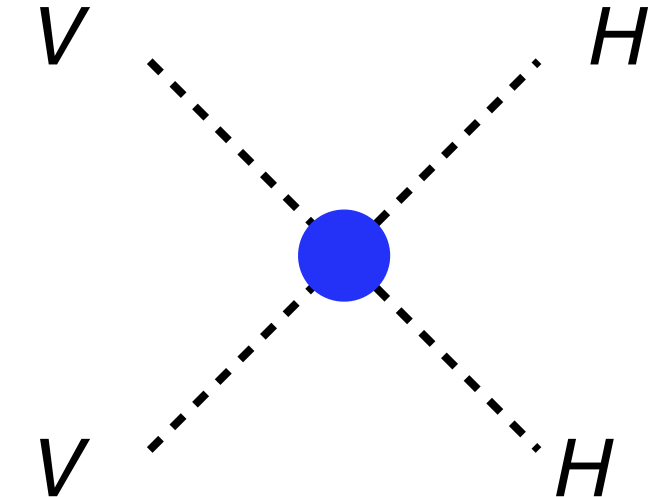
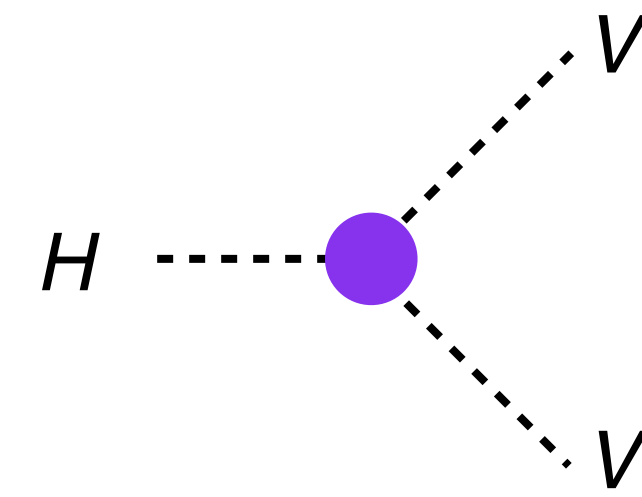


- ▶ In the SM, relevant part of the Lagrangian is

$$\mathcal{L} \supset -\kappa_t \frac{m_t}{v} \bar{t}tH + \kappa_\lambda \frac{m_H^2}{2v} H^3 + \frac{m_H^2}{8v^2} H^4$$



$$+ \kappa_V \delta_V \frac{2m_V^2}{v} V_\mu V^\mu H + \kappa_{2V} \delta_V \frac{m_V^2}{v^2} V_\mu V^\mu H^2 + \dots$$

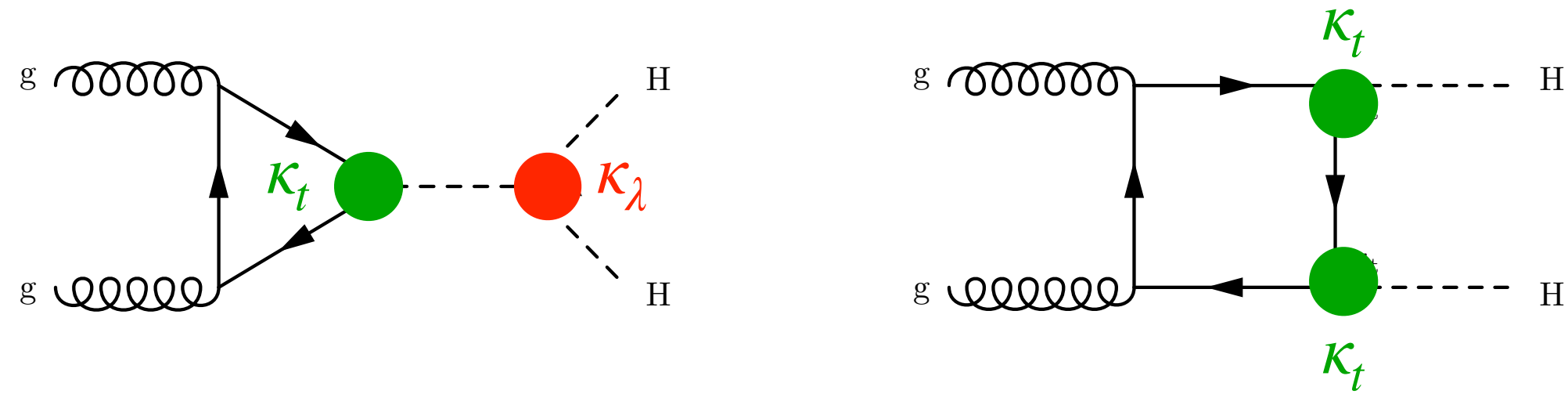


where $V = W^\pm$ or Z and $\delta_W = 1$, $\delta_Z = 1/2$

- ▶ Many BSM scenarios conceivable for interpreting results
 - ▶ Focus on modified couplings w.r.t. the SM: κ_λ , κ_V , κ_{2V} , and κ_t

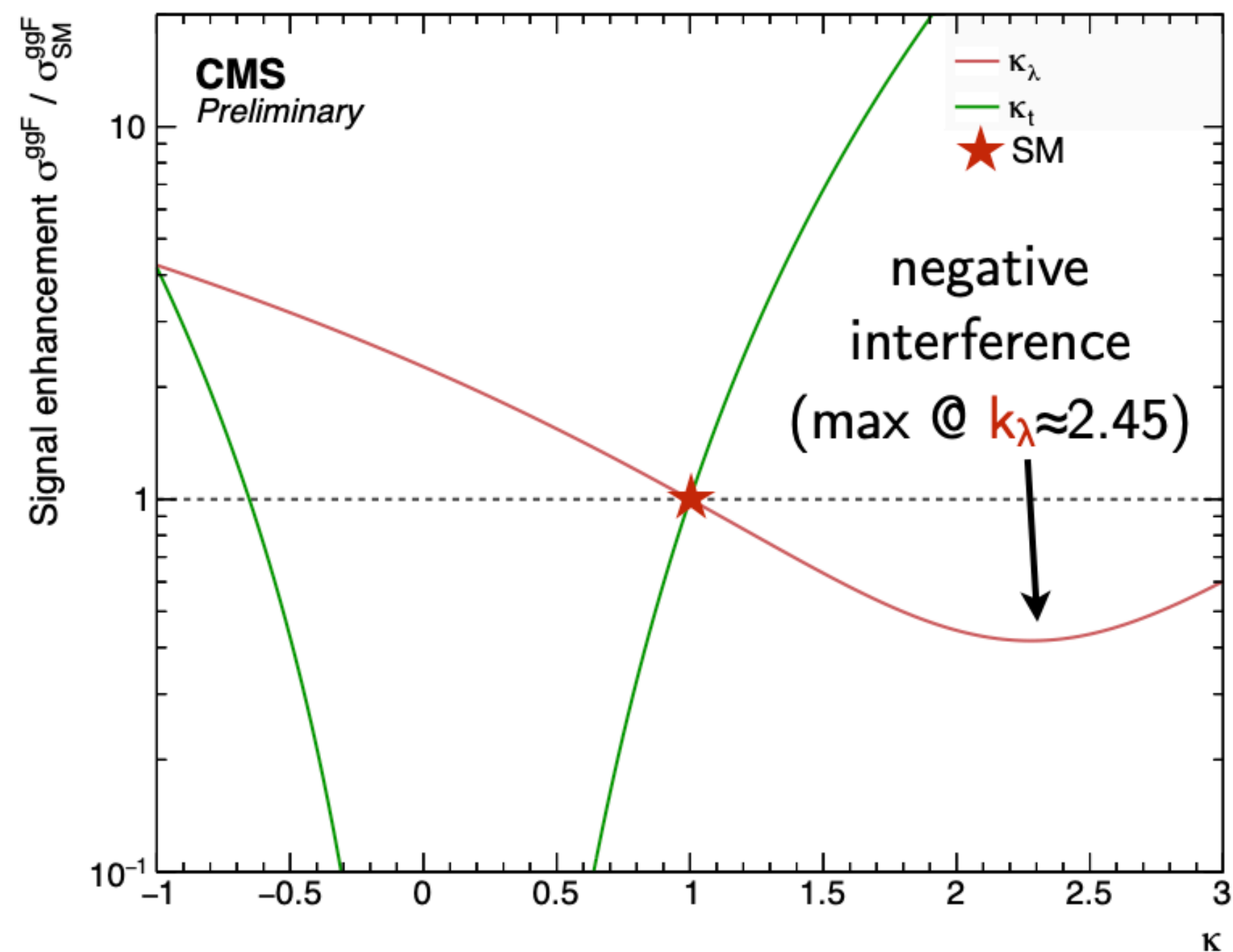
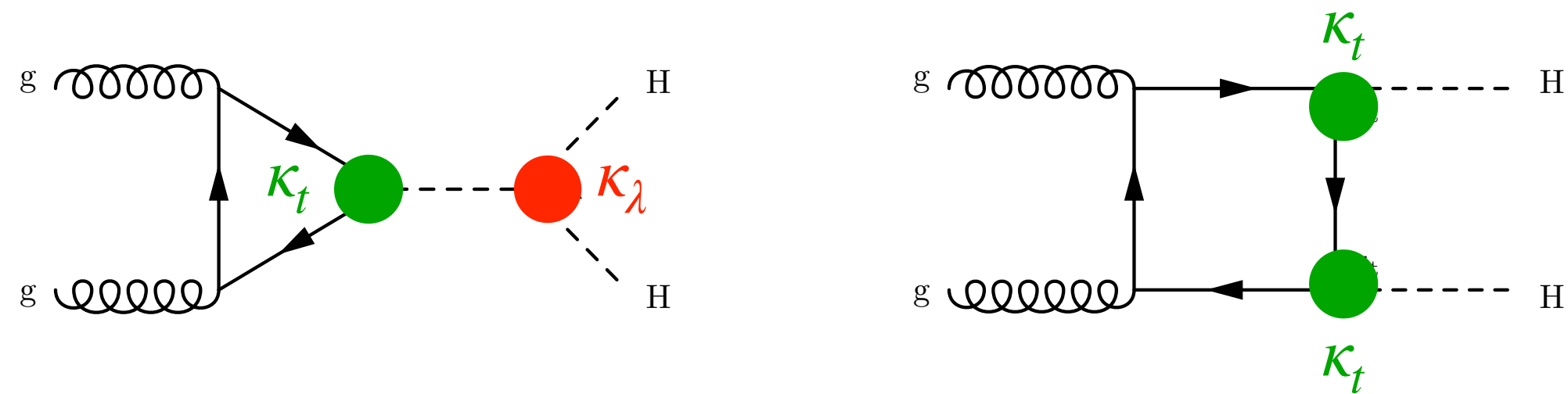
HH PRODUCTION AT THE LHC

- ▶ Dominant gluon-gluon fusion (ggF) production mode ($\sigma_{ggF} = 31.05 \text{ fb}$) gives best access to H self-coupling



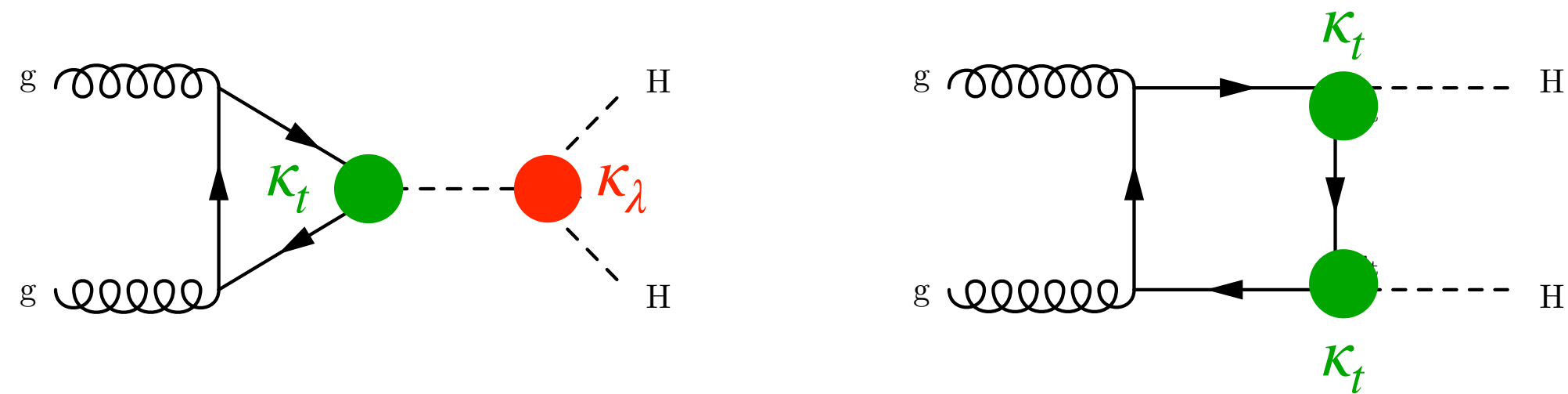
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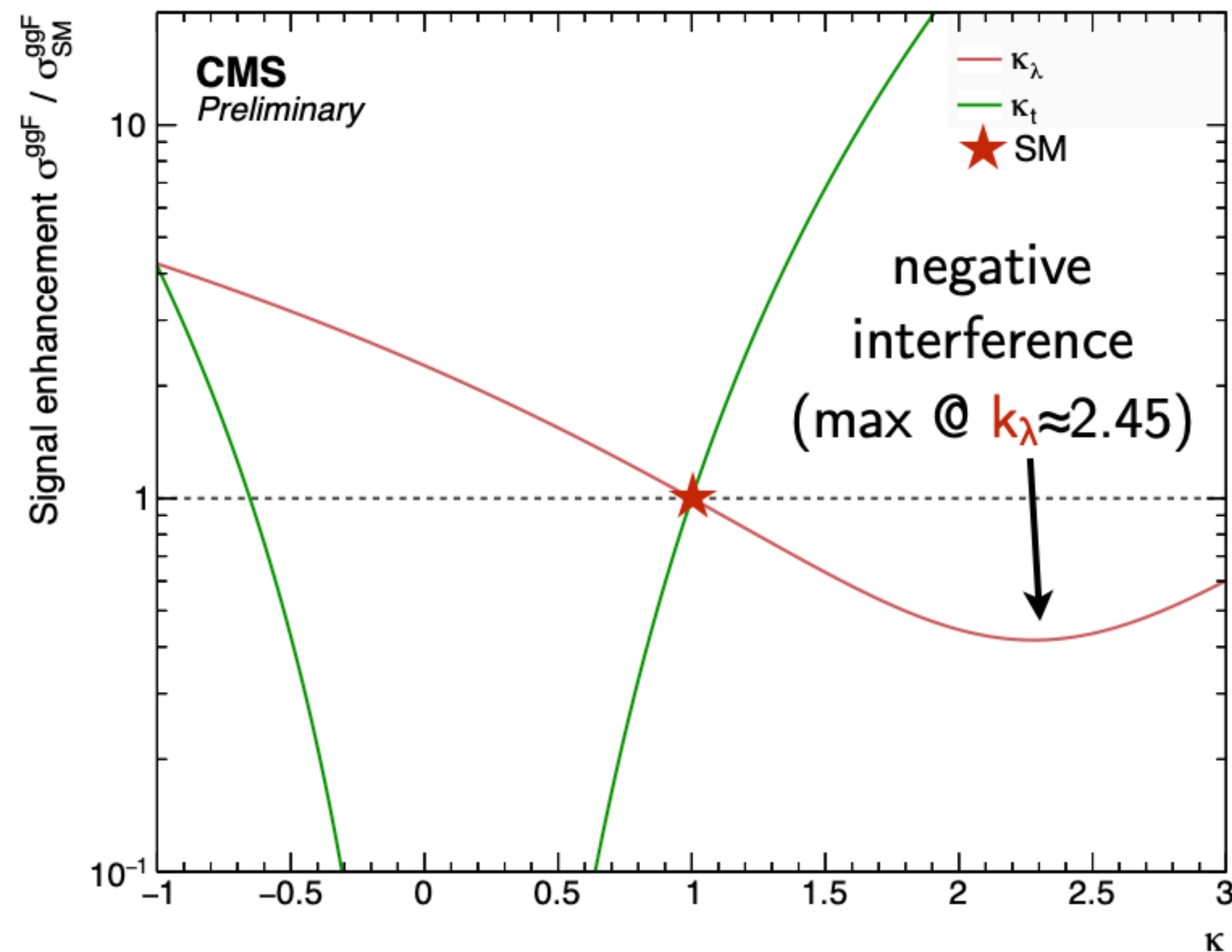
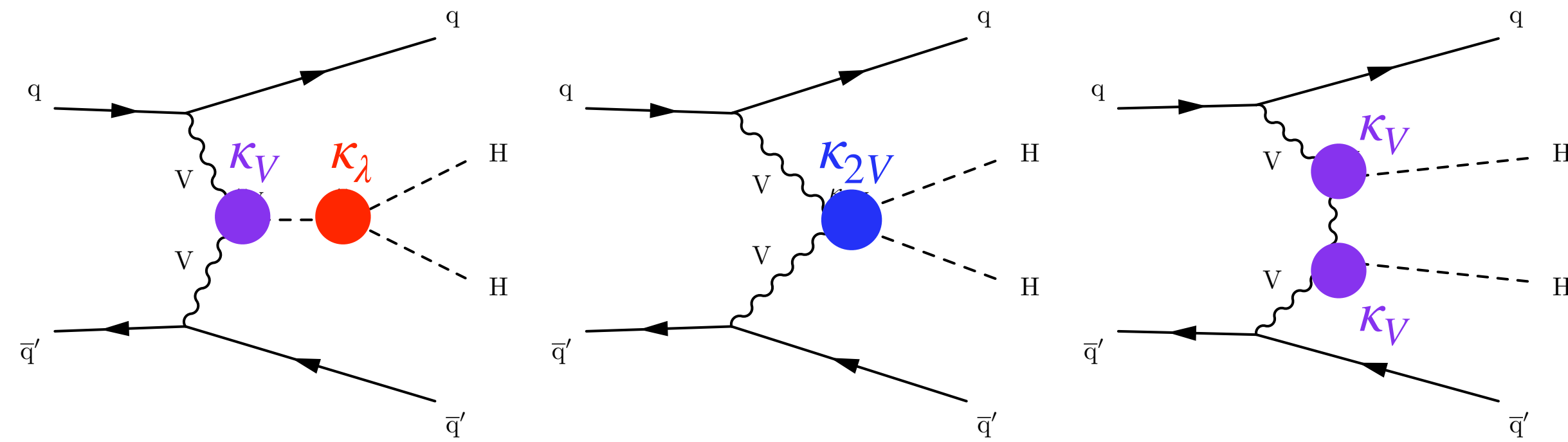


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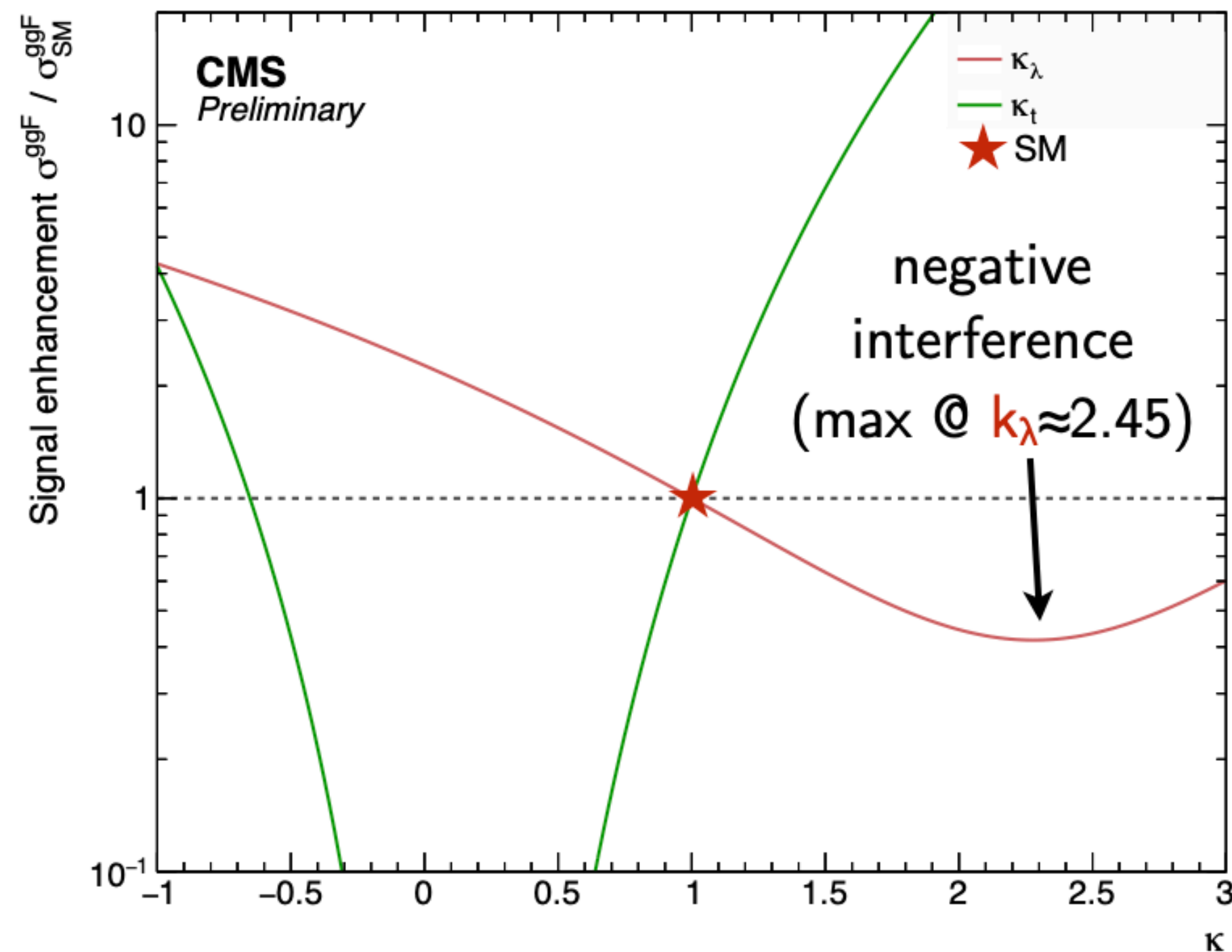
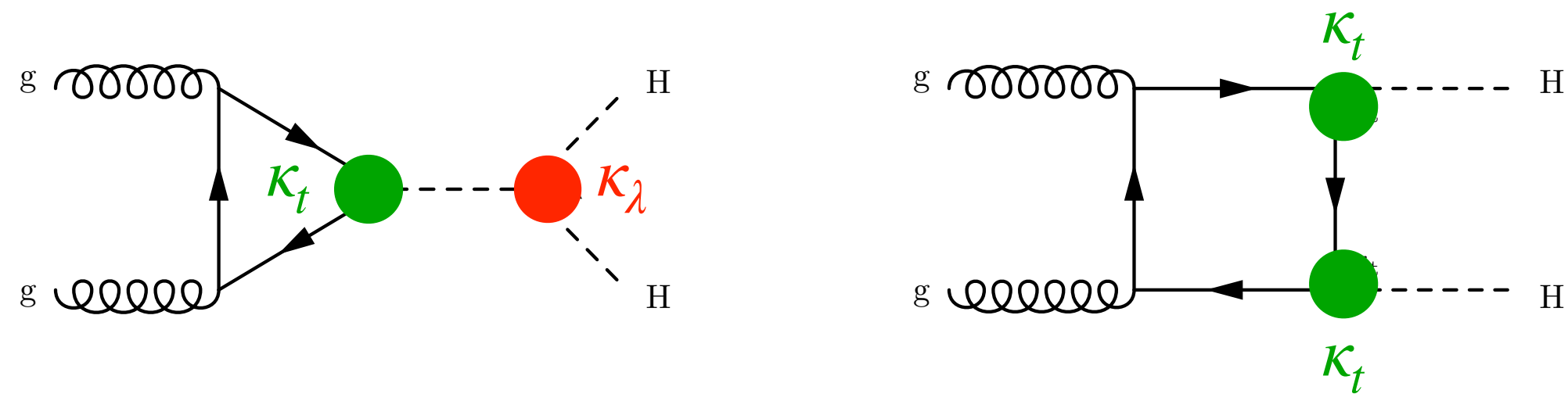


- ▶ Vector boson fusion (VBF) ($\sigma_{VBF} = 1.73 \text{ fb}$) uniquely sensitive to HHVV coupling

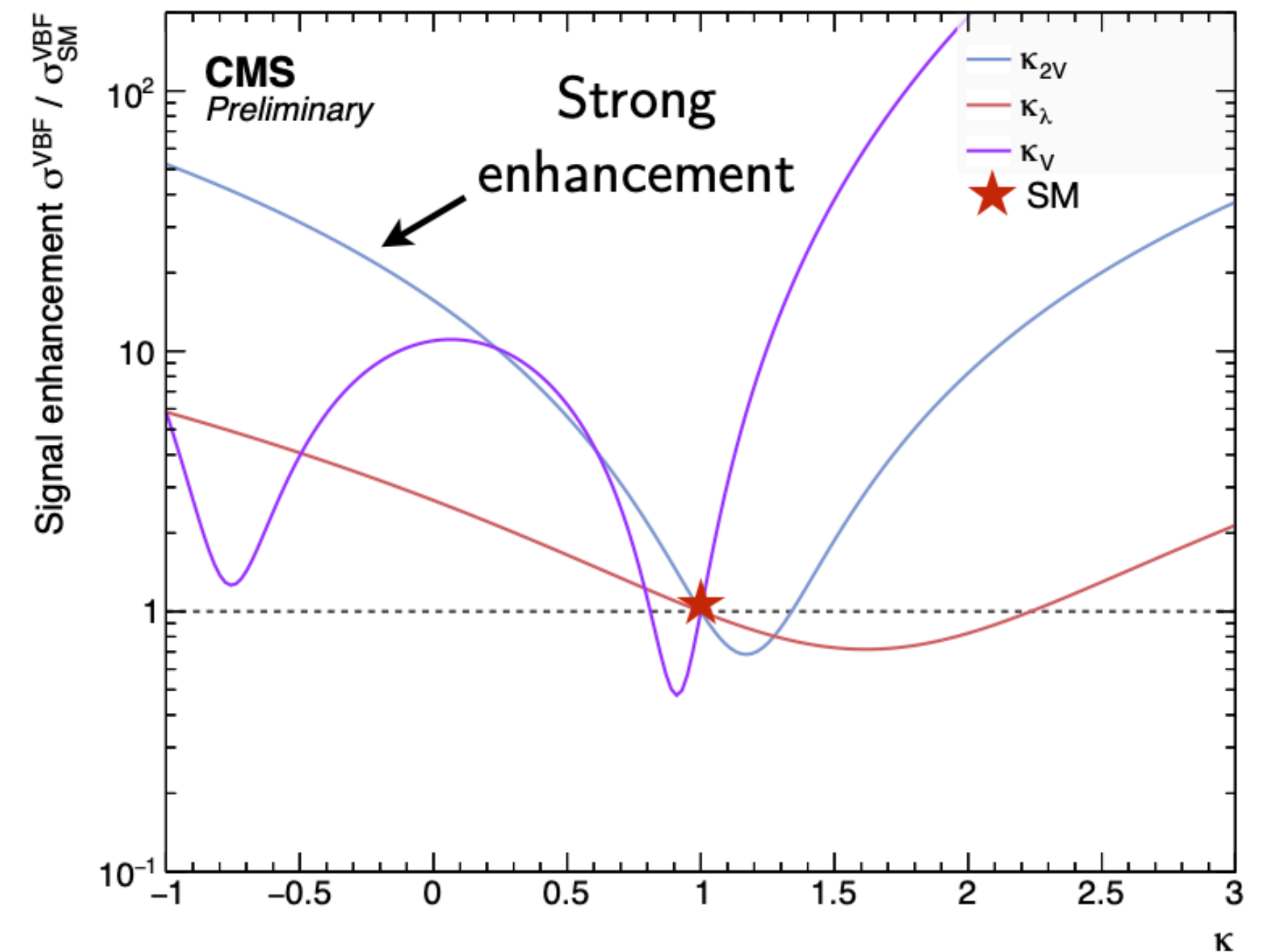
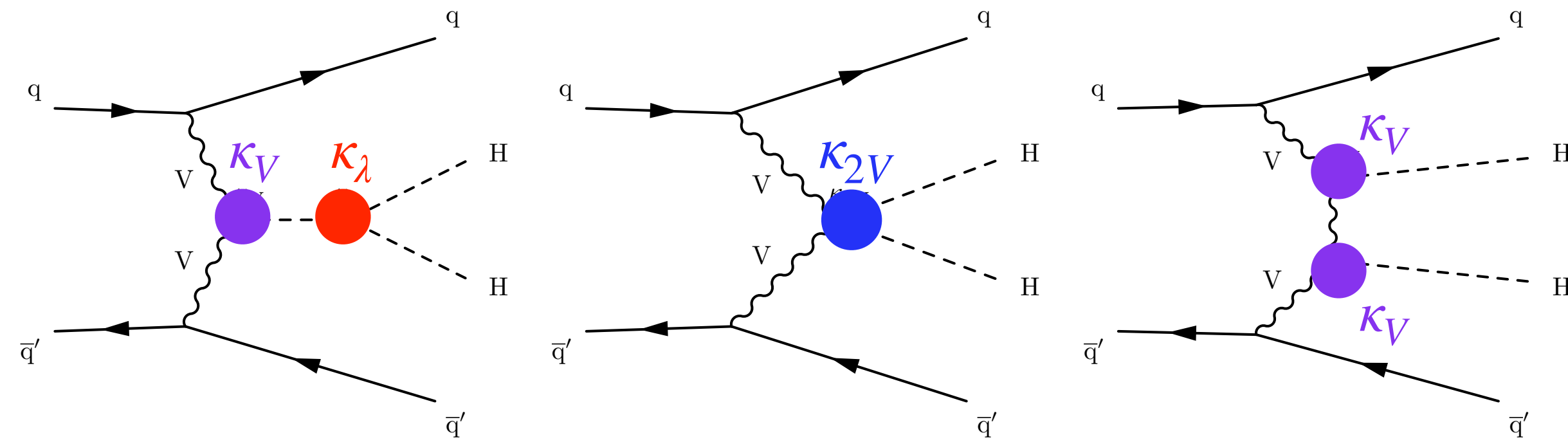


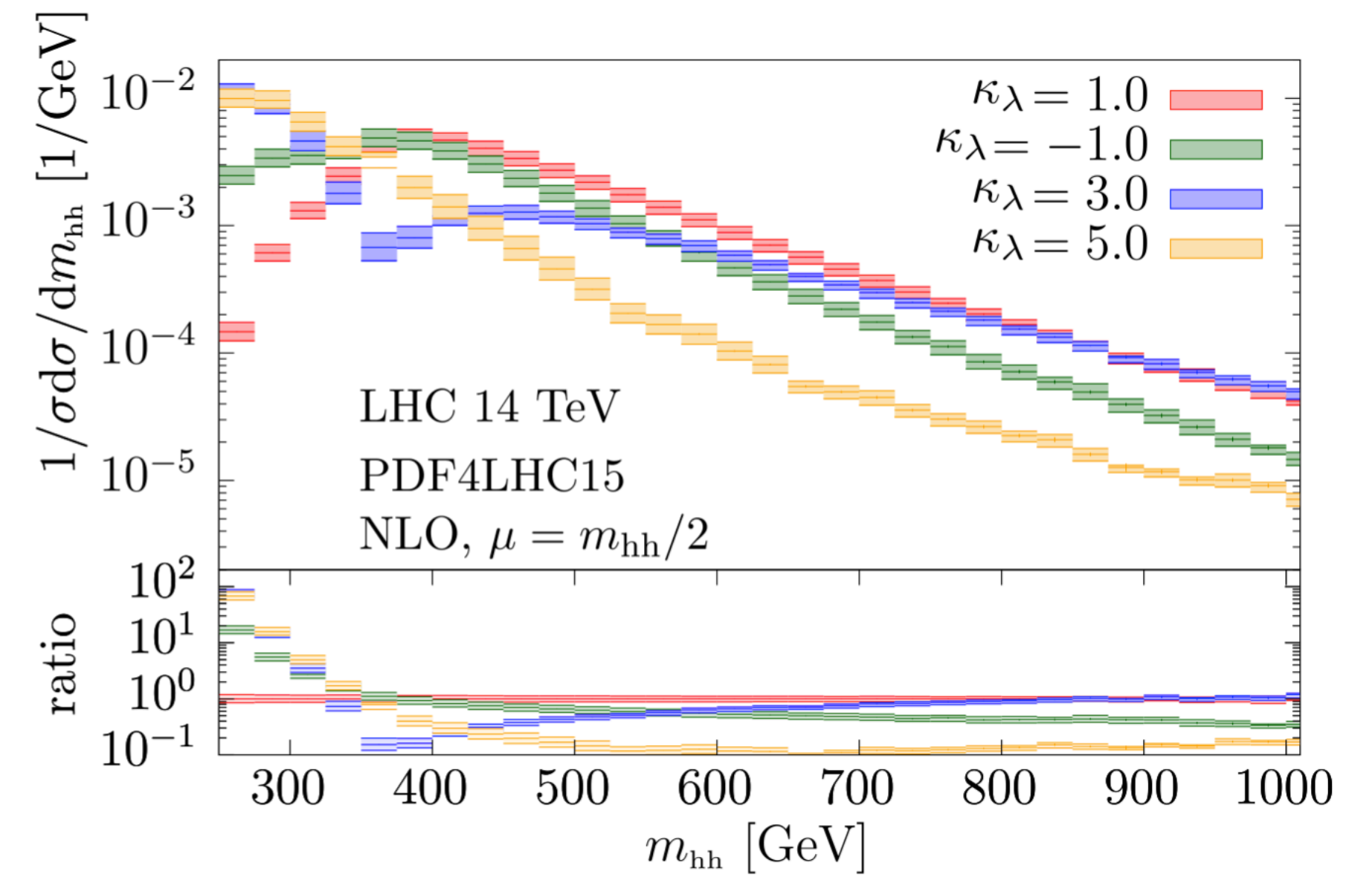
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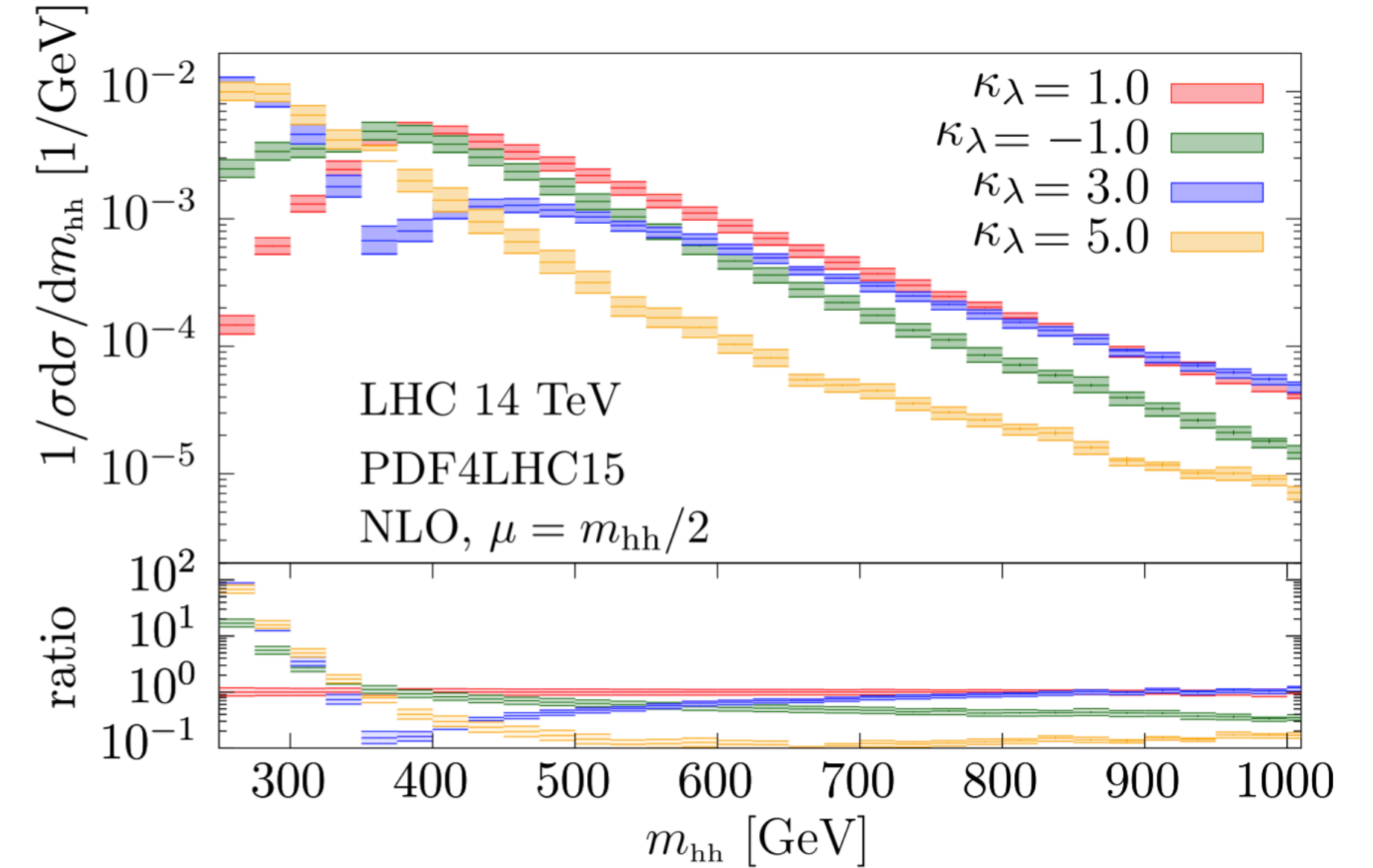


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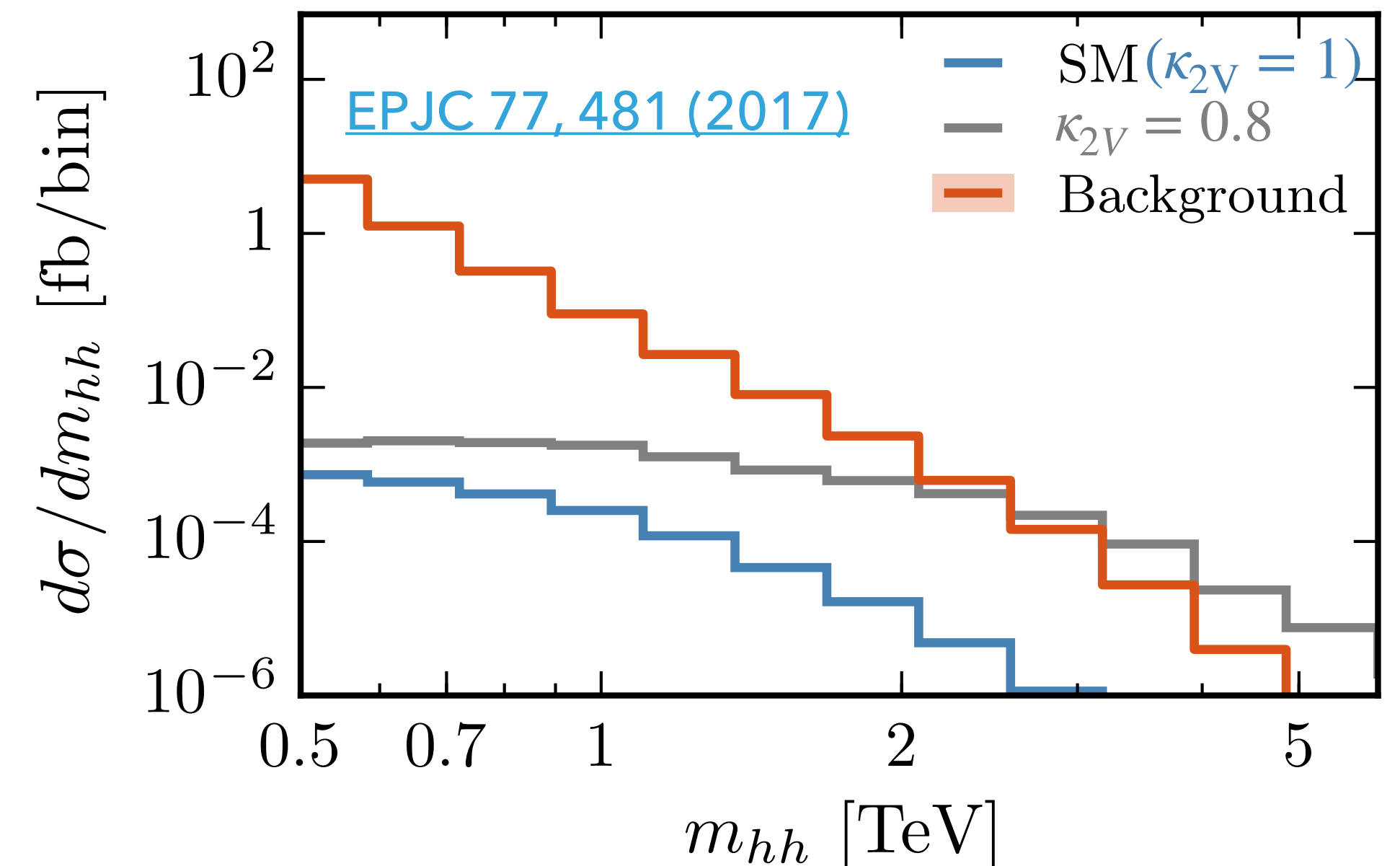
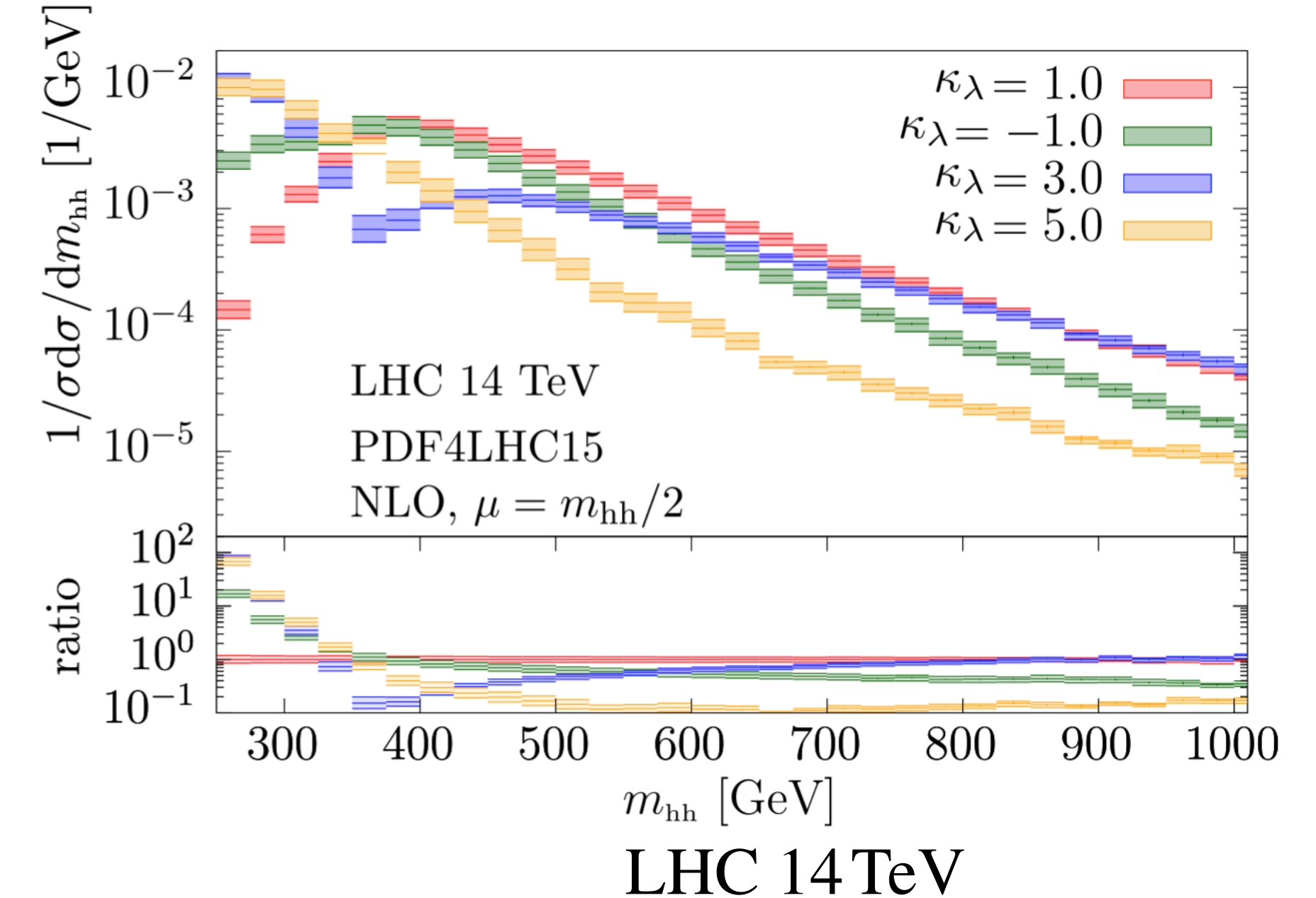




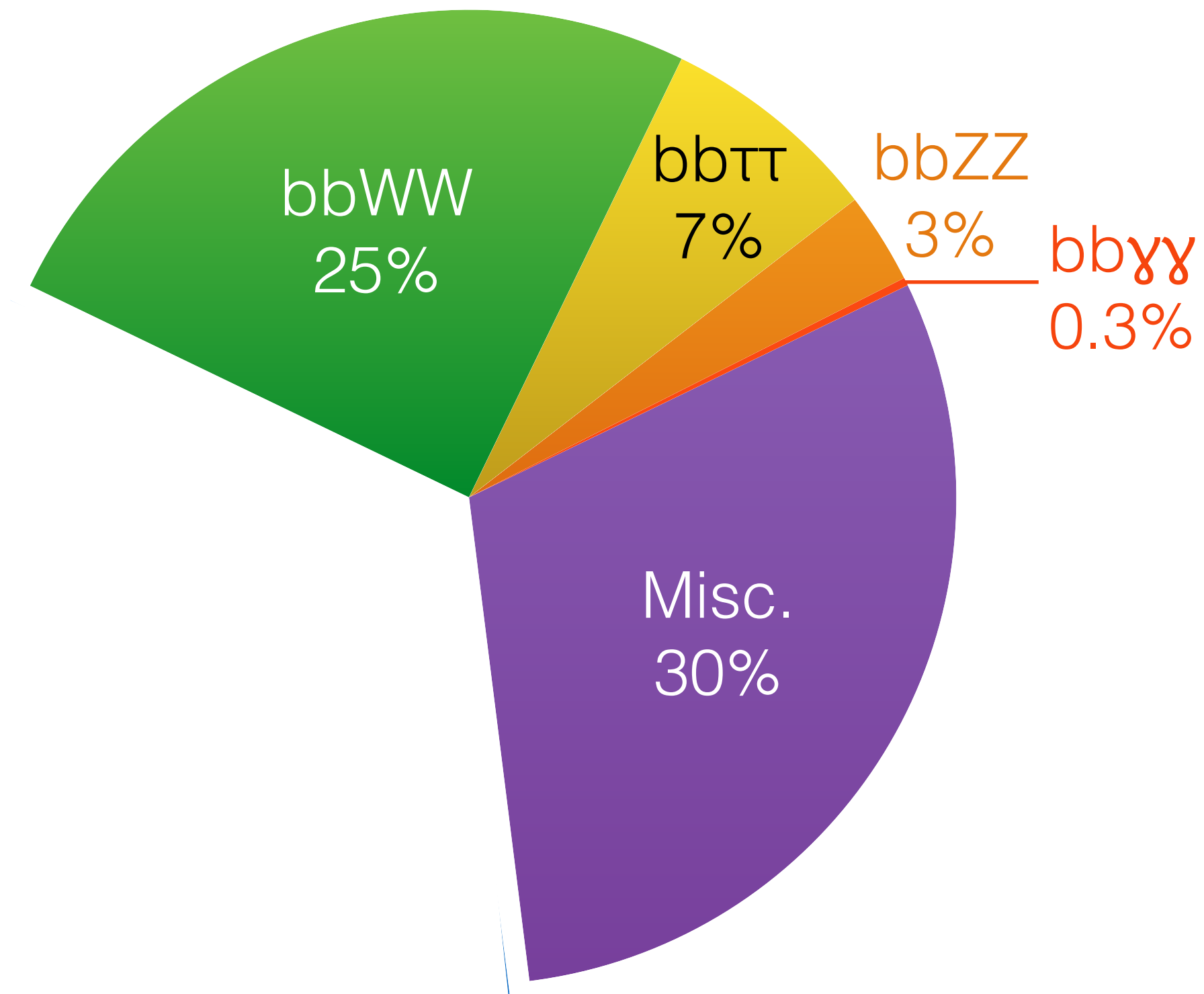
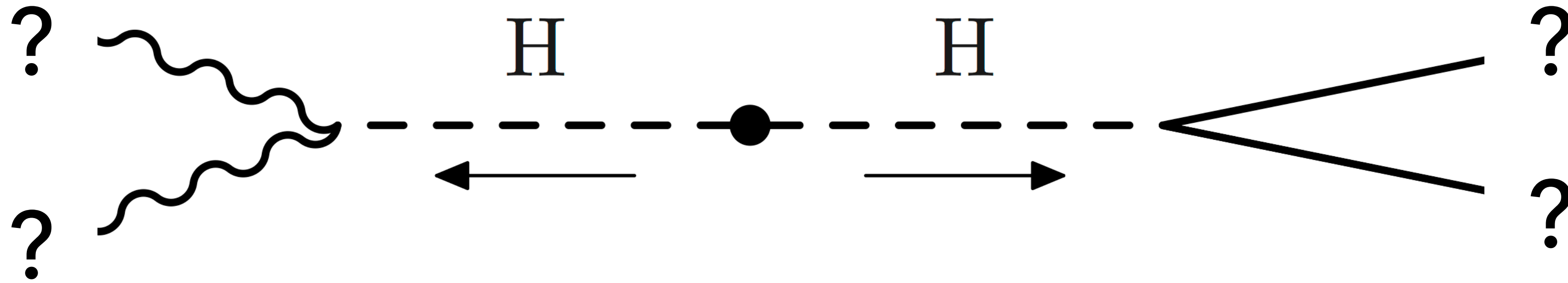
- ▶ Spectrum of m_{HH} depends on κ_λ
 - ▶ Softer for large $|\kappa_\lambda|$
 - ▶ Intermediate $|\kappa_\lambda|$ leads to harder m_{HH} spectrum and boosted ggF signatures, but overall cross section reduction due to interference

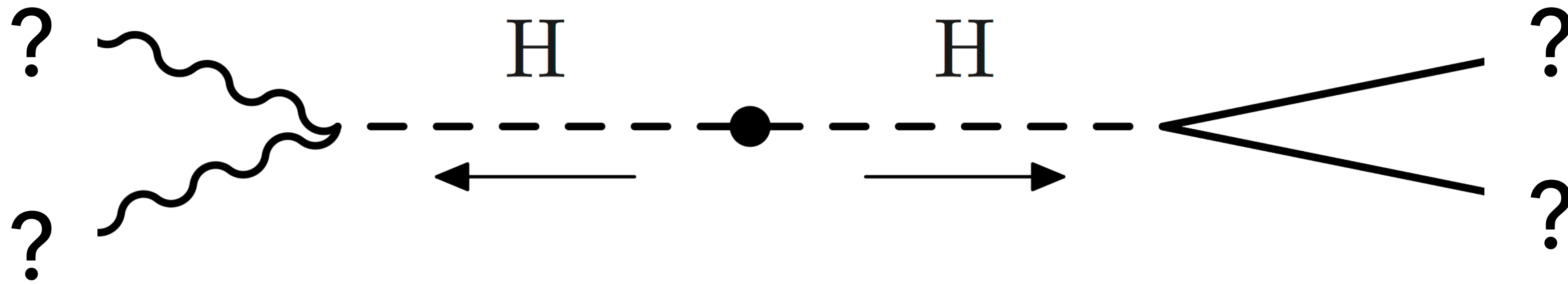


- ▶ Spectrum of m_{HH} depends on κ_λ
 - ▶ Softer for large $|\kappa_\lambda|$
 - ▶ Intermediate $|\kappa_\lambda|$ leads to harder m_{HH} spectrum and boosted ggF signatures, but overall cross section reduction due to interference
- ▶ Alternatively, smaller κ_{2V} leads to larger cross section, harder m_{HH} spectrum, and boosted VBF signatures

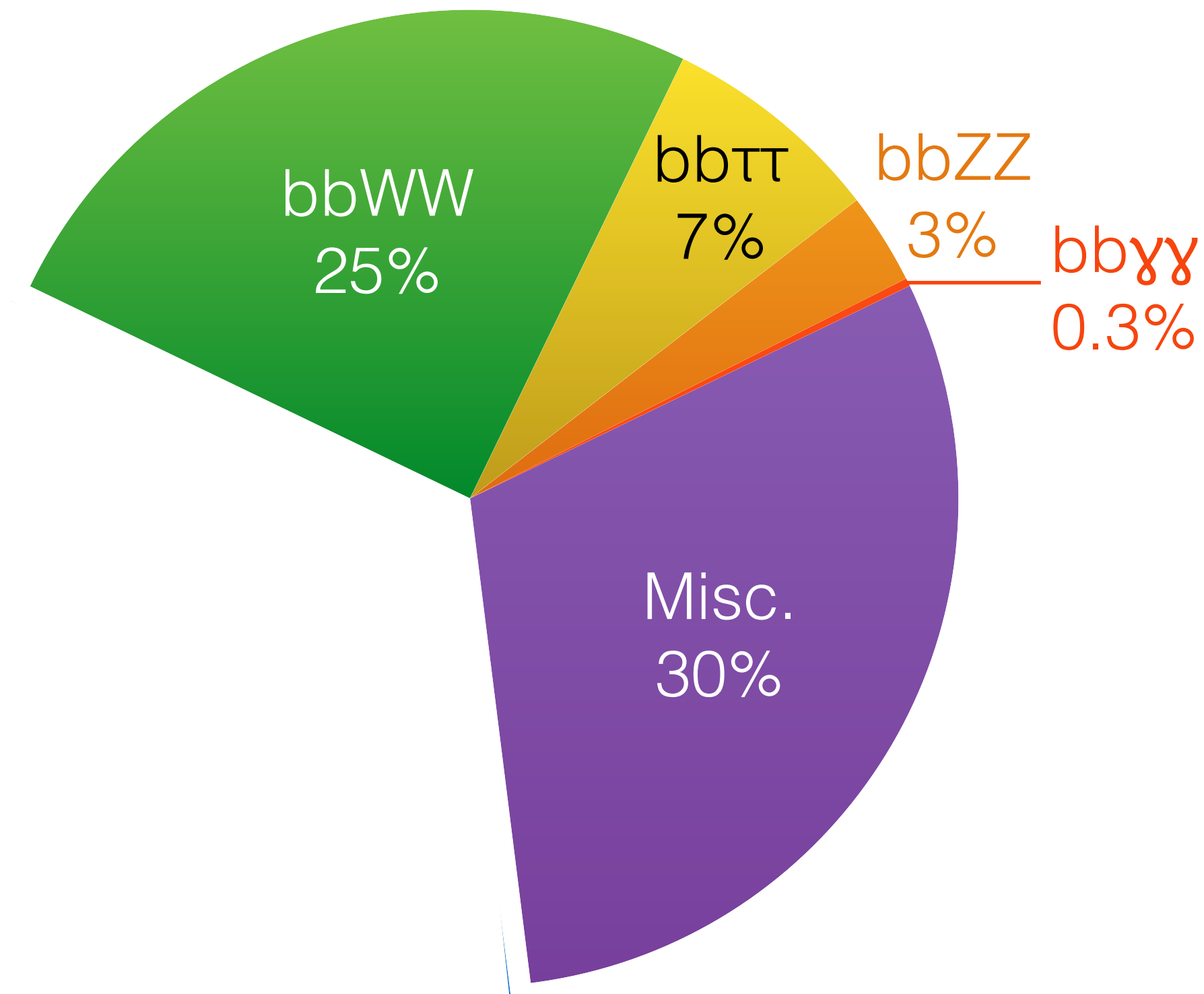


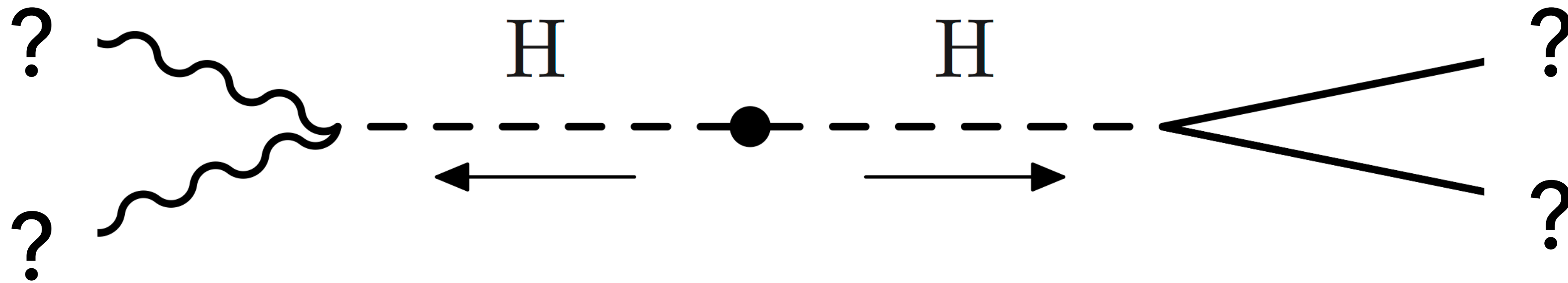
HOW DO WE DETECT HH PRODUCTION?



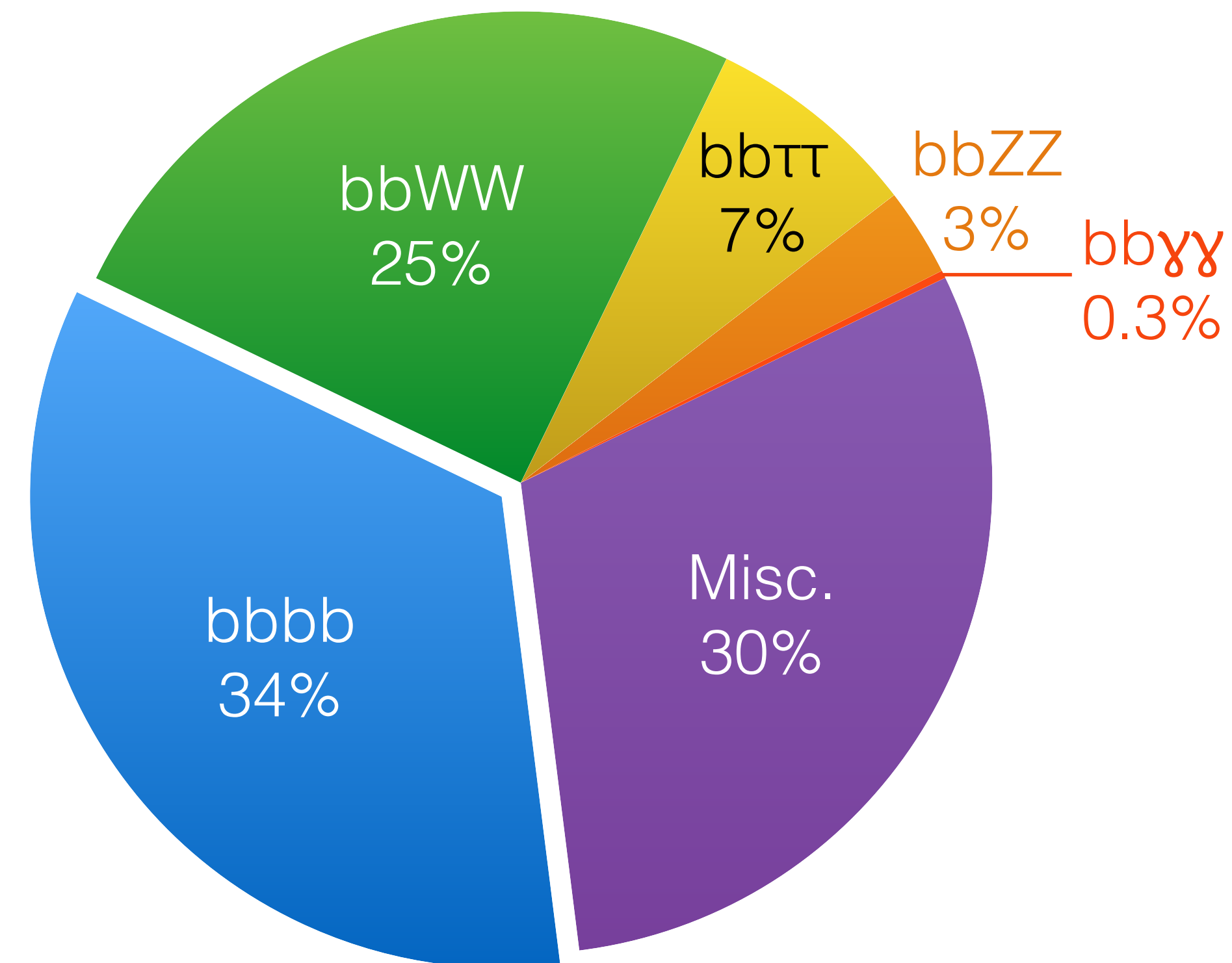


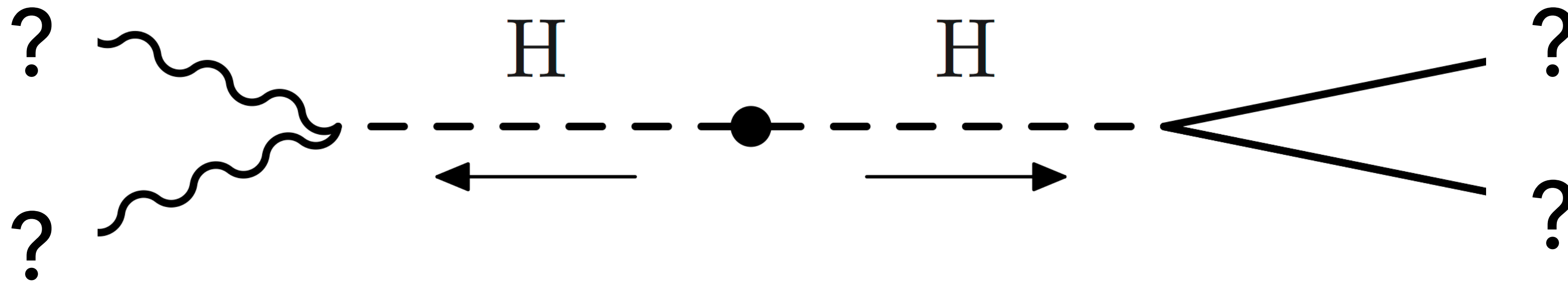
- ▶ $bb\gamma\gamma$ has small rate but is traditionally thought to be "golden channel"



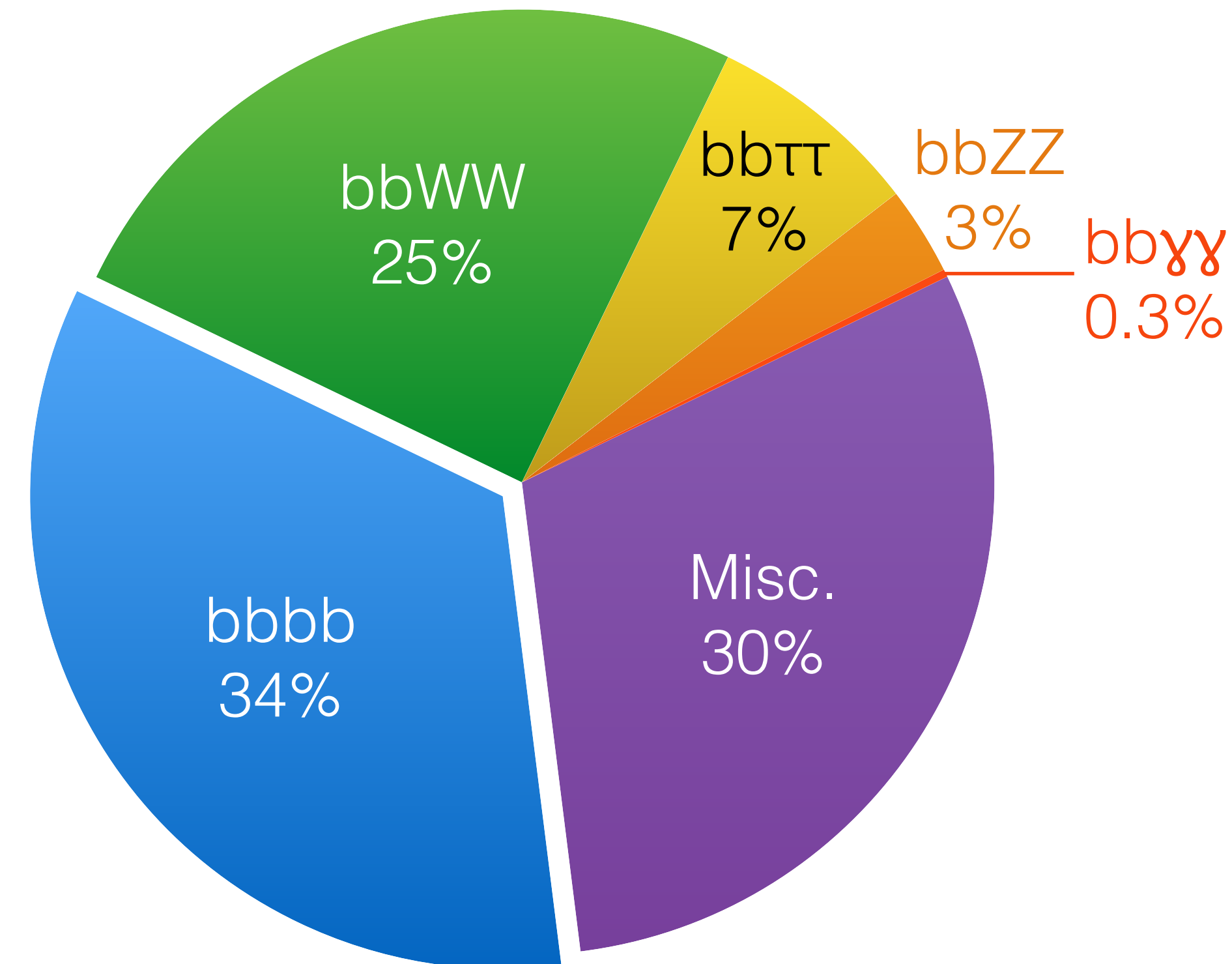


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- ▶ $bbbb$ is the largest fraction, but more challenging due to large backgrounds



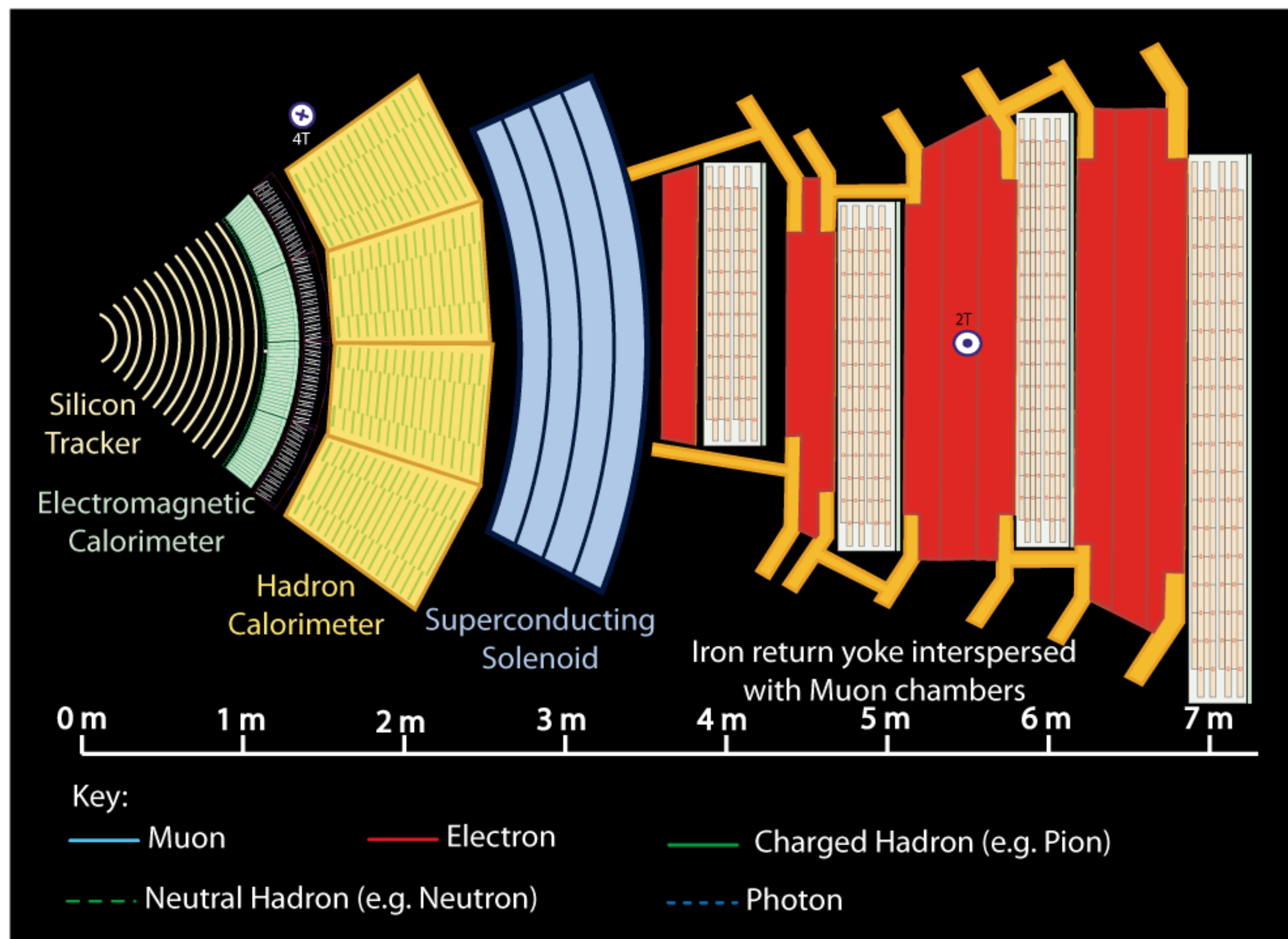


- ▶ $bb\gamma\gamma$ has small rate but is traditionally thought to be “golden channel”
- ▶ $bbbb$ is the largest fraction, but more challenging due to large backgrounds
 - ▶ ***This talk:*** using new tools & phase space to make $bbbb$ channel ***among the most sensitive***



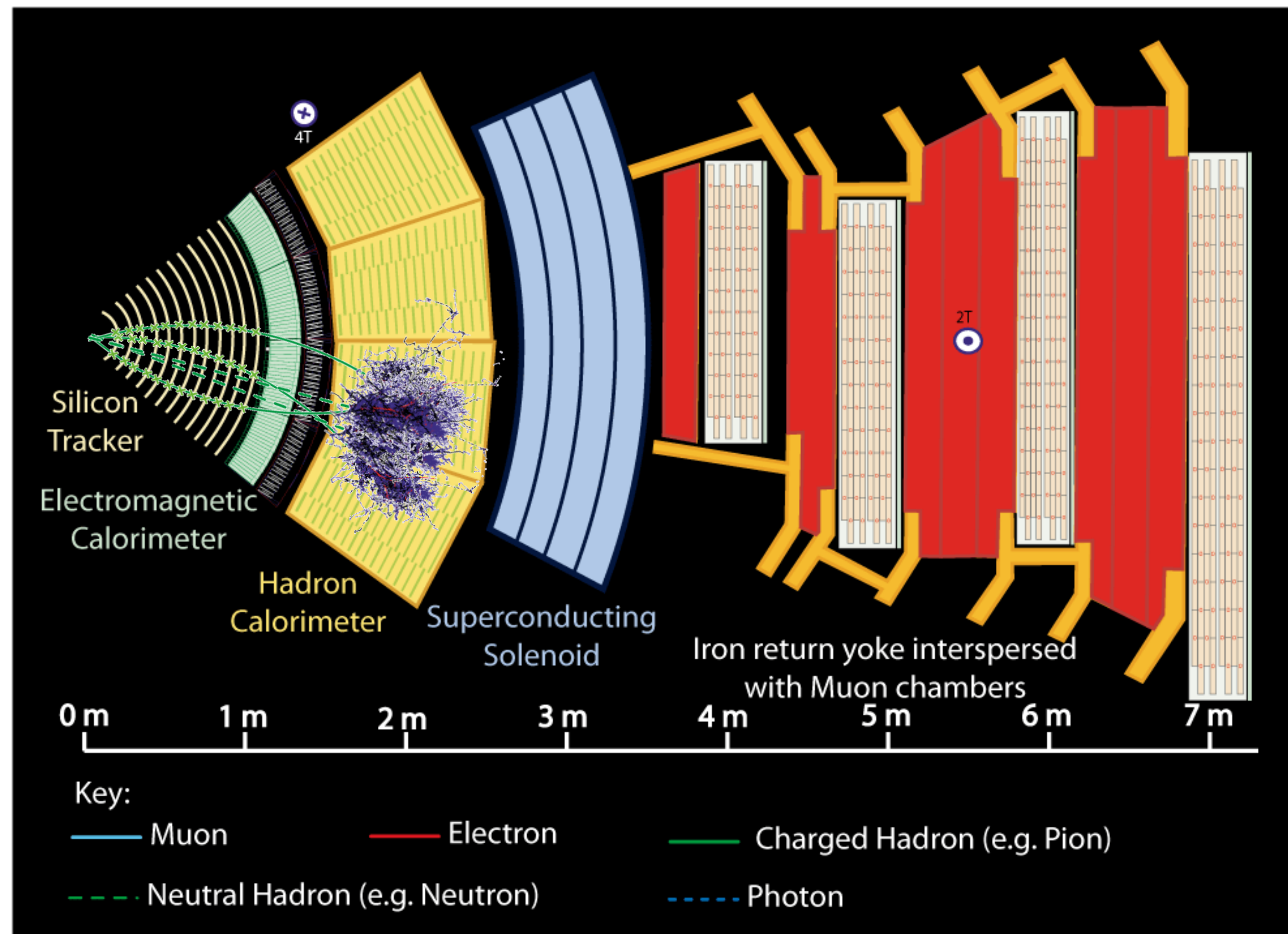
HOW CMS SEES QUARKS AND GLUONS

- ▶ Quarks and gluons interact via the strong force and are never seen in isolation
→ become *jets* of hadrons (bound states)



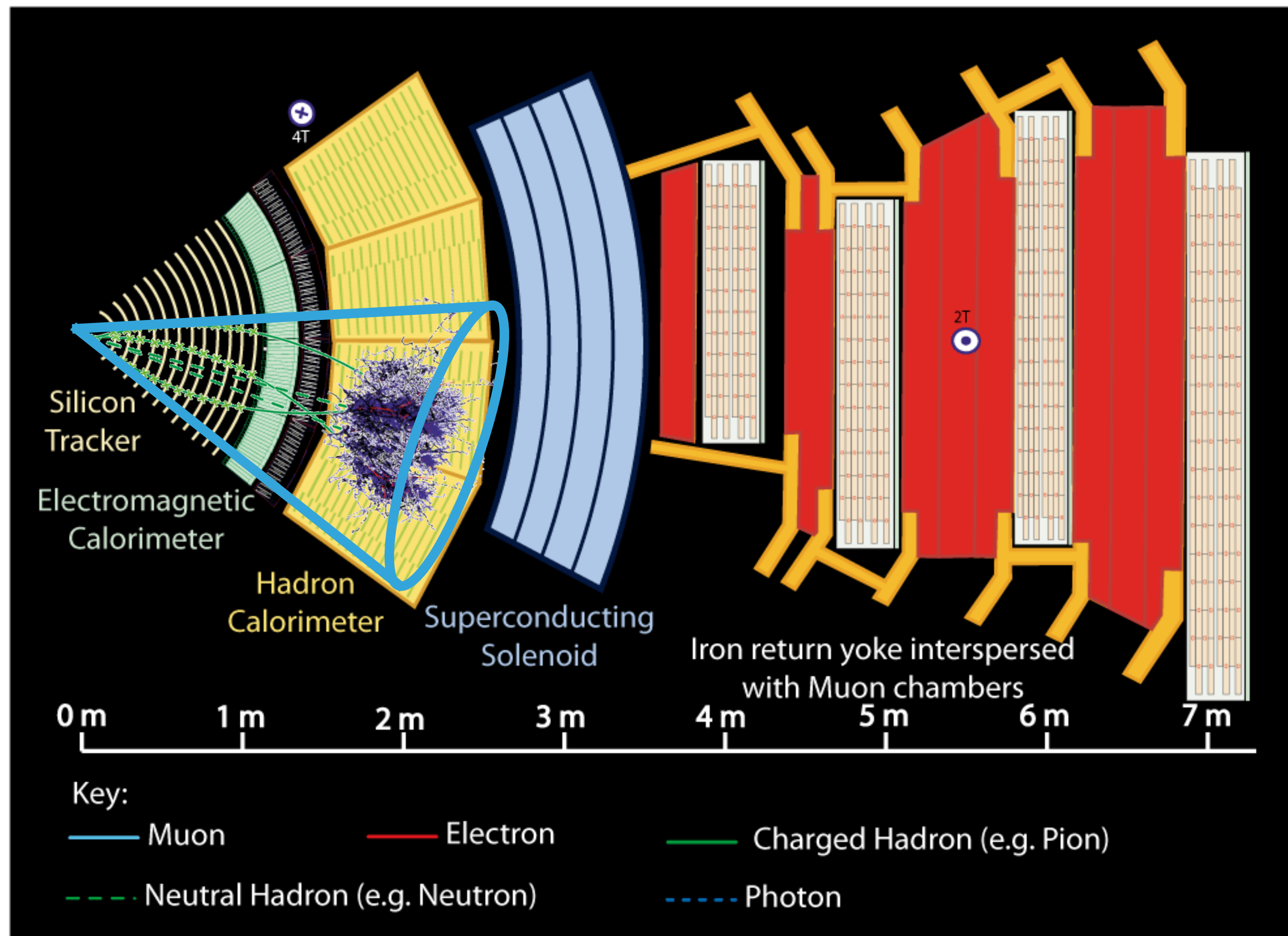
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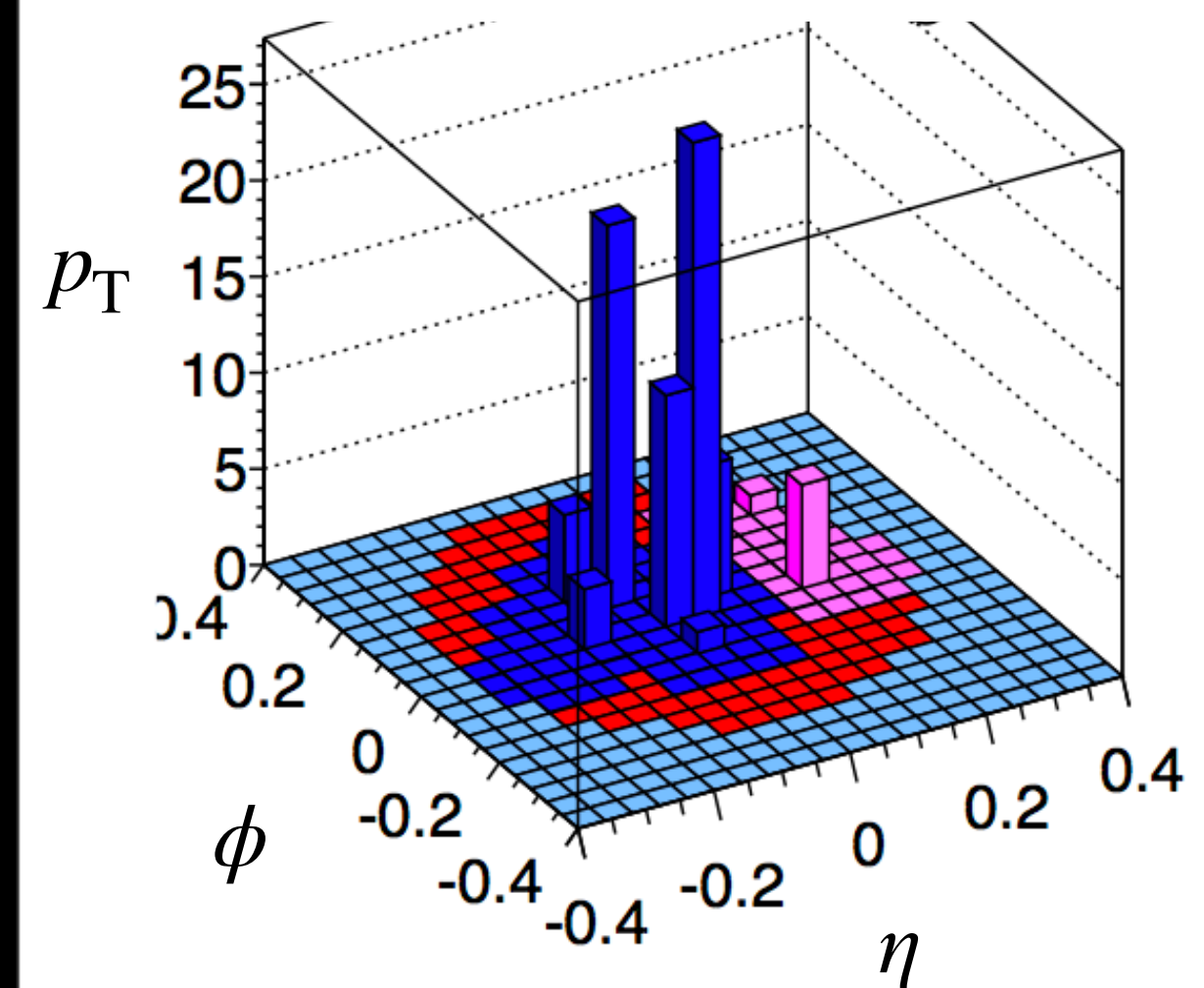


HOW CMS SEES QUARKS AND GLUONS

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- ▶ Cluster the tracks and energy into a cone-shaped jet



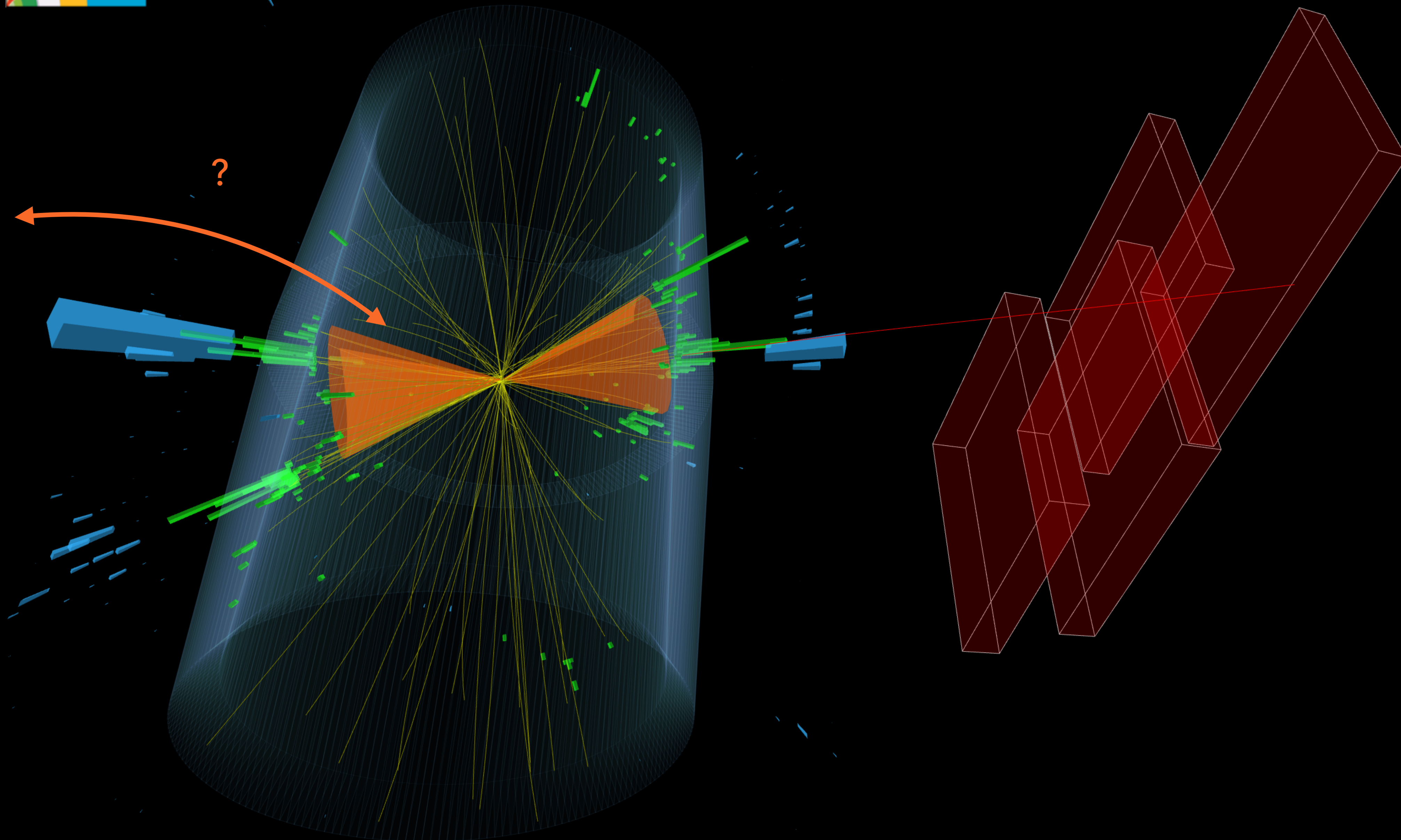
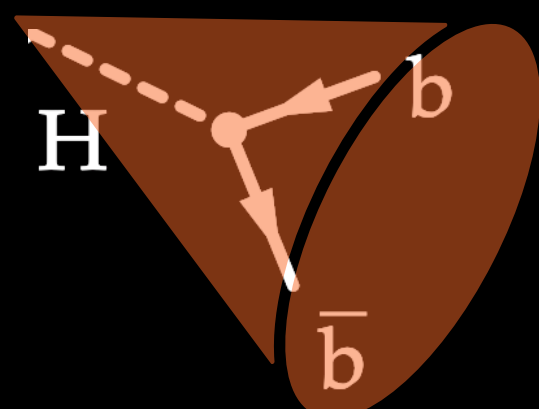


CMS Experiment at the LHC, CERN

Data recorded: 2016-Aug-13 16:51:13.749568 GMT

Run / Event / LS: 278803 / 465417690 / 259

Signal:



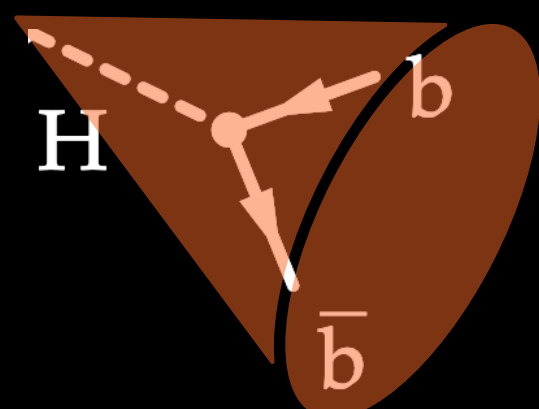


CMS Experiment at the LHC, CERN

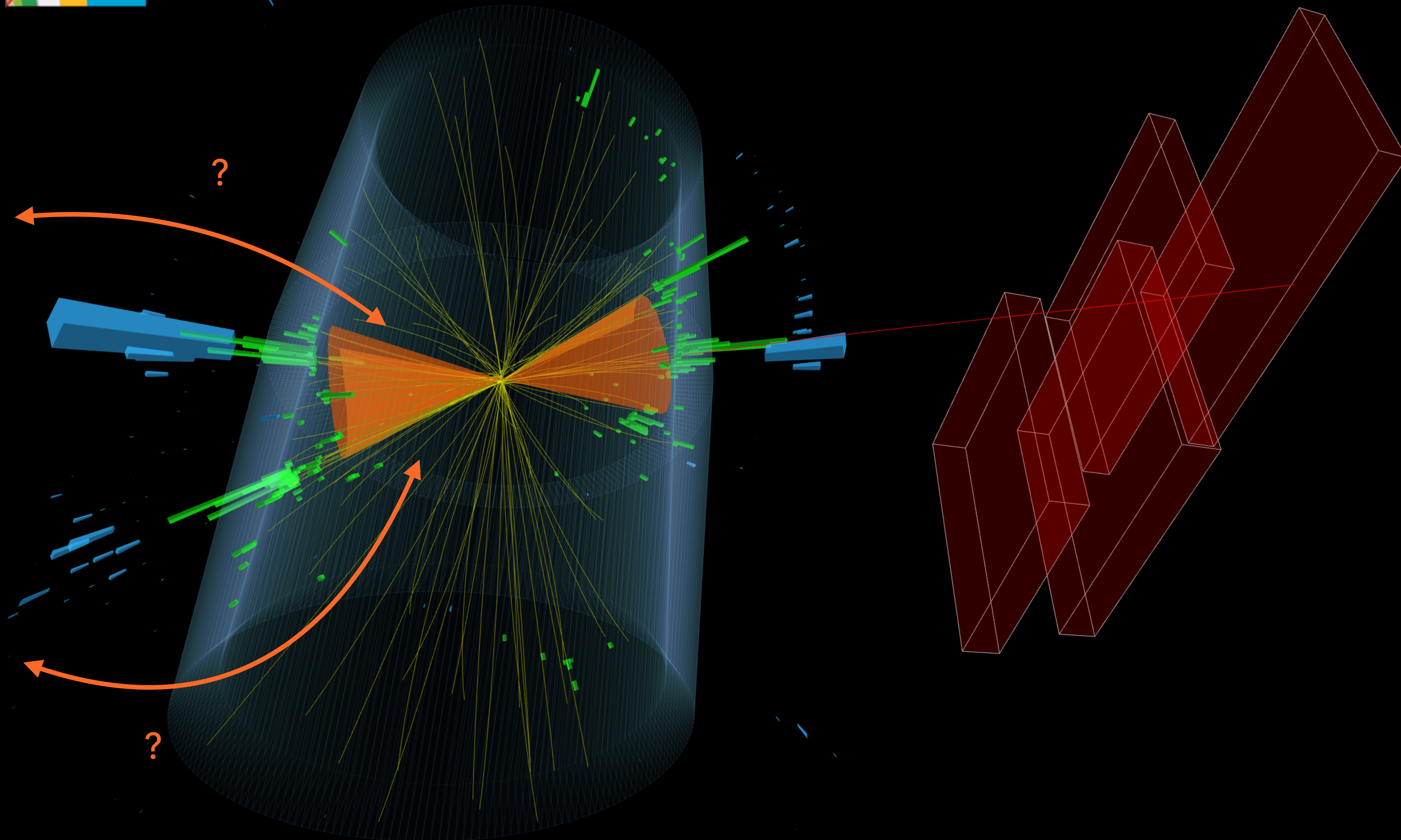
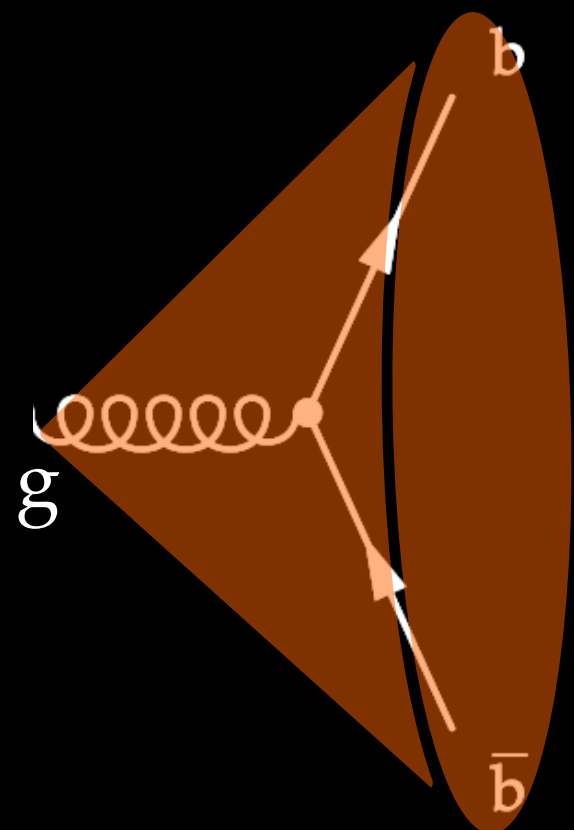
Data recorded: 2016-Aug-13 16:51:13.749568 GMT

Run / Event / LS: 278803 / 465417690 / 259

Signal:

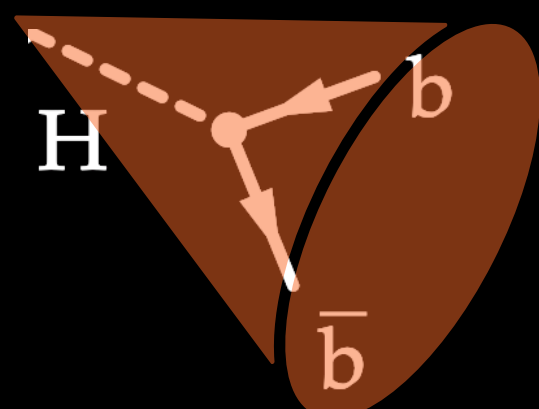


Background:

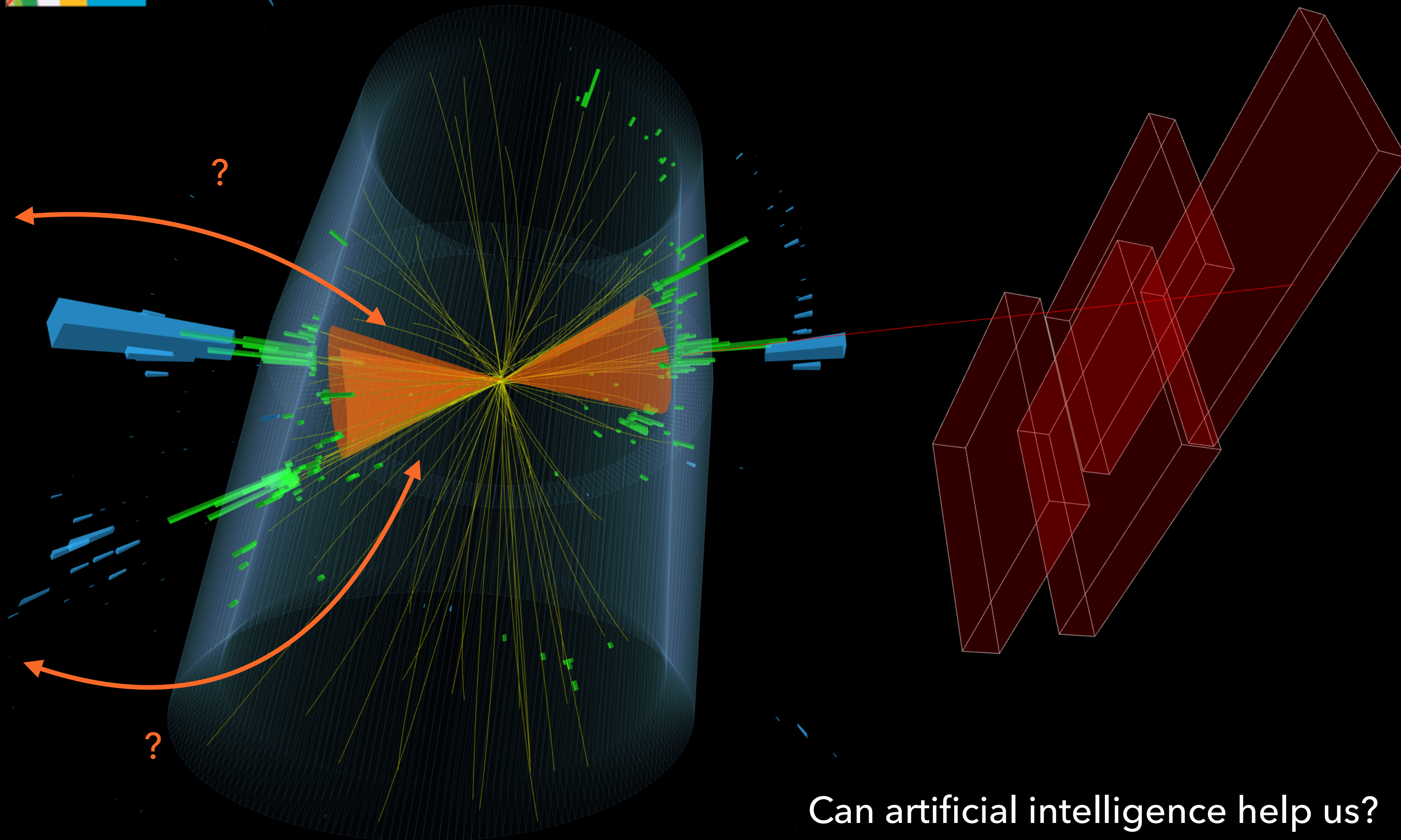
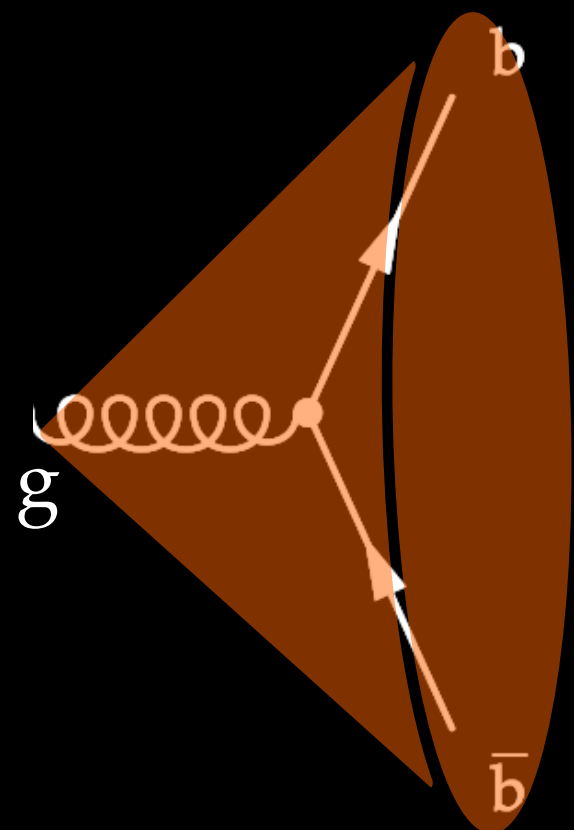




Signal:



Background:



Can artificial intelligence help us?

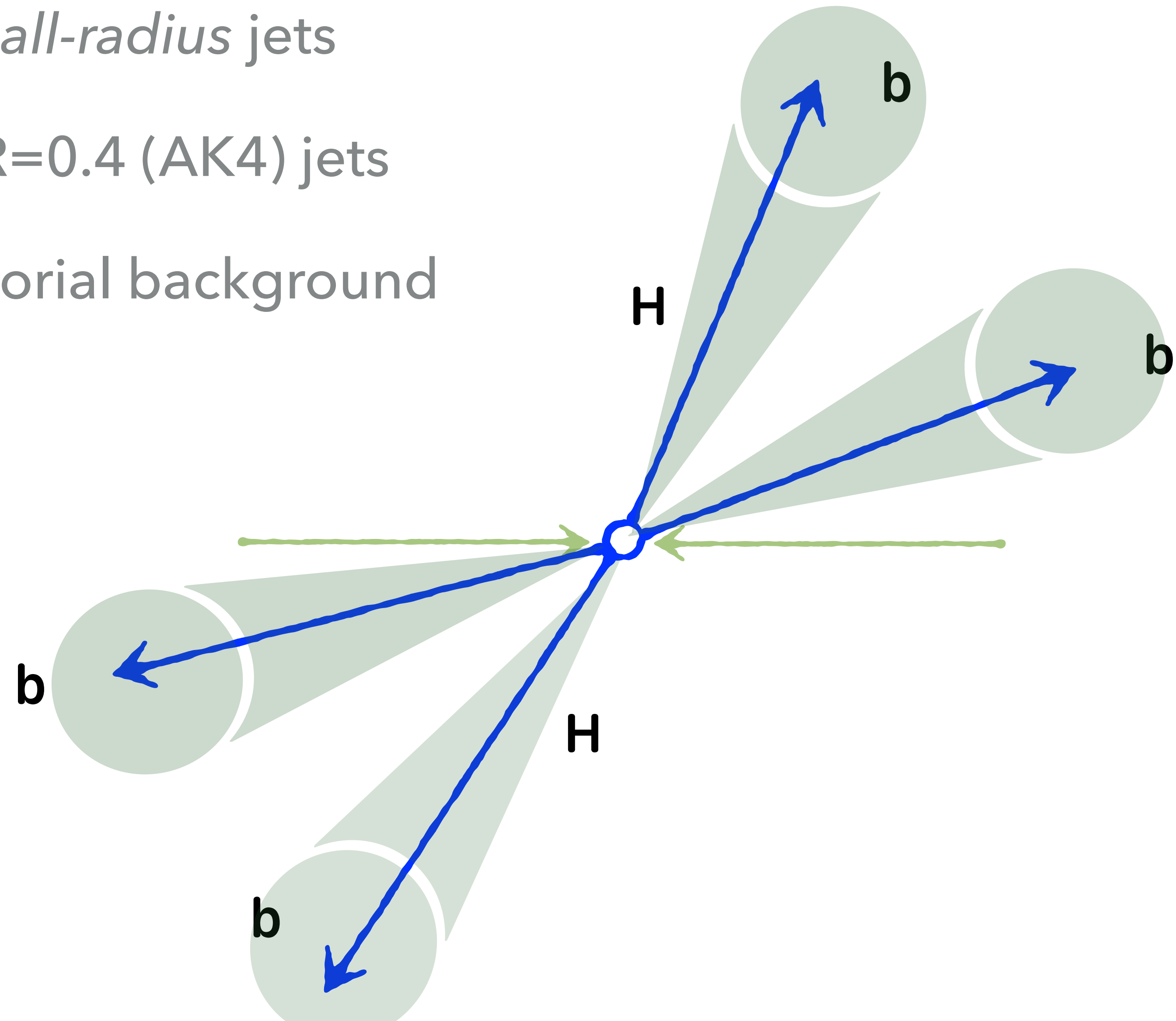
I. HH PRODUCTION AT THE LHC

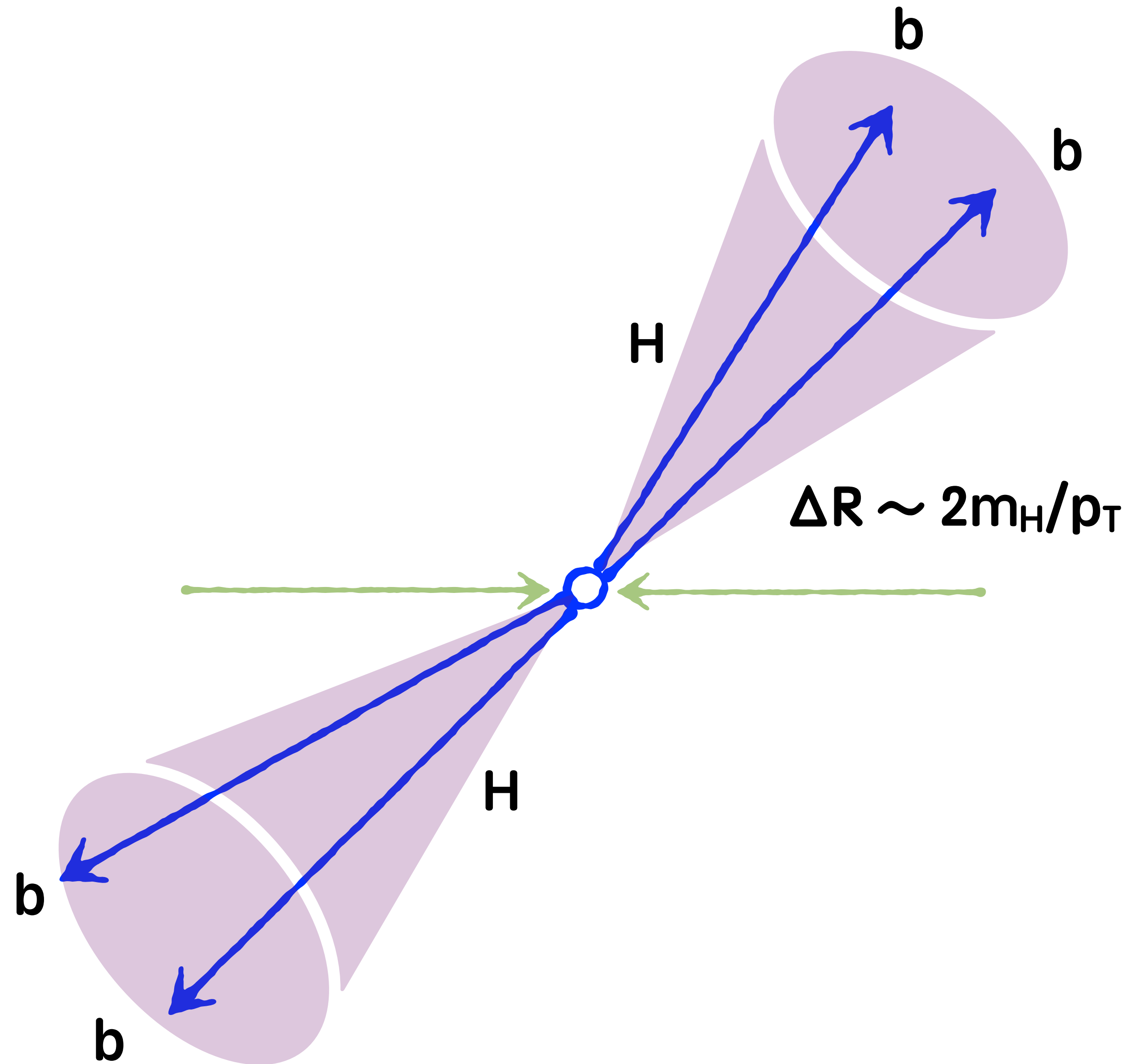
II. GNNs FOR JET PHYSICS

III. BOOSTED HH SEARCH

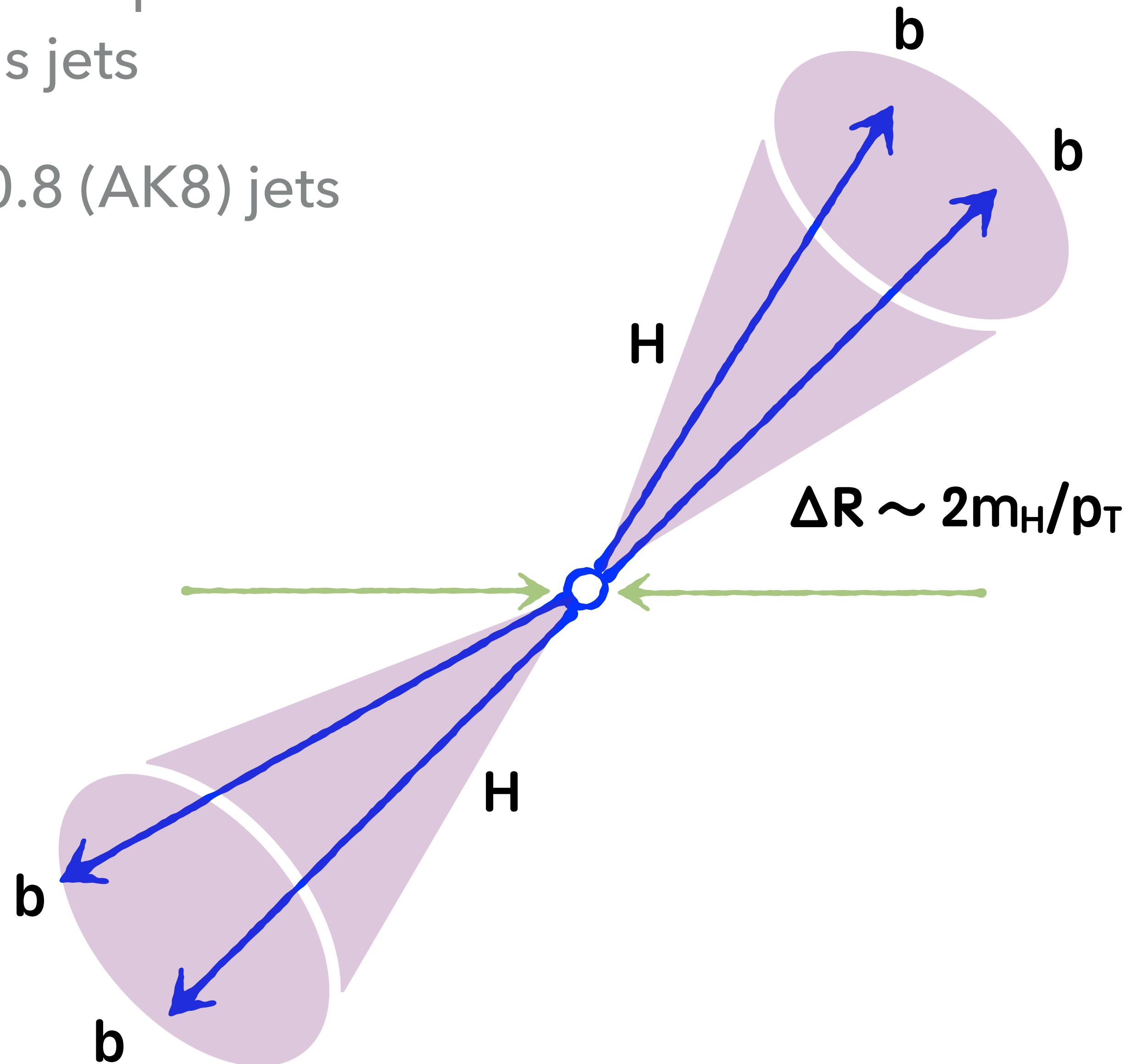
IV. OUTLOOK

- ▶ At low momentum, the bottom quarks are resolved into separate *small-radius* jets
- ▶ Anti- k_T algorithm with $R=0.4$ (AK4) jets
- ▶ Large QCD and combinatorial background

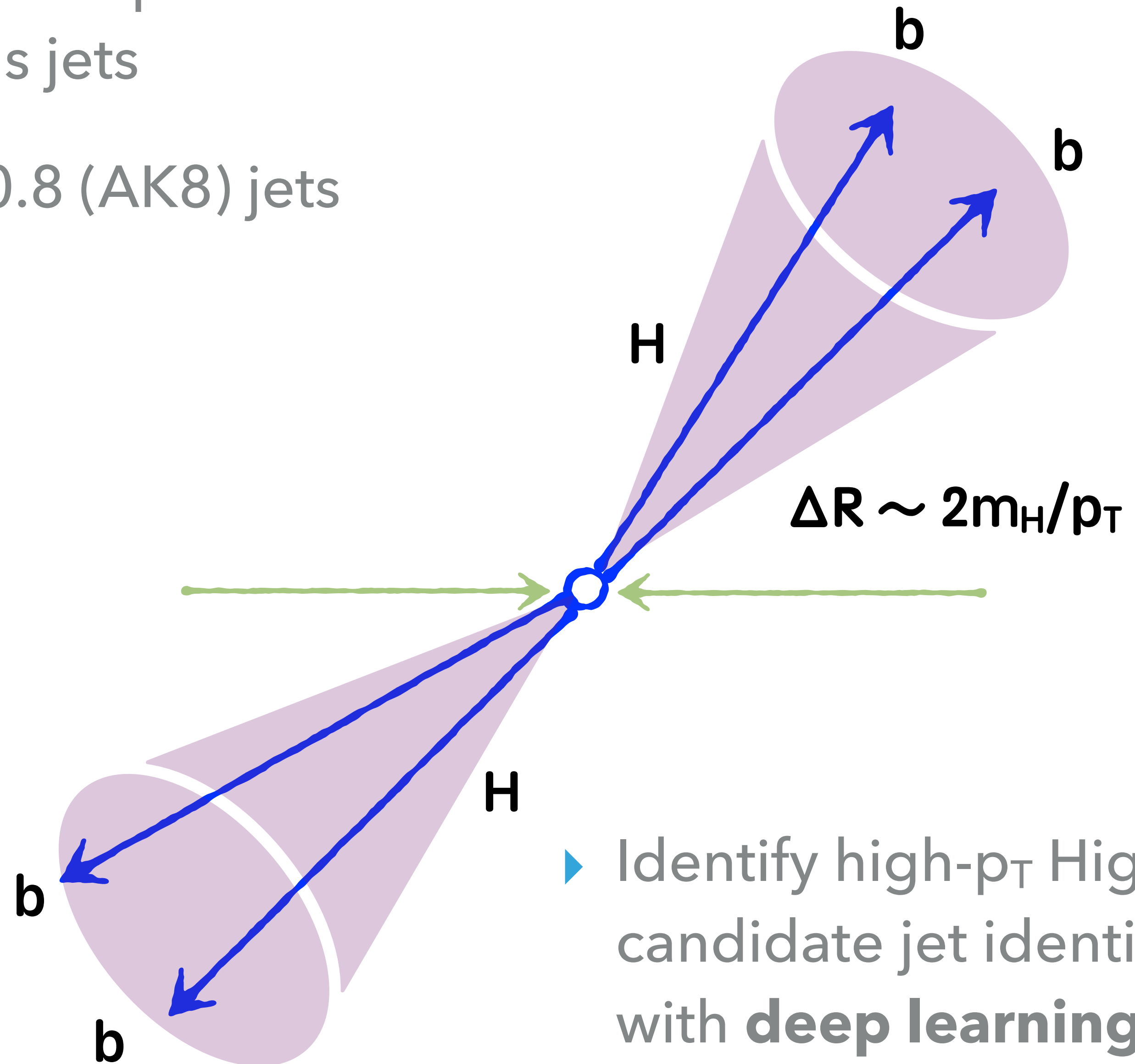




- ▶ At high momentum, the bottom quarks are **boosted** into large-radius jets
- ▶ Anti- k_T algorithm with $R=0.8$ (AK8) jets



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- ▶ Identify high- p_T Higgs candidate jet identified with **deep learning**

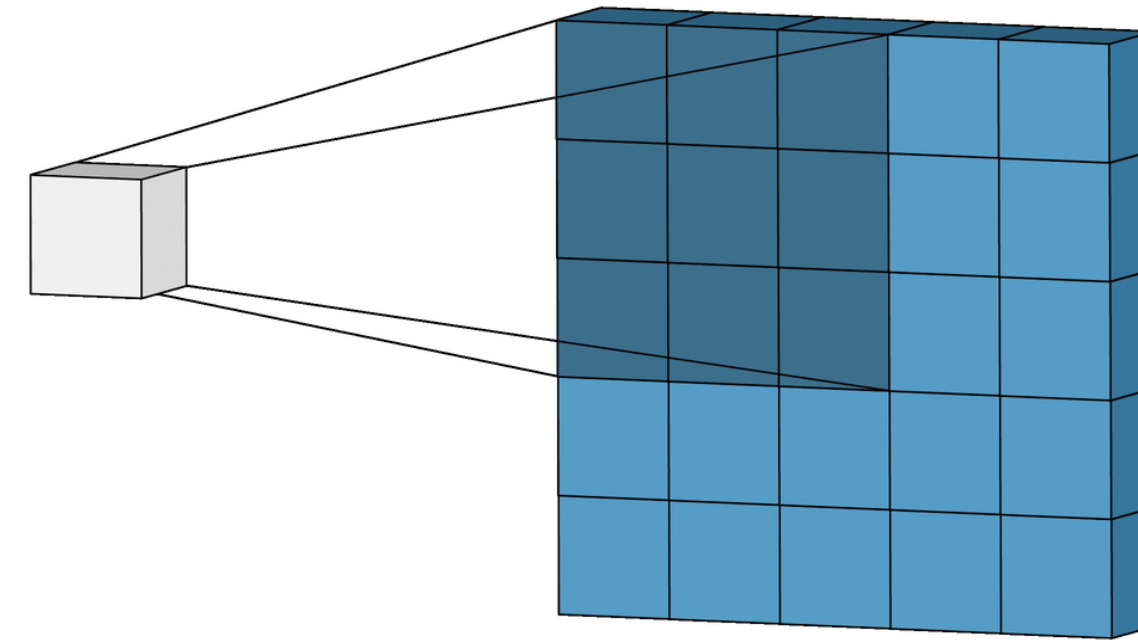
INNOVATING JET TAGGING WITH NEW JET REPRESENTATIONS

[arXiv:2007.13681](https://arxiv.org/abs/2007.13681)

[arXiv:2012.01249](https://arxiv.org/abs/2012.01249) 14

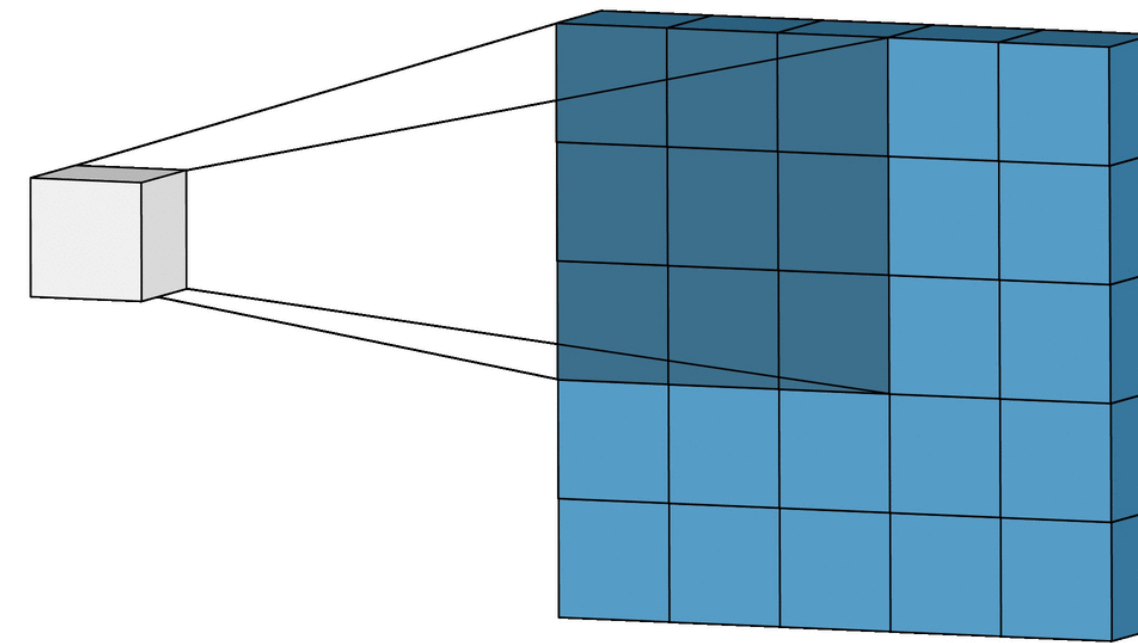
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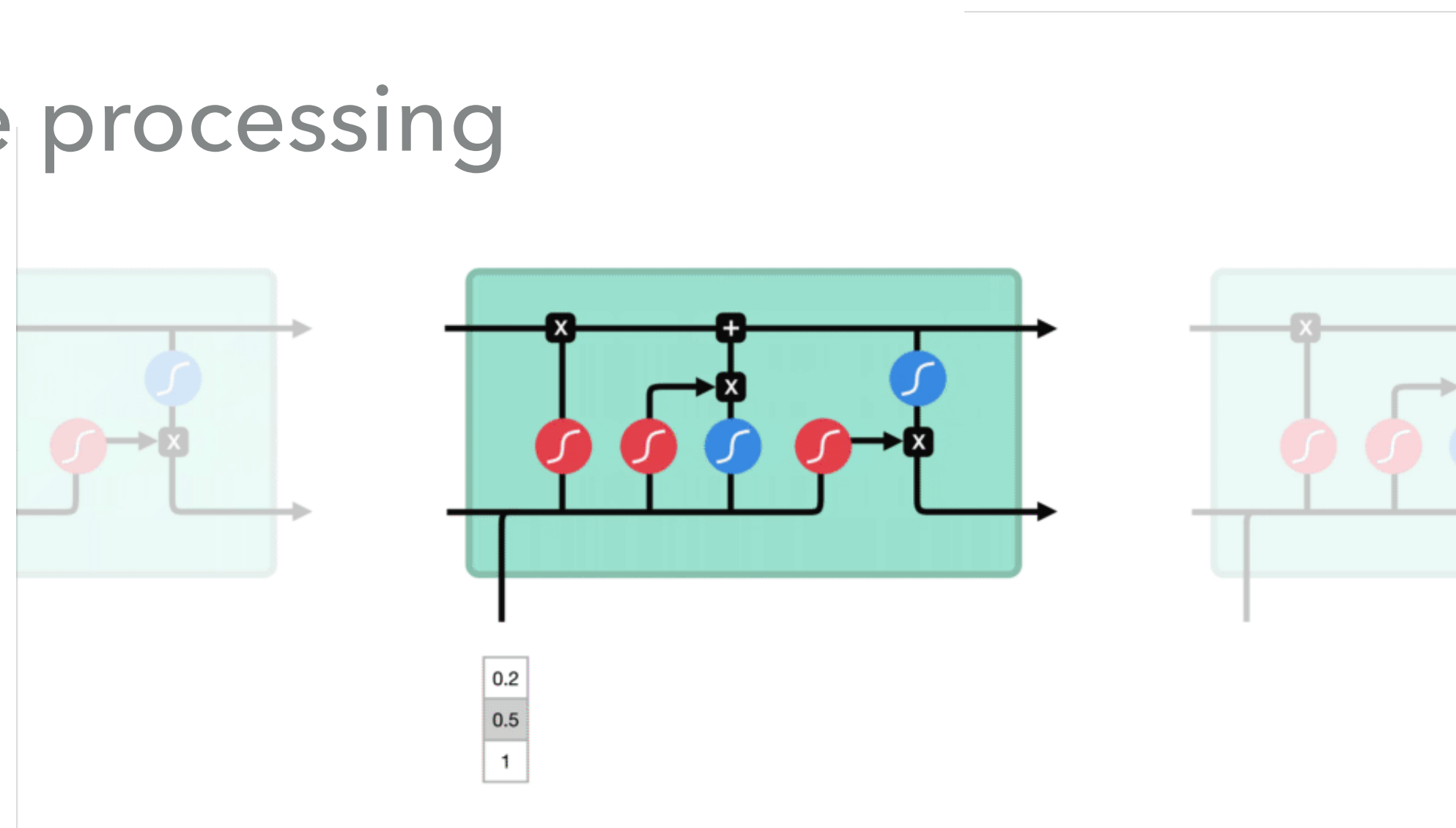


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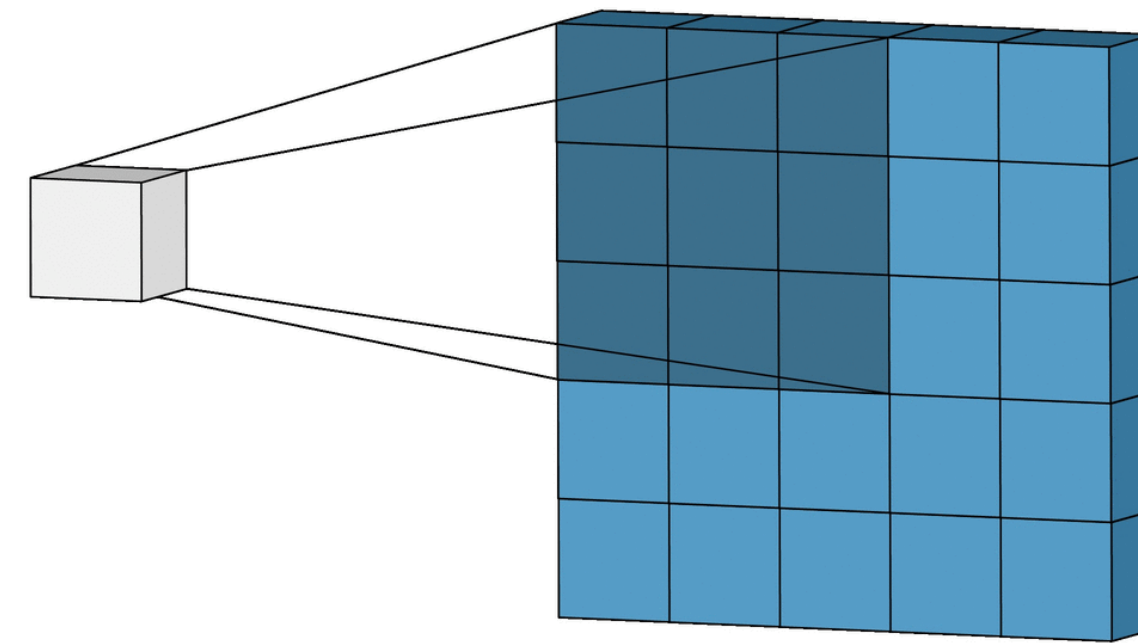


- ▶ RNNs for language processing

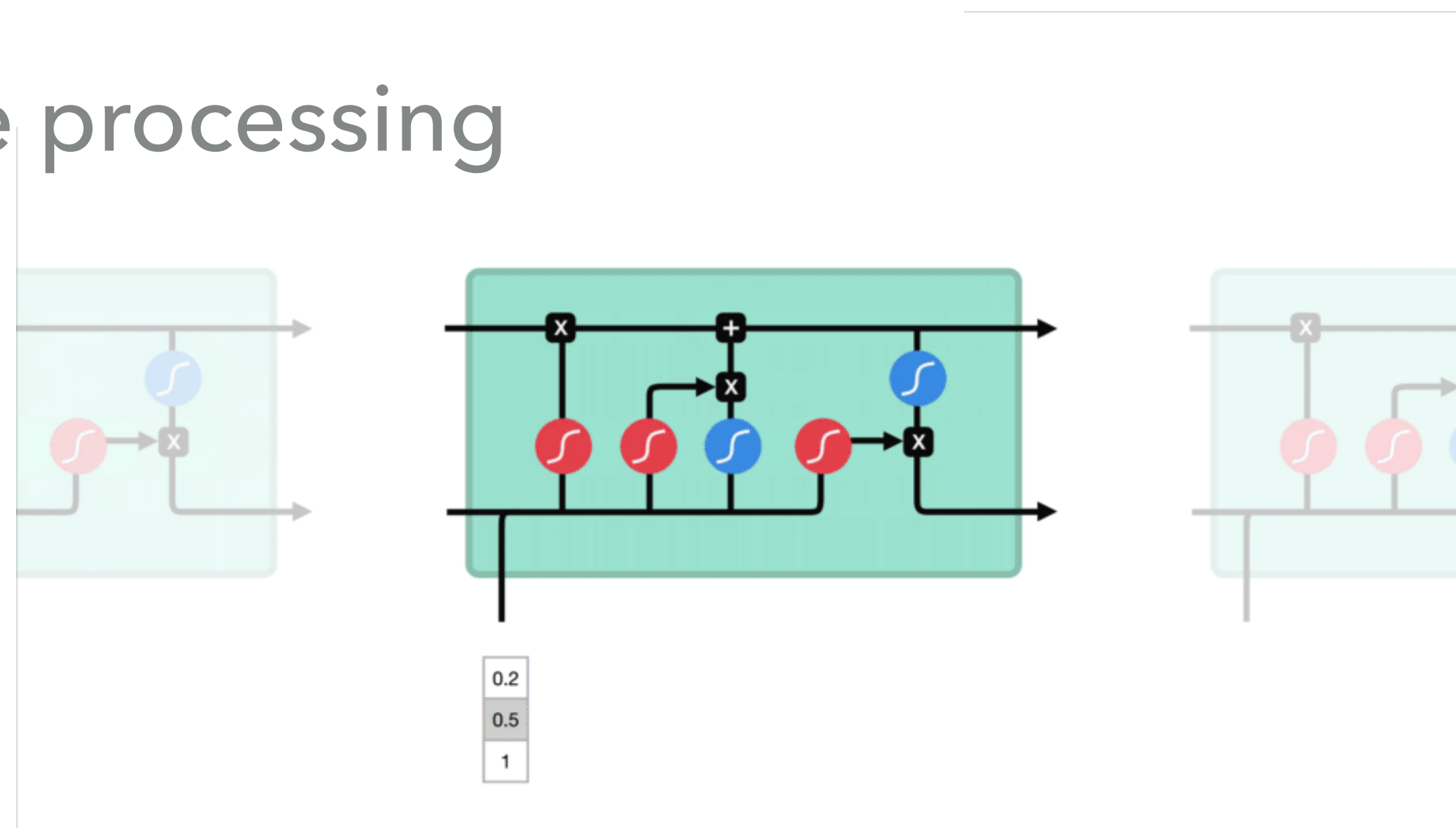


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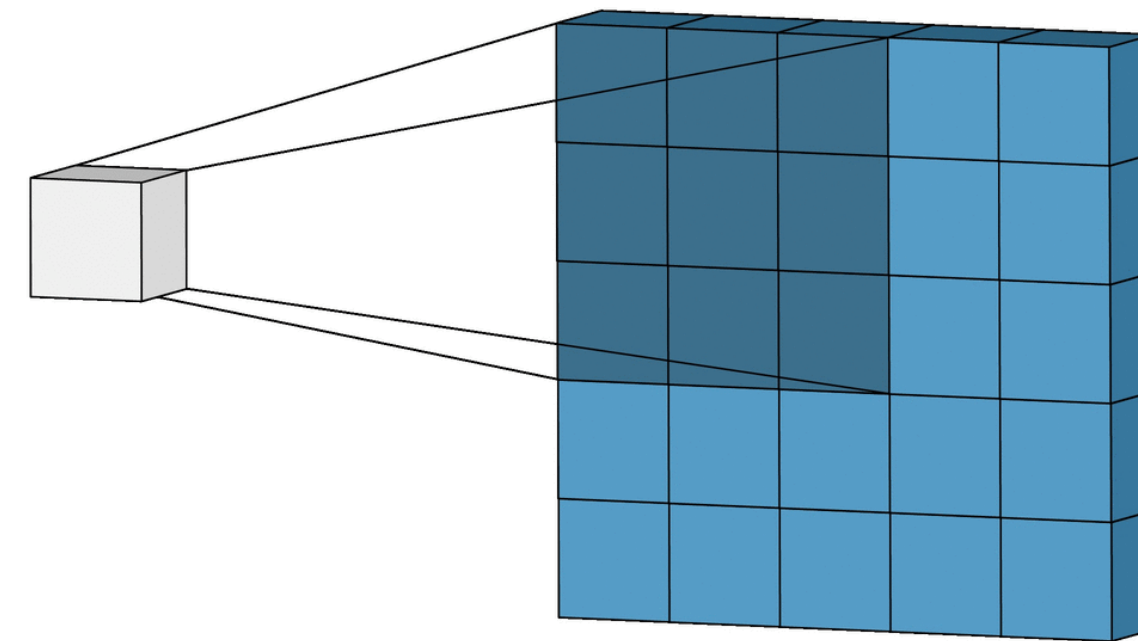
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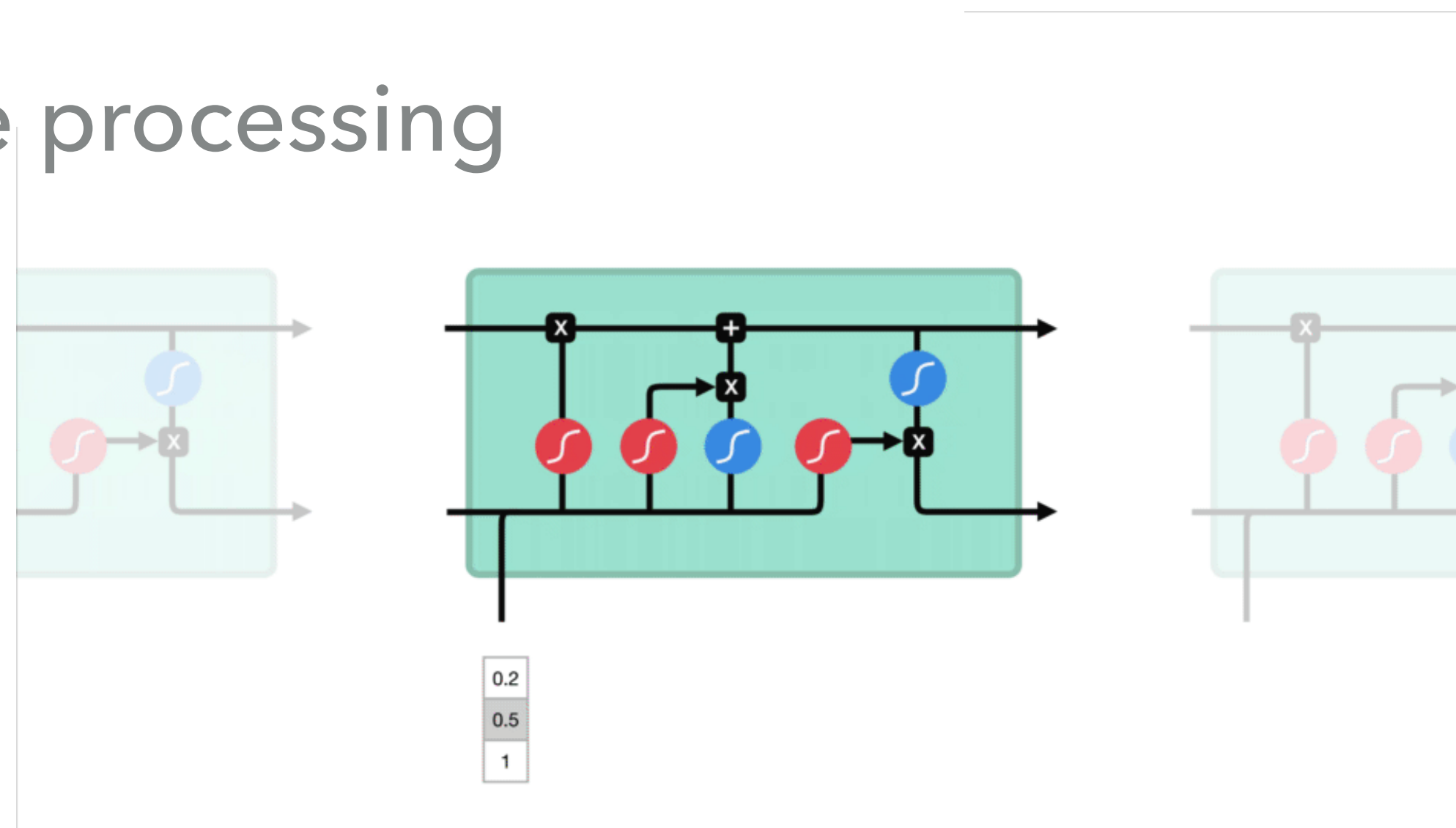
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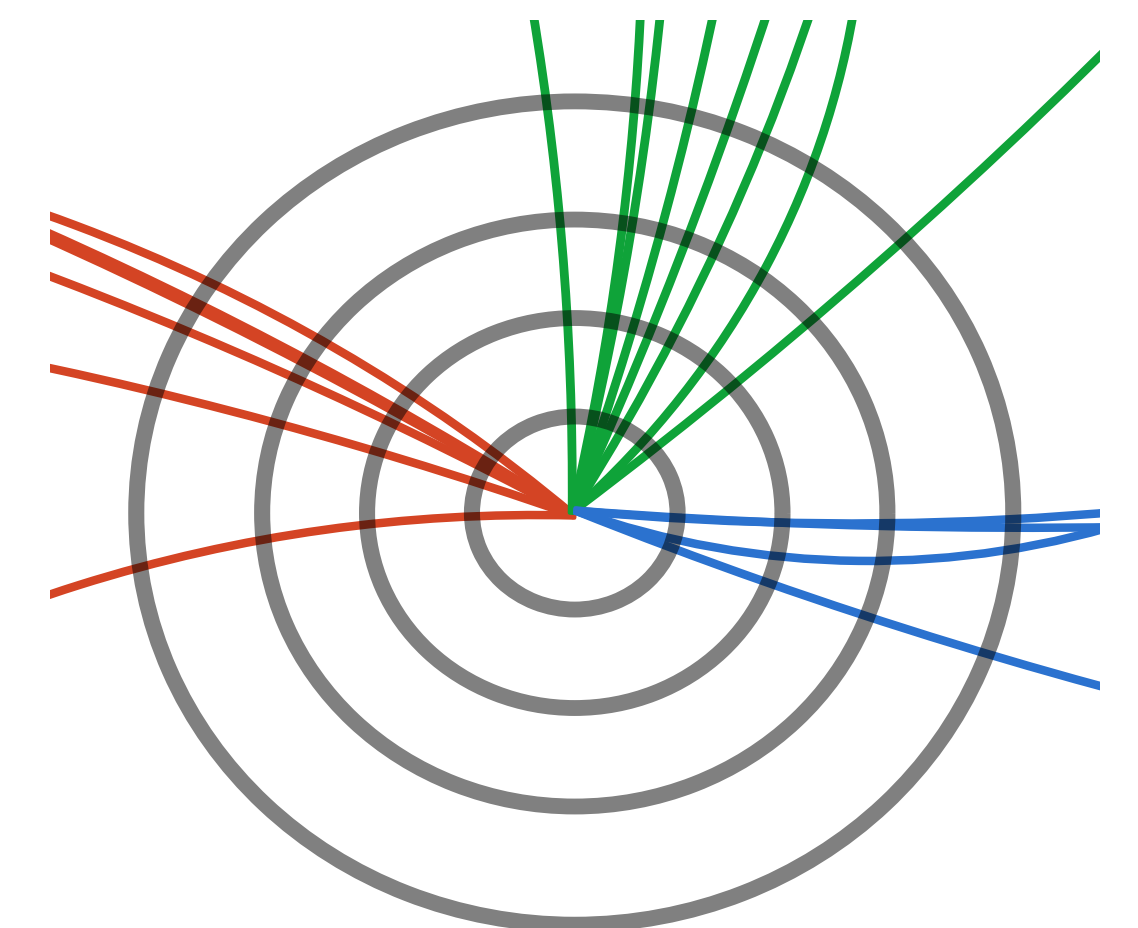
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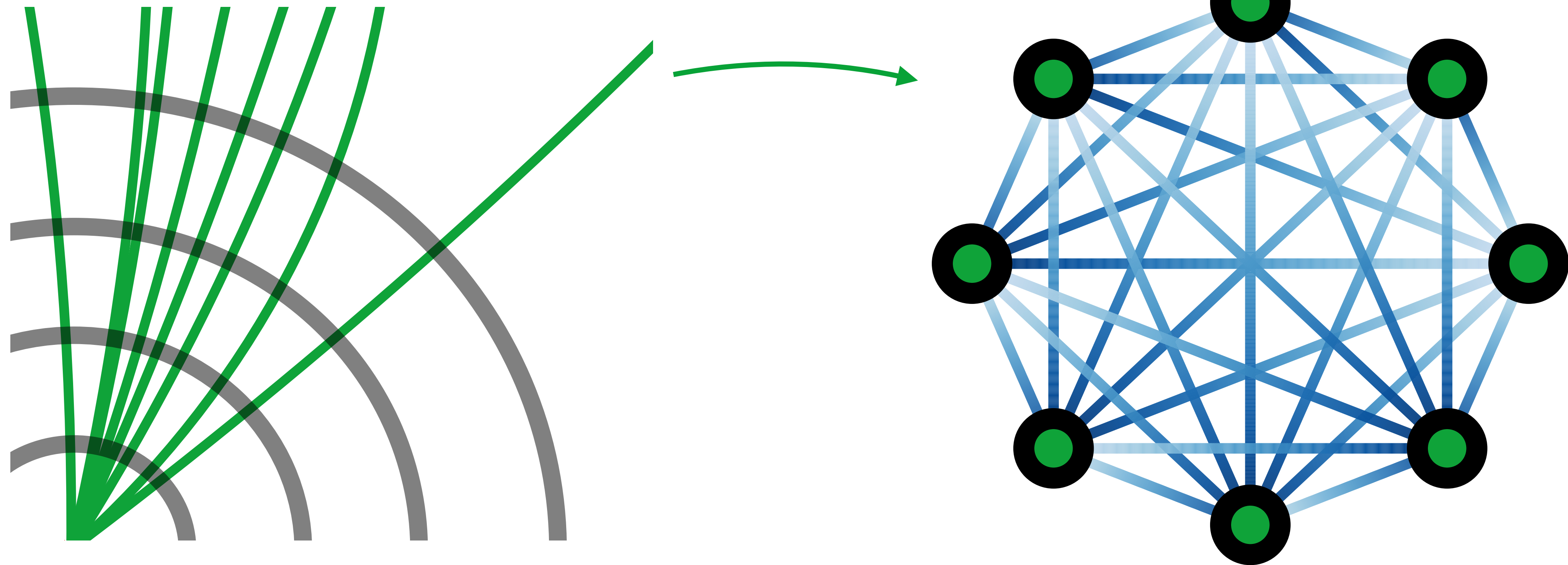
- ▶ RNNs for language processing



- ▶ Distributed unevenly in space
- ▶ Sparse
- ▶ Variable size
- ▶ No defined order
- ▶ Interconnections → Graphs

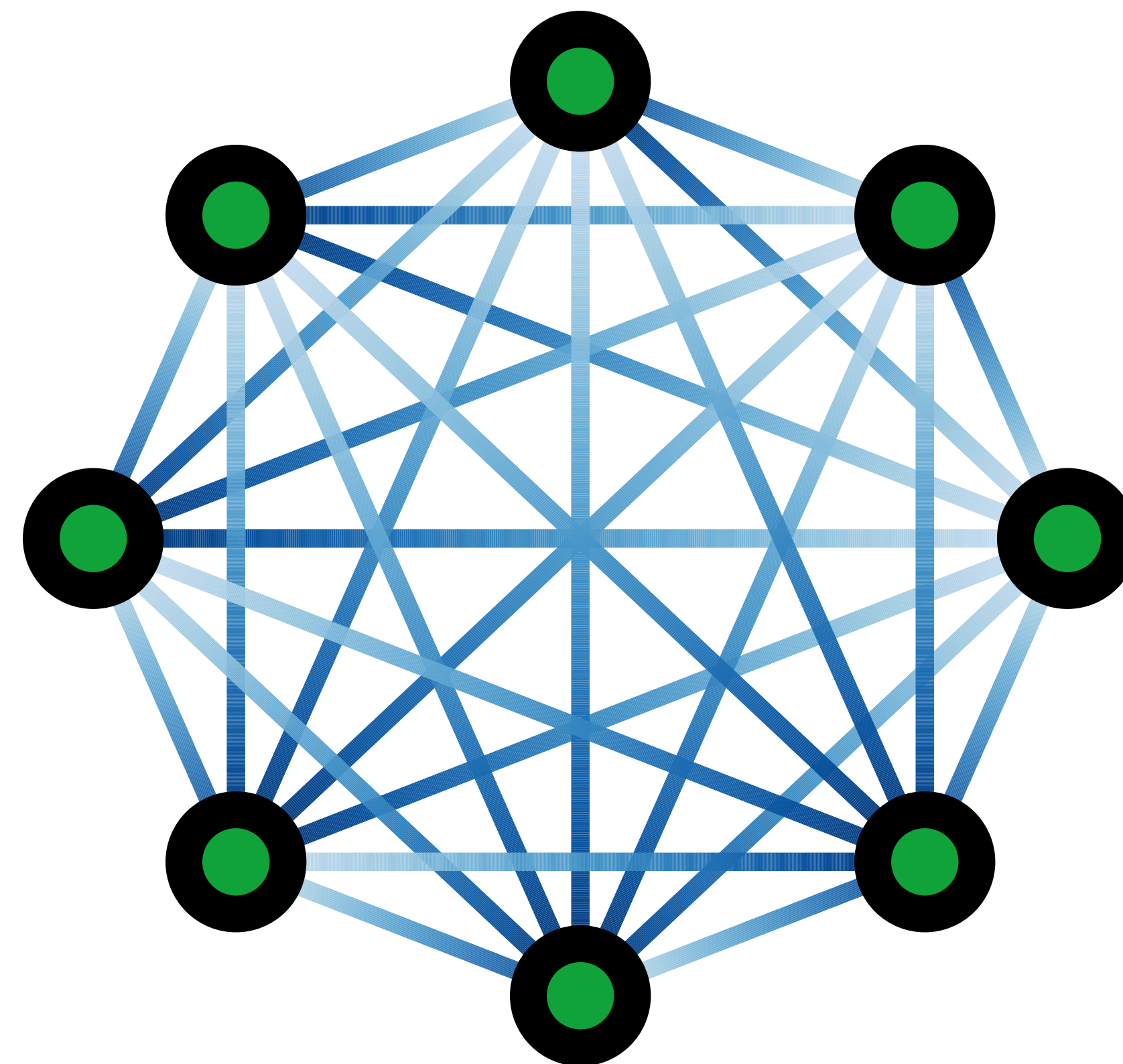


- ▶ What about high energy physics data like jets?



- ▶ Node features \mathbf{v}_i : particle 4-momentum

$$p = [E, p_x, p_y, p_z] \equiv [p_T, \eta, \phi, m]$$

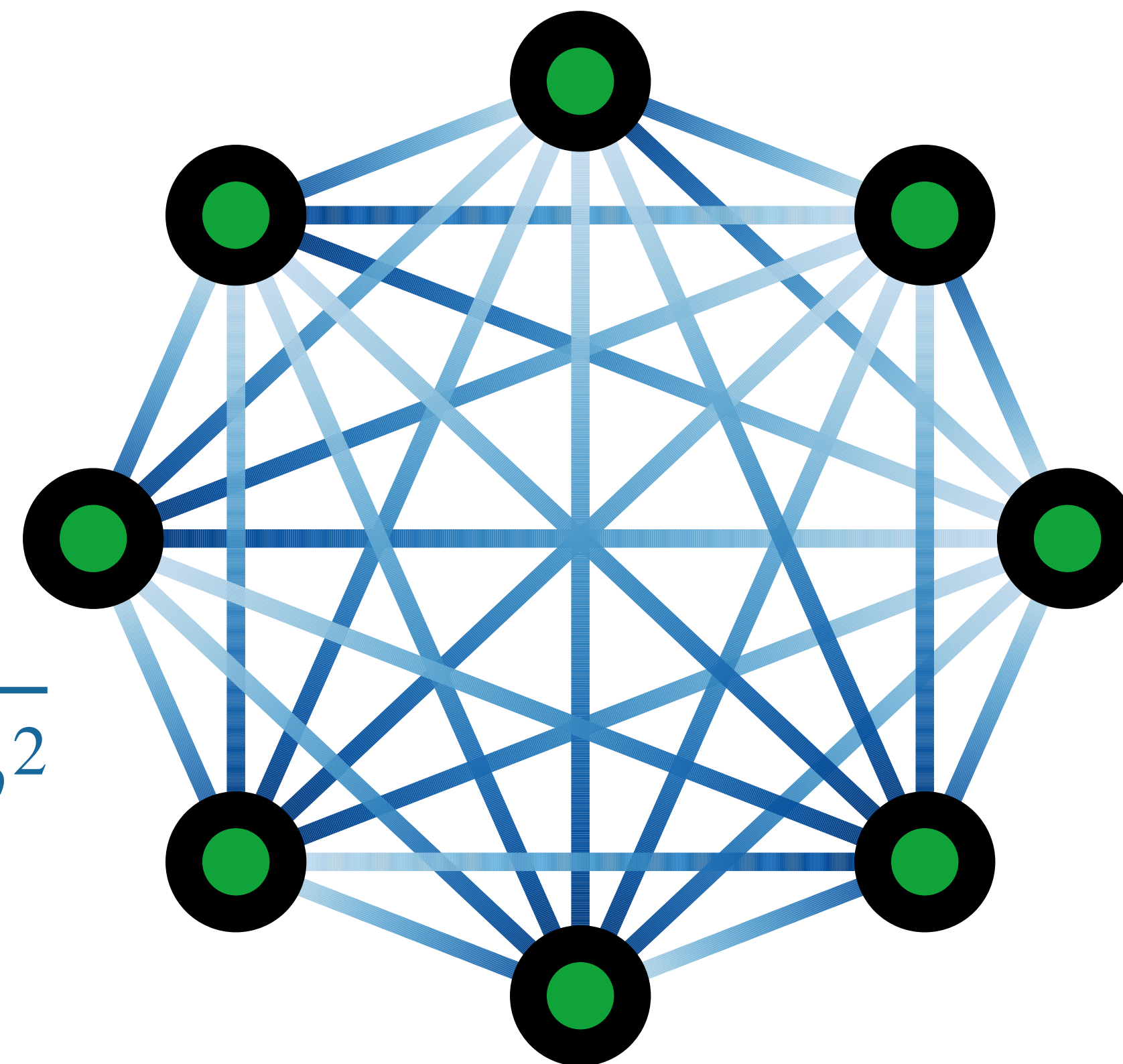


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$$\Delta R = \sqrt{\Delta\eta^2 + \Delta\phi^2}$$

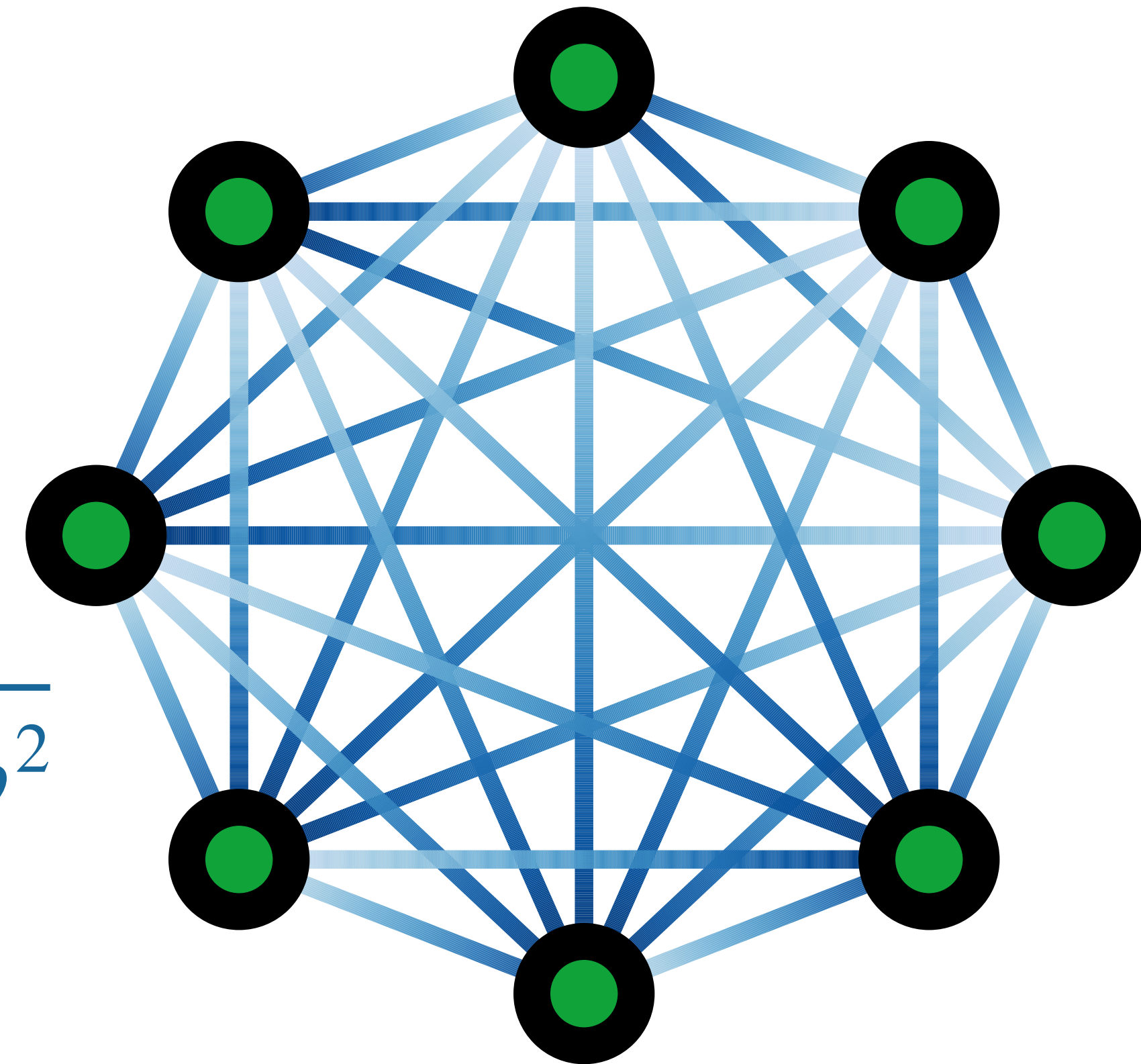


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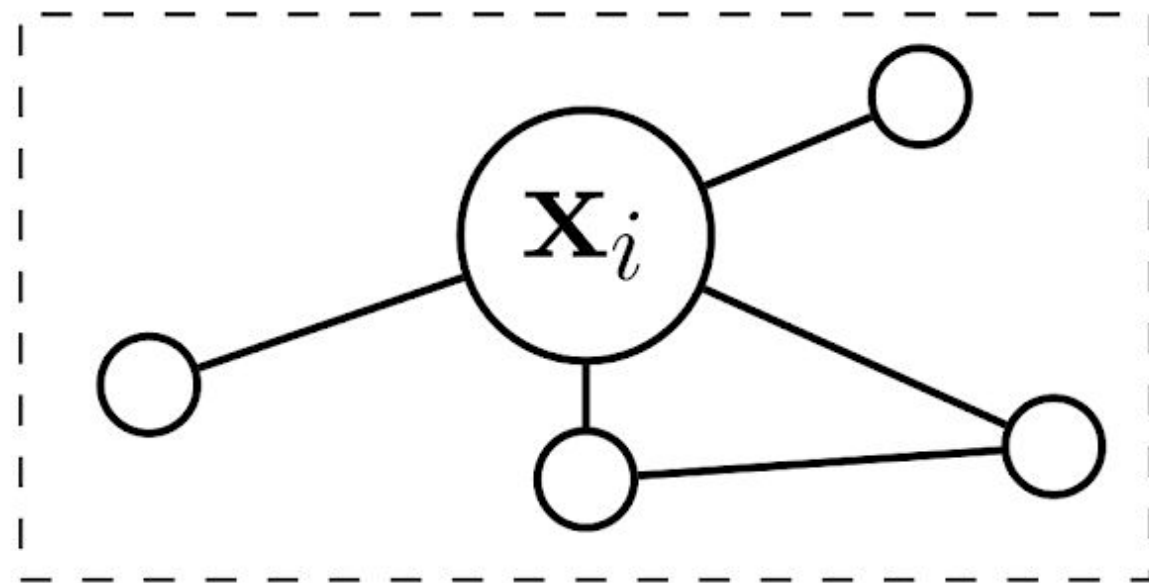
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- ▶ Graph (global) features \mathbf{u} : jet mass

$$m = \sqrt{\sum_{i \in \text{jet}} E_i^2 - p_{x,i}^2 - p_{y,i}^2 - p_{z,i}^2}$$

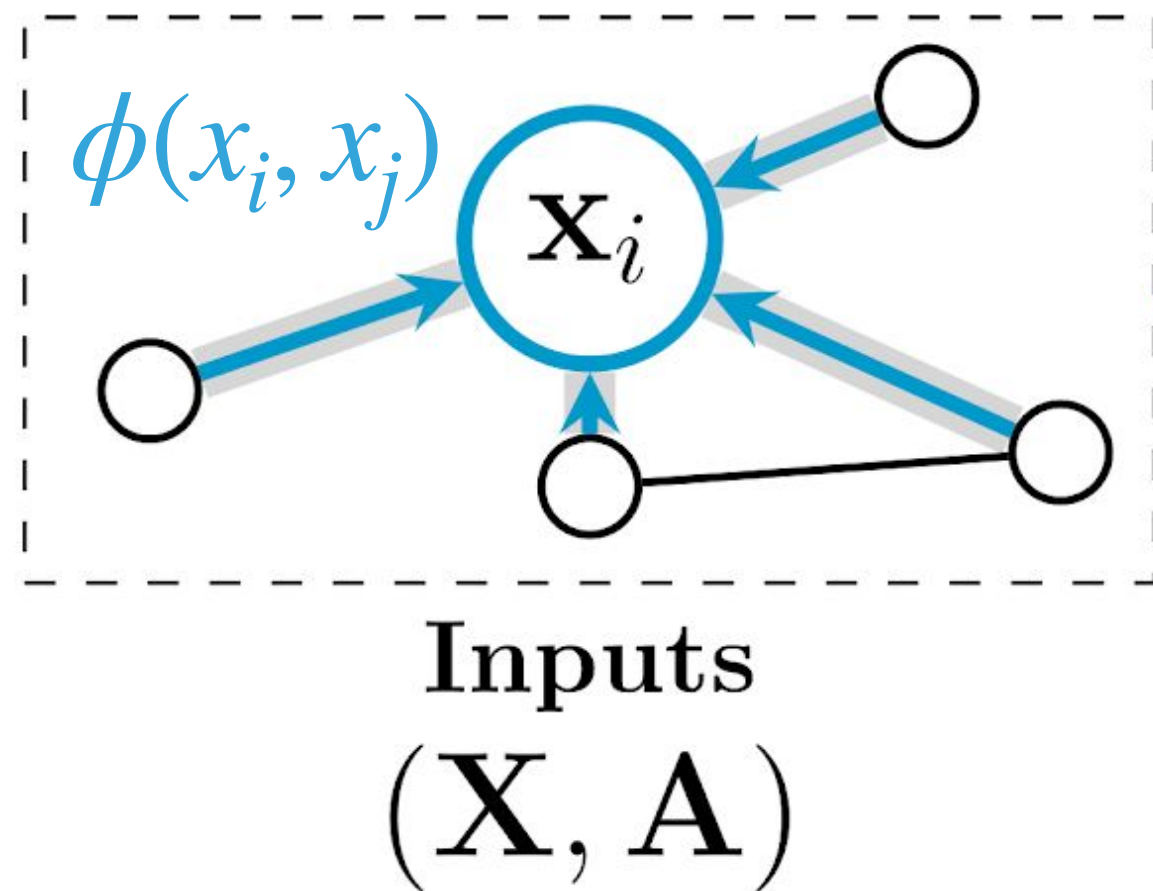
GNN'S MAIN INGREDIENT: MESSAGE PASSING



Inputs
(\mathbf{X}, \mathbf{A})

GNN'S MAIN INGREDIENT: MESSAGE PASSING

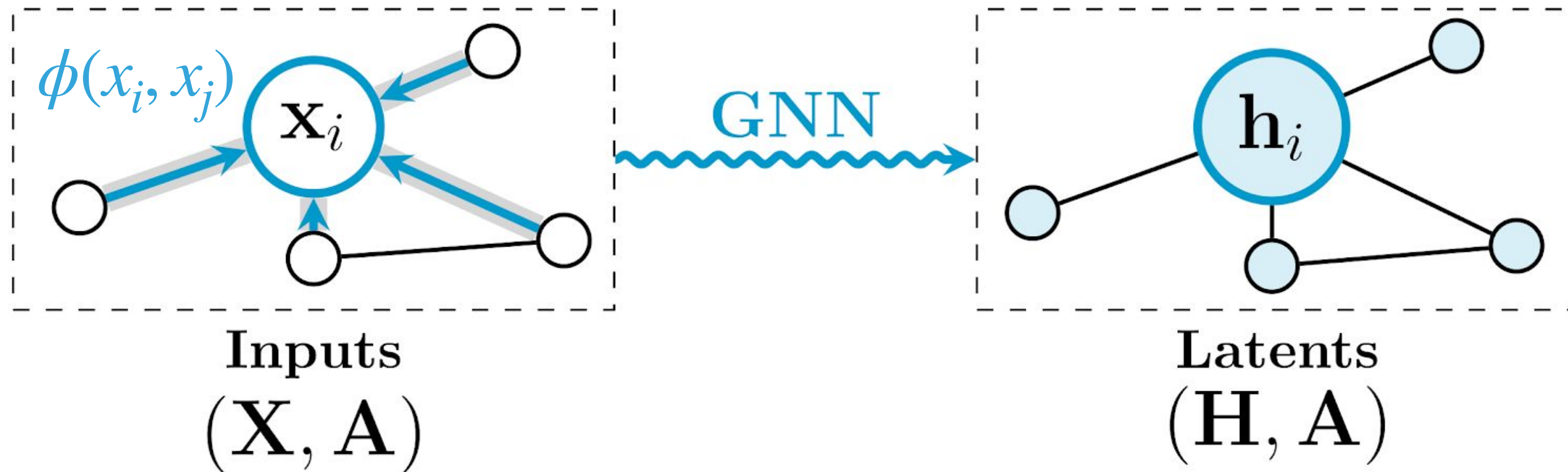
- ▶ For all neighbors j of node i compute a "message" via a NN: $\phi(x_i, x_j)$



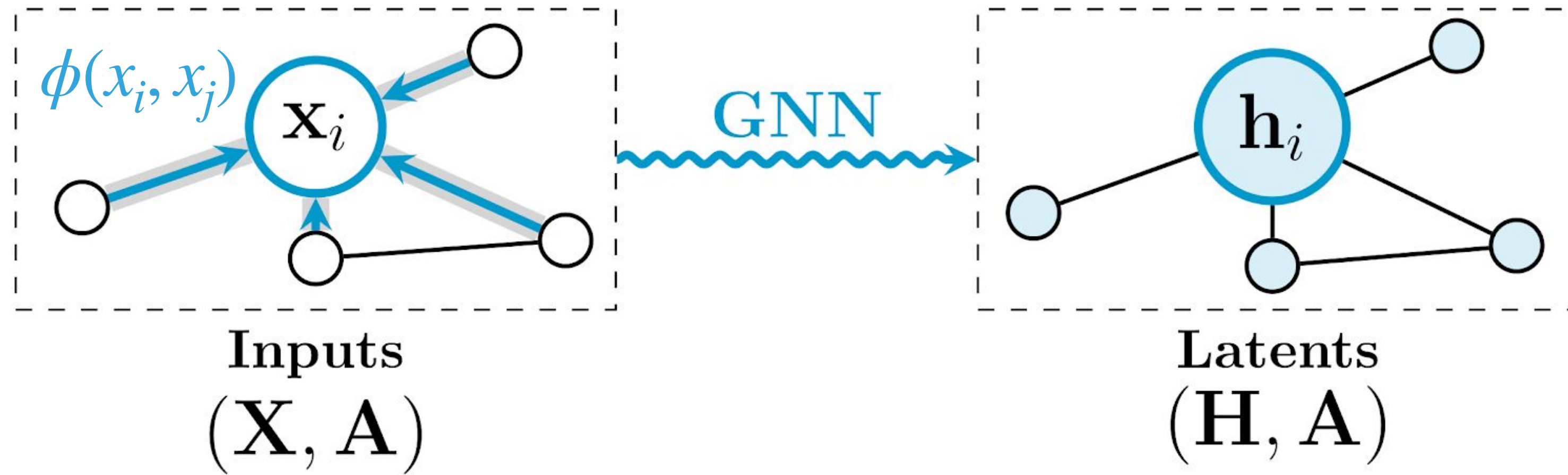
GNN'S MAIN INGREDIENT: MESSAGE PASSING

- ▶ For all neighbors j of node i compute a "message" via a NN: $\phi(x_i, x_j)$
- ▶ Update the node features by summing all messages:

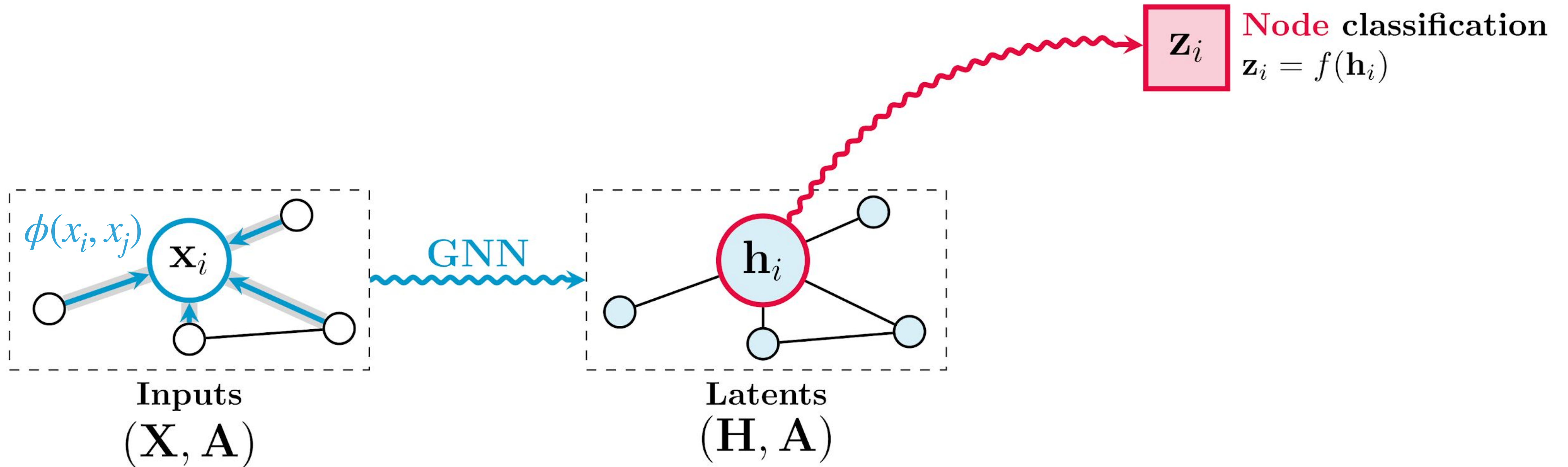
$$h_i = \sum_j \phi(x_i, x_j)$$



"message passing"

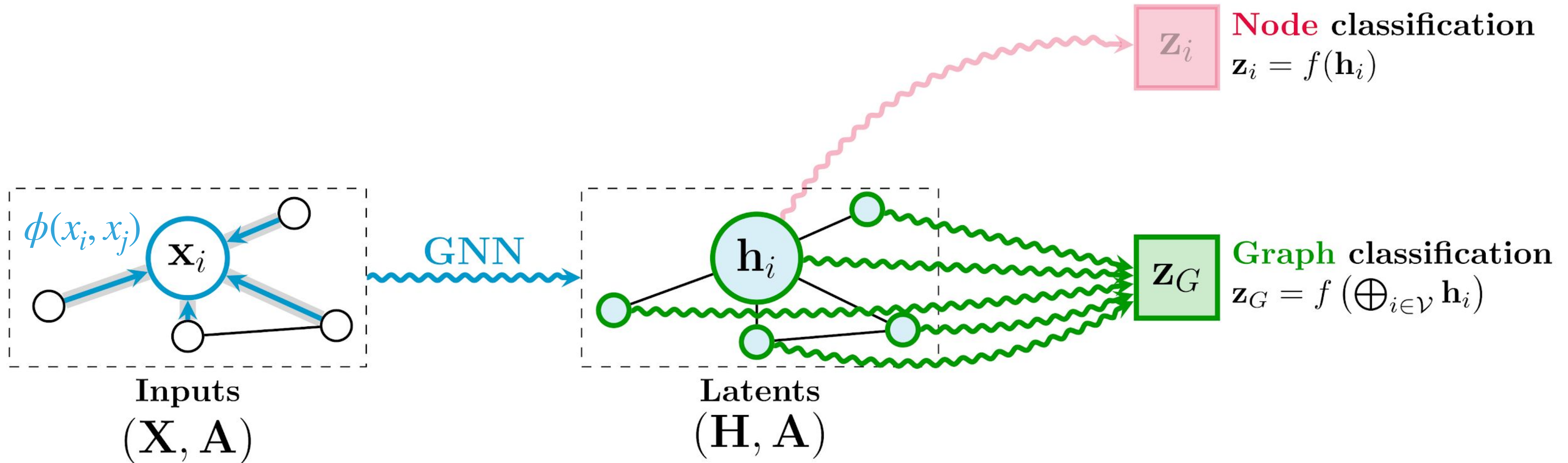


- ▶ Node-level tasks
 - ▶ Identify "pileup" particles



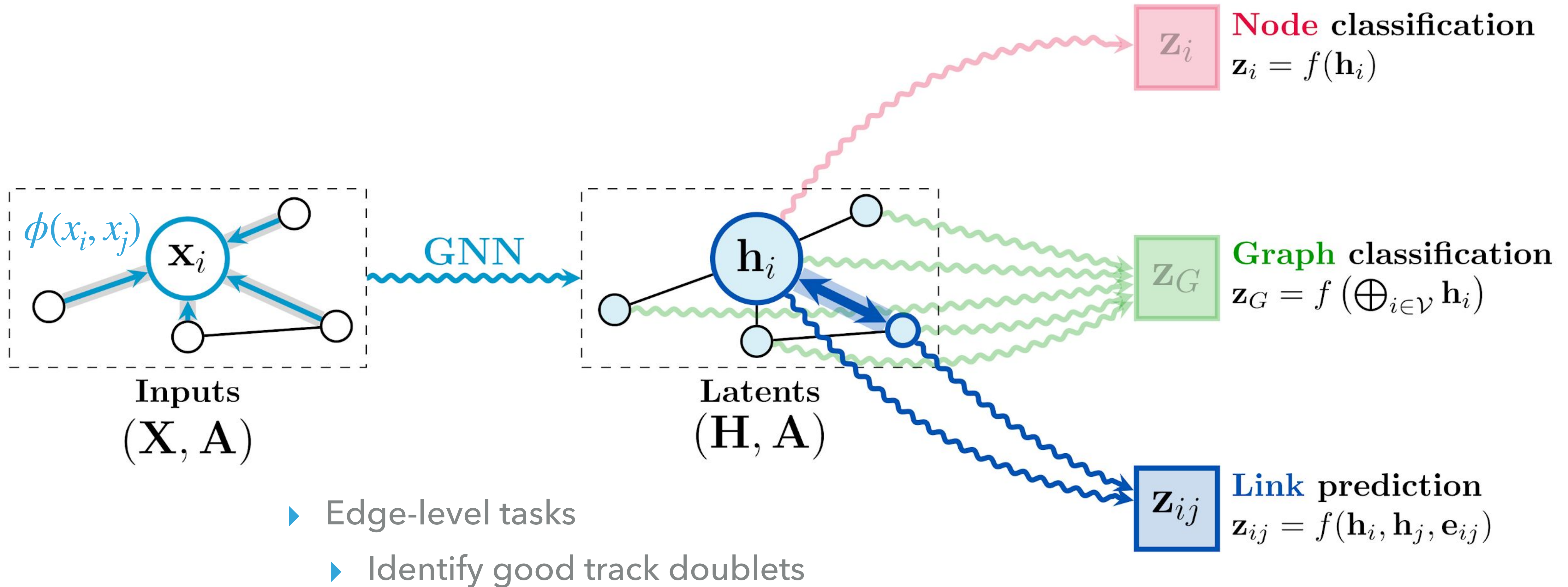
HOW TO USE GNNS IN HEP

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 - ▶ Identify "pileup" particles
- ▶ Graph-level tasks
 - ▶ **Jet tagging**

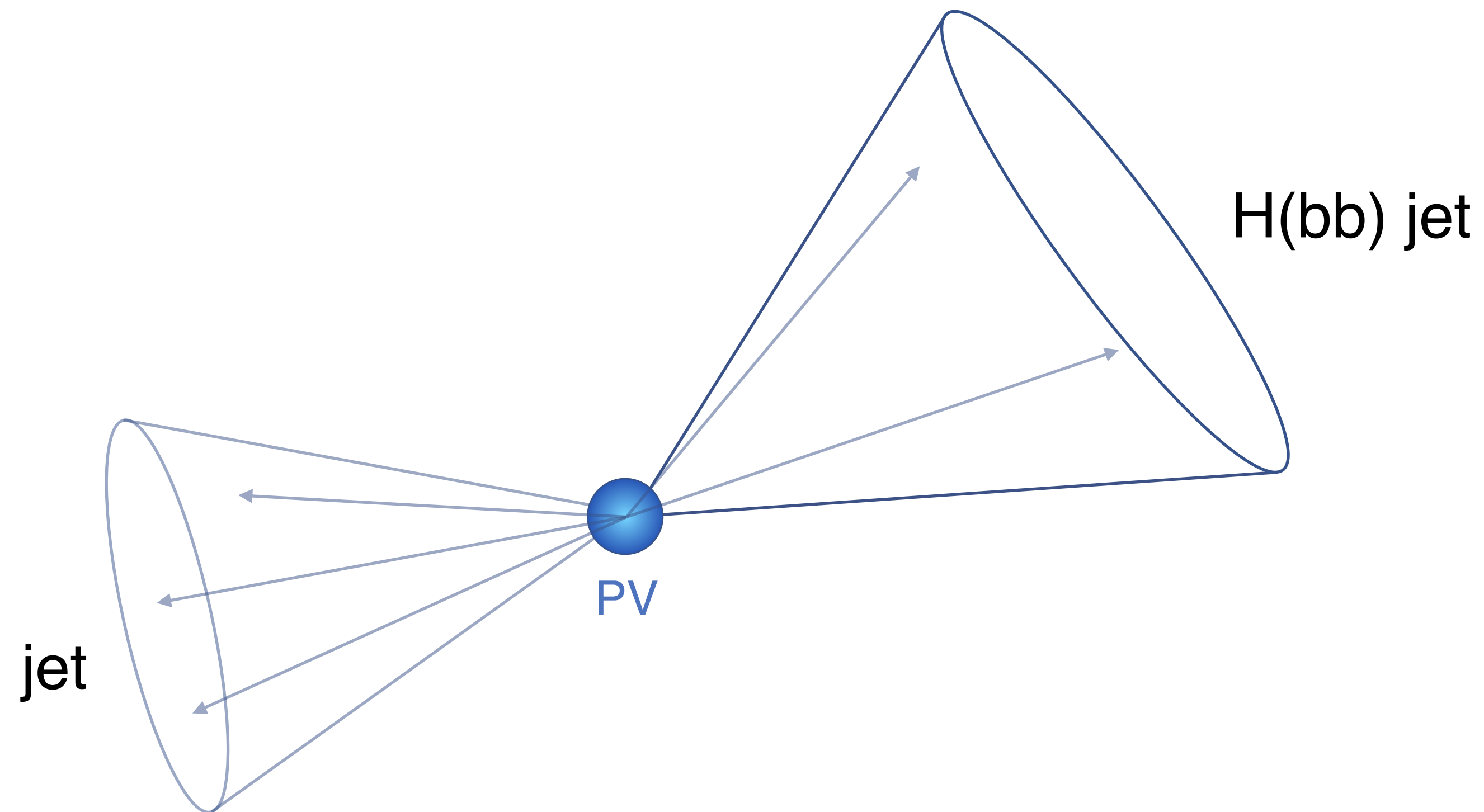


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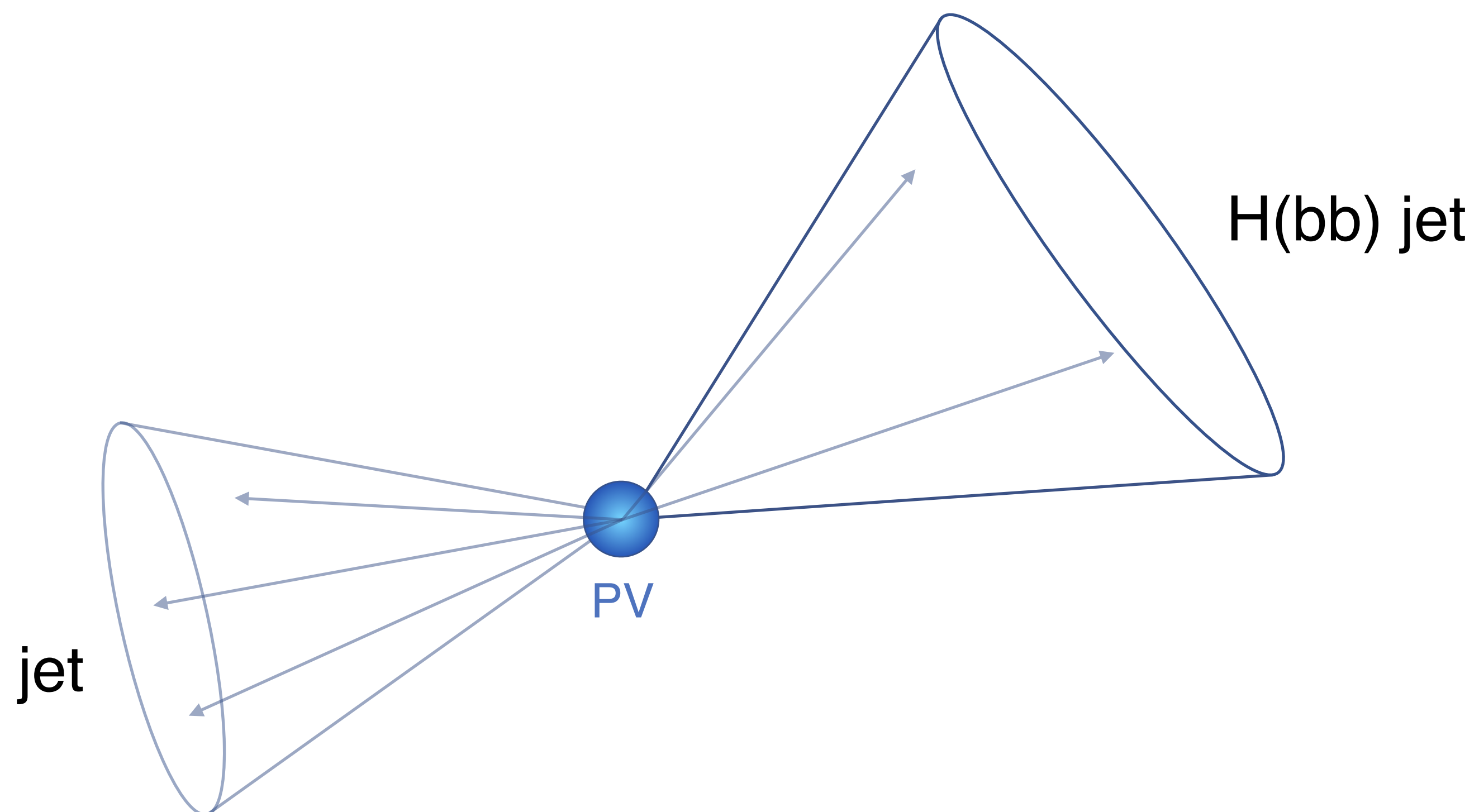


b hadrons have long lifetimes:
travel $O(\text{mm})$ before decay!



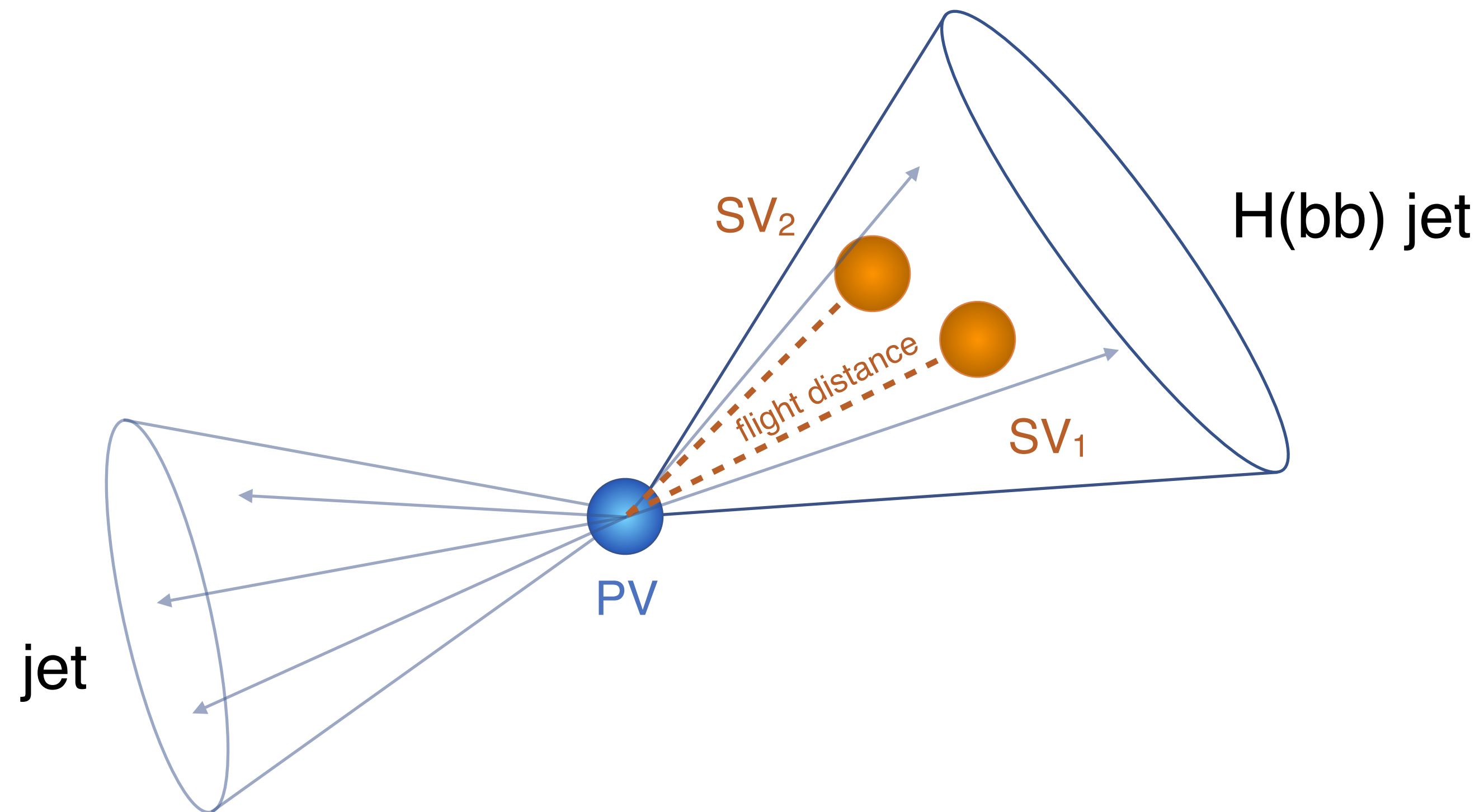
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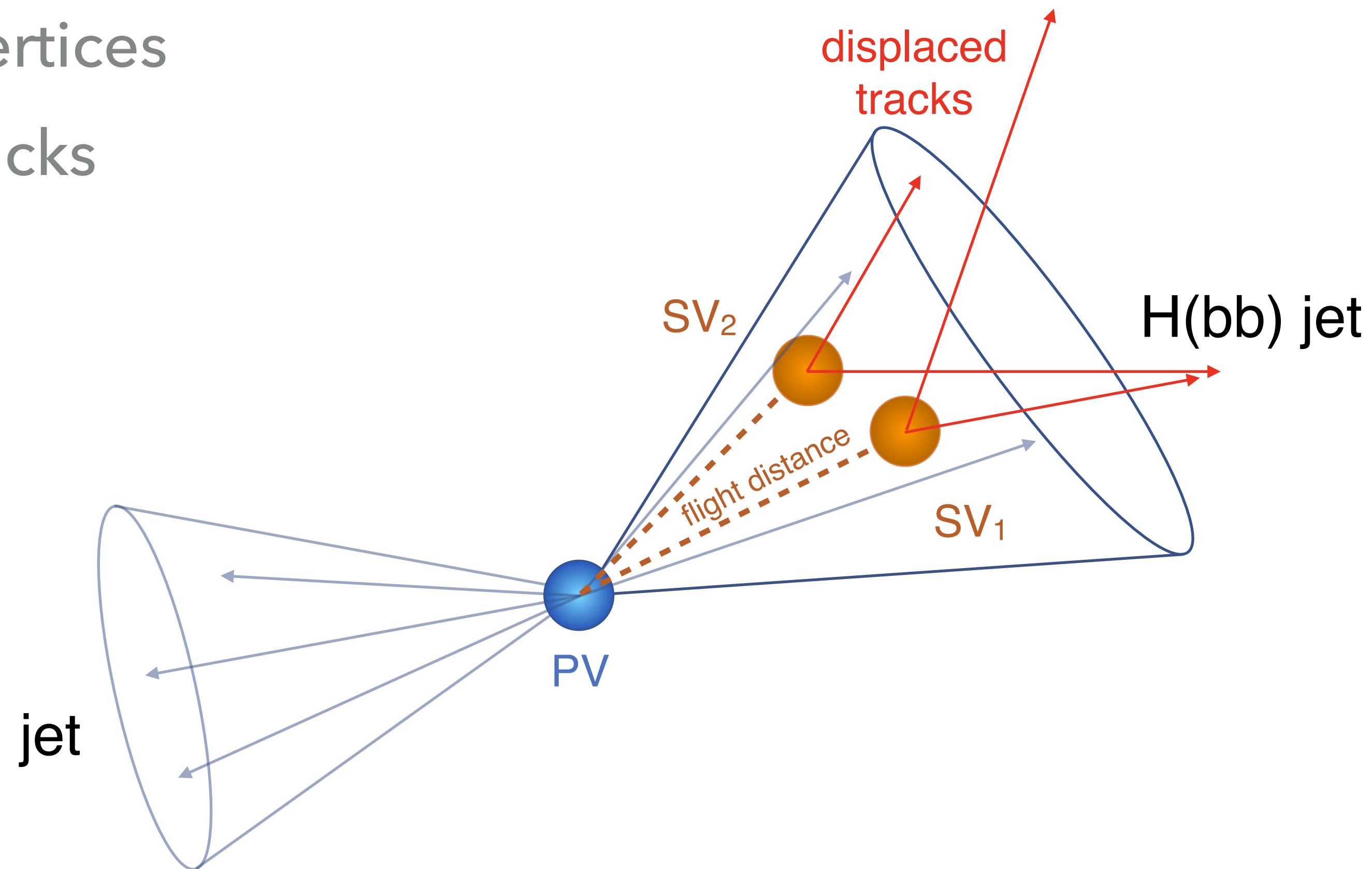
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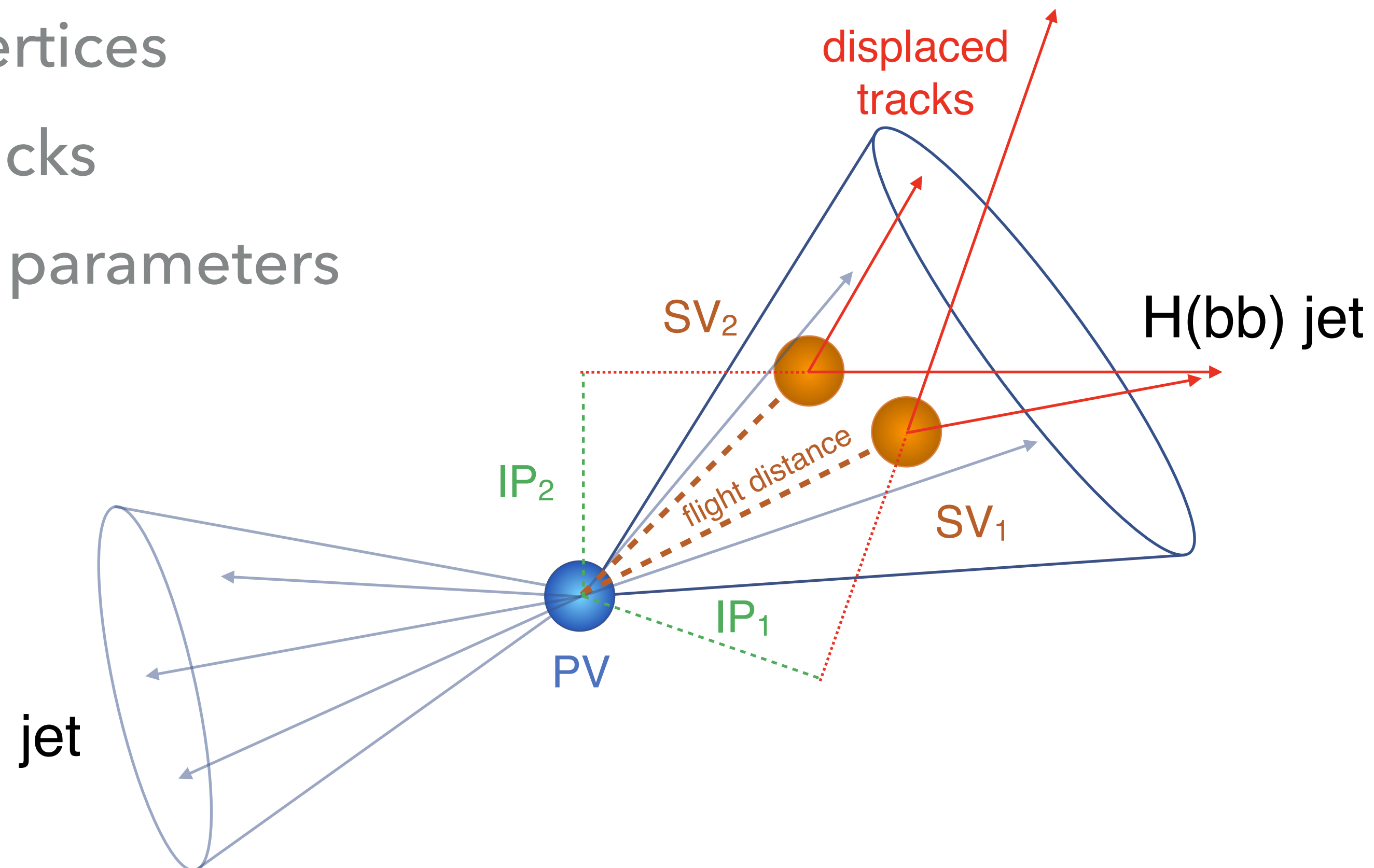
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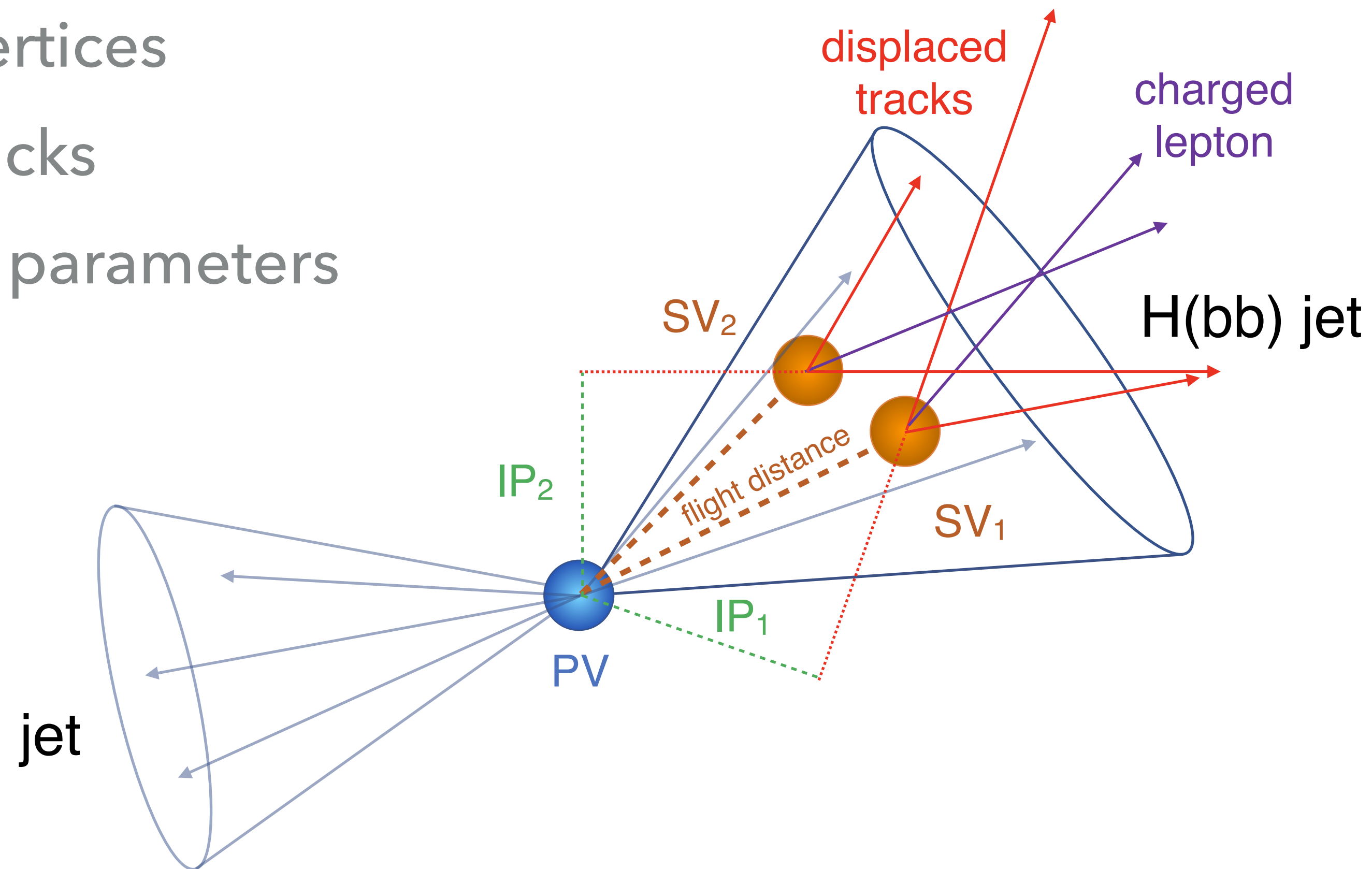
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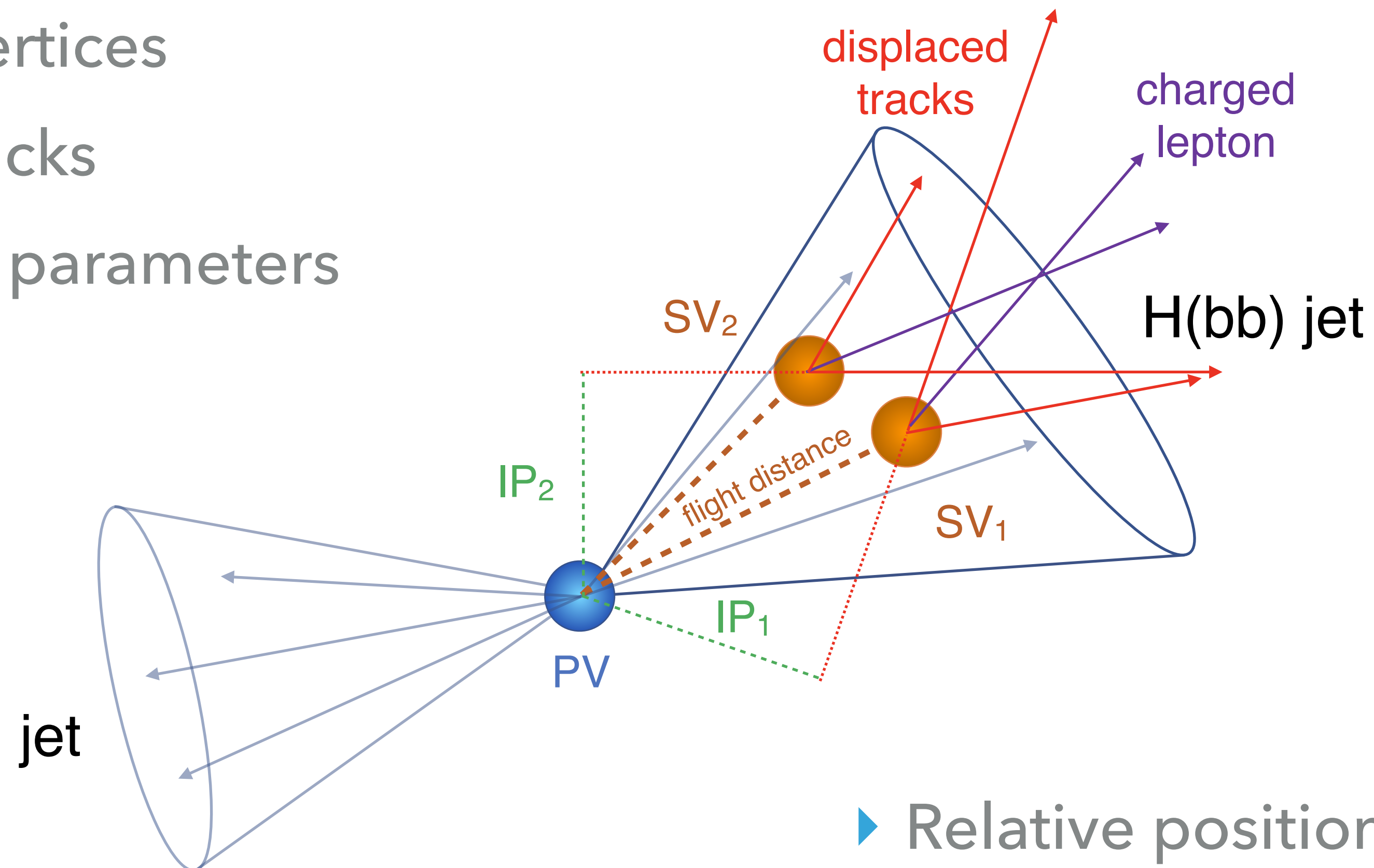
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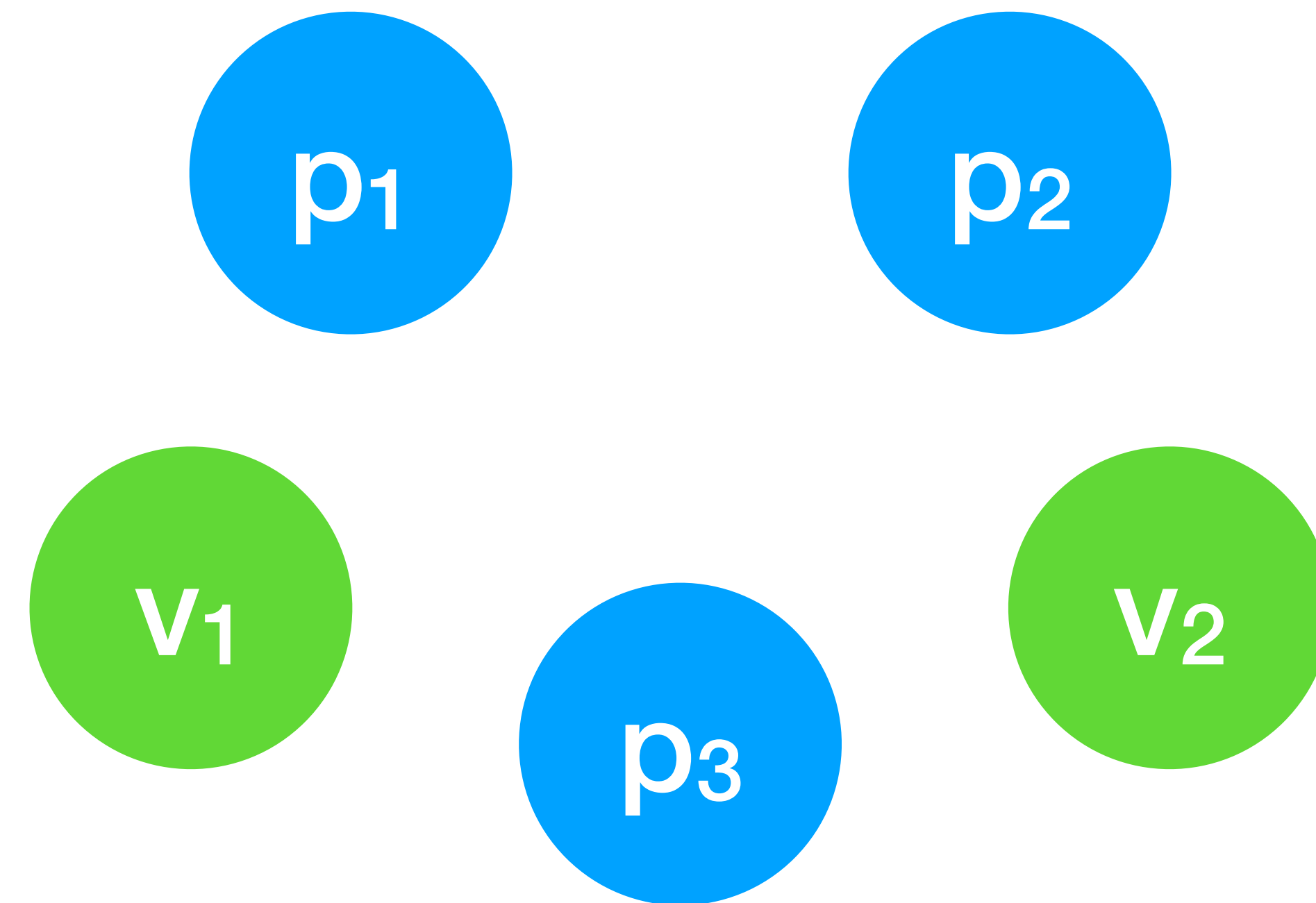


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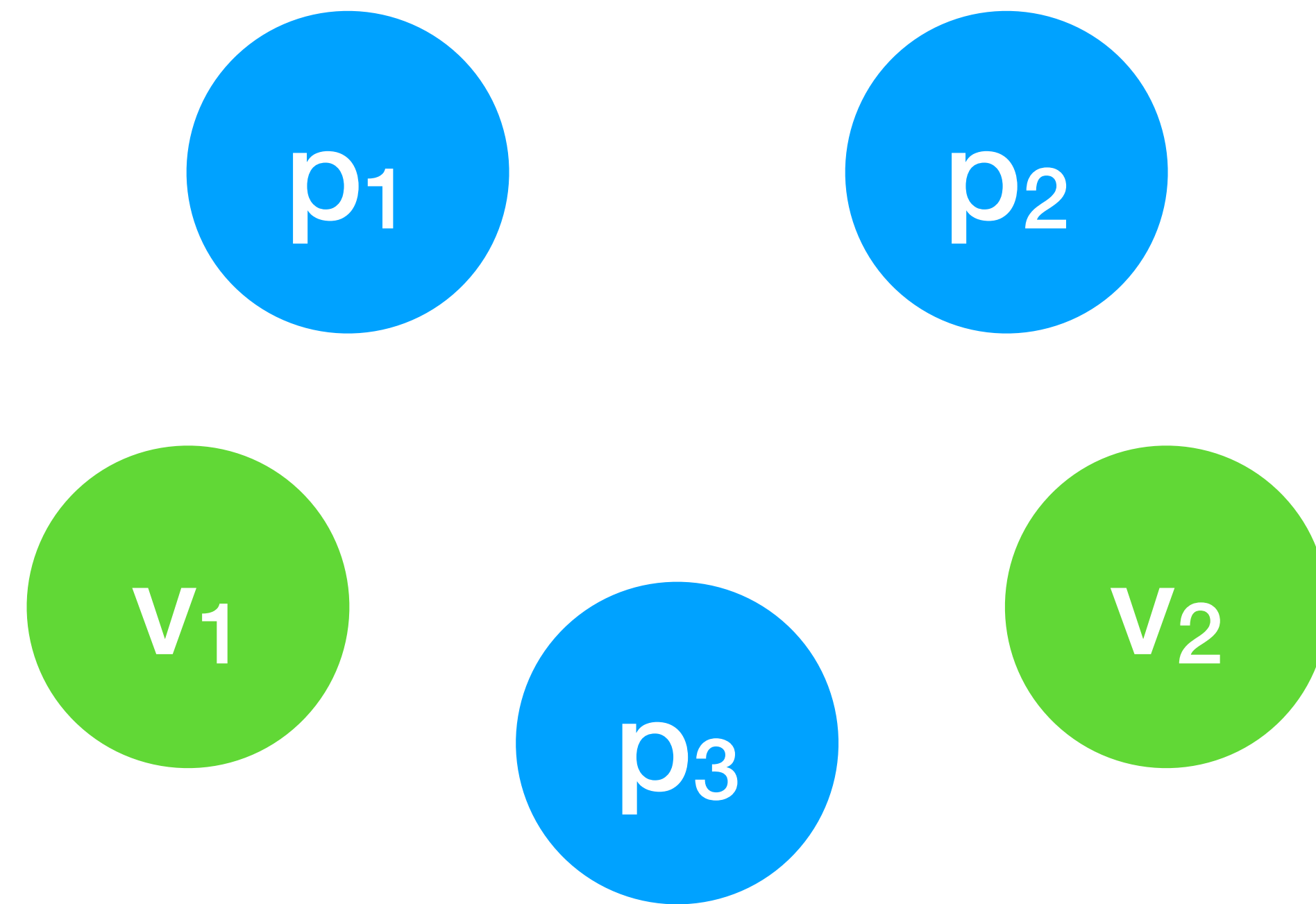
$$p_i = [p_T^{\text{rel}}, \phi^{\text{rel}}, \eta^{\text{rel}}, \dots, d_{3D}, \text{cov}(p_T, p_T), \dots]$$



$$v_i = [p_T^{\text{rel}}, \phi^{\text{rel}}, \eta^{\text{rel}}, \dots, n_{\text{tracks}}, \cos \theta_{PV}, \dots]$$

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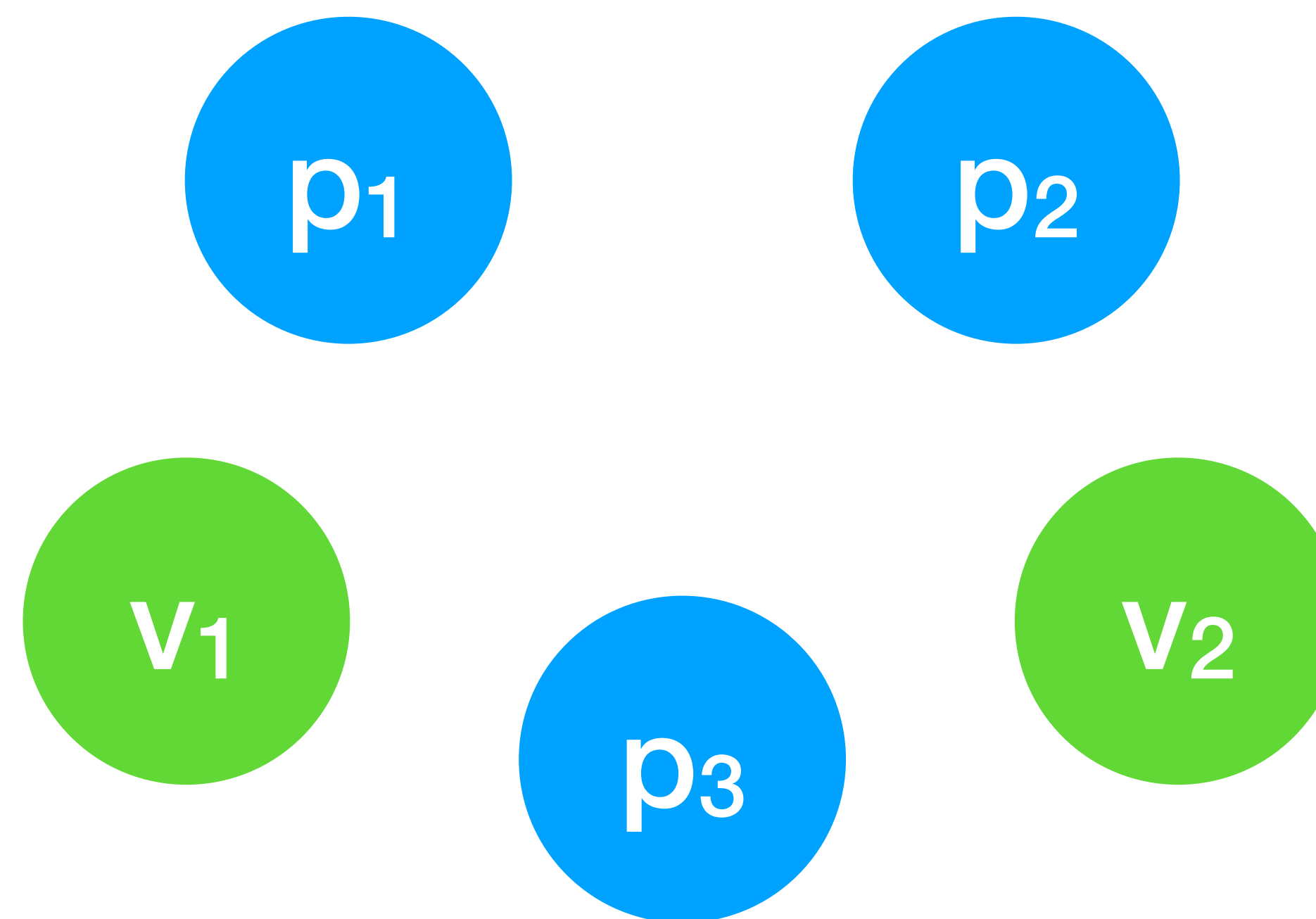


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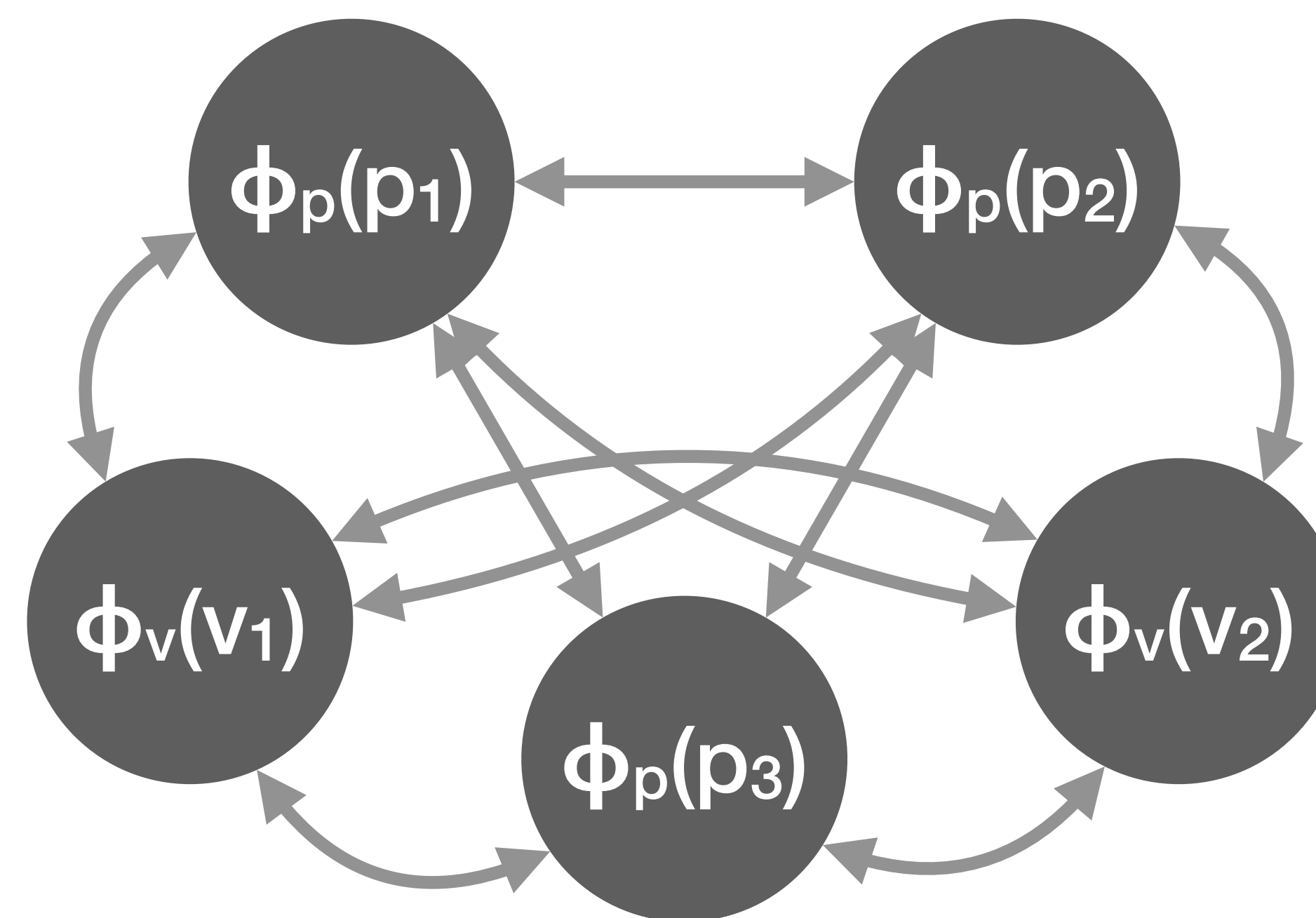


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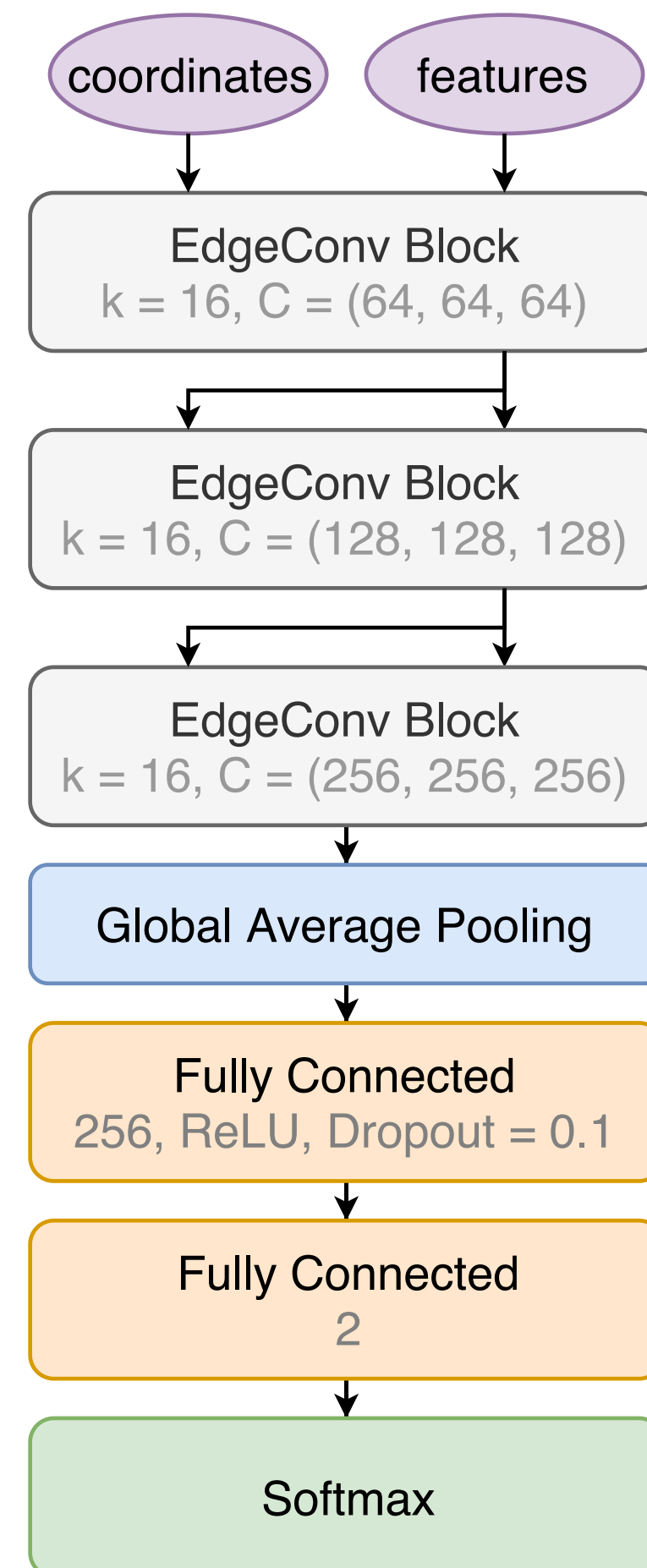
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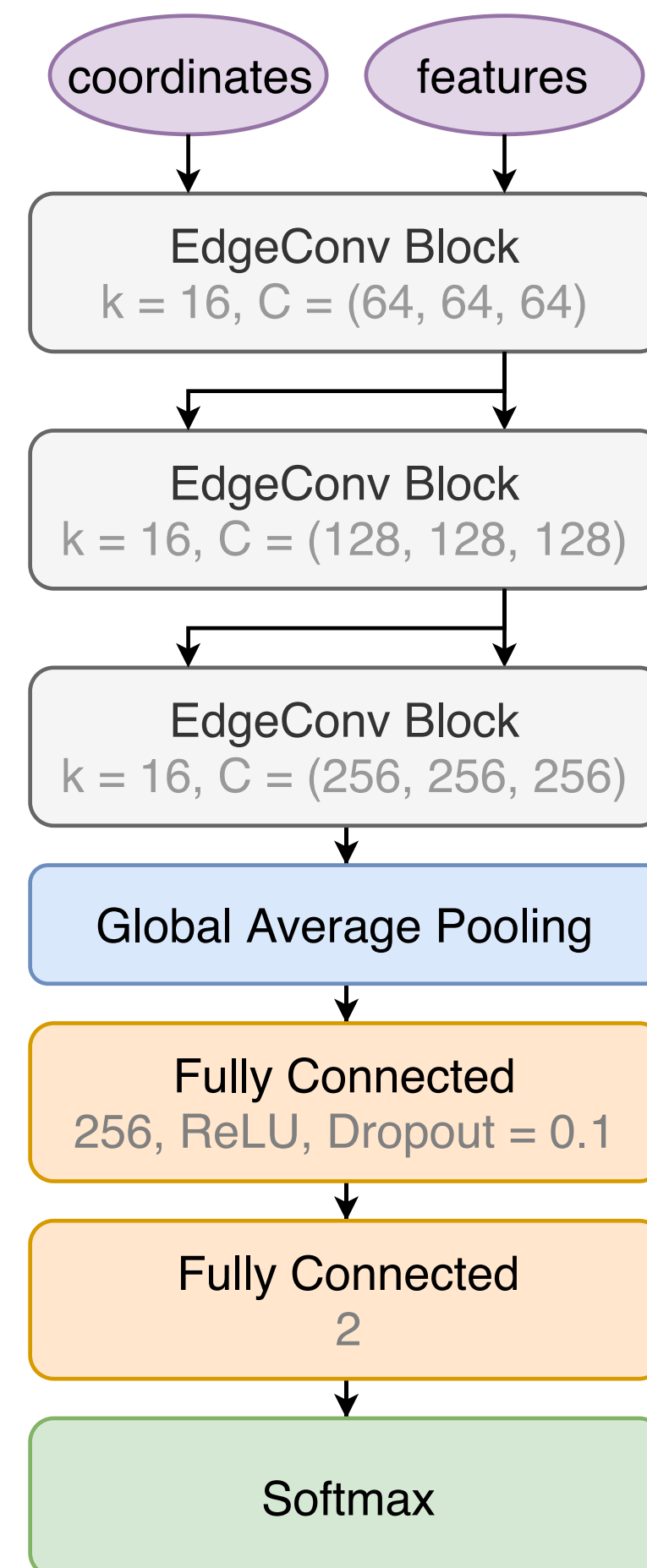


- ▶ After embedding feature vectors in a common *latent space* (via a NN), *combined graph* can be constructed

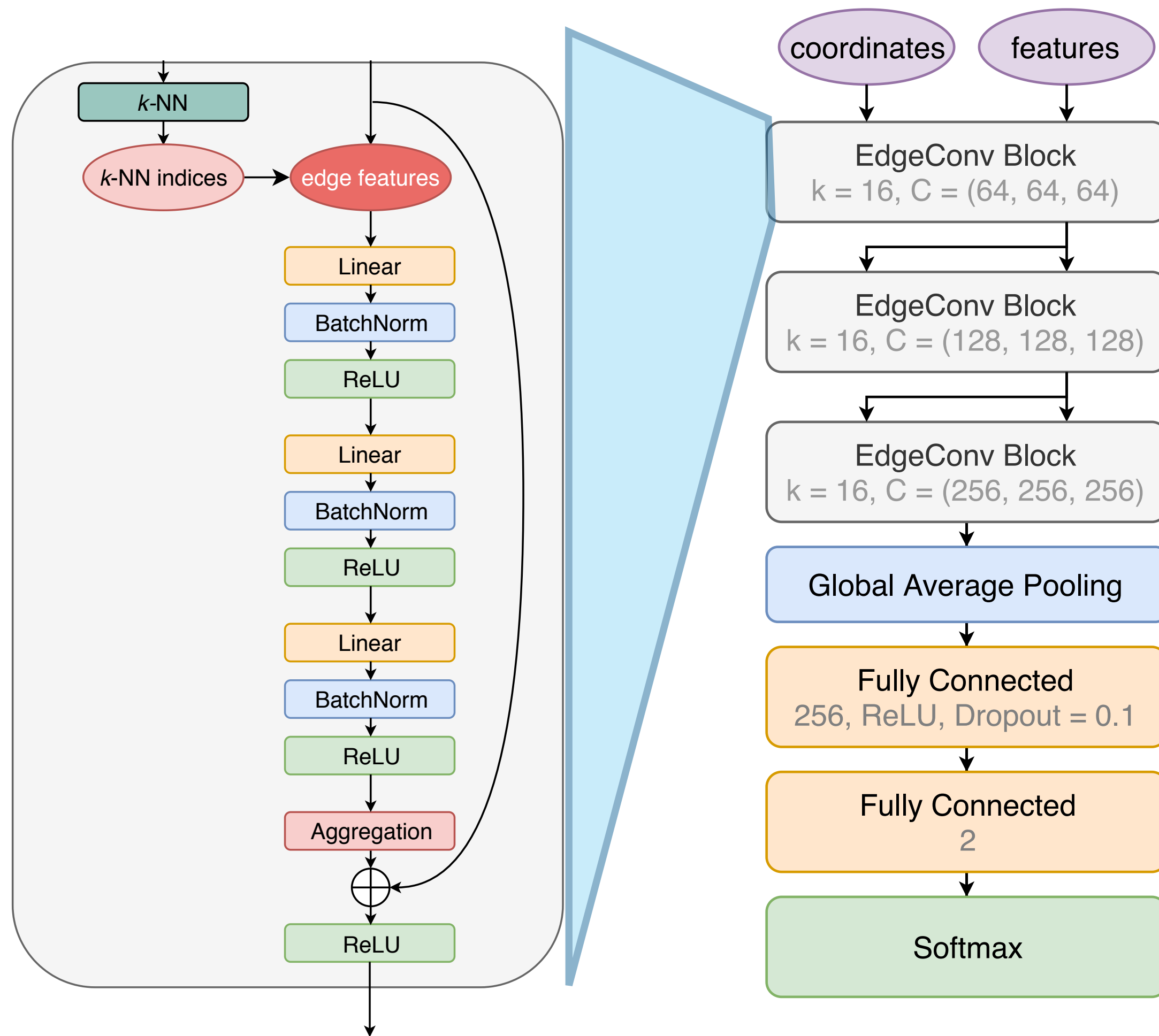
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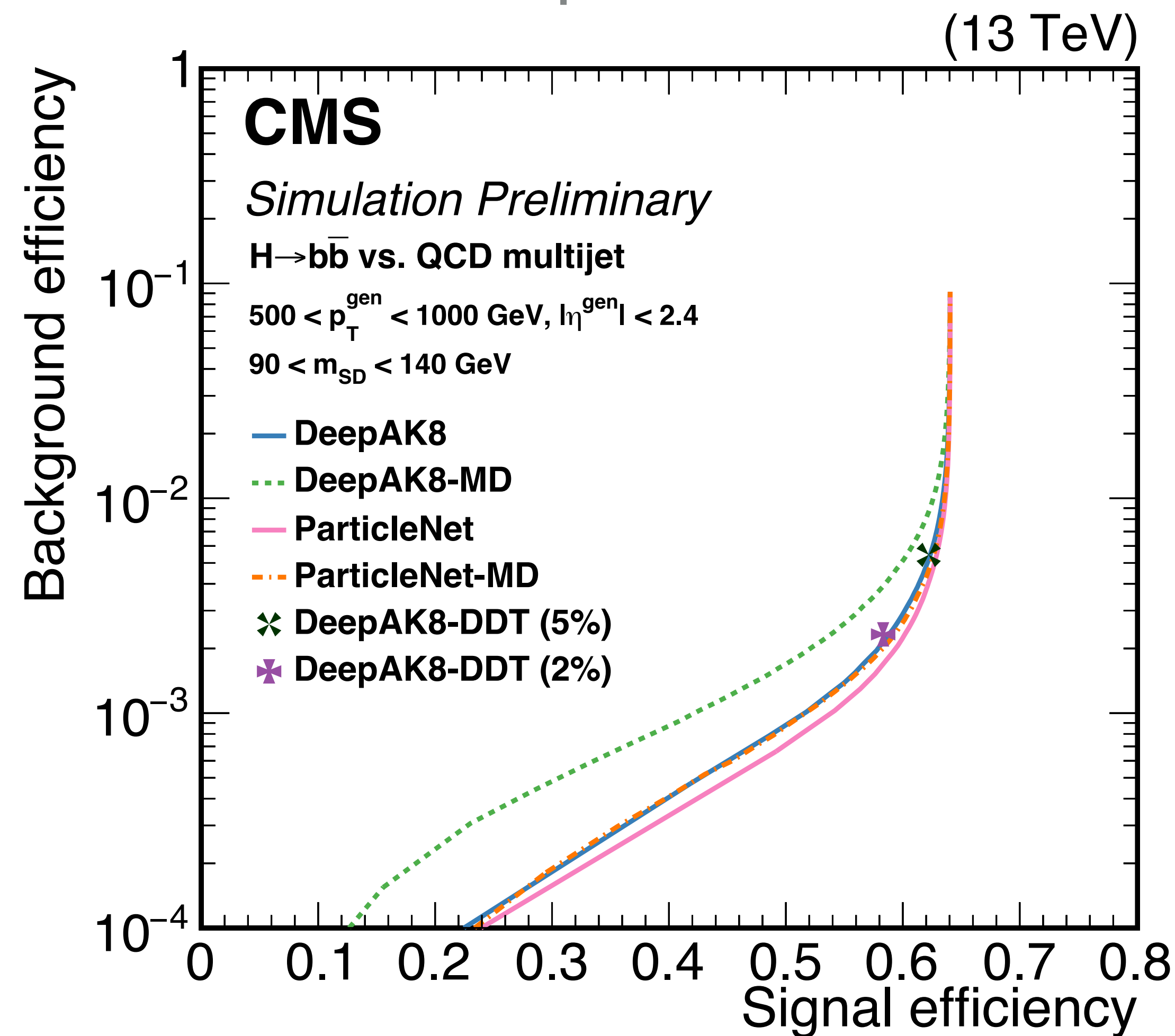
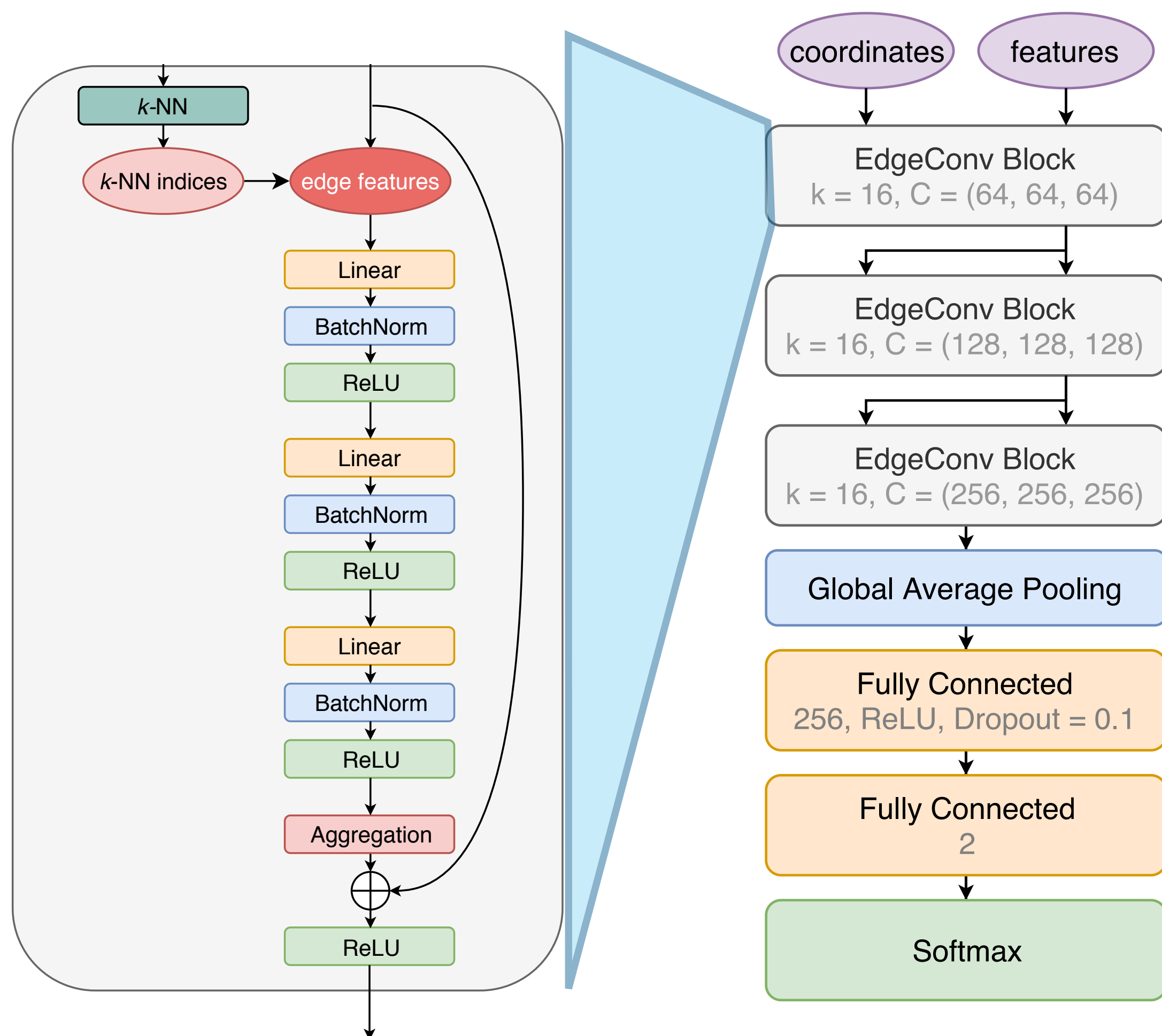
- ▶ ParticleNet, using “dynamic edge convolutions:” graph is constructed based on “closeness” in the latent space



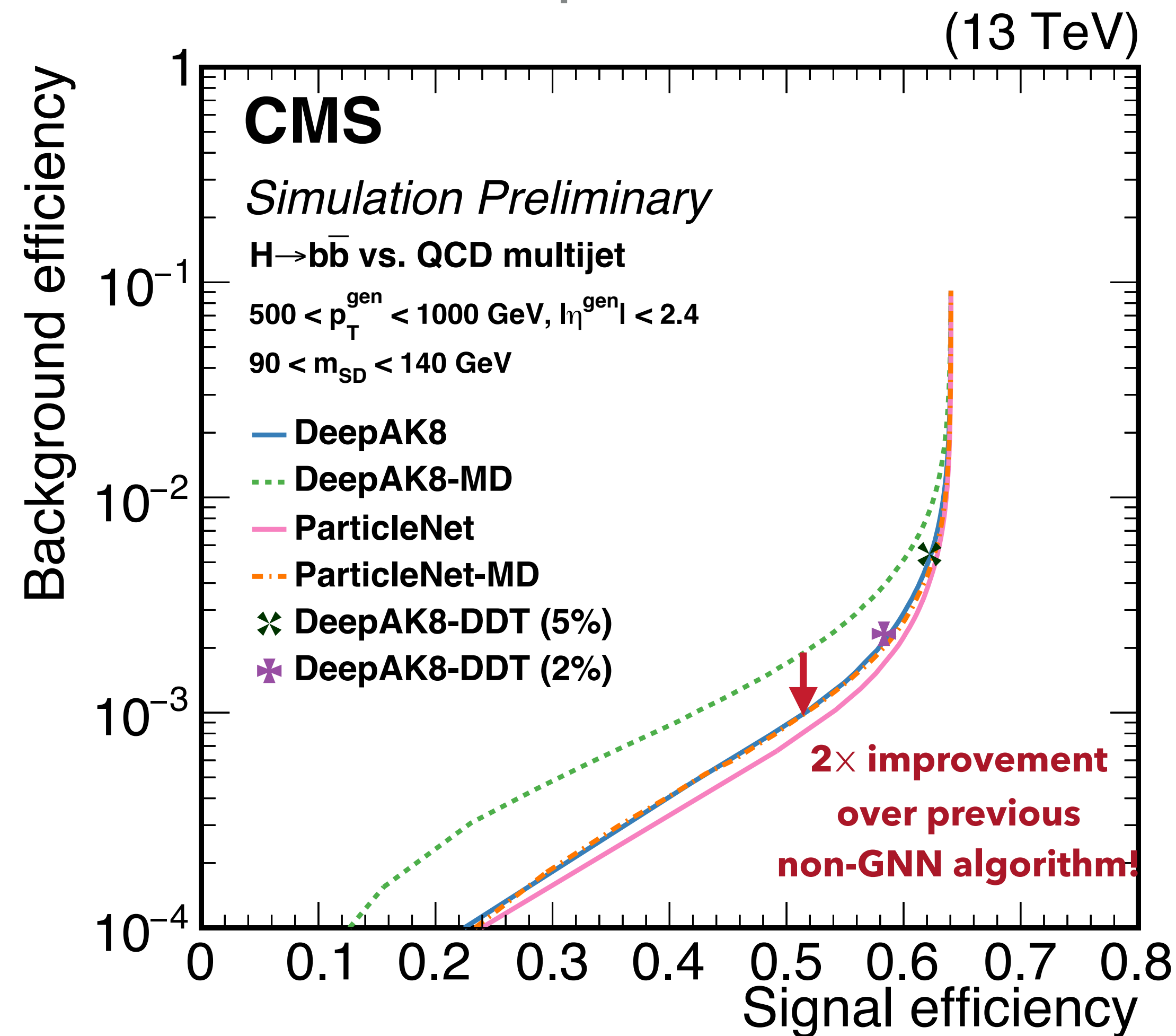
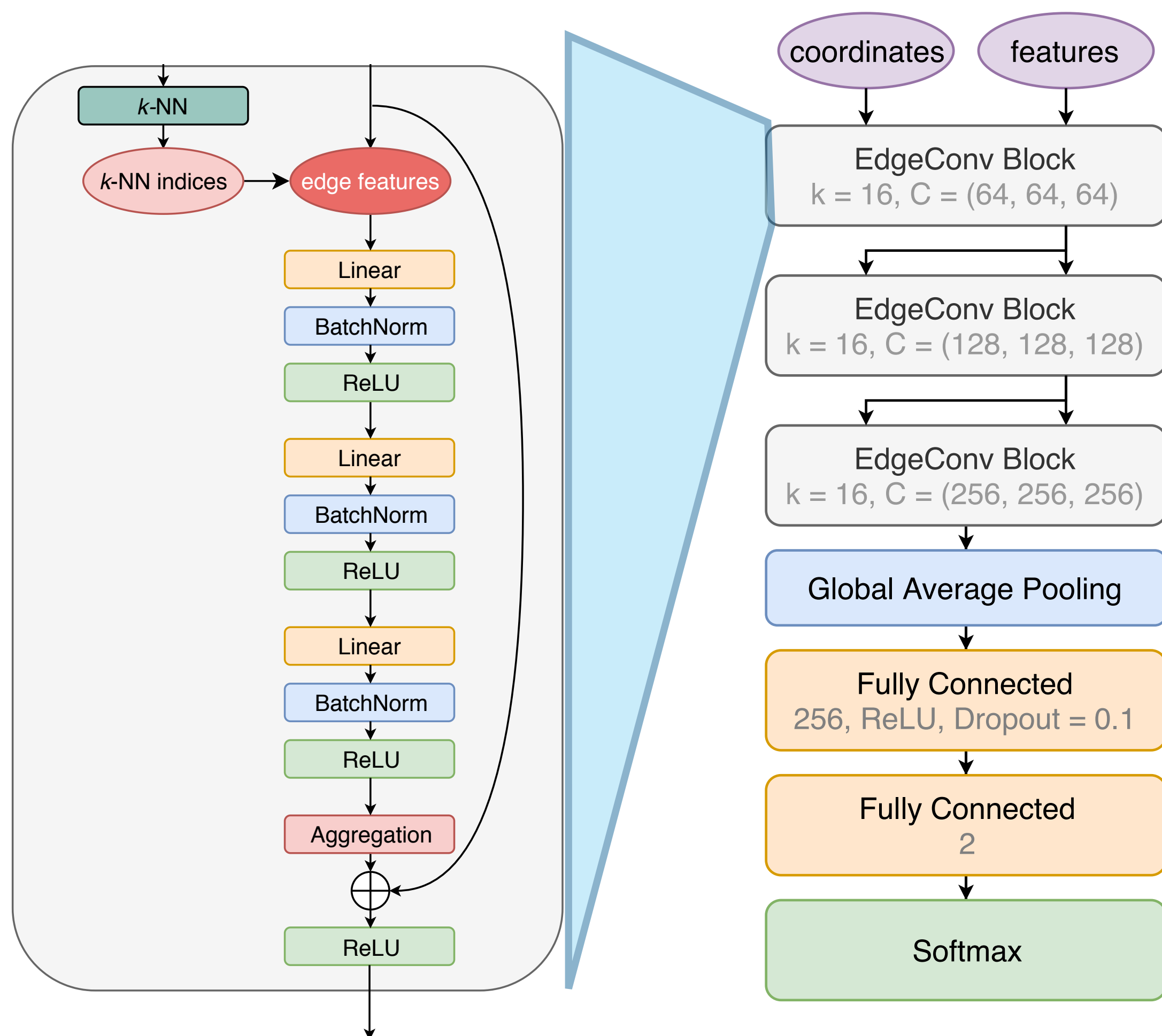
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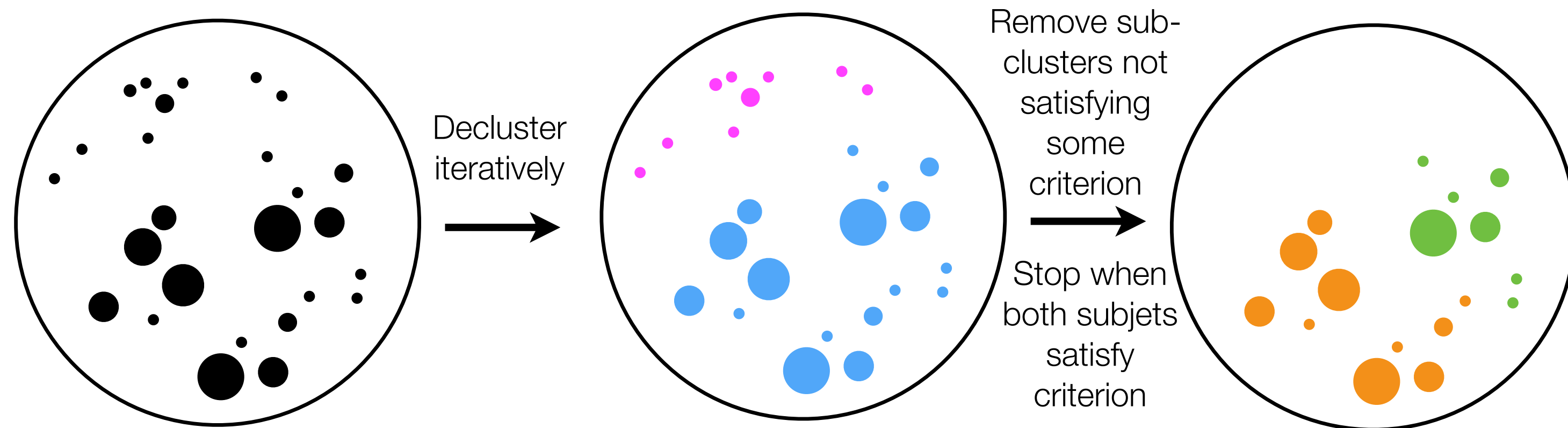


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- ▶ Identifies H(bb) with true positive rate of ~50% and false positive rate of 0.1% (13 TeV)

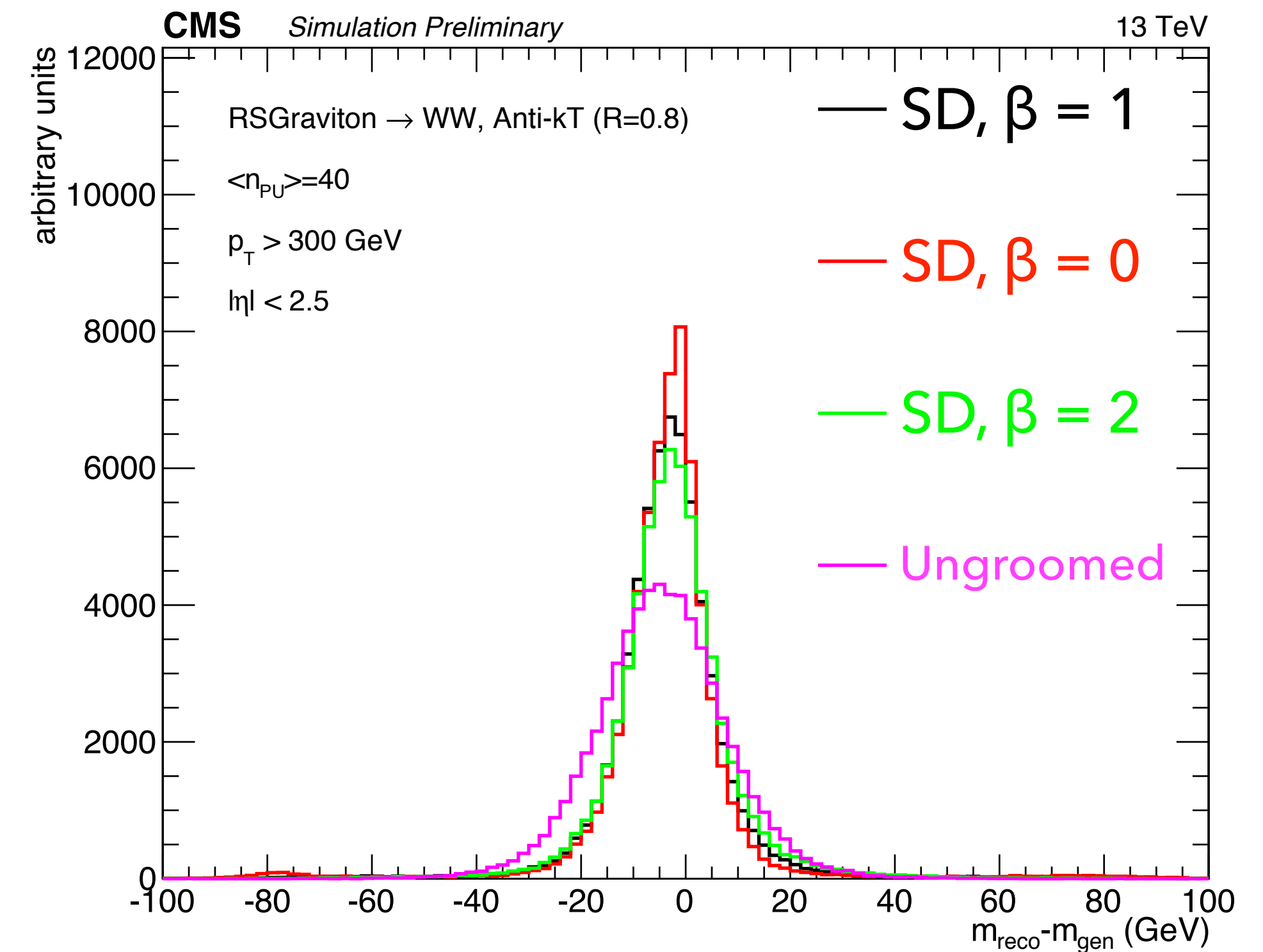


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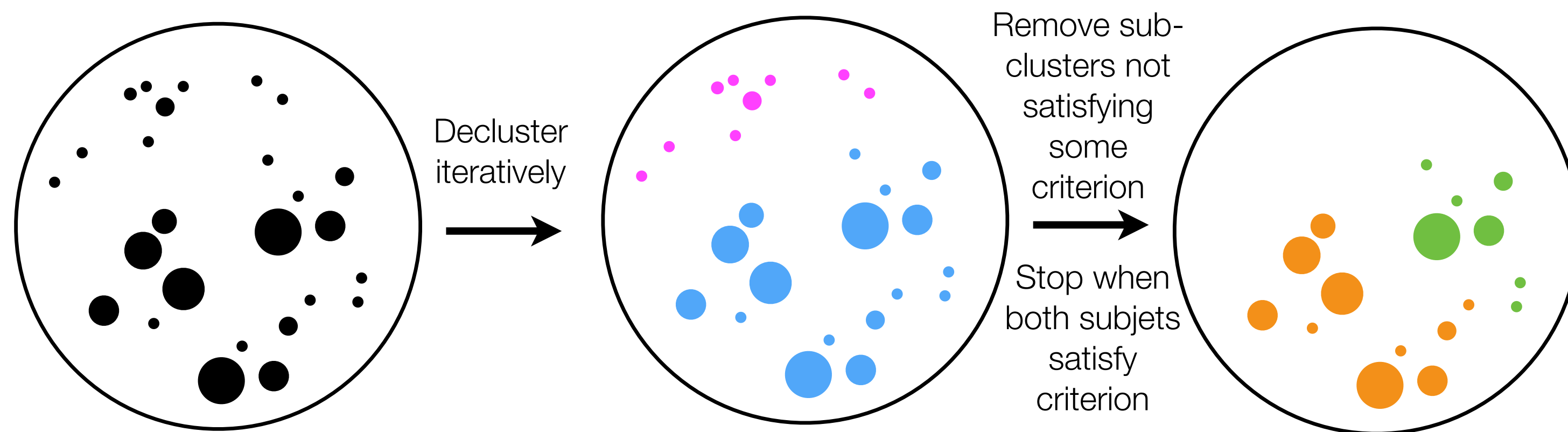


Soft Drop Condition:
$$\frac{\min(p_{T1}, p_{T2})}{p_{T1} + p_{T2}} > z_{\text{cut}} \left(\frac{\Delta R_{12}}{R_0} \right)^\beta$$

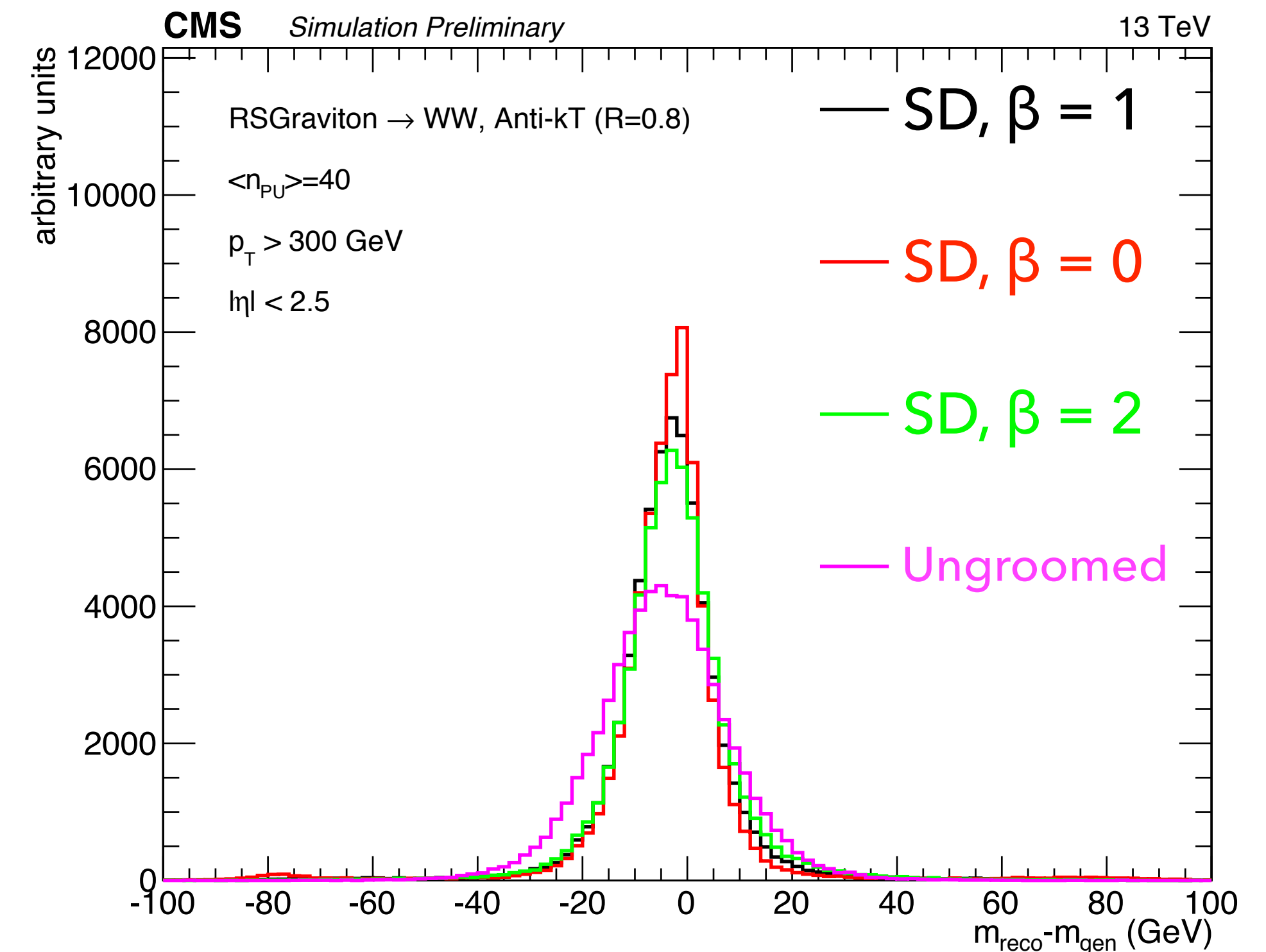


CMS: $z_{\text{cut}} = 0.1, \beta = 0$

- ▶ An important property used to analyze Higgs boson jets is the **soft drop mass**
 - ▶ Grooming removes soft/wide-angle radiation and improves mass resolution

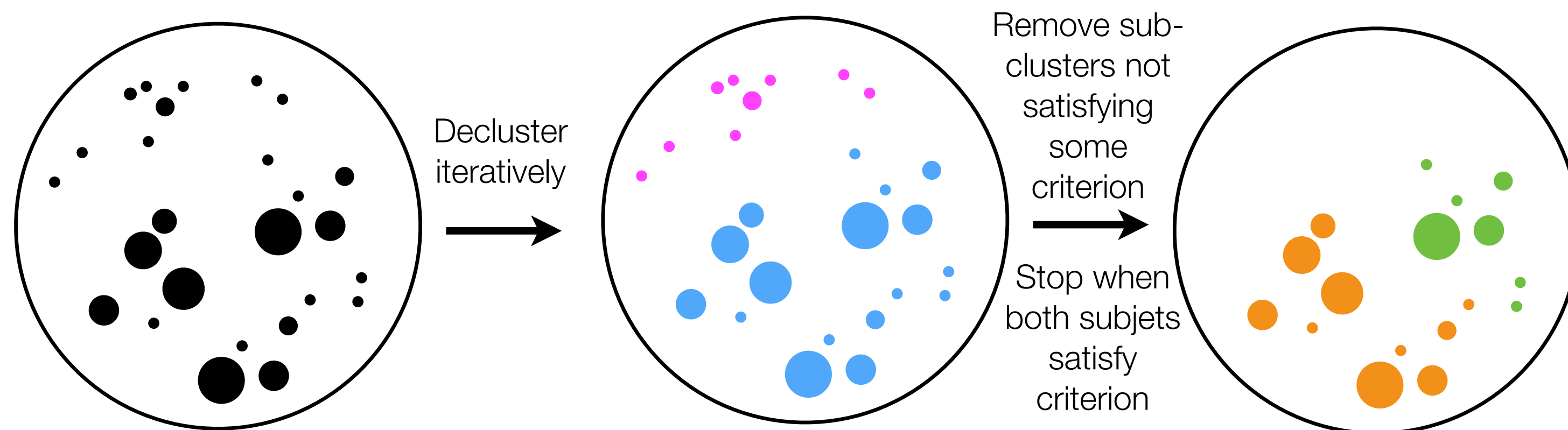


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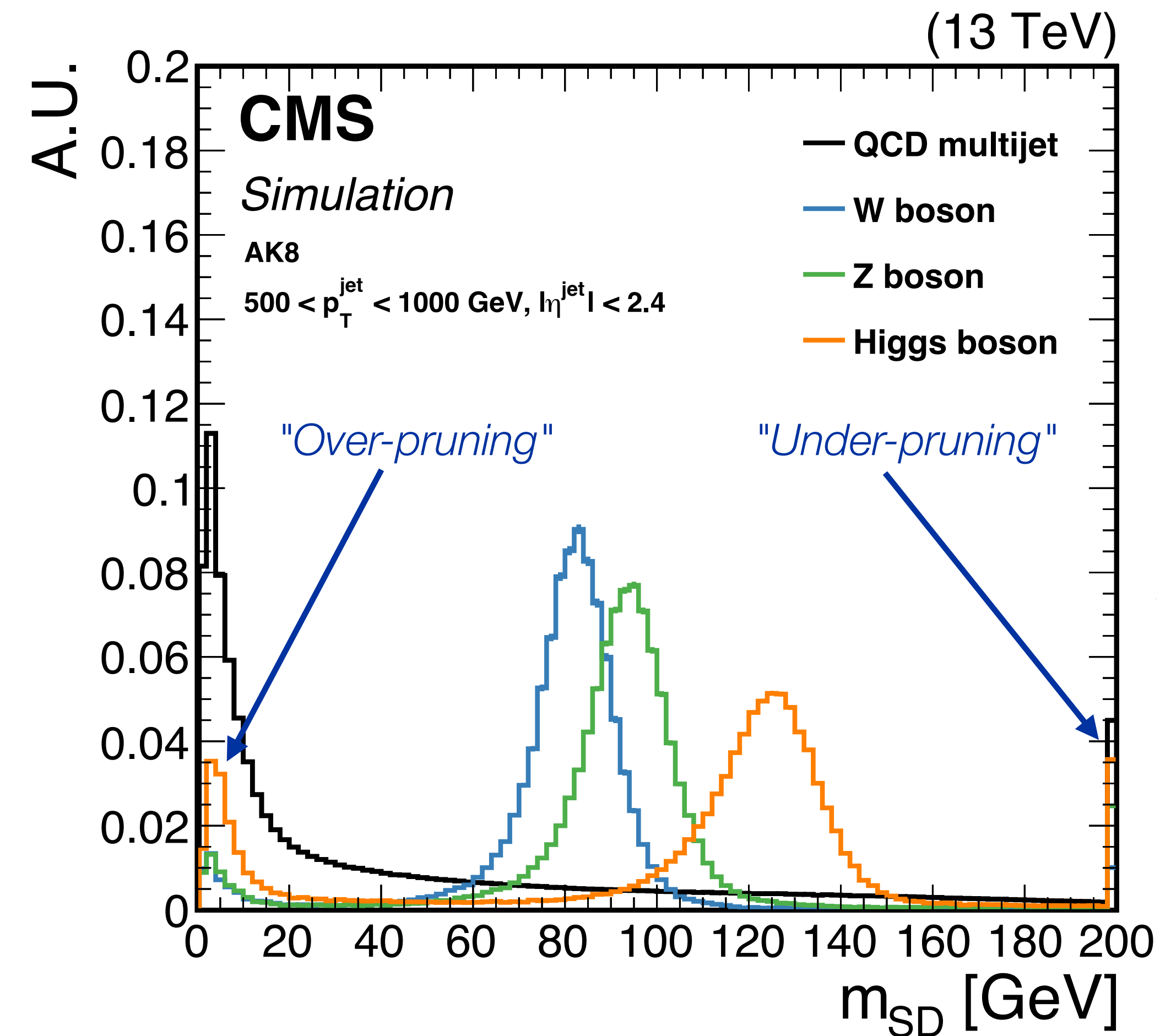
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- ▶ An important property used to analyze Higgs boson jets is the ***soft drop mass***
 - ▶ Grooming removes soft/wide-angle radiation and improves mass resolution
 - ▶ However, grooming can *over-prune* or *under-prune*
 - ▶ Can we do better with ML?



Soft Drop Condition:

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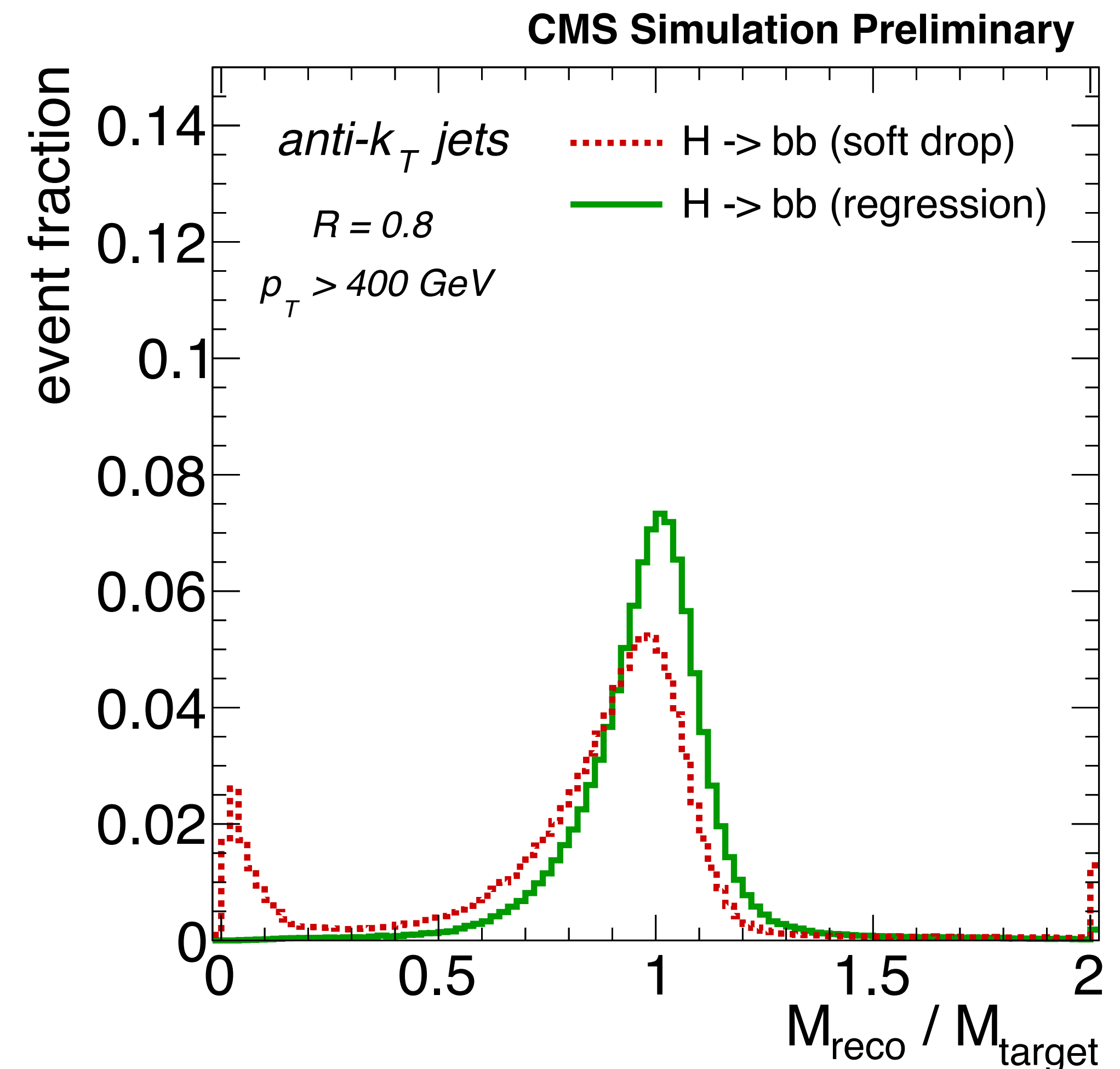
- ▶ Minimize difference between output

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- ▶ Substantial scale and resolution improvement



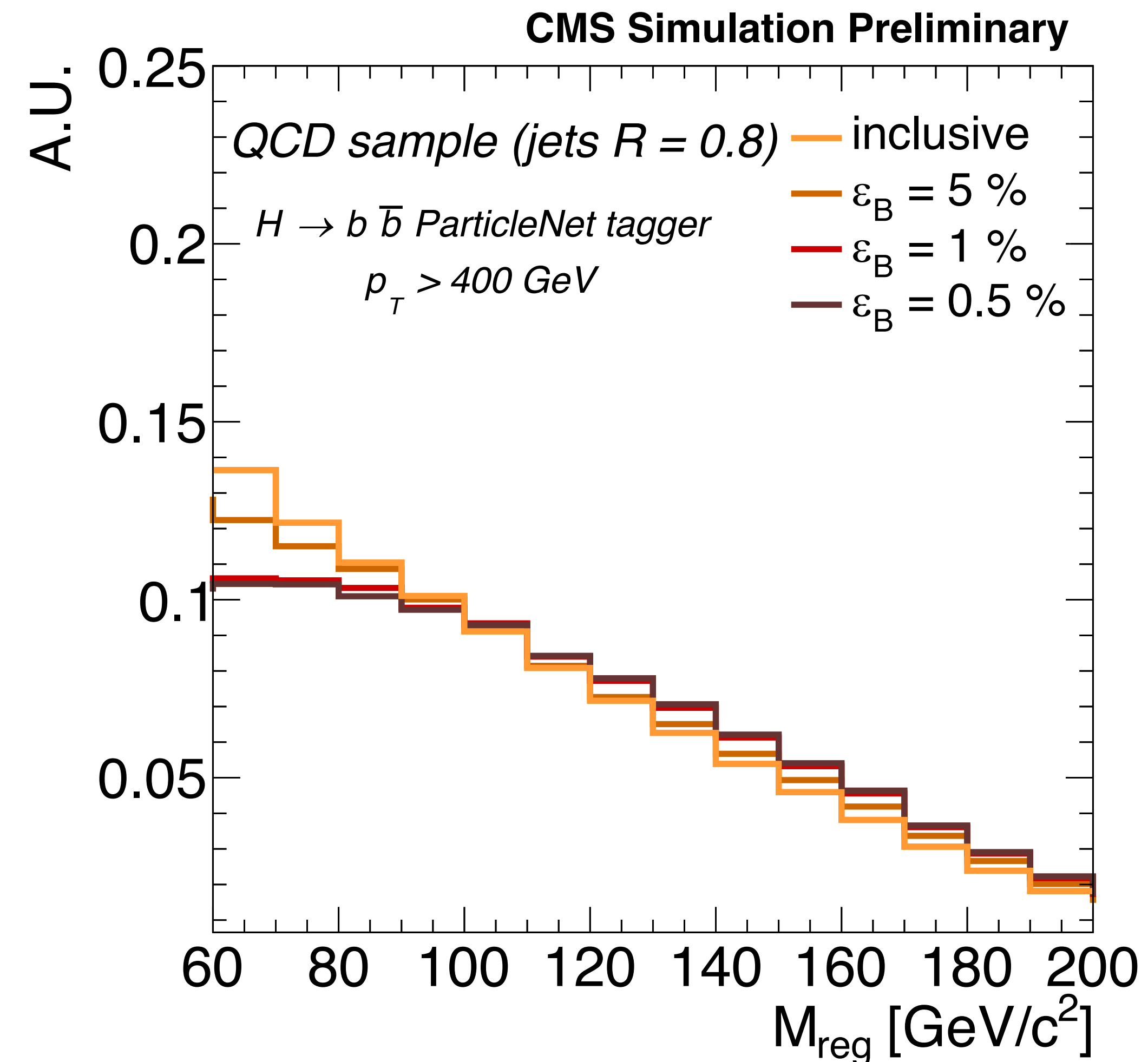
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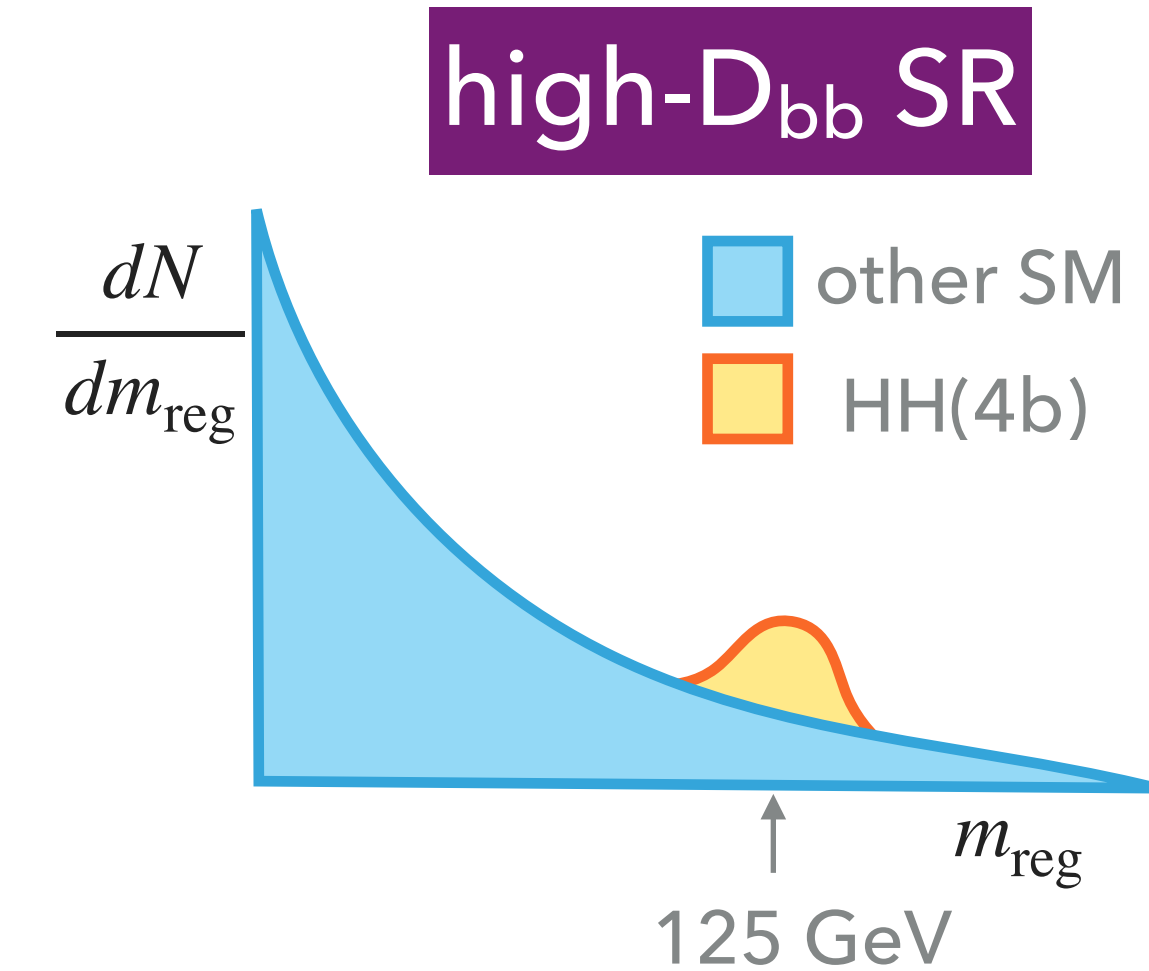
- ▶ Substantial scale and resolution improvement
- ▶ No significant mass sculpting near $m_H = 125$ GeV for QCD background



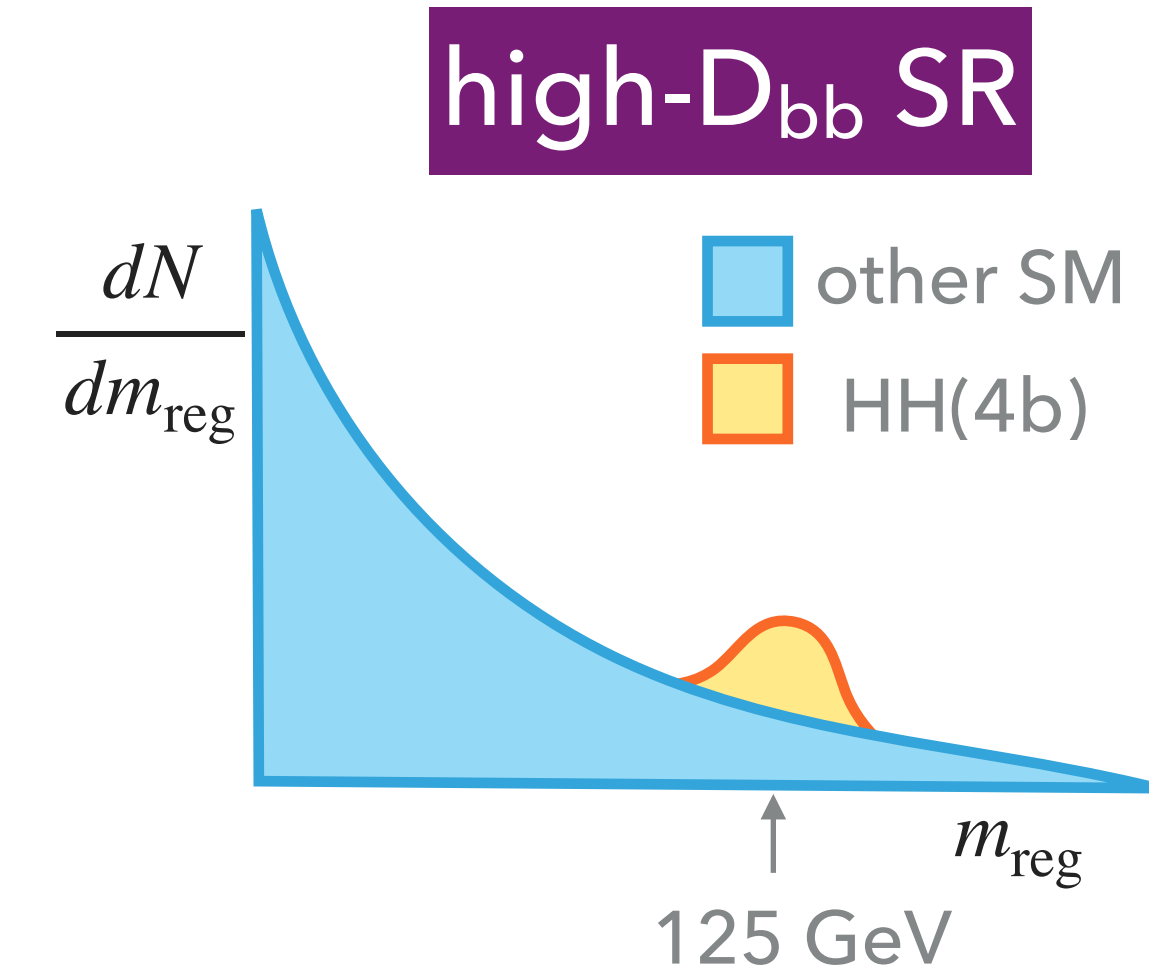
- 
- A visualization of a particle collision at the LHC. Two blue beams enter from the left and right, colliding at a central point. From this point, a large orange cone of particles expands outwards. Numerous green and yellow lines radiate from the collision point, representing individual particles. The background is dark with faint blue and red geometric shapes.
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- ▶ Apply kinematic selections for ggF or VBF

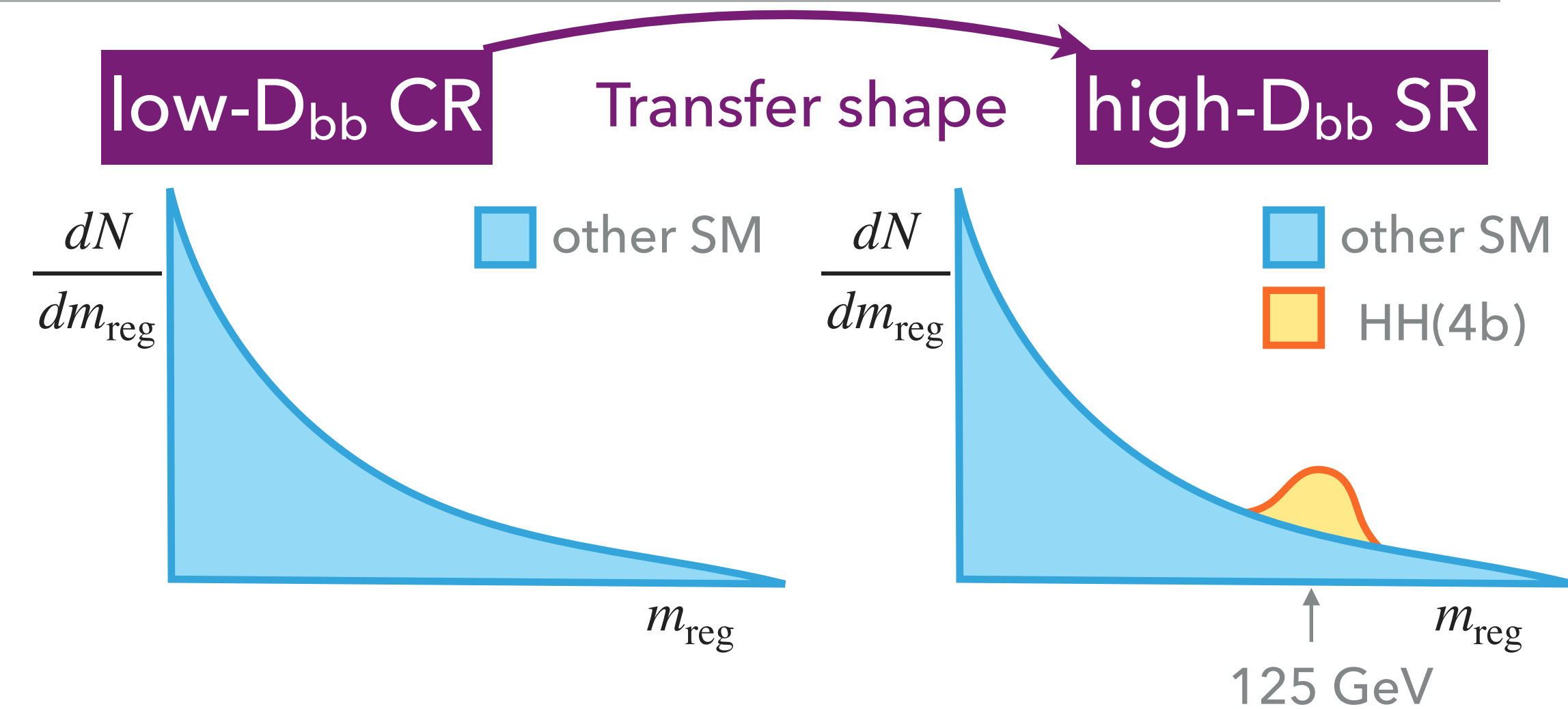
- ▶ Apply kinematic selections for ggF or VBF
- ▶ Identify high- p_T Higgs candidate jets with
 - ▶ ParticleNet $H \rightarrow bb$ tagger D_{bb}
 - ▶ ParticleNet regressed jet mass m_{reg}



- ▶ Apply kinematic selections for ggF or VBF
- ▶ Identify high- p_T Higgs candidate jets with
 - ▶ ParticleNet $H \rightarrow bb$ tagger D_{bb}
 - ▶ ParticleNet regressed jet mass m_{reg}
- ▶ Categorize events using m_{HH} , ...

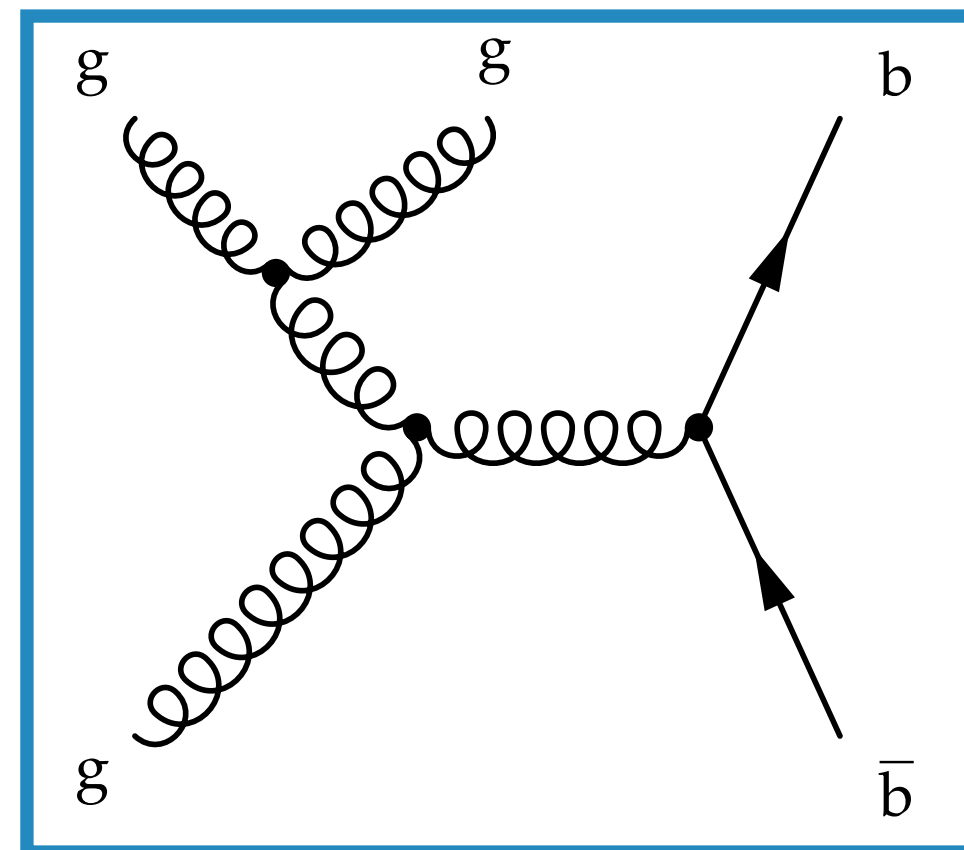


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 - ▶ ParticleNet $H \rightarrow bb$ tagger D_{bb}
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- ▶ Categorize events using m_{HH} , ...
- ▶ Given independence of D_{bb} and m_{reg} , apply *data-driven estimate*

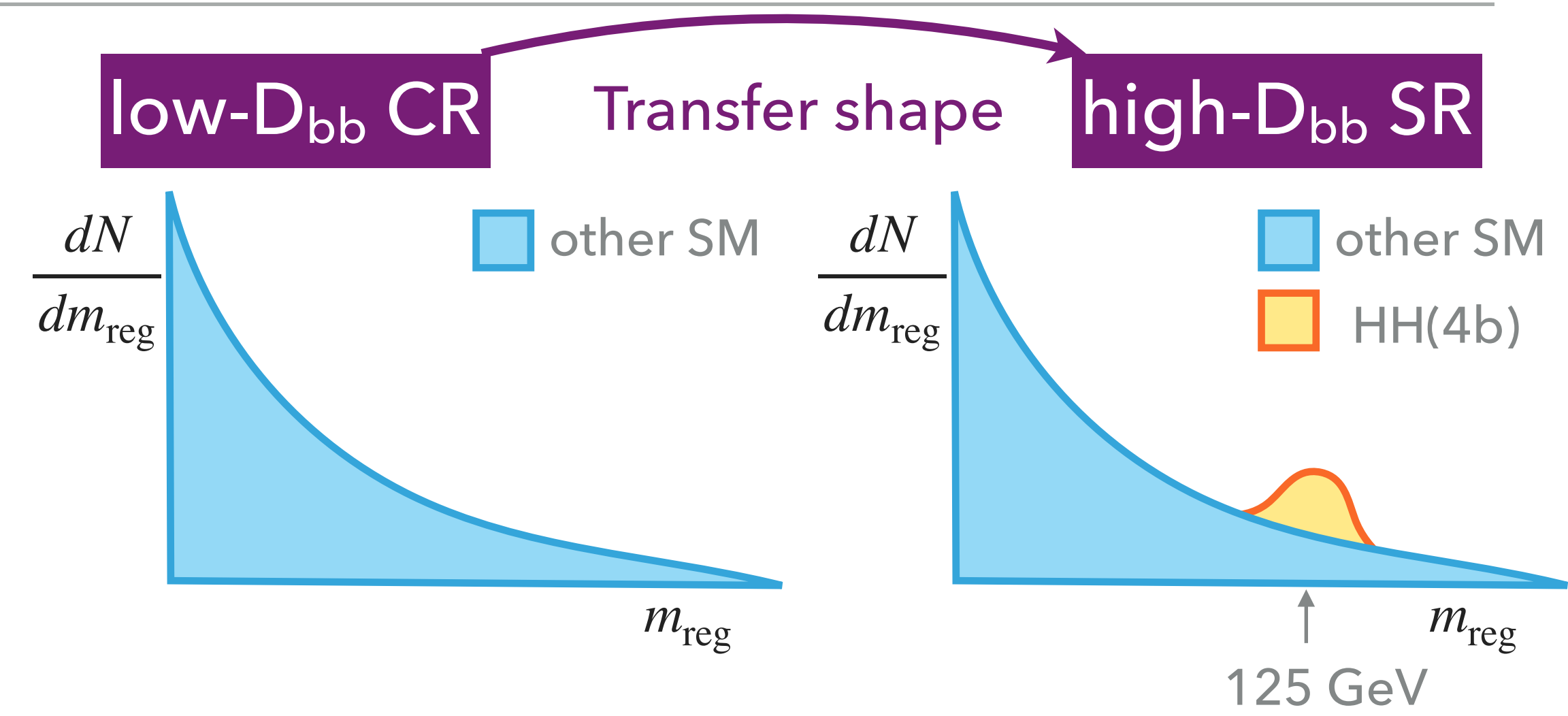
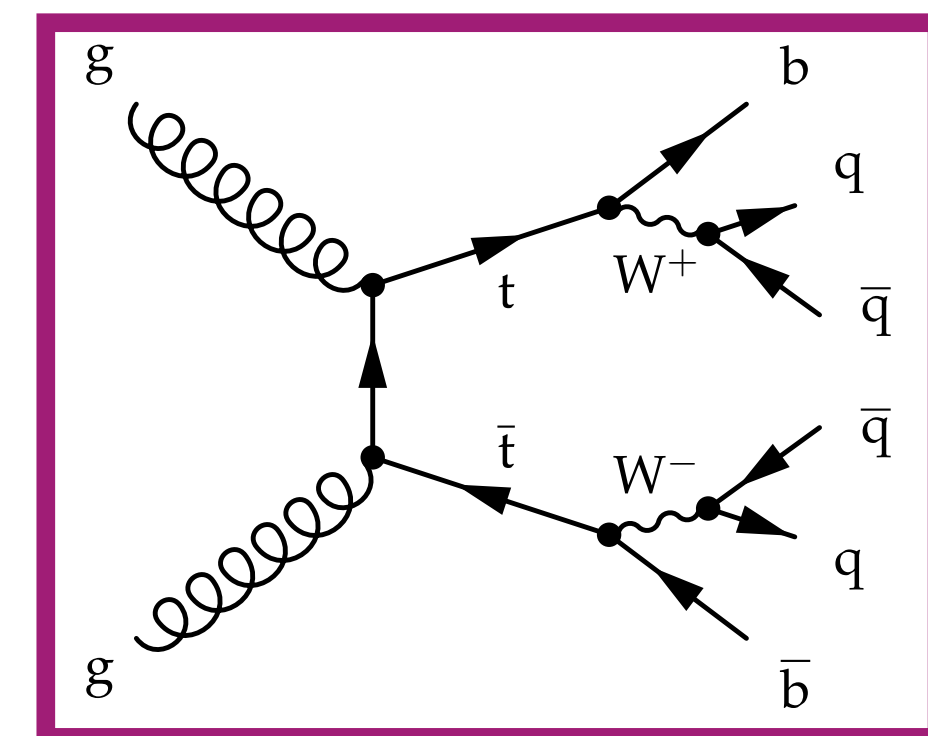


- ▶ Apply kinematic selections for ggF or VBF
- ▶ Identify high- p_T Higgs candidate jets with
 - ▶ ParticleNet $H \rightarrow bb$ tagger D_{bb}
 - ▶ ParticleNet regressed jet mass m_{reg}
- ▶ Categorize events using m_{HH}, \dots
- ▶ Given independence of D_{bb} and m_{reg} , apply *data-driven estimate*
- ▶ Main backgrounds:

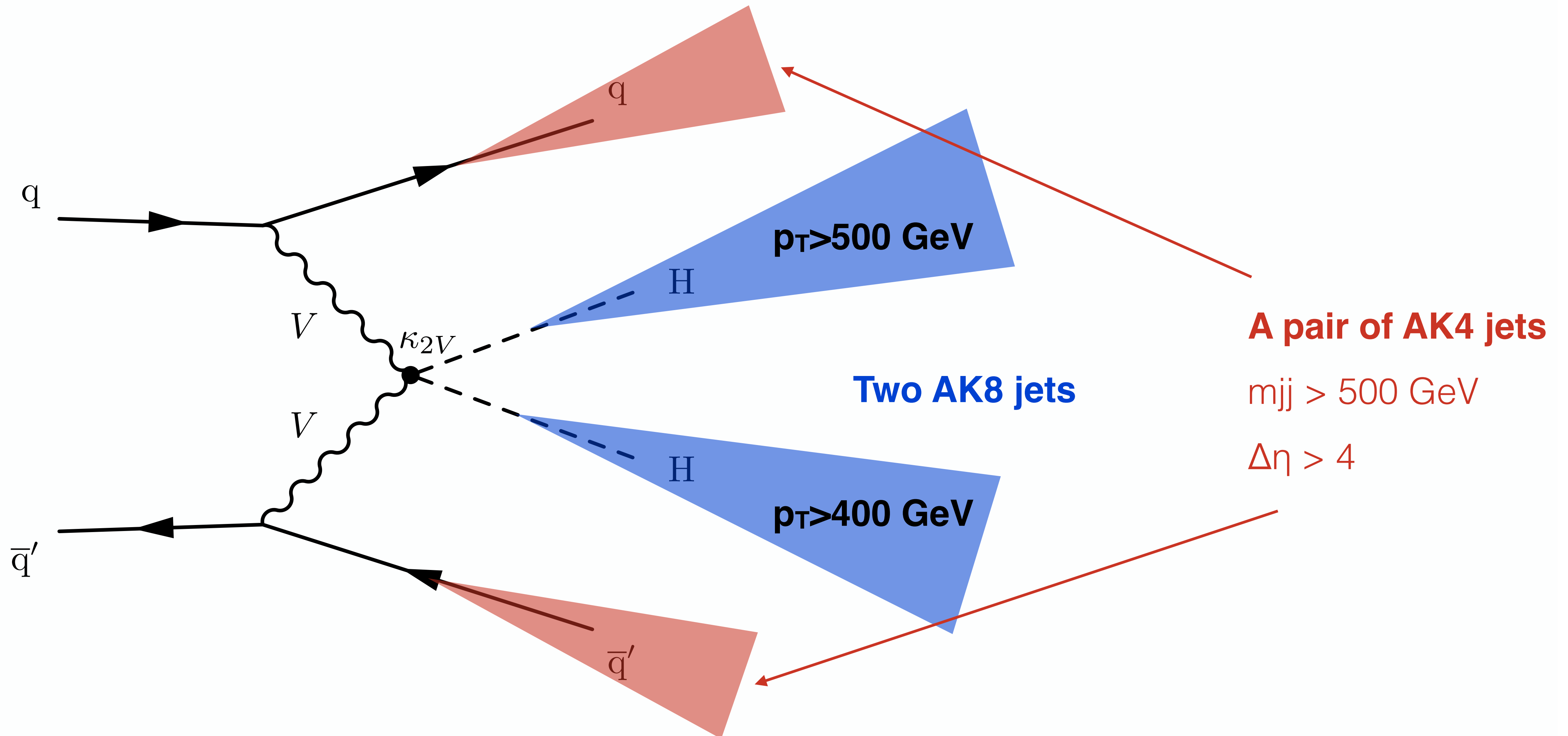
QCD



tt+jets



- ▶ Two AK8 jets and two AK4 jets with $m_{jj} > 500$ GeV and $|\Delta\eta_{jj}| > 4$
 - ▶ Tight kinematic selection means we need **maximal** H identification efficiency



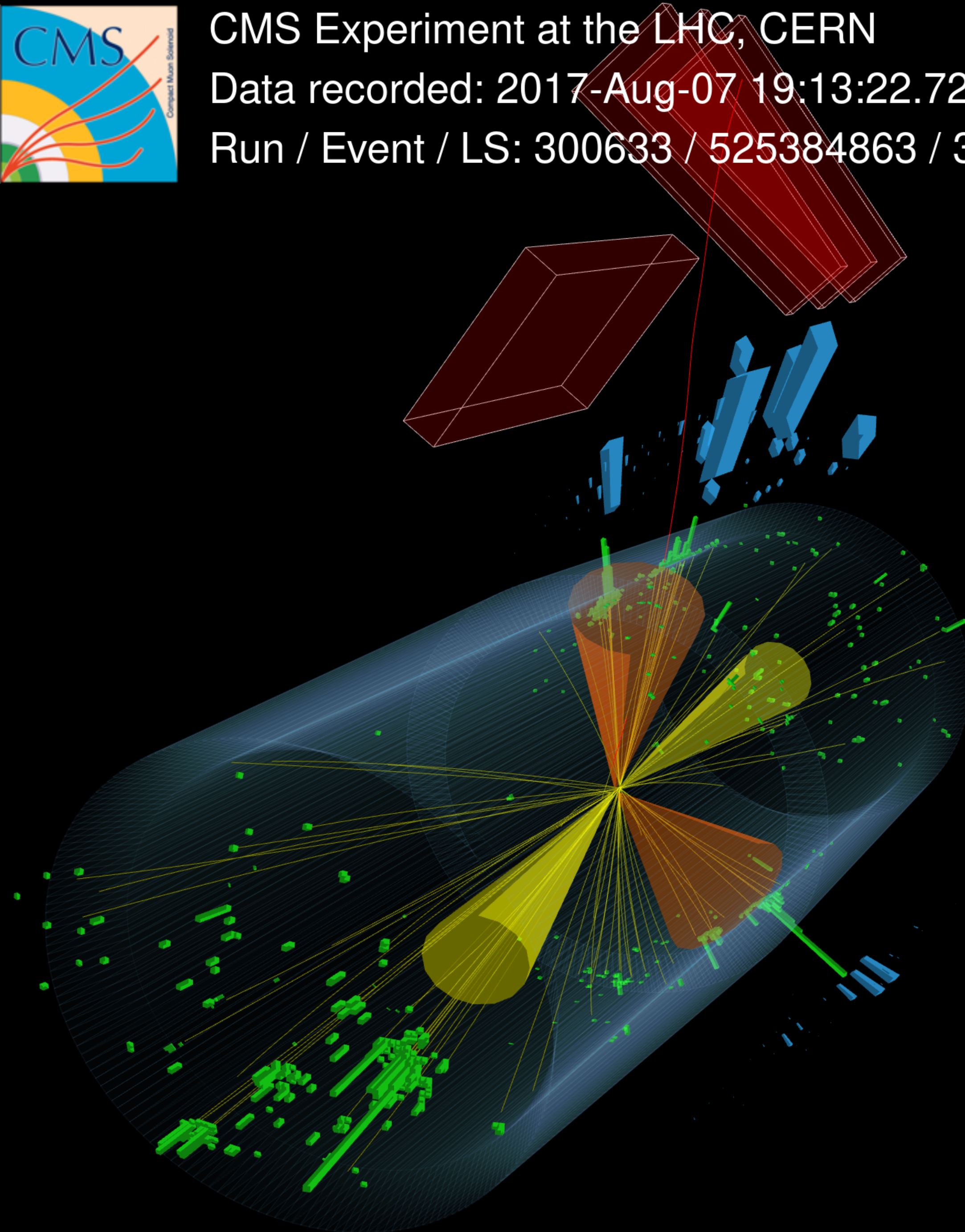
VBF: KINEMATIC SELECTION



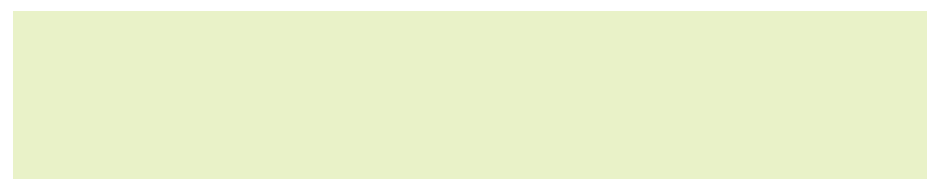
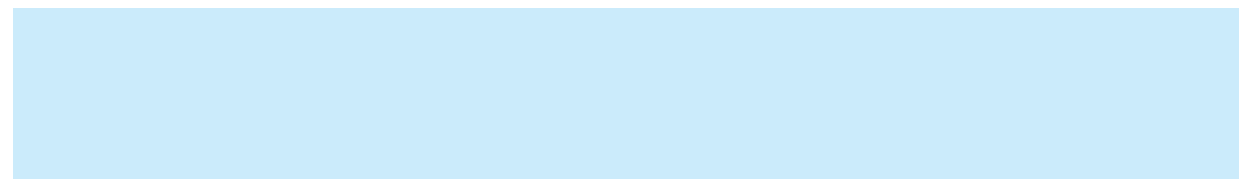
CMS Experiment at the LHC, CERN

Data recorded: 2017-Aug-07 19:13:22.727552 GMT

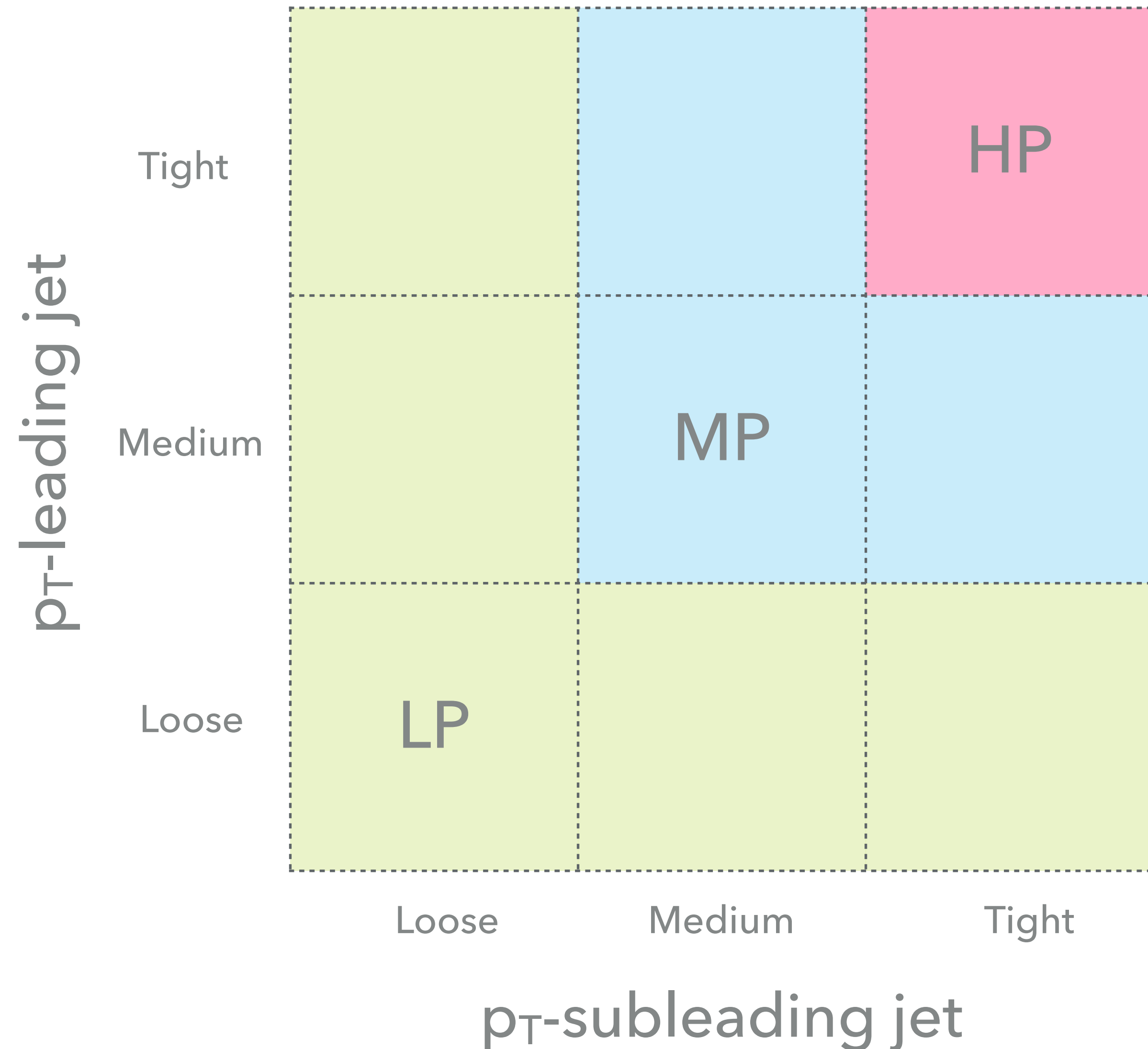
Run / Event / LS: 300633 / 525384863 / 347

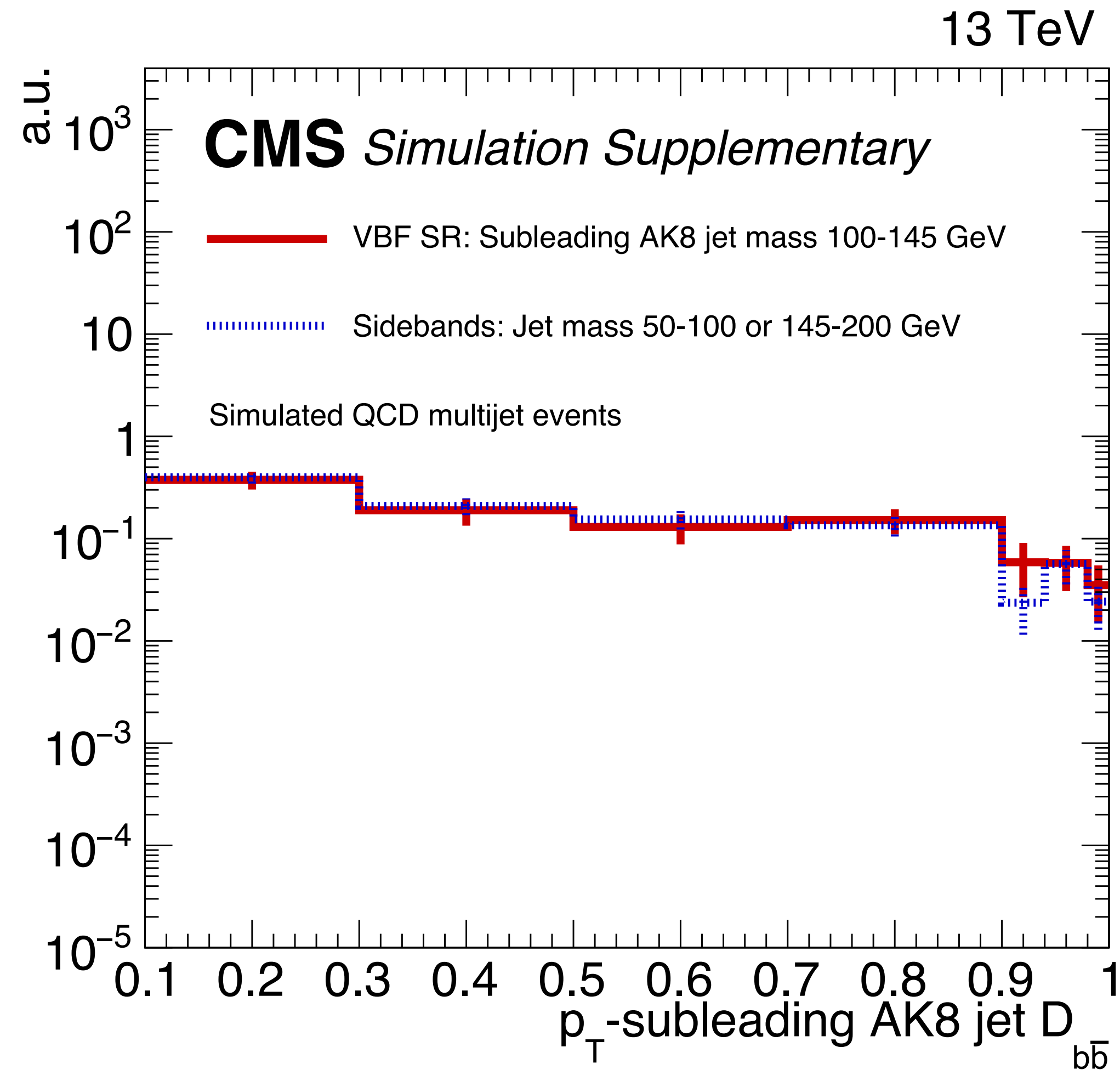


- ▶ Three D_{bb} working points (WPs)
 - ▶ **Tight WP:** $\epsilon_S \sim 60\%$, $\epsilon_B \sim 0.3\%$
 - ▶ **Medium WP:** $\epsilon_S \sim 80\%$, $\epsilon_B \sim 1\%$
 - ▶ **Loose WP:** $\epsilon_S \sim 90\%$, $\epsilon_B \sim 2\%$

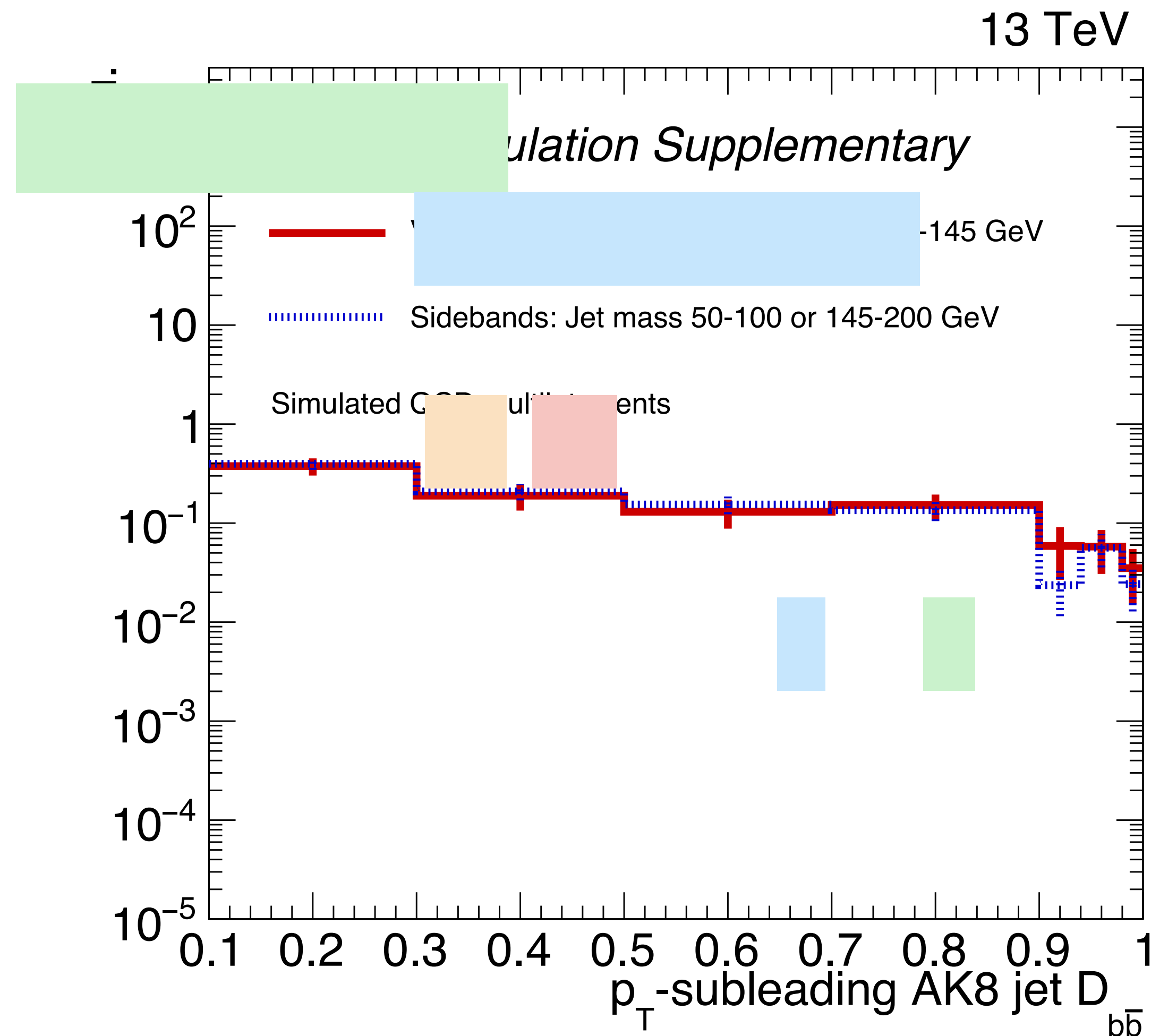


- ▶ Three D_{bb} working points (WPs)
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- ▶ Three exclusive regions based on WPs:
 - ▶ **High Purity (HP)**: Both Higgs candidate jets pass **tight** WP
 - ▶ **Medium Purity (MP)**: Both pass **medium** WP, but not tight WP
 - ▶ **Low Purity (LP)**: Both pass **loose** WP, but not medium WP

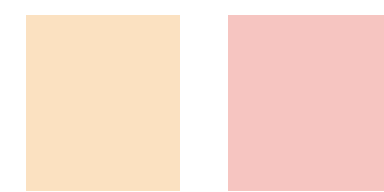




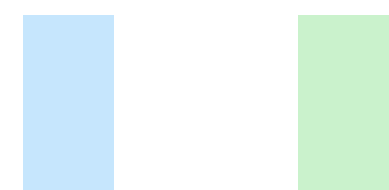
- ▶ Key observation: D_{bb} score for QCD similar in sidebands and in search region



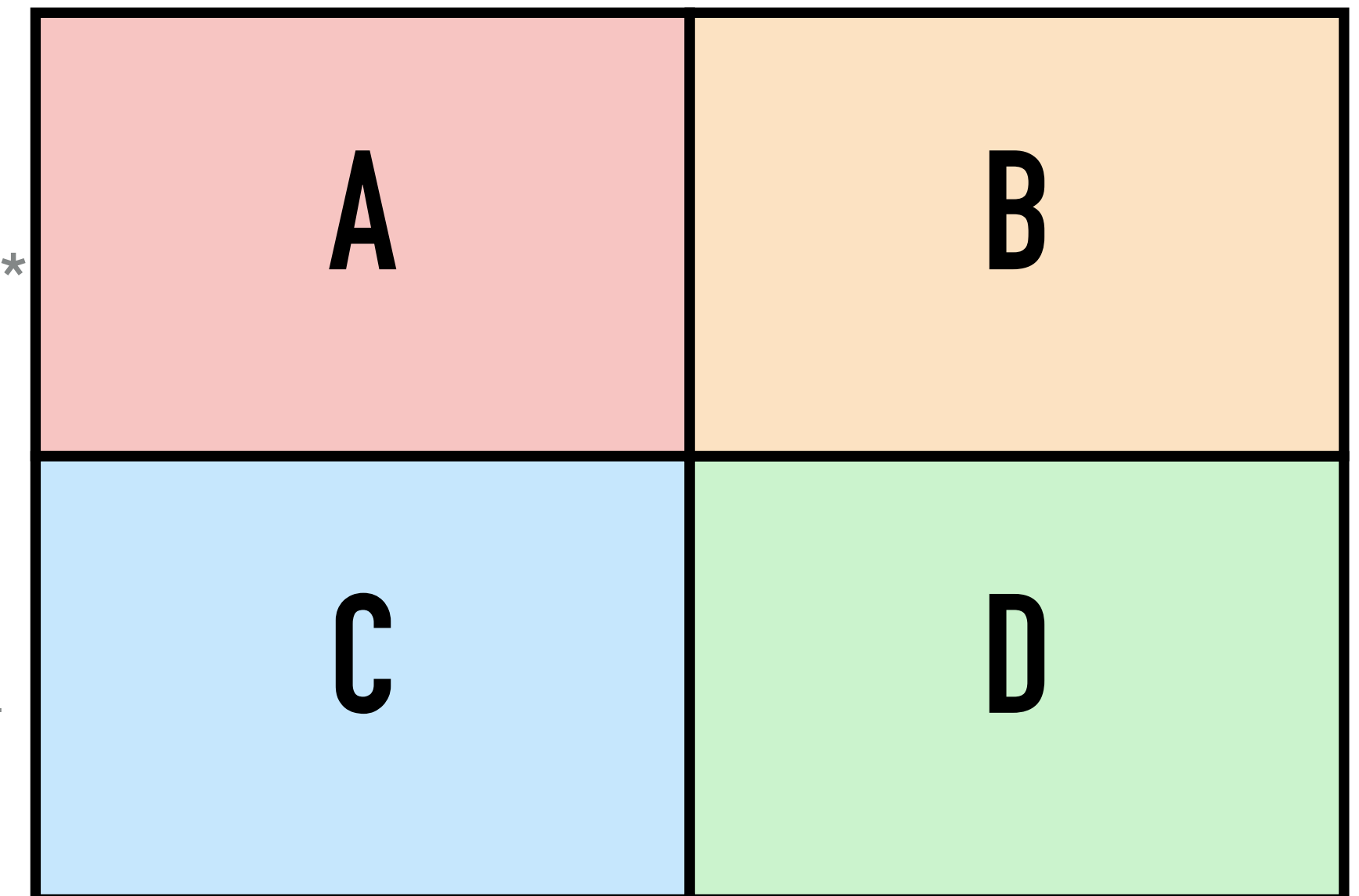
- ▶ Key observation: D_{bb} score for QCD similar in sidebands and in search region
- ▶ ABCD method to estimate QCD background in search region D
- ▶ QCD-enriched control region C with low D_{bb} score (0.1–0.9) for both AK8 jets



Jet mass sidebands*



Jet mass close to m_{H^\dagger}



Low D_{bb} score

High D_{bb} score

* $m_{reg,1} \in [50, 200]$ GeV

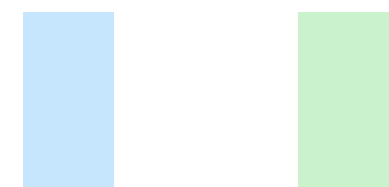
$m_{reg,2} \in [50, 90] \cup [145, 200]$ GeV

[†] $m_{reg,1} \in [110, 150]$ GeV

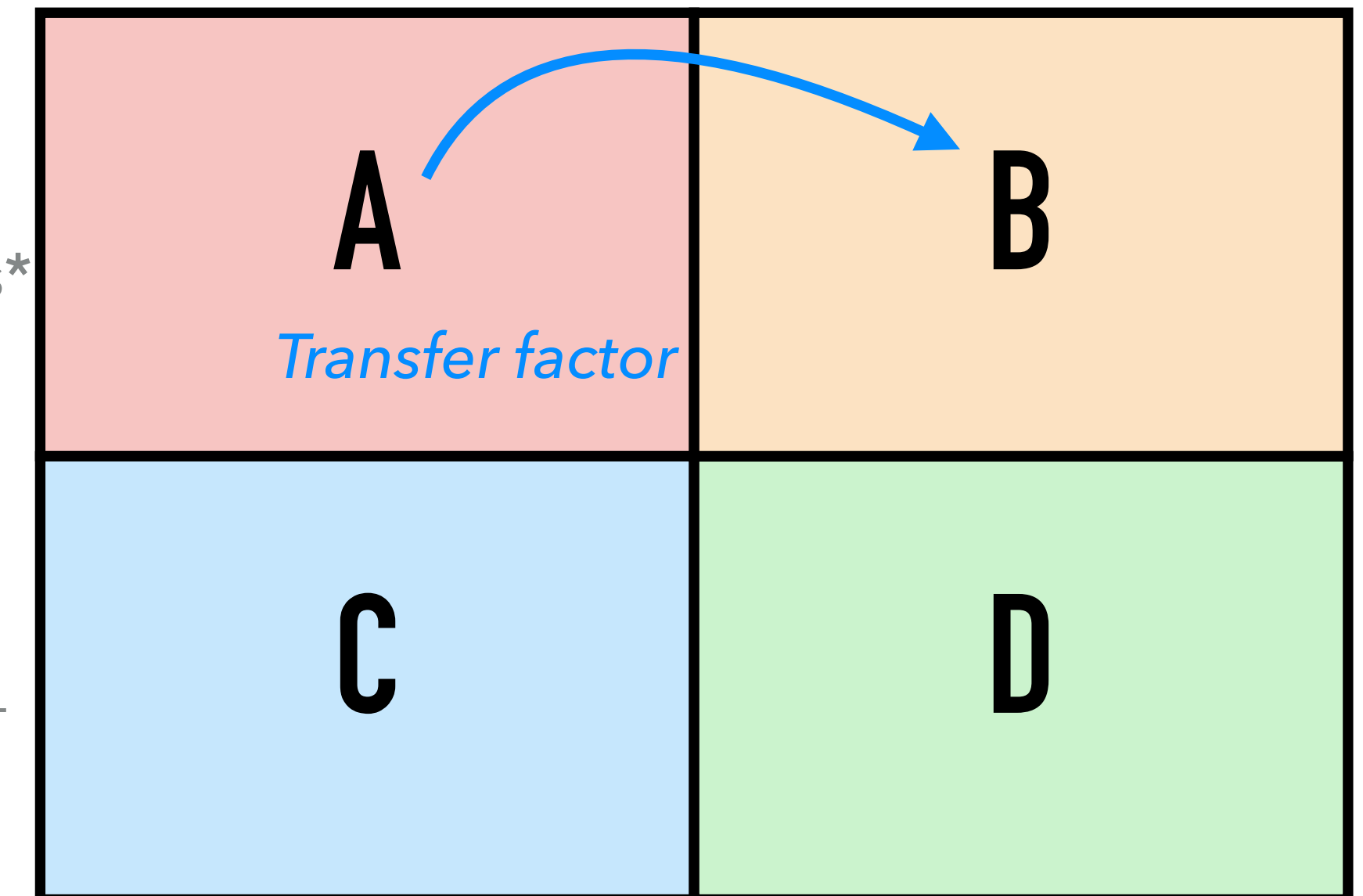
$m_{reg,2} \in [90, 145]$ GeV

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- ▶ ABCD method to estimate QCD background in search region D
- ▶ QCD-enriched control region C with low D_{bb} score (0.1–0.9) for both AK8 jets
- ▶ Transfer factor (N_B/N_A) obtained in $p_{Tsubleading}$ AK8 jet mass sidebands

$$\left(\frac{N_B}{N_A} \right)$$



Jet mass sidebands*
 Jet mass close to m_{H^\dagger}



* $m_{reg,1} \in [50, 200]$ GeV

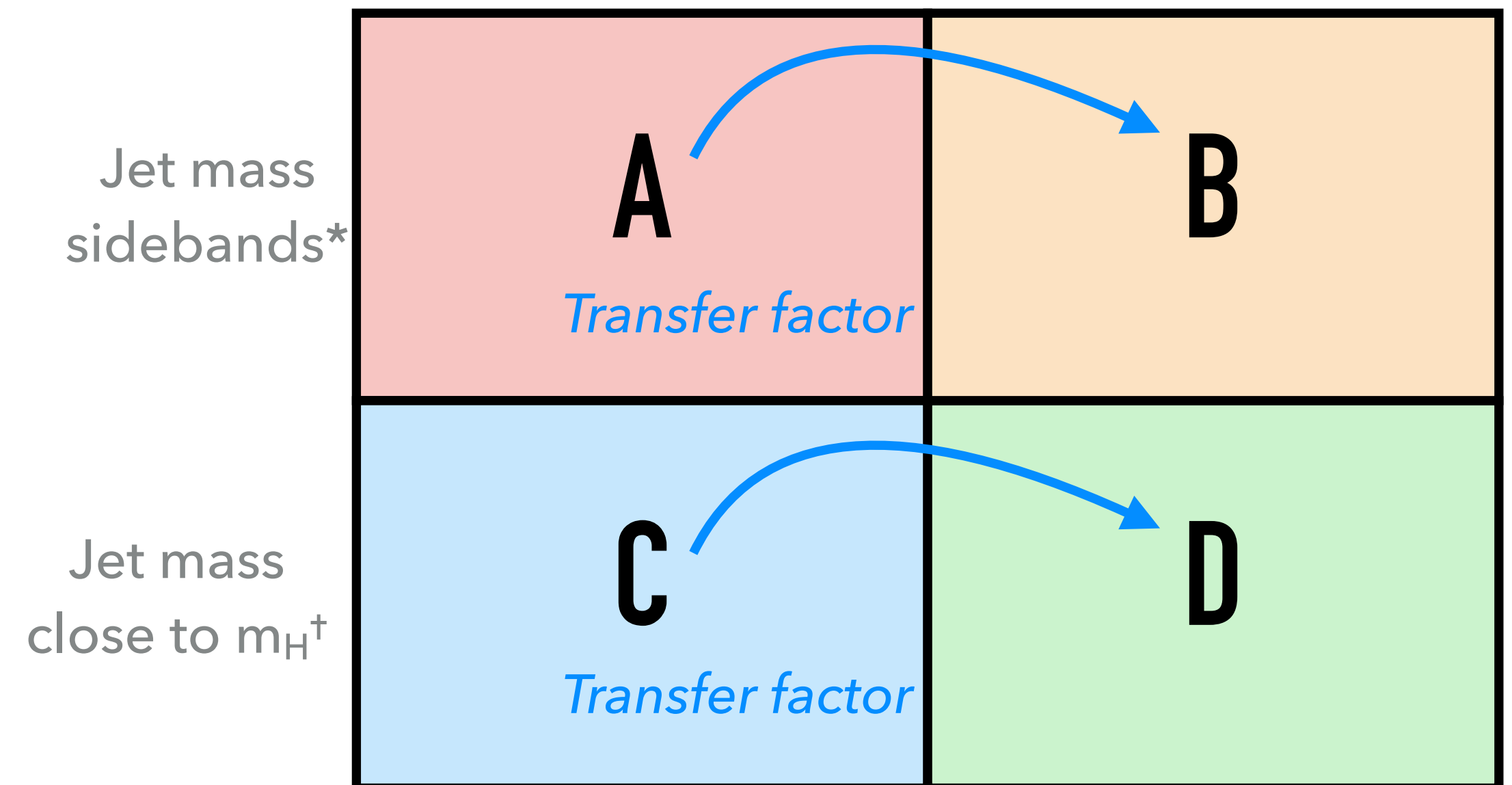
$m_{reg,2} \in [50, 90] \cup [145, 200]$ GeV

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- ▶ Key observation: D_{bb} score for QCD similar in sidebands and in search region
- ▶ ABCD method to estimate QCD background in search region **D**
- ▶ QCD-enriched control region **C** with low D_{bb} score (0.1–0.9) for both AK8 jets
- ▶ Transfer factor (N_B/N_A) obtained in $p_{T\text{subleading}}$ AK8 jet mass sidebands
- ▶ TF applied to predict from **C** to **D**

$$N_D = \left(\frac{N_B}{N_A} \right) N_C$$



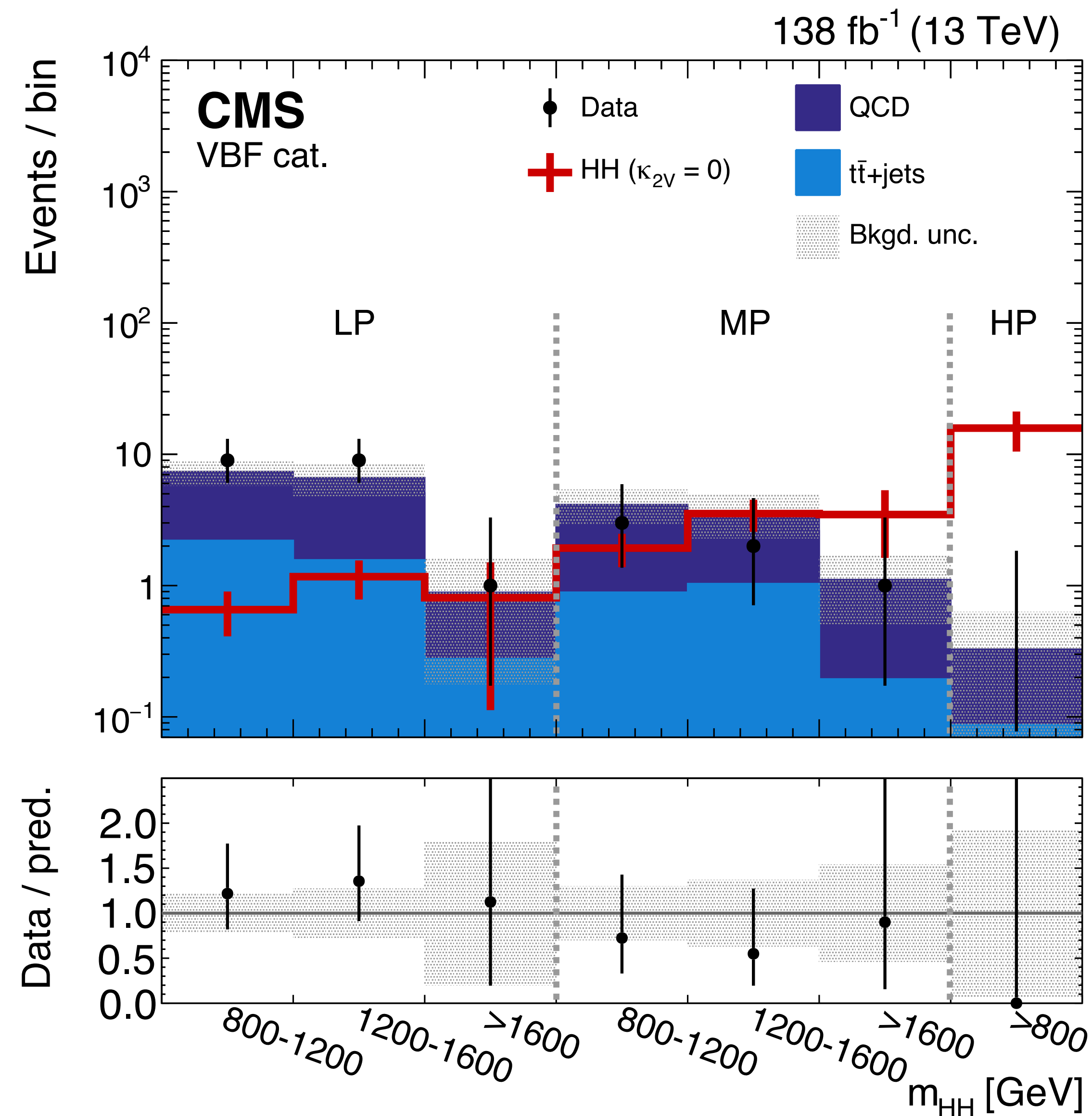
* $m_{\text{reg},1} \in [50, 200]$ GeV

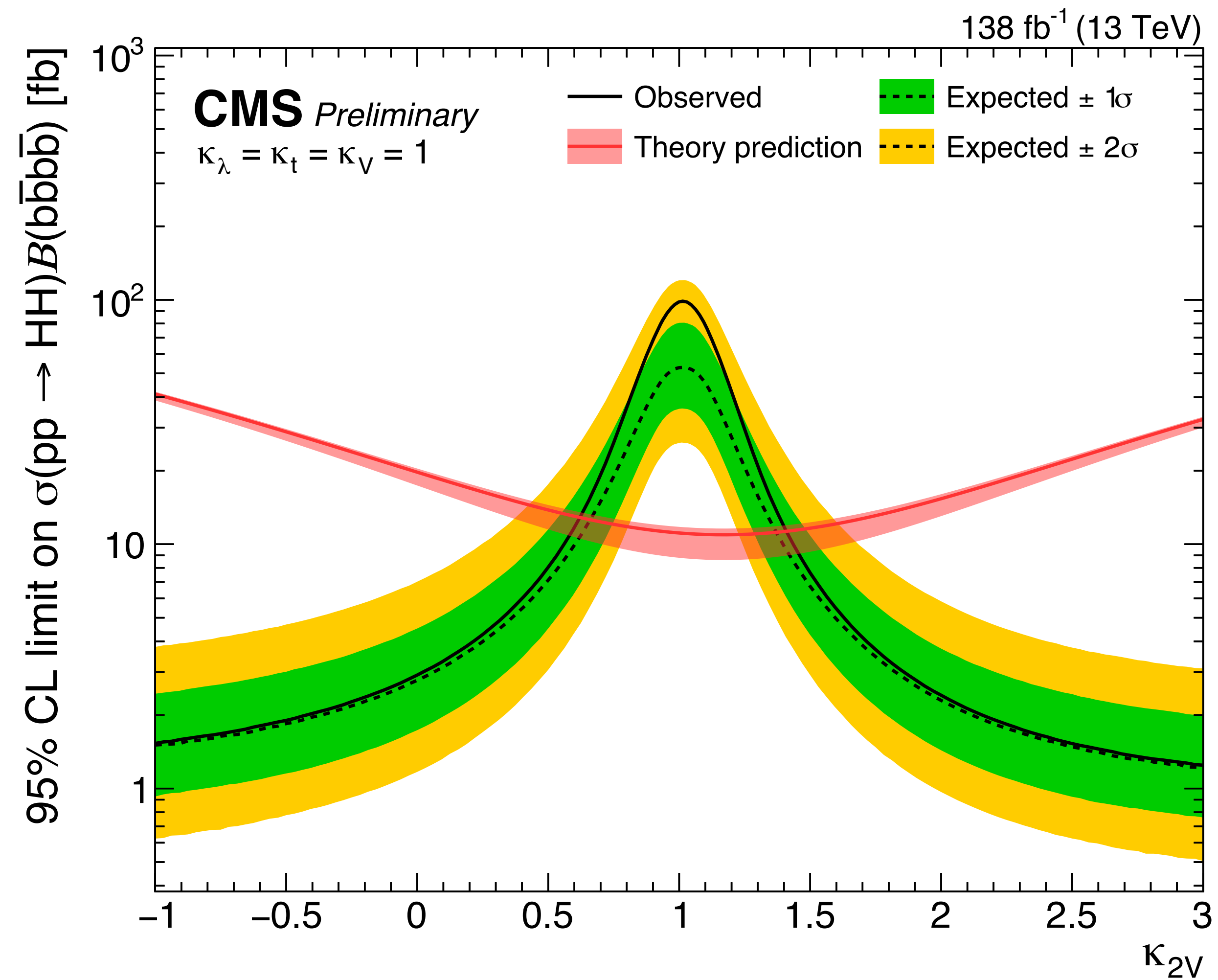
$m_{\text{reg},2} \in [50, 90] \cup [145, 200]$ GeV

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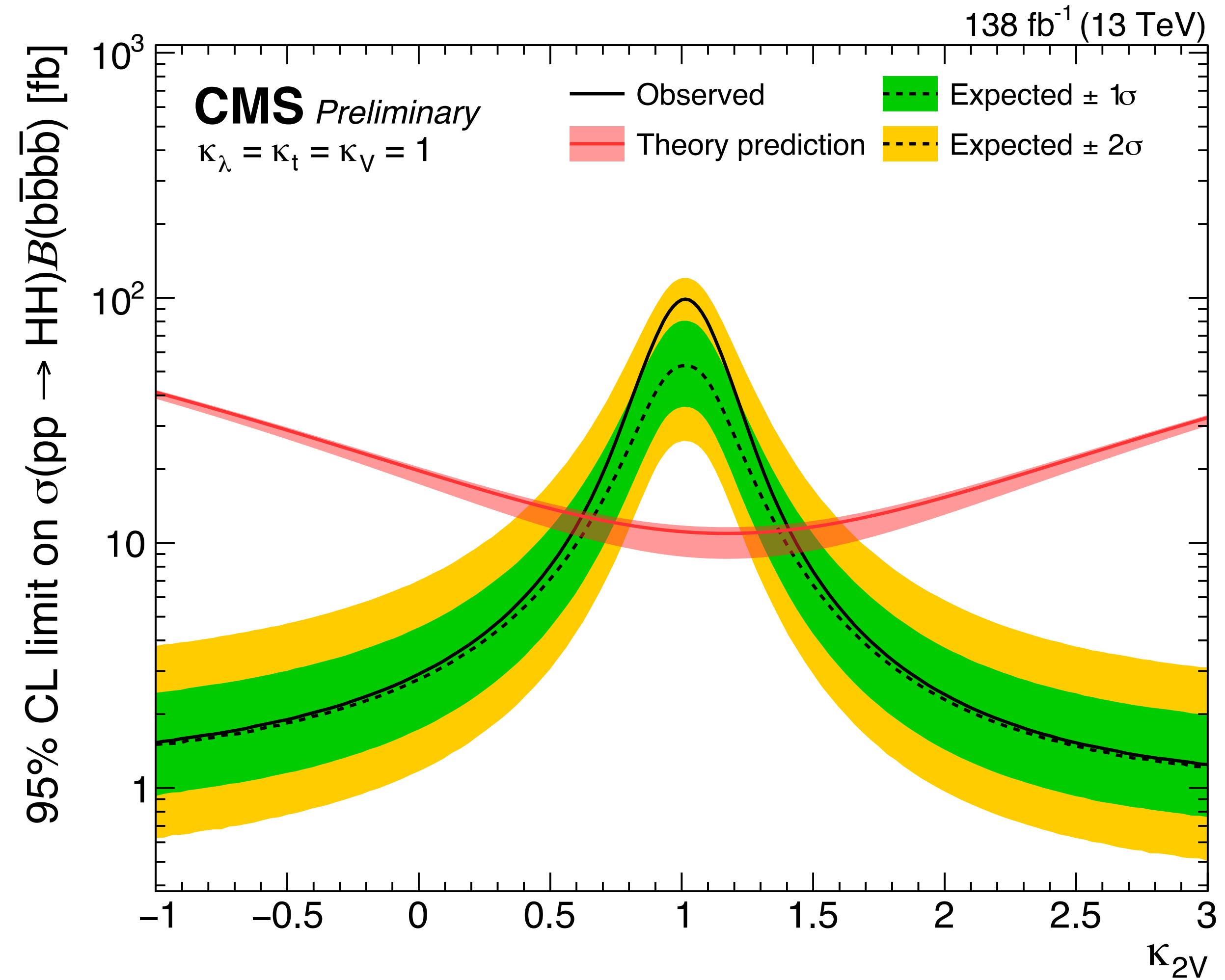
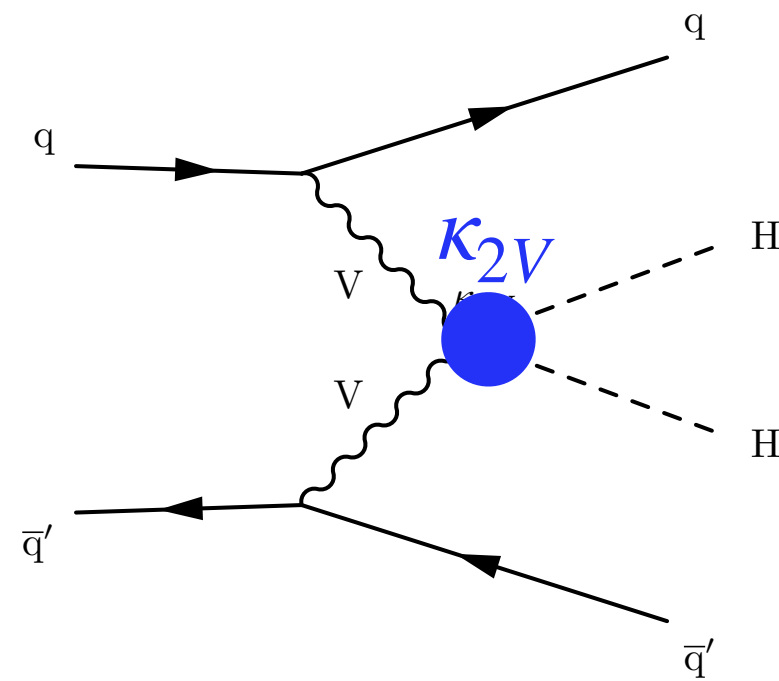
$m_{\text{reg},2} \in [90, 145]$ GeV

- ▶ Three categories (LP, MP, HP) based on the D_{bb} discriminant of the H candidates
 - ▶ Categorize further in m_{HH}
- ▶ Data-driven QCD estimate
- ▶ Prediction agrees with observed data
 - ▶ Compare to expected contribution for $\kappa_{2V} = 0$ (other couplings at SM values)

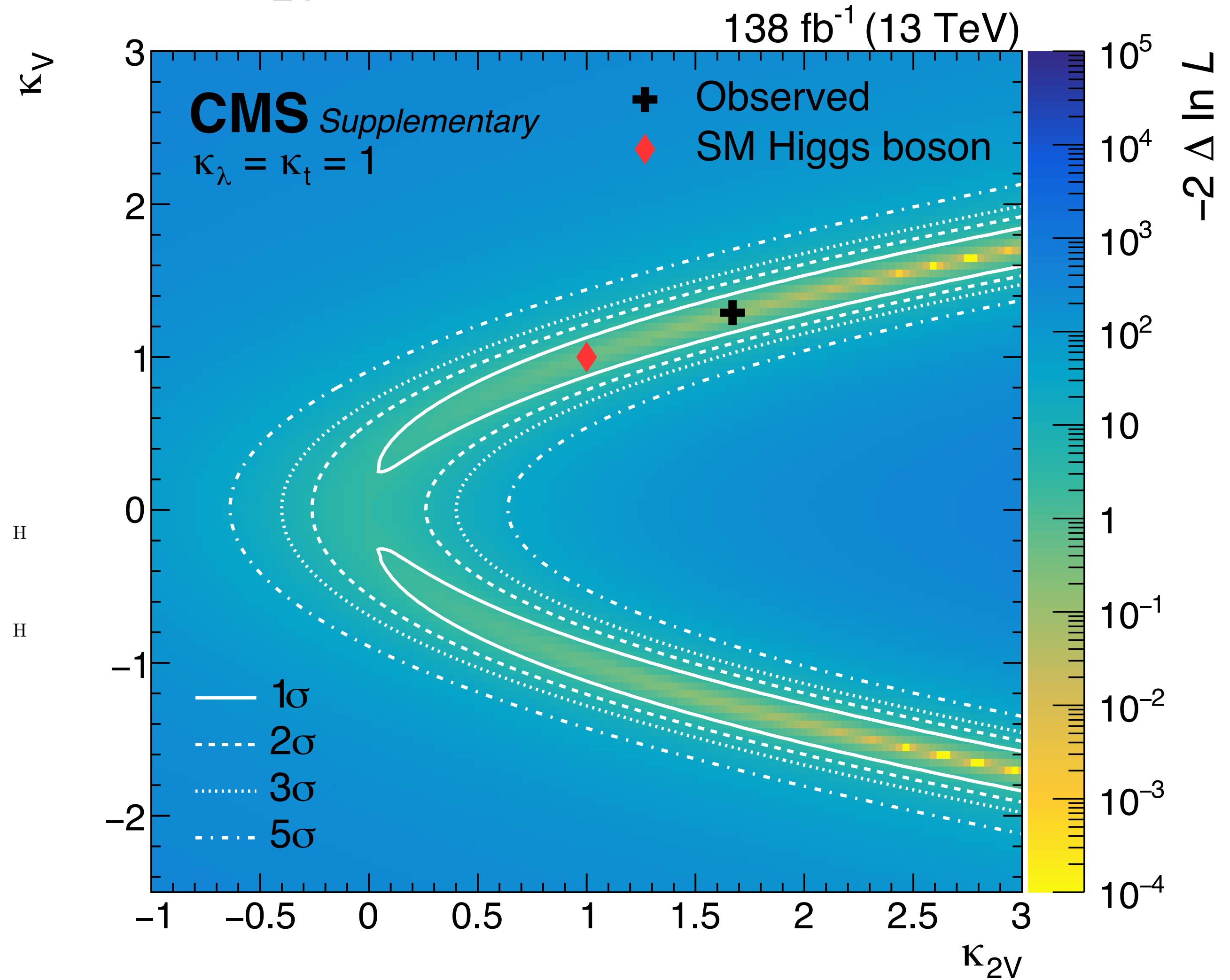
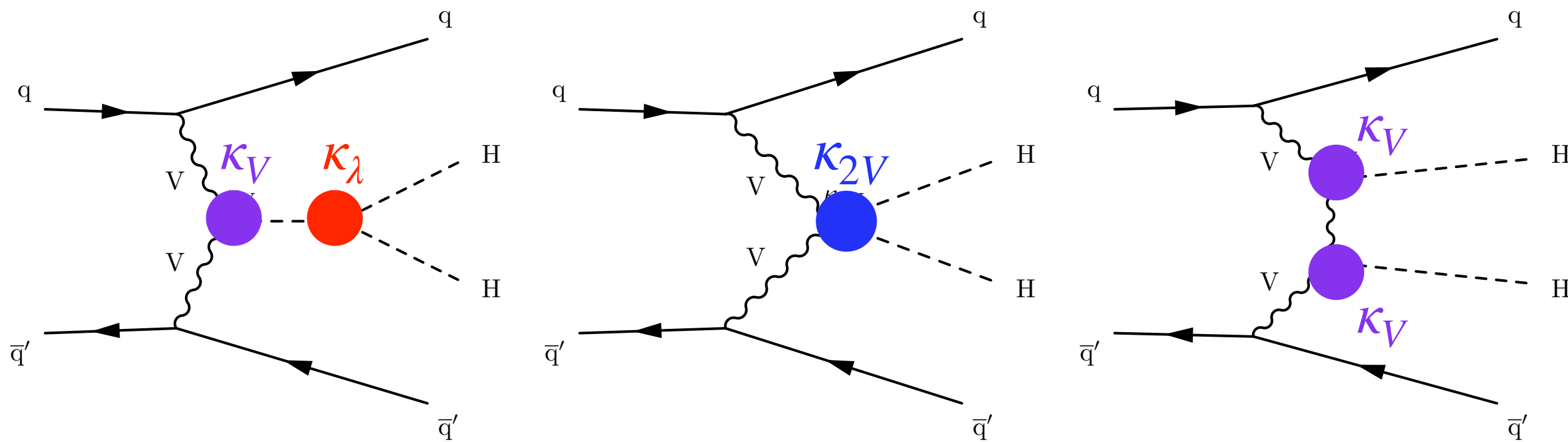




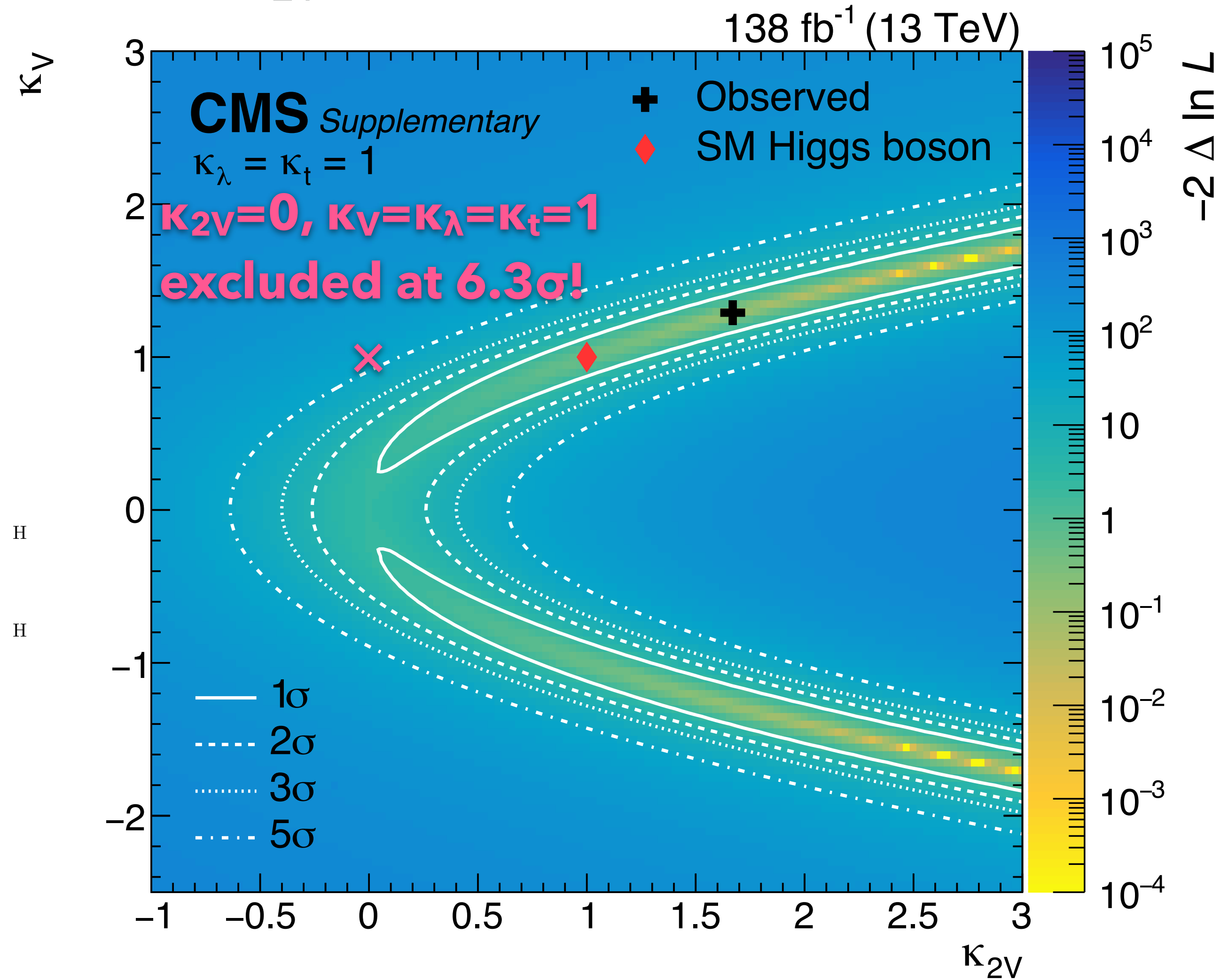
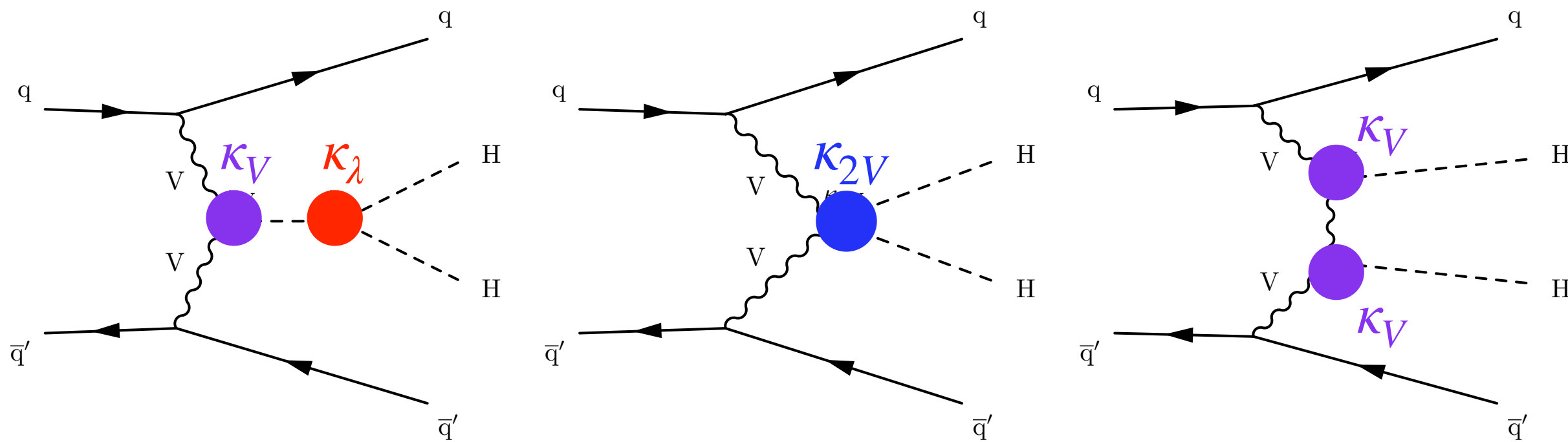
- ▶ **Strongest constraints on κ_{2V} to date: $0.62 < \kappa_{2V} < 1.41$ at 95% CL**
(all other couplings are SM)



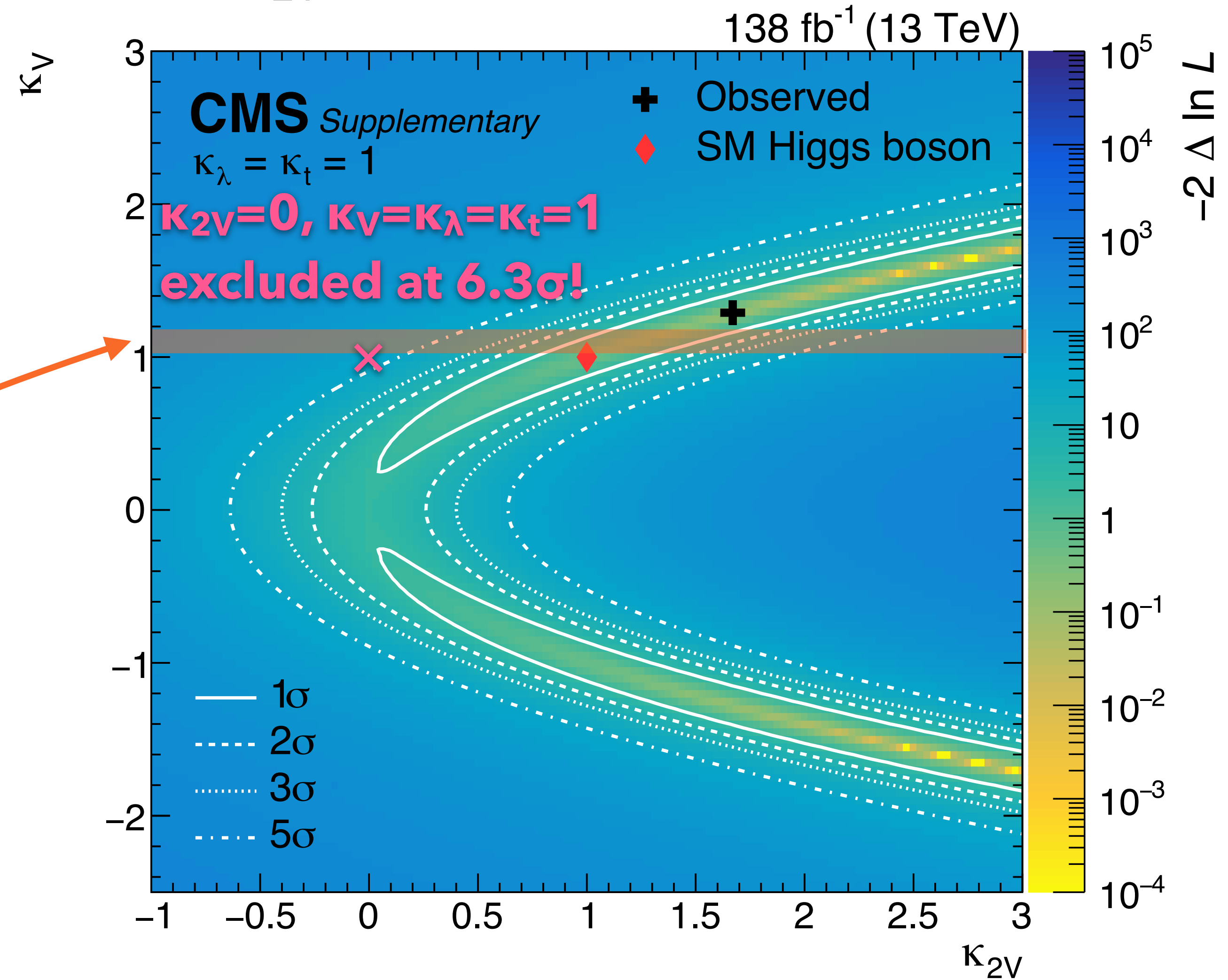
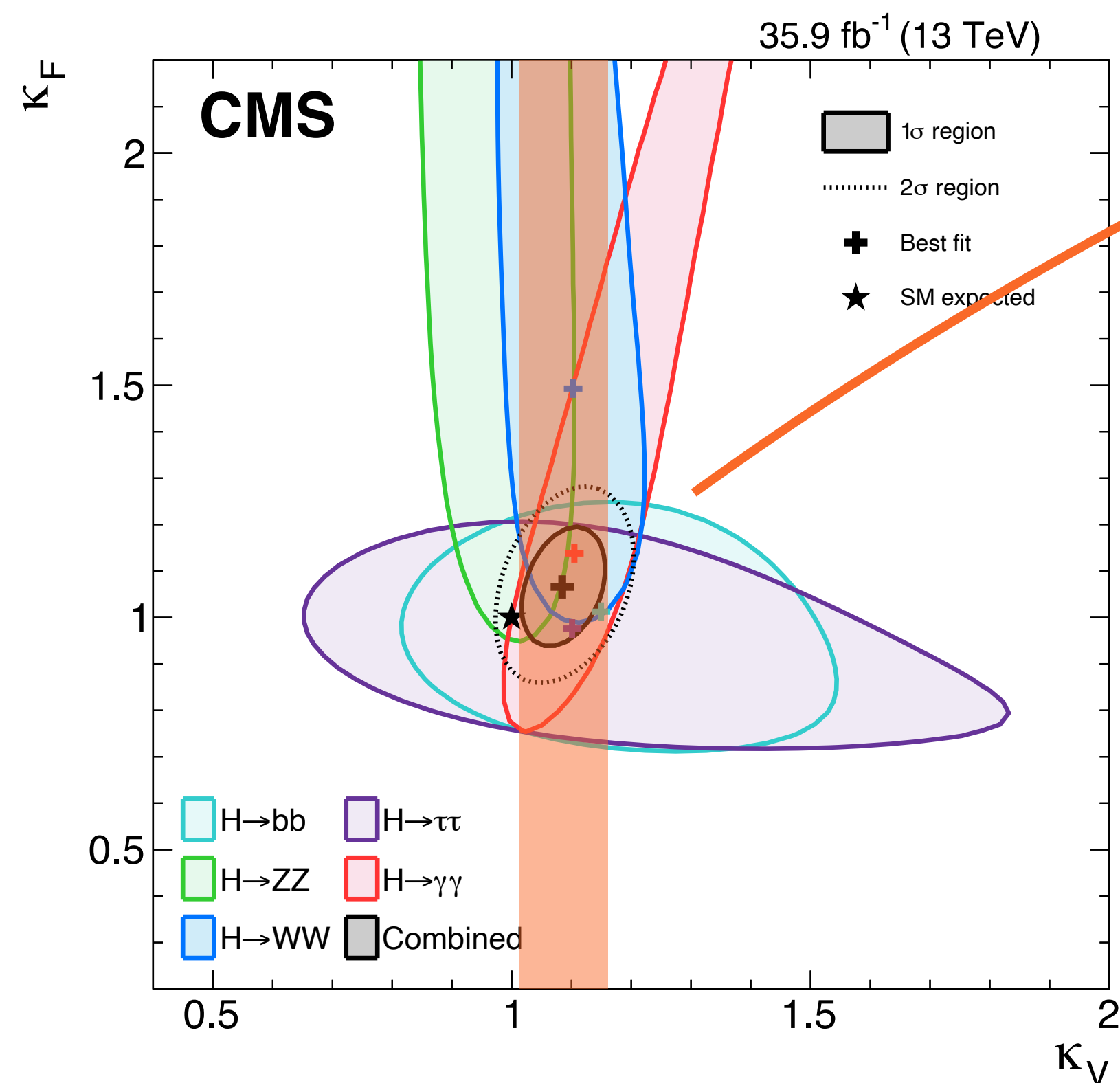
- ▶ **Strongest constraints on κ_{2V} to date: $0.62 < \kappa_{2V} < 1.41$ at 95% CL**
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- ▶ Interplay between κ_V and κ_{2V}



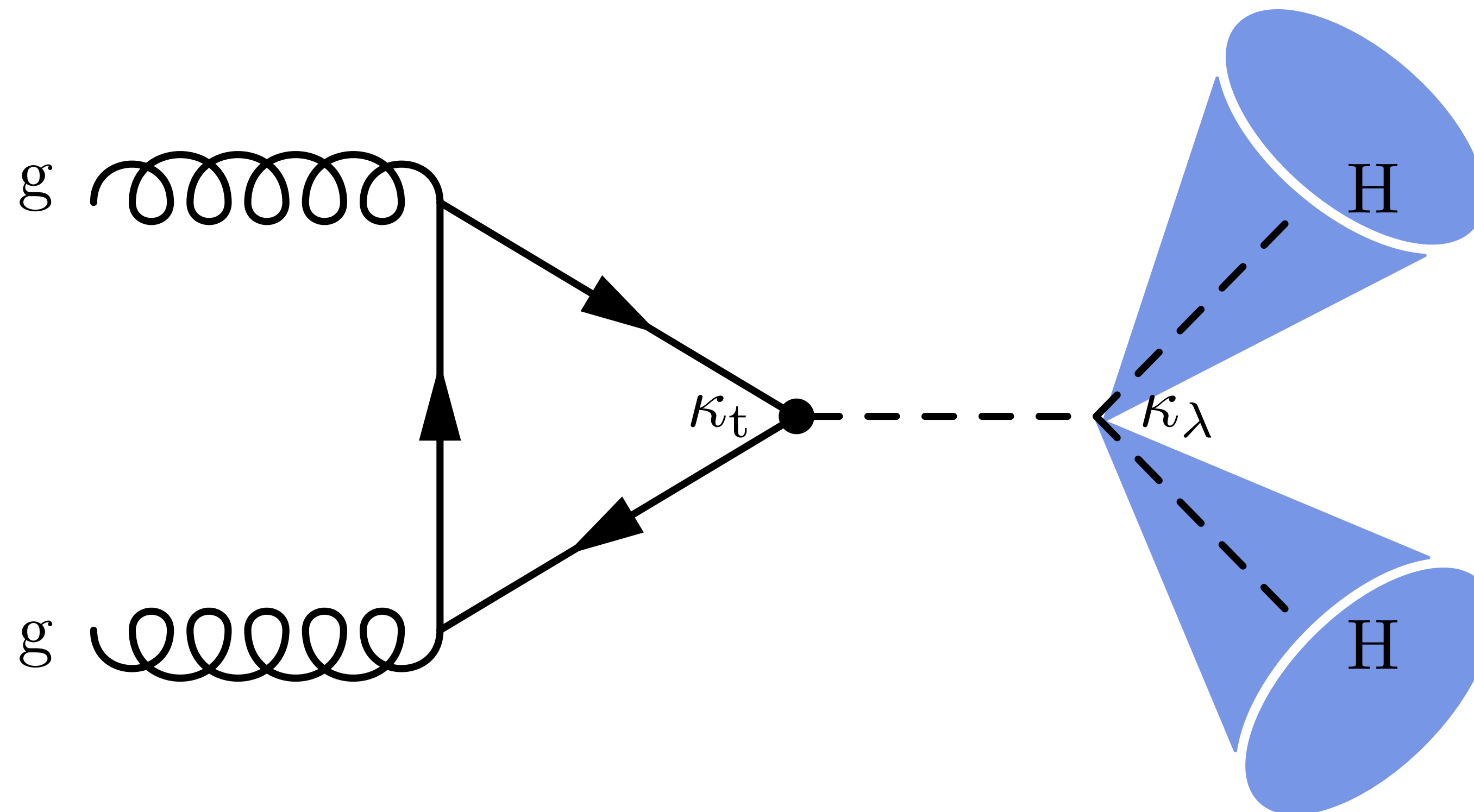
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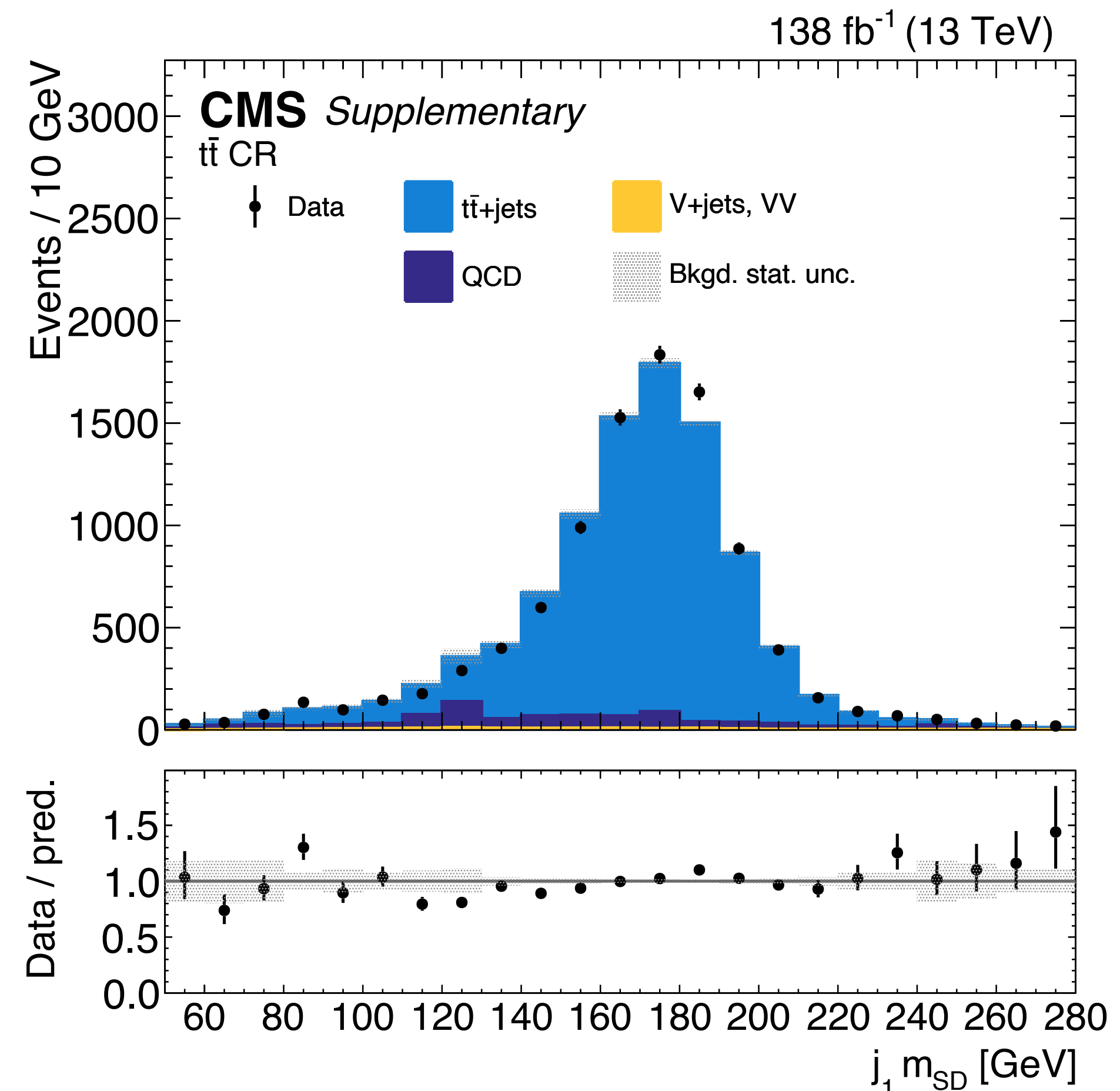
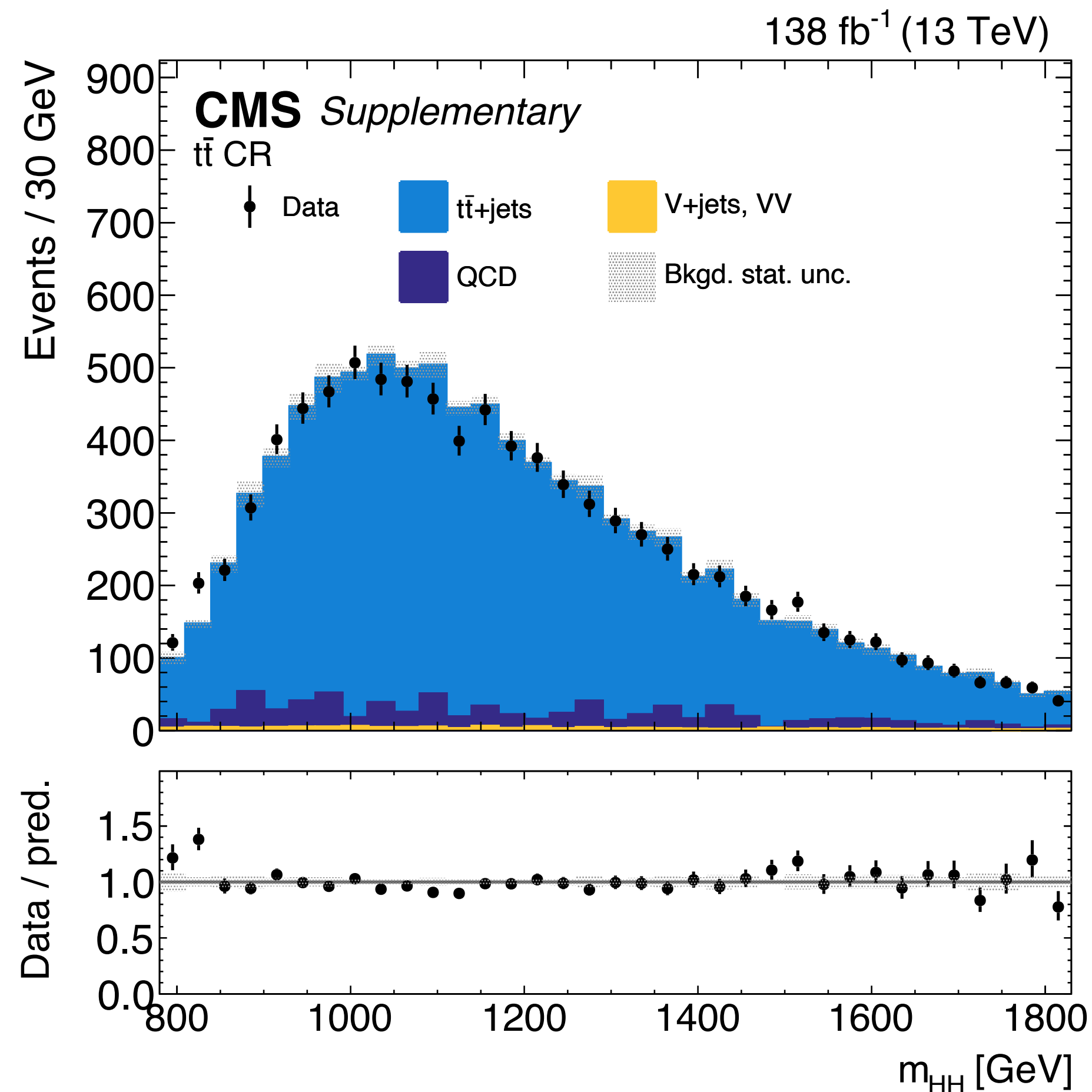
- ▶ **Strongest constraints on κ_{2V} to date: $0.62 < \kappa_{2V} < 1.41$ at 95% CL**
(all other couplings are SM)
- ▶ Interplay between κ_V and κ_{2V}
- ▶ $\kappa_{2V} = 0$ hypothesis highly disfavored with single-Higgs constraints on κ_V



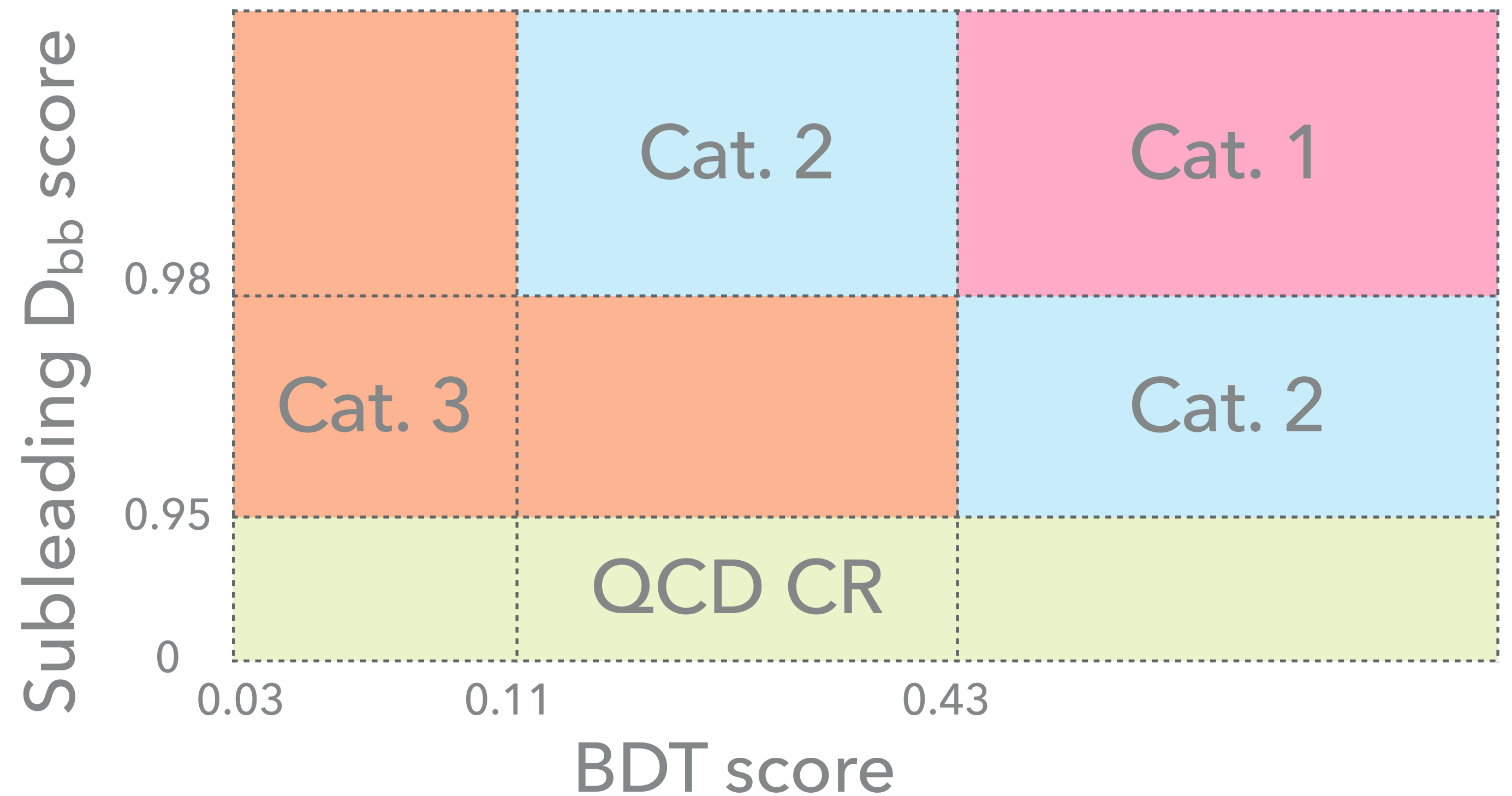
- ▶ Two AK8 jets with $p_T > 300$ GeV, sorted by D_{bb} score
 - ▶ Jet 1 $m_{SD} > 50$ GeV, jet 2 $m_{reg} > 50$ GeV
- ▶ Veto events passing VBF selection



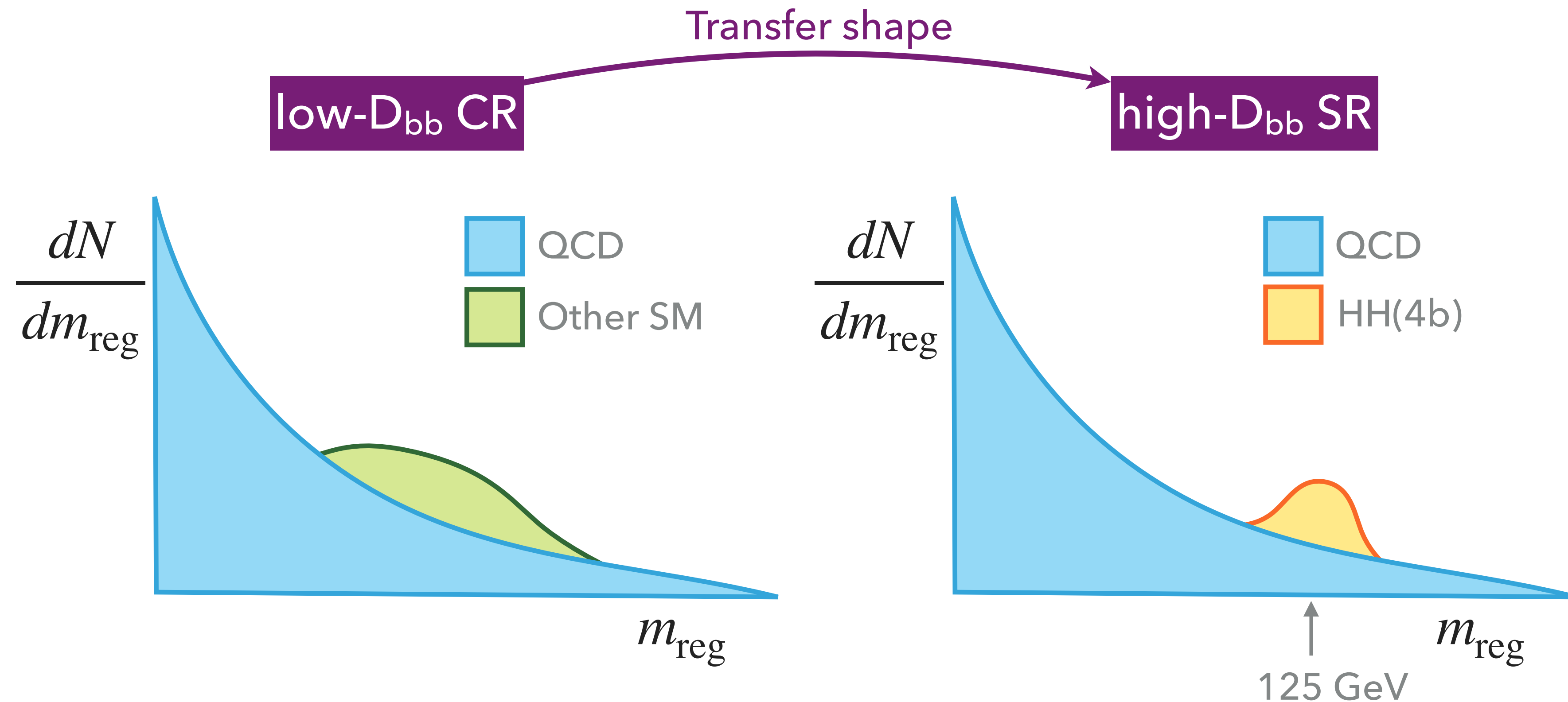
- ▶ A boosted decision tree is trained to select events using 17 input variables, including m_{HH} , $p_{T,j1}/m_{HH}$, jet 1 m_{SD} , jet 1 D_{bb} , ...
- ▶ BDT has 2× better bkgd. rejection than cut-based: $\epsilon_B \sim 0.05\%$ for $\epsilon_S \sim 15\%$



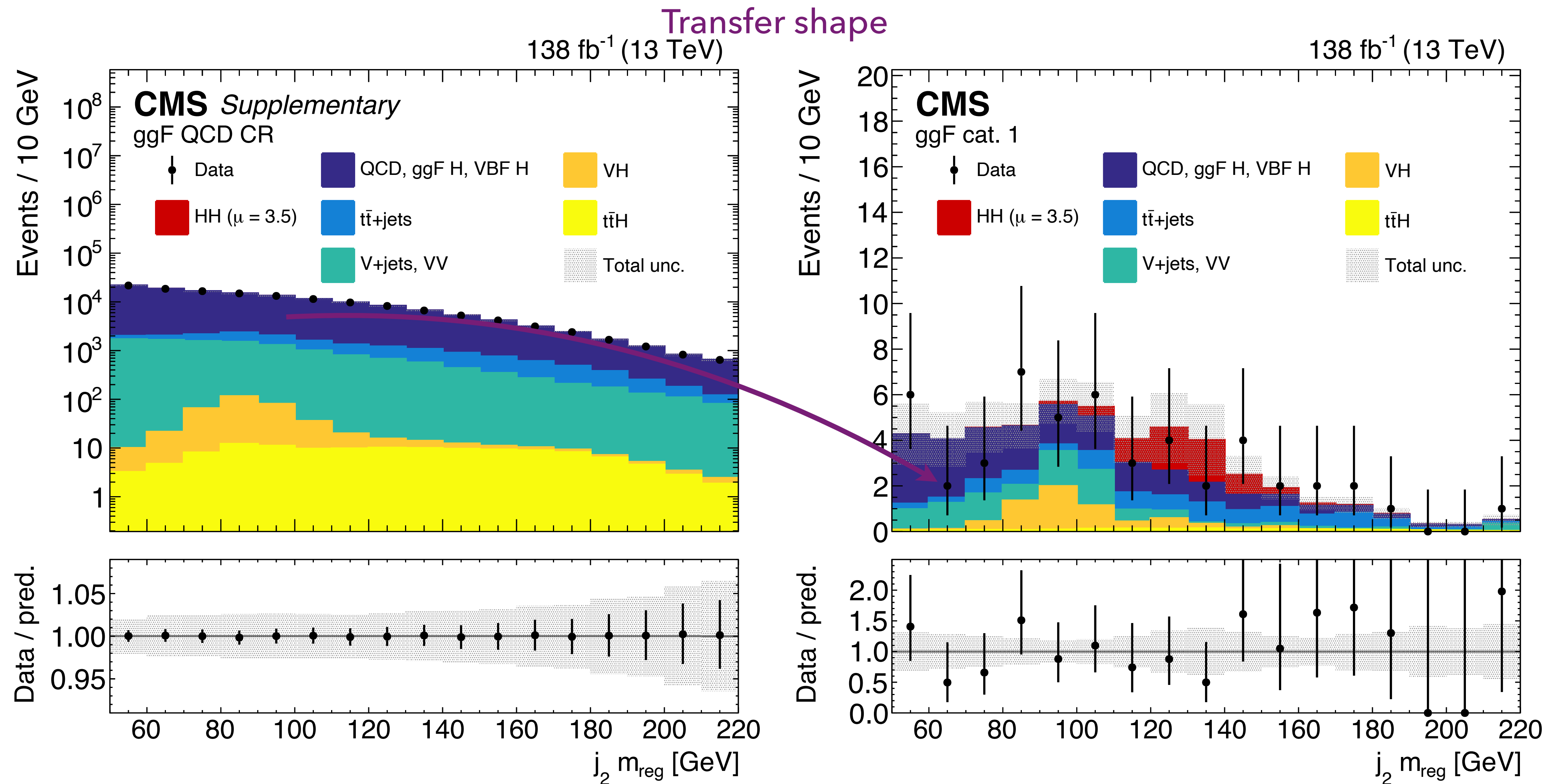
- ▶ Three signal region categories defined based on BDT score and subleading D_{bb} score
- ▶ QCD control region defined based on events that fail the D_{bb} selection



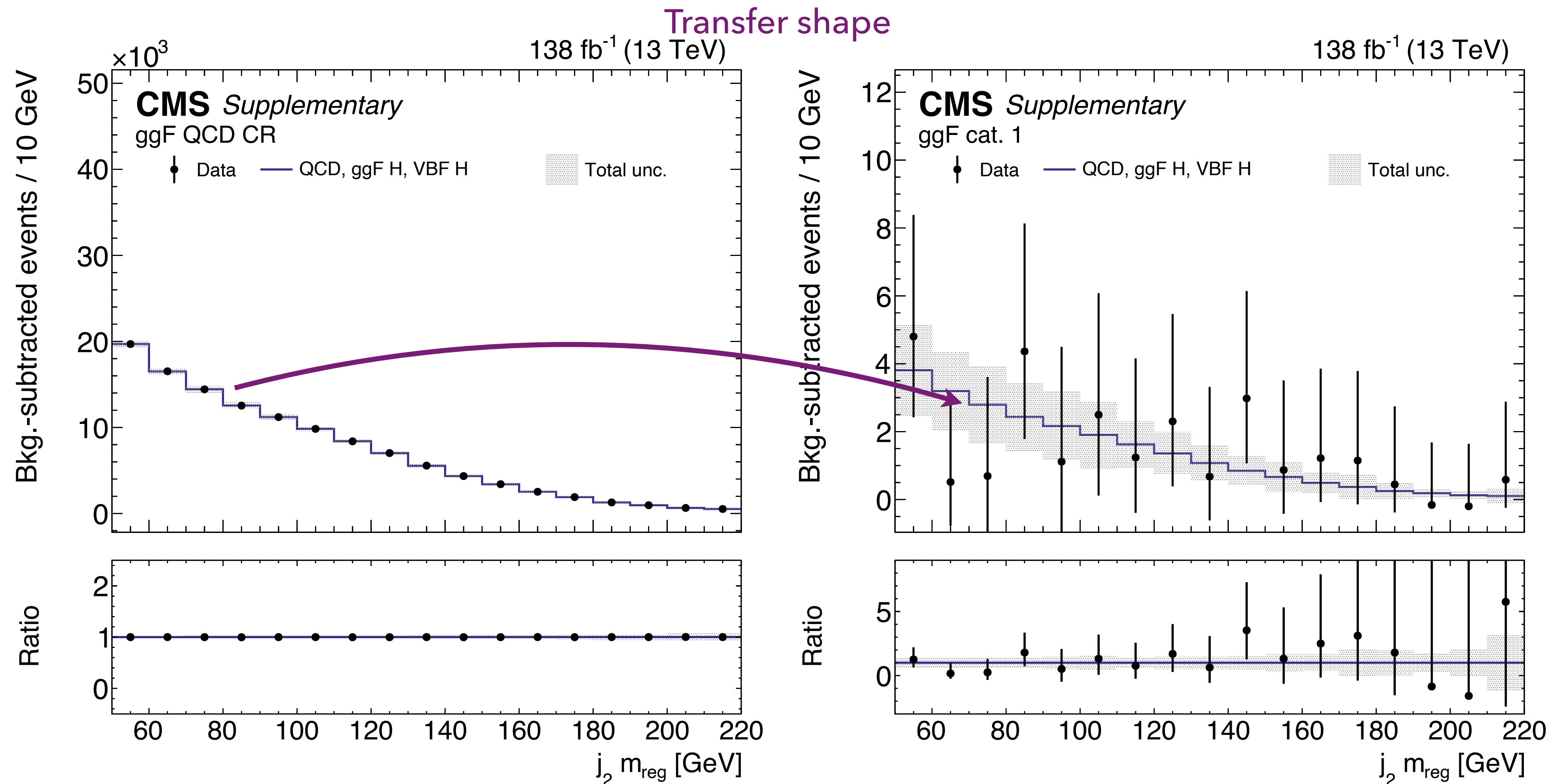
- ▶ After accounting for other SM backgrounds, Derive the shape of the QCD background using the jets that fail the D_{bb} selection



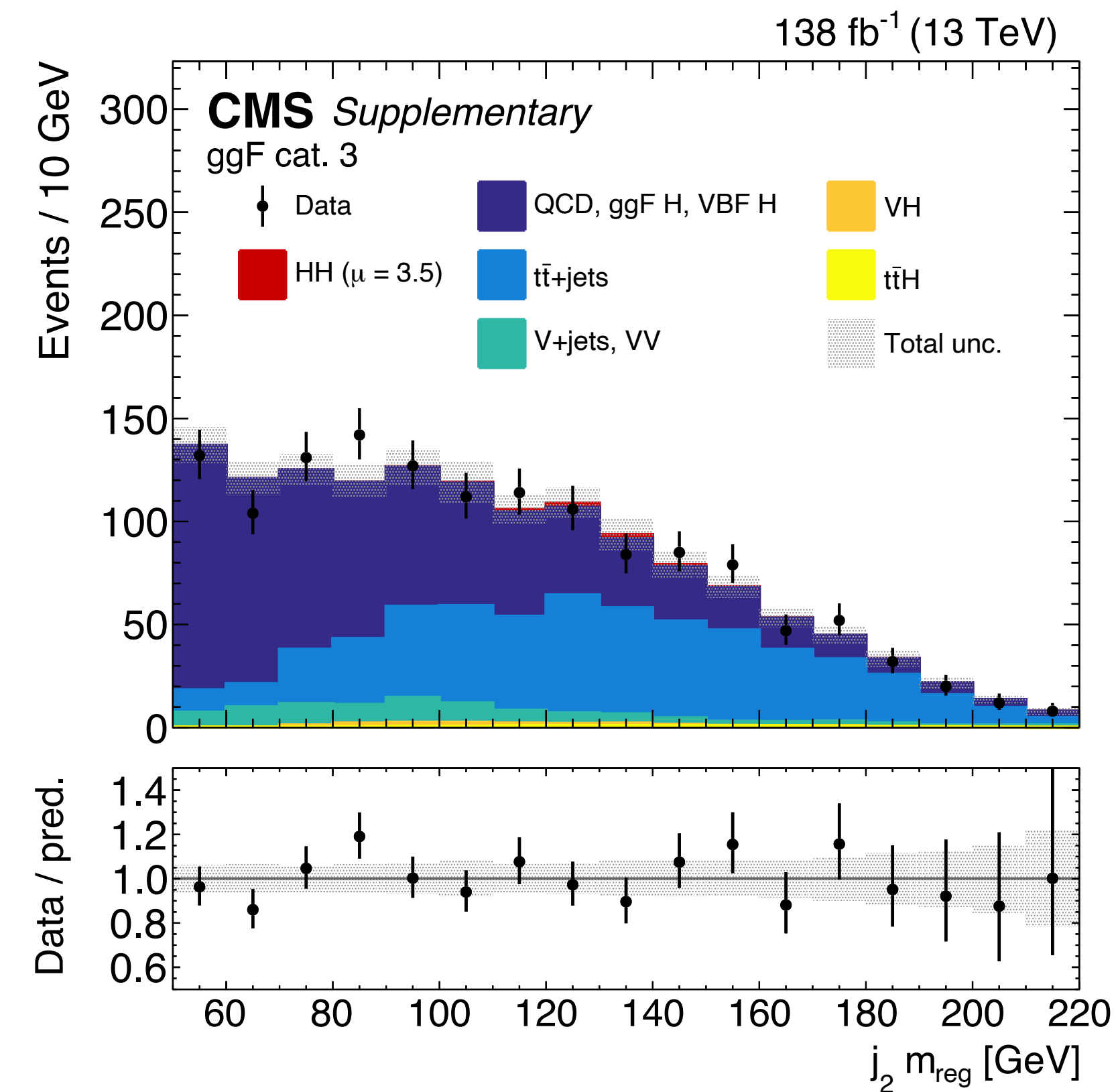
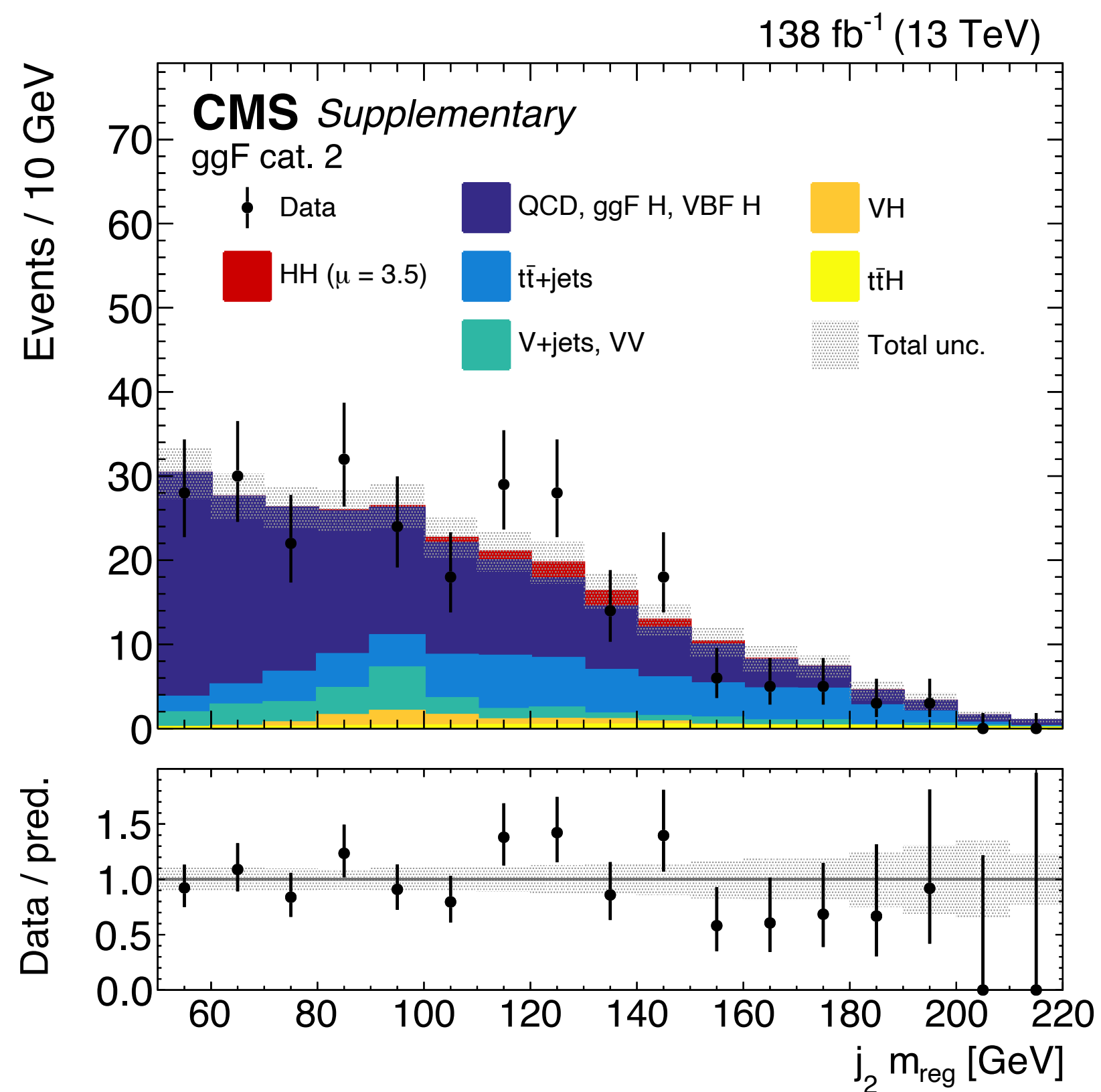
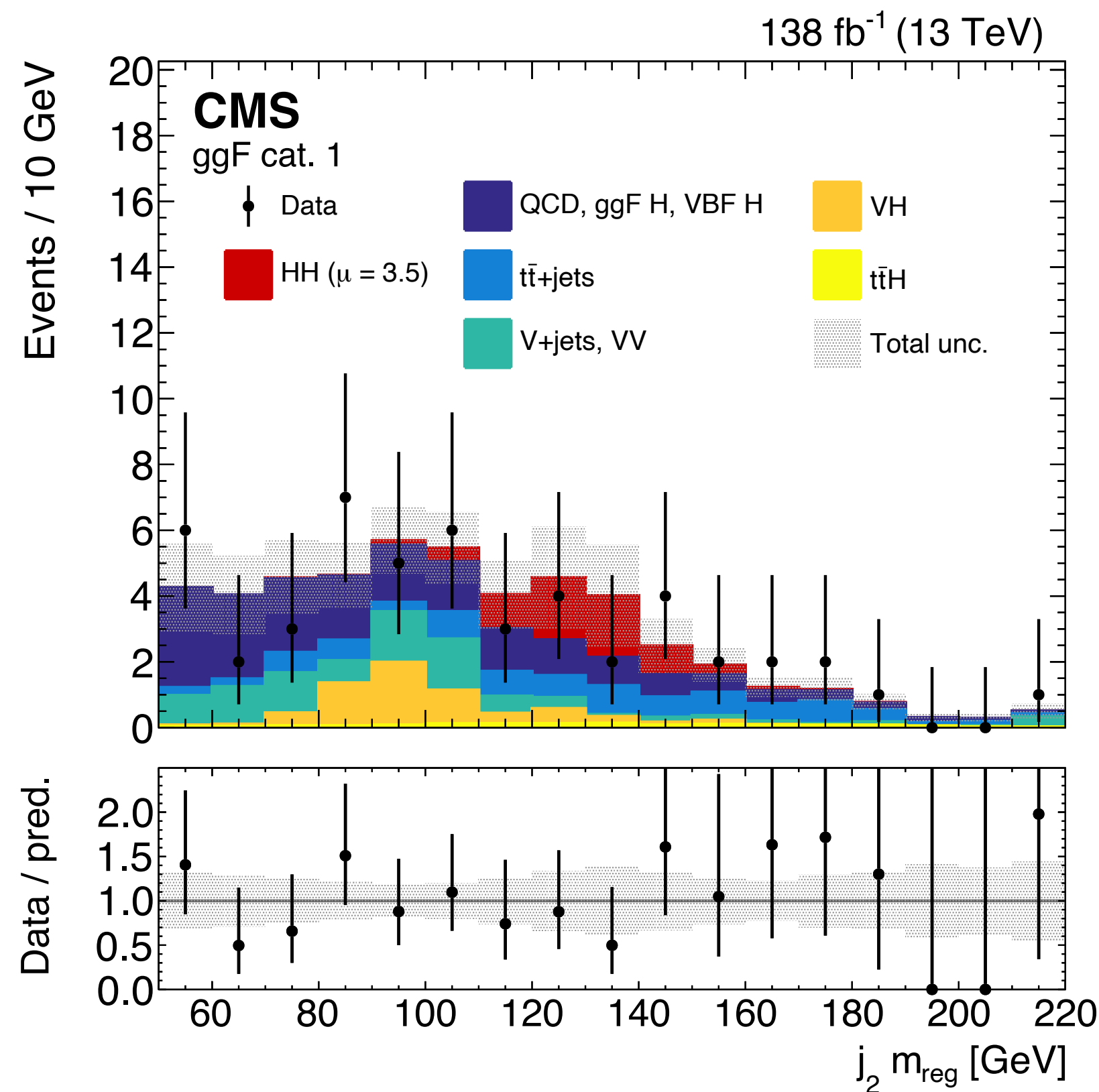
- ▶ After accounting for other SM backgrounds, Derive the shape of the QCD background using the jets that fail the D_{bb} selection



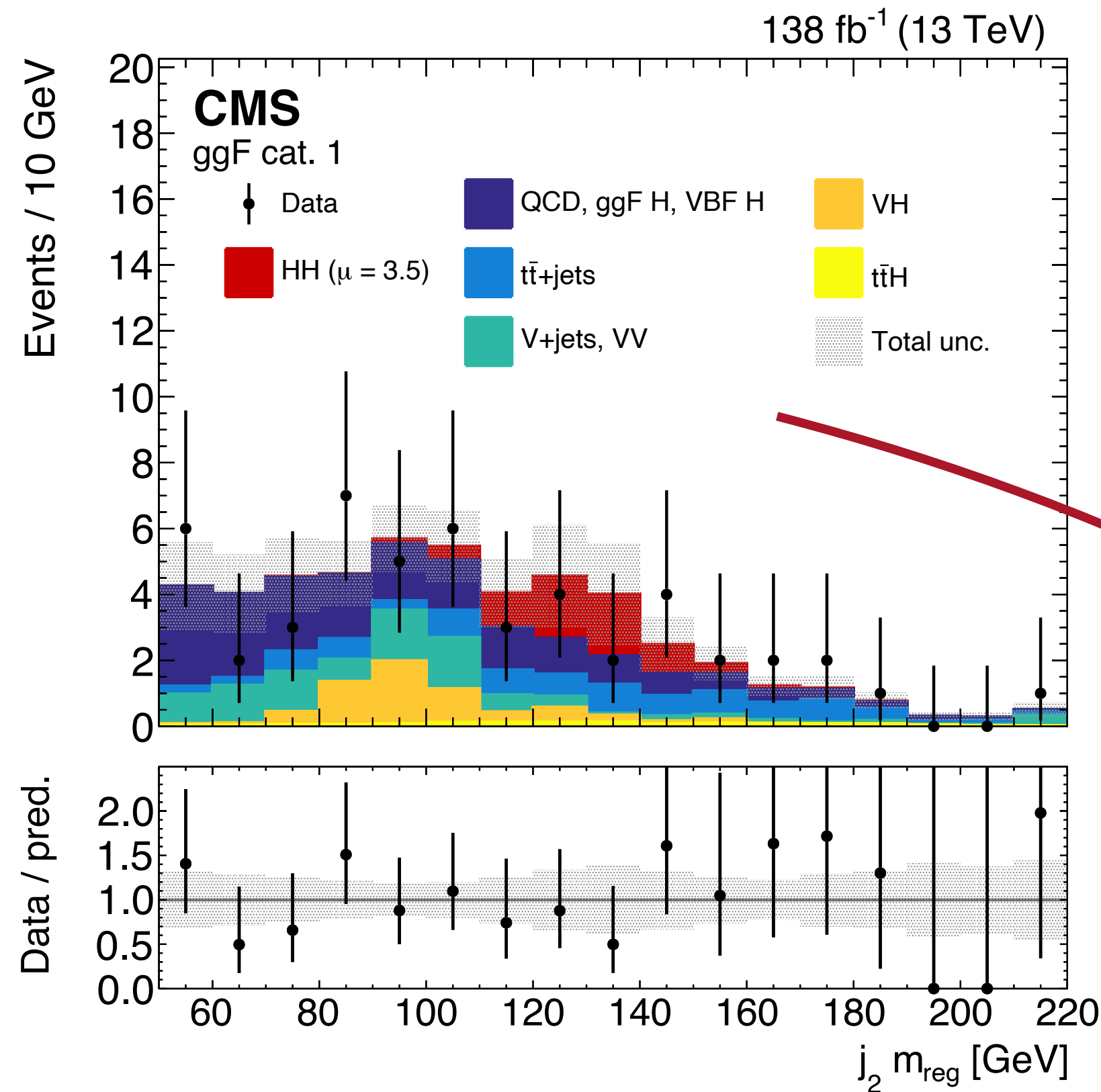
- ▶ After accounting for other SM backgrounds, Derive the shape of the QCD background using the jets that fail the D_{bb} selection



- ▶ Three ggF signal categories and VBF category are fit simultaneously to extract the HH signal strength $\mu = 3.5^{+3.3}_{-2.5}$ ($\sim 1.4\sigma$ excess over SM!)



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Most sensitive category for SM HH

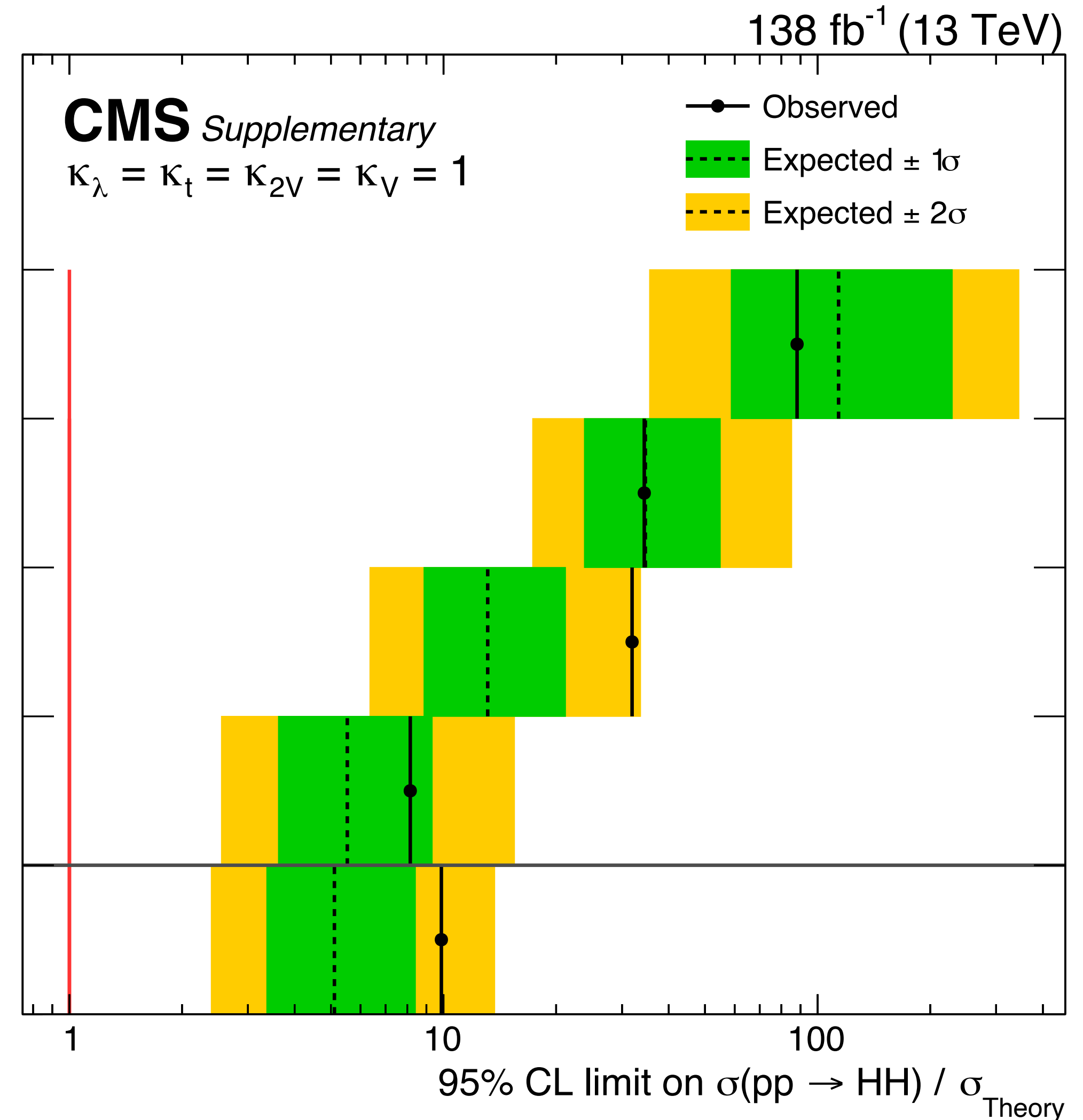
VBF cat.
Expected: 114
Observed: 88

ggF cat. 3
Expected: 35
Observed: 34

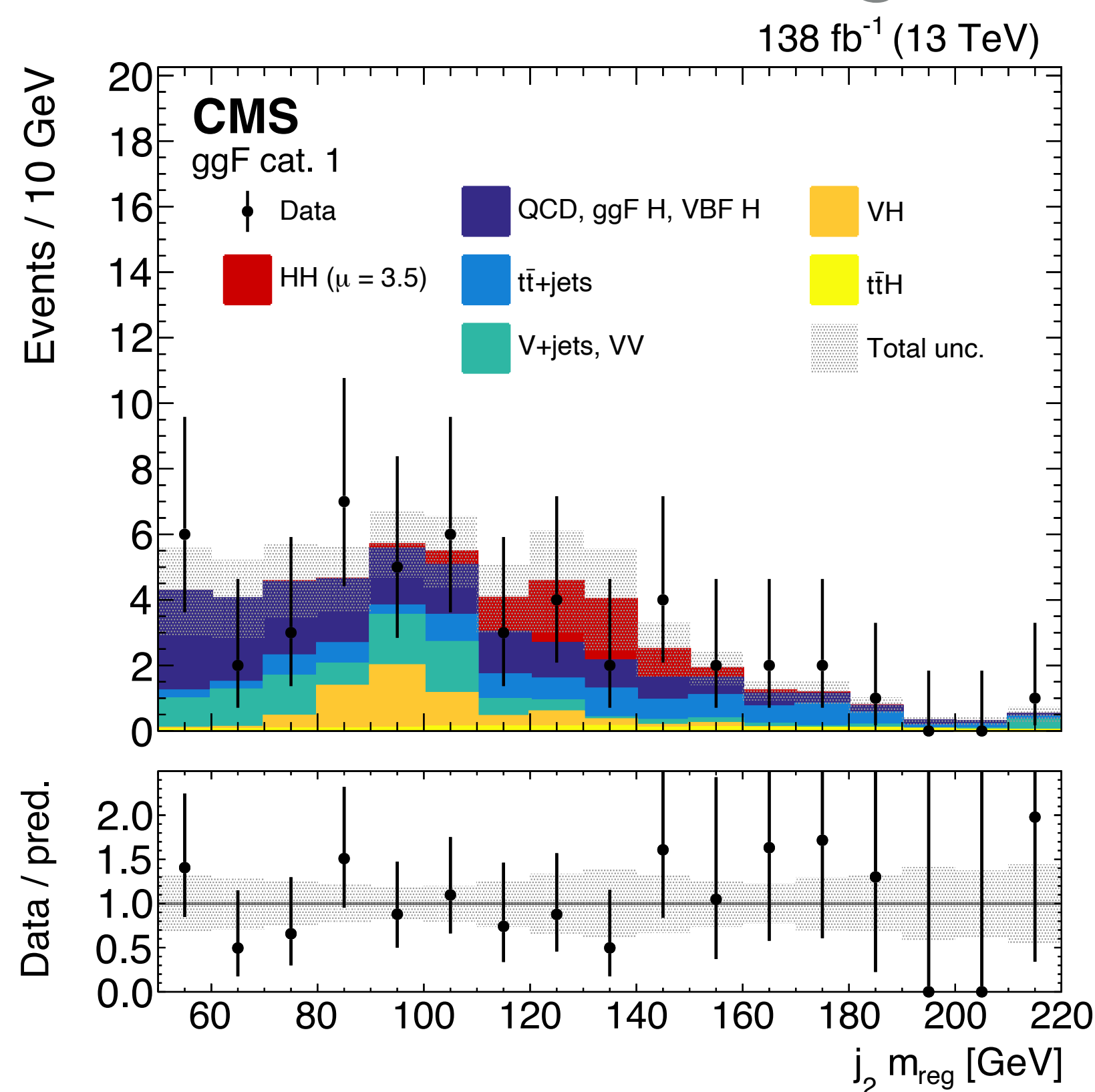
ggF cat. 2
Expected: 13
Observed: 32

ggF cat. 1
Expected: 5.5
Observed: 8.1

Combined
Expected: 5.1
Observed: 9.9



▶ Three ggF signal categories and VBF category are fit simultaneously to extract the HH signal strength $\mu = 3.5^{+3.3}_{-2.5}$ ($\sim 1.4\sigma$ excess over SM!)



Most sensitive category for SM HH

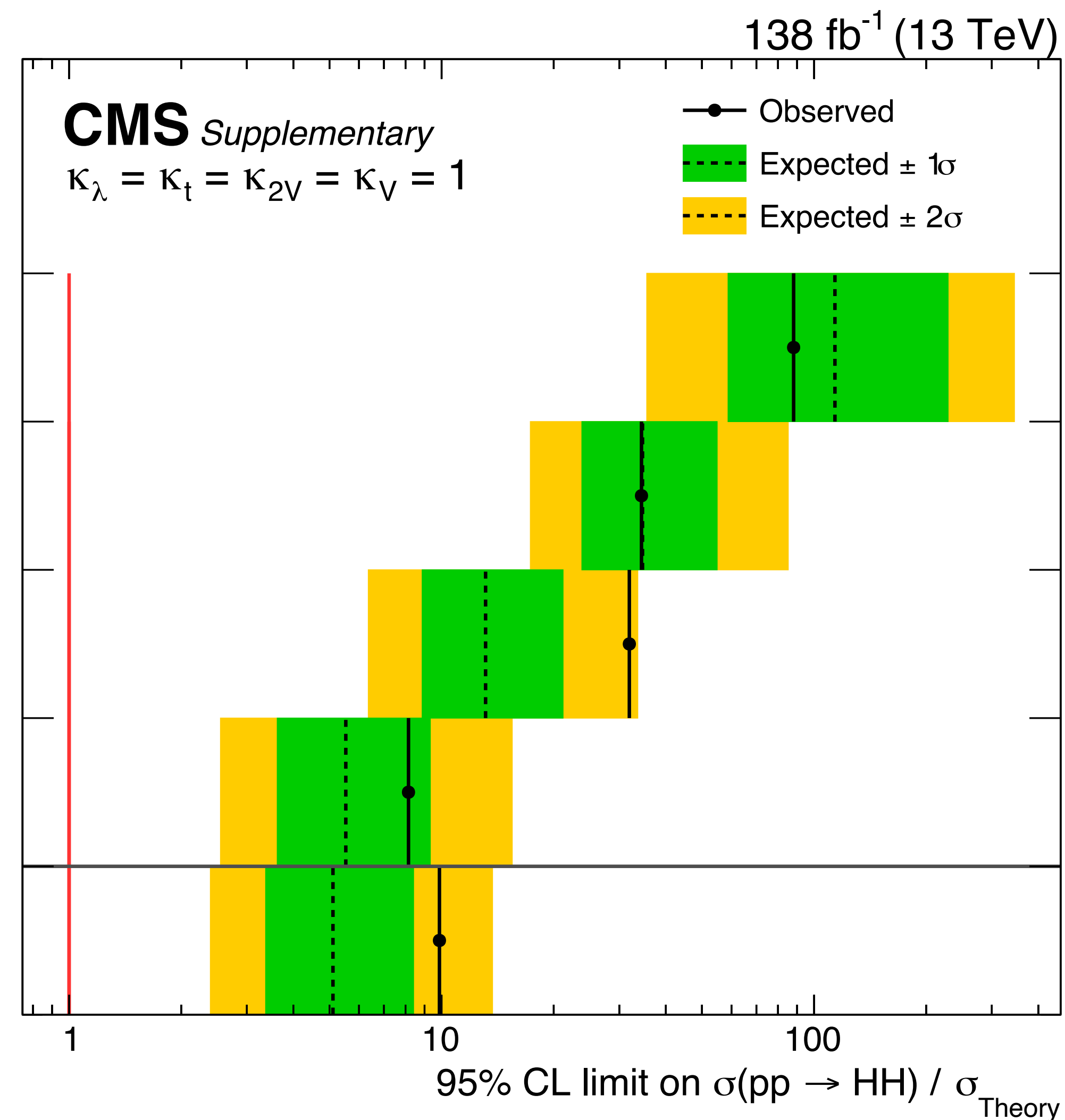
VBF cat.
Expected: 114
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ggF cat. 3
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ggF cat. 2
Expected: 13
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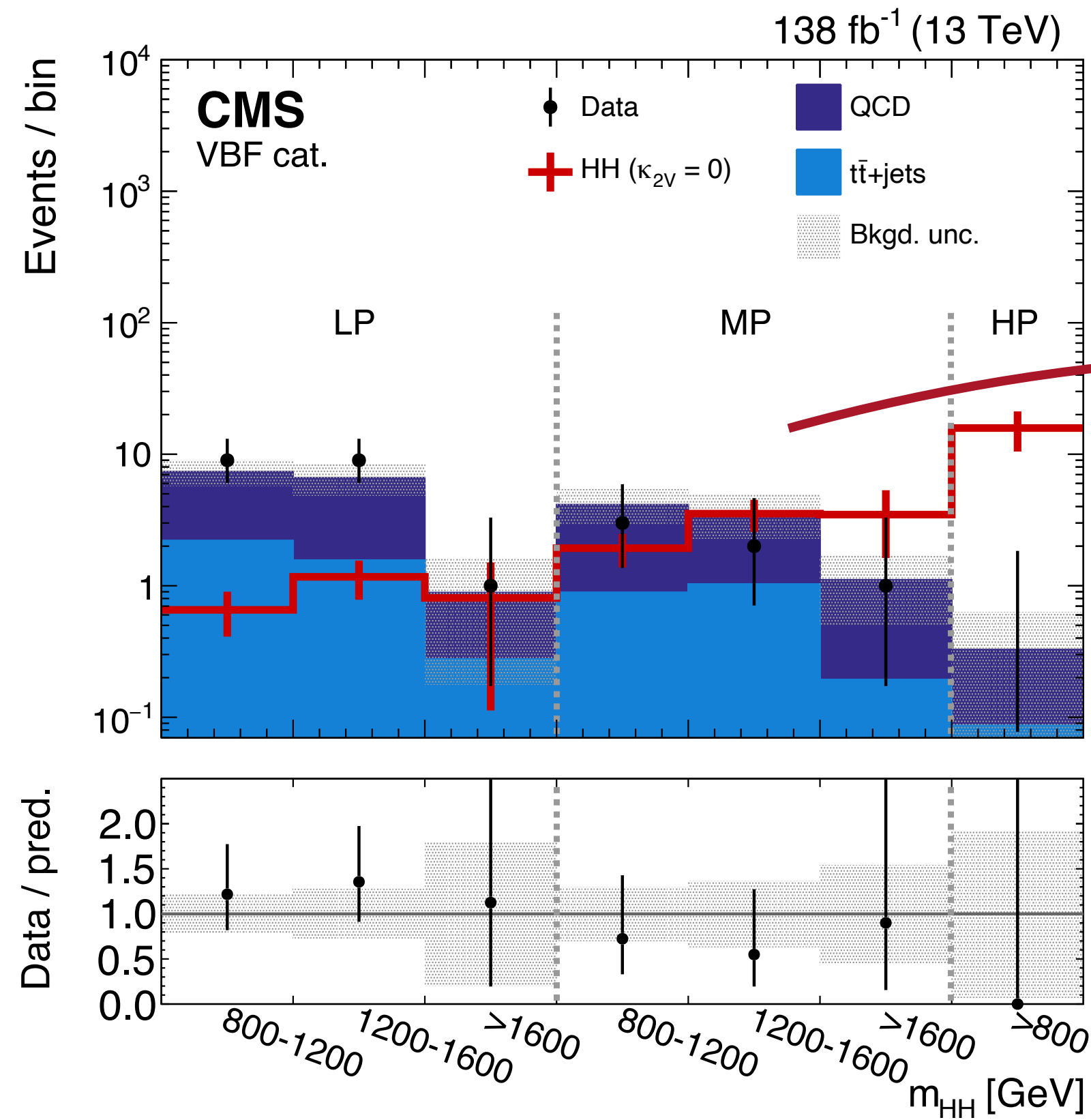
ggF cat. 1
Expected: 5.5
Observed: 8.1

Combined
Expected: 5.1
Observed: 9.9



**Observed (expected) 95% CL
UL on HH: 9.9 (5.1) \times SM!**

- ▶ While ggF categories dominate for inclusive SM HH signal, VBF category dominates for BSM VBF signal



Most sensitive category for BSM VBF

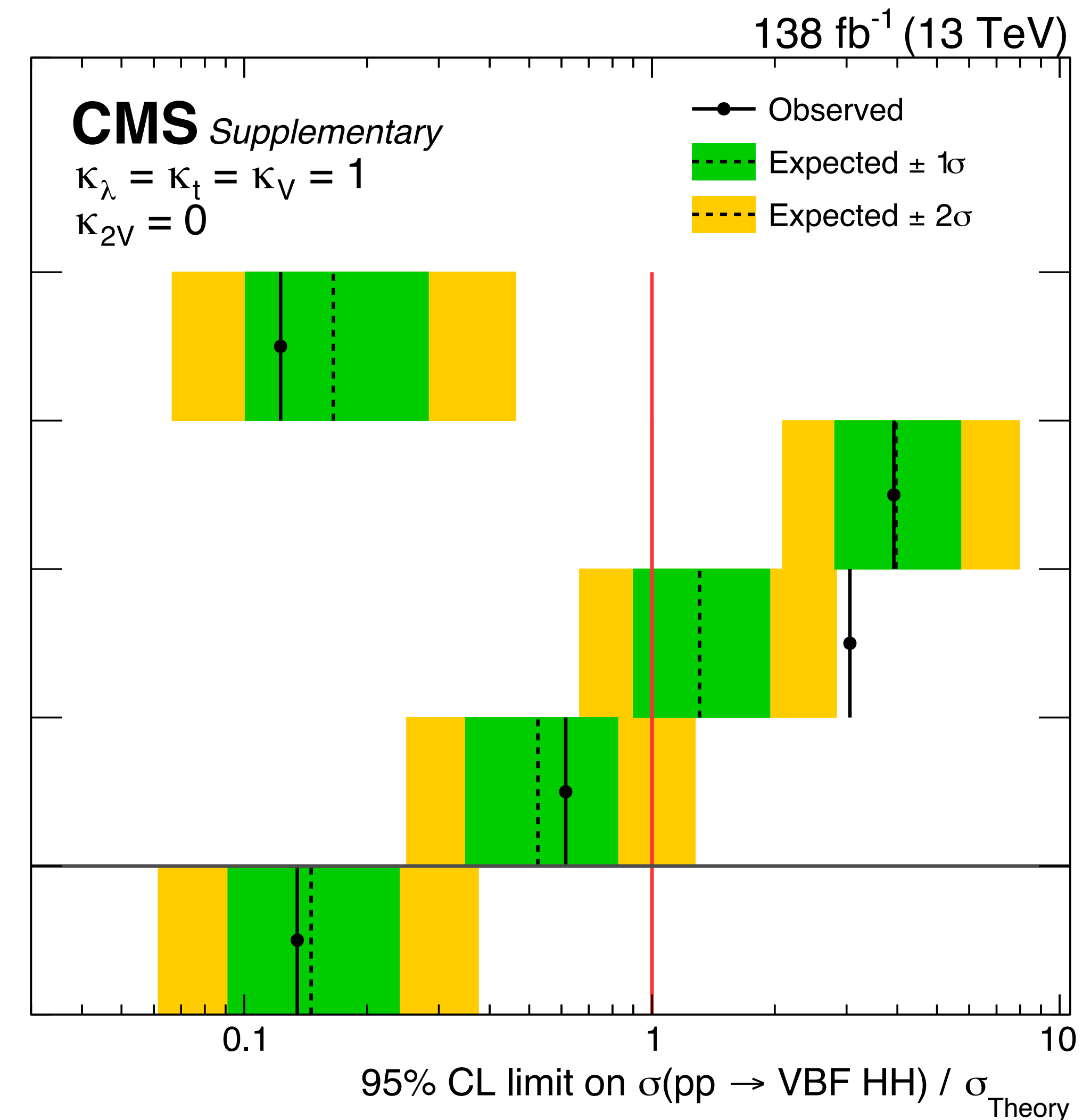
VBF cat.
Expected: 0.17
Observed: 0.12

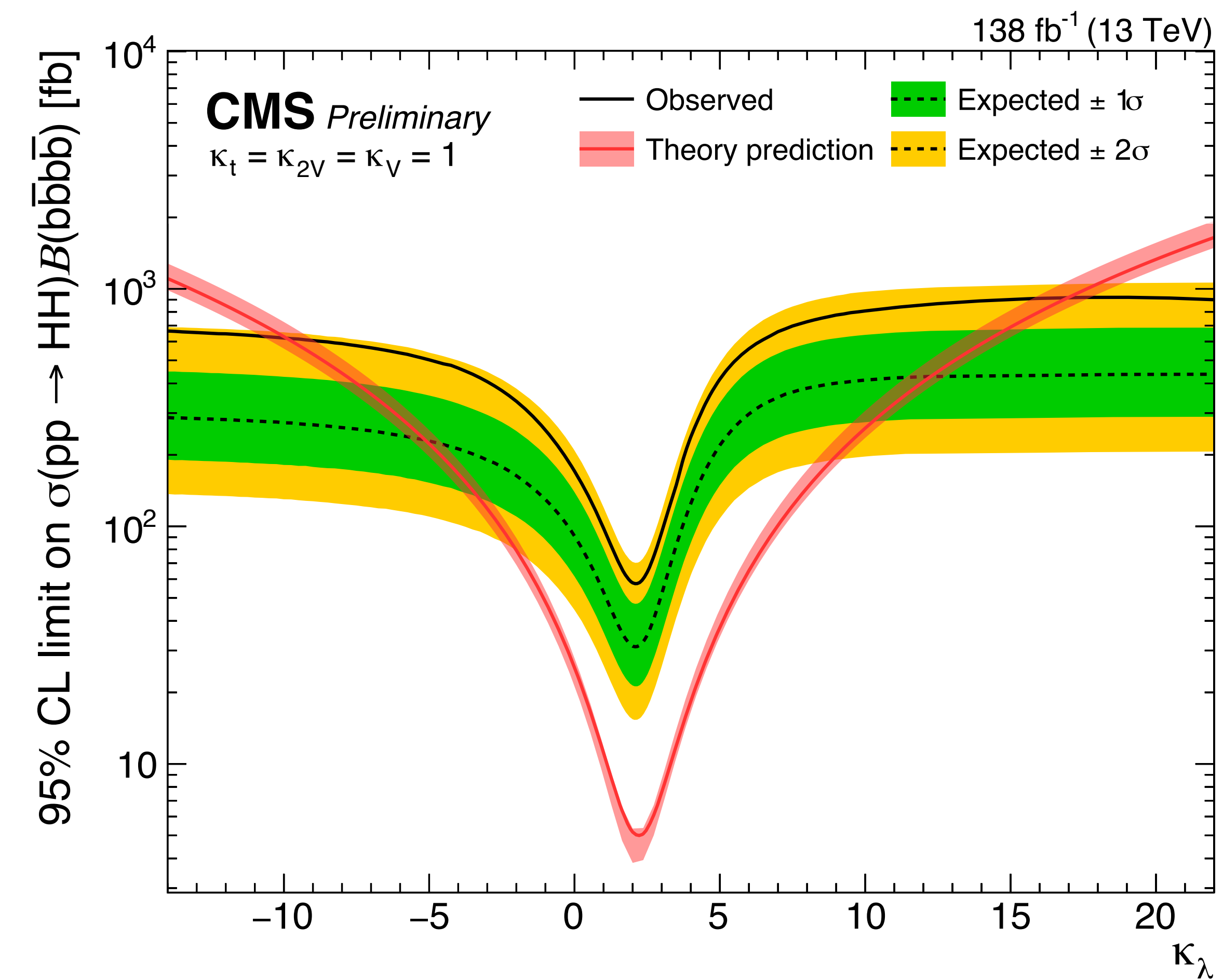
ggF cat. 3
Expected: 4.0
Observed: 3.9

ggF cat. 2
Expected: 1.3
Observed: 3.1

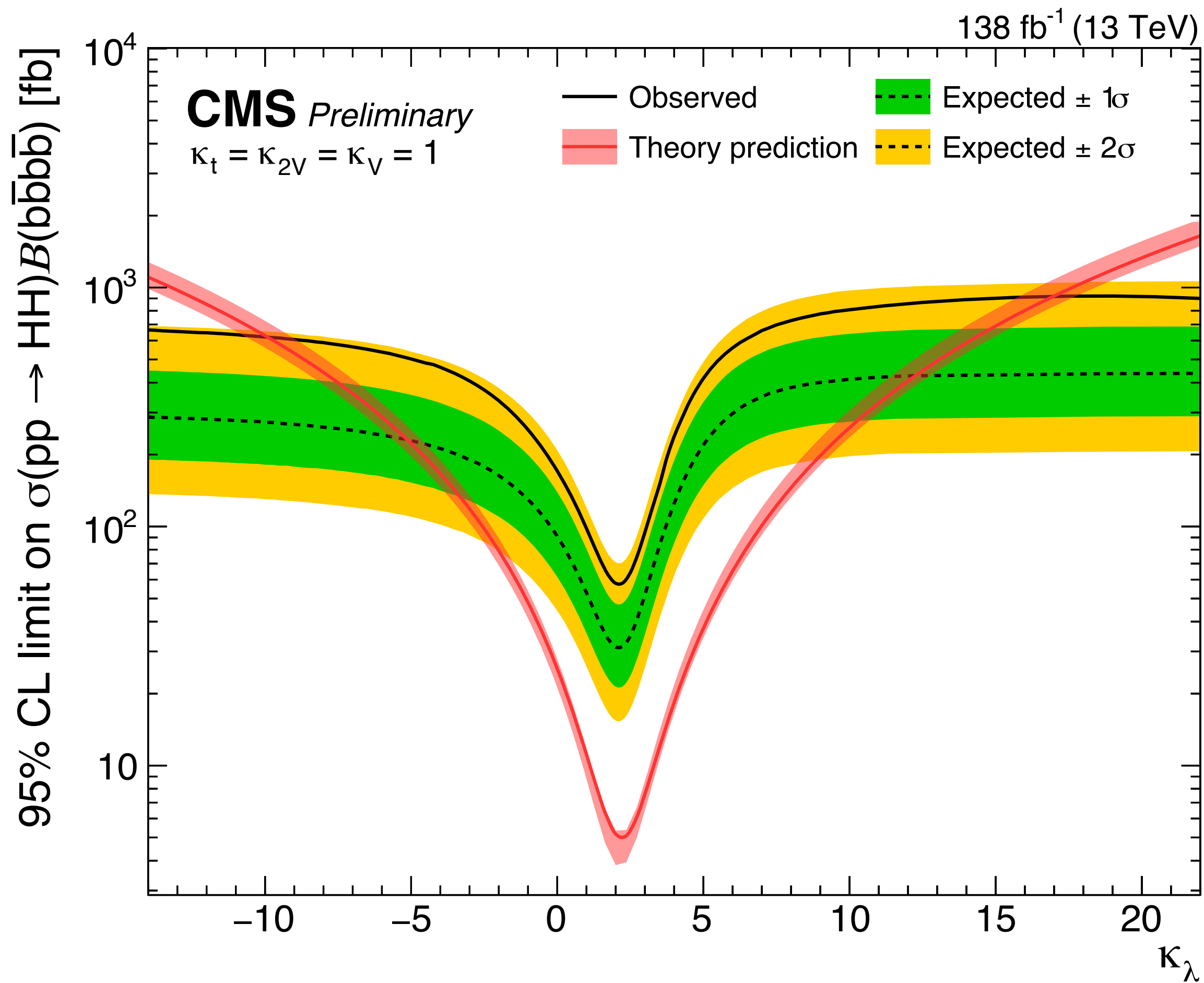
ggF cat. 1
Expected: 0.52
Observed: 0.61

Combined
Expected: 0.15
Observed: 0.13

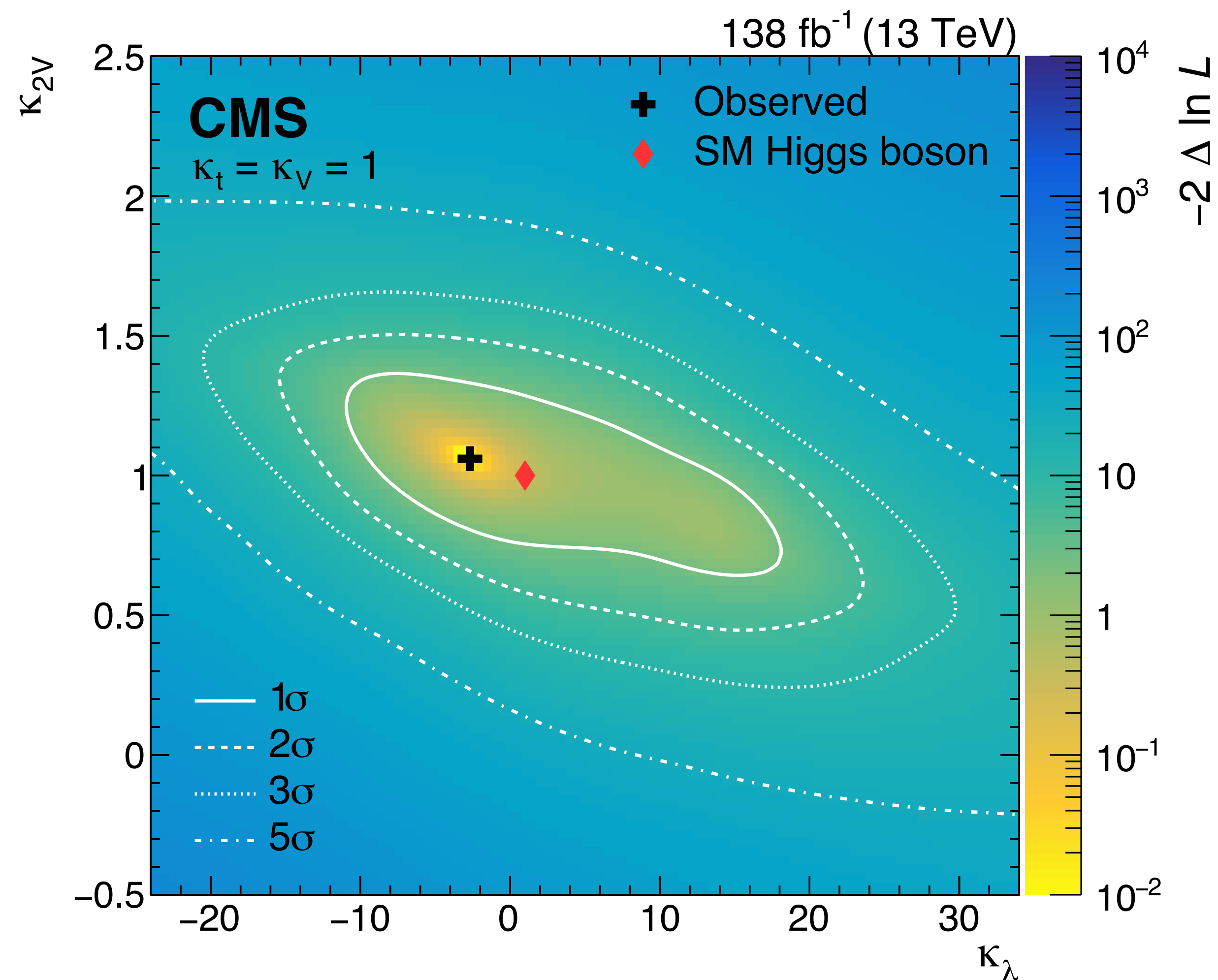
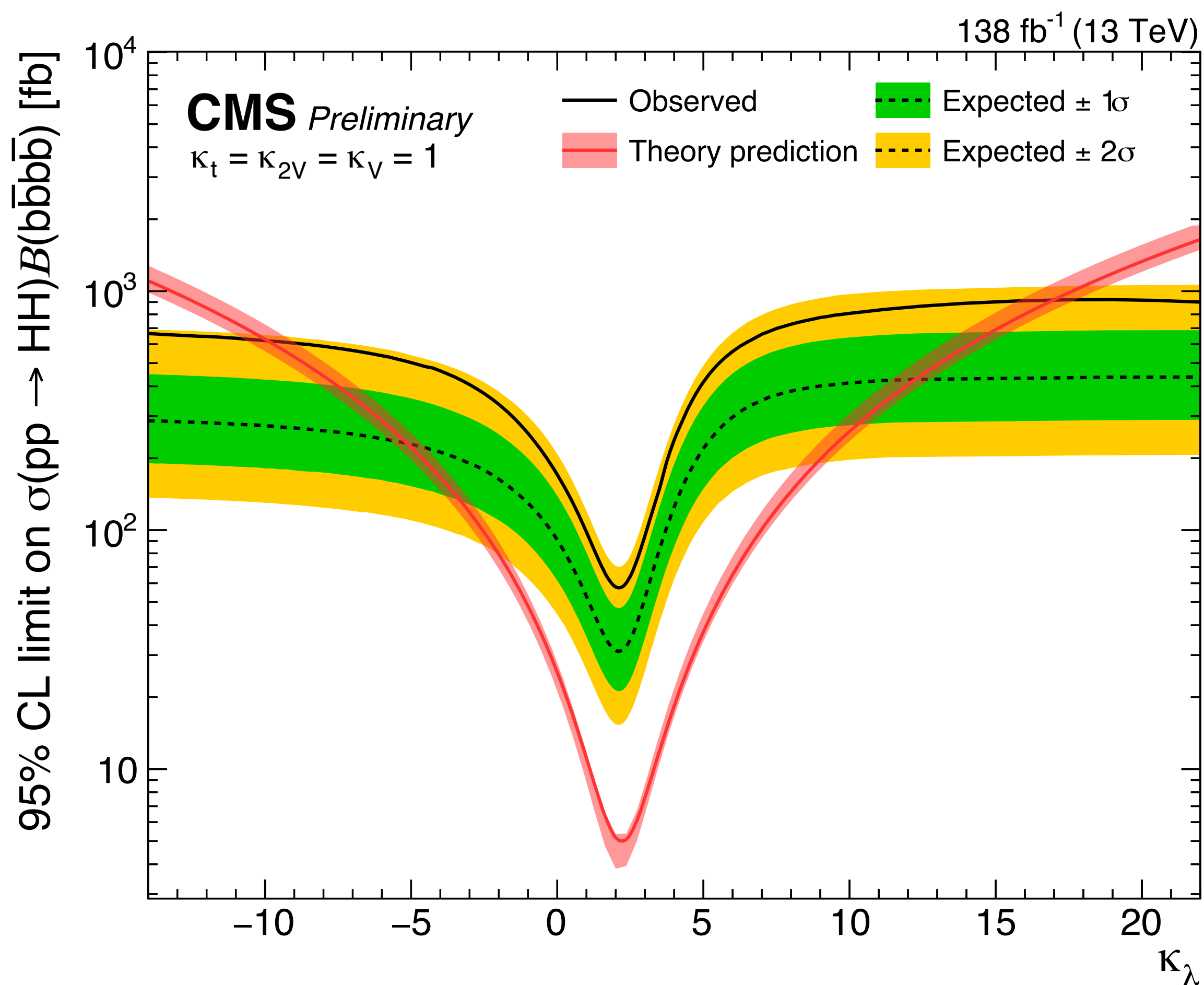




- ▶ Based on combined fit, κ_λ constrained to be in $[-9.9, 16.9]$ at 95% CL

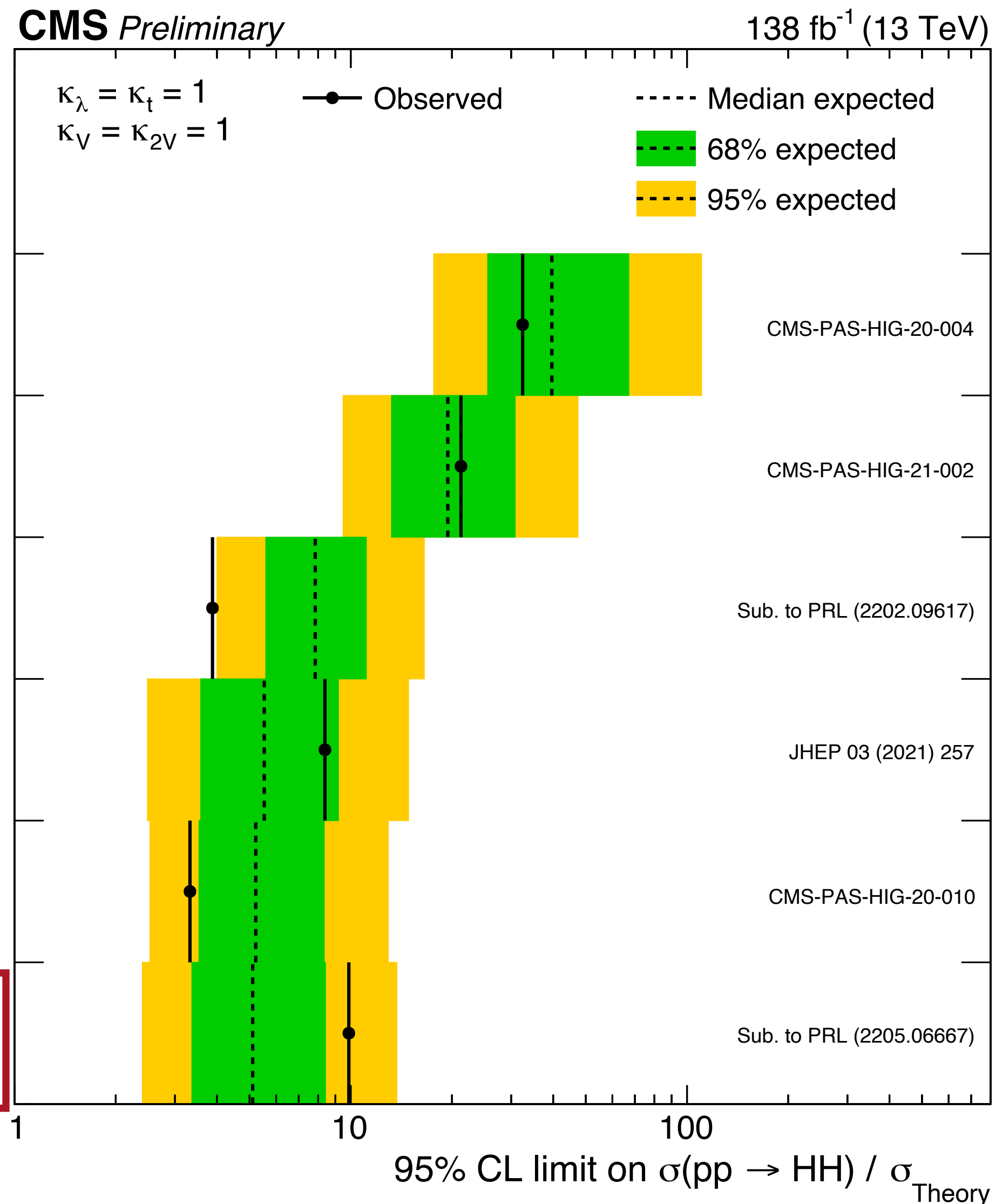


- ▶ Based on combined fit, κ_λ constrained to be in $[-9.9, 16.9]$ at 95% CL
- ▶ 2D likelihood scan ($\kappa_\lambda, \kappa_{2V}$) shows complementarity between two channels

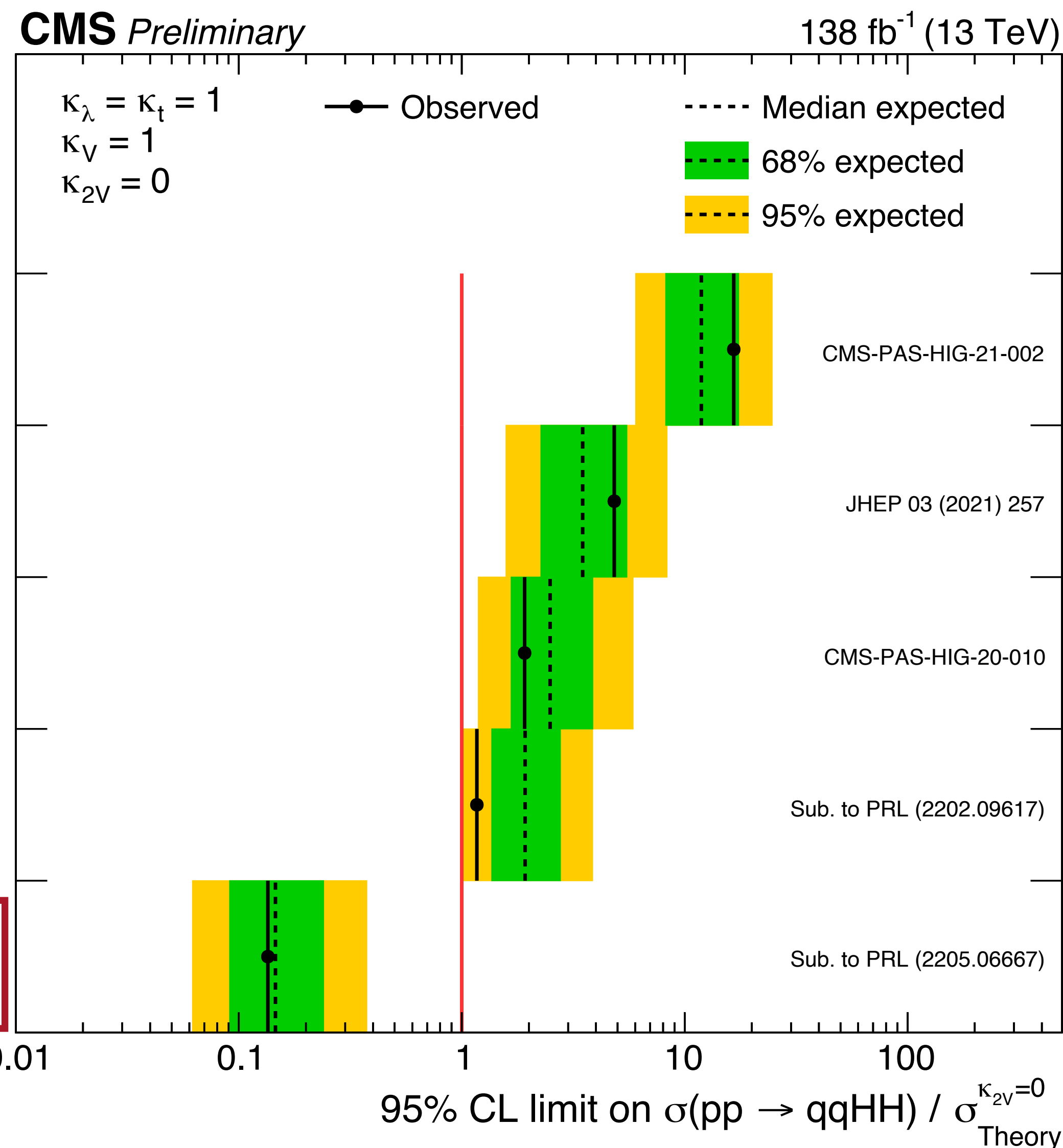
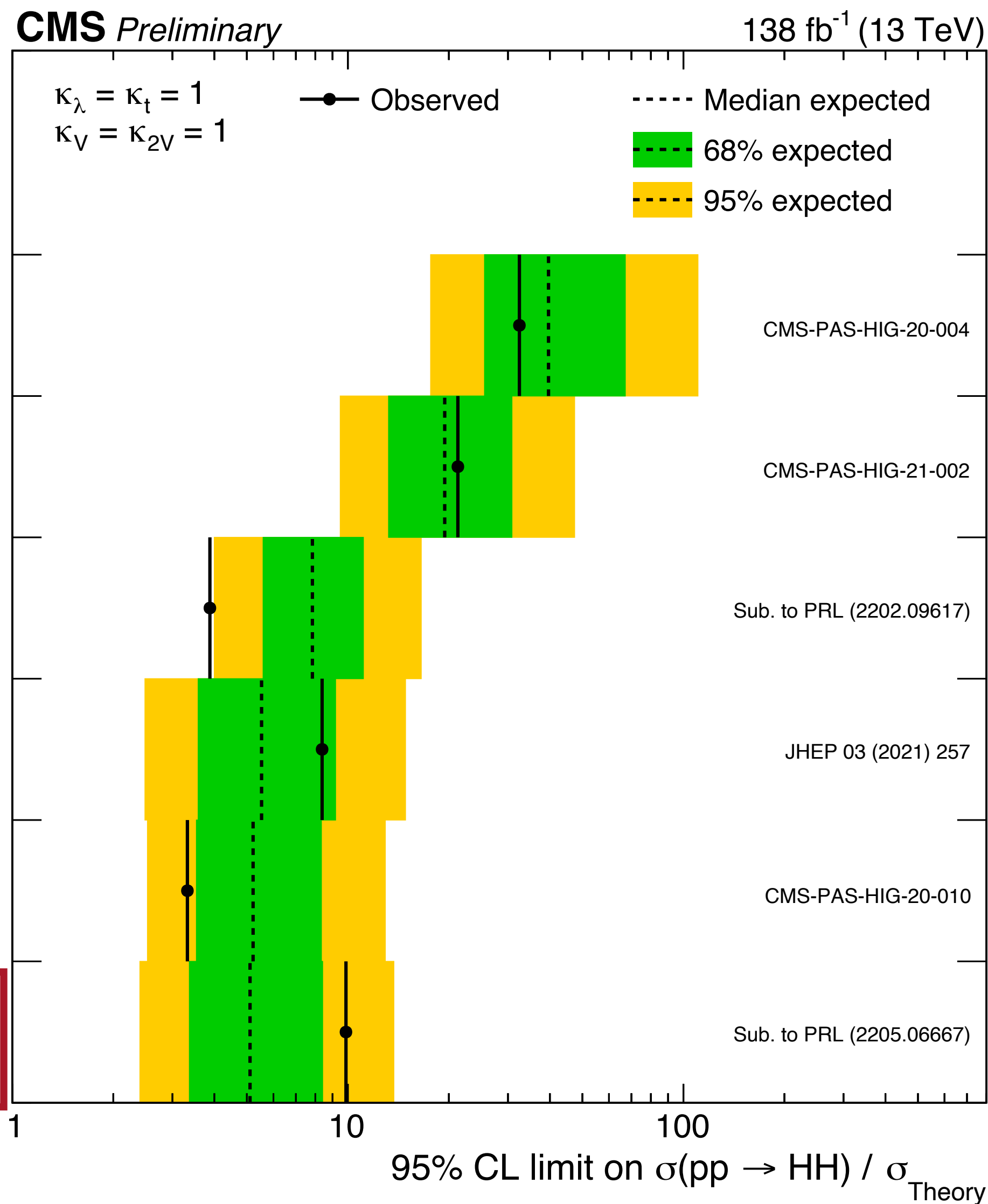


- I. HH PRODUCTION AT THE LHC
- II. GNNs FOR JET PHYSICS
- III. BOOSTED HH SEARCH
- IV. OUTLOOK**

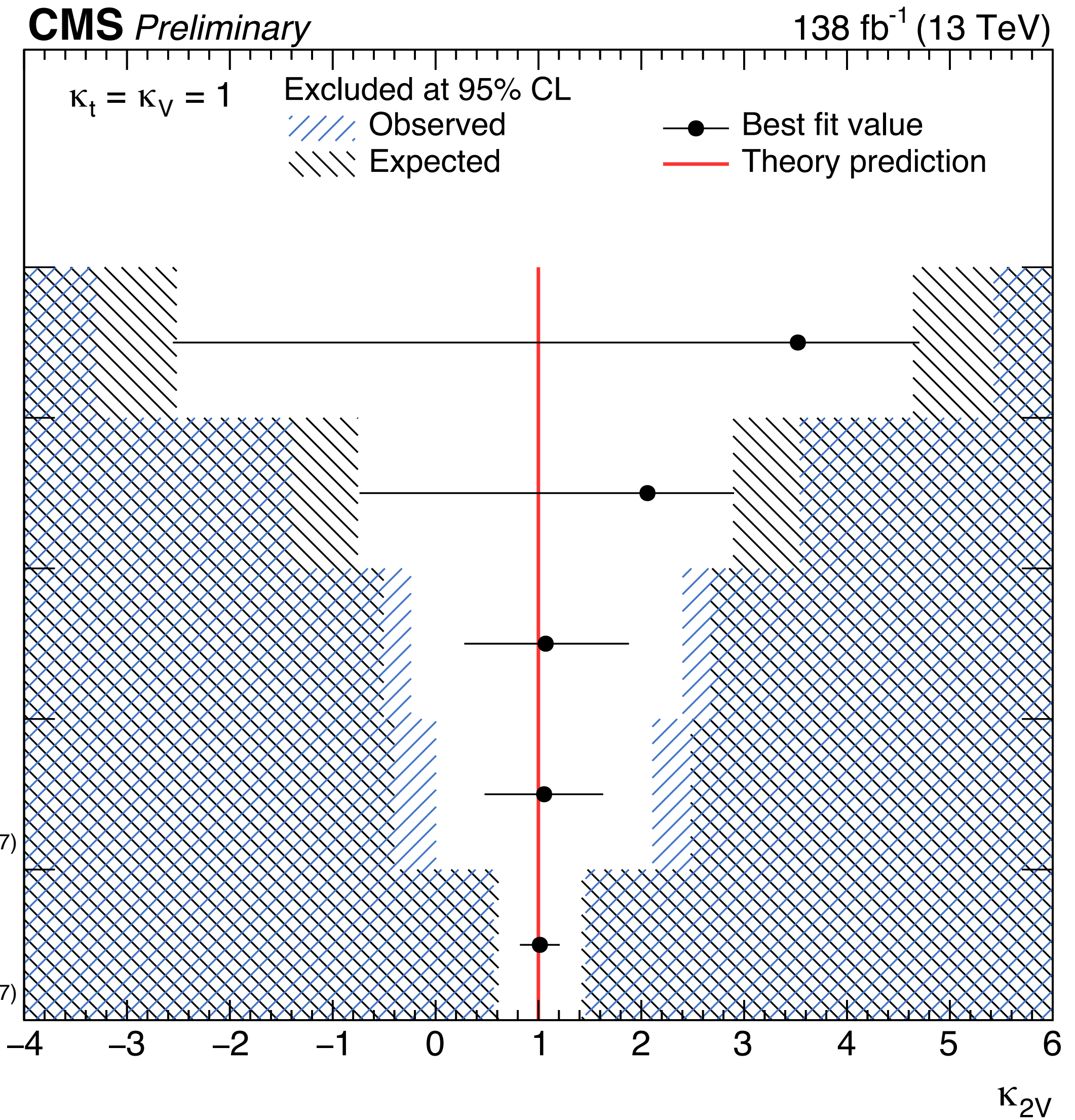
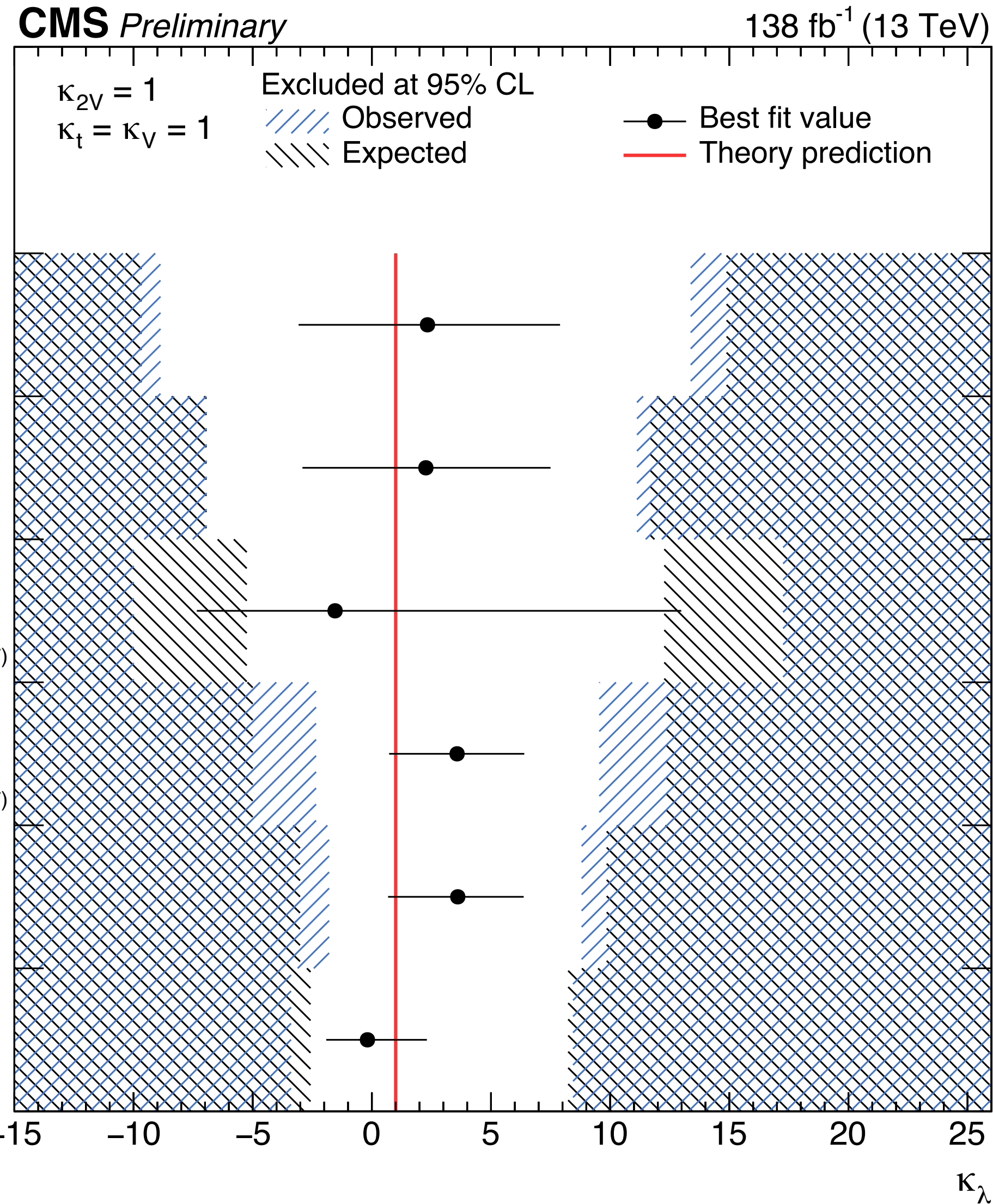
► Best sensitivity to SM ggF HH production



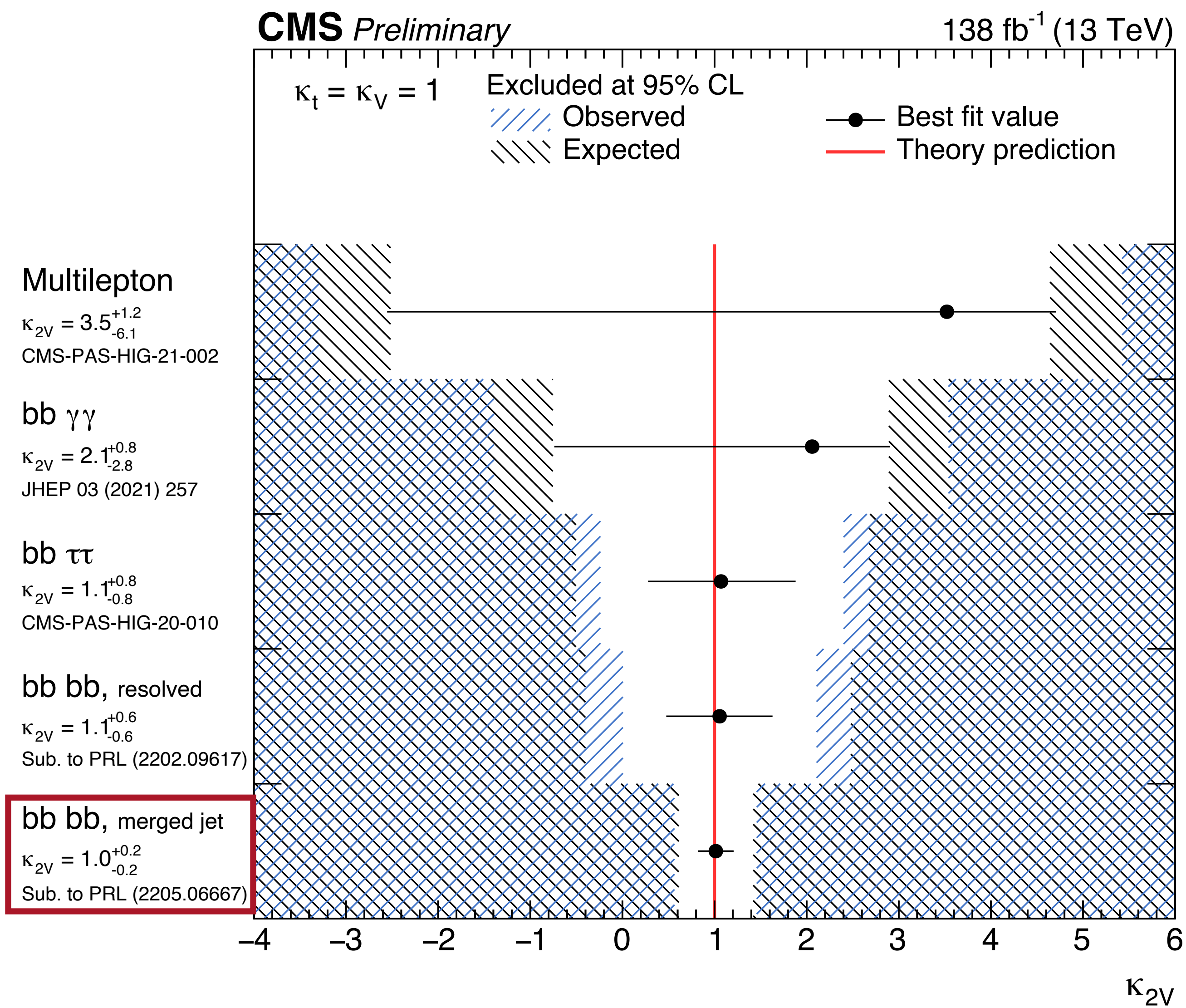
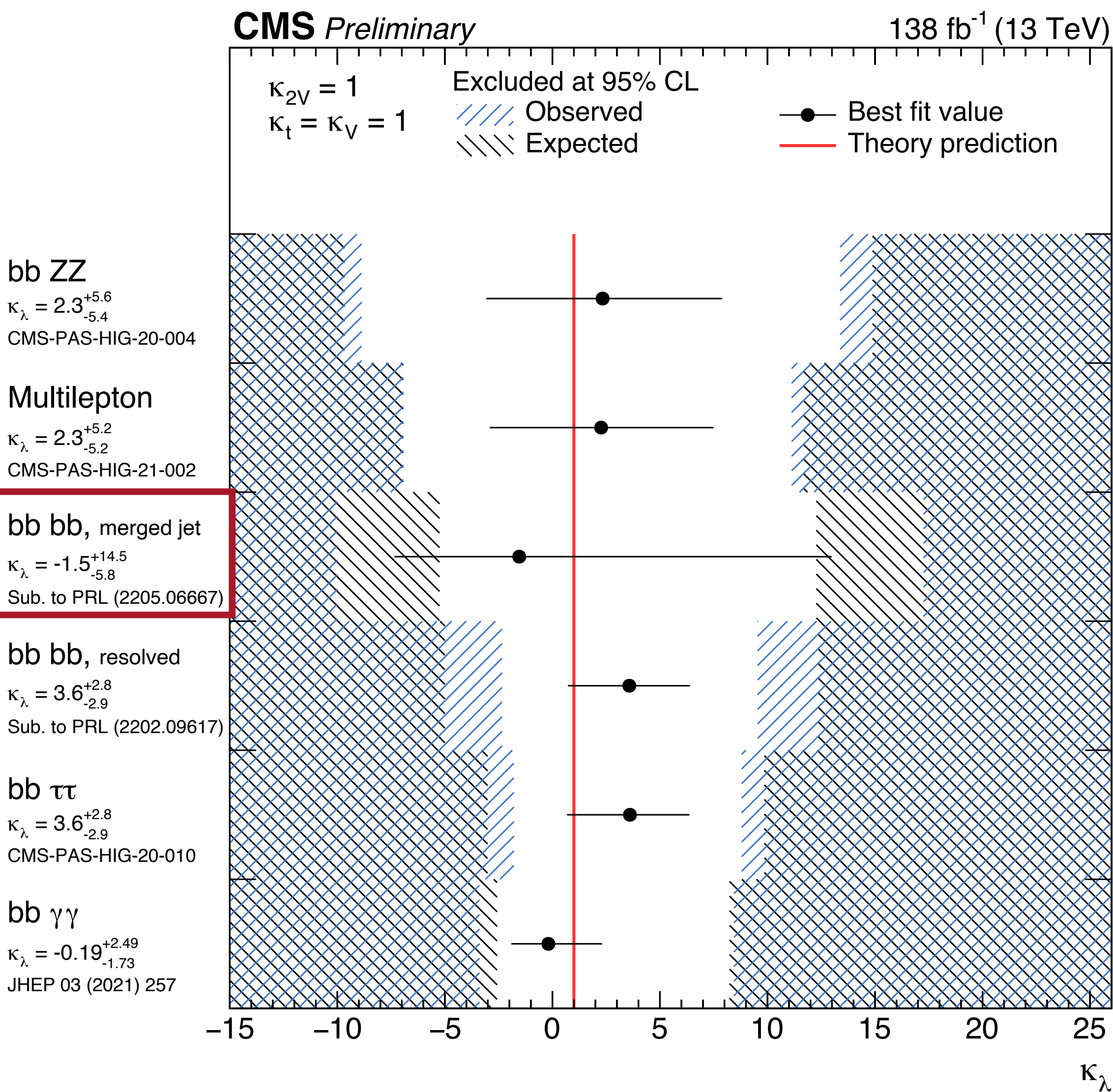
► Best sensitivity to SM ggF HH production and BSM VBF HH production



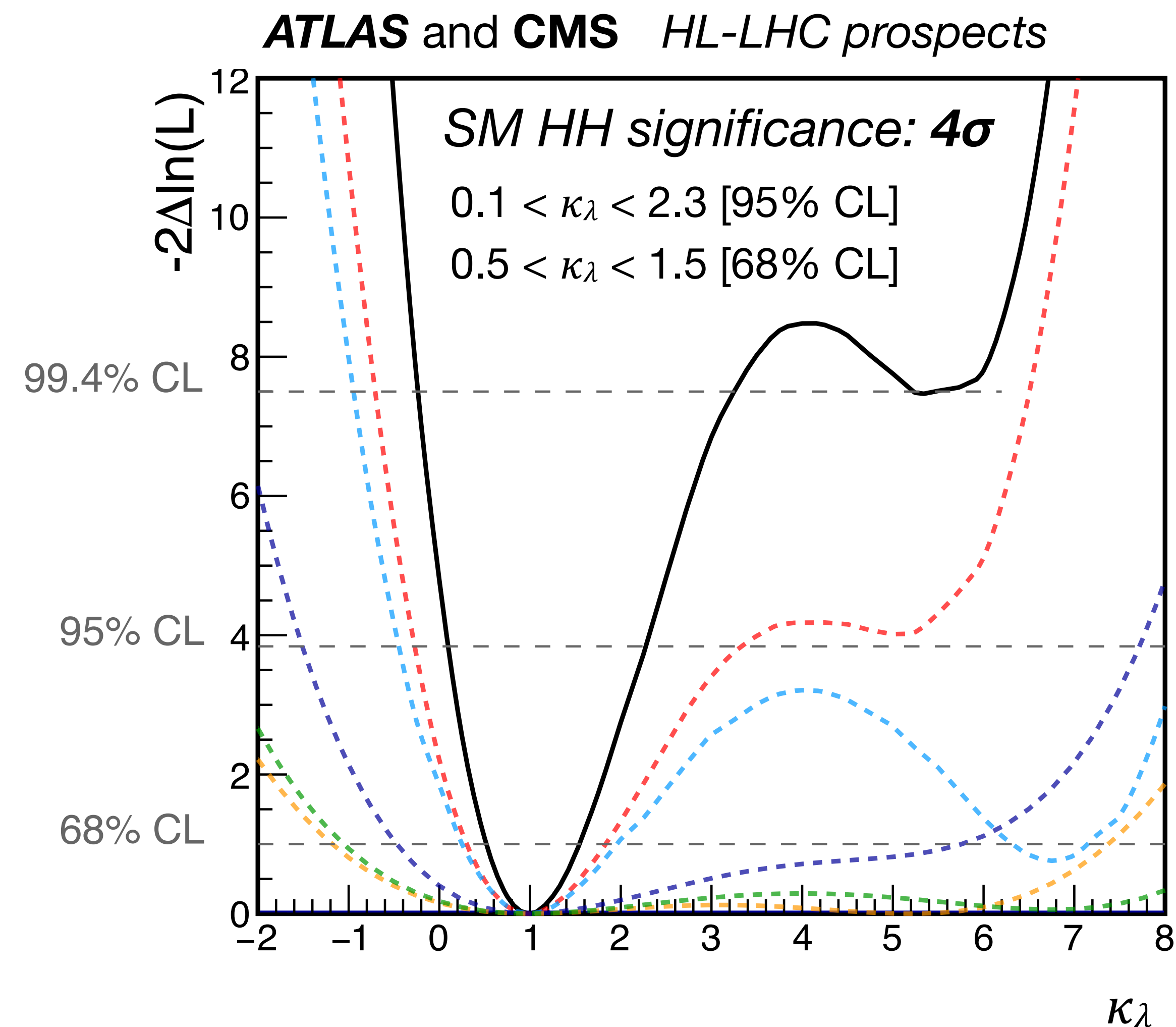
► Best constraint on κ_{2V}



► Best constraint on κ_{2V}

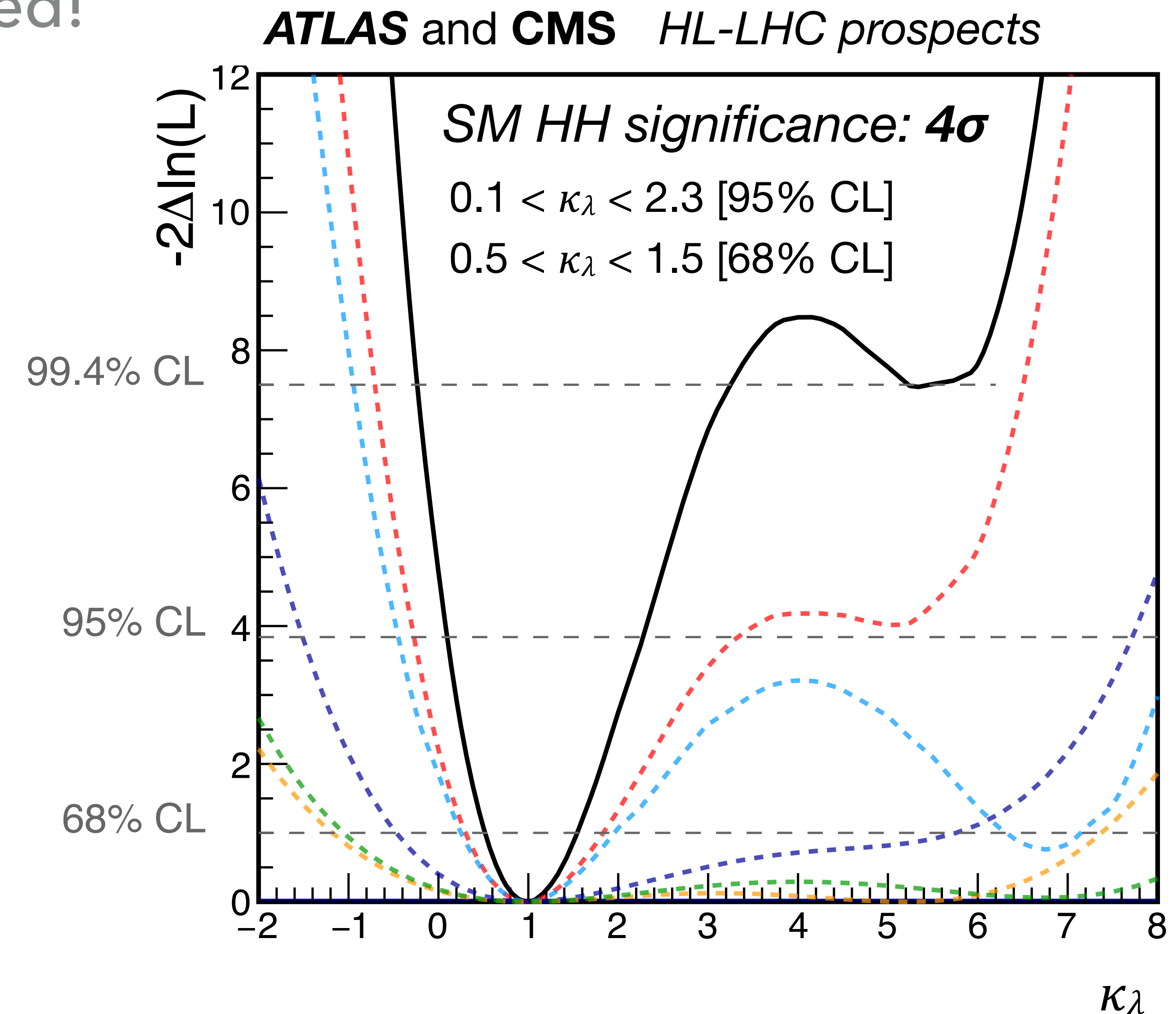


| | Statistical + Systematic | |
|---------------------------------------|--------------------------|------|
| | ATLAS | CMS |
| $HH \rightarrow b\bar{b}b\bar{b}$ | 0.61 | 0.95 |
| $HH \rightarrow b\bar{b}\tau\tau$ | 2.1 | 1.4 |
| $HH \rightarrow b\bar{b}\gamma\gamma$ | 2.0 | 1.8 |
| $HH \rightarrow b\bar{b}VV(ll\nu\nu)$ | - | 0.56 |
| $HH \rightarrow b\bar{b}ZZ(4l)$ | - | 0.37 |
| combined | 3.0 | 2.6 |
| | Combined | |
| | 4.0 | |



- ▶ Based on 2018 HL-LHC projection, SM HH significance is 4σ for 3000 fb^{-1}
- ▶ Boosted bbbb channels ***can put us over the edge of "discovery"***
- ▶ Plus many more ***improvements*** anticipated!

| | Statistical + Systematic | |
|---------------------------------------|--------------------------|------|
| | ATLAS | CMS |
| $HH \rightarrow b\bar{b}b\bar{b}$ | 0.61 | 0.95 |
| $HH \rightarrow b\bar{b}\tau\tau$ | 2.1 | 1.4 |
| $HH \rightarrow b\bar{b}\gamma\gamma$ | 2.0 | 1.8 |
| $HH \rightarrow b\bar{b}VV(l\nu\nu)$ | - | 0.56 |
| $HH \rightarrow b\bar{b}ZZ(4l)$ | - | 0.37 |
| combined | 3.0 | 2.6 |
| | Combined | |
| | 4.0 | |

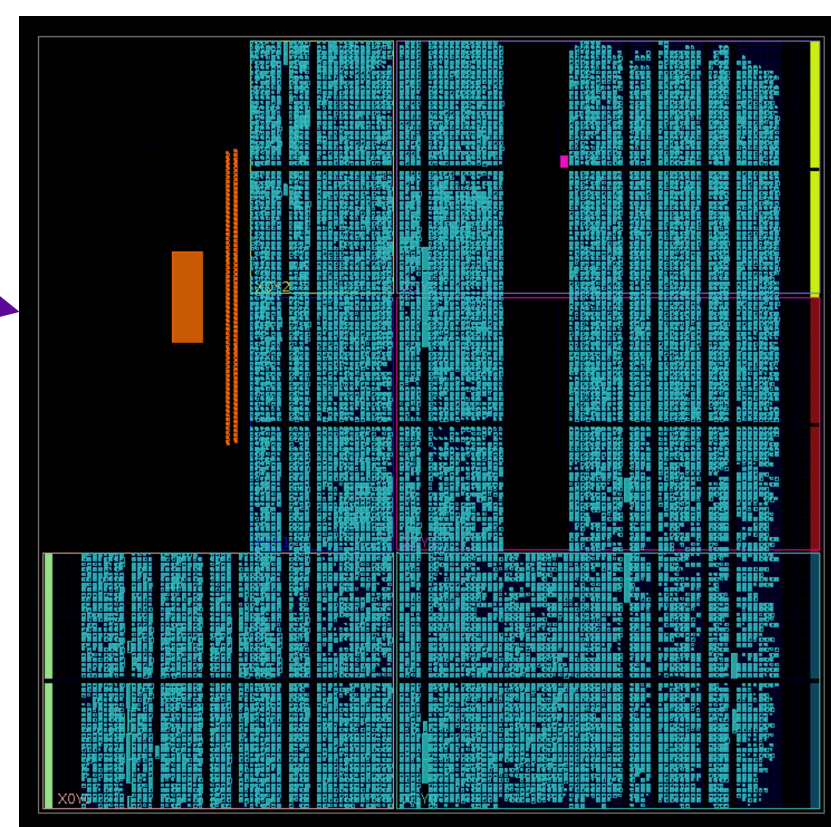
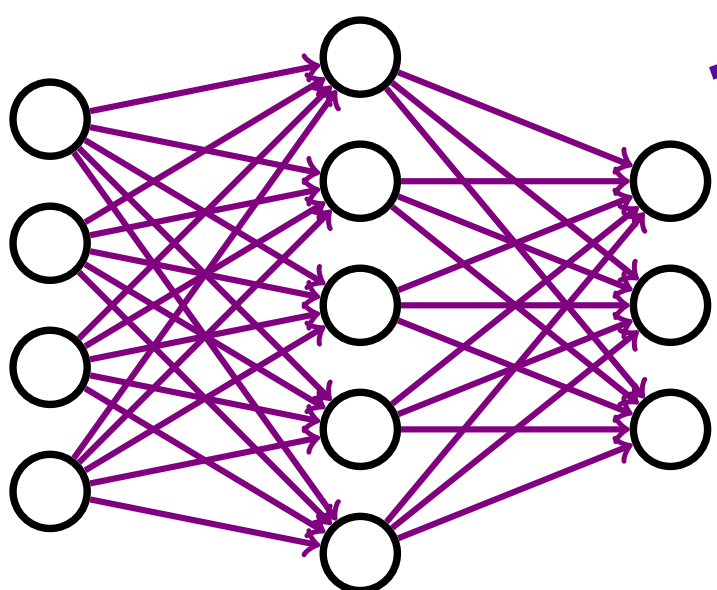


- ▶ Trigger is a limiting factor, both level-1 (FPGA-based) and high-level (software-based); ***Planned improvements:***

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 - ▶ New Run 3 high-level triggers: (1) two boosted AK8 jets with m_{SD} requirements and (2) single boosted AK8 jet with D_{bb} requirements

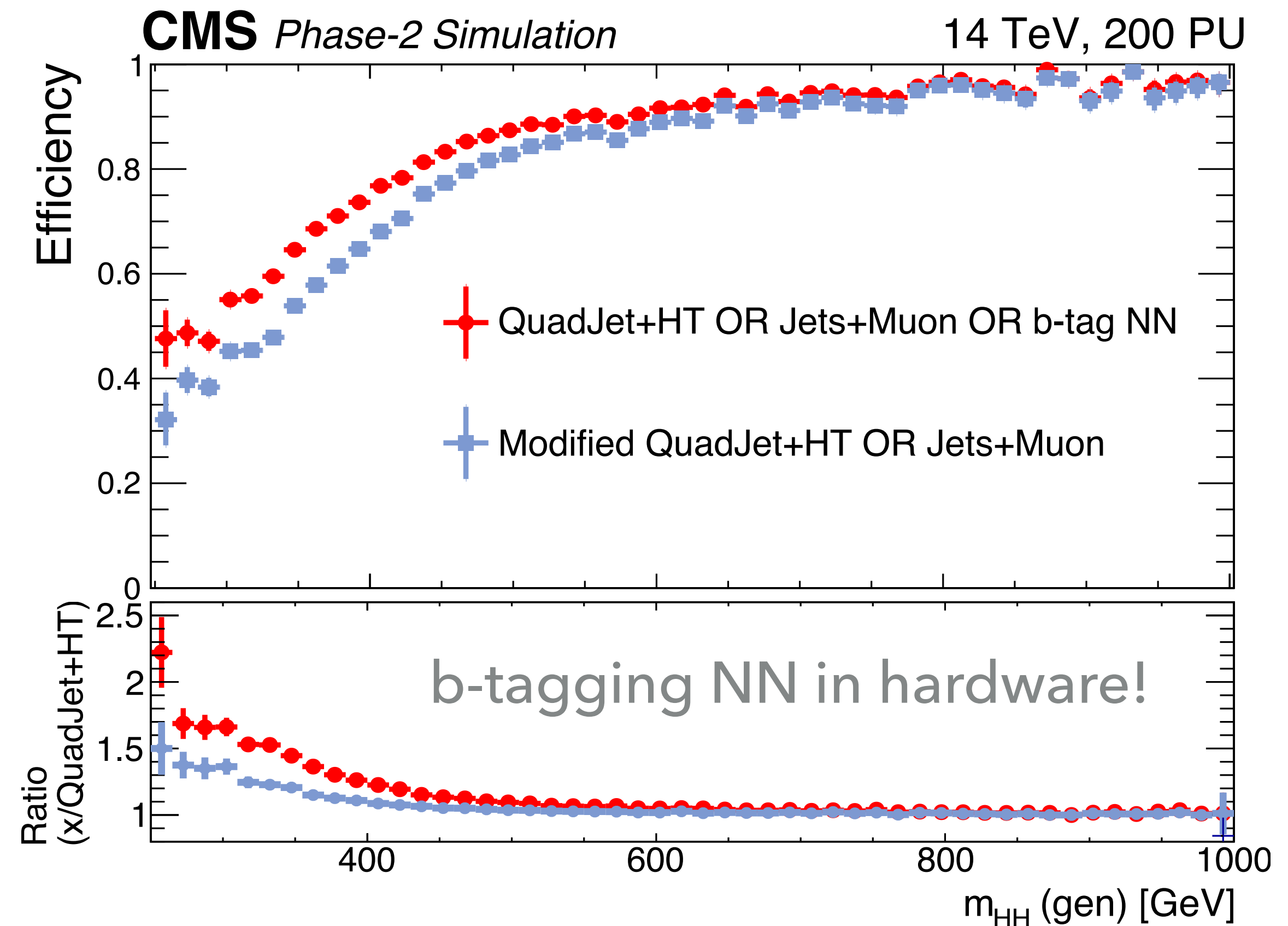
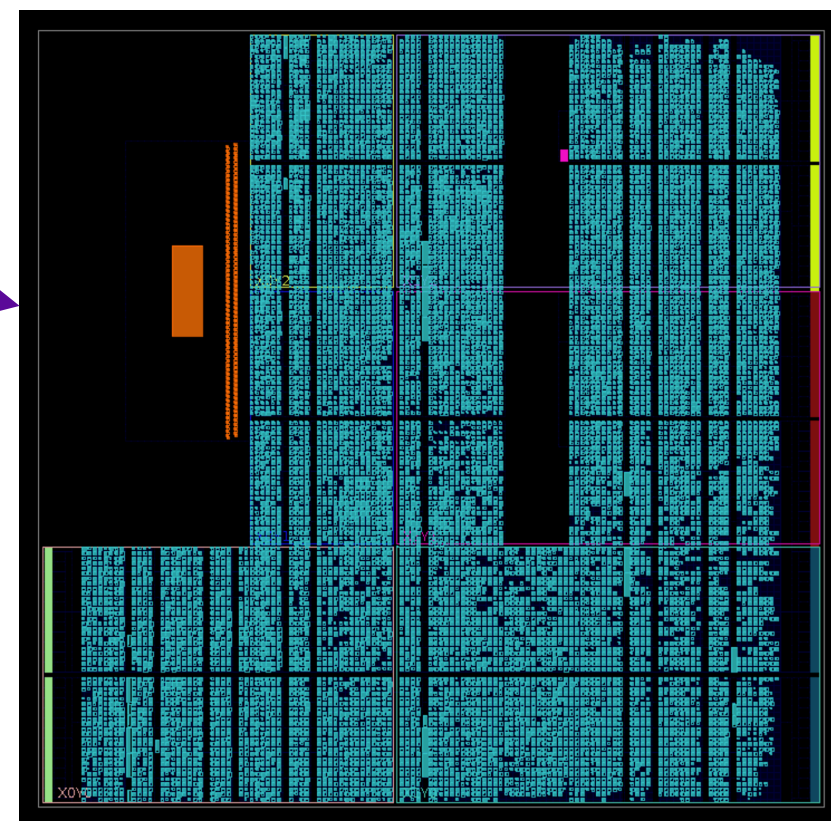
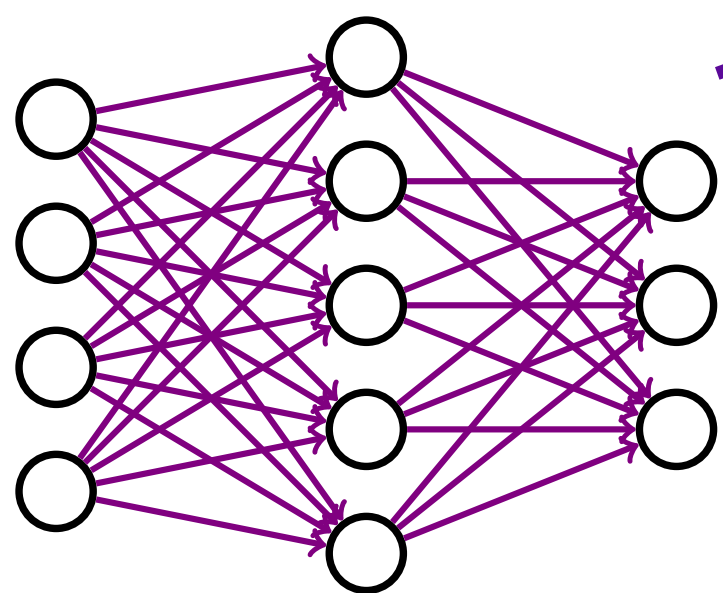
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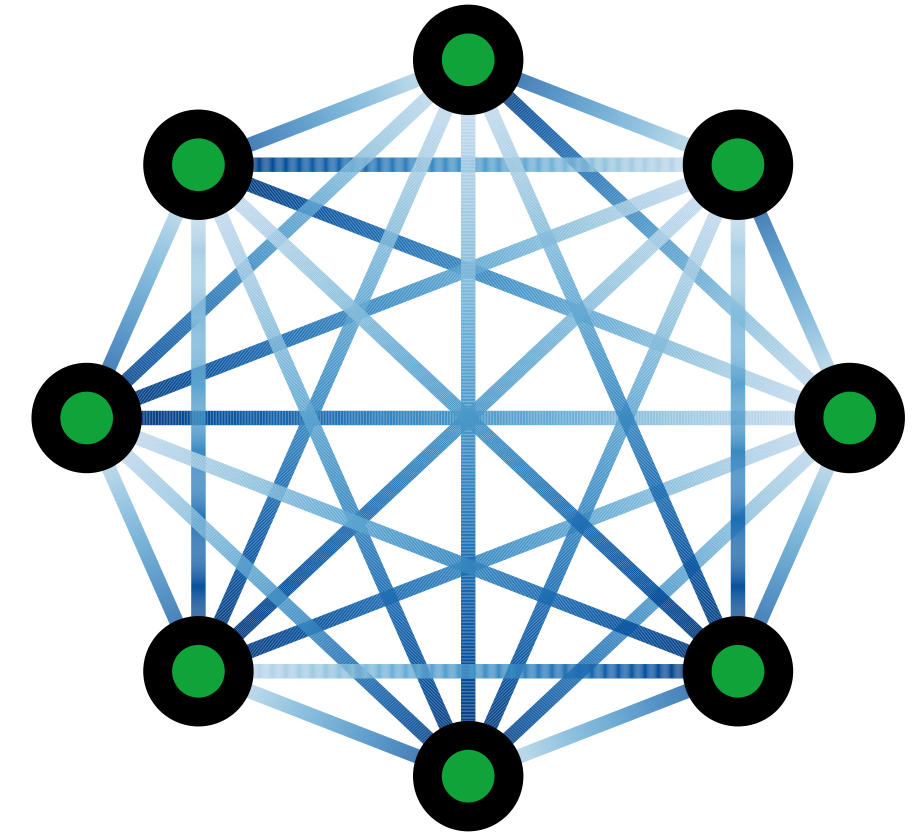
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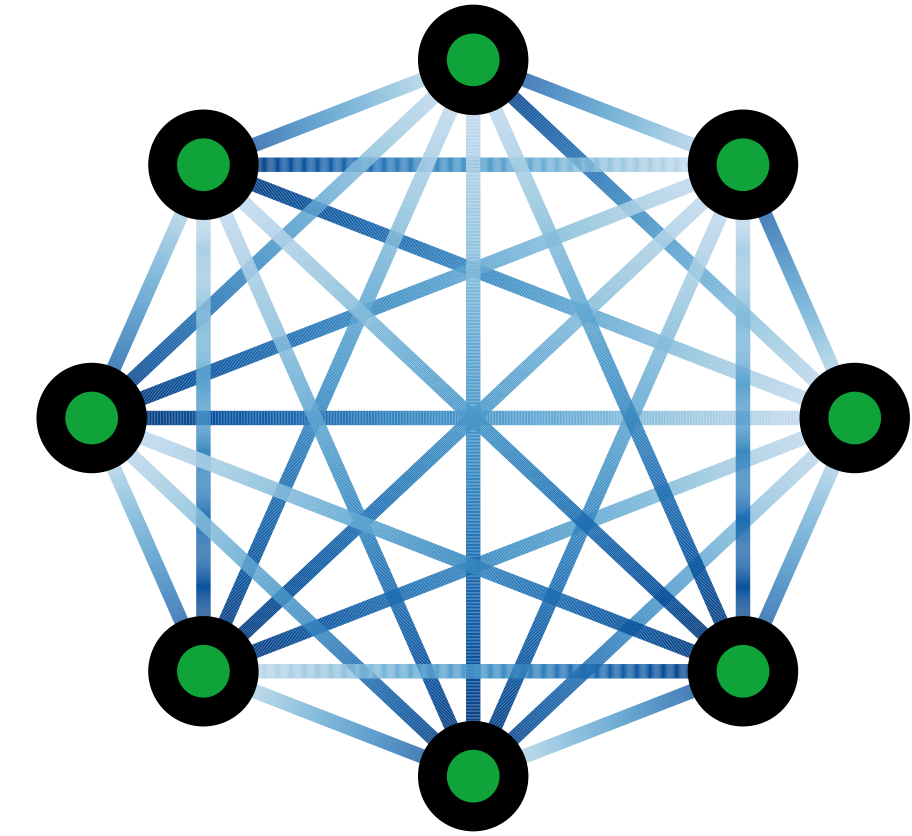
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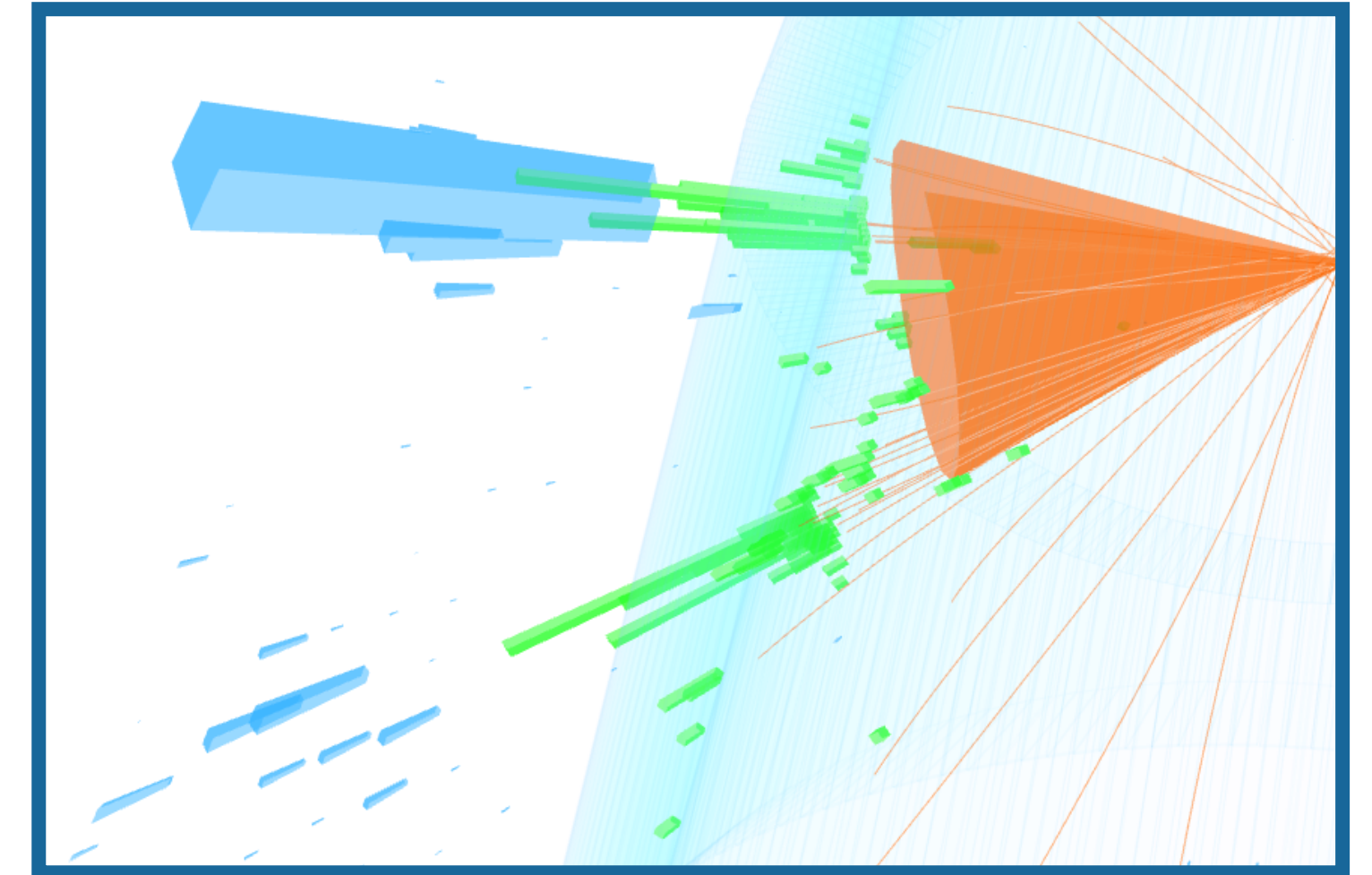




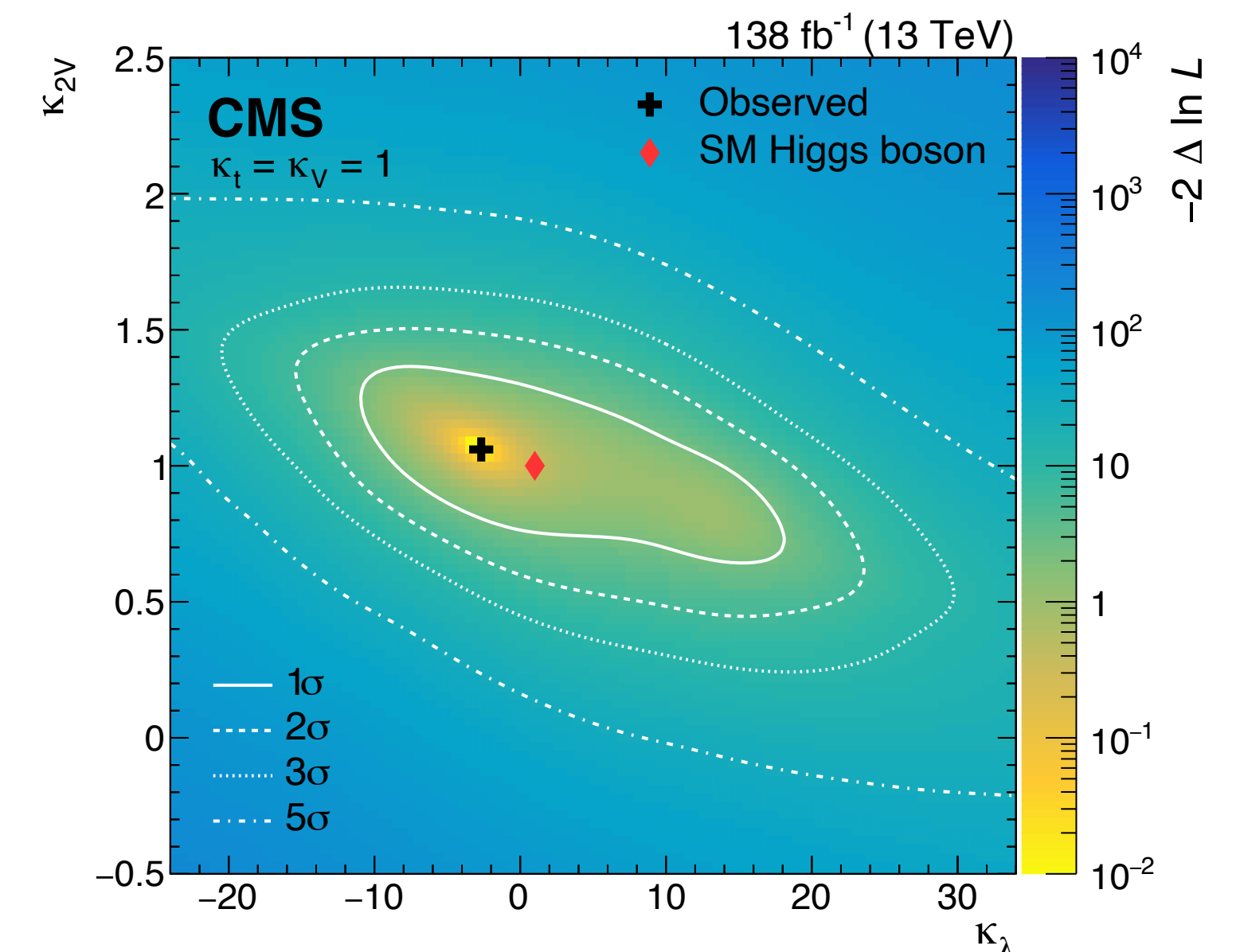
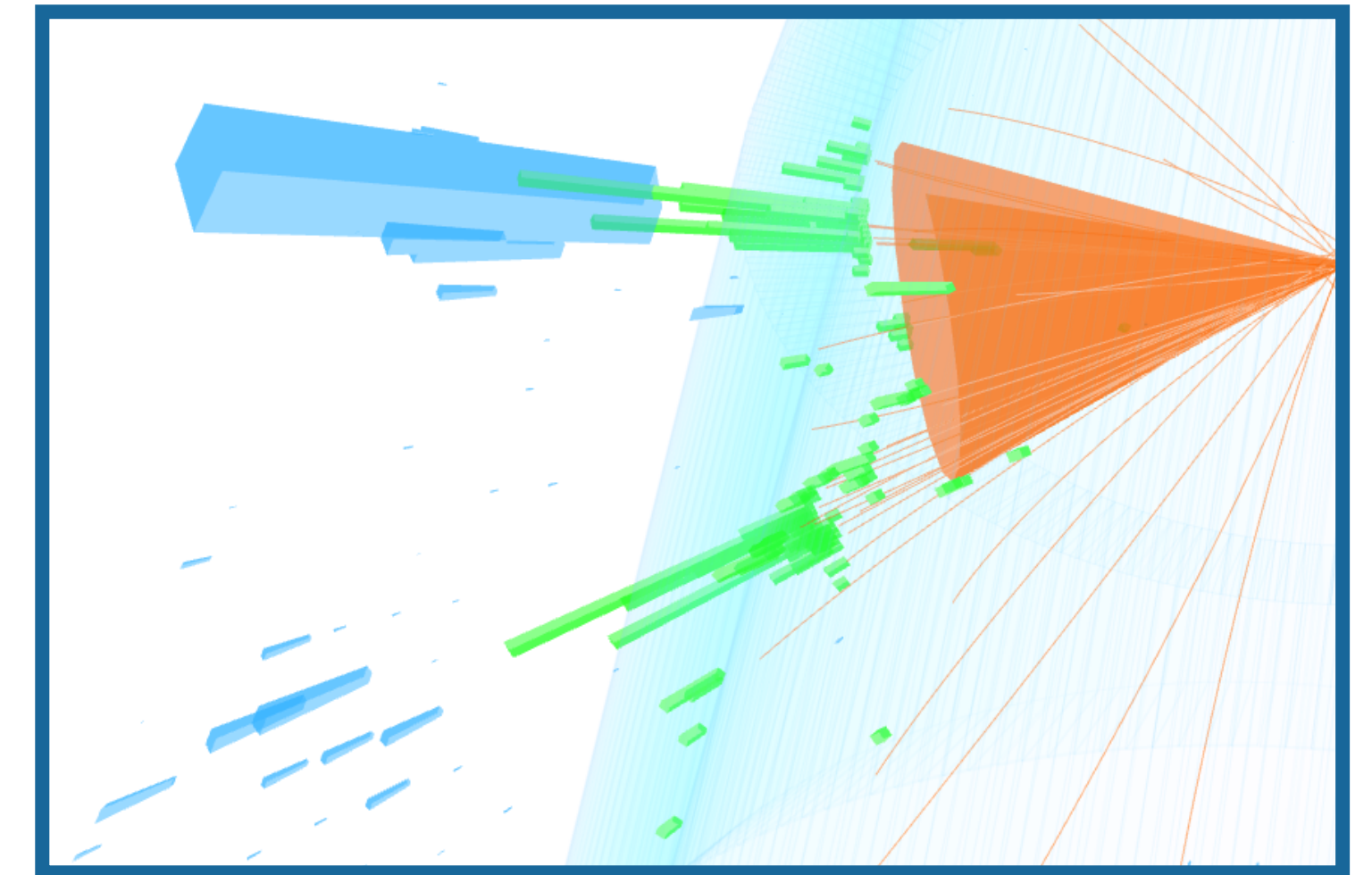
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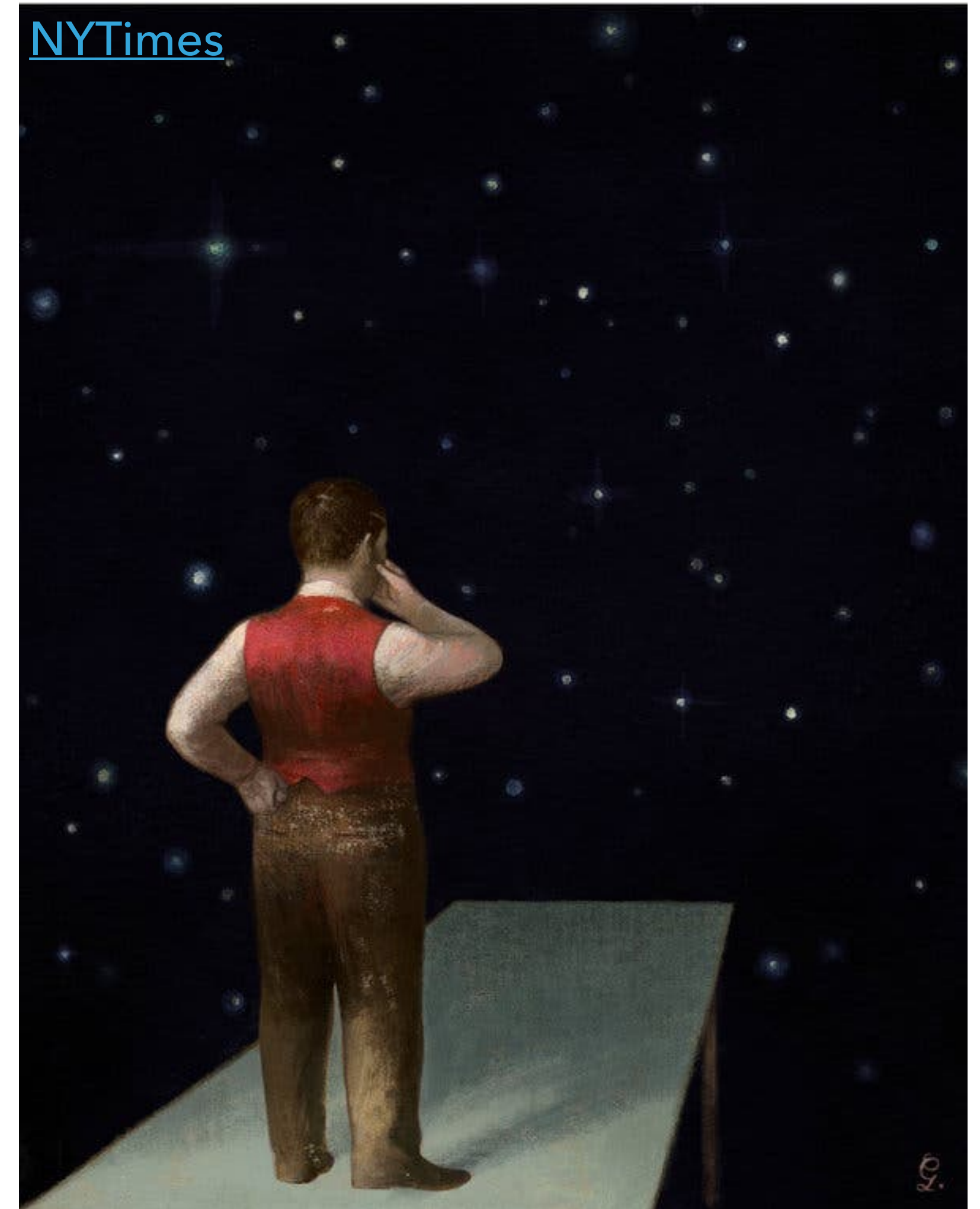
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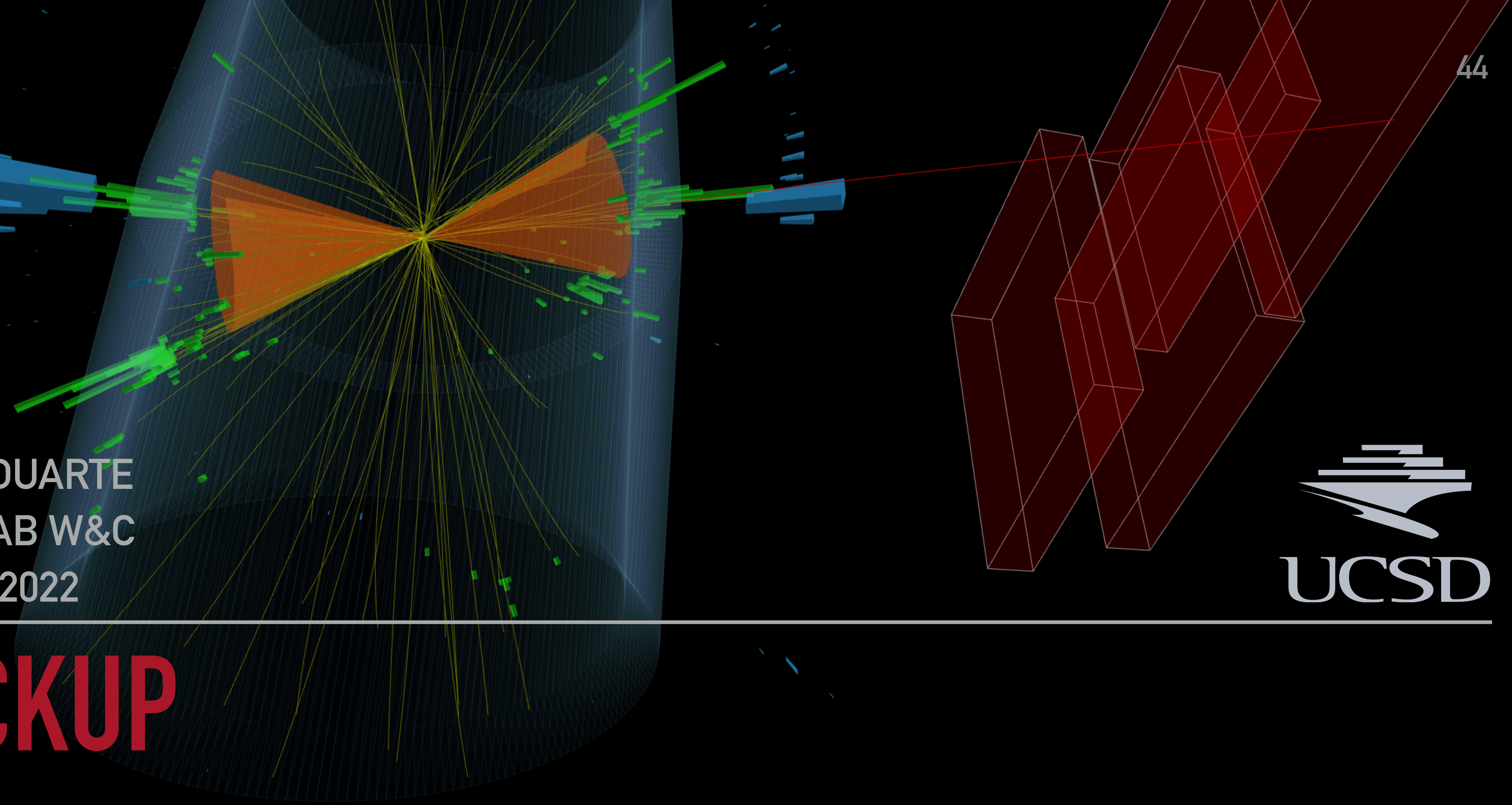
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- ▶ Looking toward the HL-LHC, boosted HH searches ***can put us over the edge of "discovery"***

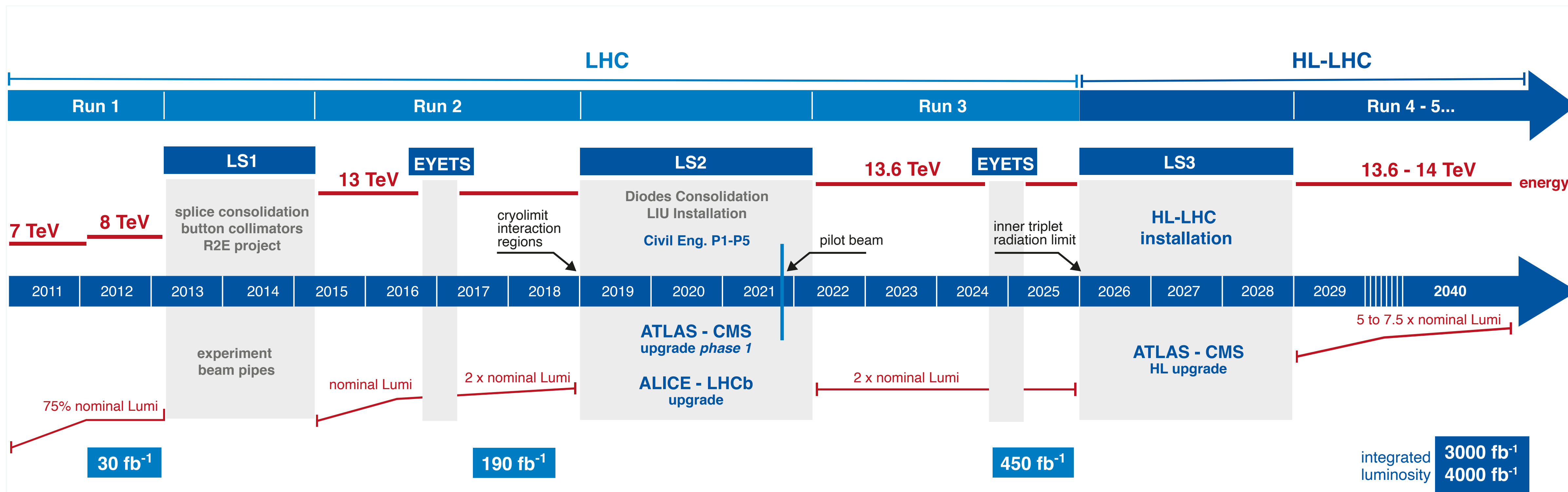


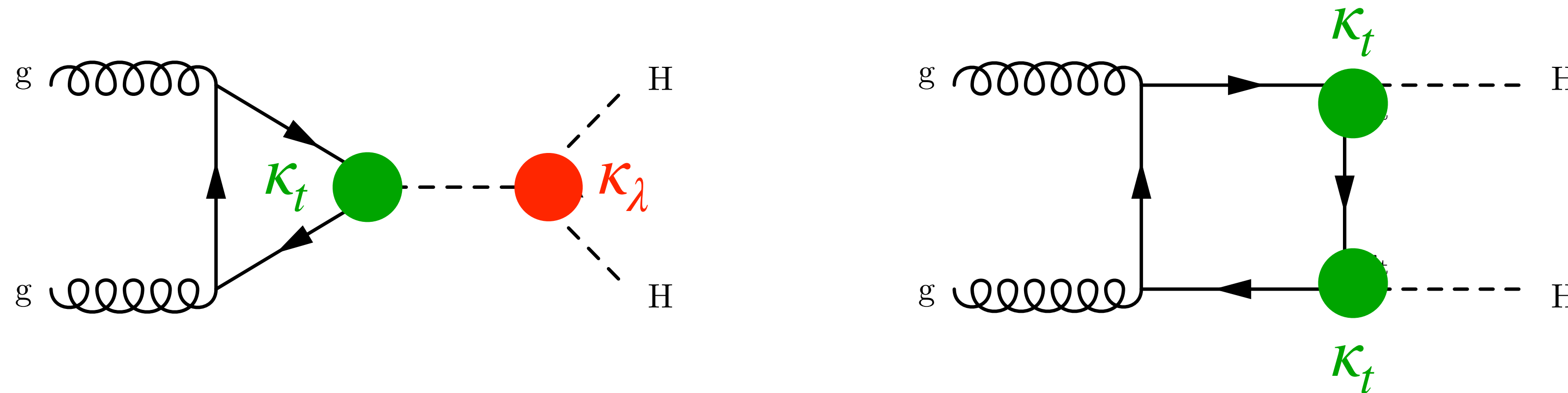
JAVIER DUARTE
FERMILAB W&C
JUNE 3, 2022



BACKUP





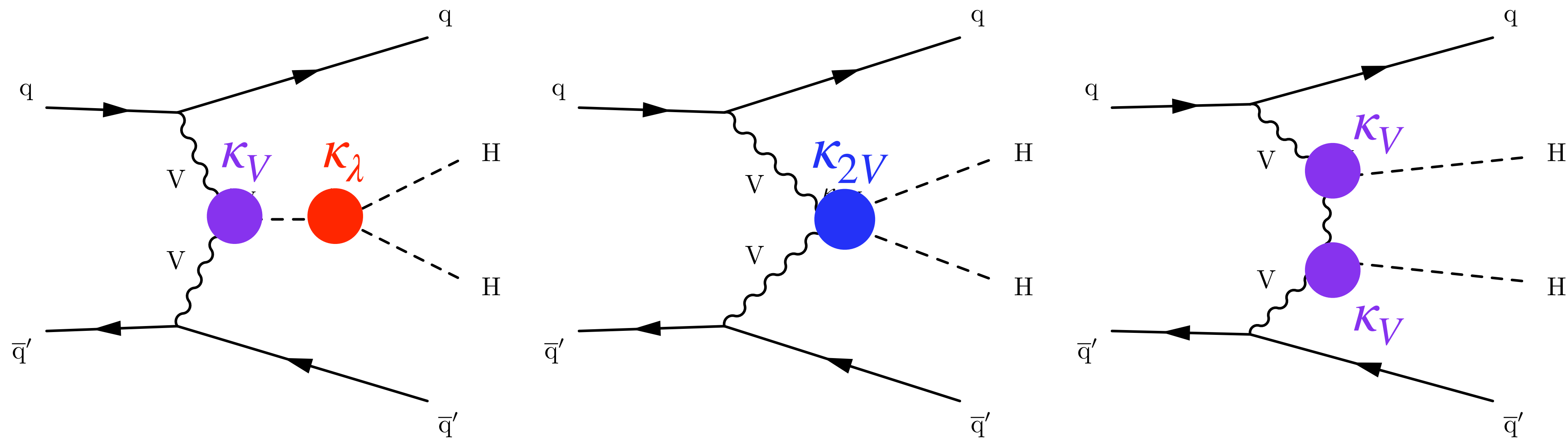


$$\mathcal{M} = \kappa_t^2 \kappa_\lambda^2 \mathcal{T} + \kappa_t^2 \mathcal{B}$$

$$\begin{aligned} \sigma(\kappa_t, \kappa_\lambda) &\sim |\mathcal{M}|^2 = \kappa_t^2 \kappa_\lambda^2 |\mathcal{T}|^2 + \kappa_t^4 |\mathcal{B}|^2 + \kappa_t^3 \kappa_\lambda |\mathcal{T}^* \mathcal{B} + \mathcal{B}^* \mathcal{T}| \\ &= \kappa_t^2 \kappa_\lambda^2 t + \kappa_t^4 b + \kappa_t^3 \kappa_\lambda i \end{aligned}$$

- ▶ Templates $(\kappa_\lambda, \kappa_t) = (1, 1), (2.45, 1), (5, 1)$ chosen for continuous morphing

$$D_{\text{ggF}}(\kappa_\lambda, \kappa_t) = \mu \mu_{\text{ggF}} \sum_i^3 f_{\text{ggF}}^i(\kappa_\lambda, \kappa_t) D_{\text{ggF}}^i$$



$$\mathcal{M} = \kappa_V \kappa_\lambda \mathcal{A} + \kappa_V^2 \mathcal{B} + \kappa_{2V} \mathcal{C}$$

$$\sigma(\kappa_\lambda, \kappa_V, \kappa_{2V}) \sim |\mathcal{M}|^2 = \kappa_V^2 \kappa_\lambda^2 a + \kappa_V^4 b + \kappa_{2V}^2 c + \kappa_V^3 \kappa_\lambda i_{ab} + \kappa_V \kappa_{2V} \kappa_\lambda i_{ac} + \kappa_V^2 \kappa_{2V} i_{bc}$$

- Templates $(\kappa_{2V}, \kappa_V, \kappa_\lambda) = (1, 1, 1), (1, 1, 0), (1, 1, 2), (1, 0, 1), (1, 2, 1), (1.5, 1, 1)$ chosen for continuous morphing

$$D_{\text{VBF}}(\kappa_{2V}, \kappa_V, \kappa_\lambda) = \mu \mu_{\text{VBF}} \sum_i^6 f_{\text{VBF}}^i(\kappa_{2V}, \kappa_V, \kappa_\lambda) D_{\text{VBF}}^i$$

► Specialized components to measure different particles

► 100 million channels

