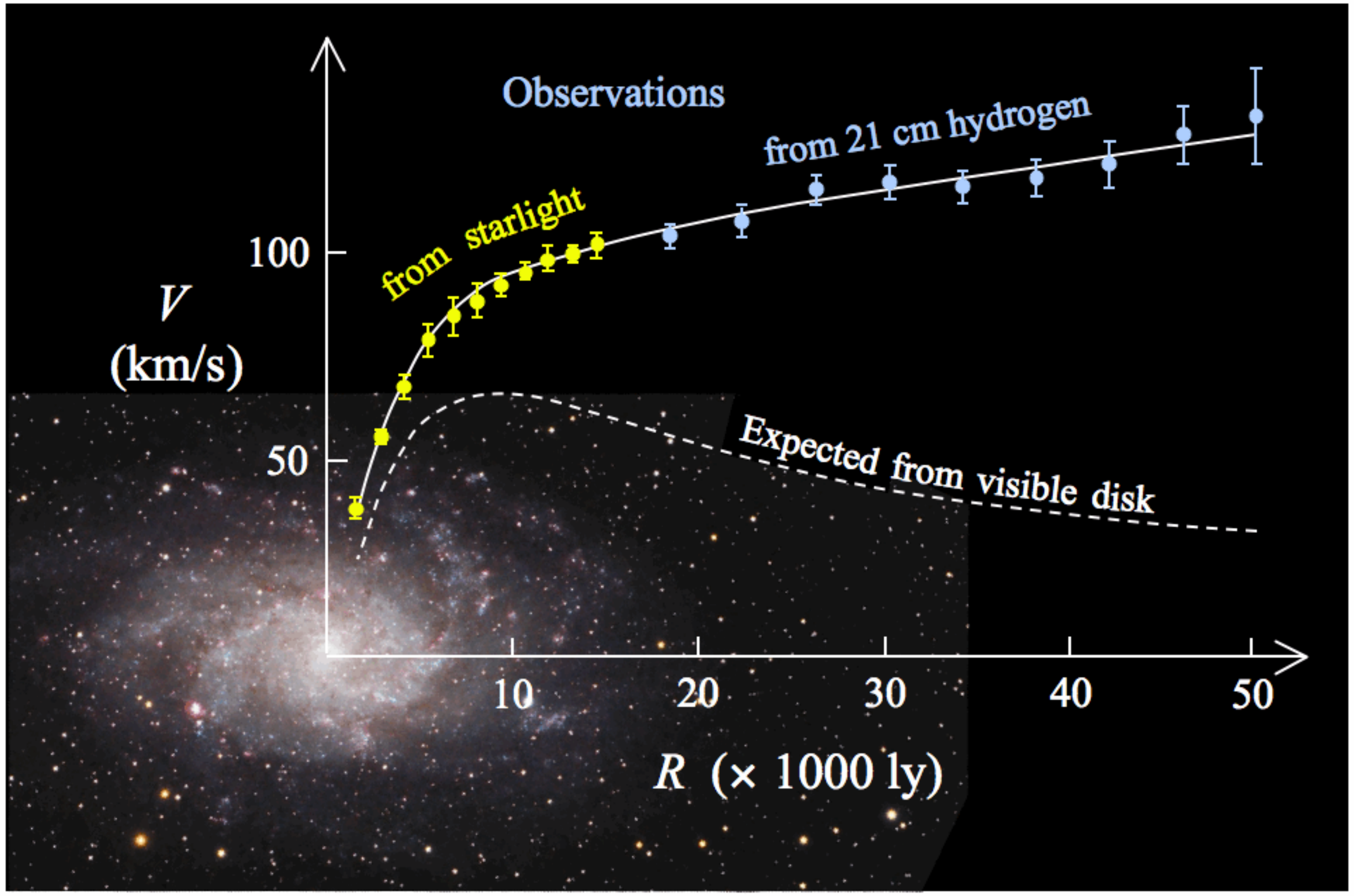
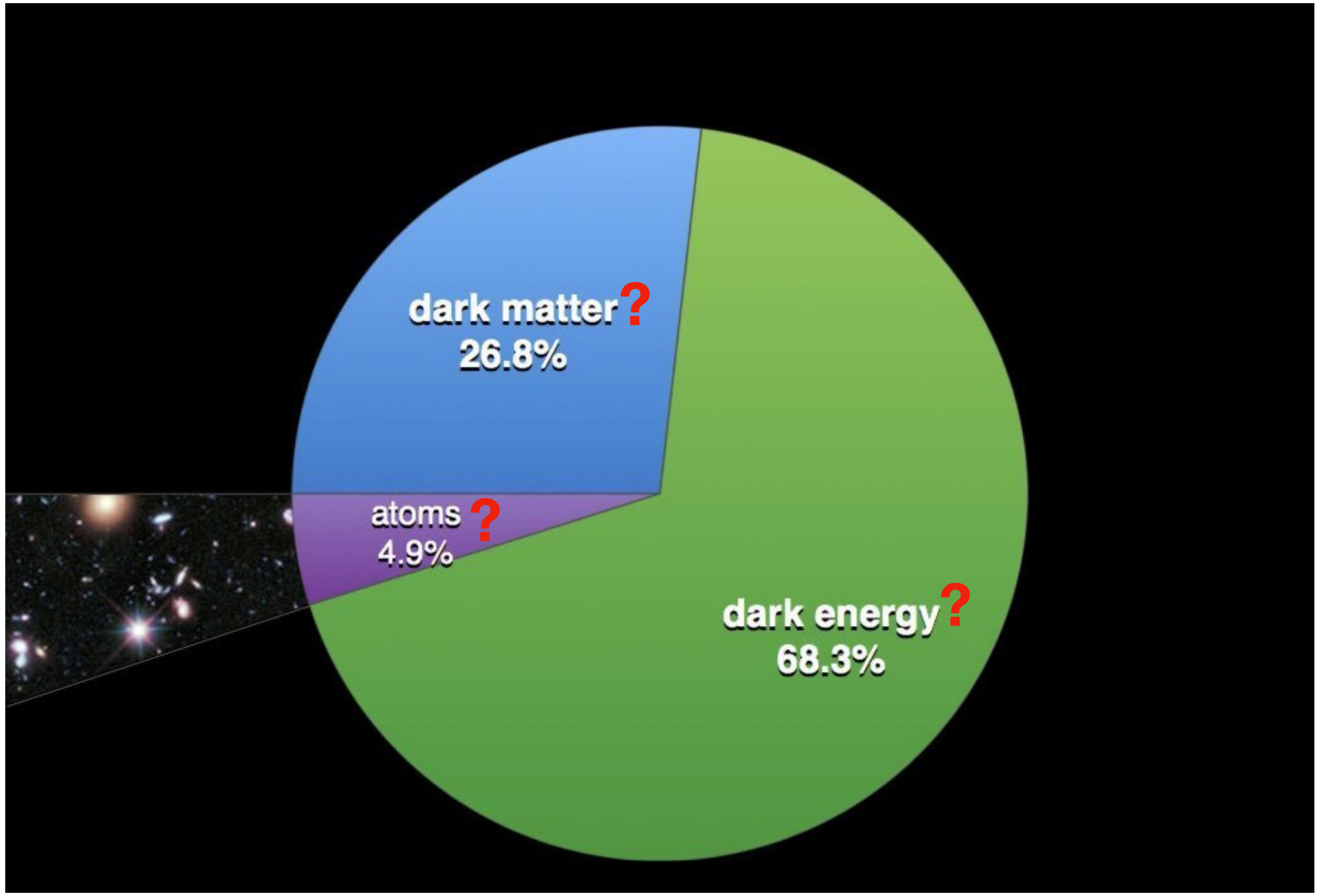
Why stop at two?
The search for HHH production

Kevin Nelson
SLAC Seminar
21 January, 2025

We've already seen "new physics"





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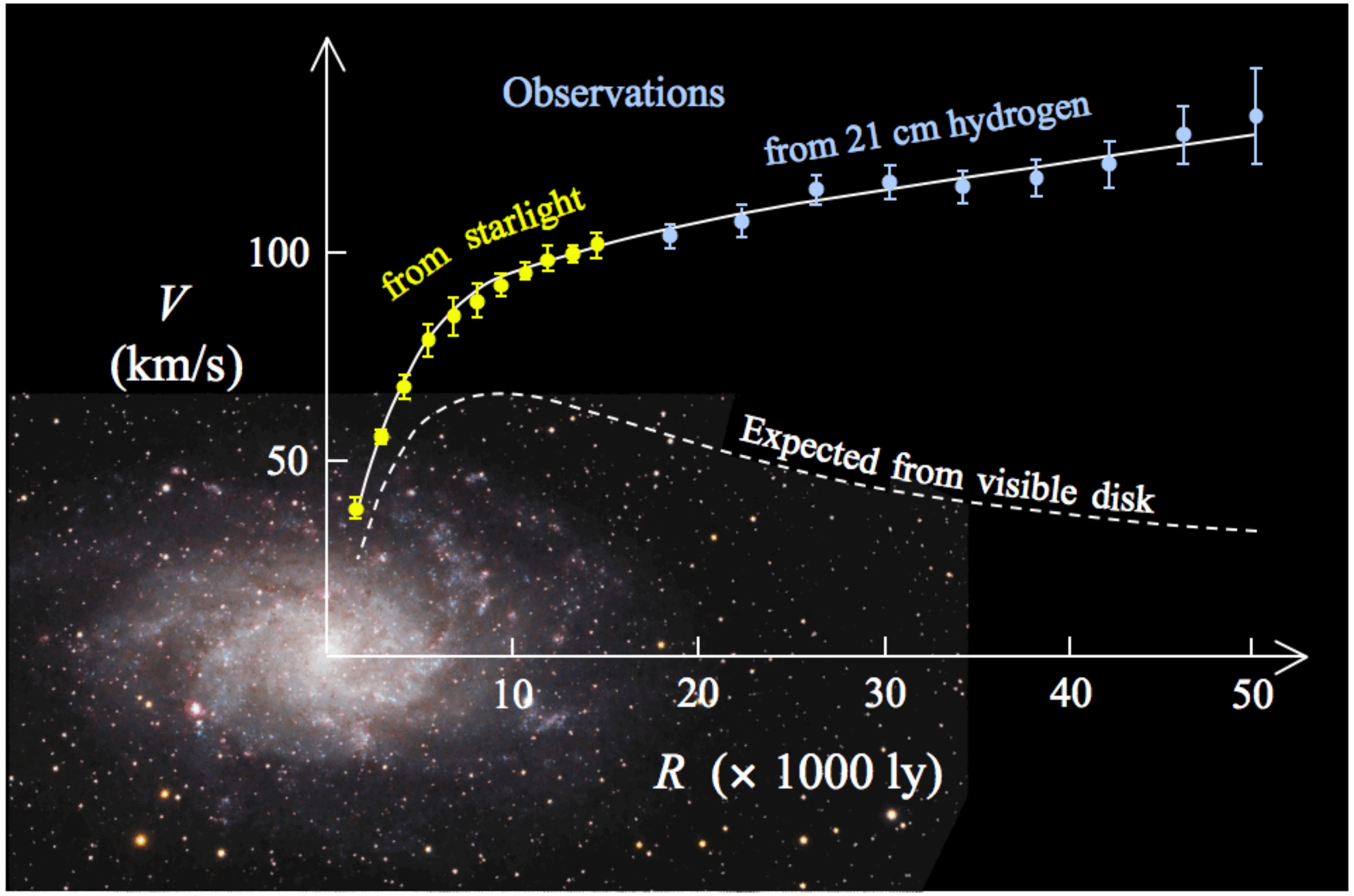

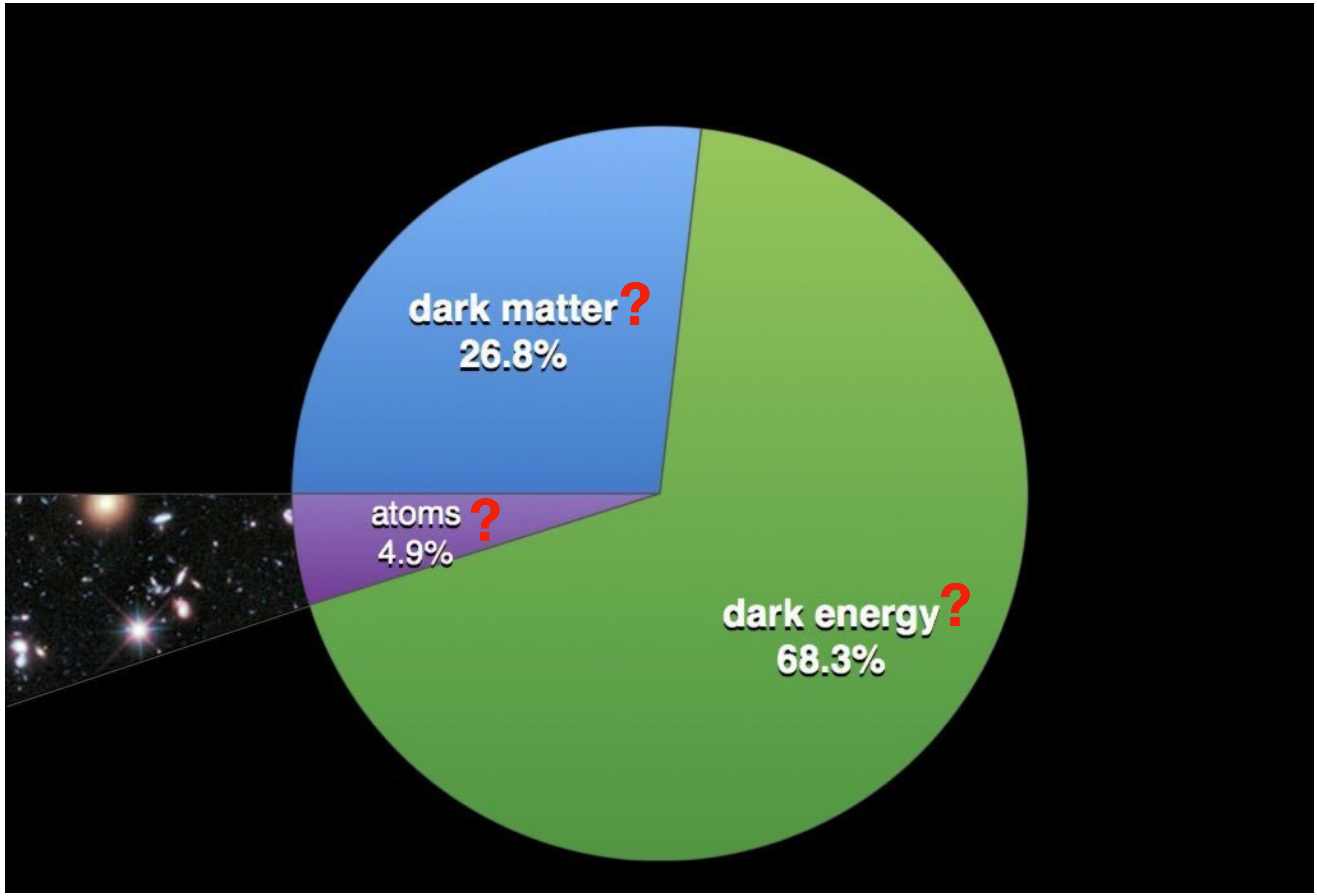

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  - Are there mediators between dark and luminous matter?
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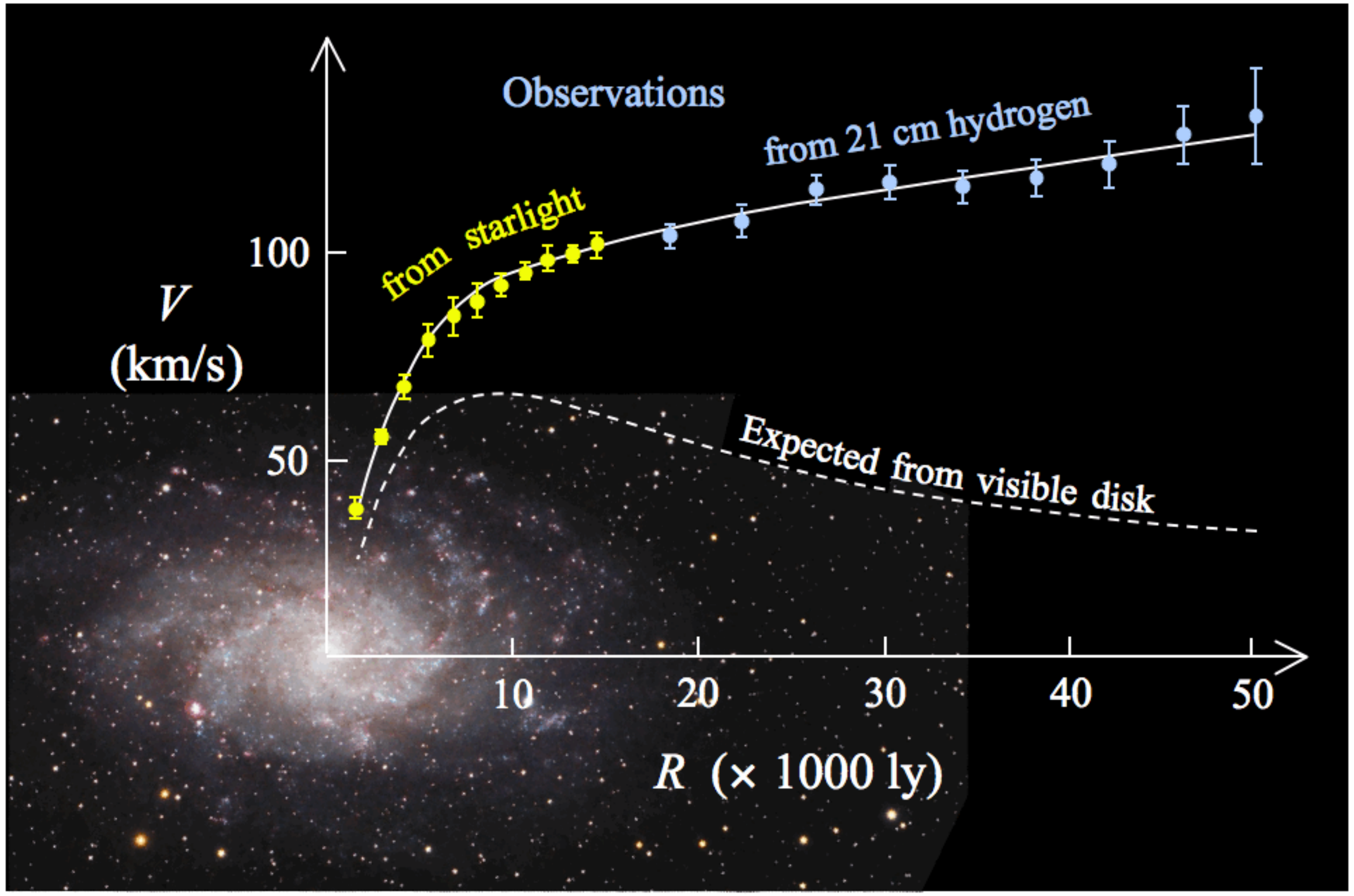

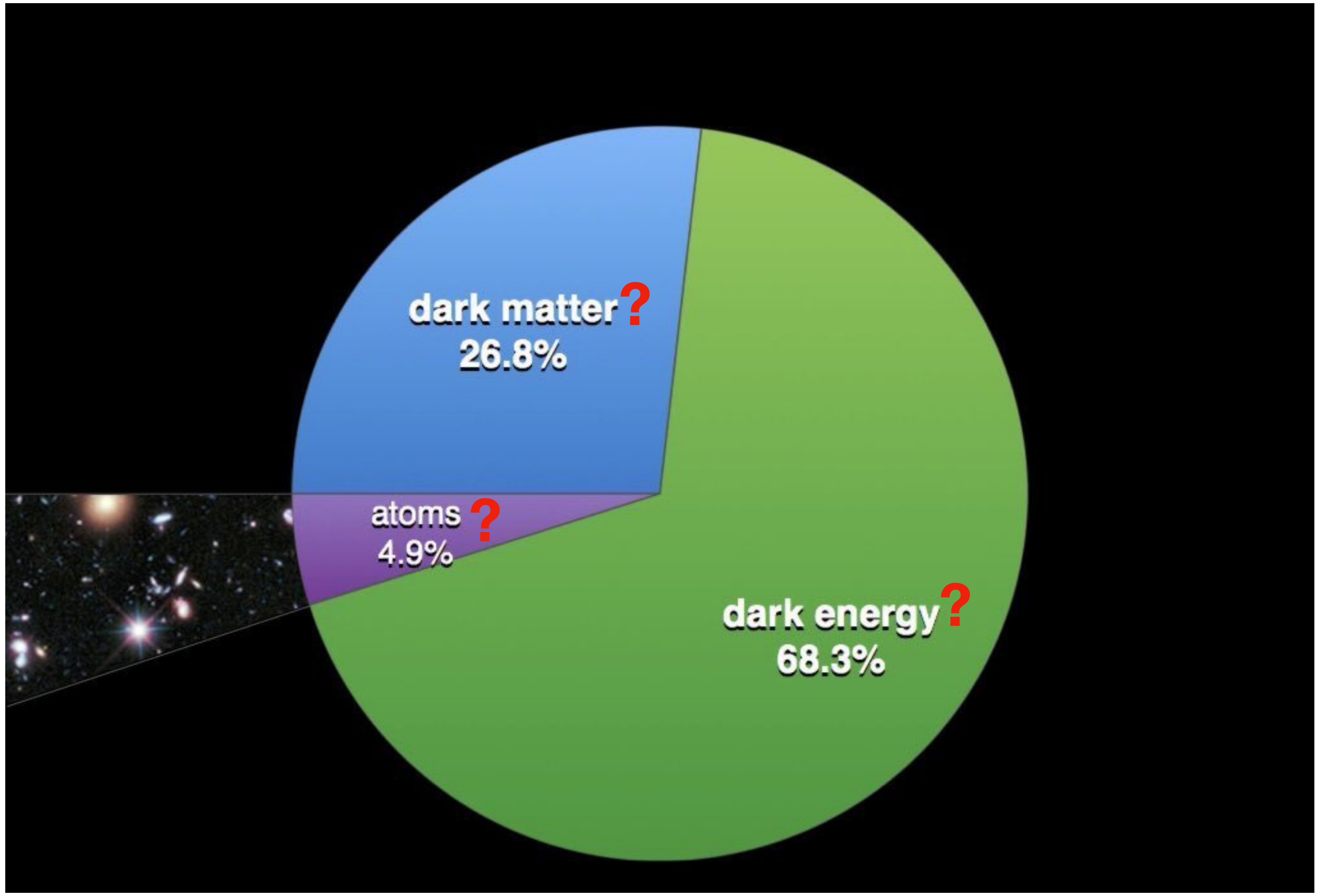

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All of these questions are related to the search for HHH!

Can we use modern AI methods to find it?

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Yes, there is physics beyond the Standard Model. The Standard Model of particle physics is a highly successful theory that describes the electromagnetic, weak, and strong nuclear forces, along with the particles that make up matter, such as quarks, leptons, and bosons. However, it is known to be incomplete and has several limitations. Some of the major areas of physics beyond the Standard Model (BSM) include:

1. Gravity

The Standard Model does not include gravity. General relativity describes gravity on a large scale, but it is not compatible with quantum mechanics, which underlies the Standard Model. A theory of


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Automated data
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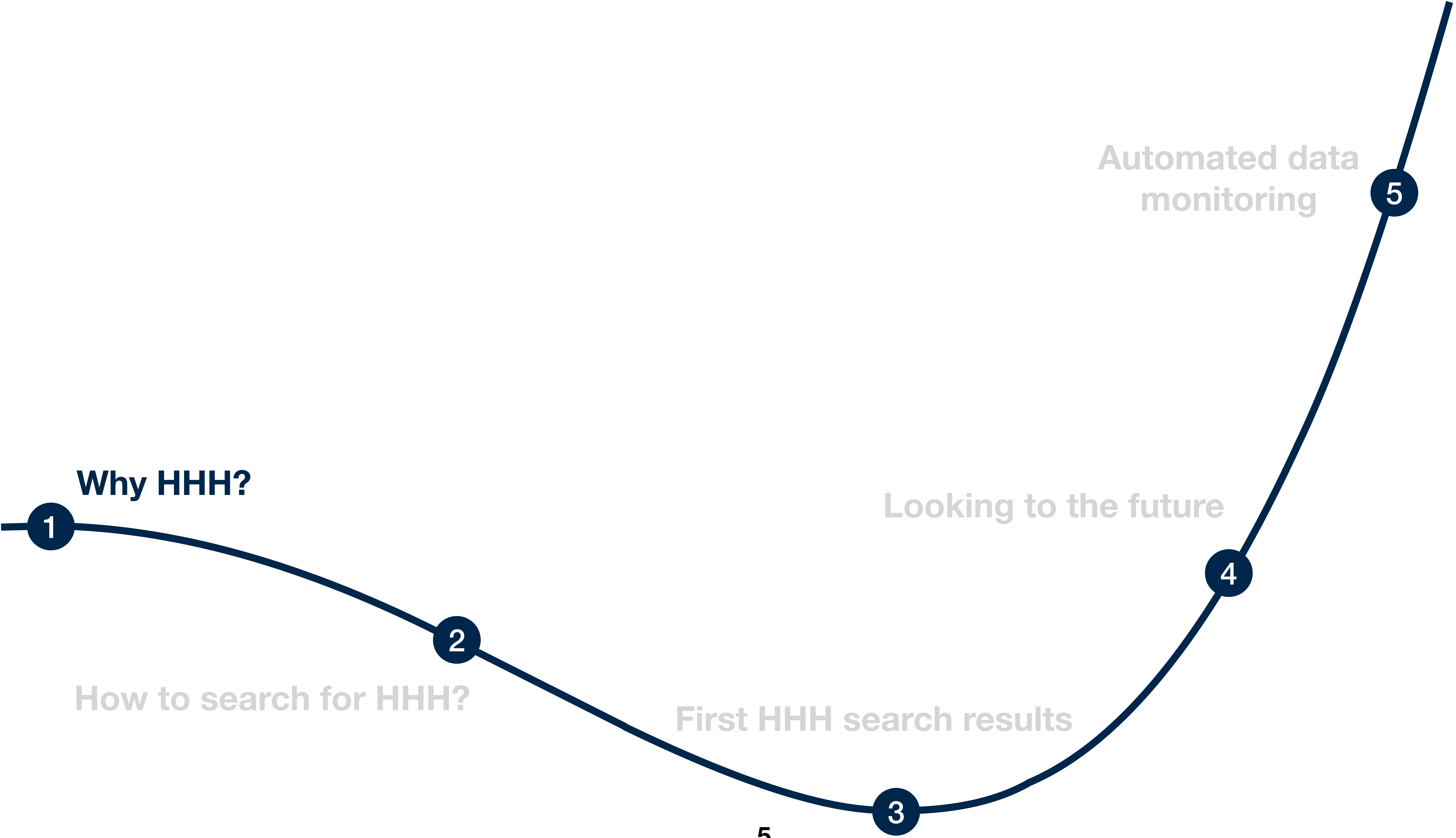
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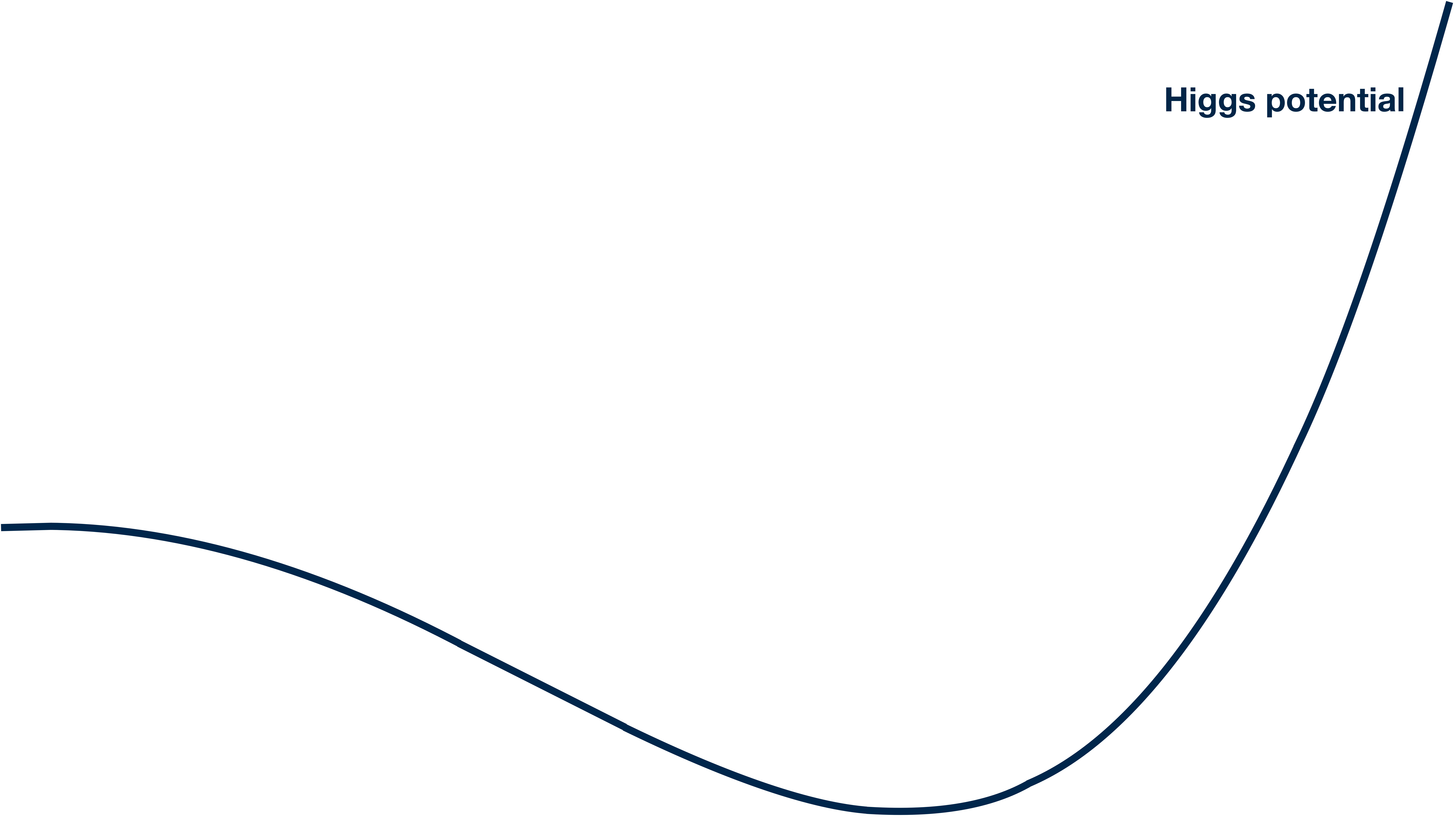
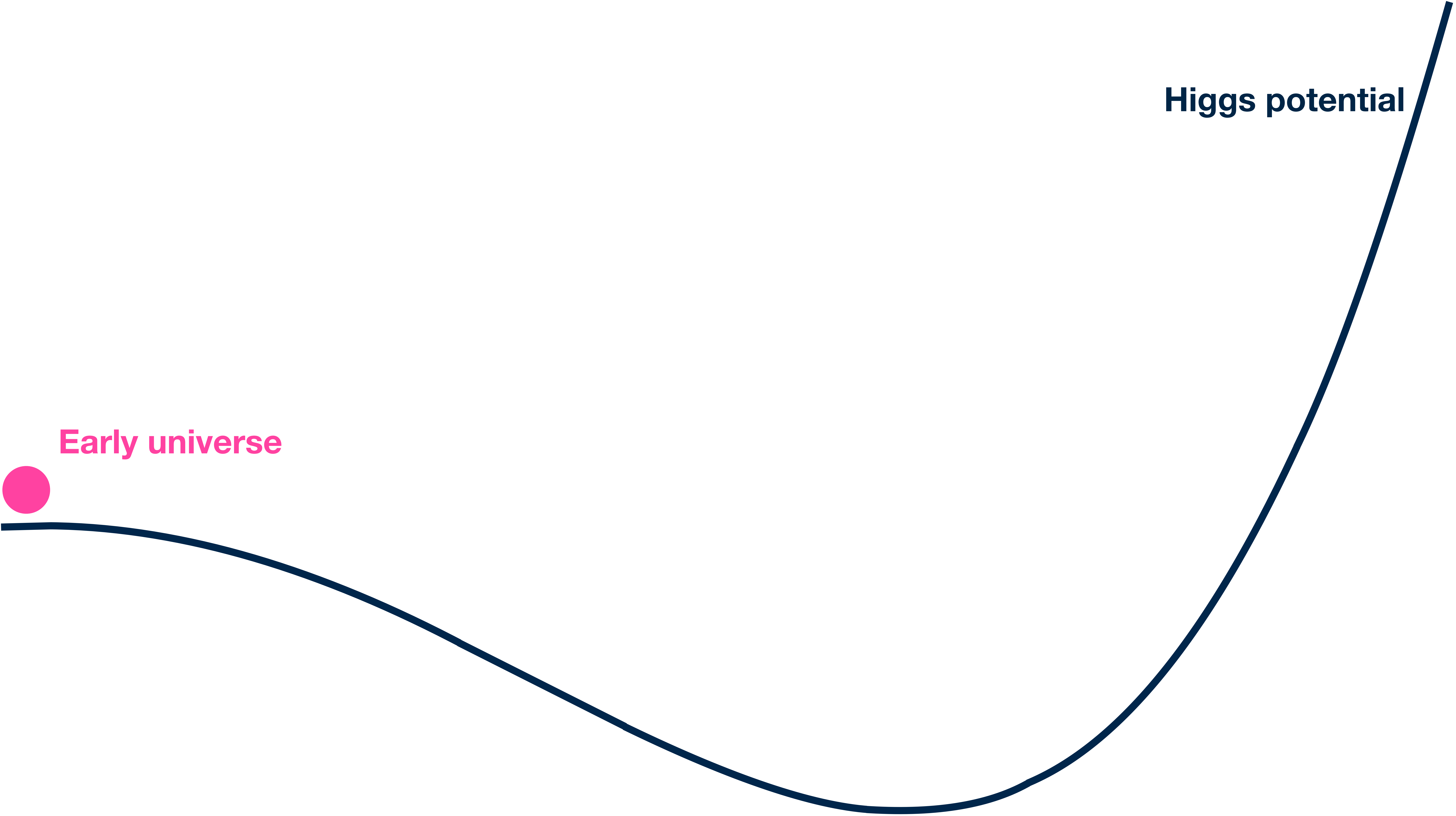
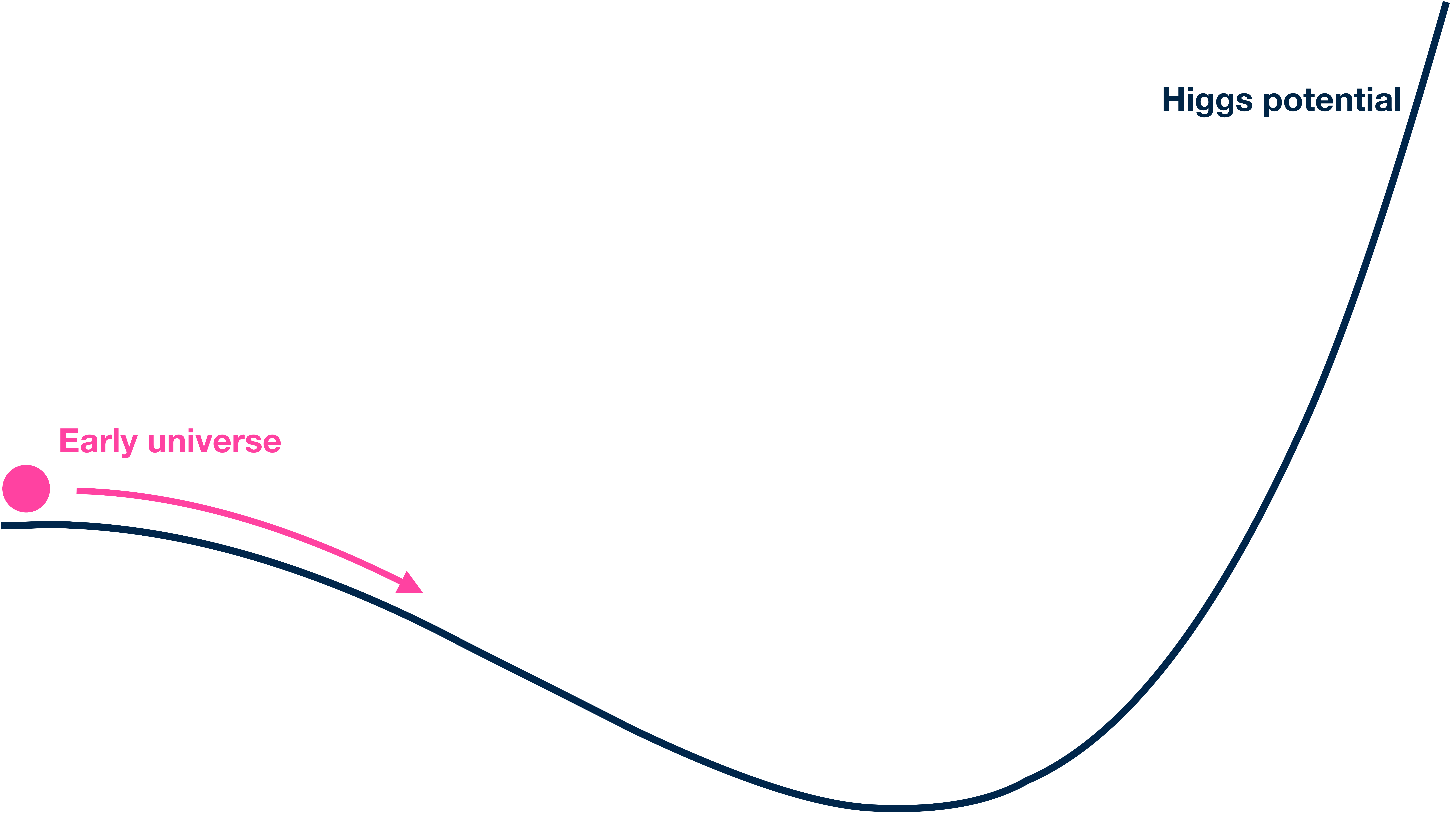

Higgs potential


Early universe
Higgs potential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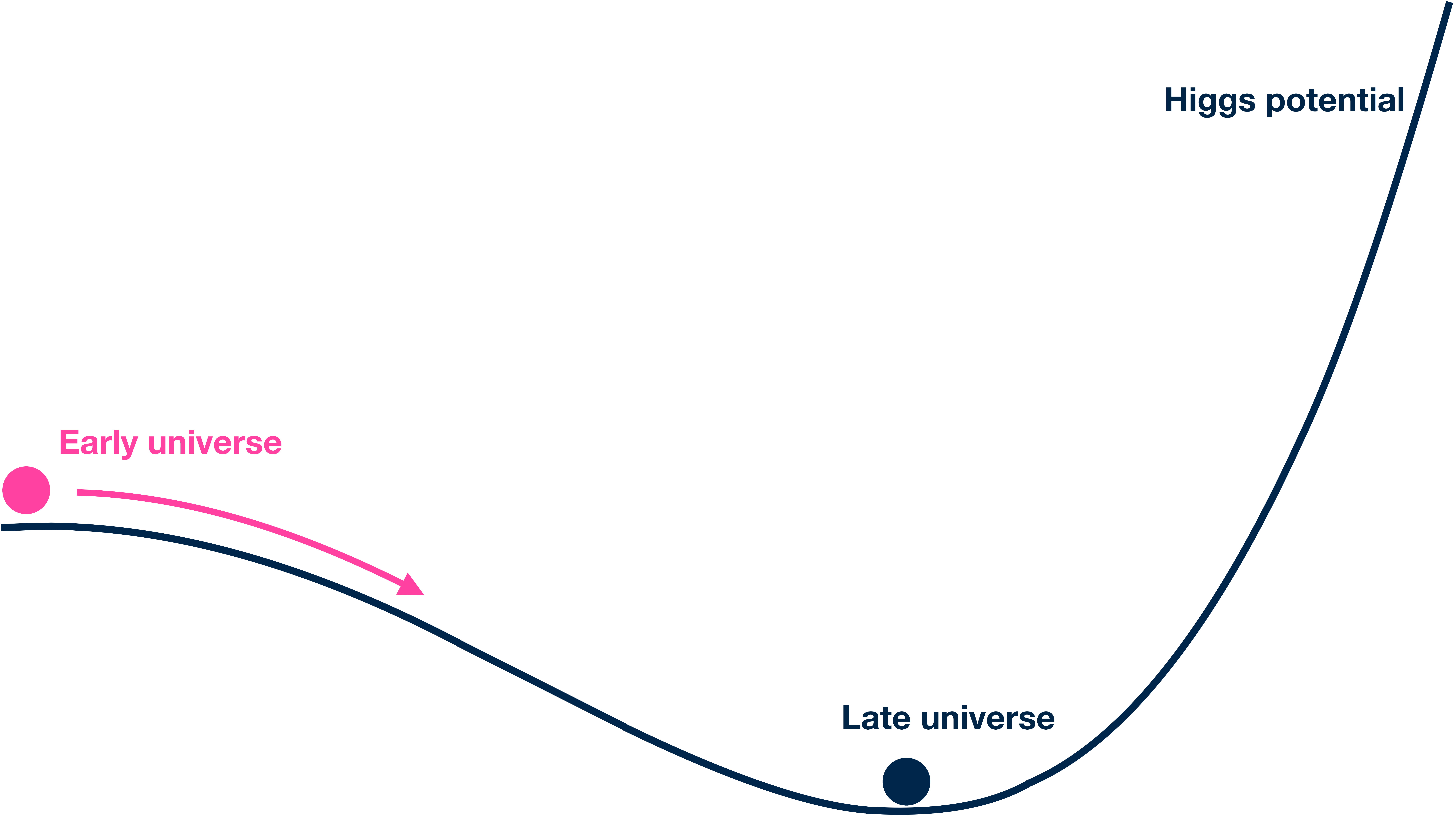
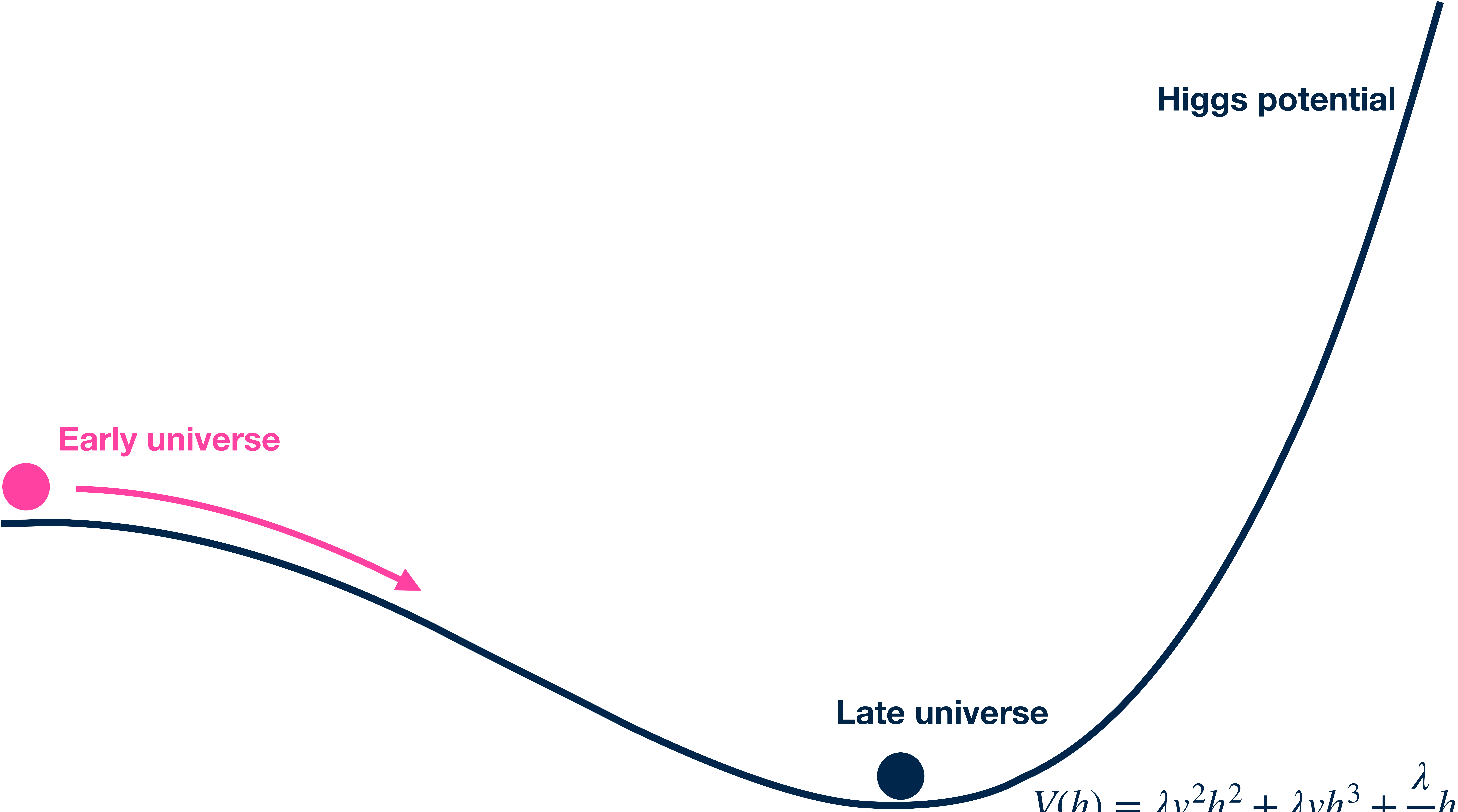

Higgs potential
Early universe
Late universe



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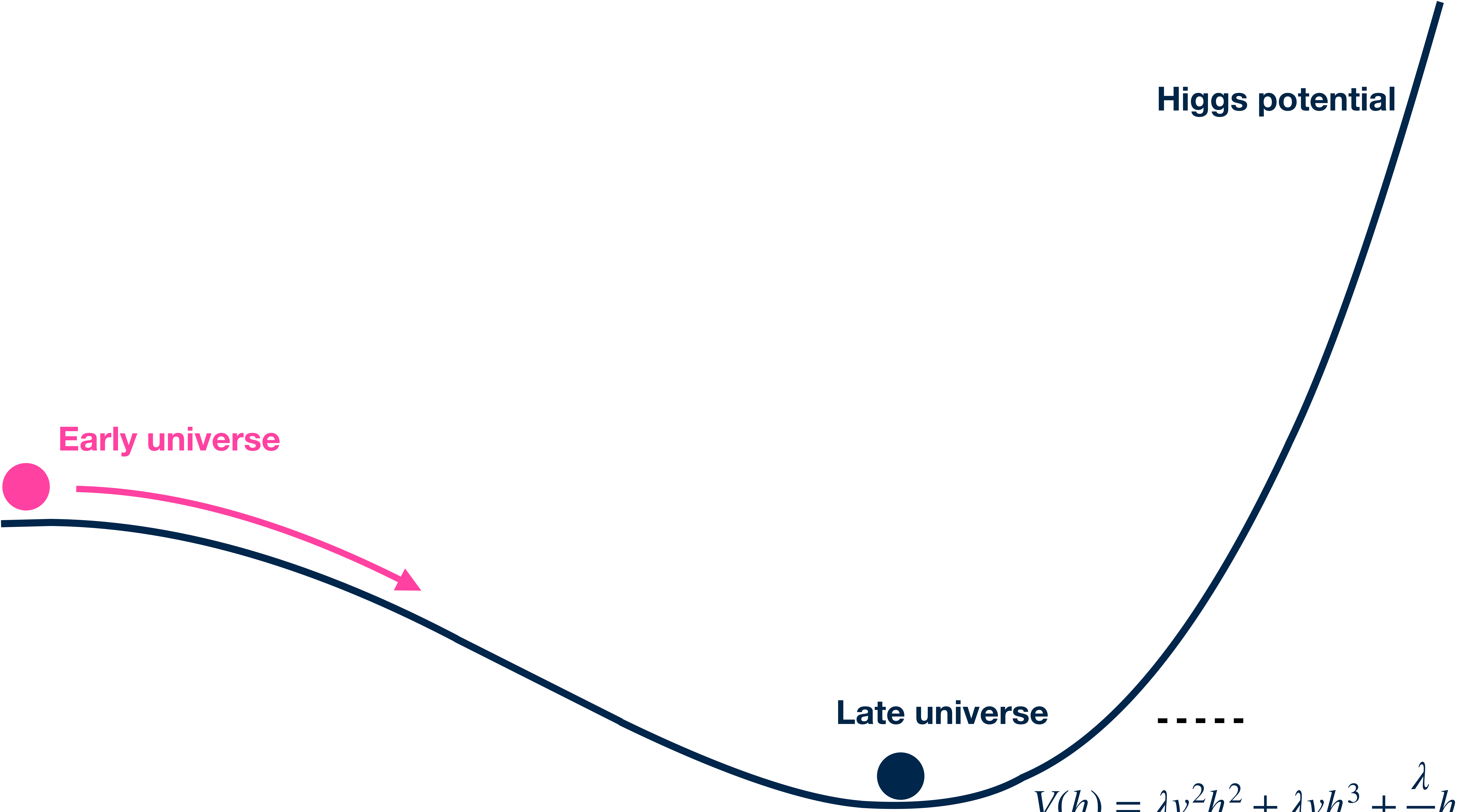

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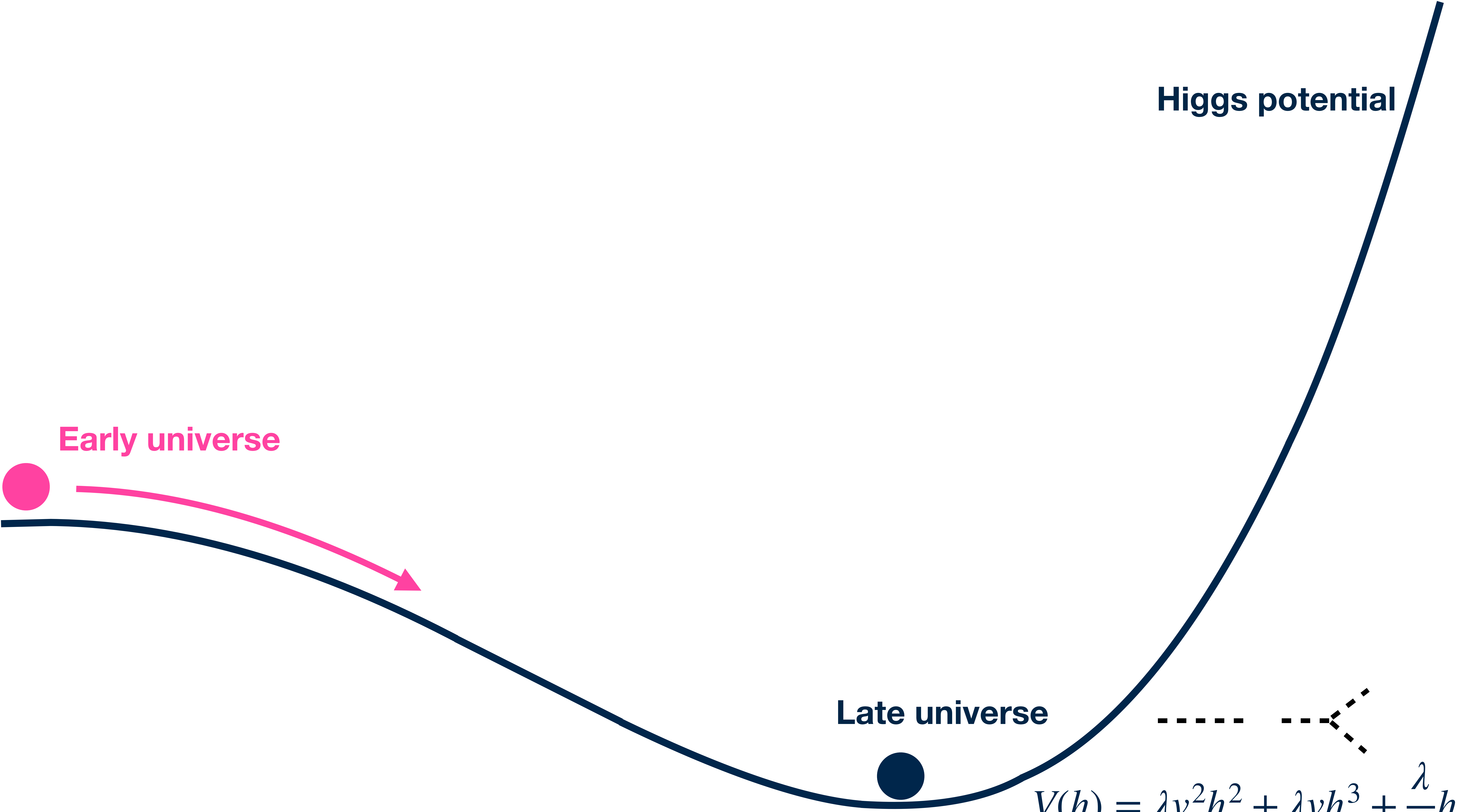

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Higgs potential
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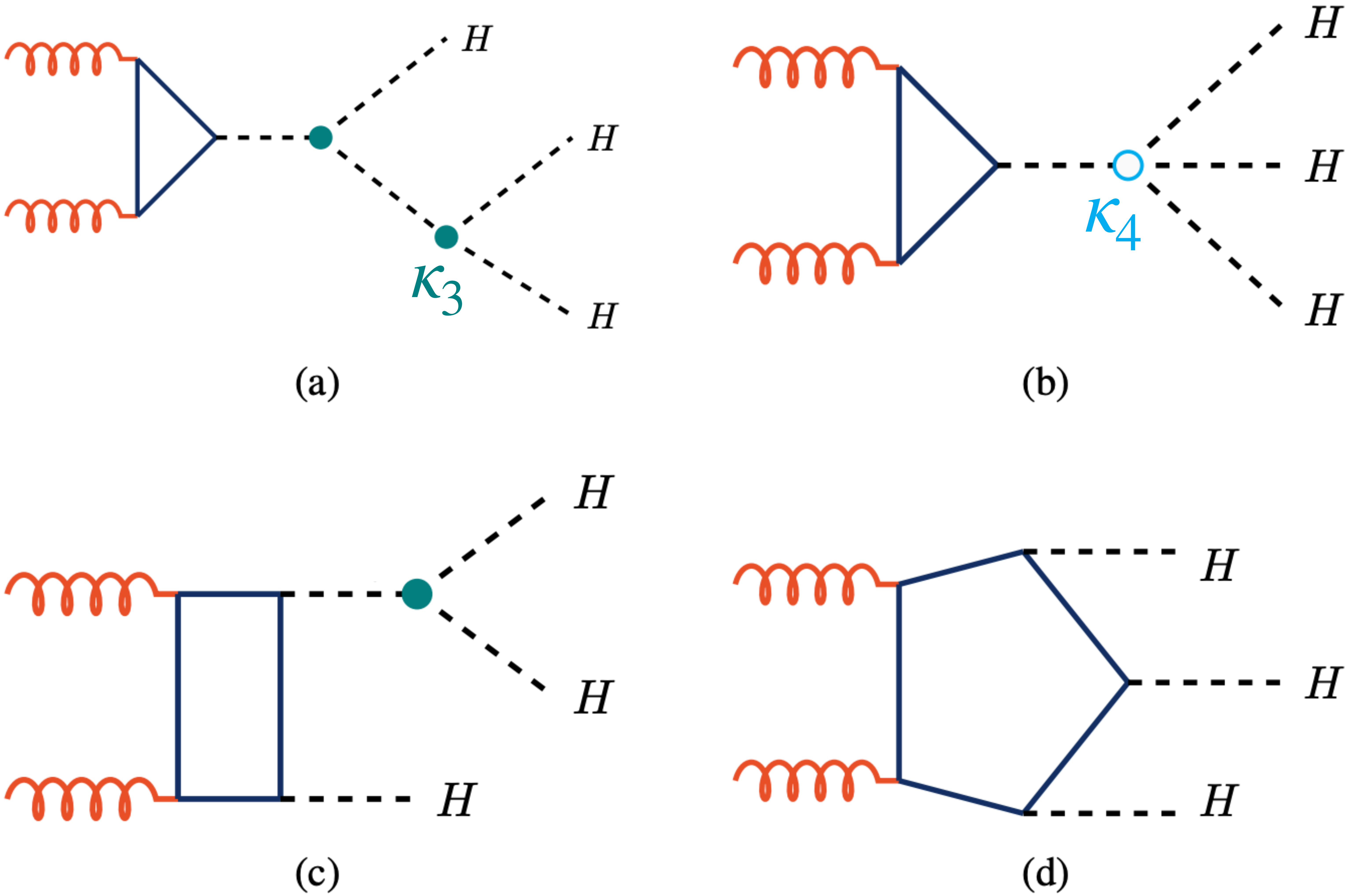
- Effect on the late universe: modifications to Higgs self-coupling κ_3, κ_4

Why HHH?



$\sigma_{SM} = 0.079$ **fb**

Why HHH?

- **Measuring the shape of the Higgs potential probes electroweak baryogenesis**
  - Provides unique access to the quartic coupling κ_4
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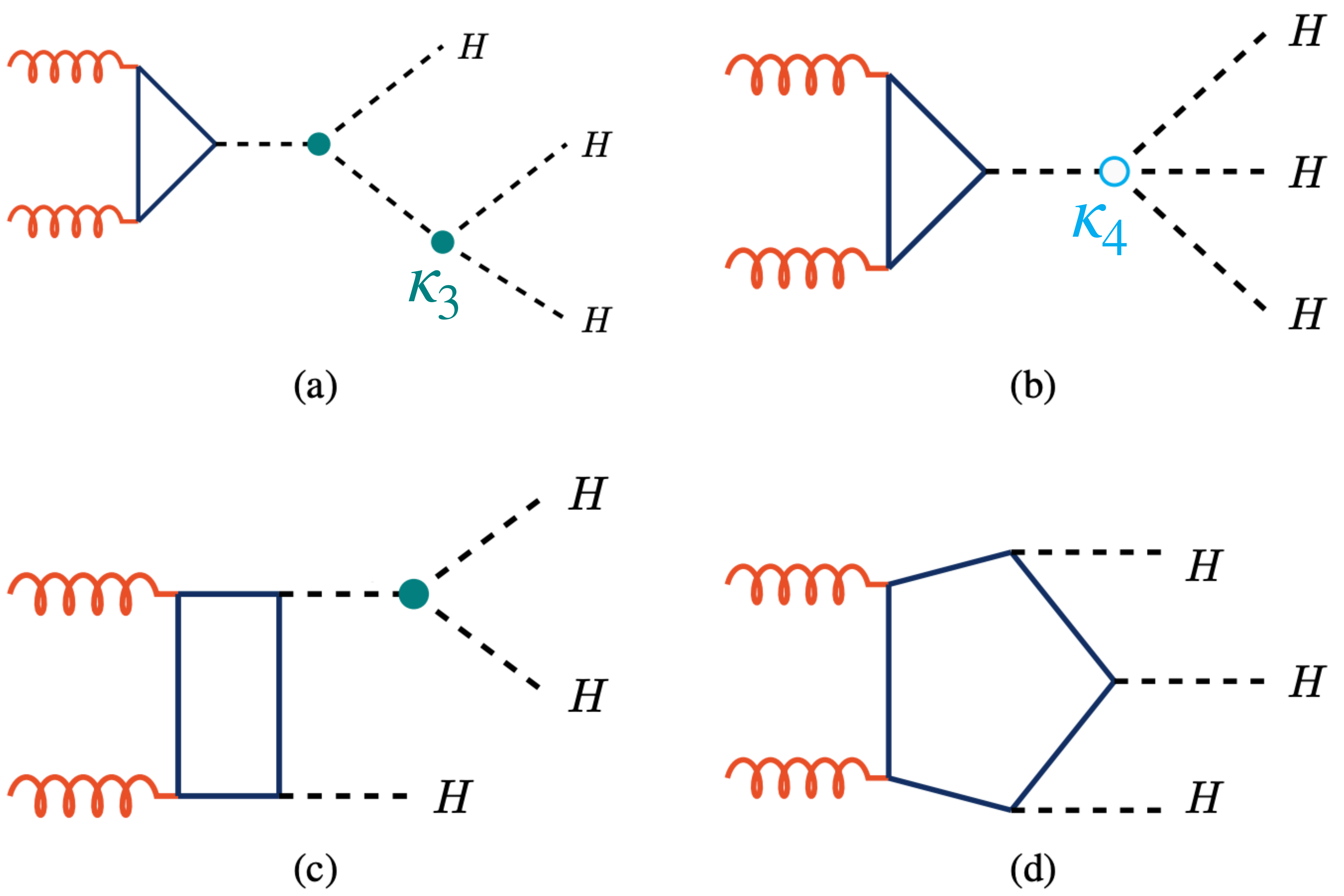

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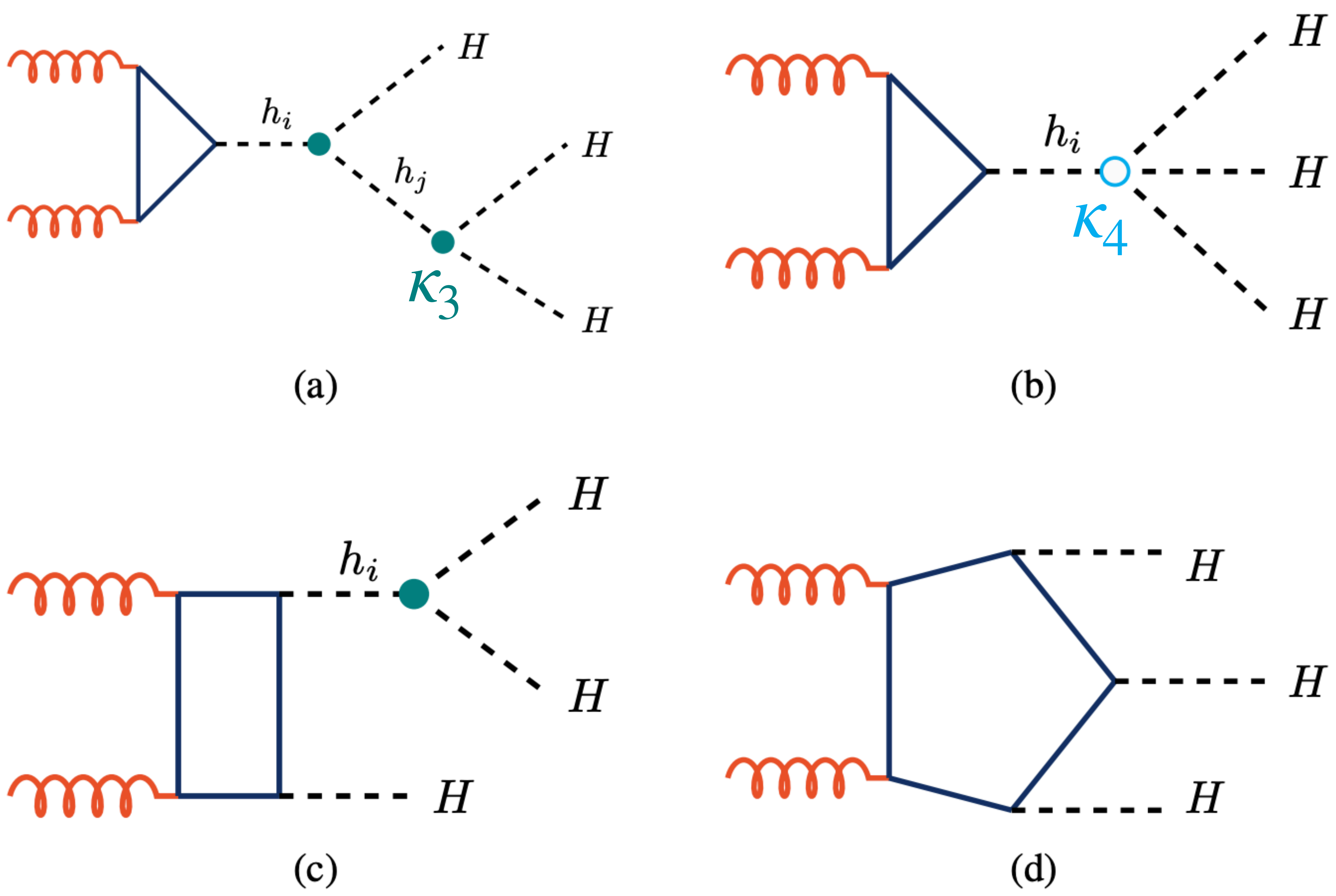
- **BSM theories can predict enhanced HHH, even above HH production**
  - h_i, h_j can be new scalars
  - HHH production can be 100s fb when new scalars are present: [1908.08554], [2211.10557]
  - Additional scalars can provide sources of dark matter, CP violation: [2202.02954]
    - CP violation in the scalar potential and/or between scalars and DM.



$\sigma_{BSM} \approx 100$ **fb**

TRSM model

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- **Add two new real singlets to SM:**
  - Both can have a VeV, which leads to HHH

$$\Phi = \begin{pmatrix} 0 \\ \frac{\phi_h + v}{\sqrt{2}} \end{pmatrix}, \quad S = \frac{\phi_S + v_S}{\sqrt{2}}, \quad X = \frac{\phi_X + v_X}{\sqrt{2}}$$

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  - Note: the new particles are SM singlets, so Z_2 symmetries have nothing to do with FCNCs here!
  - More relevant for vacuum stability: bounding scalar potential from below.

$$\mathbb{Z}_2{}^S : \quad S \to -S\,, \; X \to X\,, \; \mathrm{SM} \to \mathrm{SM}\,,$$
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  - 3 mixing angles
  - 2 unkown masses
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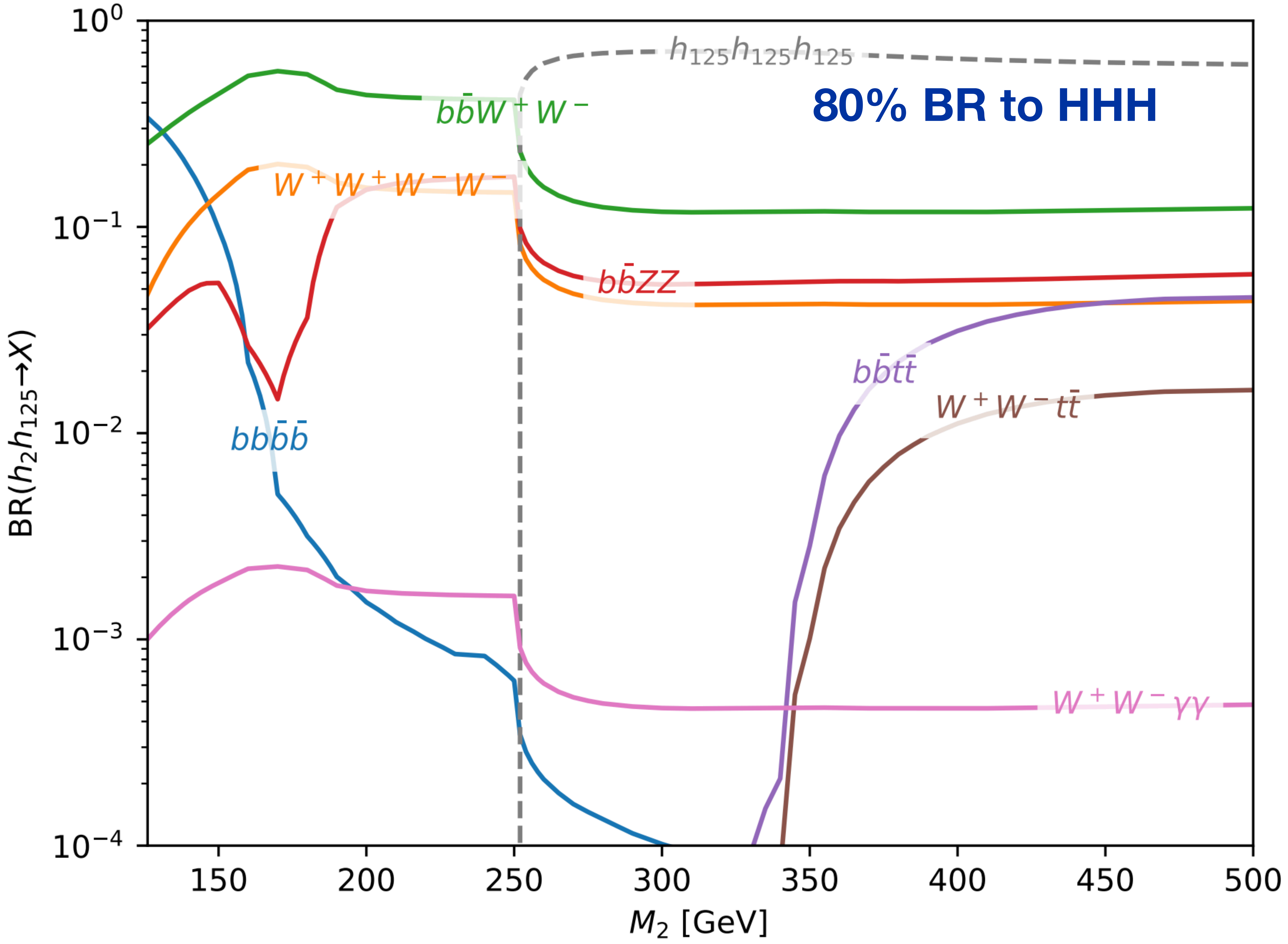
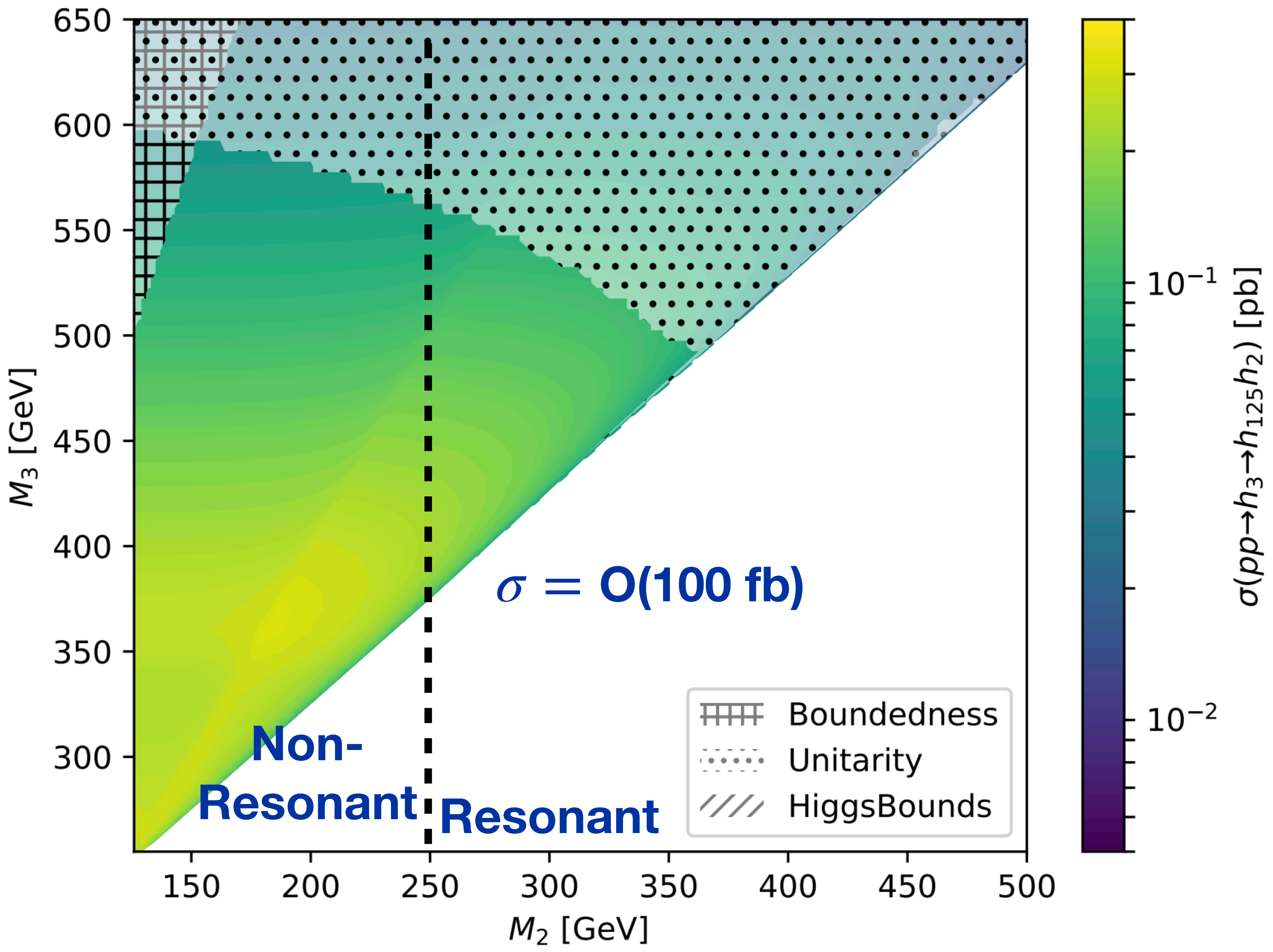
- **Scalar couplings, mixing from V:**
  - Remember, any can have VeV

$$V = \mu_\Phi^2 \Phi^\dagger \Phi + \lambda_\Phi (\Phi^\dagger \Phi)^2 + \mu_S^2 S^2 + \lambda_S S^4 + \mu_X^2 X^2 + \lambda_X X^4 + \lambda_{\Phi S} \Phi^\dagger \Phi S^2 + \lambda_{\Phi X} \Phi^\dagger \Phi X^2 + \lambda_{SX} S^2 X^2\,.$$

BSM searches

- In a **most favorable** scenario, $X \to SH$ is up to ~150 of fb and $Br(SH \to HHH)$ is up to 80%
- A large HHH signal which could be visible in Run 2 at the LHC





[1908.08554]

DM-CPV model

- **A simple model of dark matter and CP violation: [2202.02954]**
- **Similar phenomenology due to a complex scalar instead of 2 real scalars**
  - Also introduces a dark vector-like fermion χ
- **More free parameters and Z_2 symmetries are not imposed**
- **Produces cross sections for HHH up to 55fb. In most favorable scenarios kinematics are nearly identical to TRSM model.**
  - ATLAS tested generation of TRSM and DM-CPV signals and differences are negligible.

Measuring the Higgs potential

- **By 2040, a realistic goal of the HL-LHC program is to measure the tri-linear Higgs self-coupling to a precision $\kappa_3 = 1 \pm 1$**
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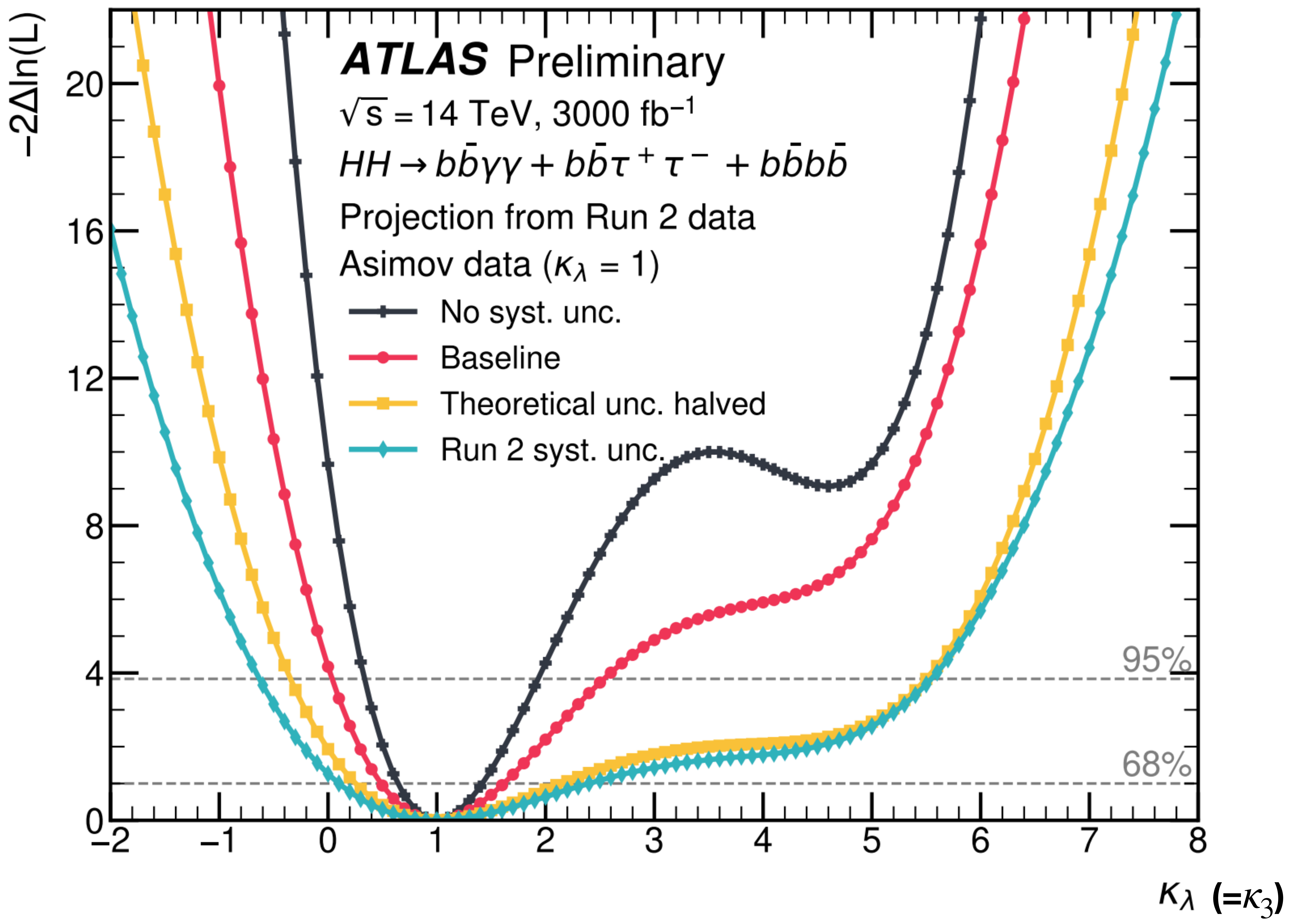

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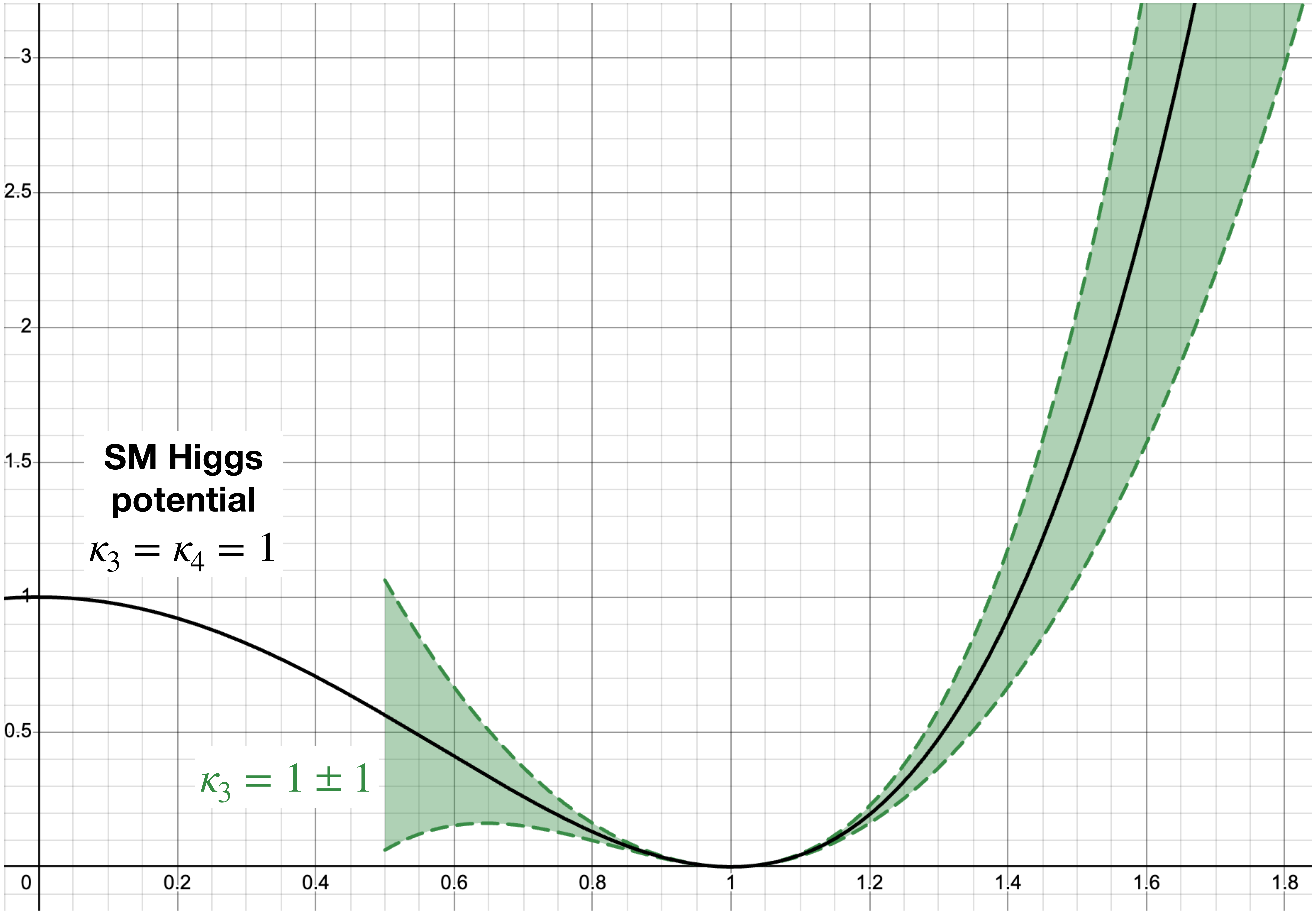

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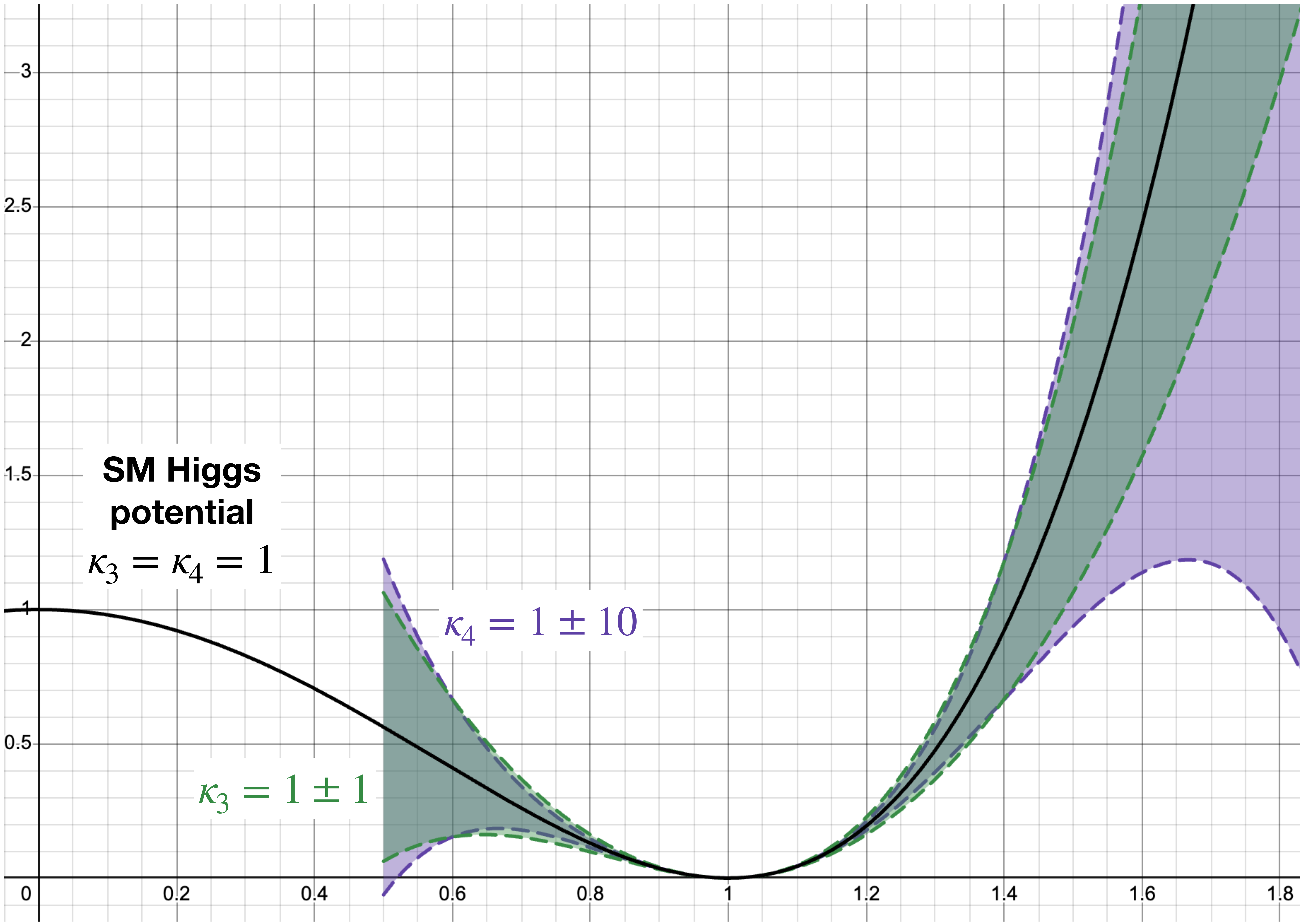
- **To obtain similar constraints on the potential shape, need $\kappa_4 = 1 \pm 10$**



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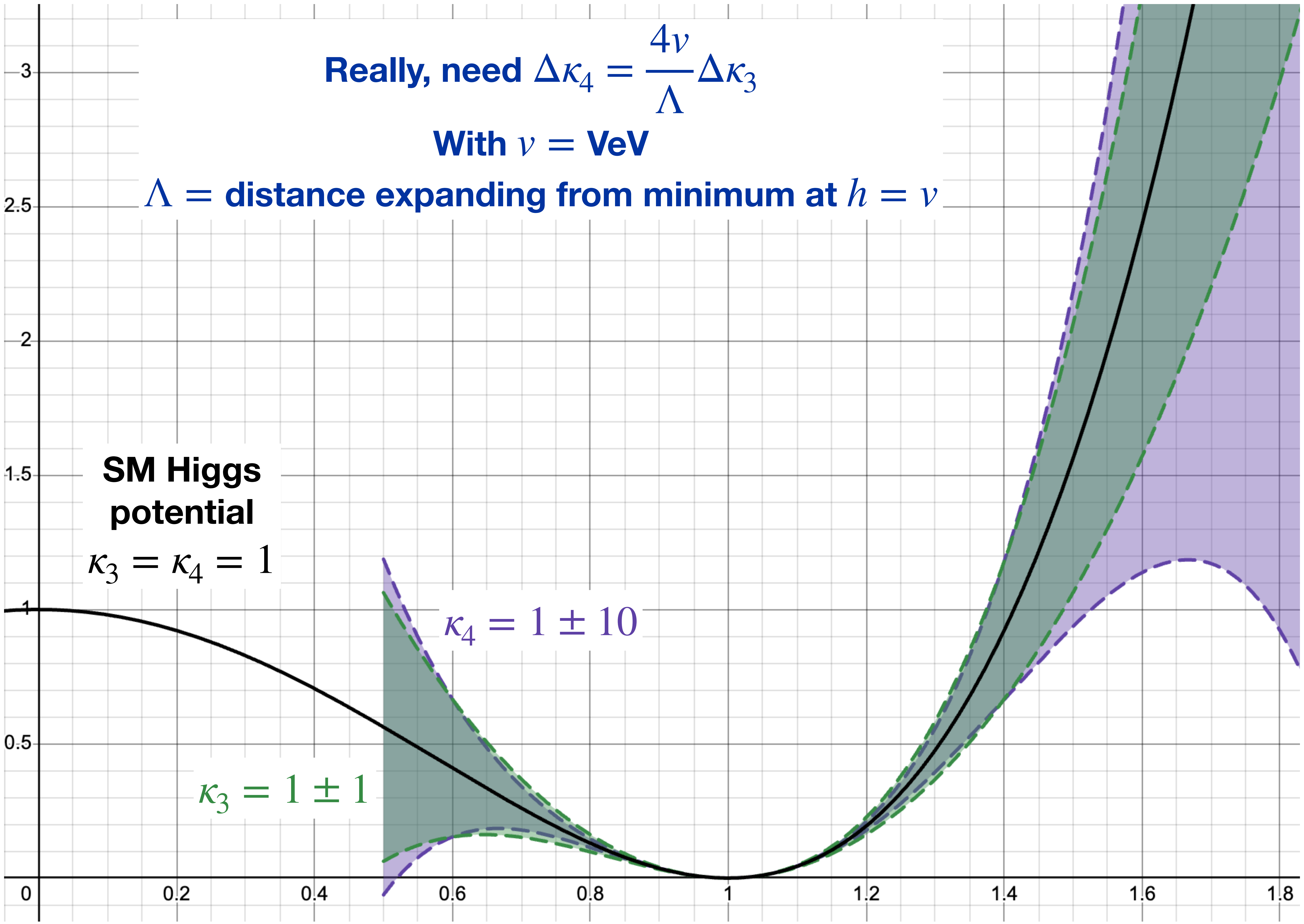

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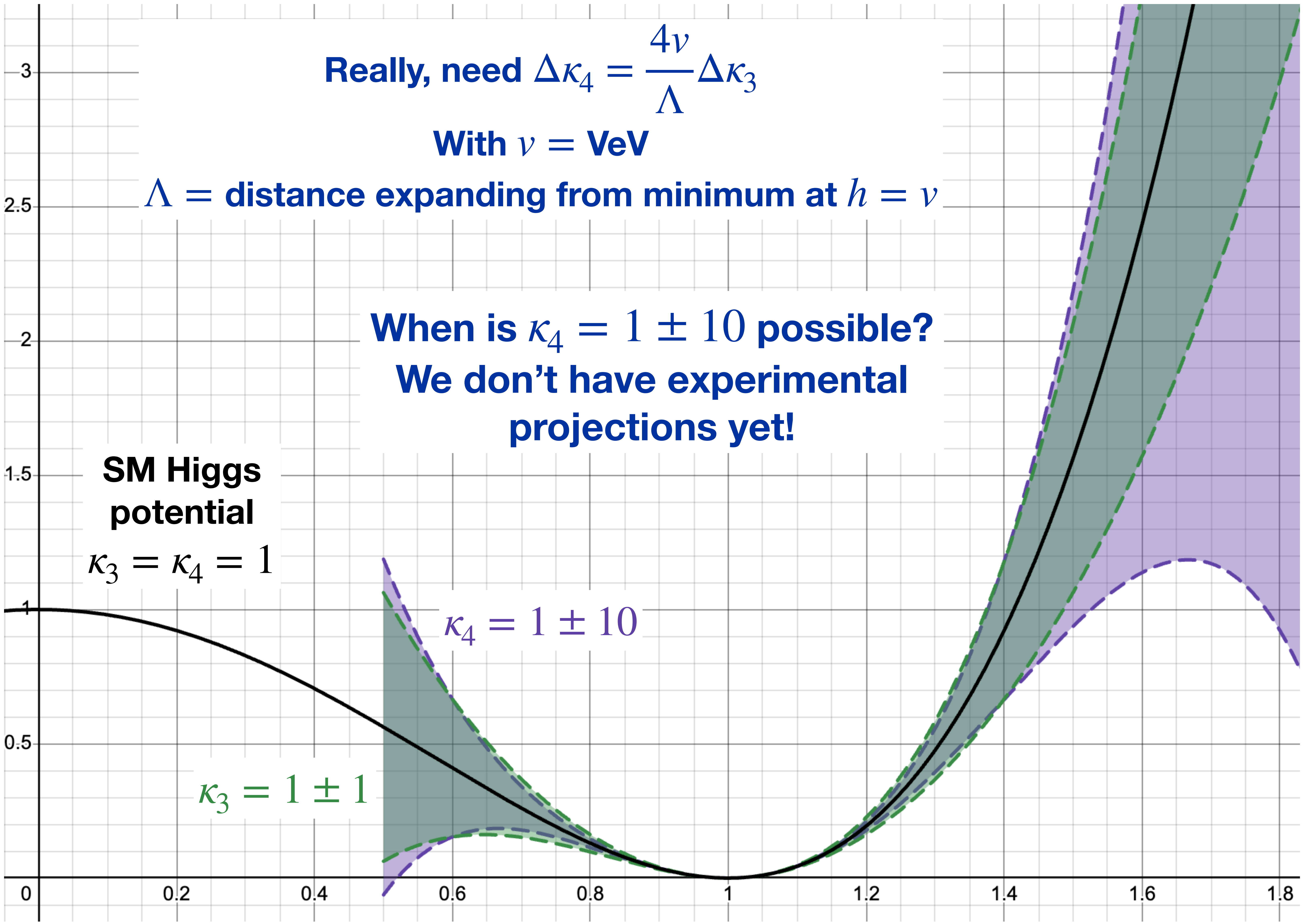

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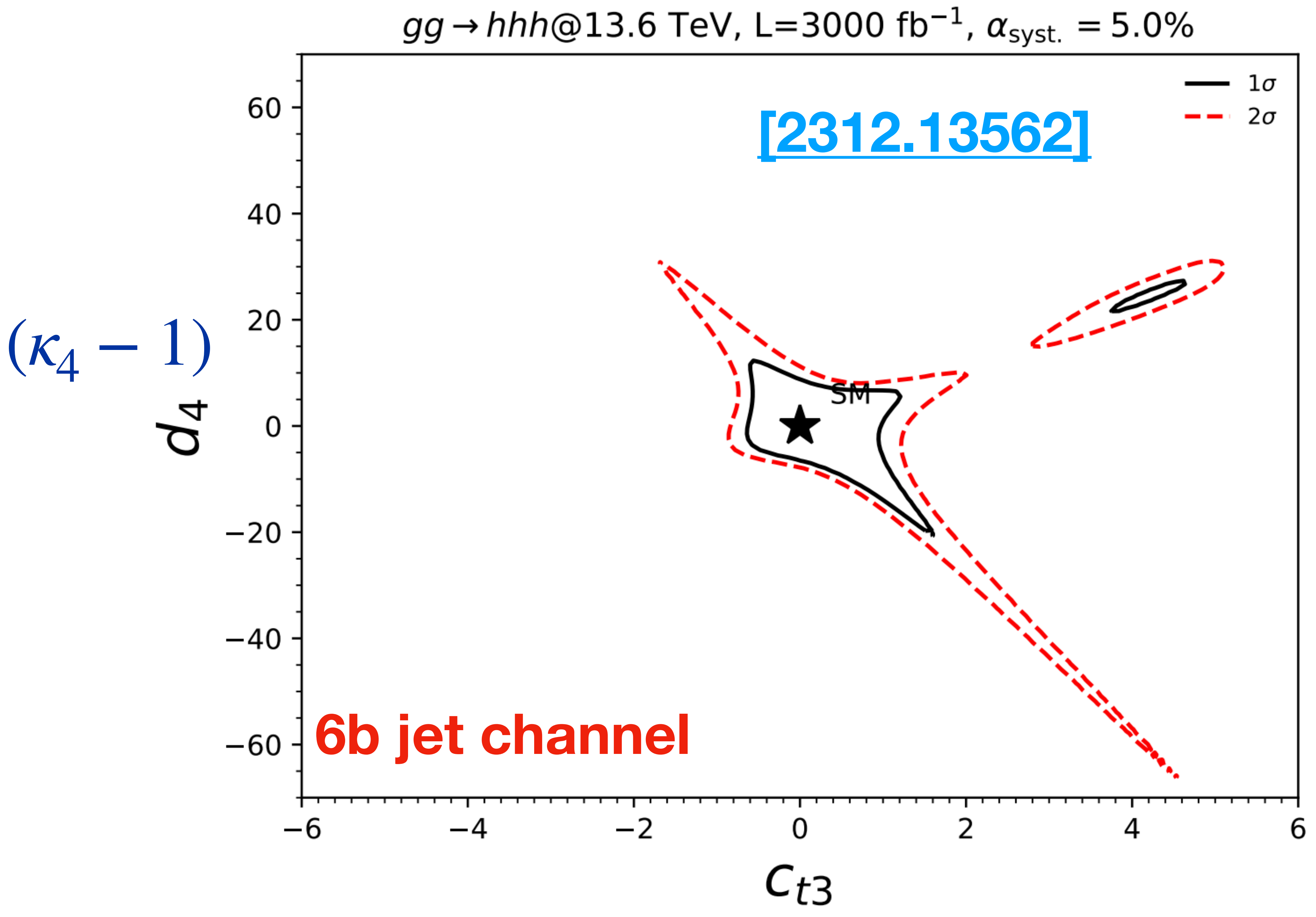
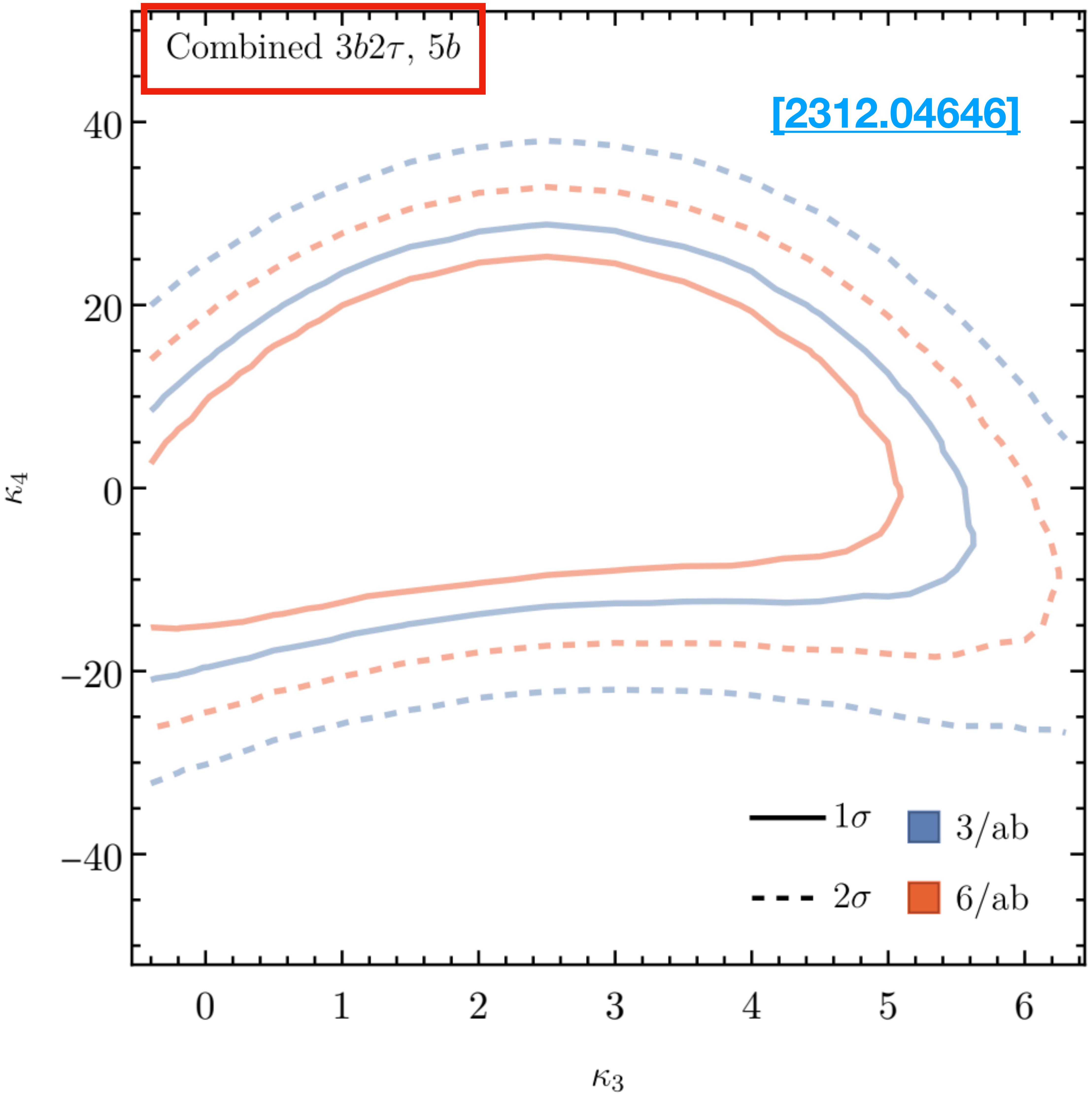
(Phenomenological) HL-LHC Projections

- Some projections from the HHH whitepaper, [2312.13562], and [2312.04646] suggest $\kappa_4 = 1 \pm 30$ is possible in HL-LHC. 95% CL.
- Take them with a grain of salt, as projections are not yet based in a published analysis.





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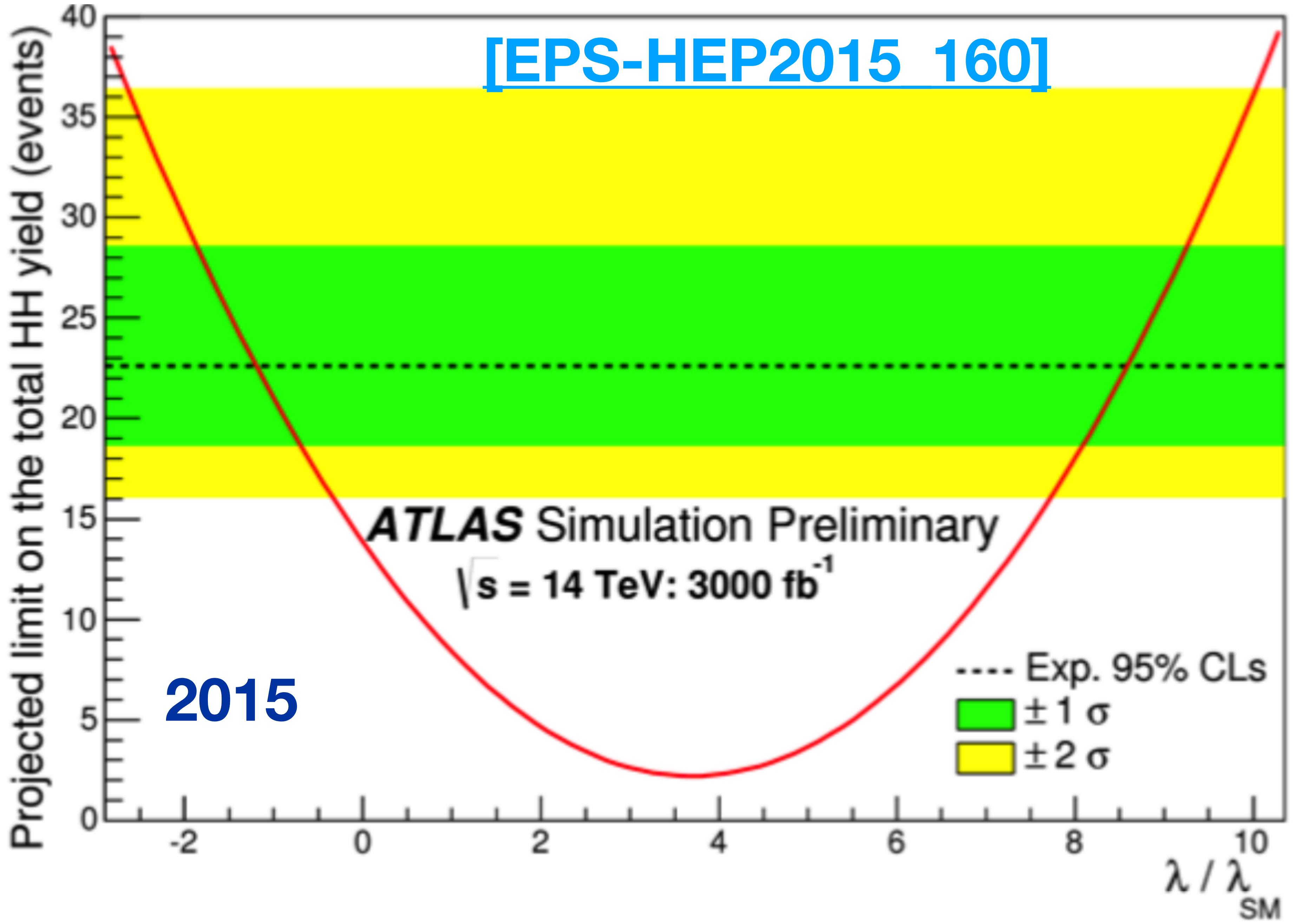

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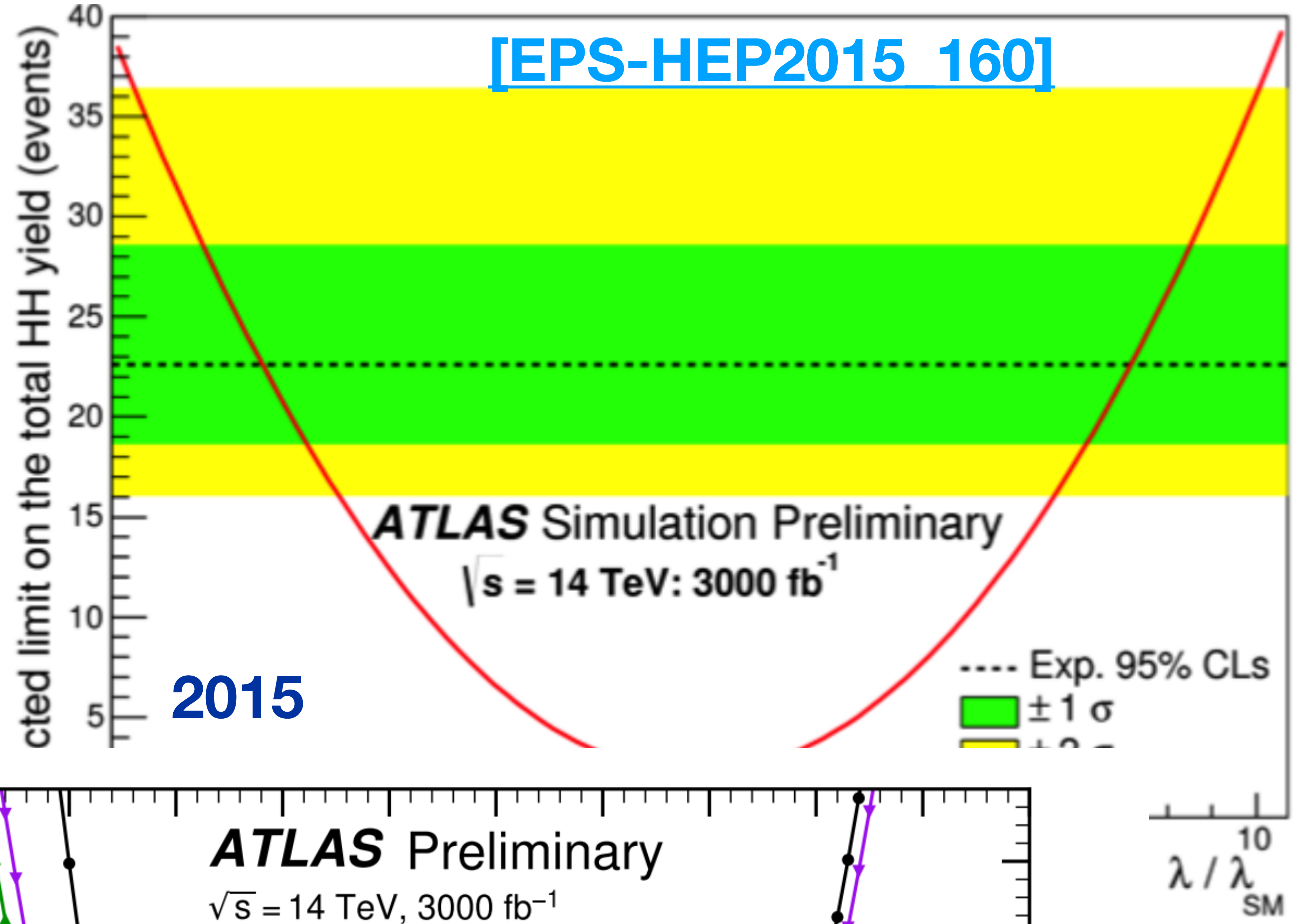

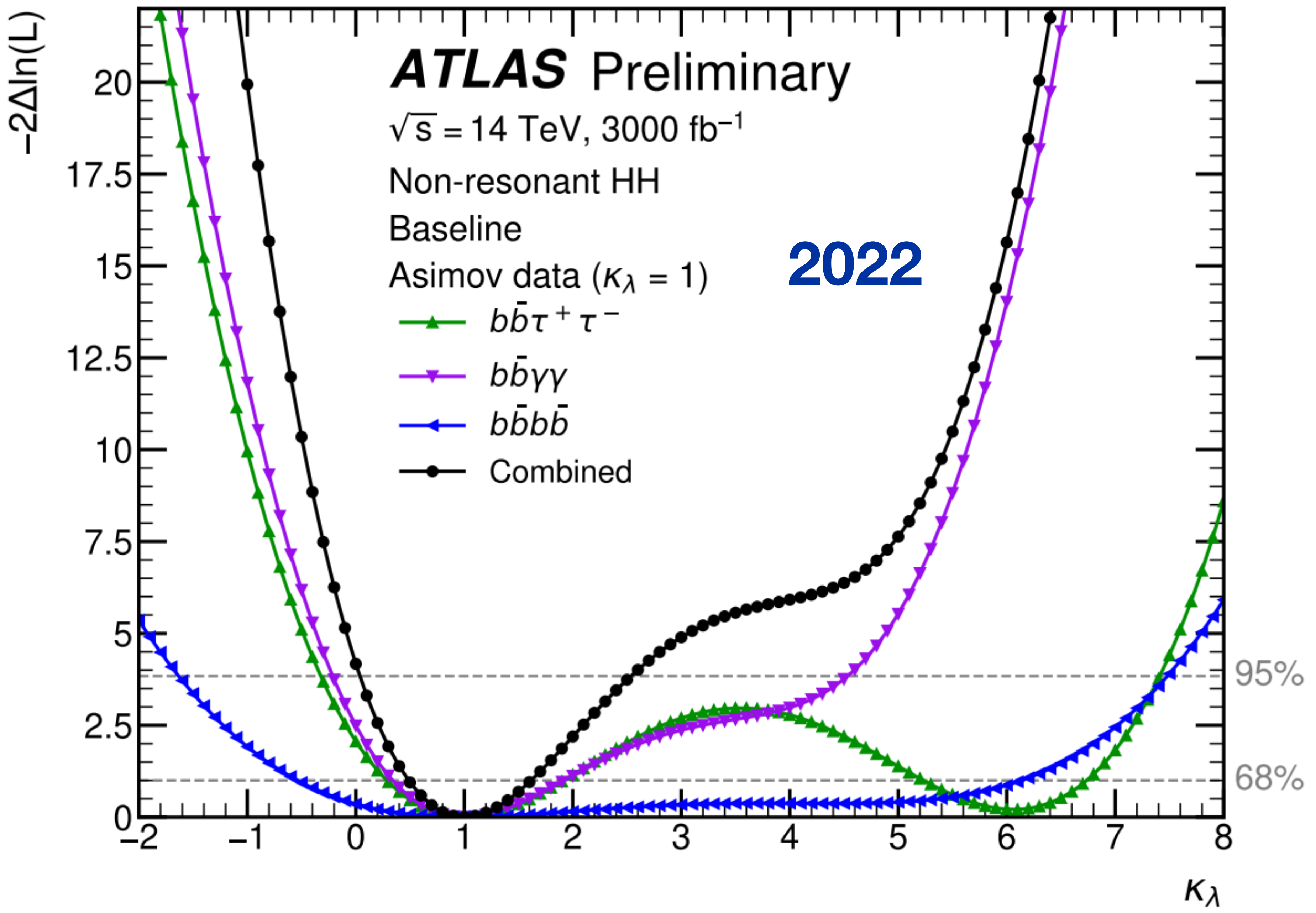

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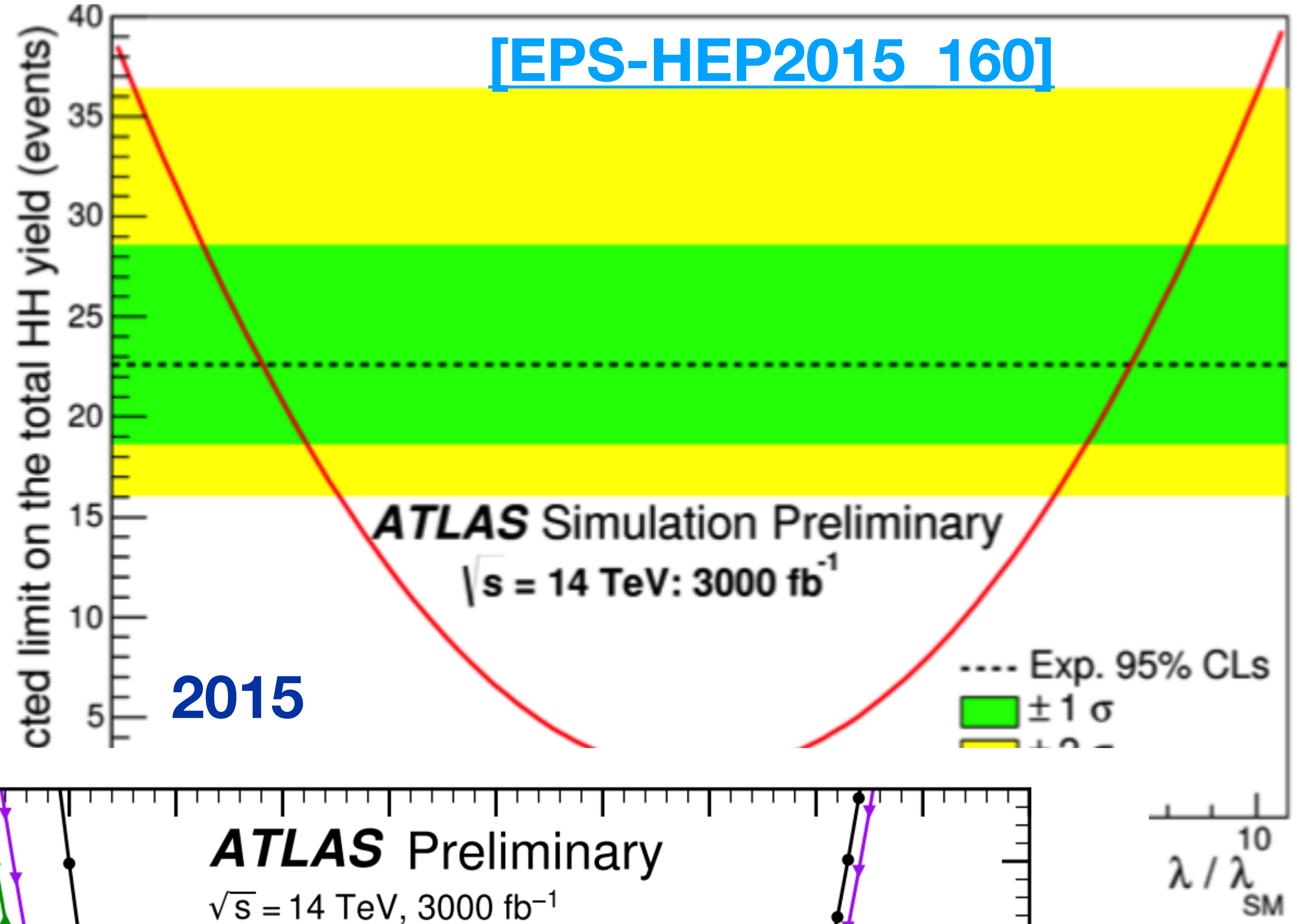

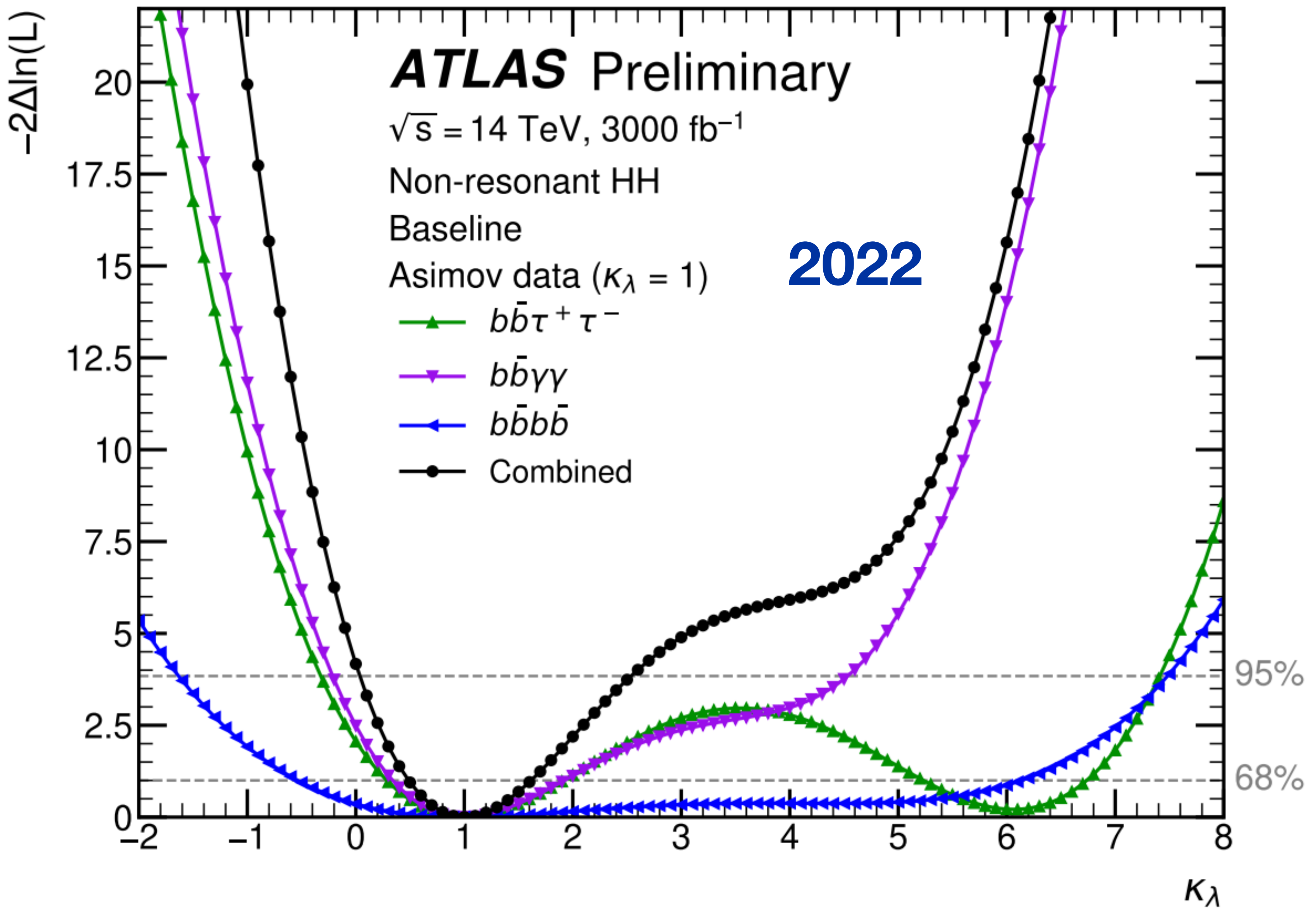

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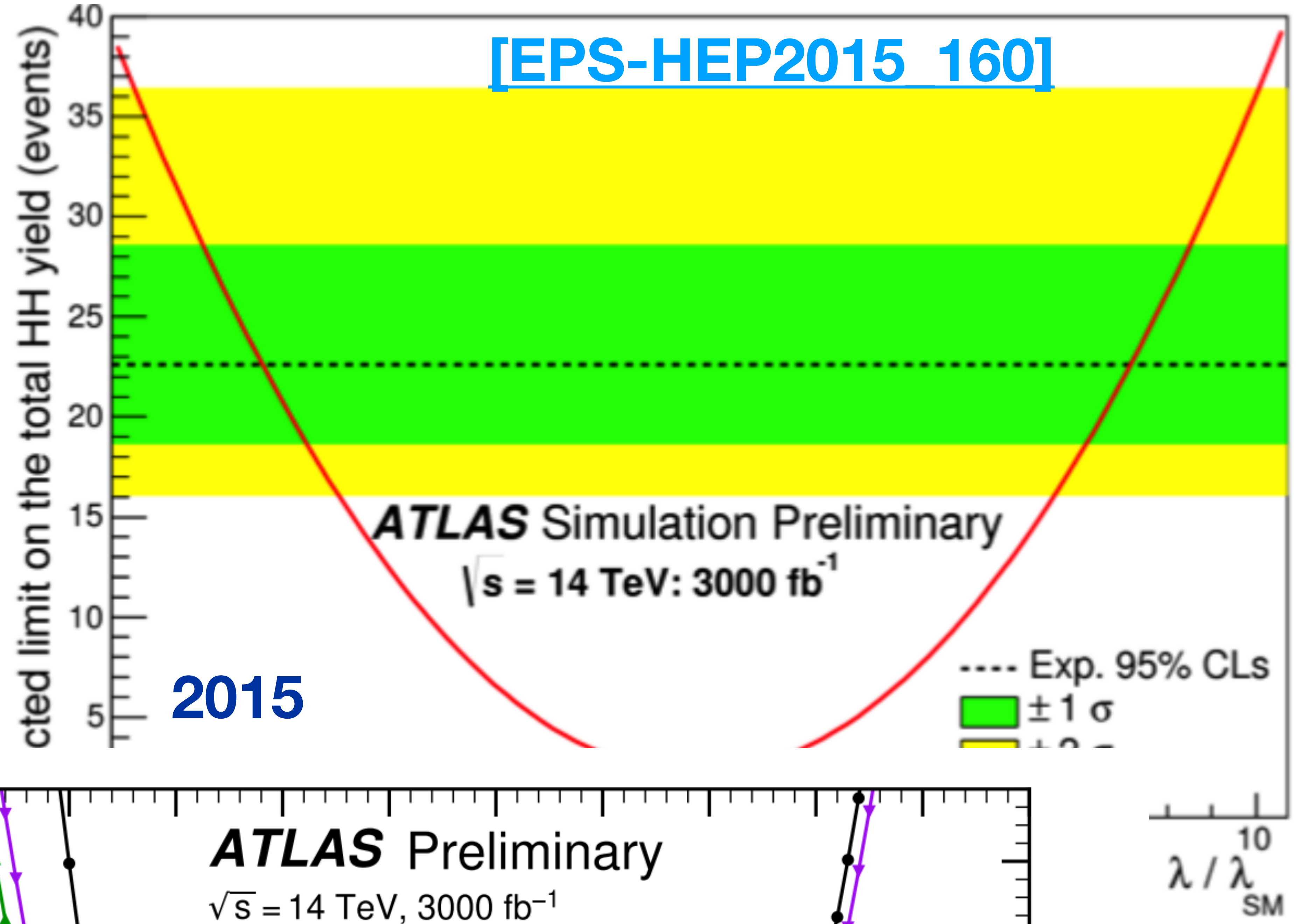
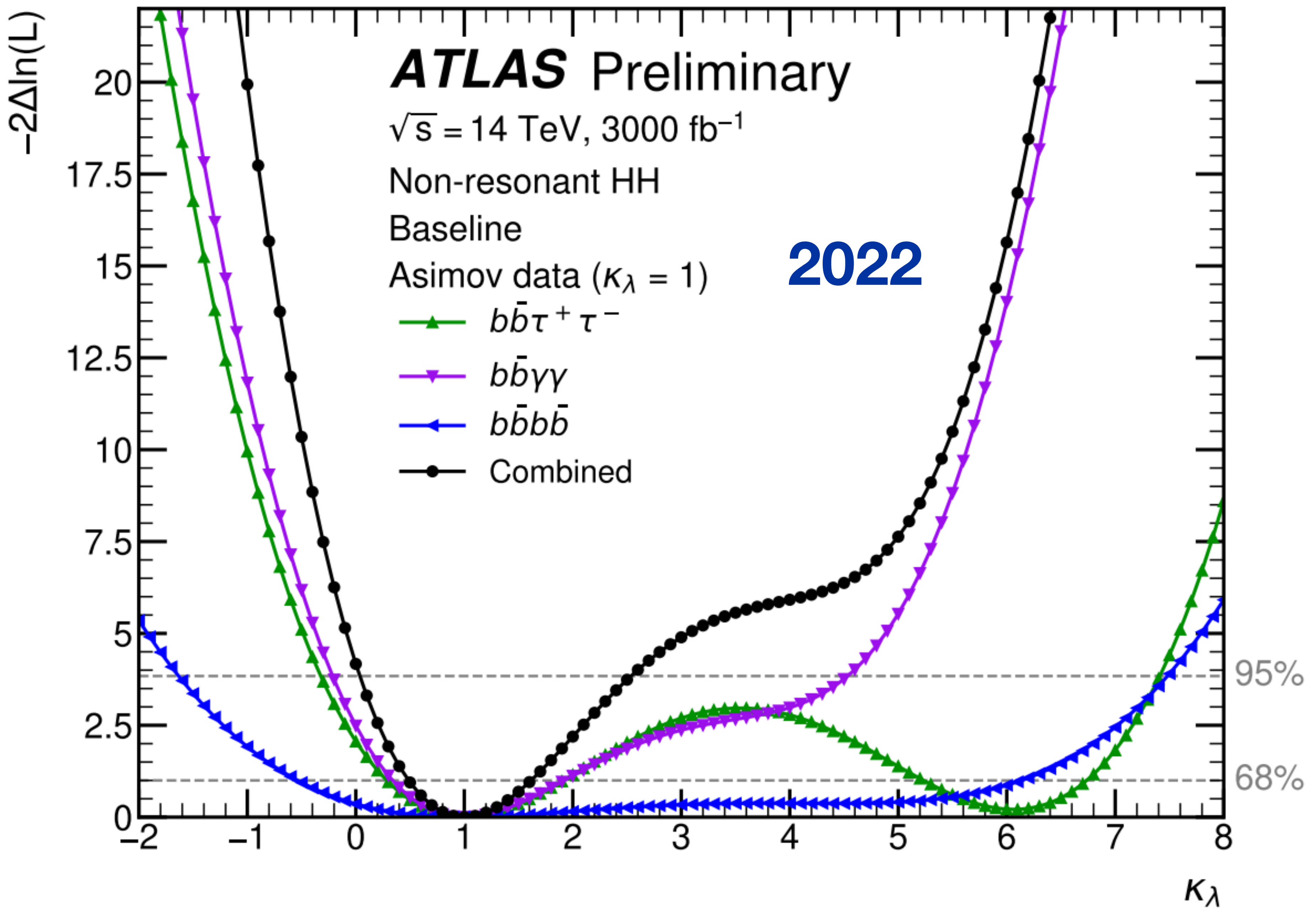
  - Detector performance improvements
  - Improvements in b-tagging
  - New analysis ideas: AI/ML, categorization
  - Reduction of theoretical uncertainties
  - Exploration of more channels

I argue both can be improved

HHH is behind in these aspects

[EPS-HEP2015_160]





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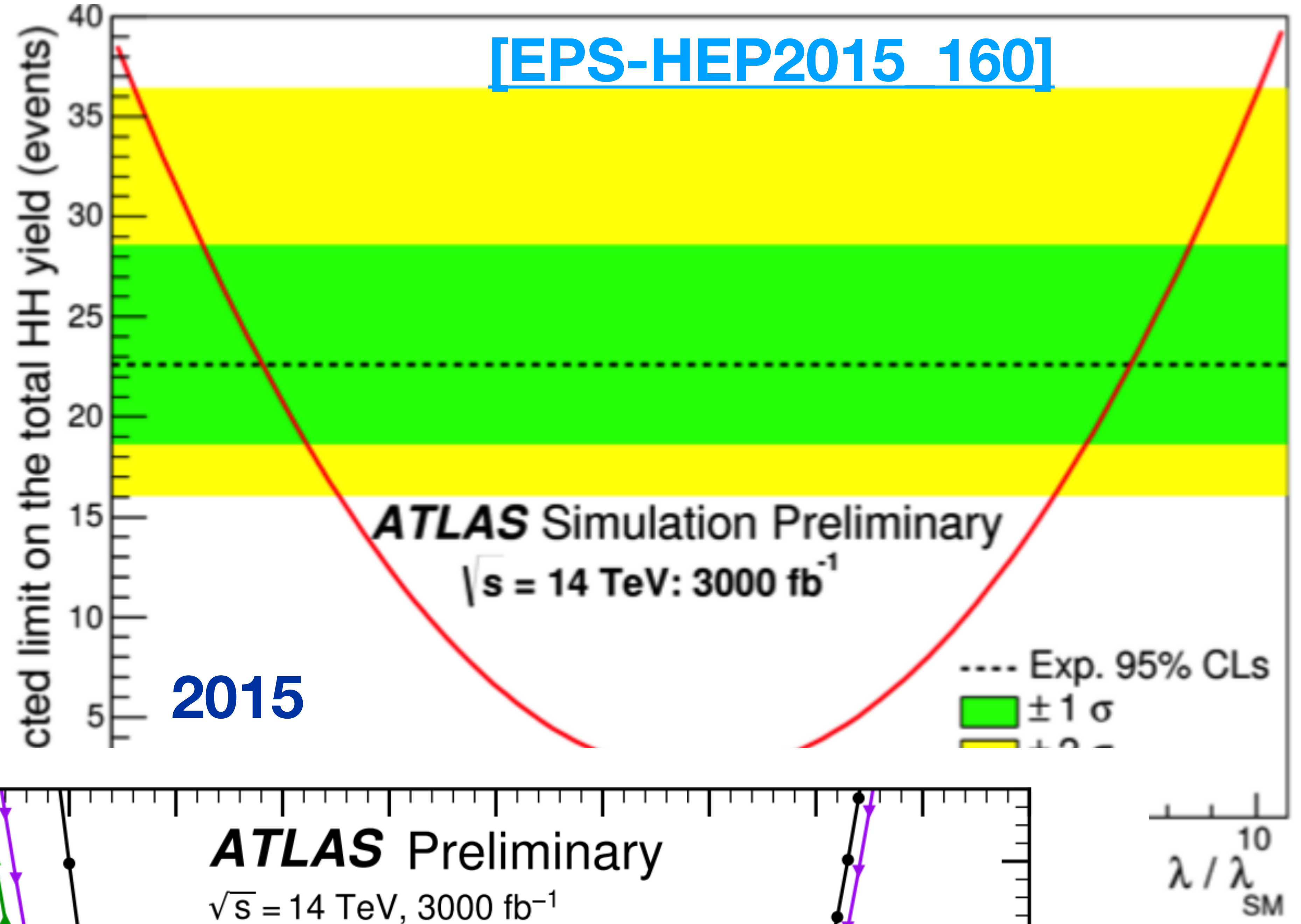
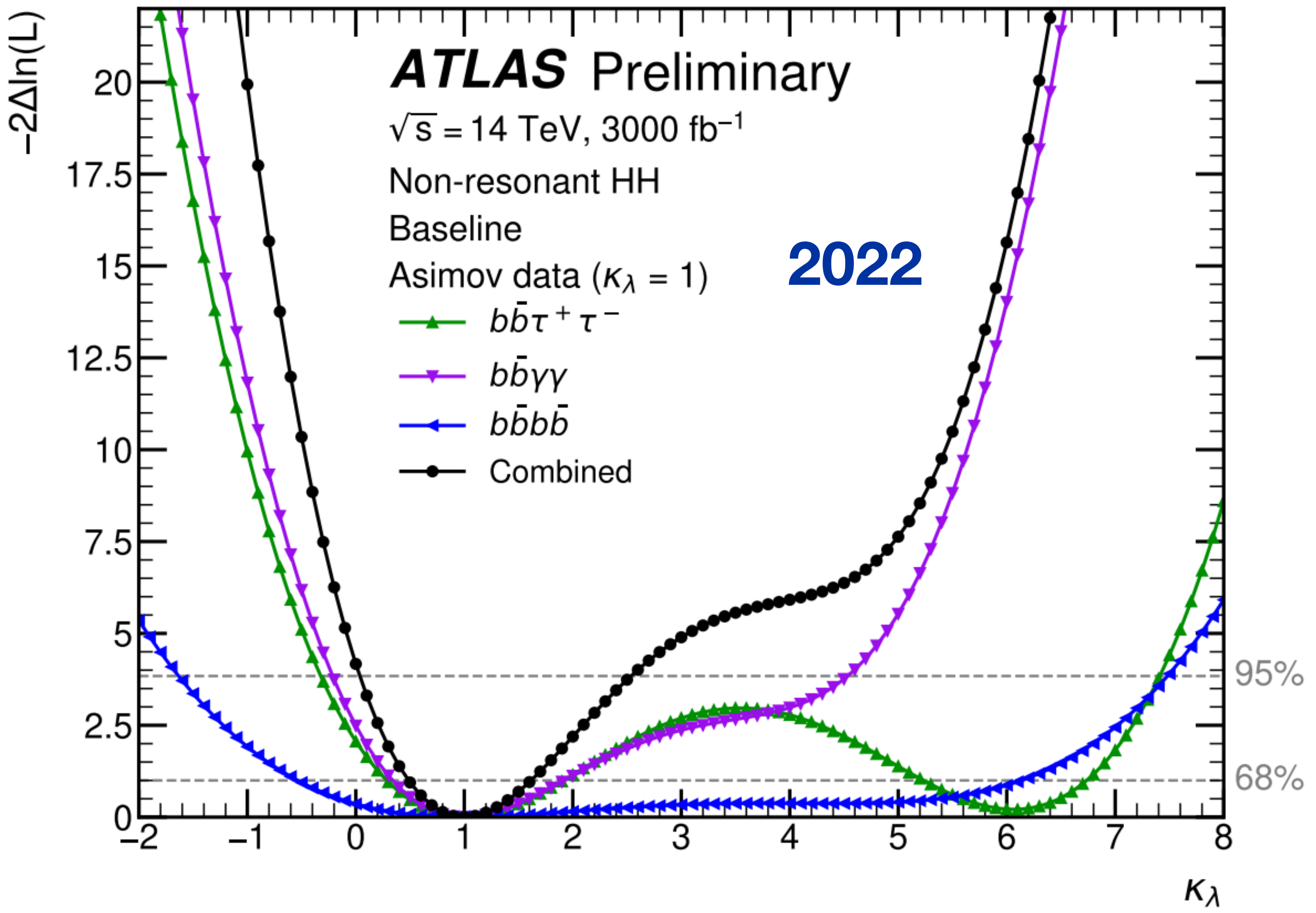
- **Is $\kappa_4 = 1 \pm 10$ within the realm of possibility? Probably not, but we don't know yet. HHH not guaranteed to evolve like of HH projections**

[EPS-HEP2015_160]





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Decay modes

Decay modes

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- **There are more options for HHH than HH**

Reminder: HH branching fractions

	bb	WW	$\tau\tau$	ZZ	$\gamma\gamma$
bb	34%				
WW	25%	4.6%			
$\tau\tau$	7.4%	2.5%	0.39%		
ZZ	3.1%	1.2%	0.34%	0.076%	
$\gamma\gamma$	0.26%	0.10%	0.029%	0.013%	0.0005%

Decay modes

- **The first question is what decay mode to search for!**
- **There are more options for HHH than HH**
- **Combinatorics can make things interesting:**
  - For example, bbbbWW is *technically* dominant, but only some of those decays will have the utility of a lepton.
  - In terms of experimental signature 6*b* is dominant.

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bb+SS leptons	1.9%

Reminder: HH branching fractions

	bb	WW	$\tau\tau$	ZZ	$\gamma\gamma$
bb	34%				
WW	25%	4.6%			
$\tau\tau$	7.4%	2.5%	0.39%		
ZZ	3.1%	1.2%	0.34%	0.076%	
$\gamma\gamma$	0.26%	0.10%	0.029%	0.013%	0.0005%

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***An understudied mode**

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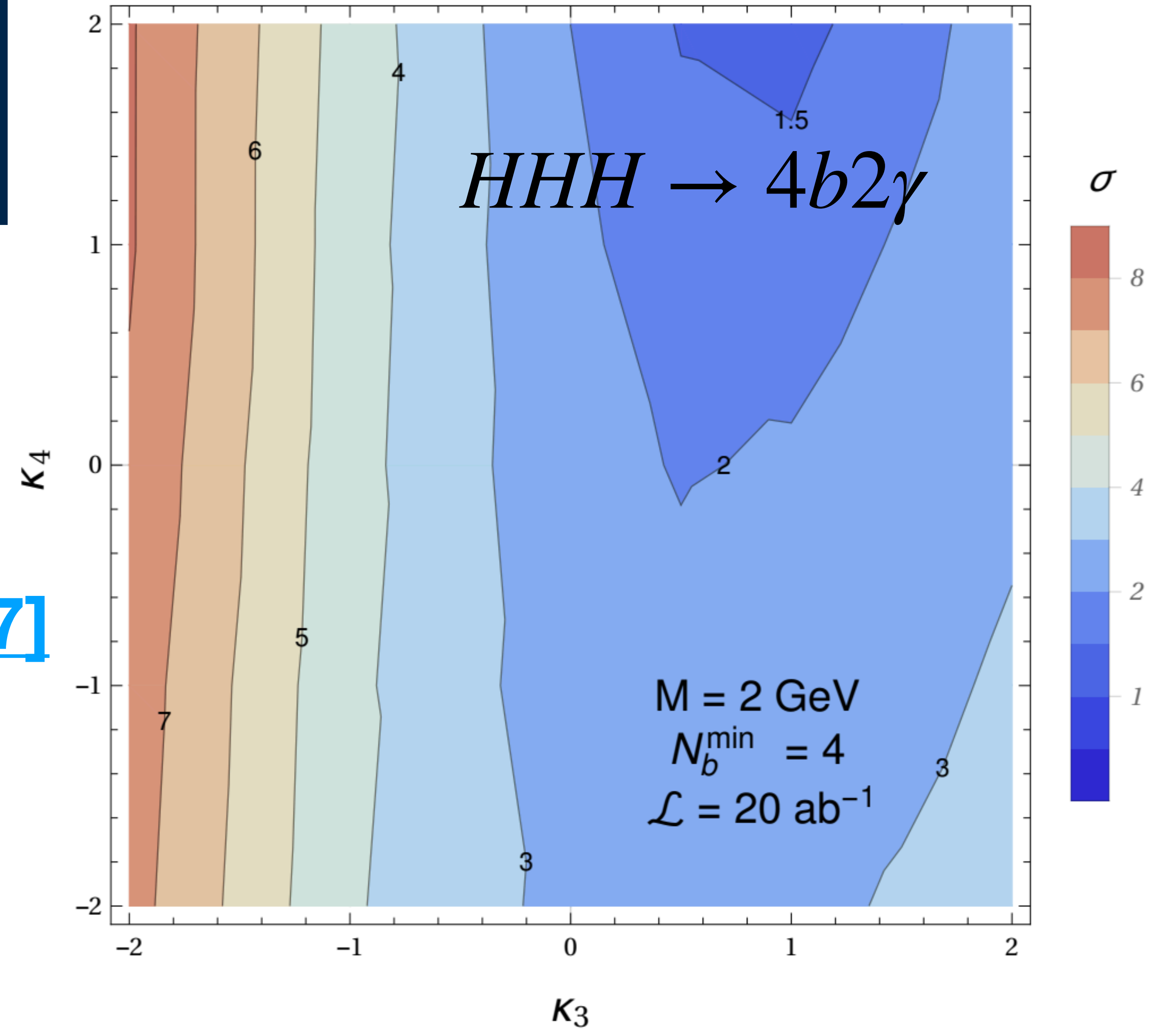
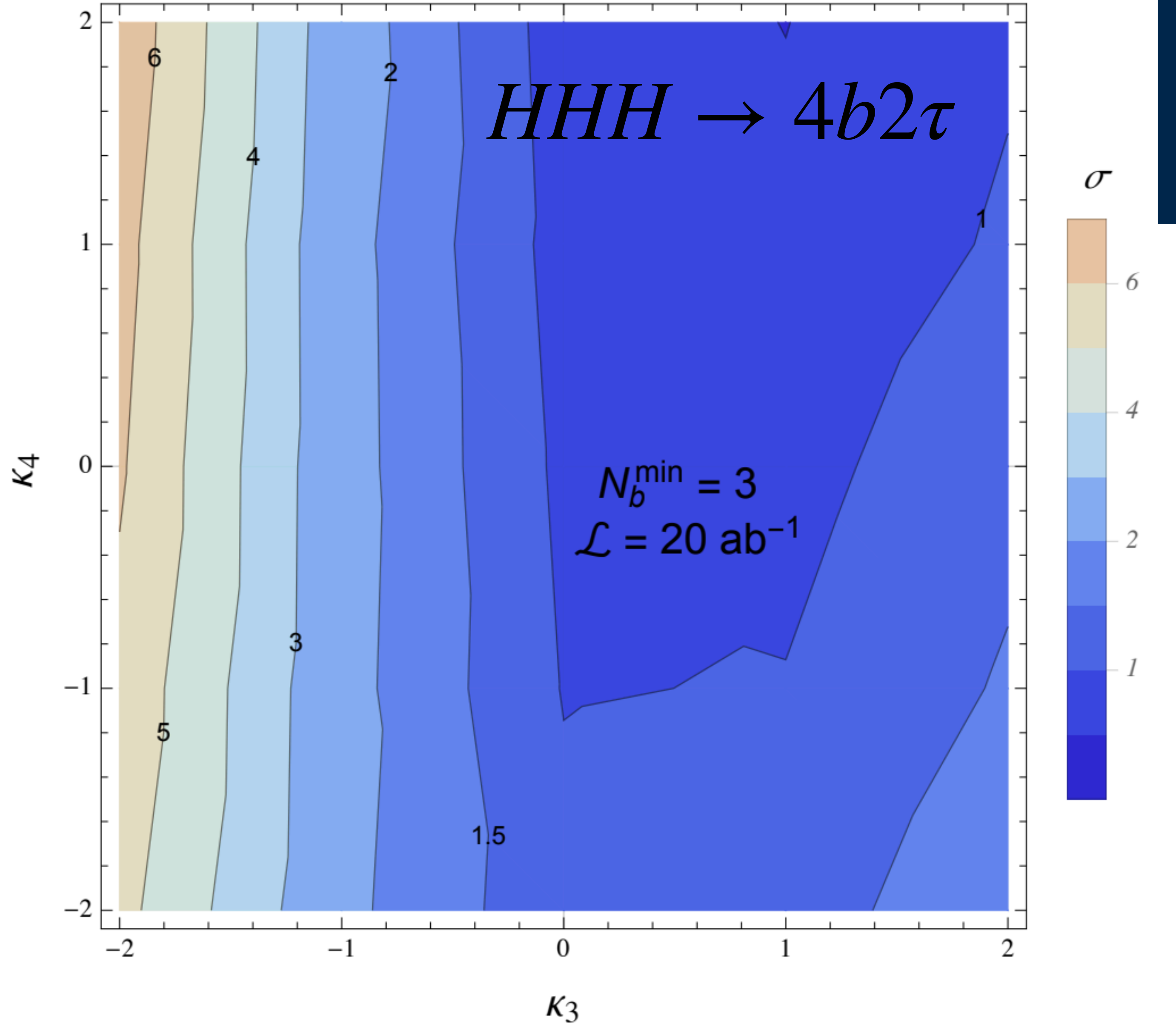
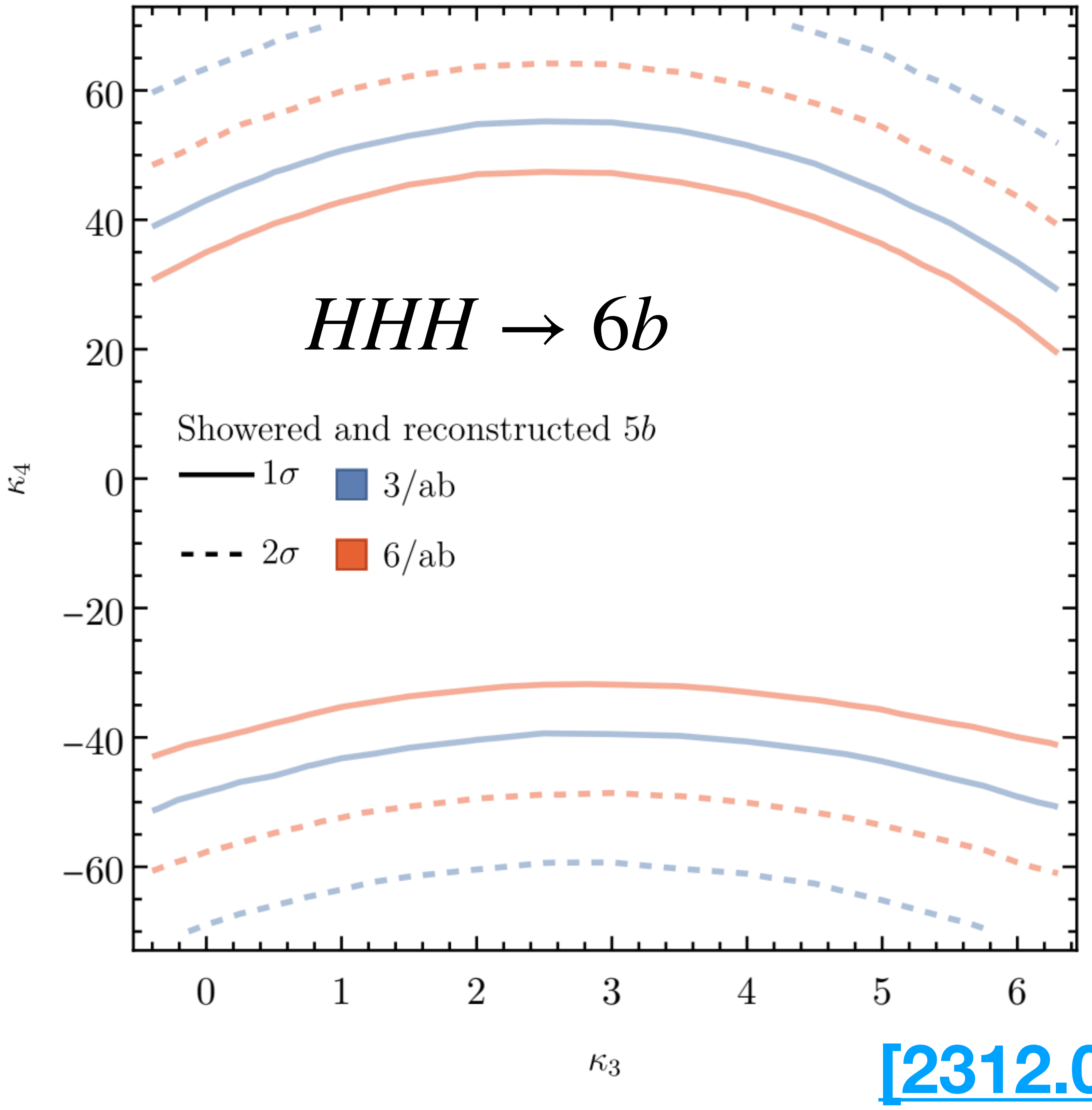
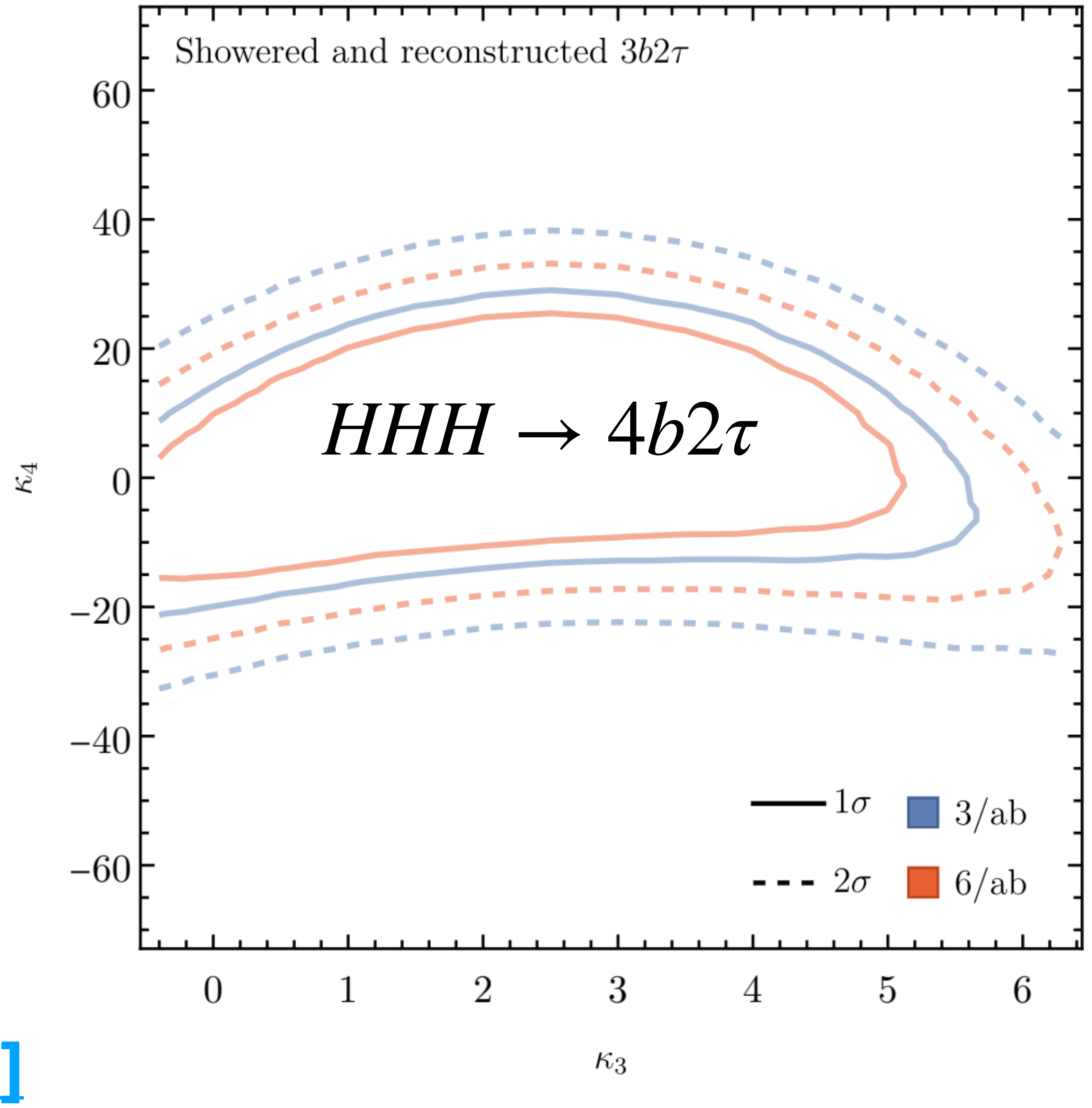
Decay modes

[1510.07697]









[2312.04646]

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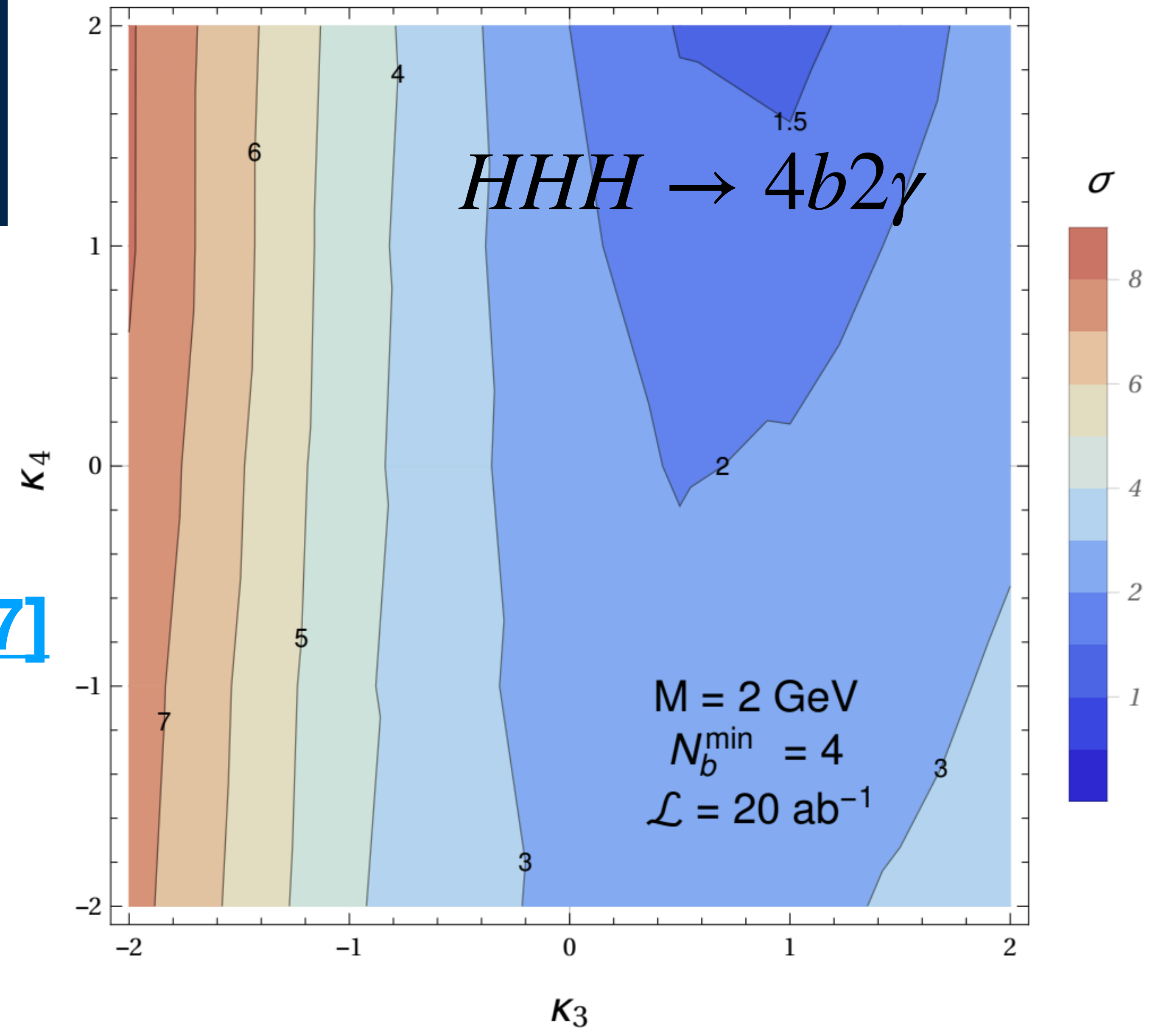
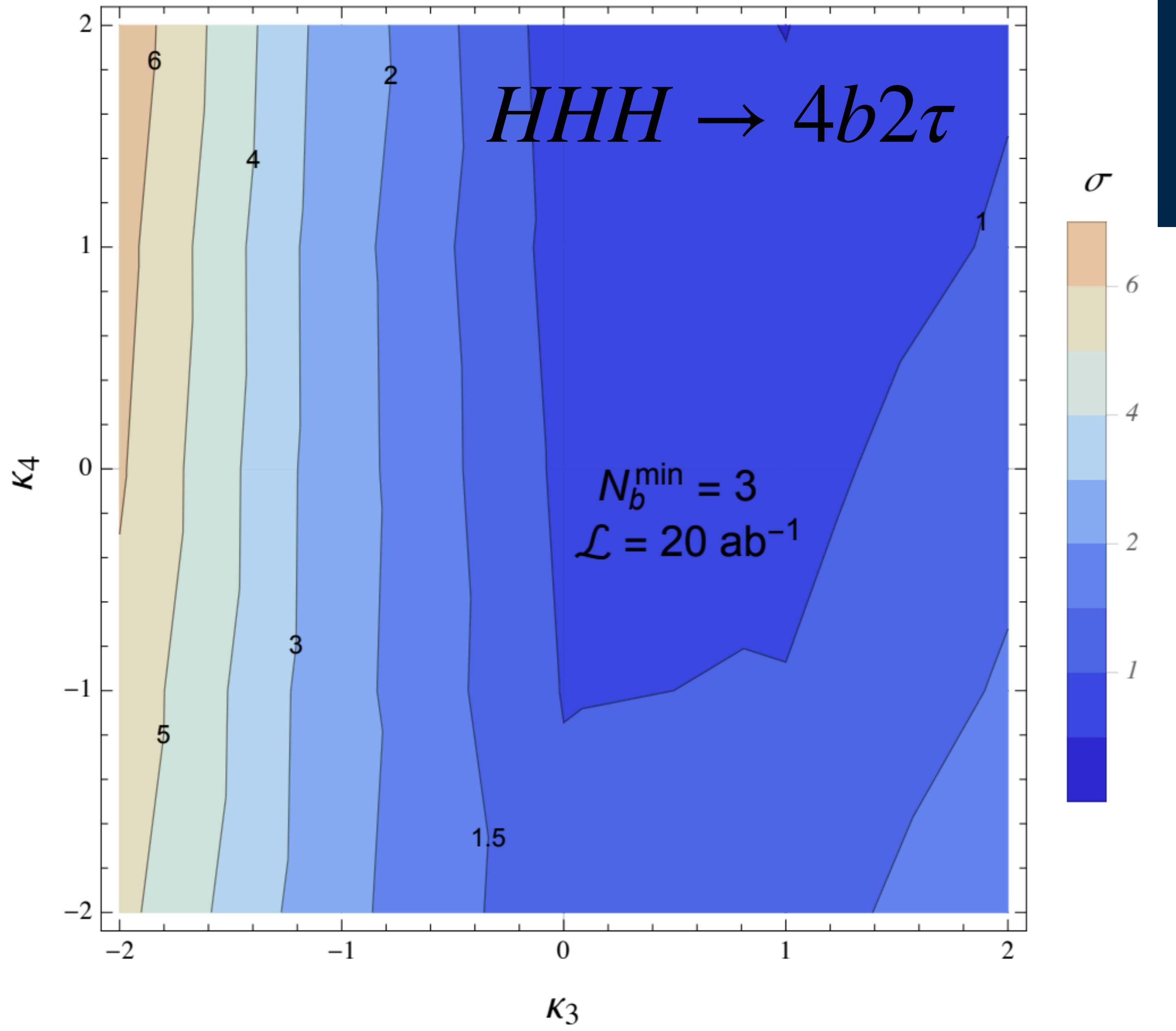
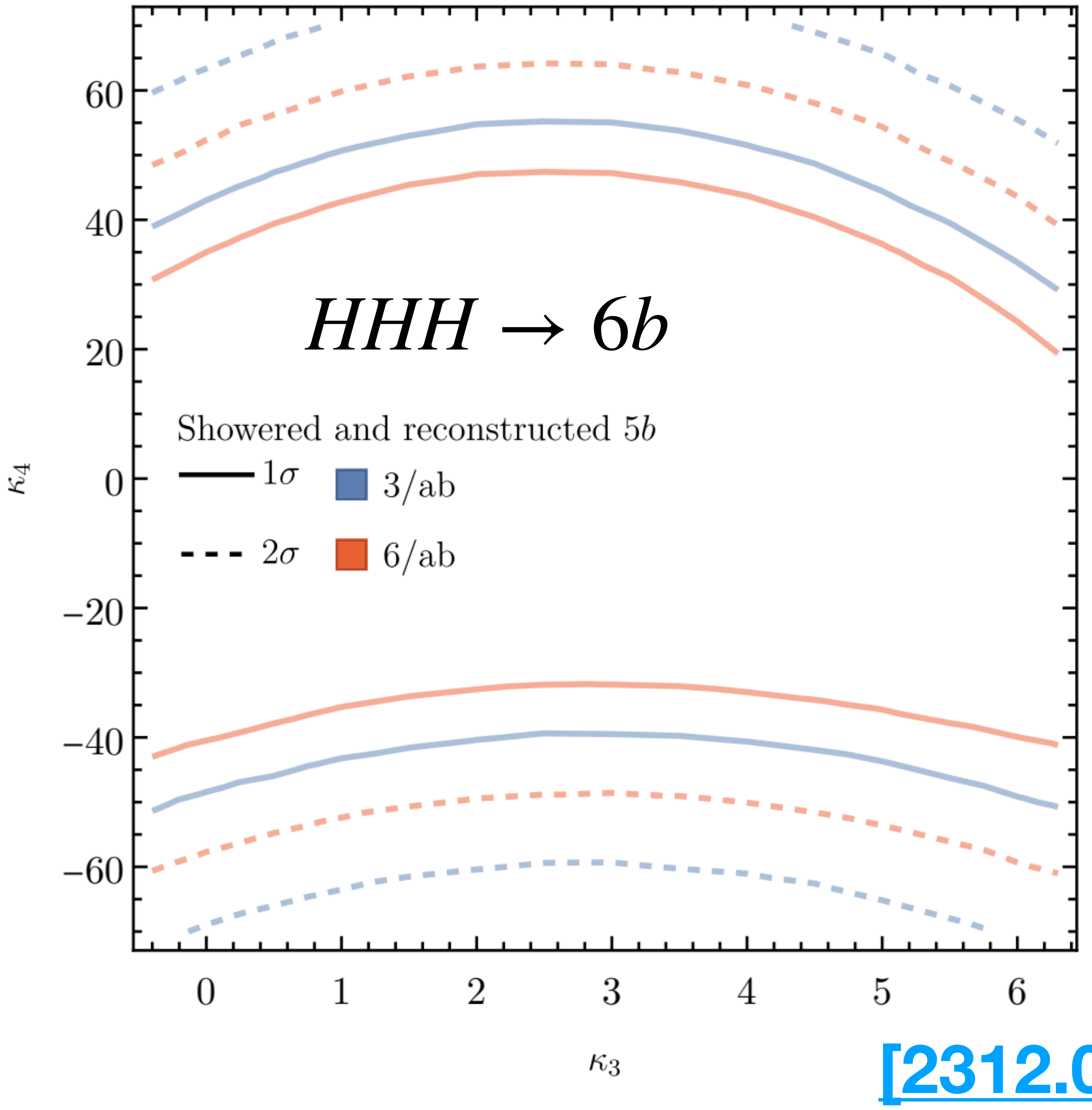
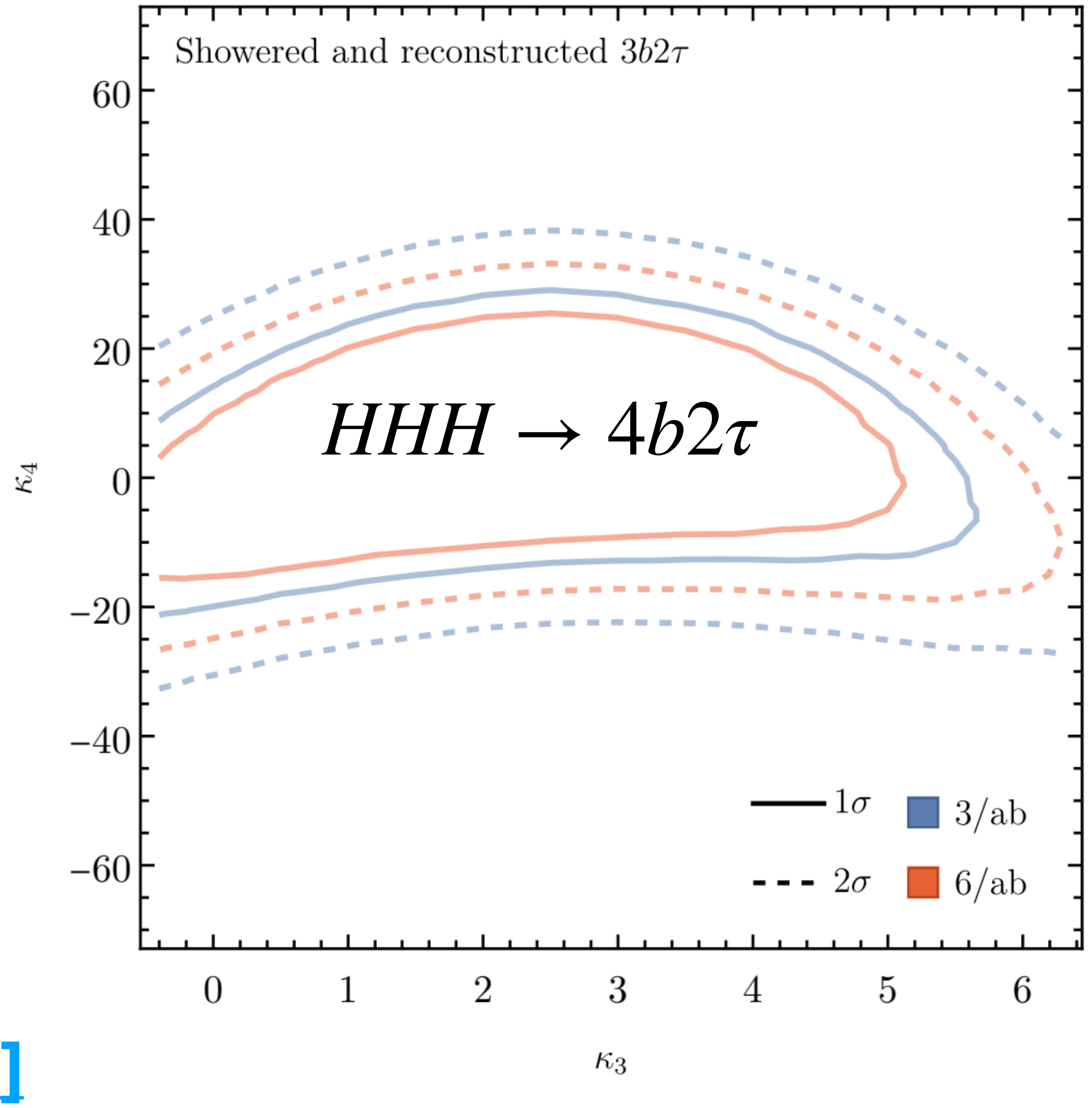
- **Studies on sensitivity of decay modes are in (slight) conflict**

[1510.07697]









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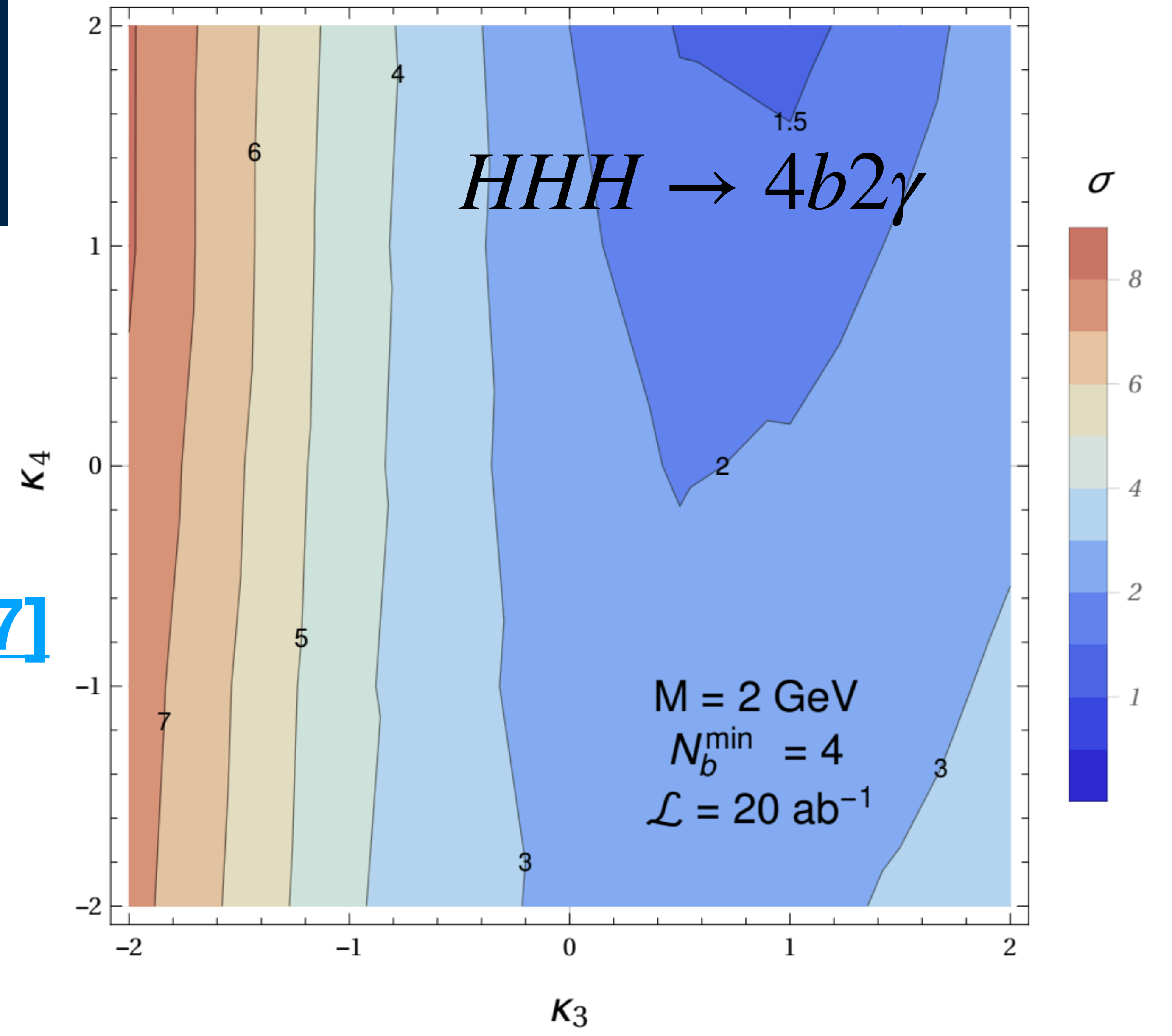

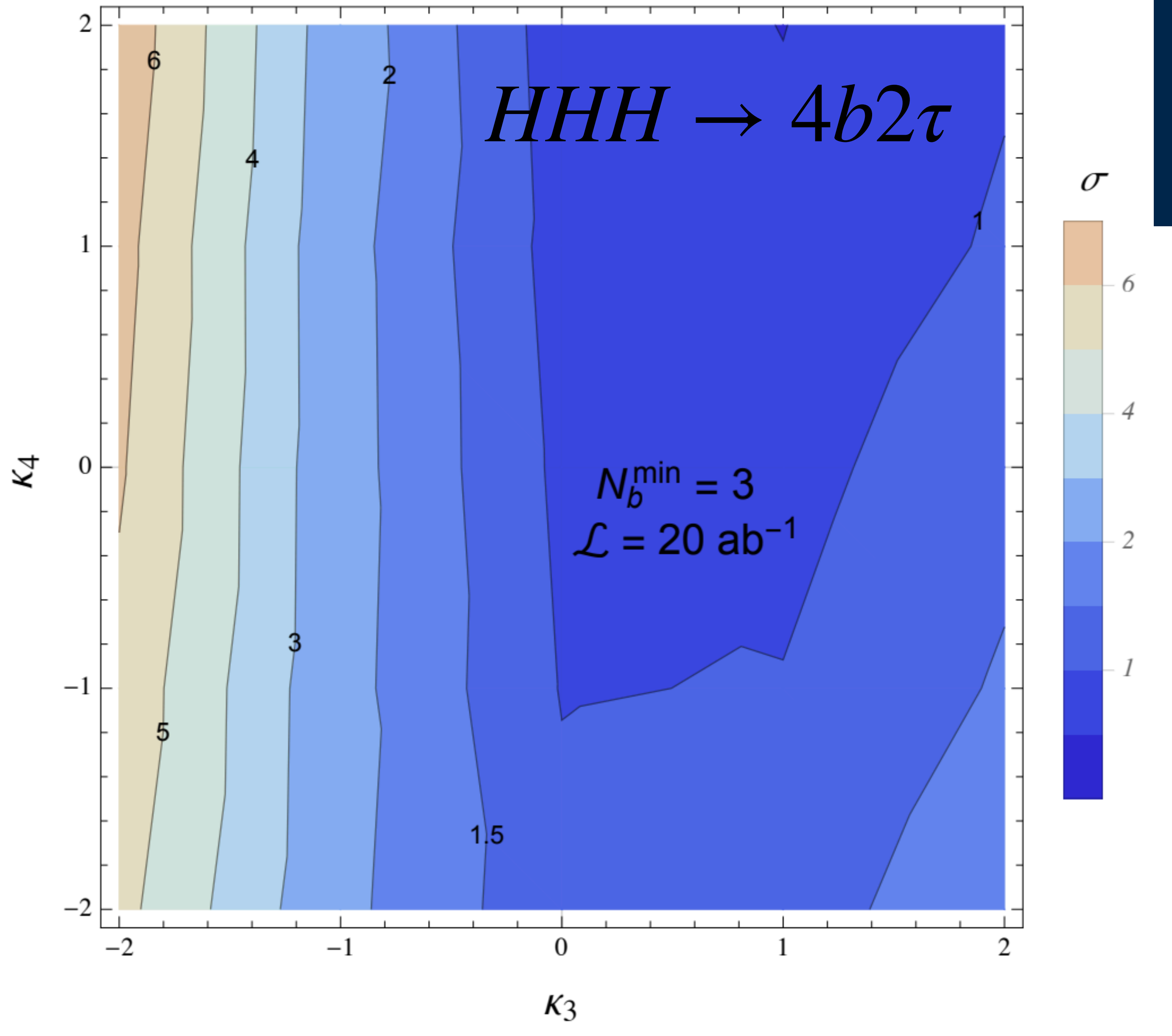

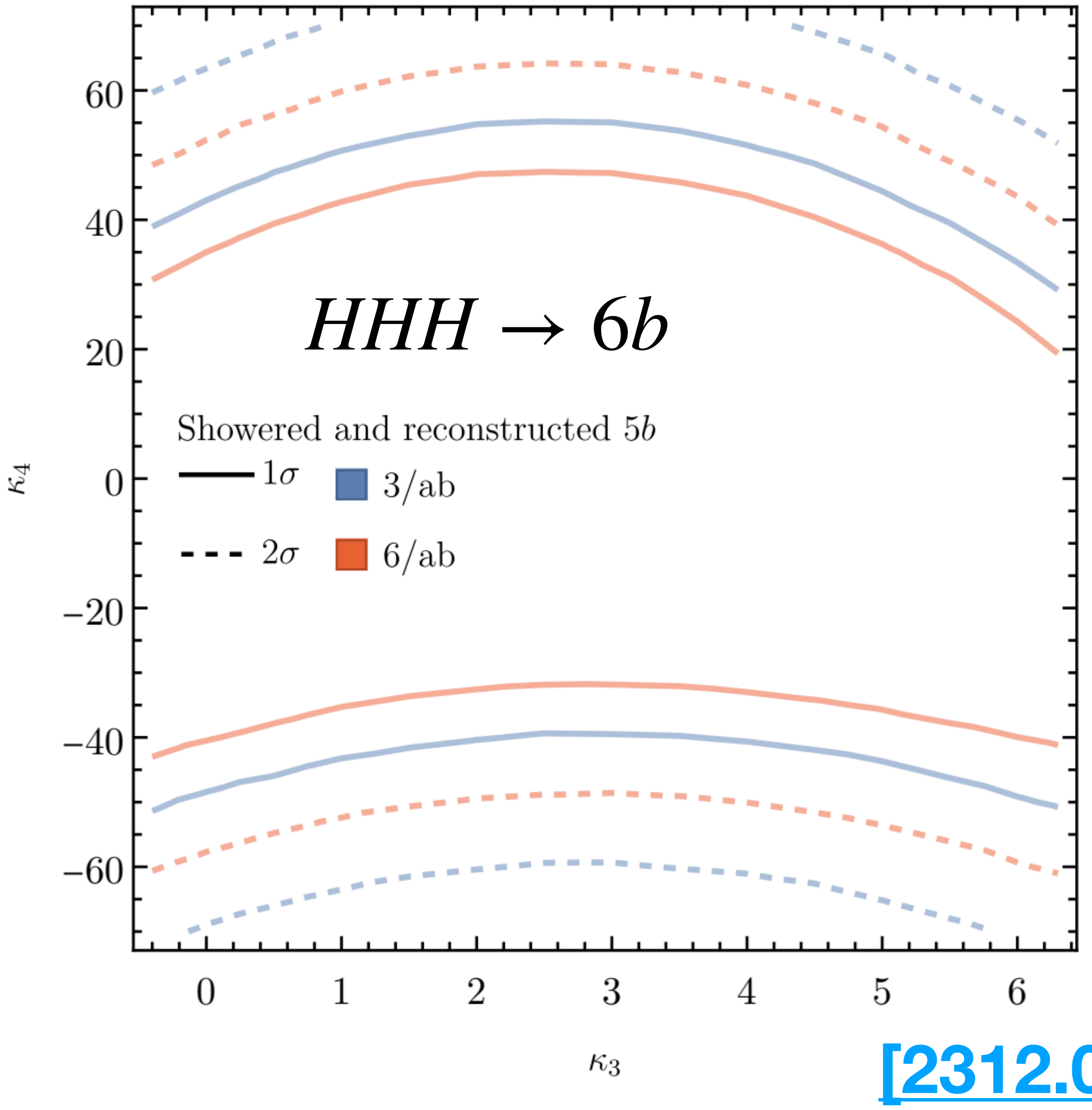

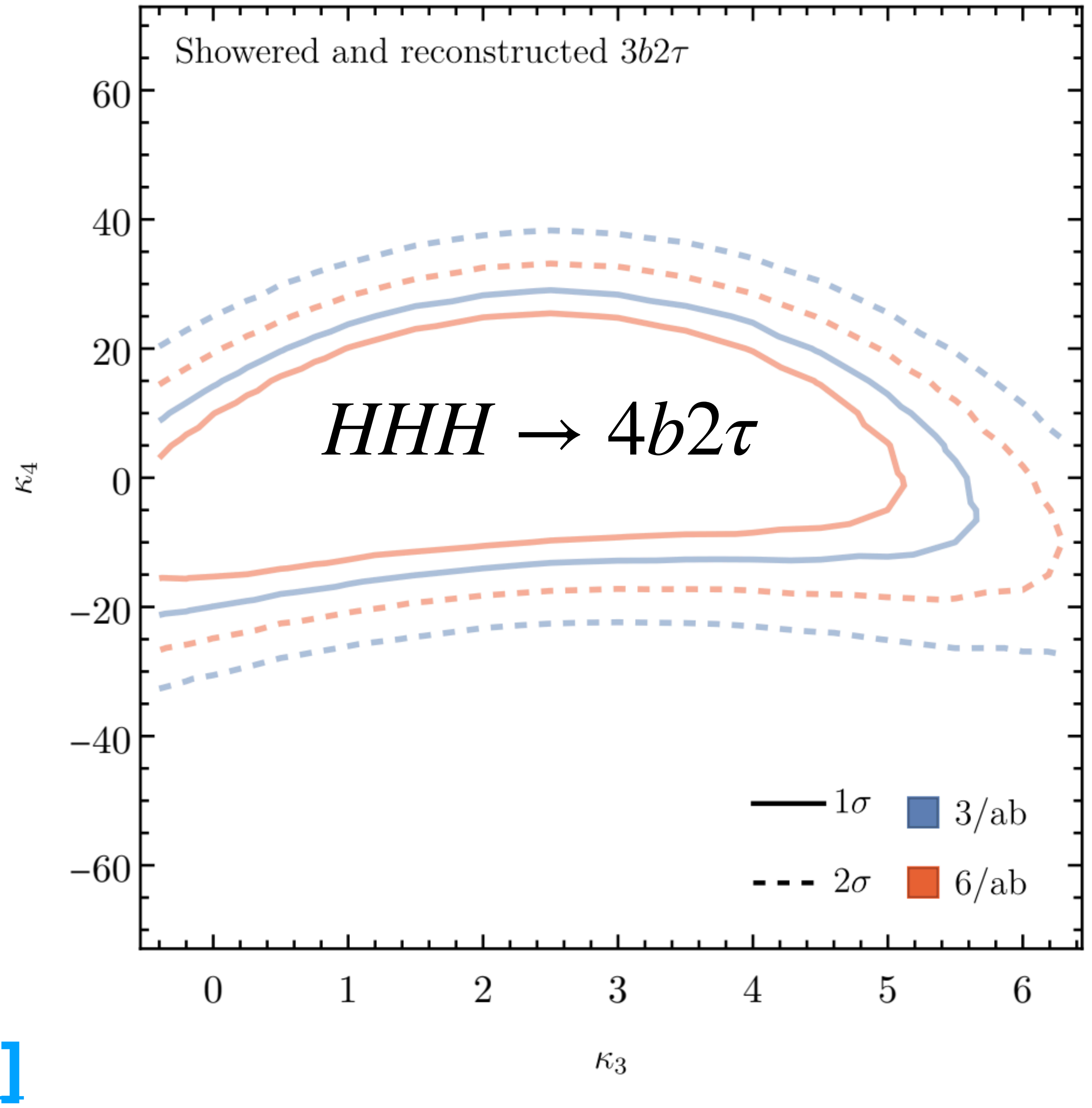

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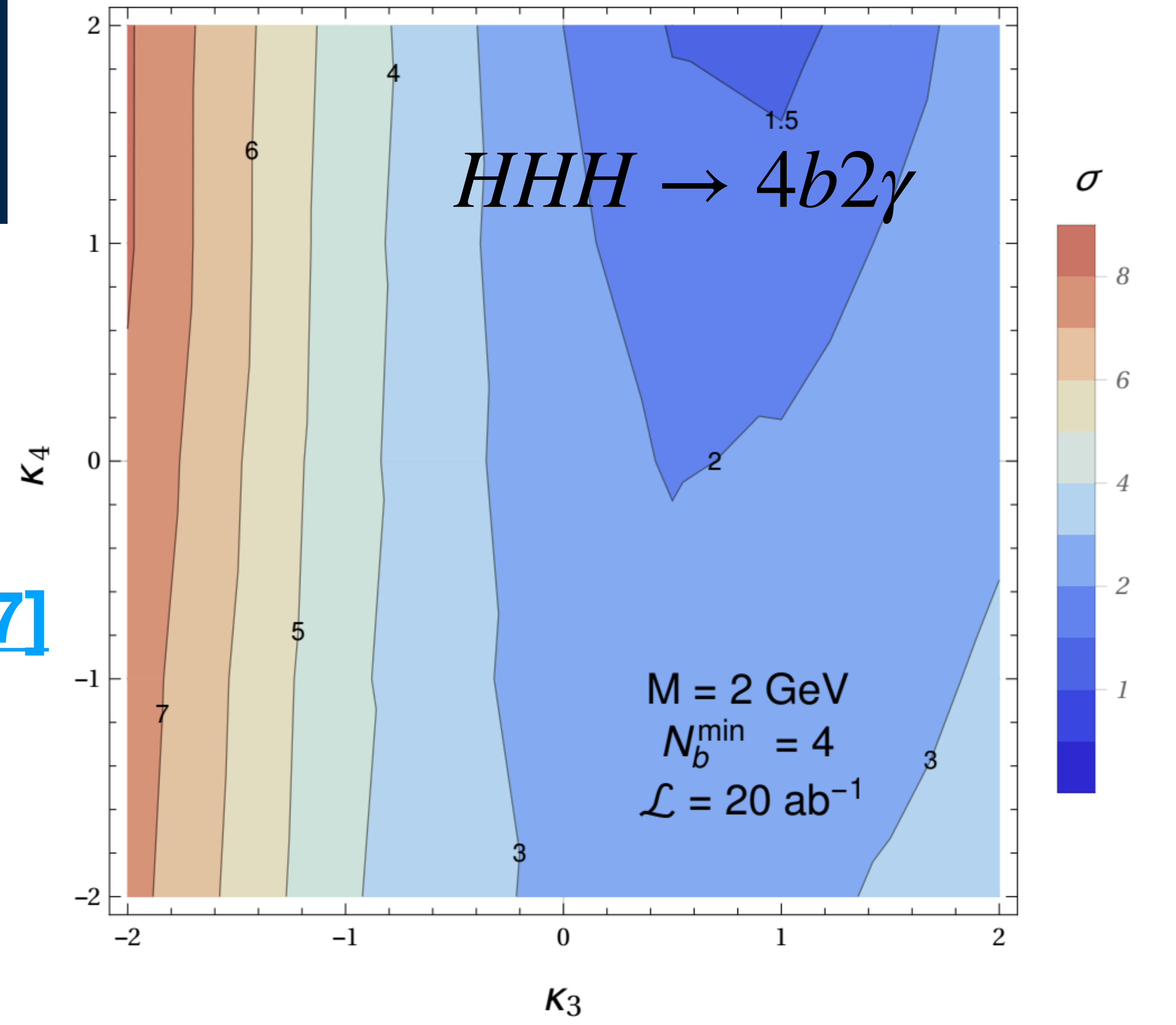

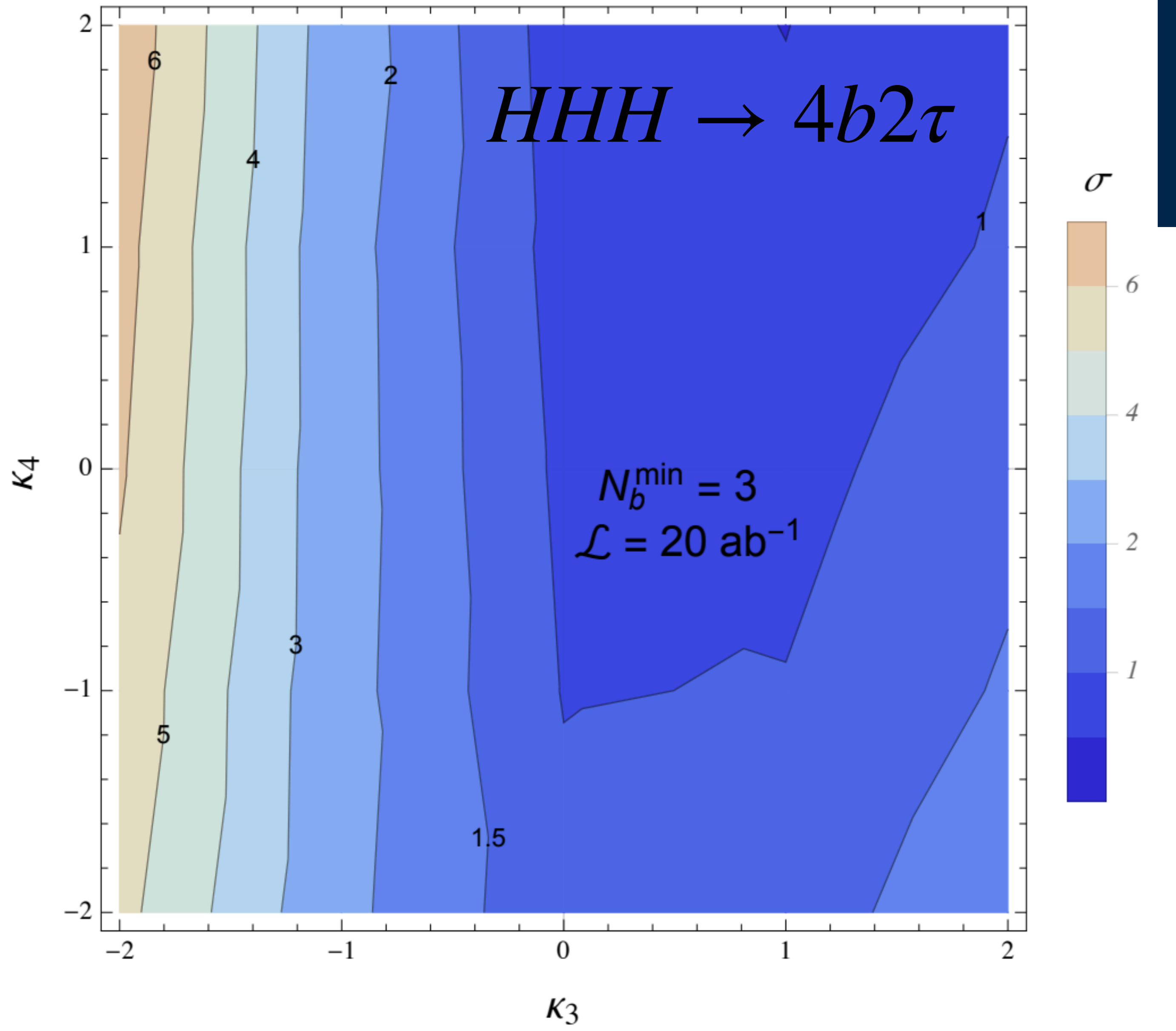

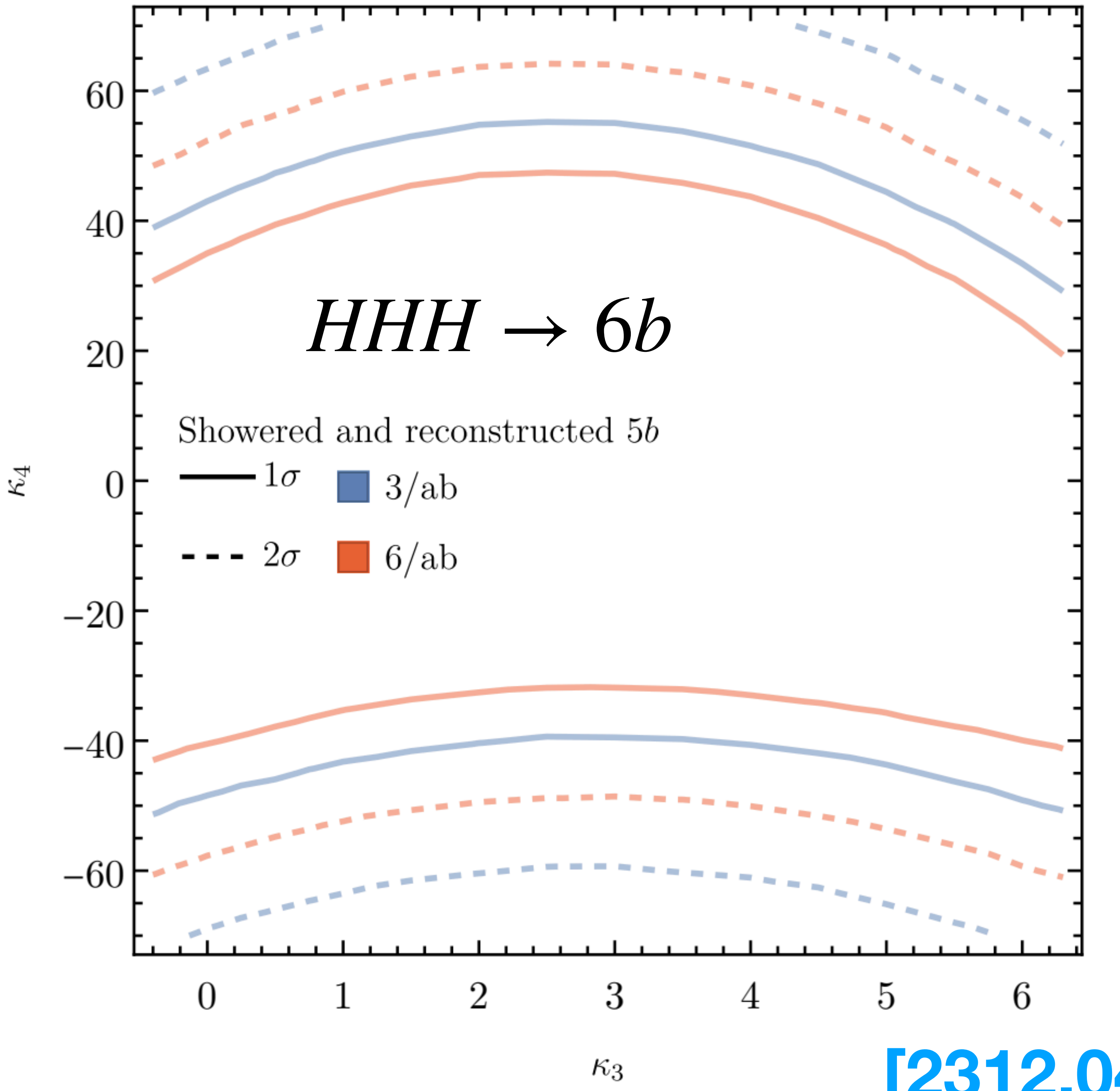

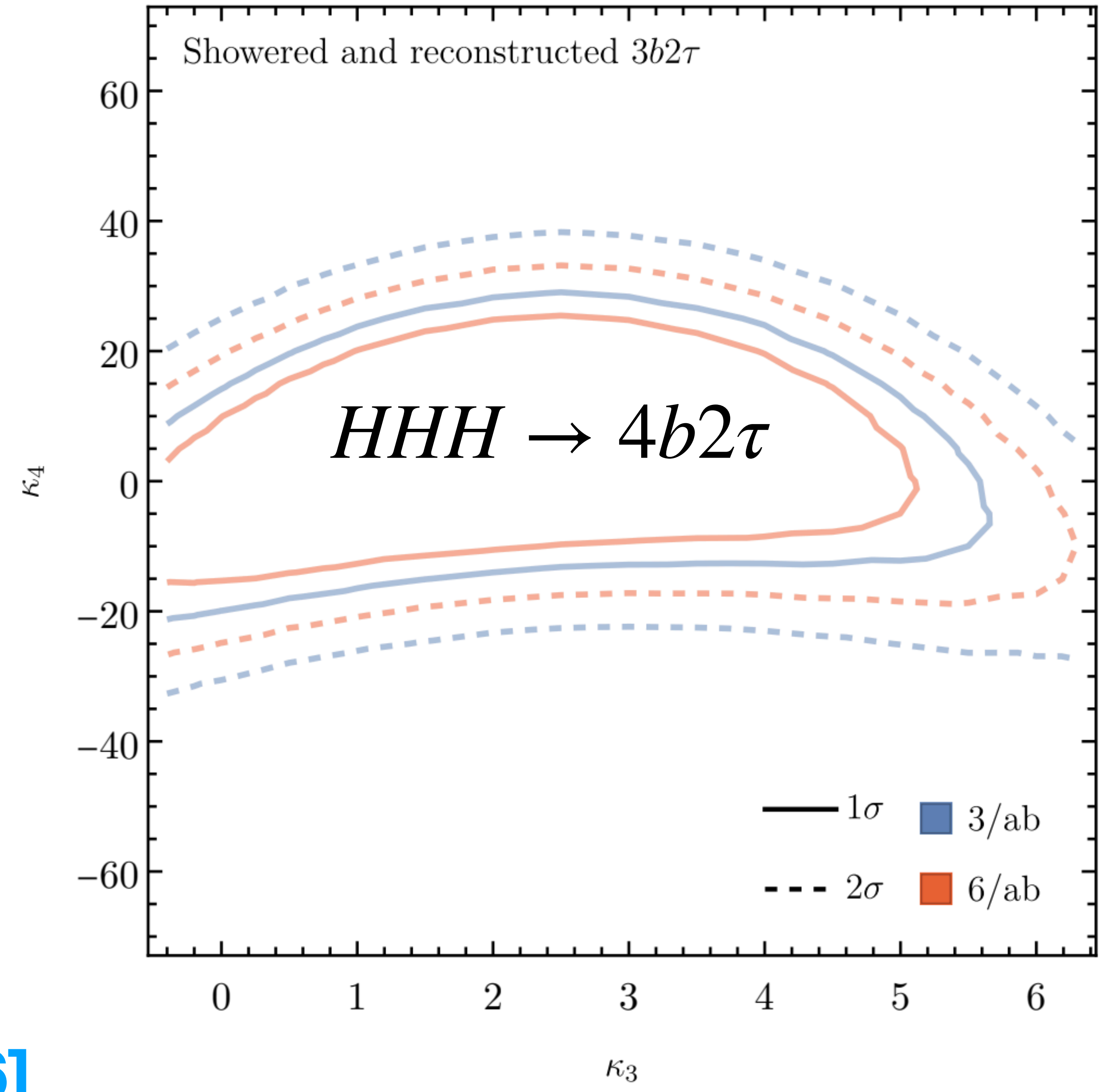

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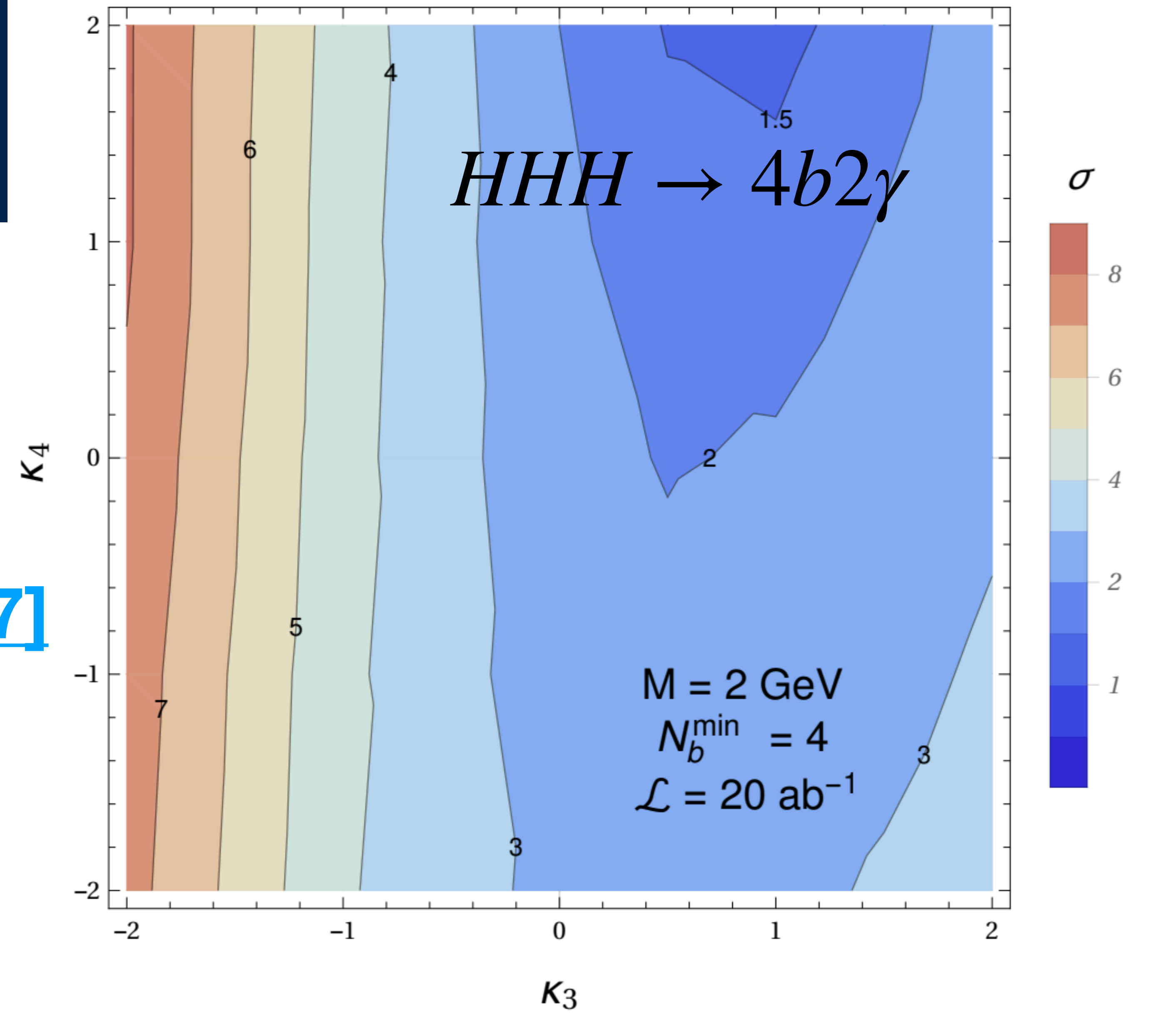

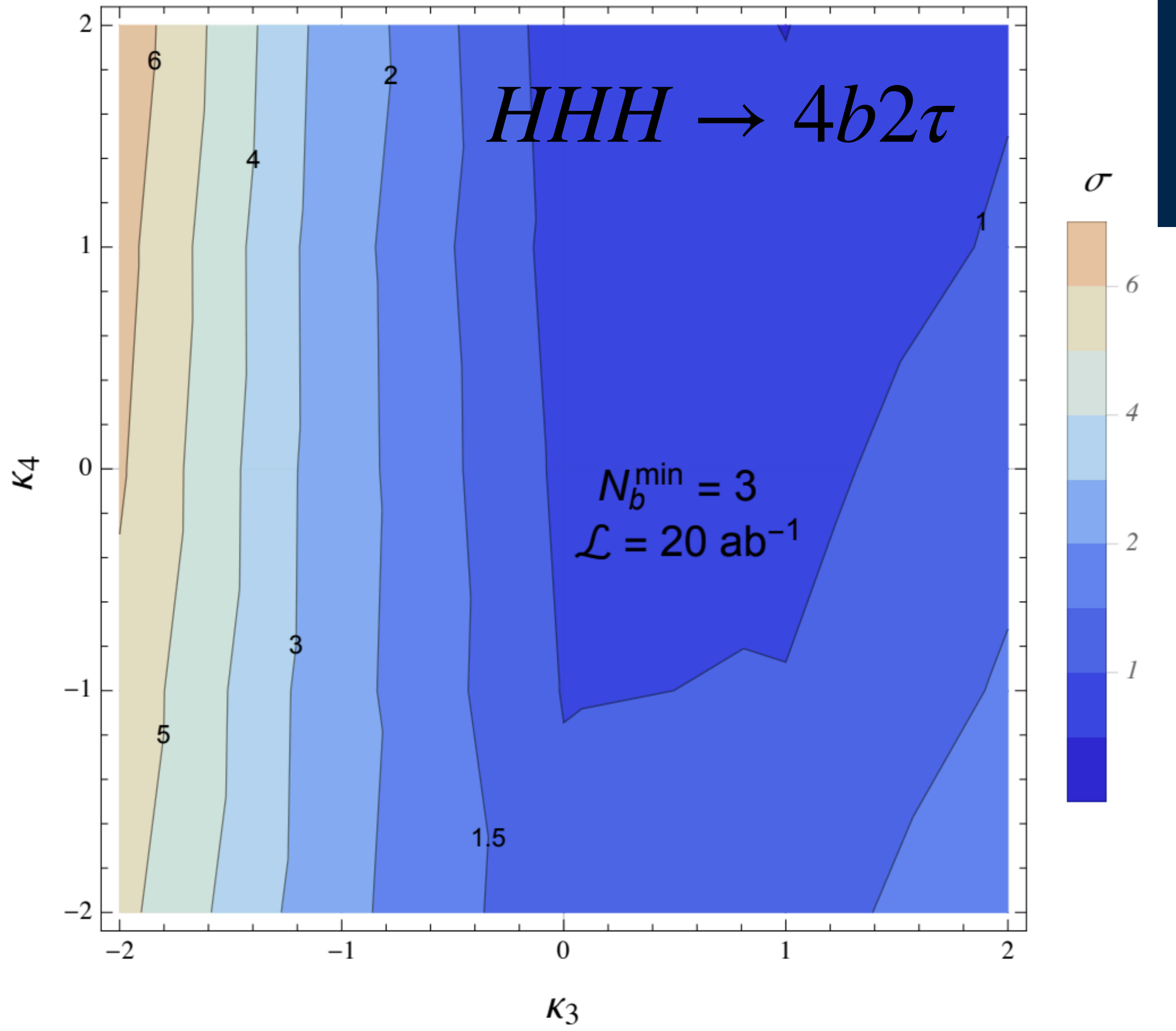

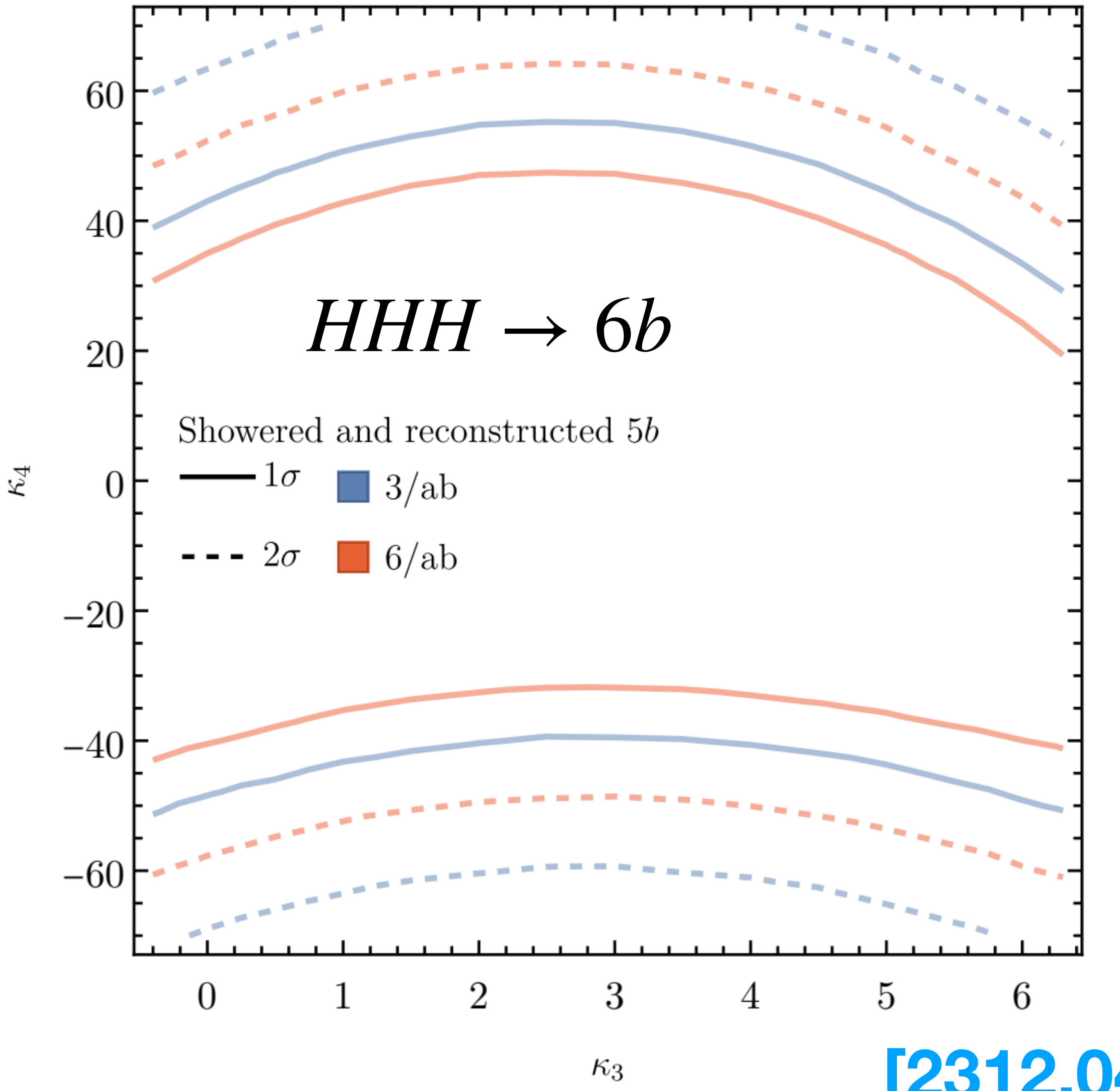

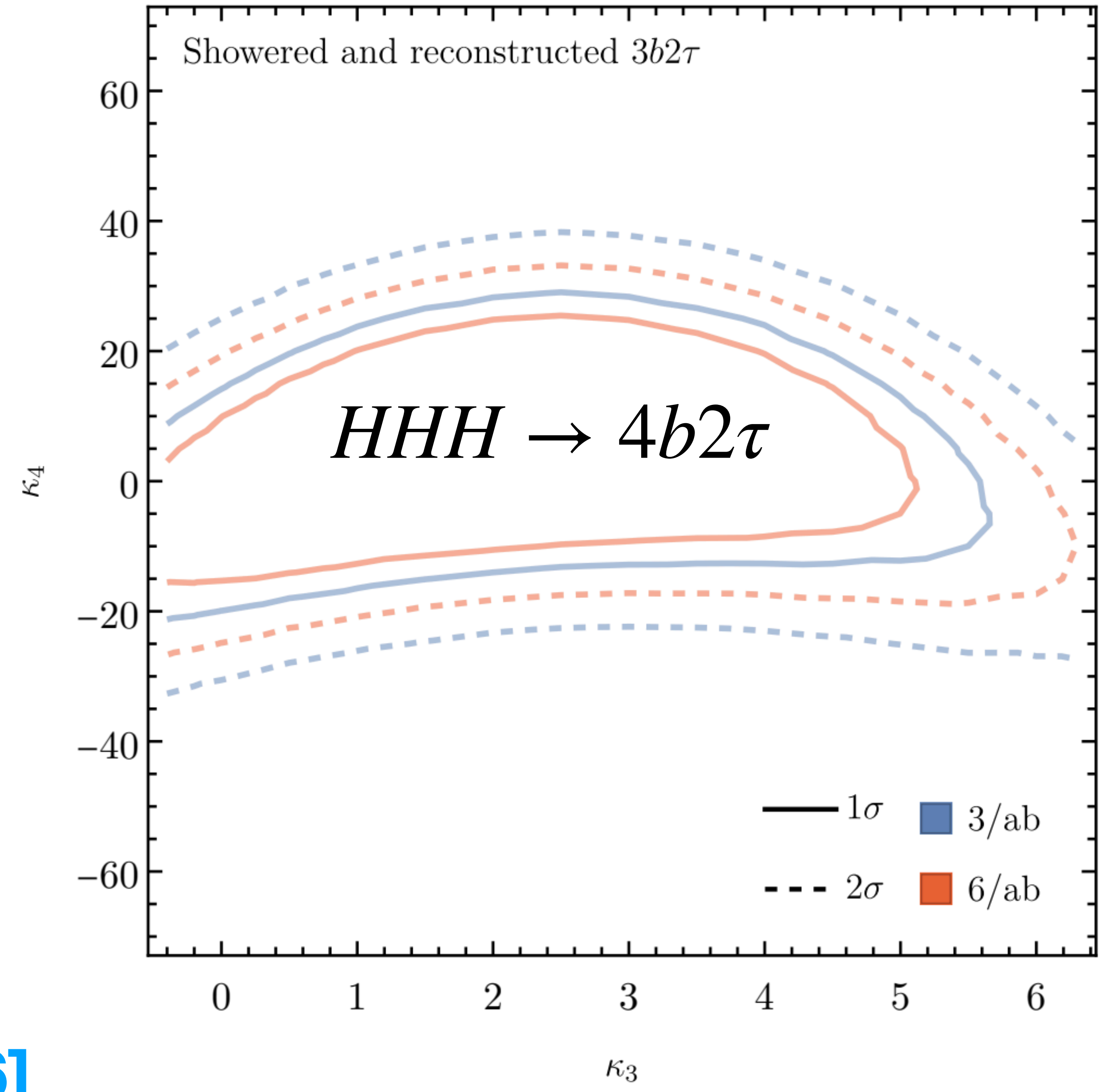

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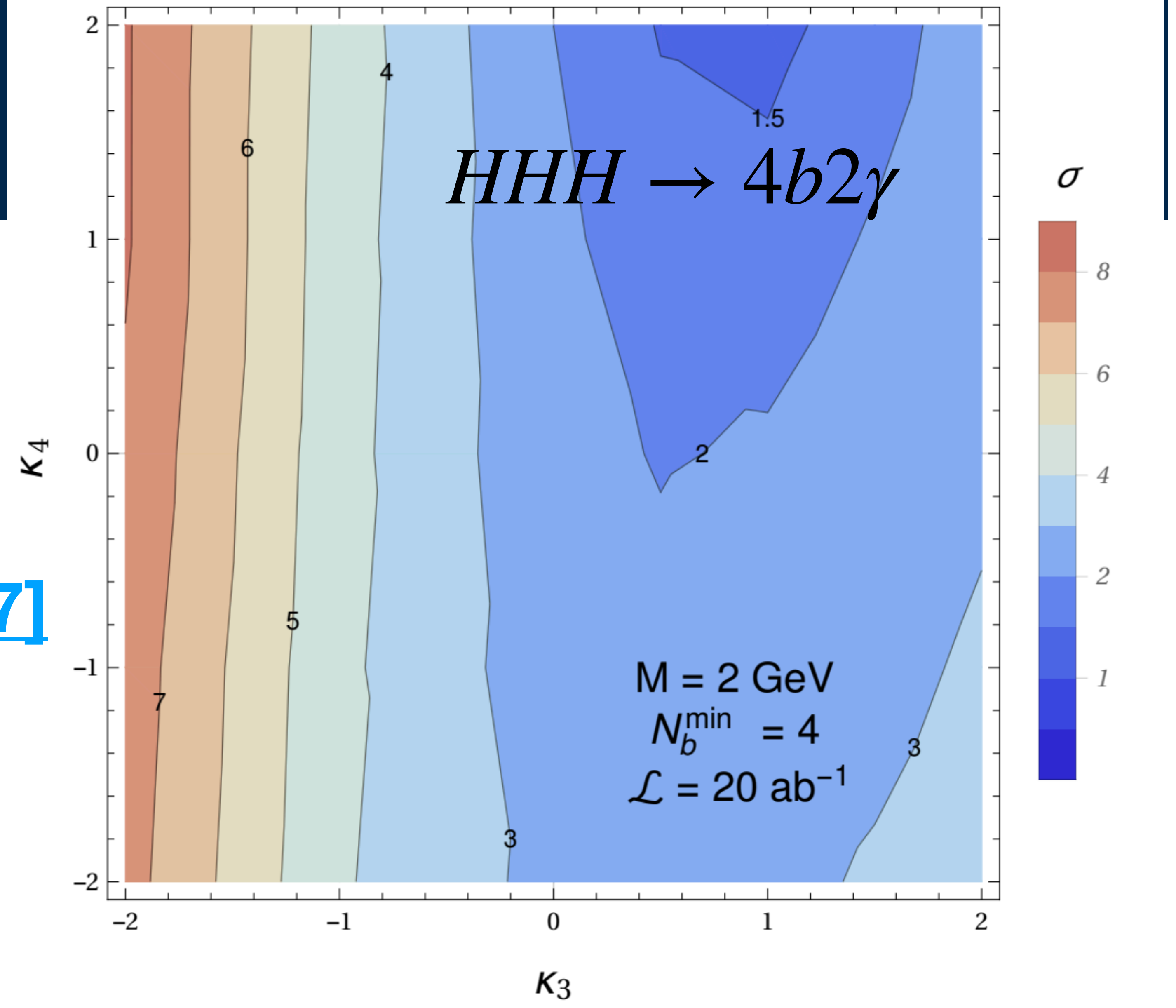

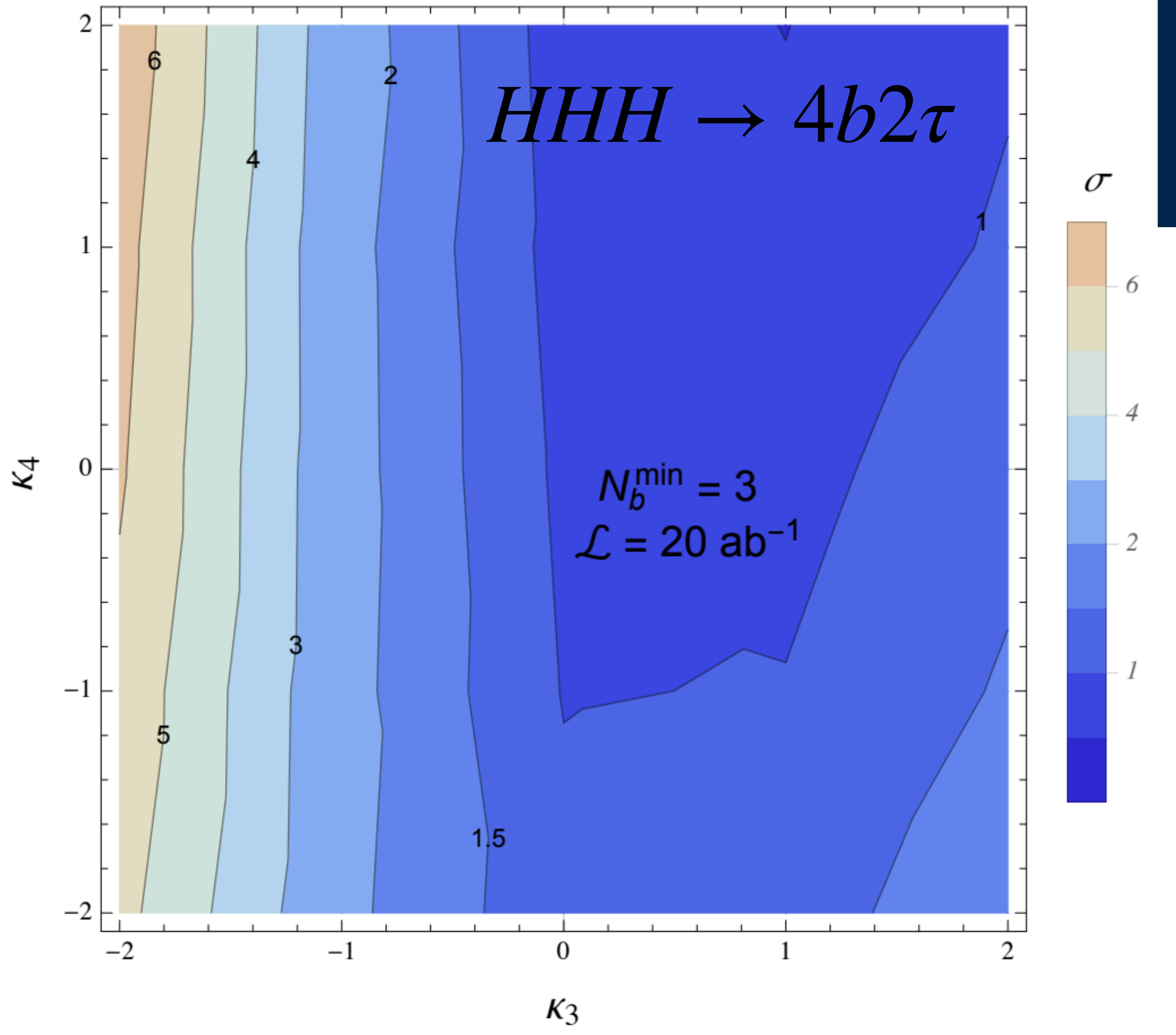

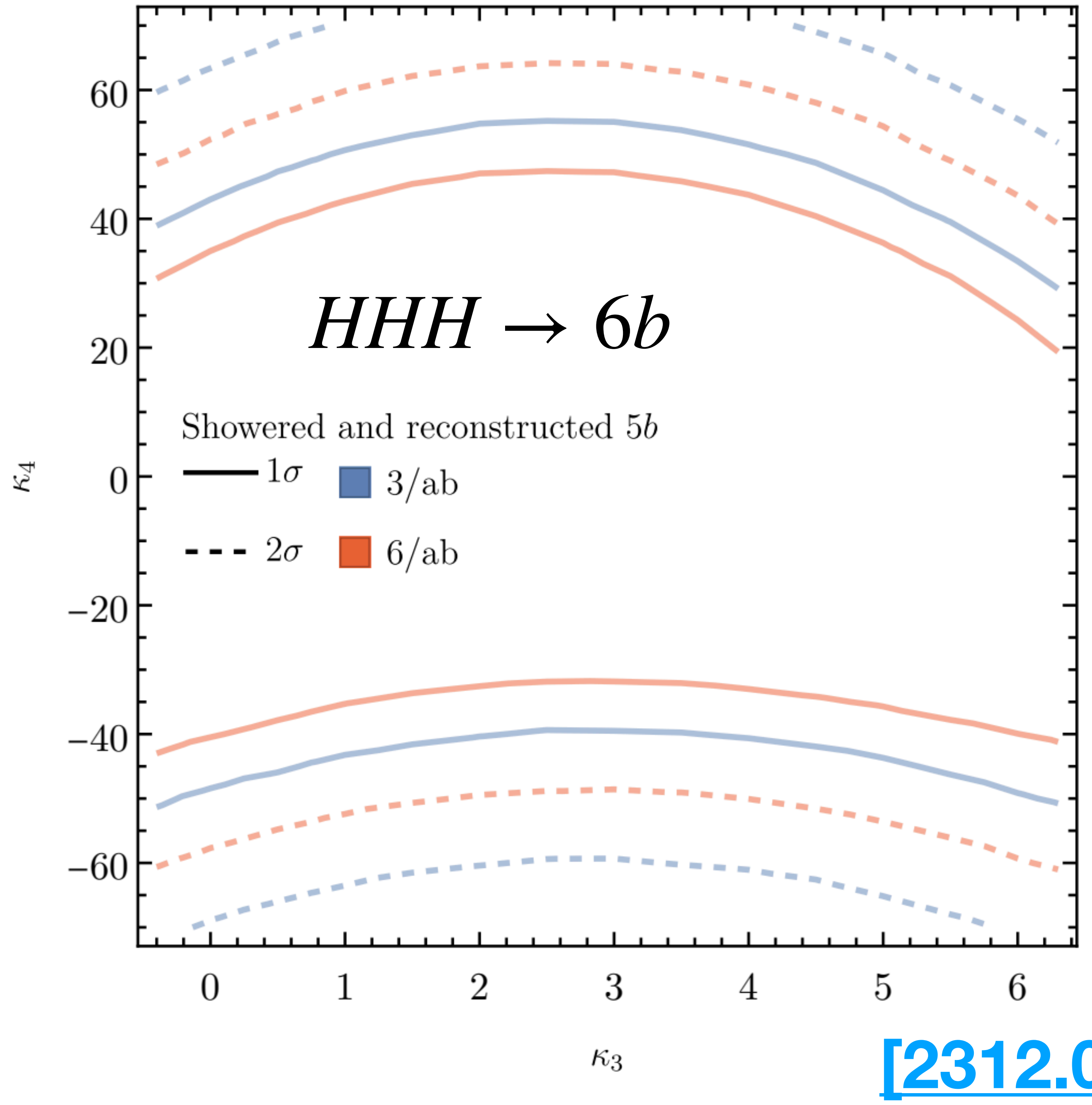

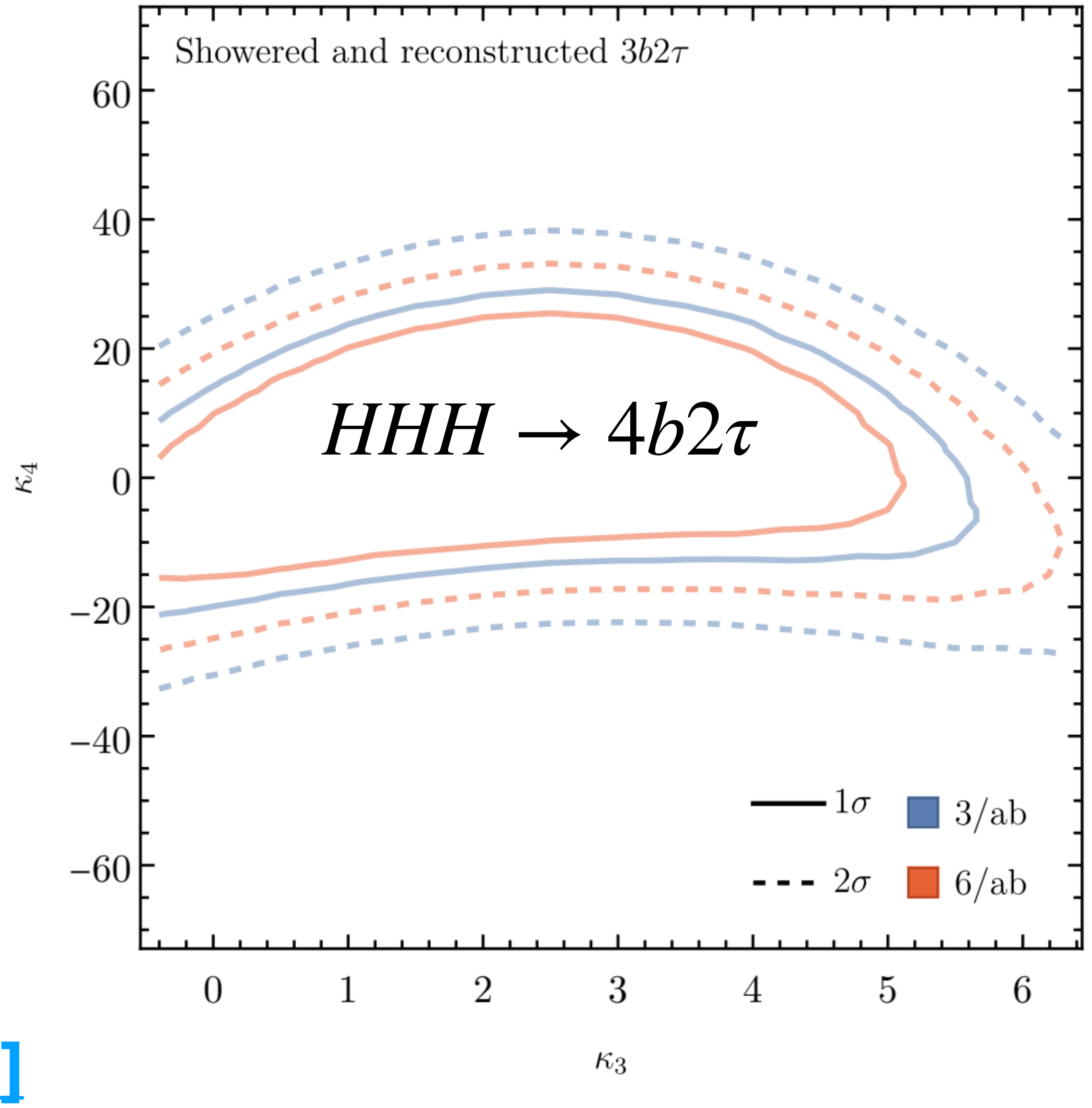

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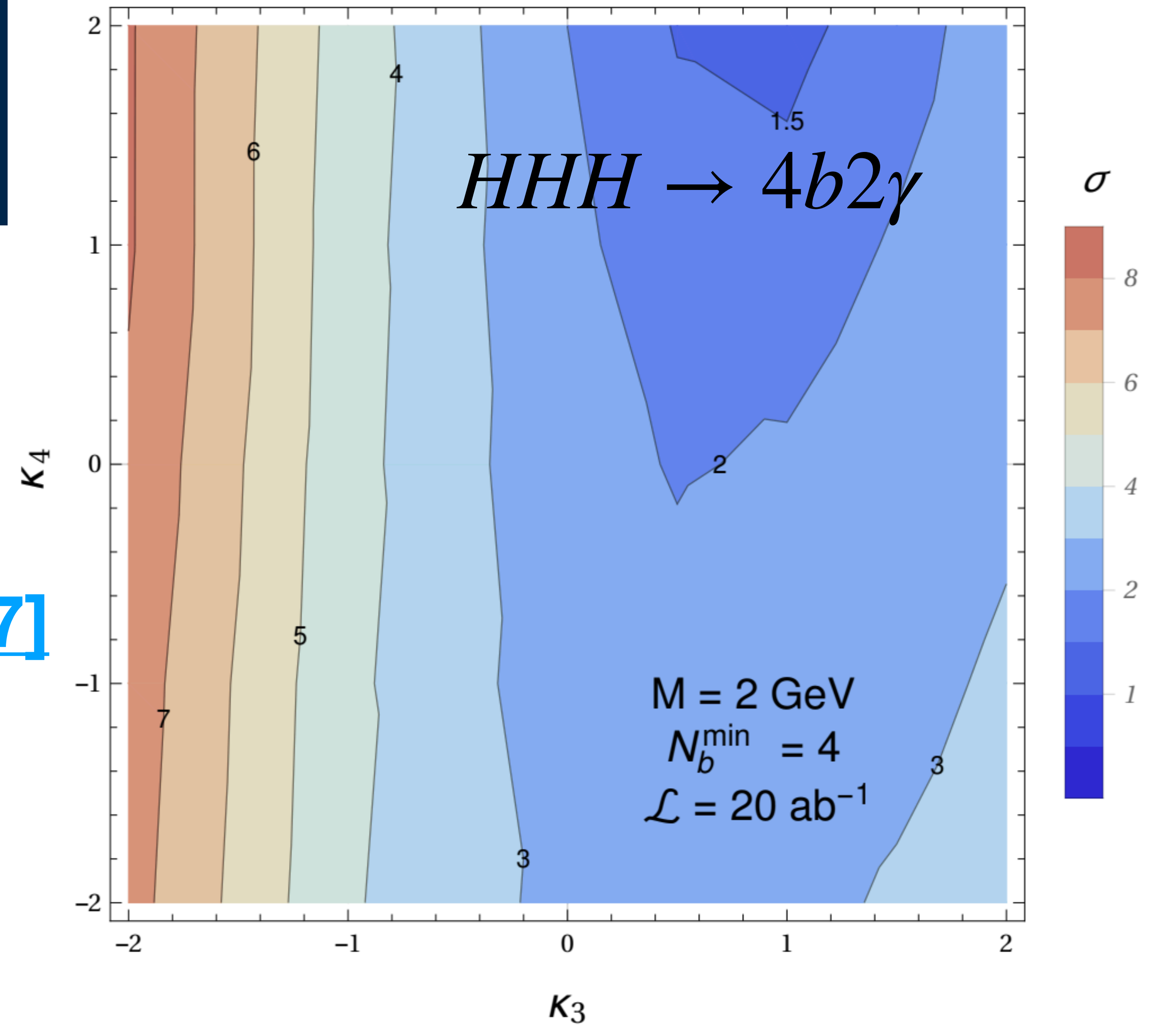
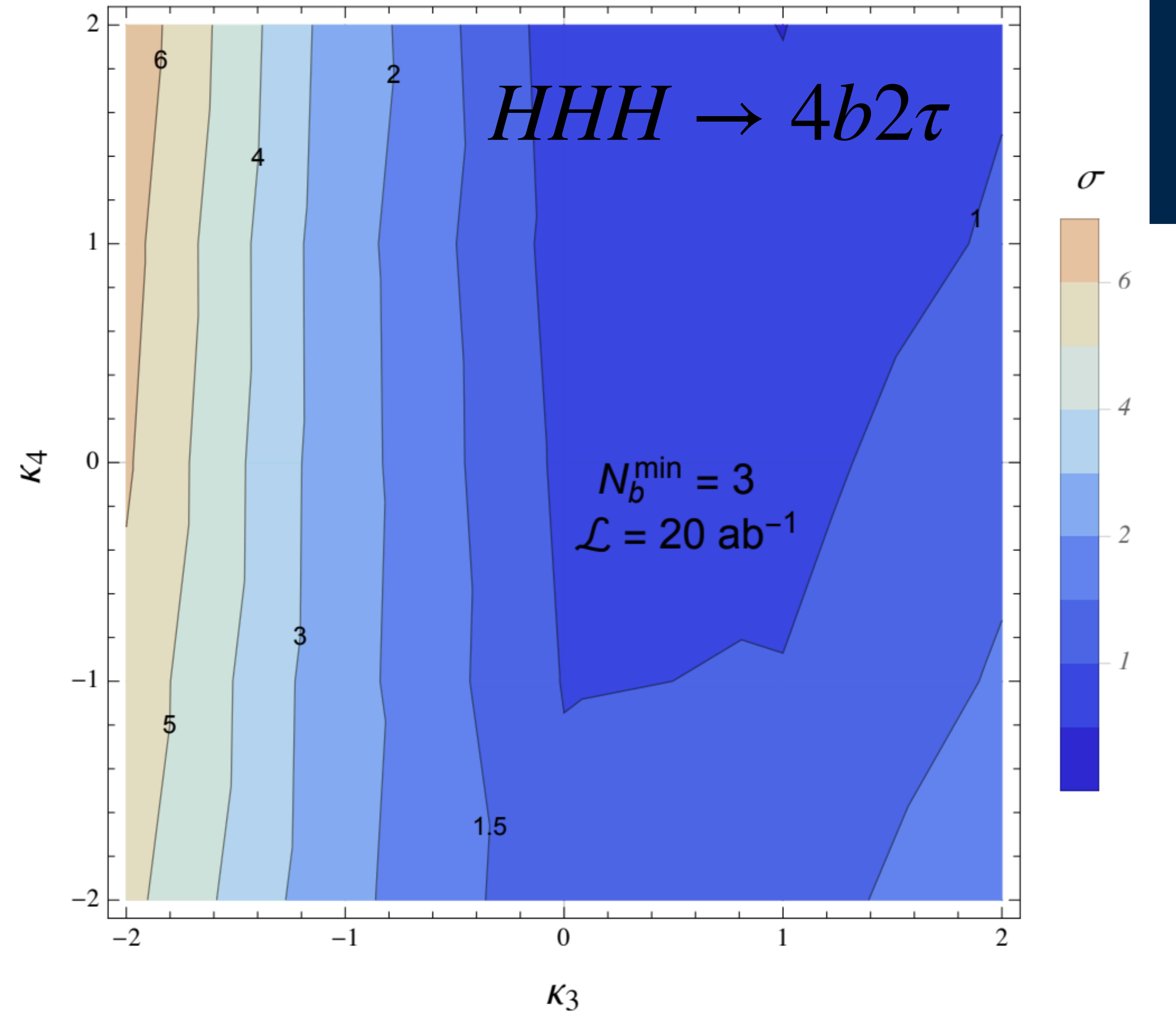
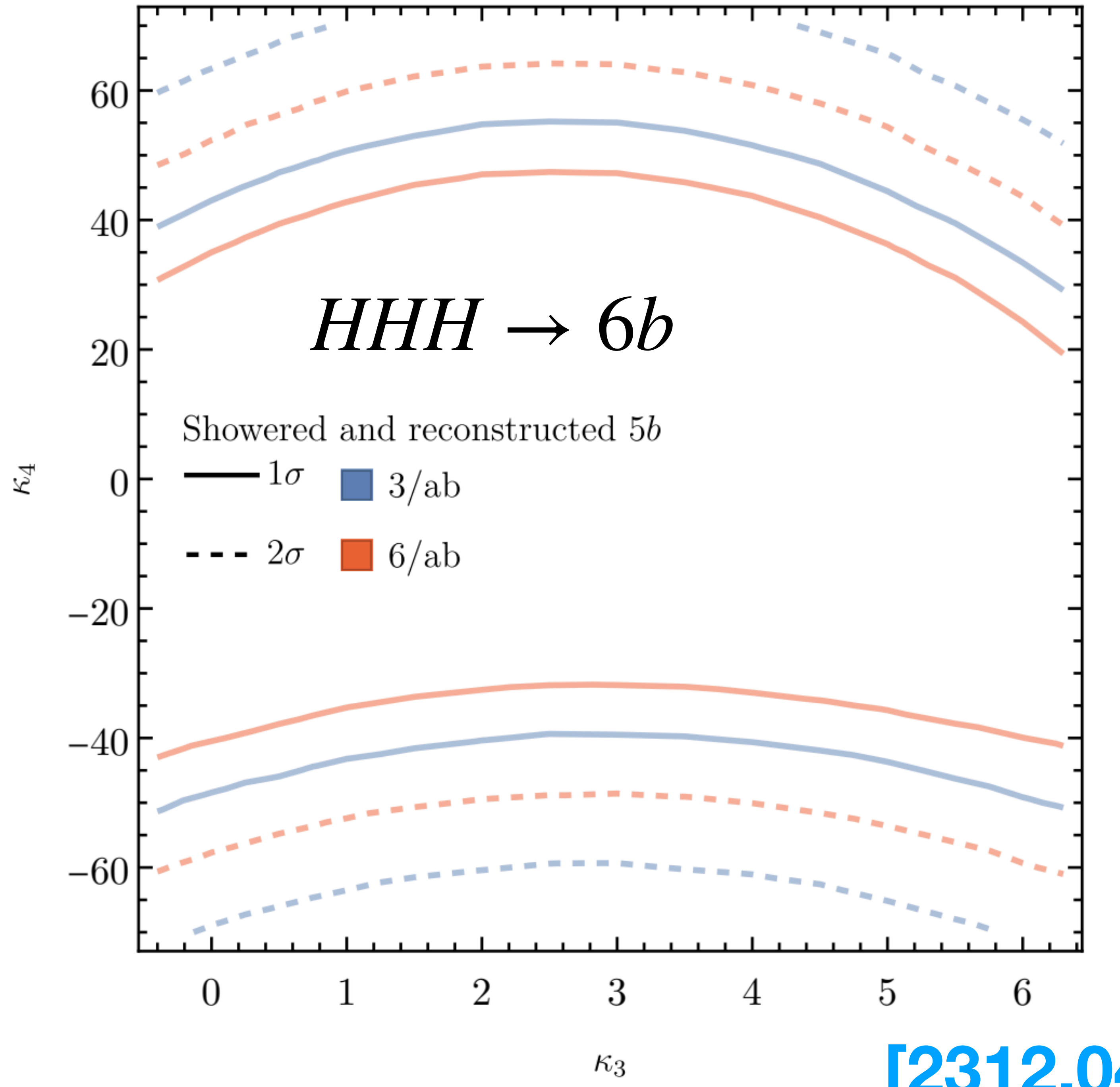
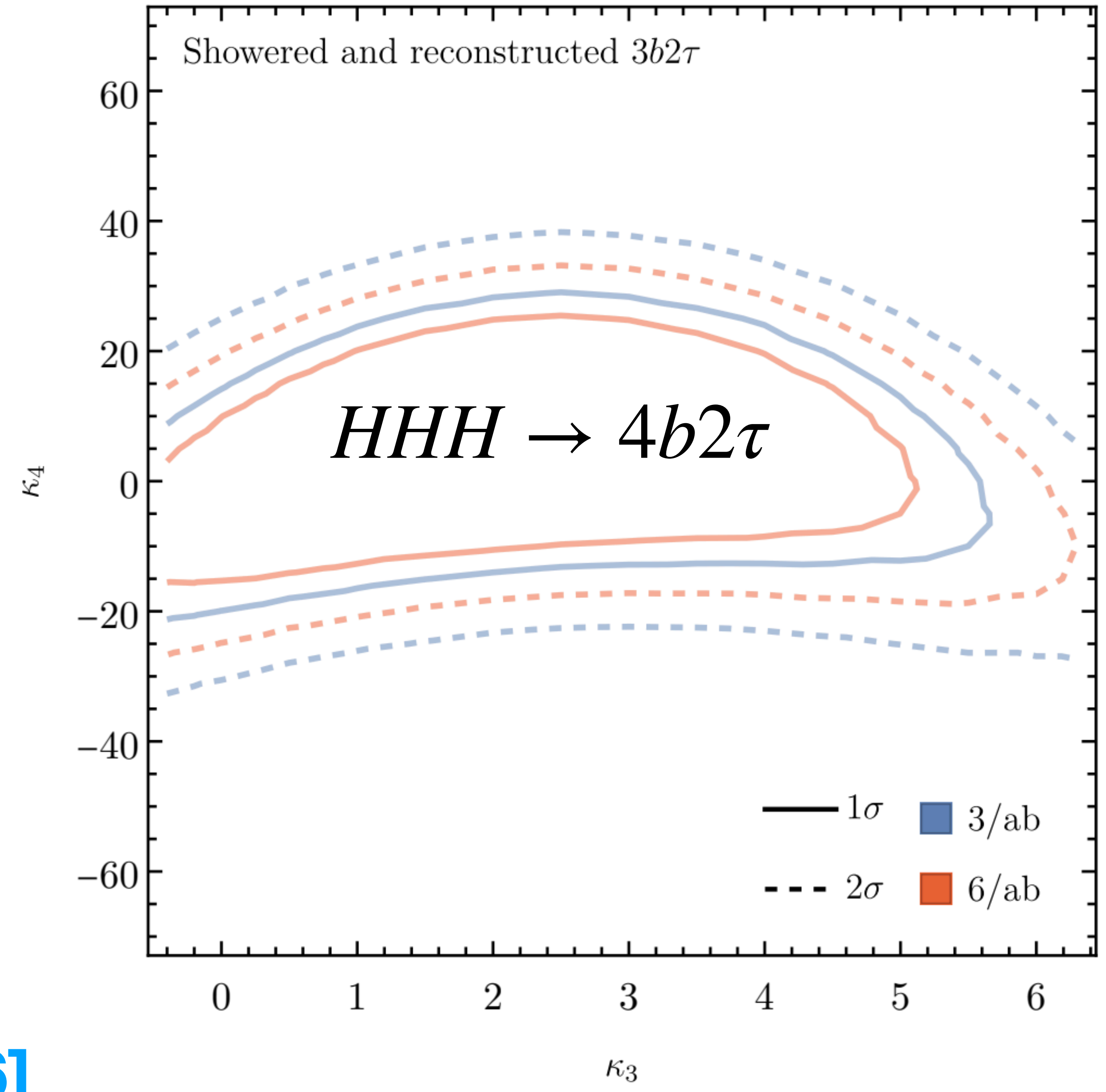
  - Benefit from at least one lepton from many final states: $WW*$, $\tau\tau$, $ZZ*$
- **ATLAS chose $6b$ for 2 reasons:**
  1. Our projections showed this was best
  2. The team had expertise from $HH \rightarrow 4b$





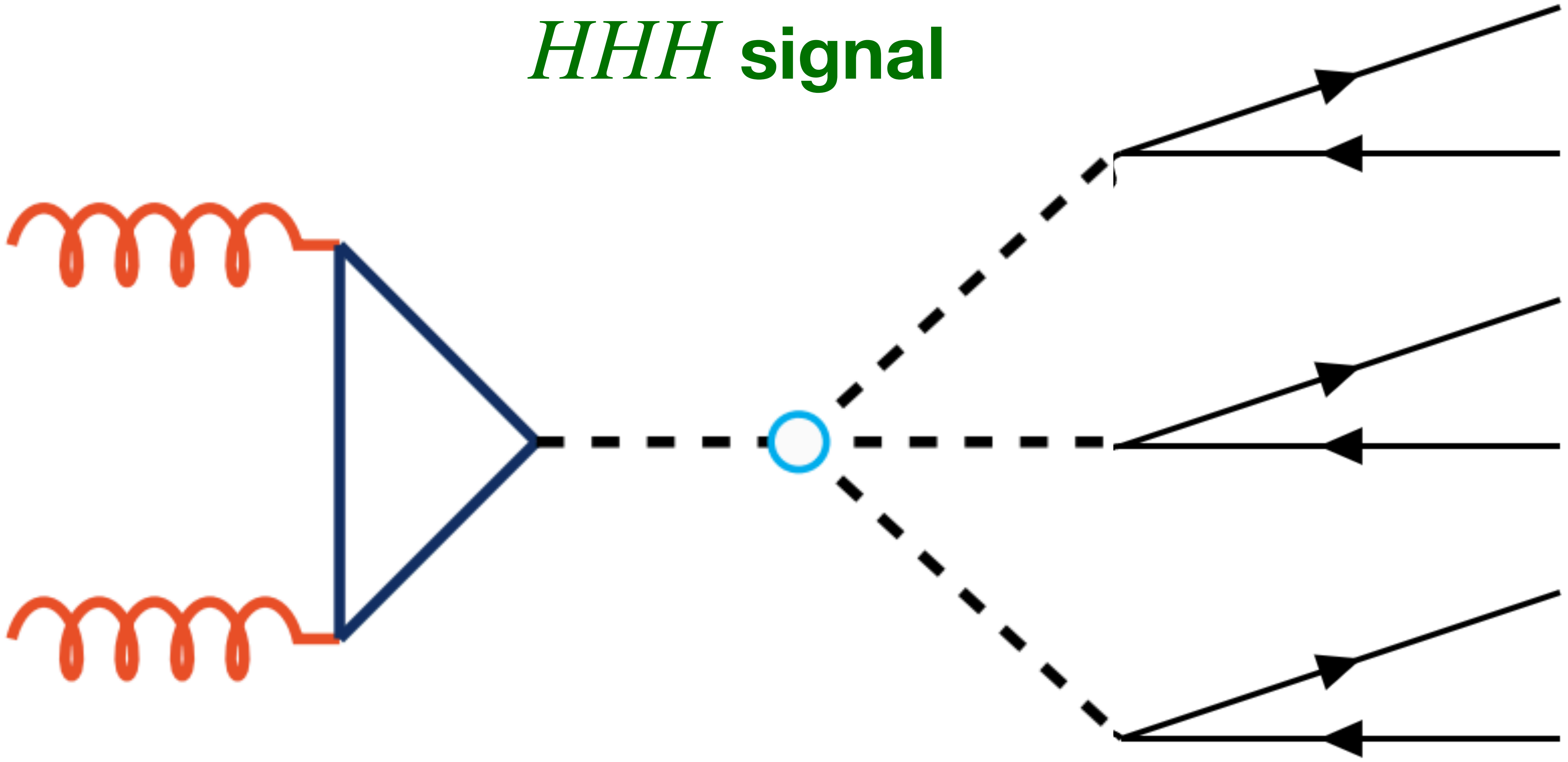




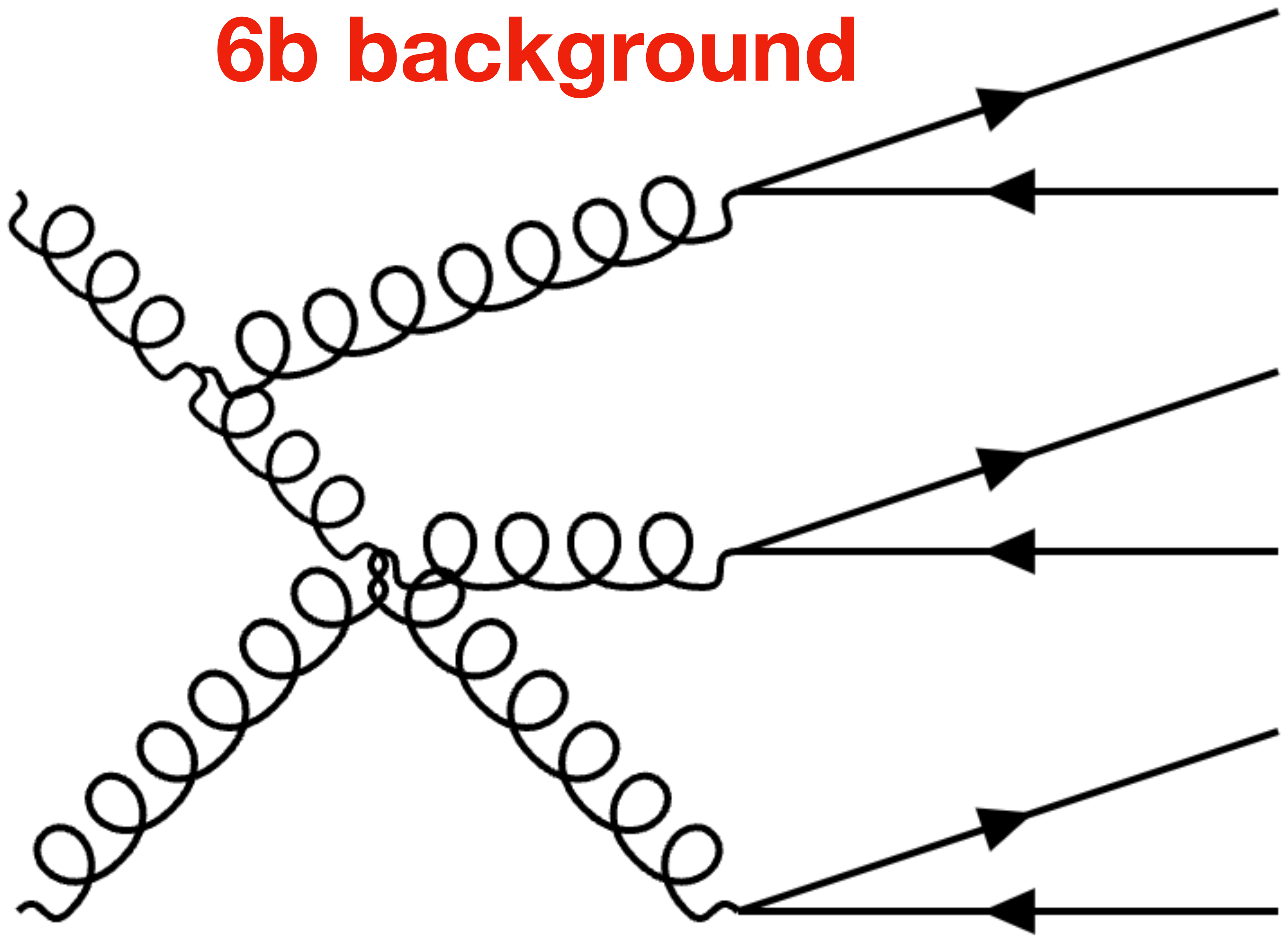
[2312.04646]

Signal and background

HHH **signal**



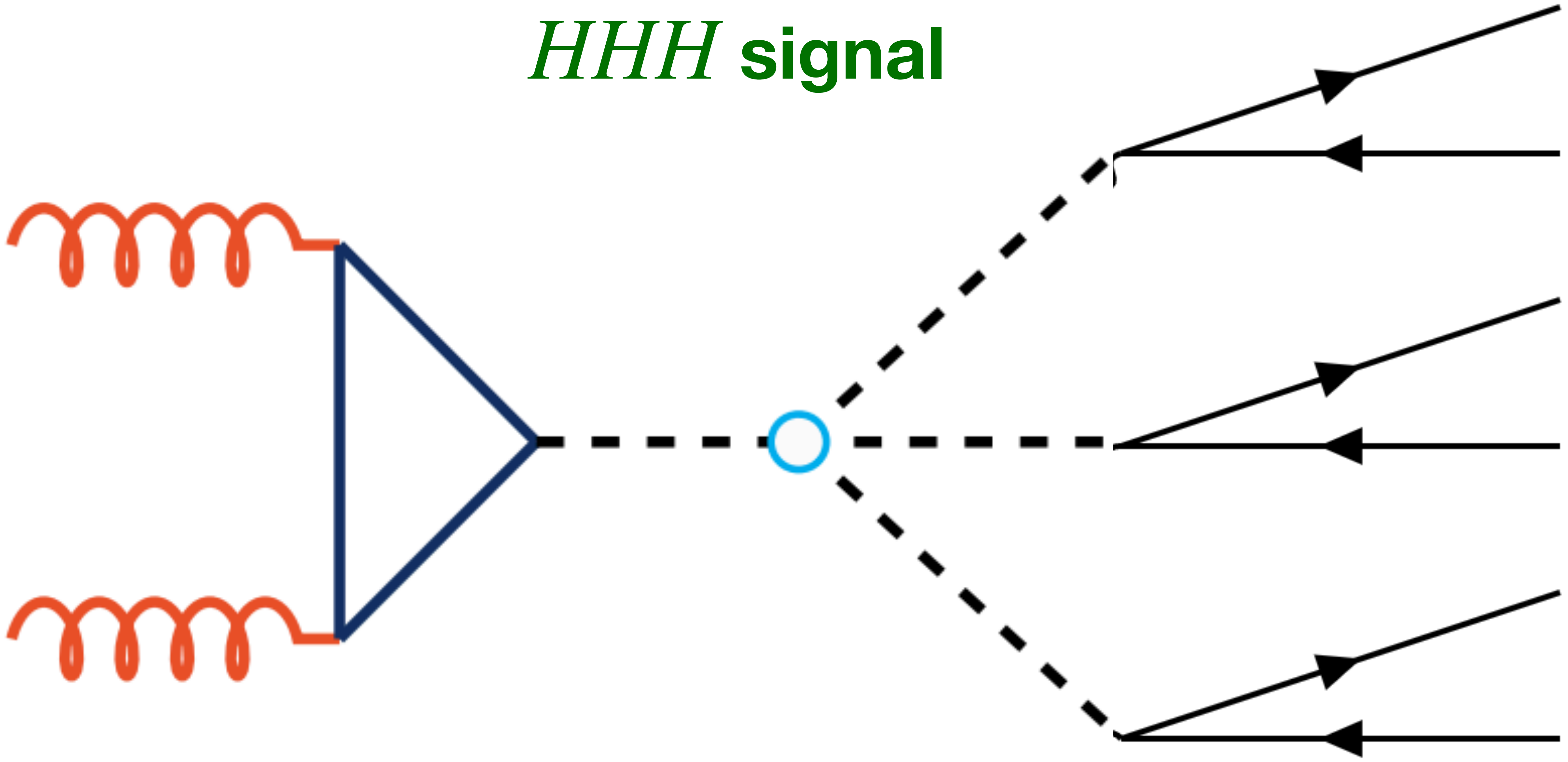
6b background



Signal and background

- We search in the 6b final state
- Primary background is from QCD multi-jet production

HHH signal



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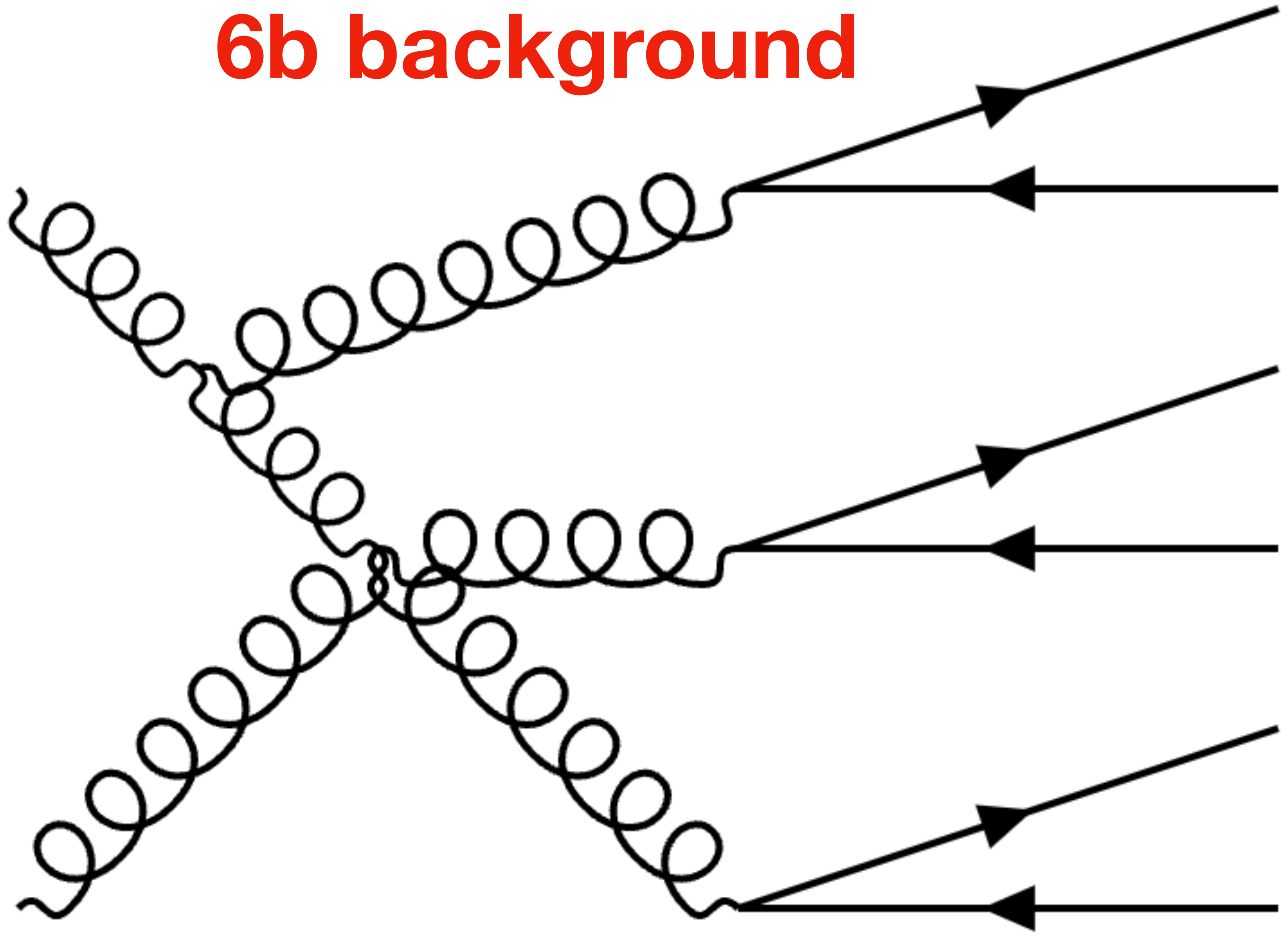
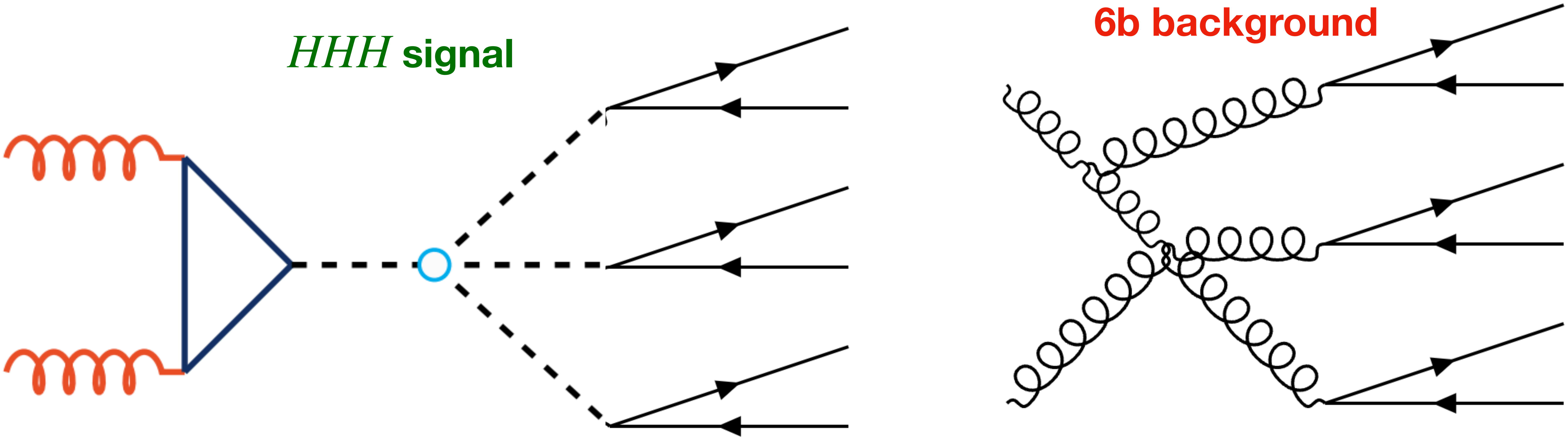


Signal and background

- We search in the 6b final state
- Primary background is from QCD multi-jet production
- Other backgrounds like $t\bar{t} + HF$ still have many additional b-jets and are difficult to model with MC
- Motivates a data-driven background estimate



Event selection

- Trigger on the jets/b-jets (some online b-tagging is used in the trigger)
- Select all events to have at least 6 jets, categorize into the 4b, 5b, 6b regions

Events

- $\geqslant$ 6 jets
- $\geqslant$ 4 jets with p_T > 40 GeV
- $\geqslant$ 4 jets passing DL1dv01 77% working point

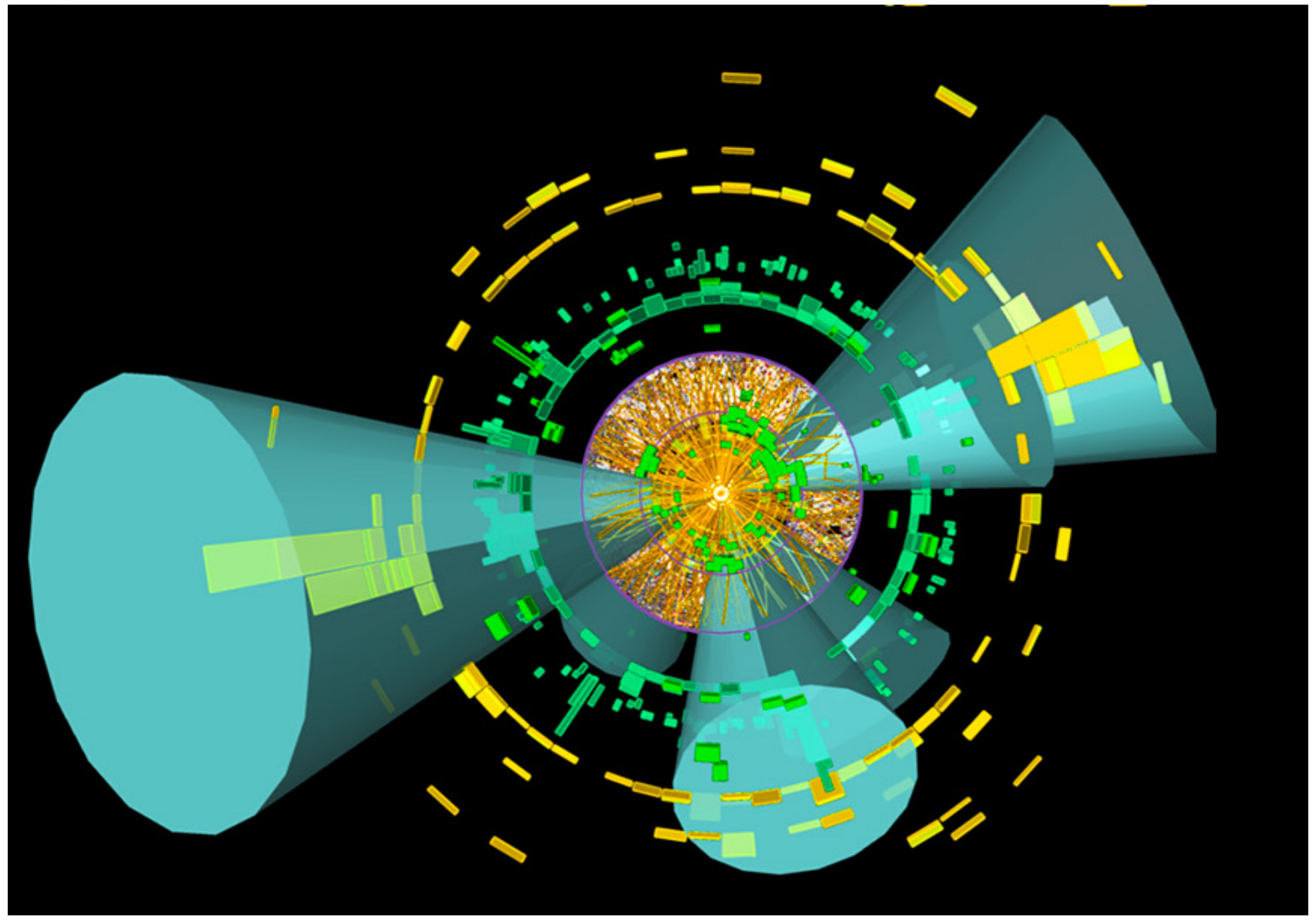
$\geqslant$ 6 *b*-tags
Signal Region

== 5 *b*-tags
Background Estimate

== 4 *b*-tags
Background Estimate/Validation


Example 6b event
Run: 349592
Event: 793710422
2018-05-06 03:37:28 UTC

Analysis strategy



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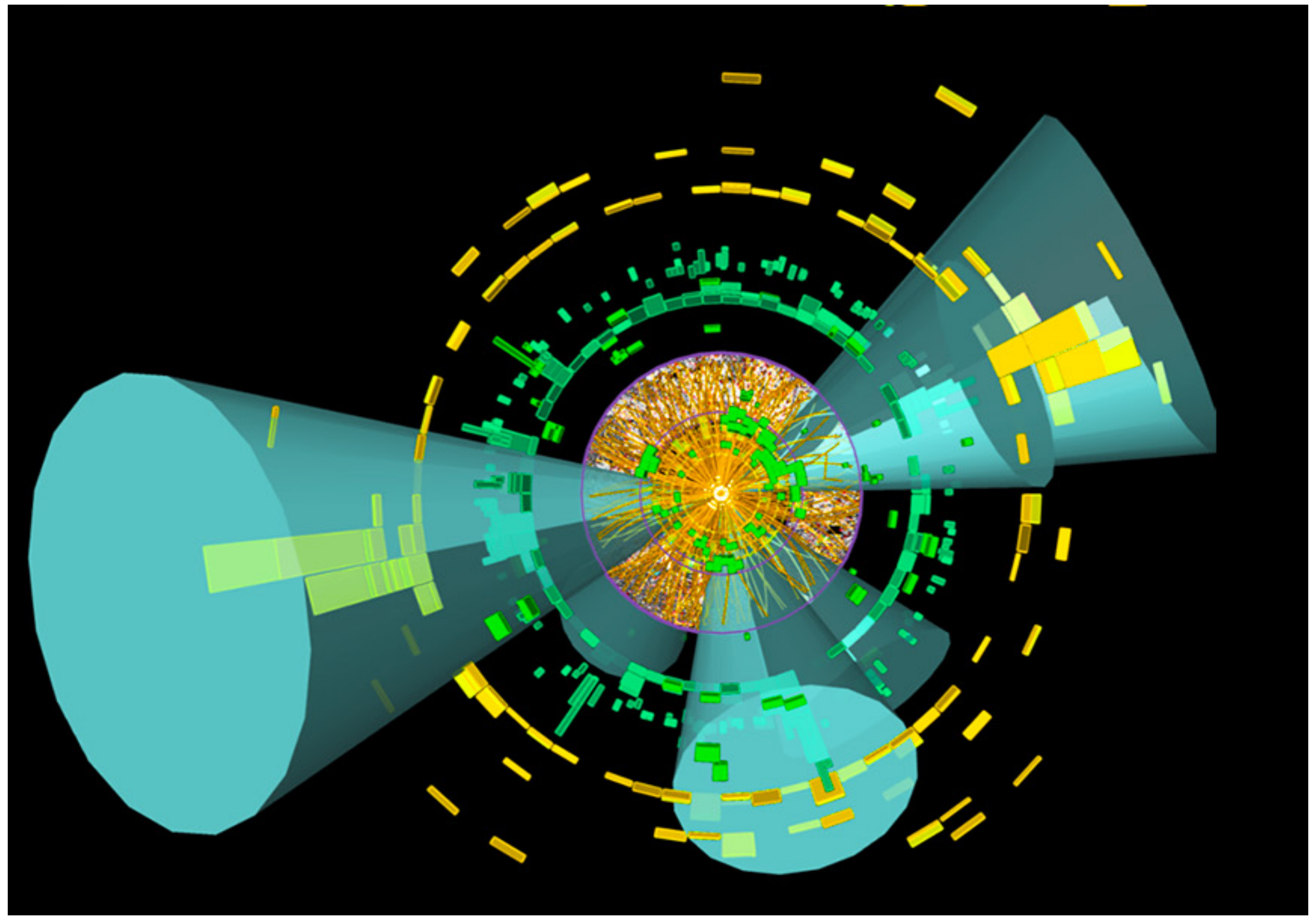

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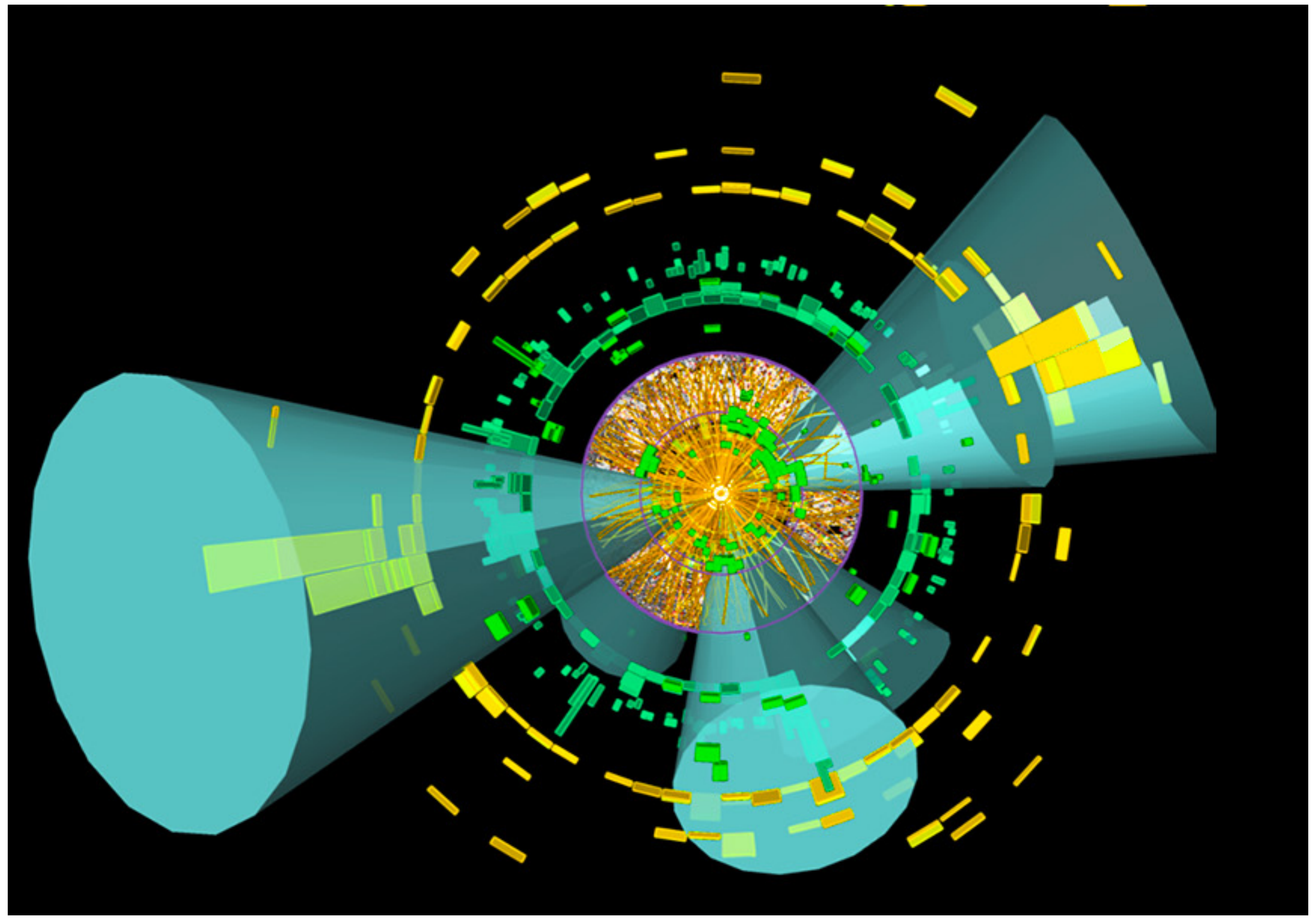

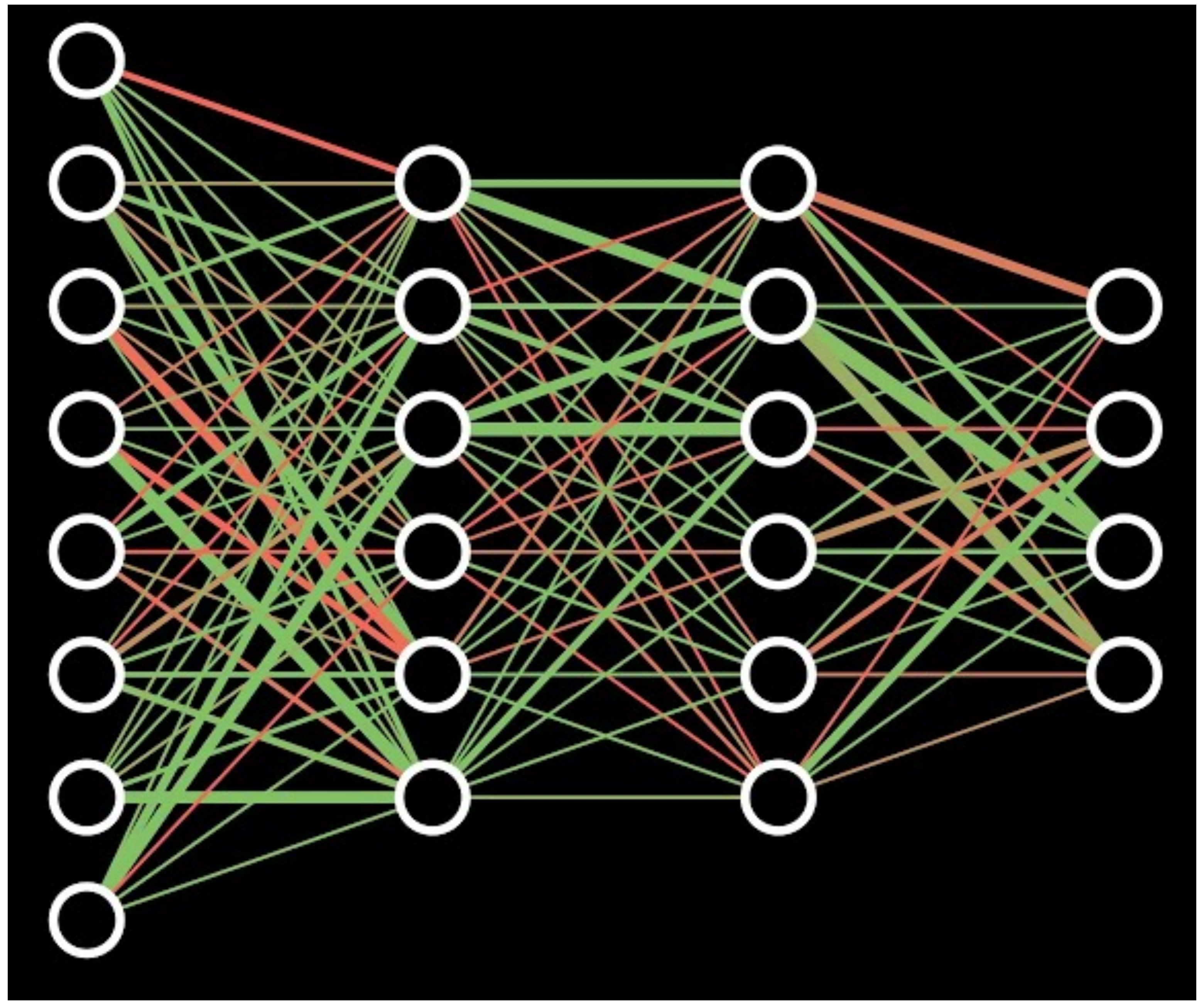

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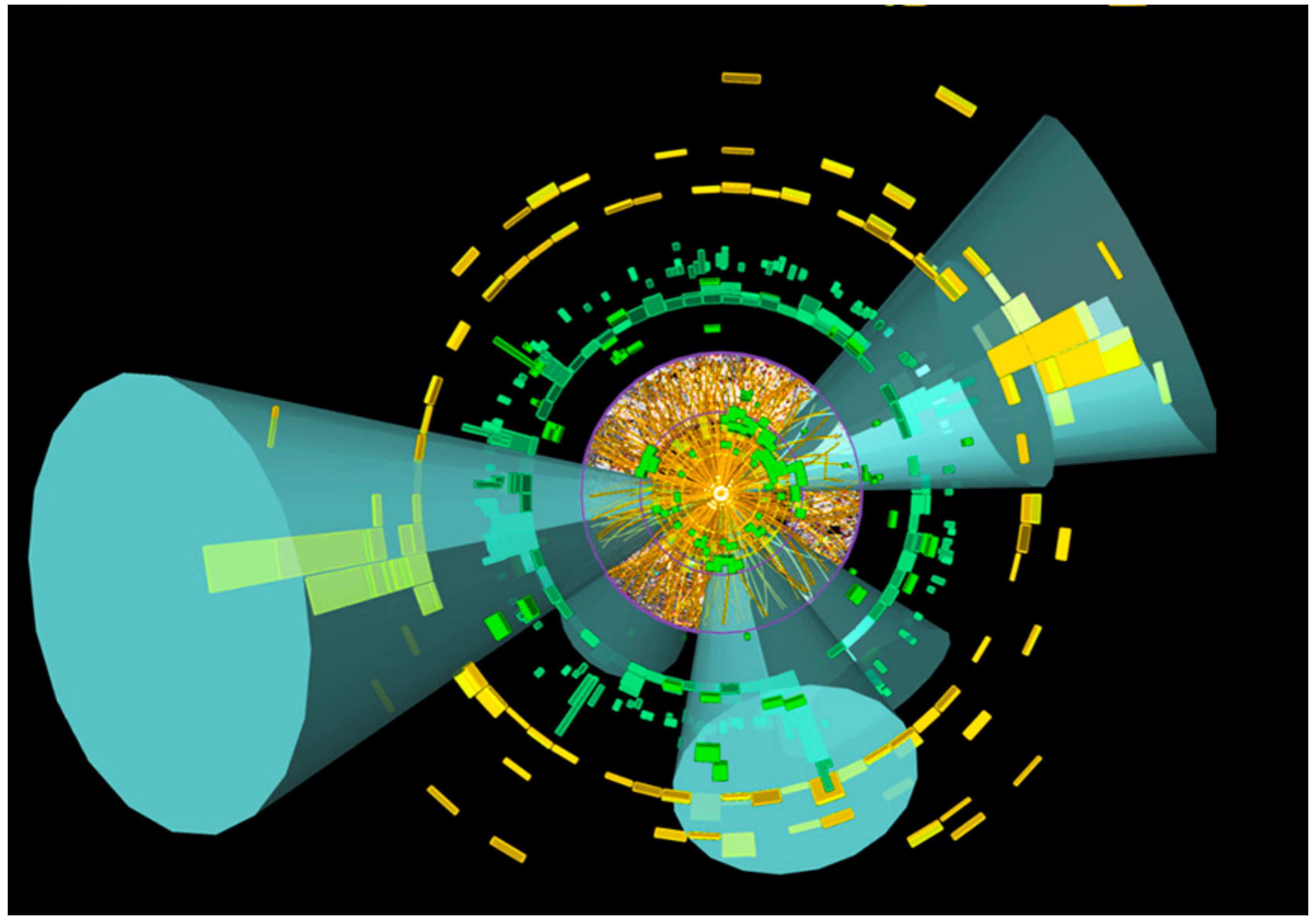
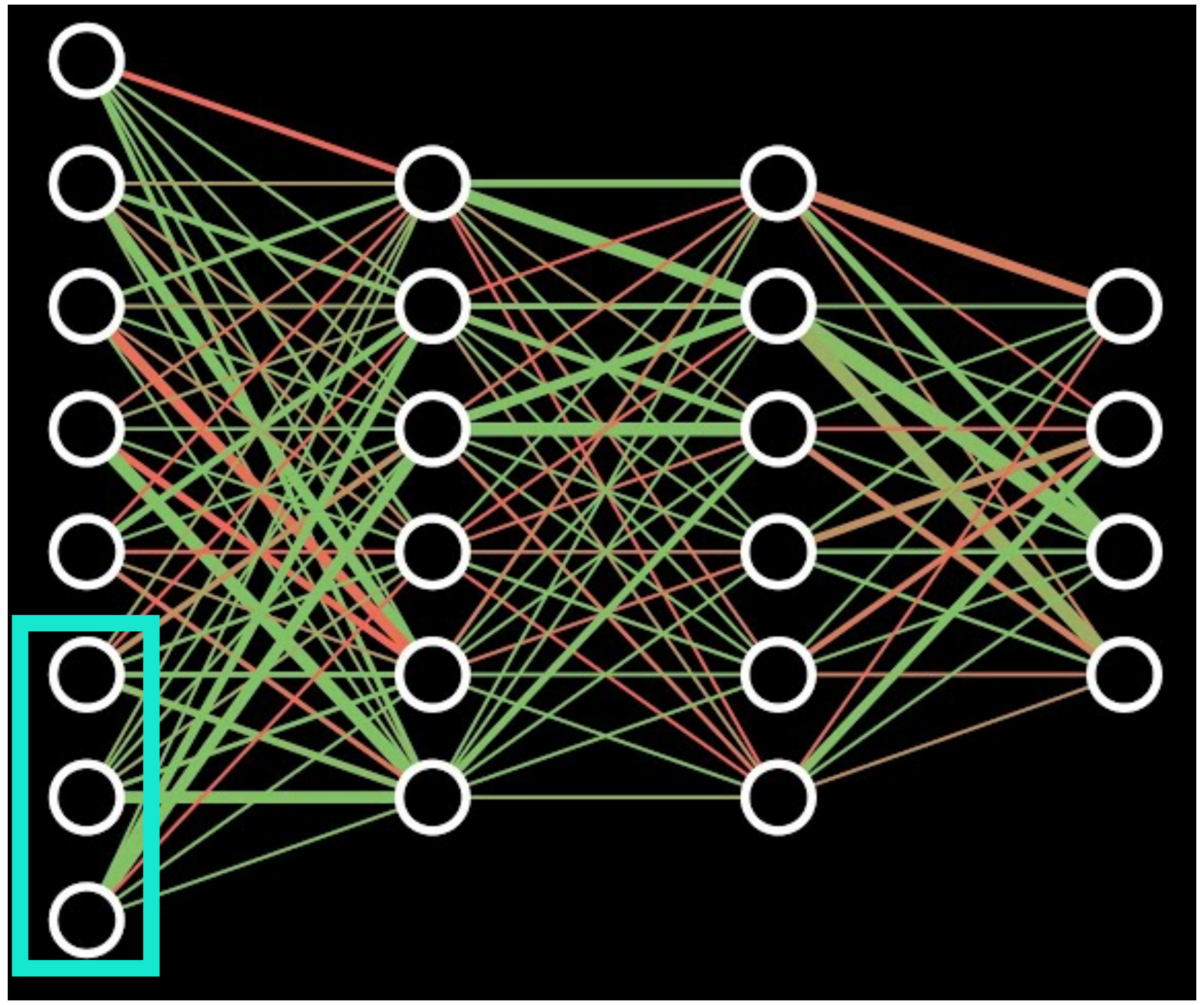
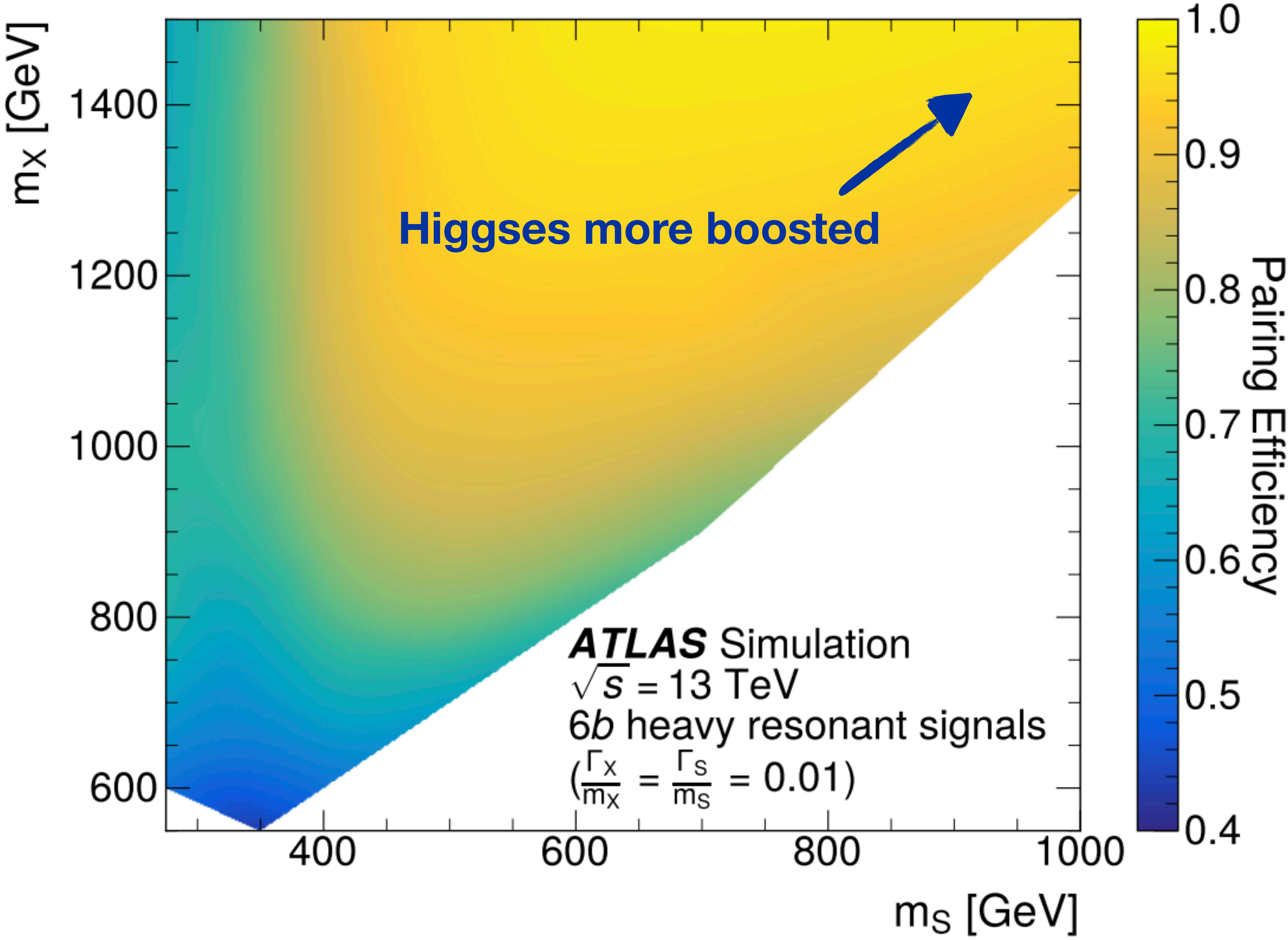




- **All events have 6 reconstructed jets. Some have 4, 5, or 6 b-tagged jets.**
- **Train a DNN to discriminate between HHH signal and 5b background.**
  - Some of the DNN inputs are reliant on paired jets, for example to compute m(bb) for the three pairs of jets.

b-jet pairing



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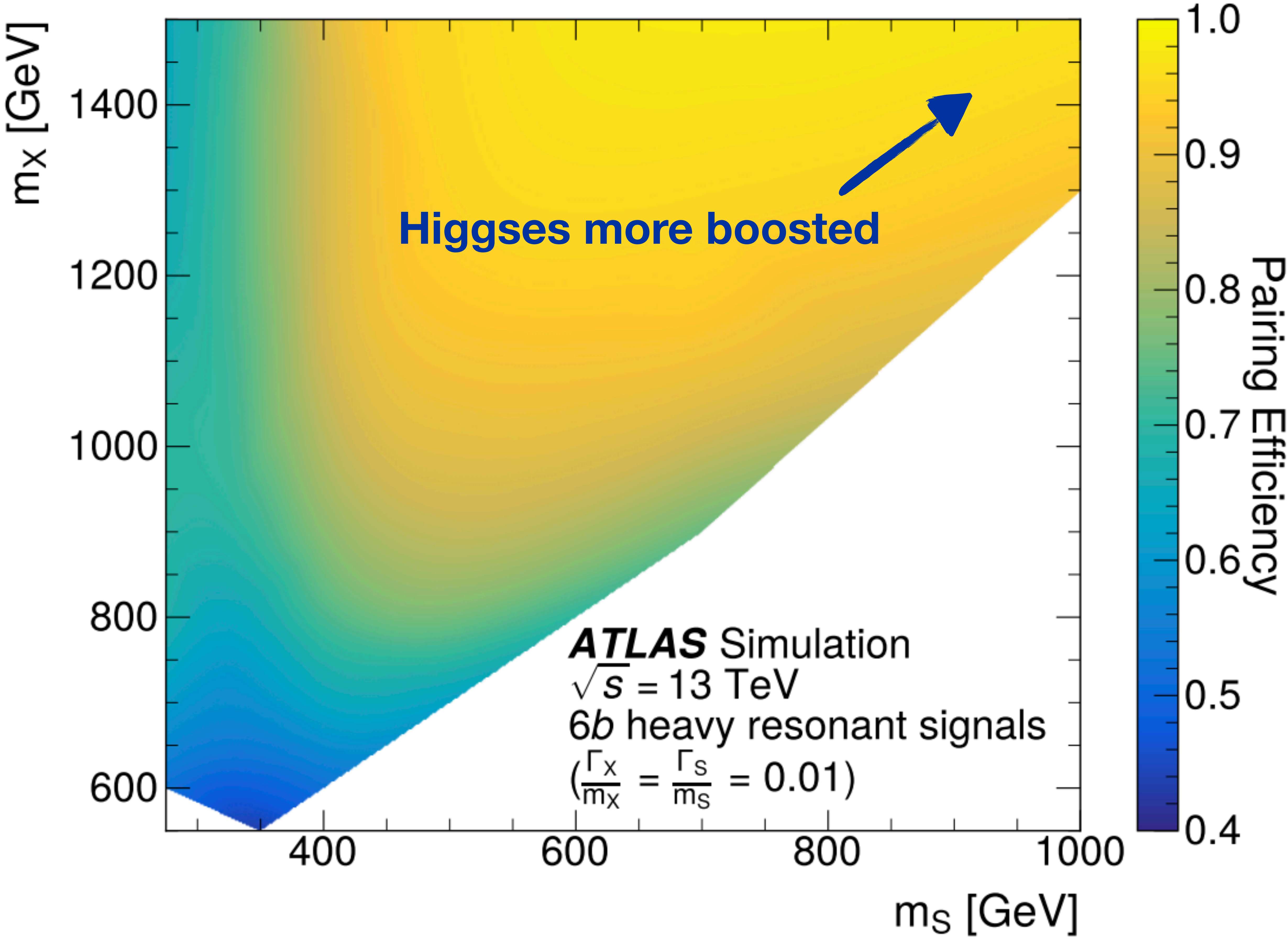

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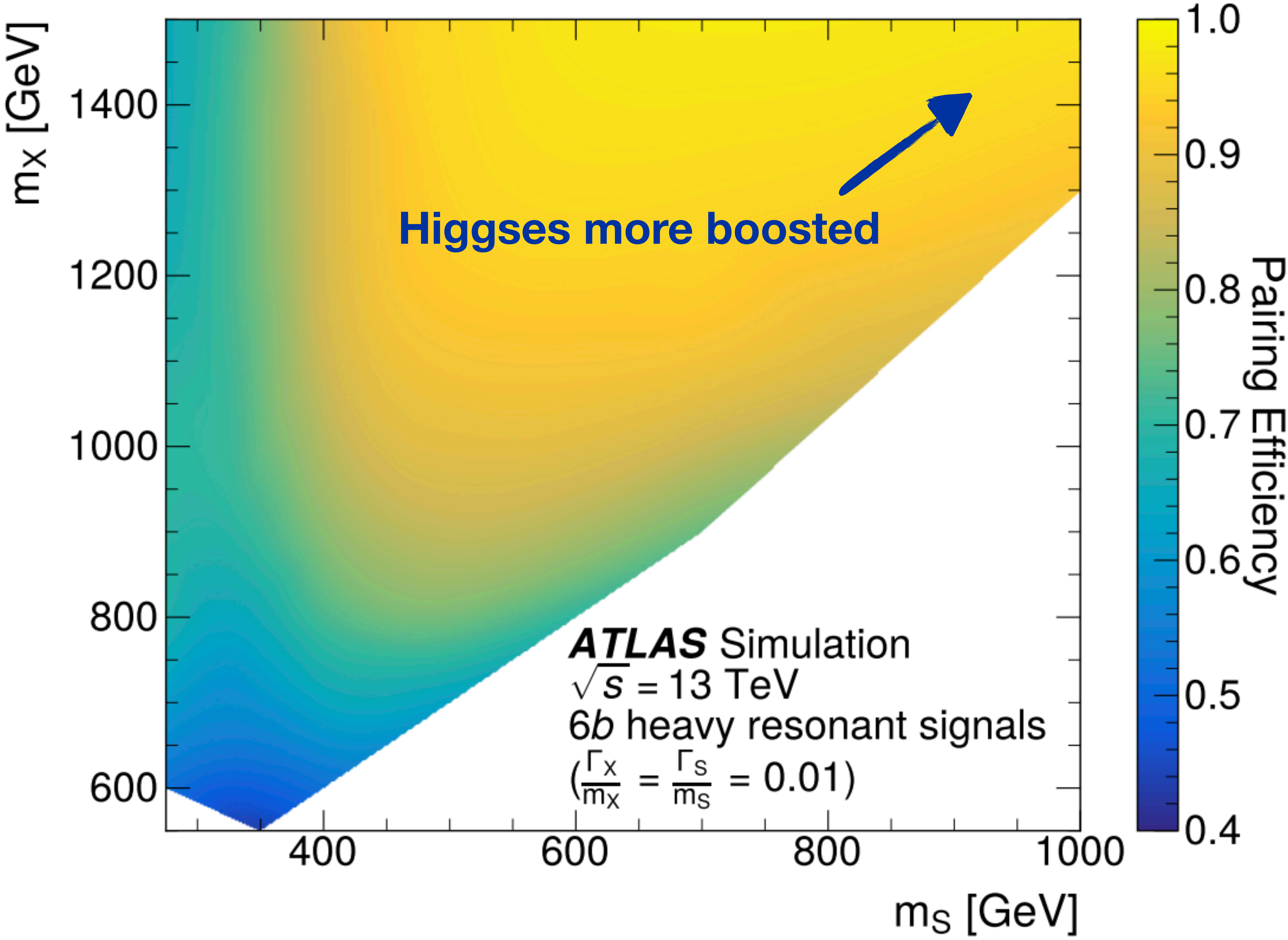

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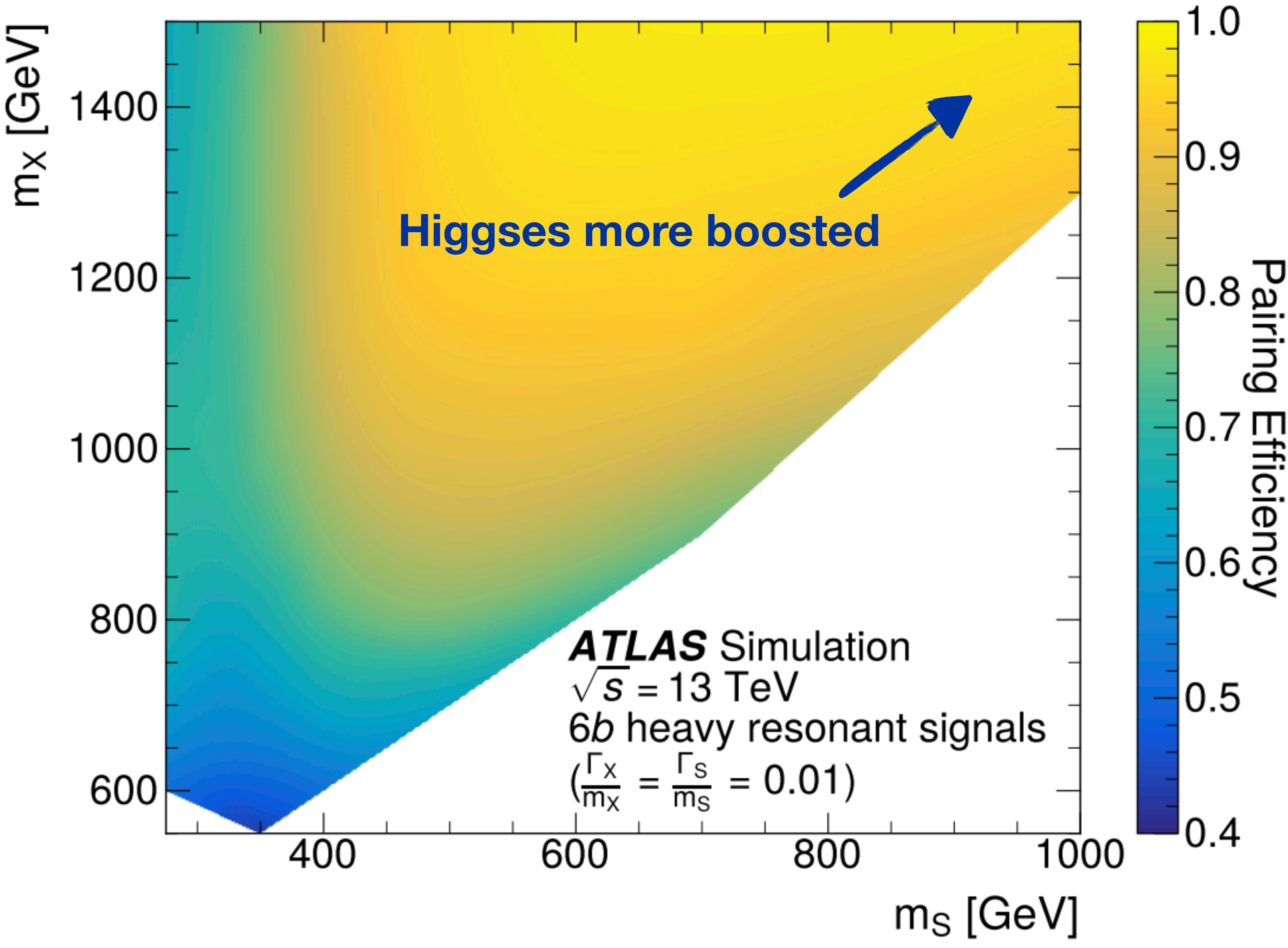
$$|m_{H1} - 120\,\mathrm{GeV}| + |m_{H2} - 115\,\mathrm{GeV}| + |m_{H3} - 110\,\mathrm{GeV}|,$$

Leading **Subleading** **Third**



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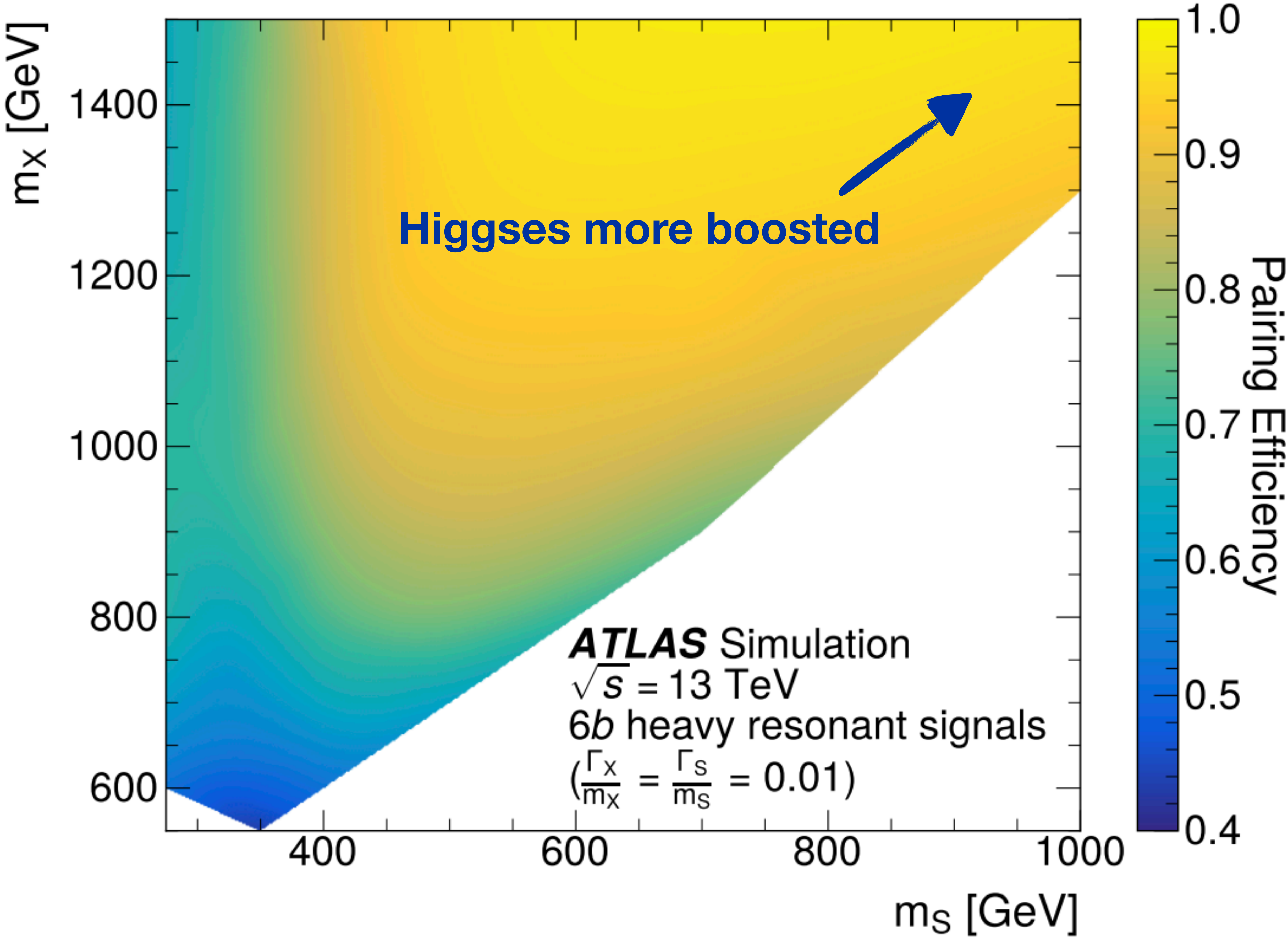

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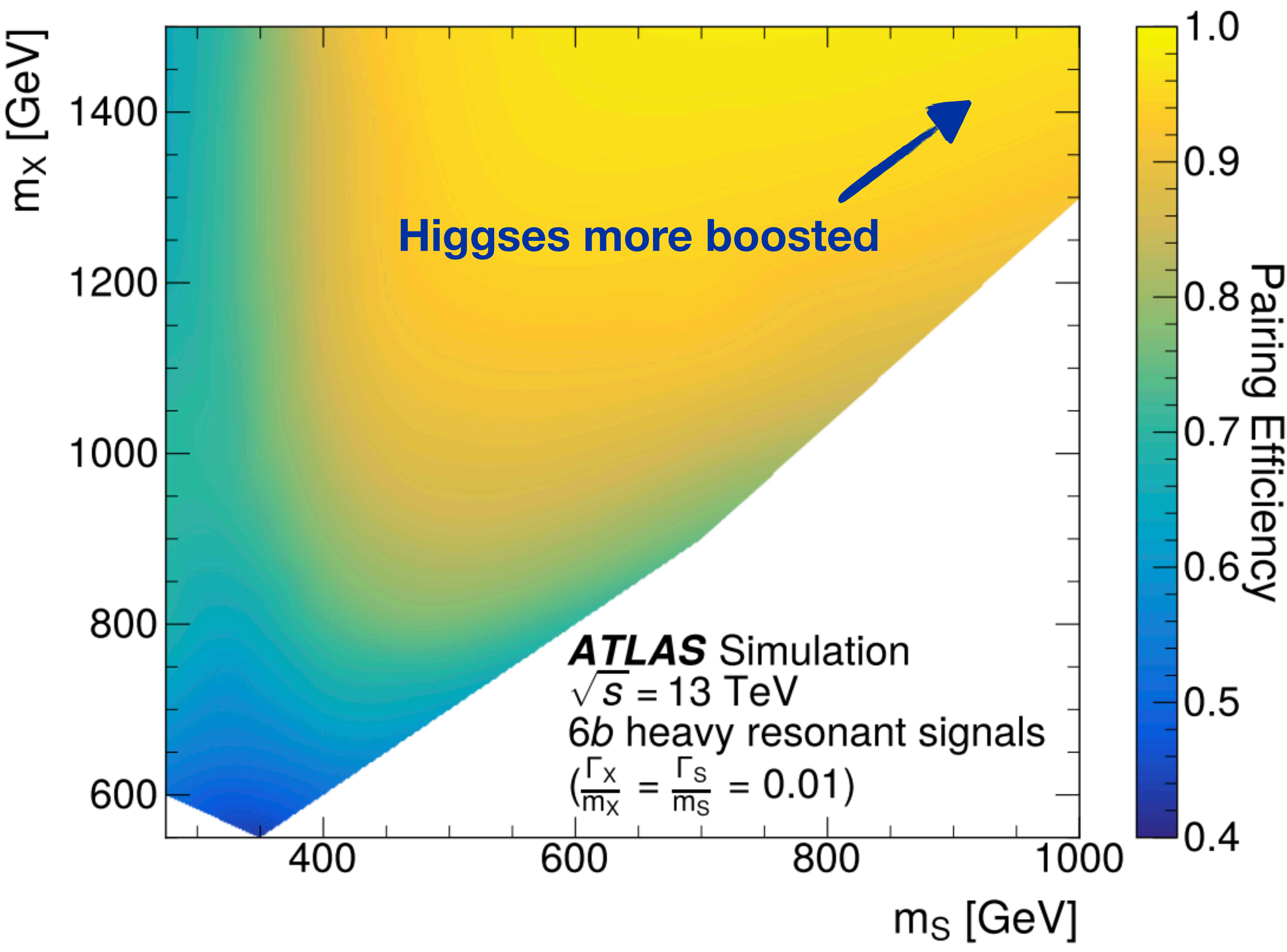
  - Still far better than random chance when not boosted, but that is a low bar.



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Leading Subleading Third

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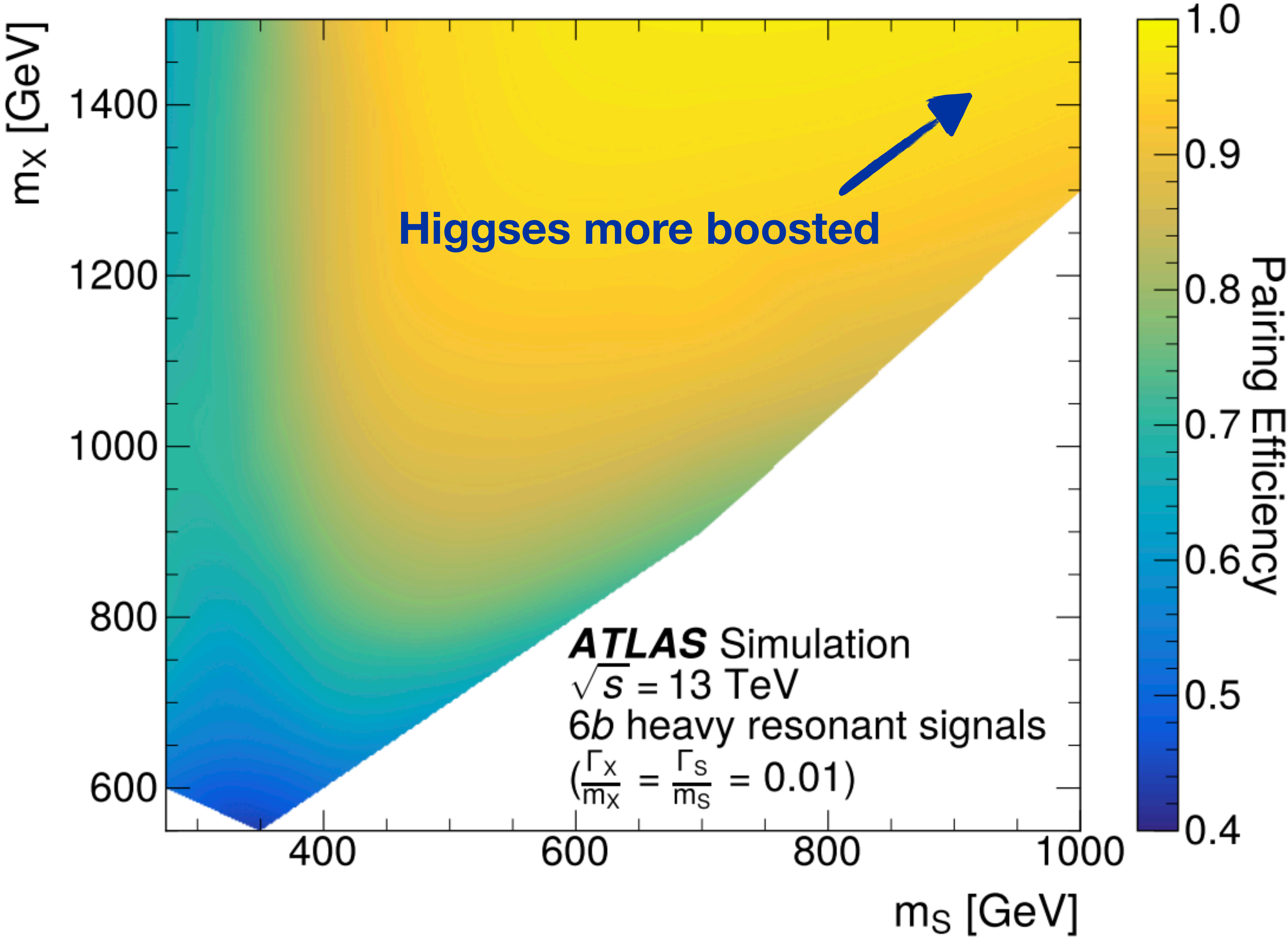
- **Pairing algorithms are one area for future R&D on HHH**



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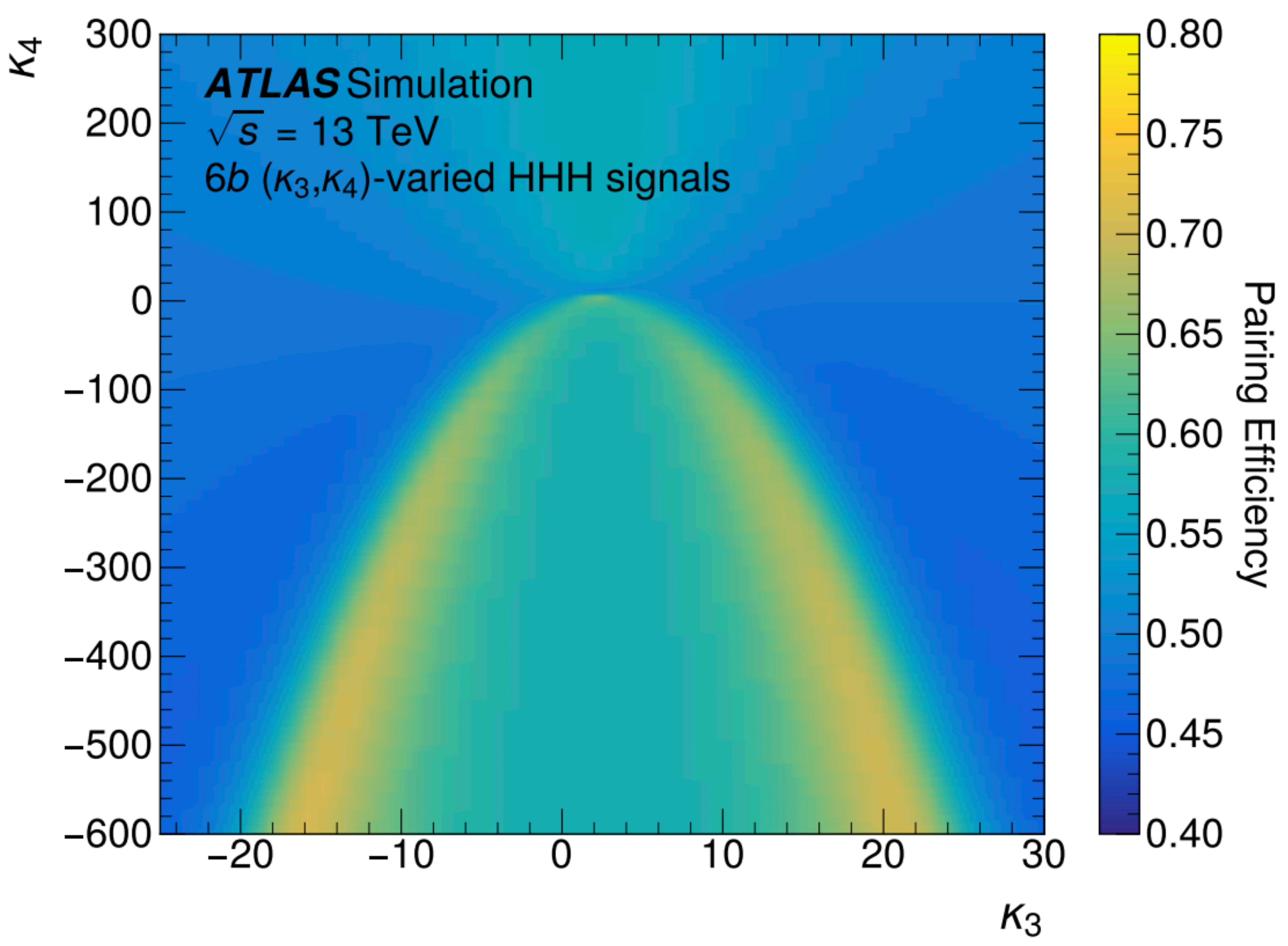
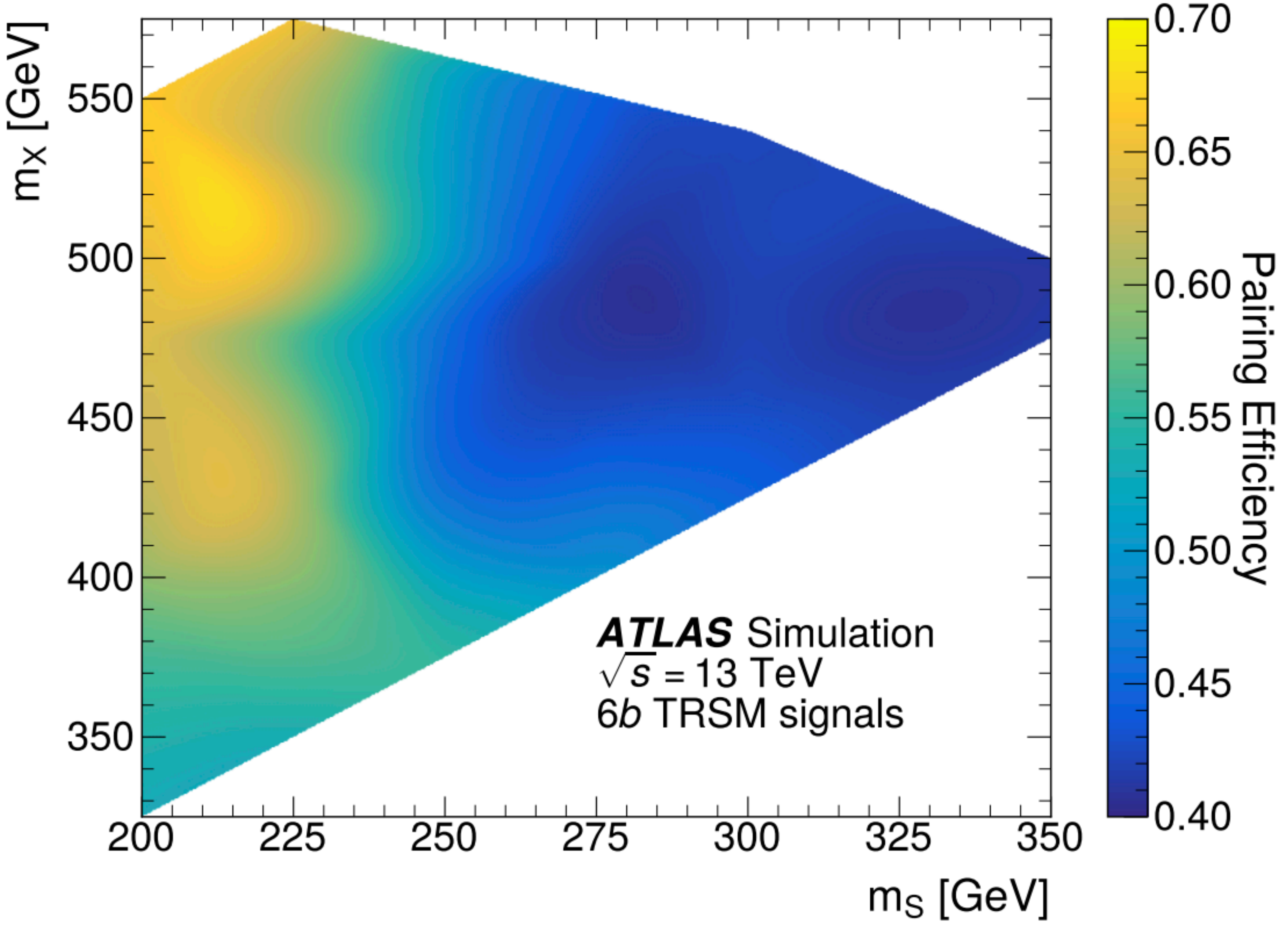
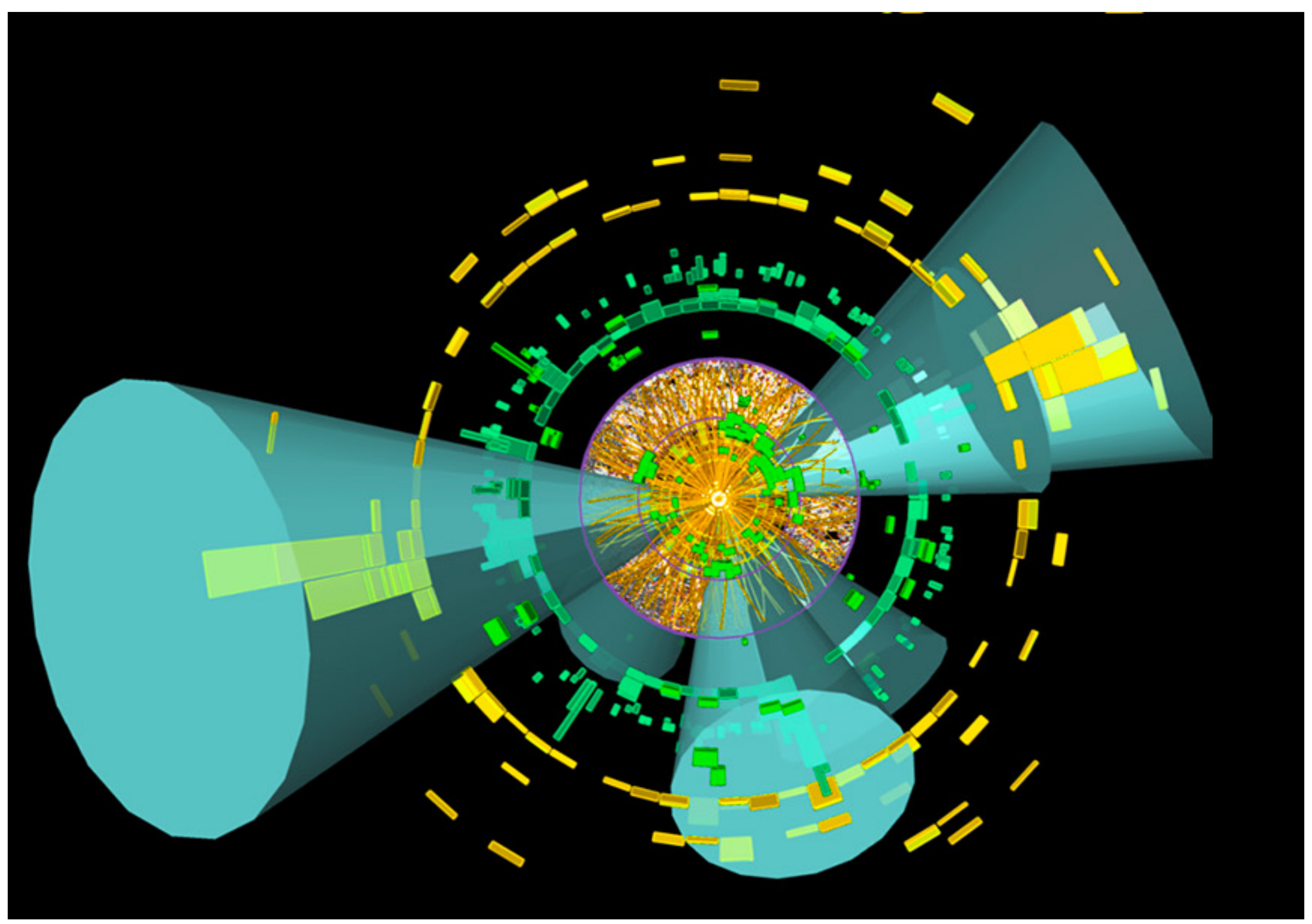
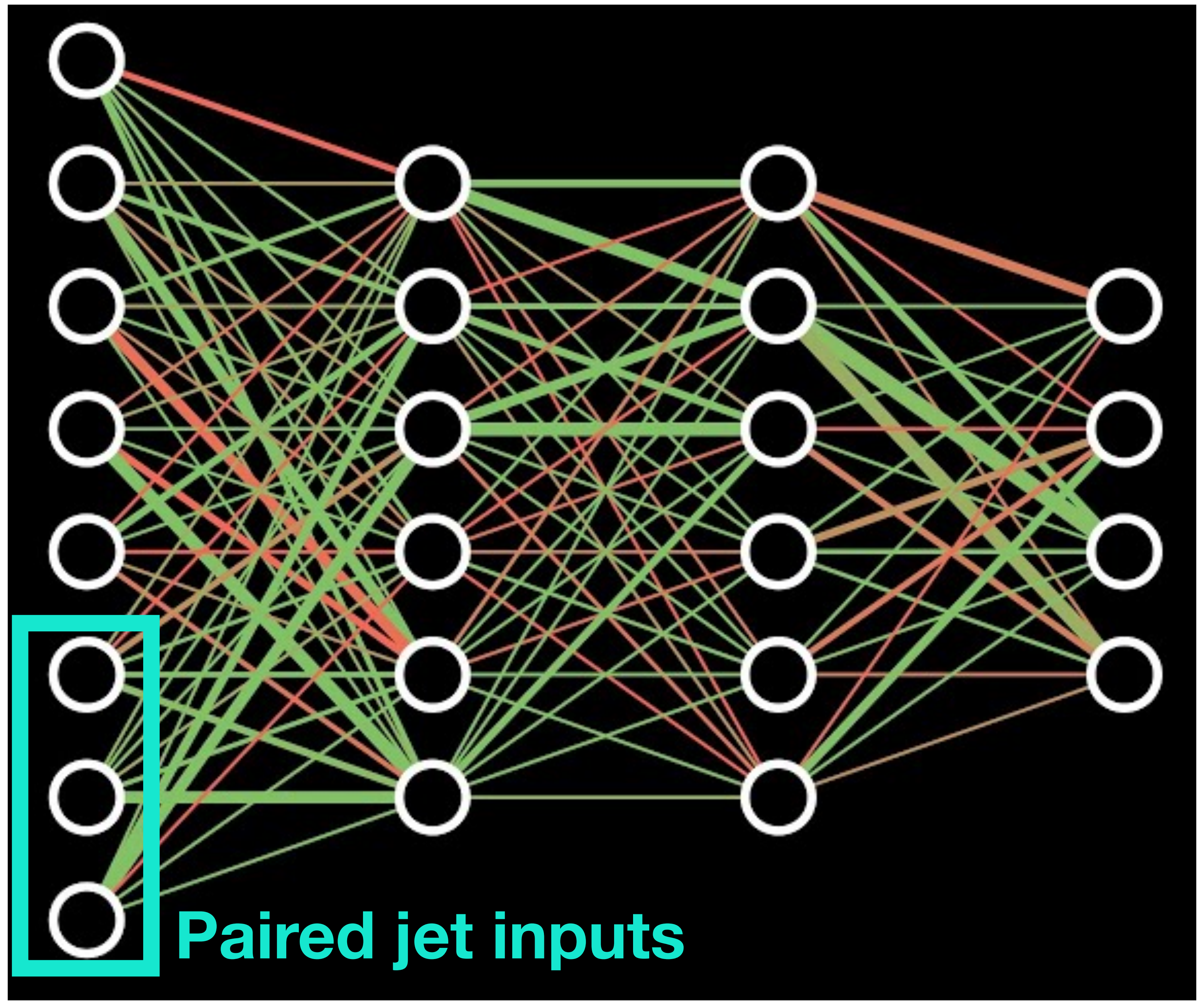




- **Without large boost, pairing efficiency is as low as 40%**
- **SM pairing efficiency: 51%**

Analysis strategy





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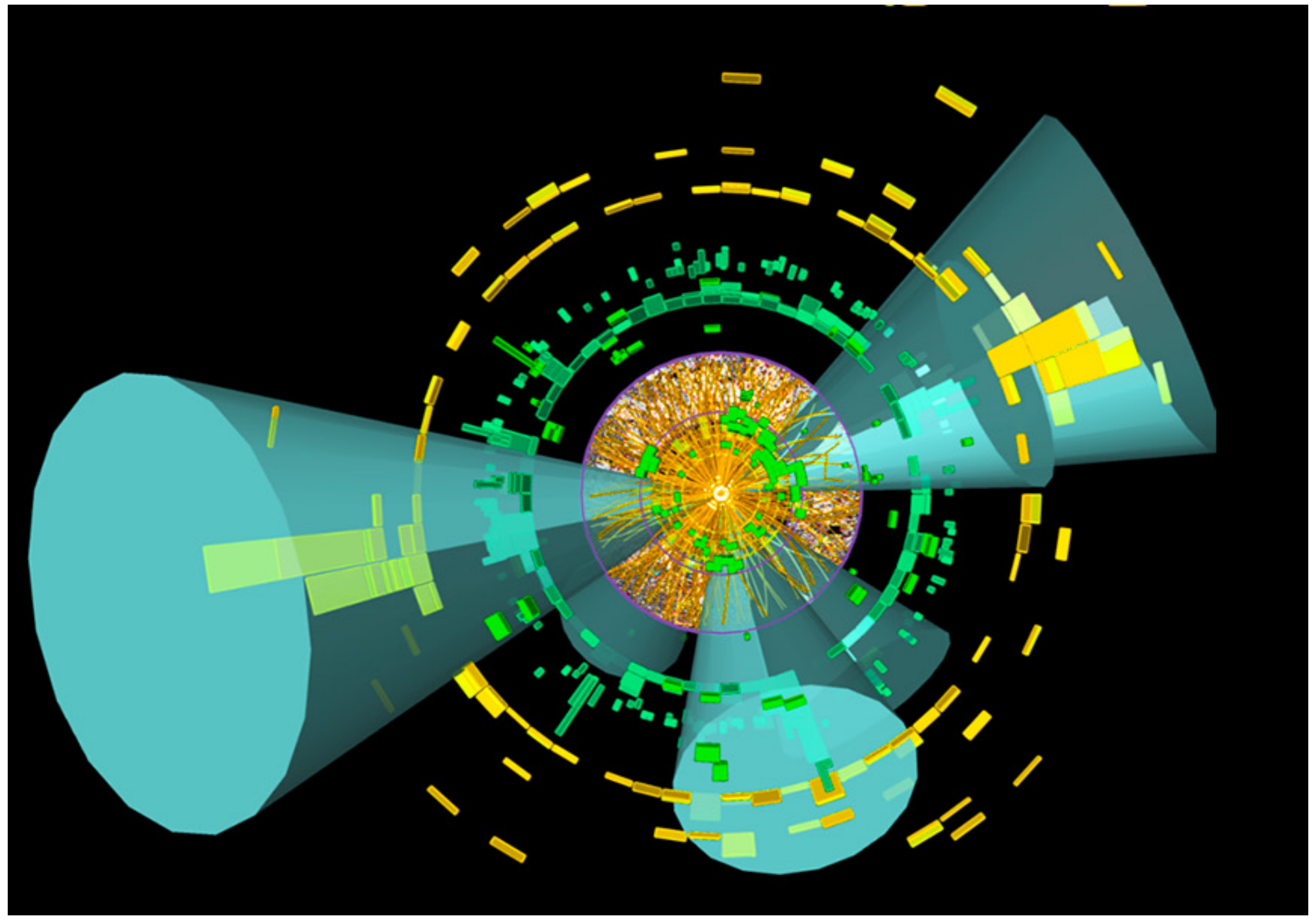

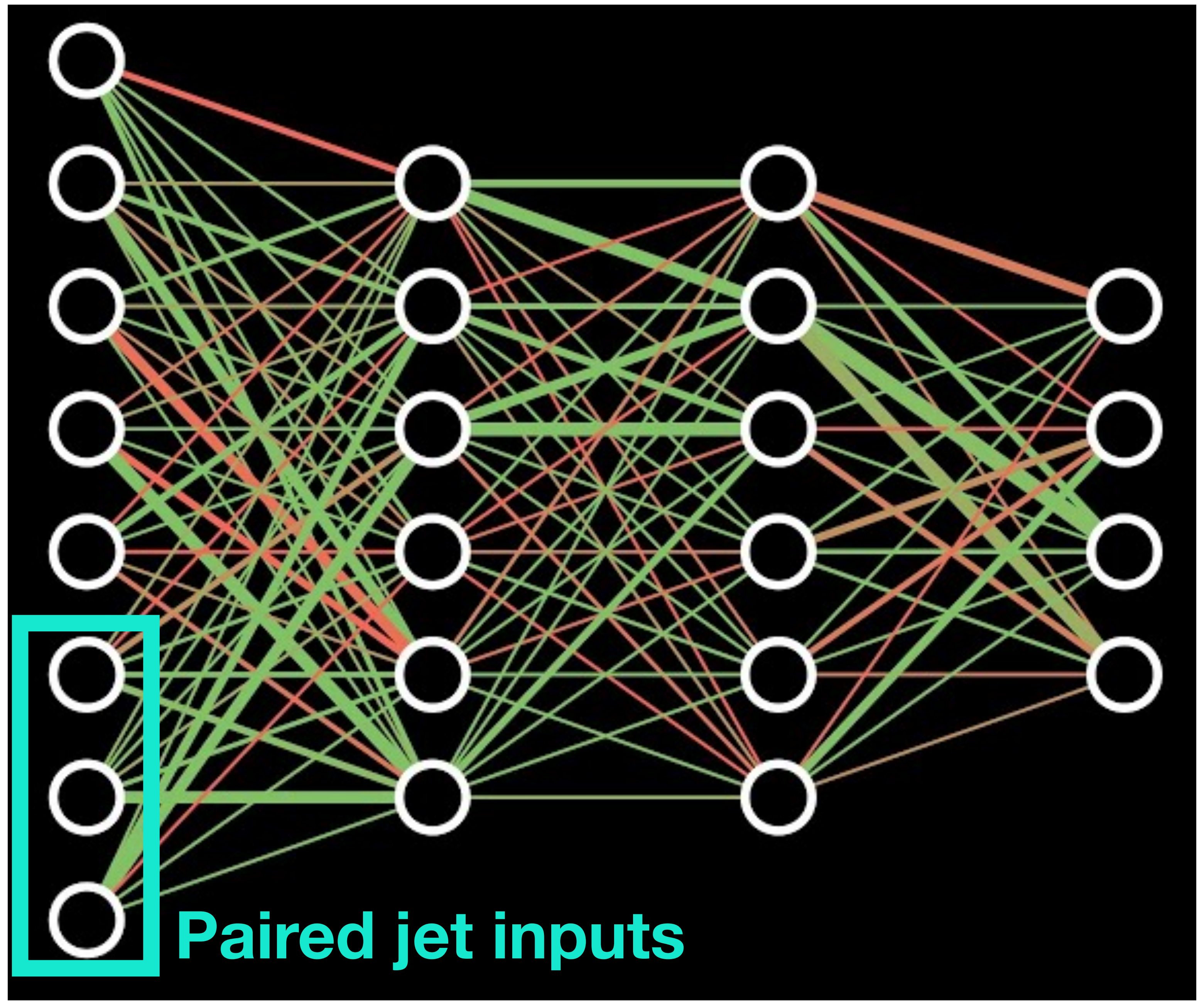

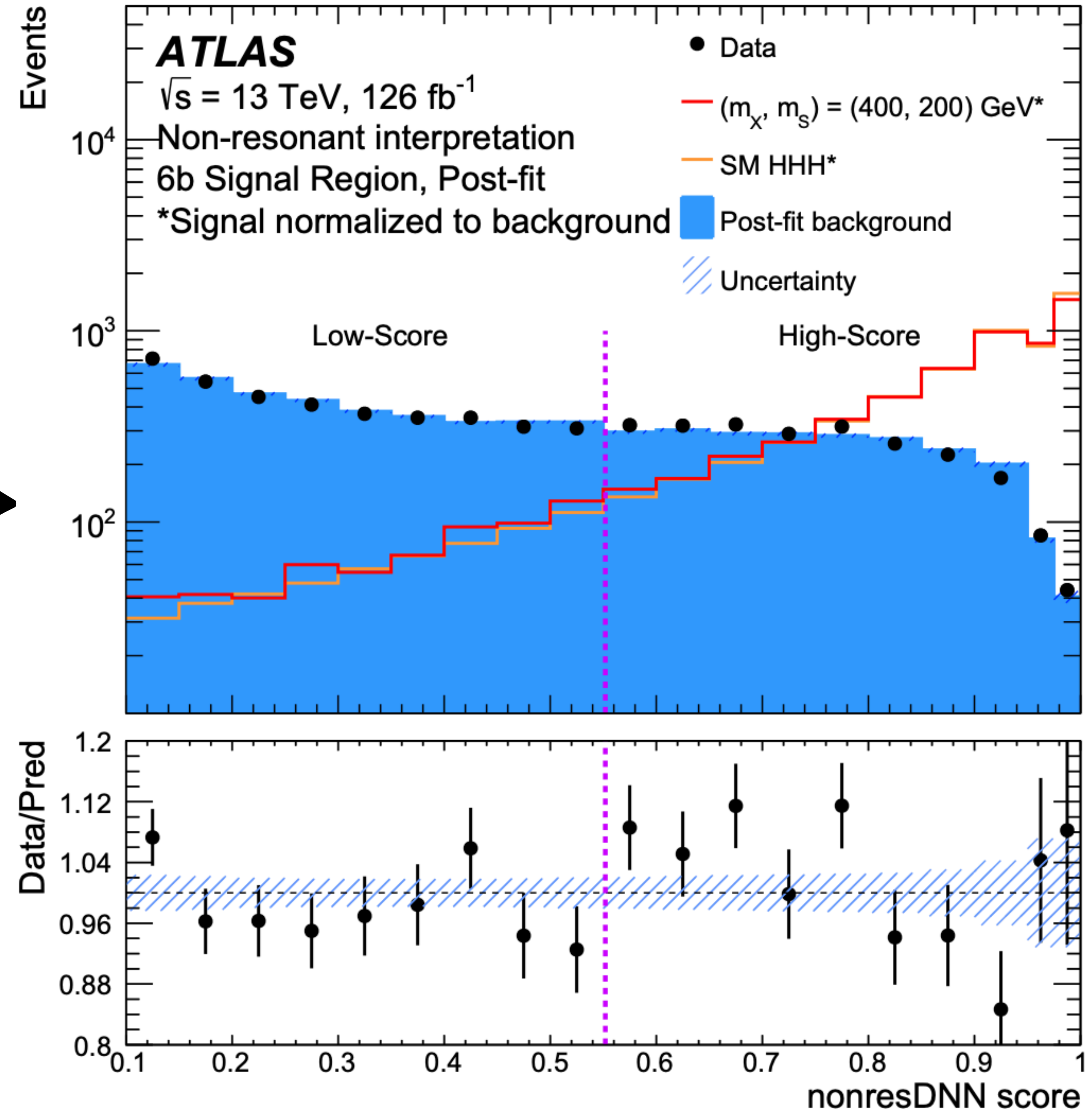

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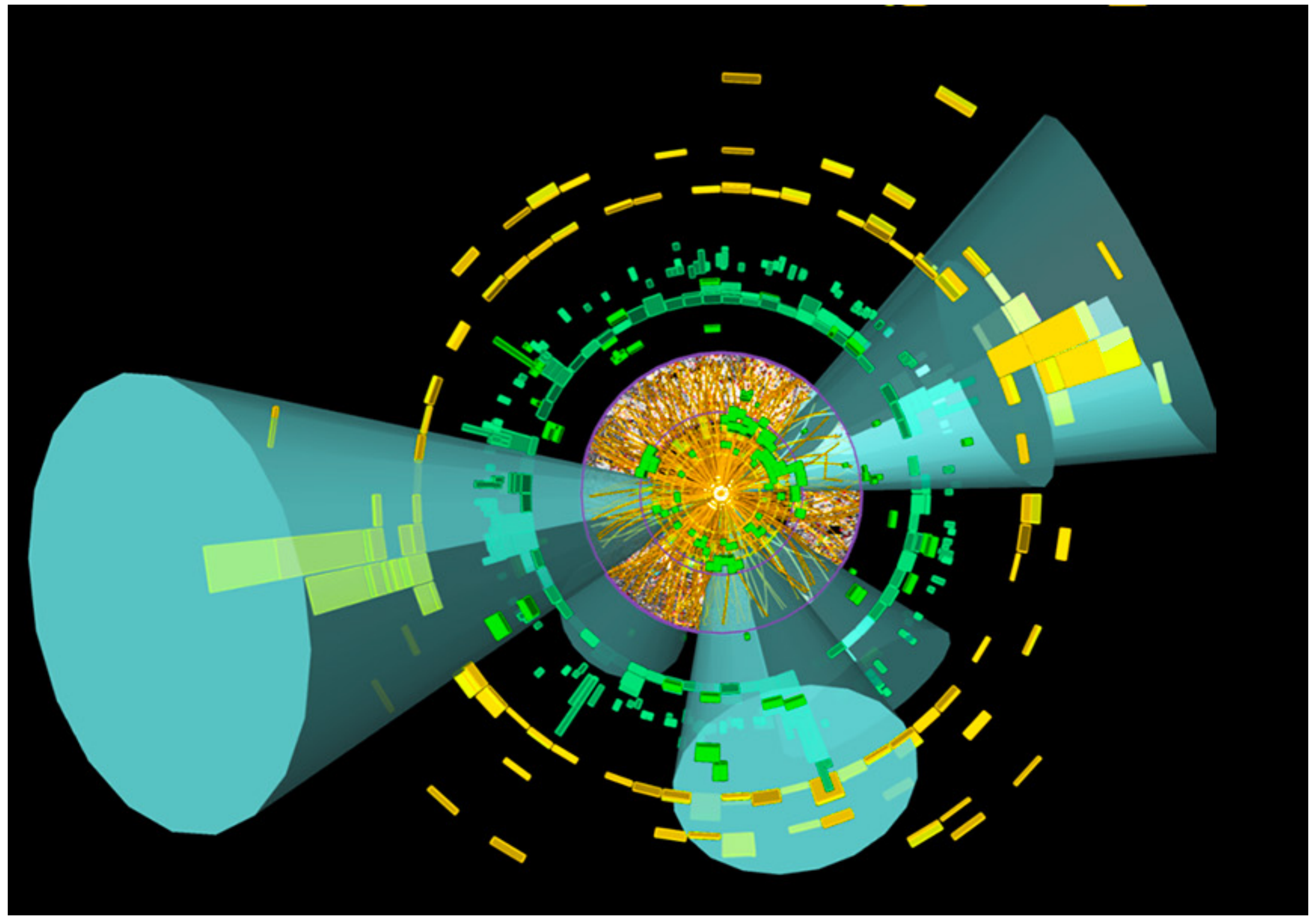
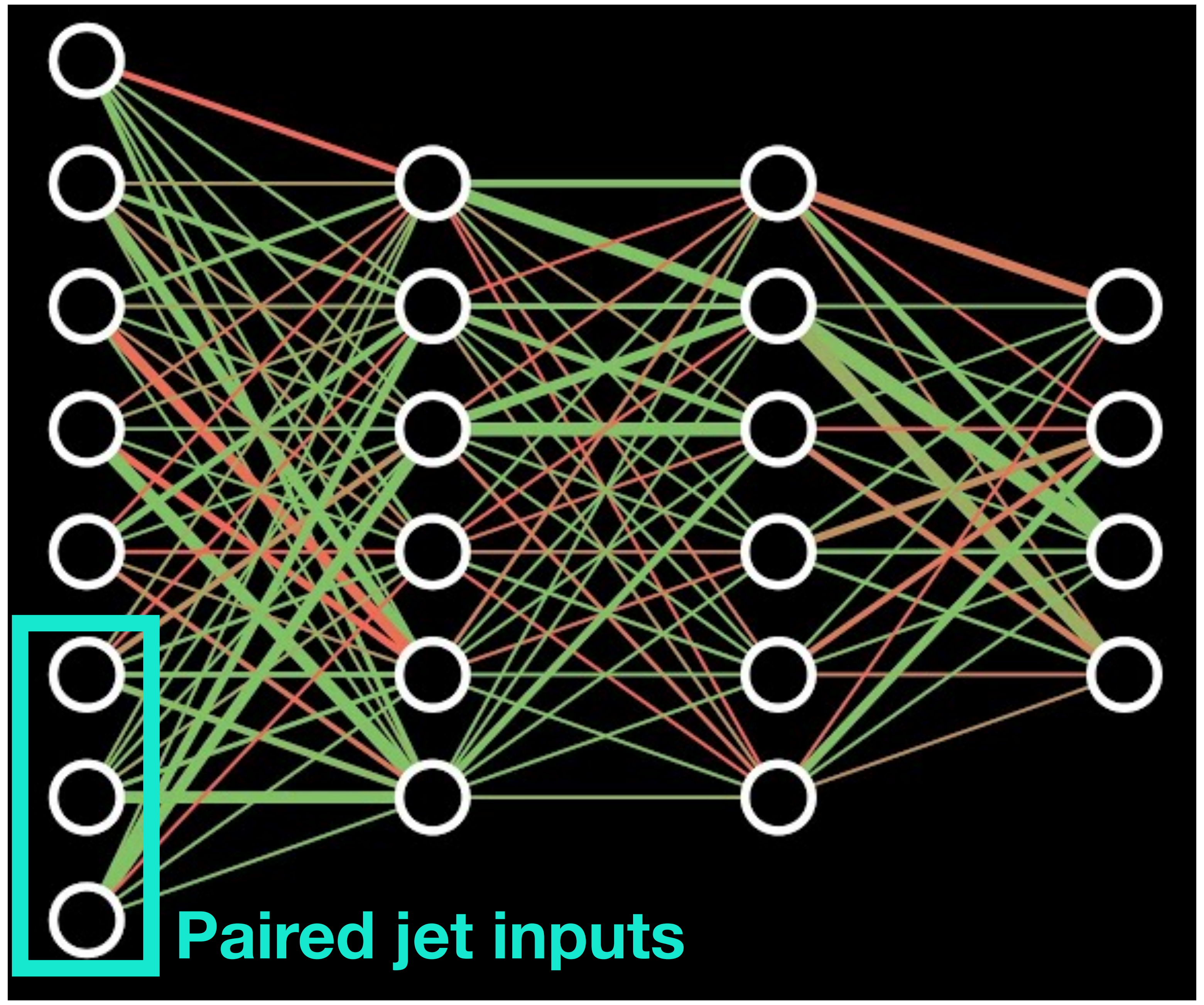
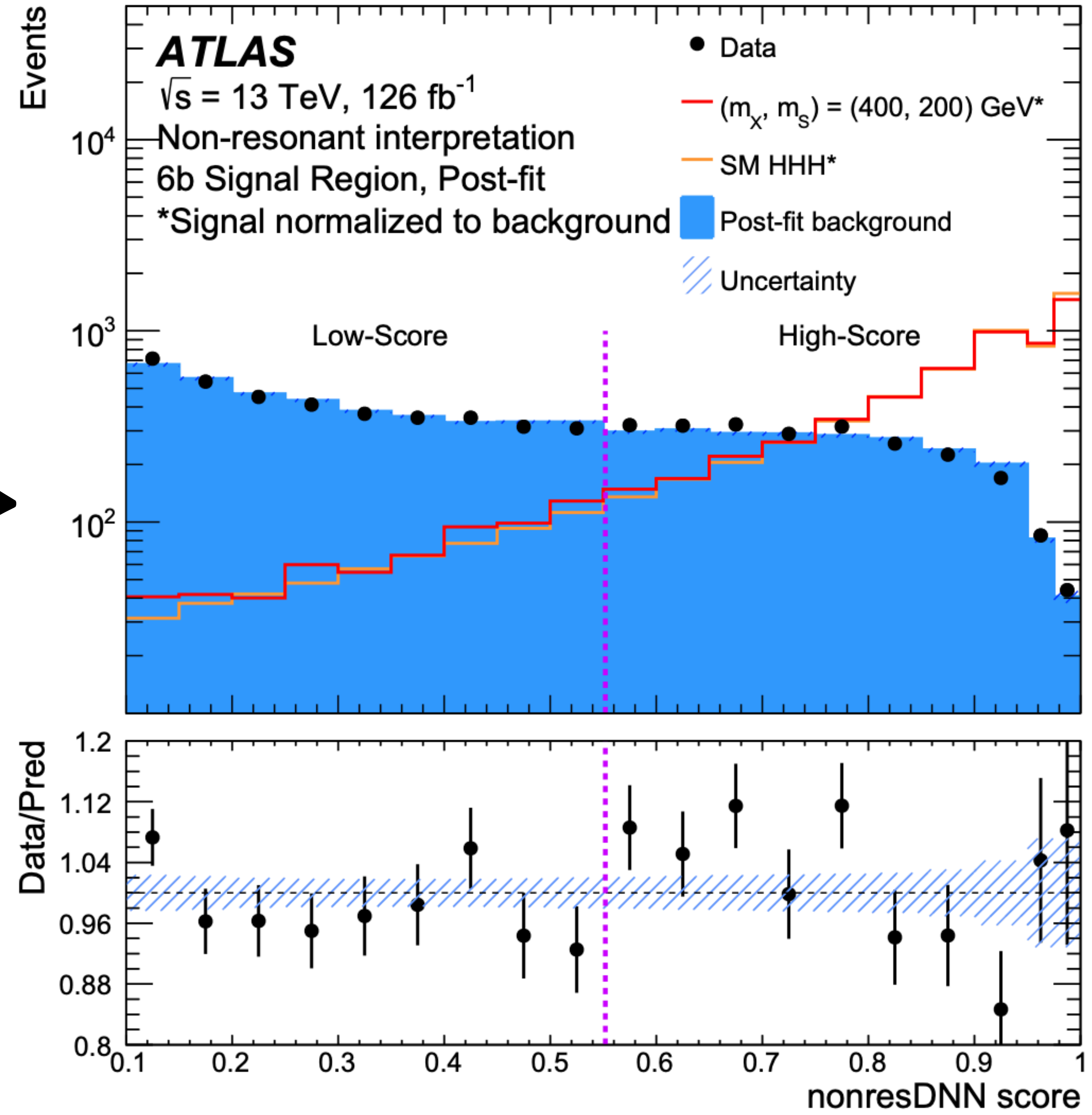
Analysis strategy







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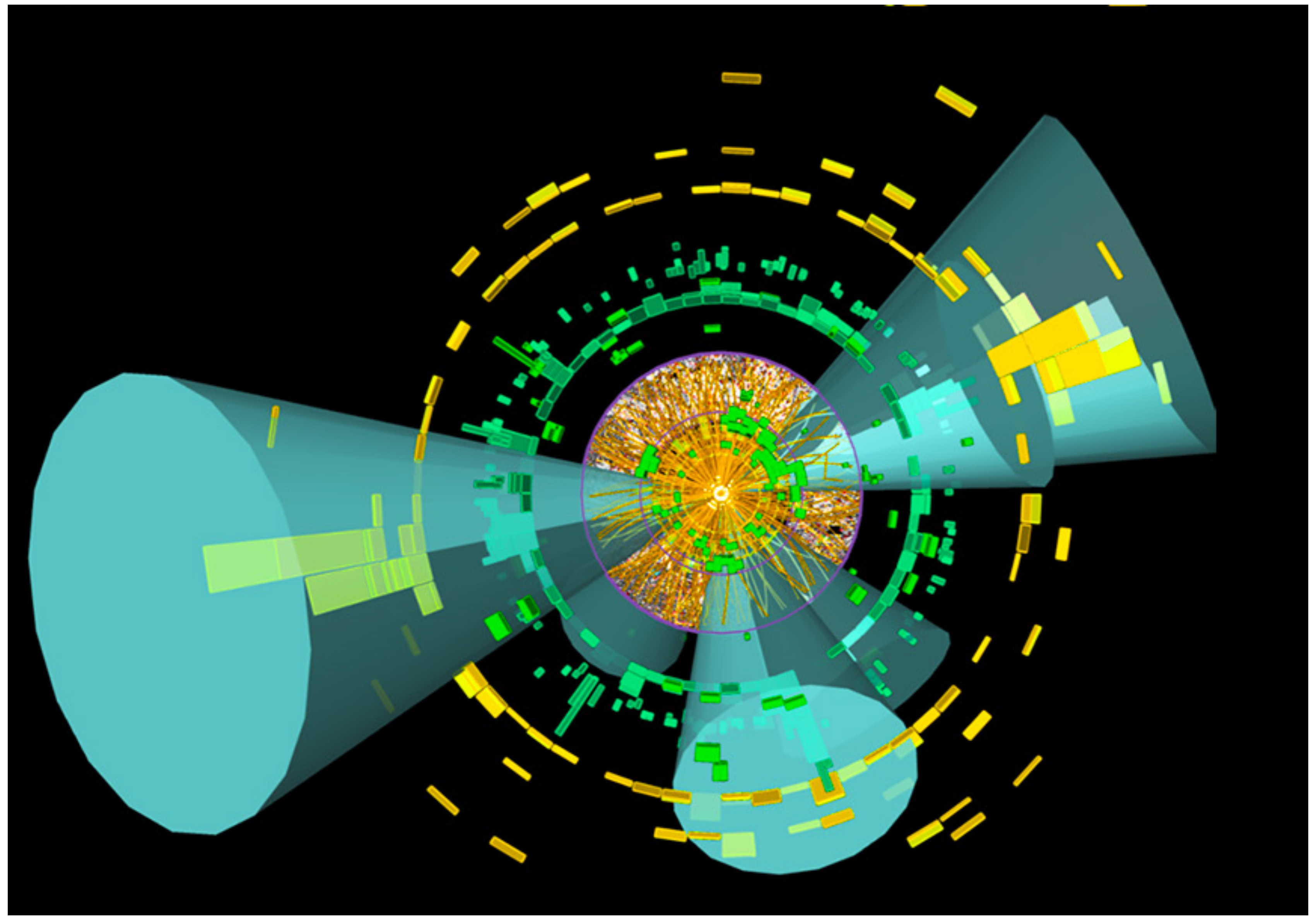

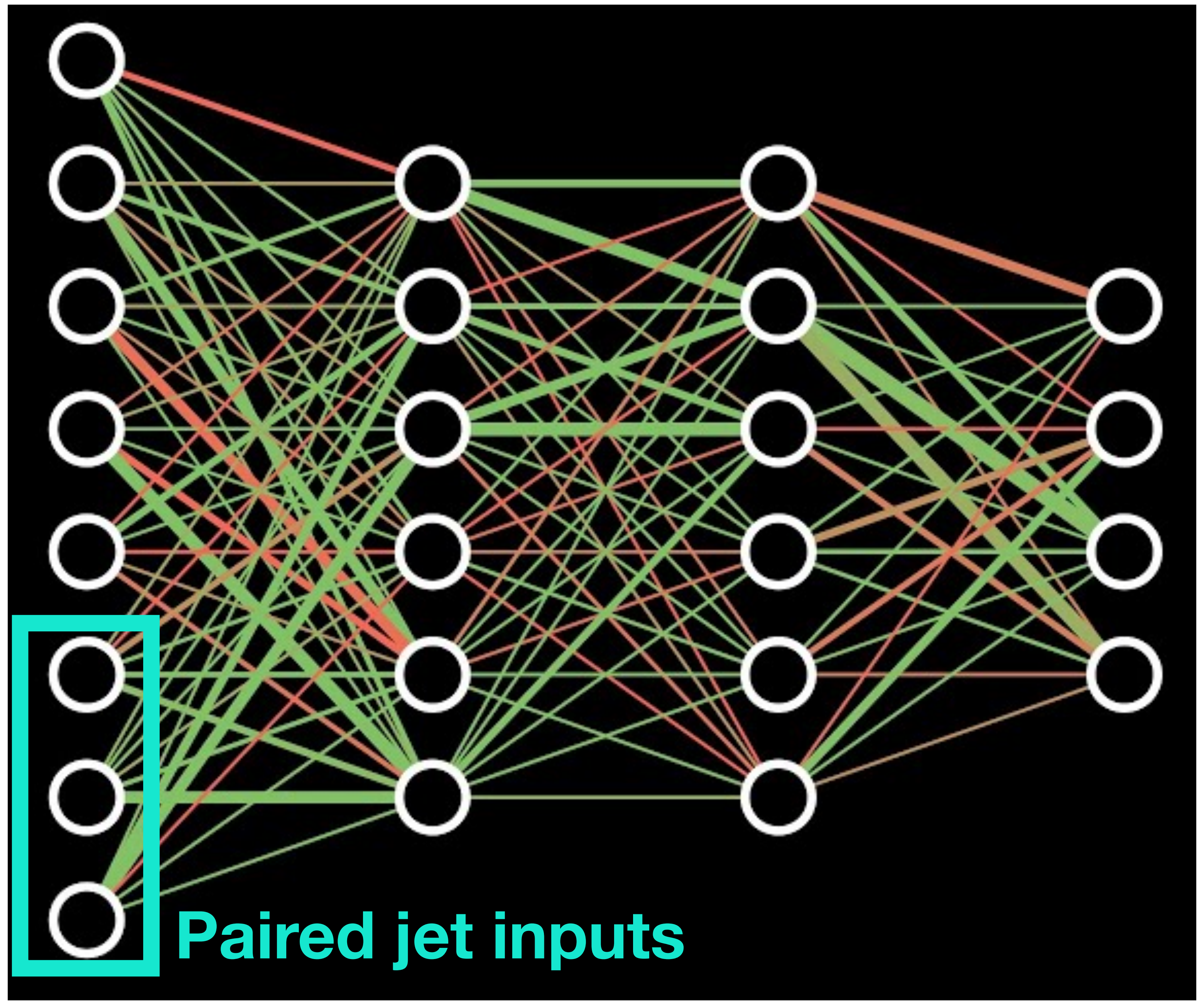

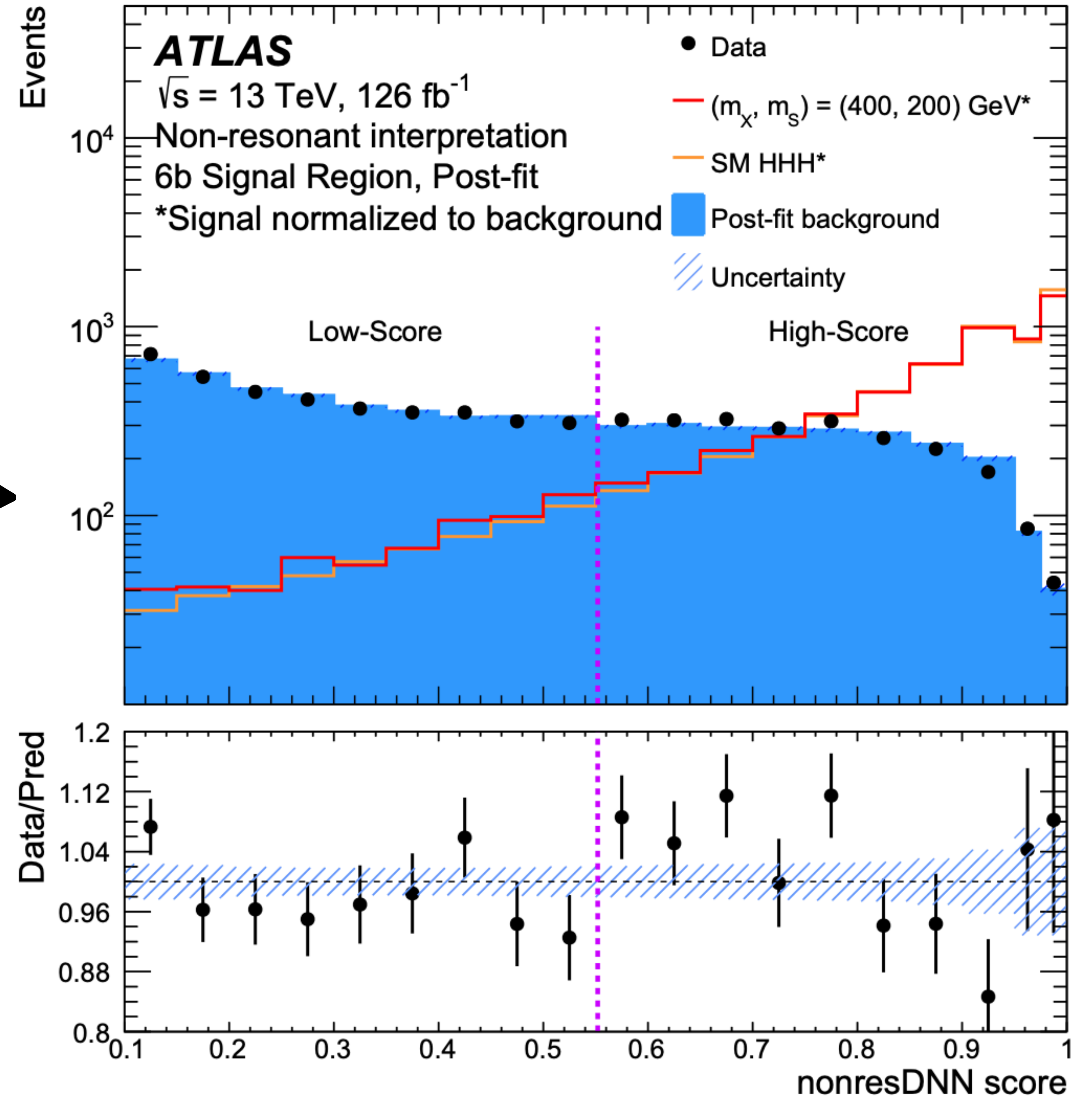

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  - Larger difference between 4b, 5b, 6b means larger systematic uncertainties
  - Need to choose DNN inputs carefully!

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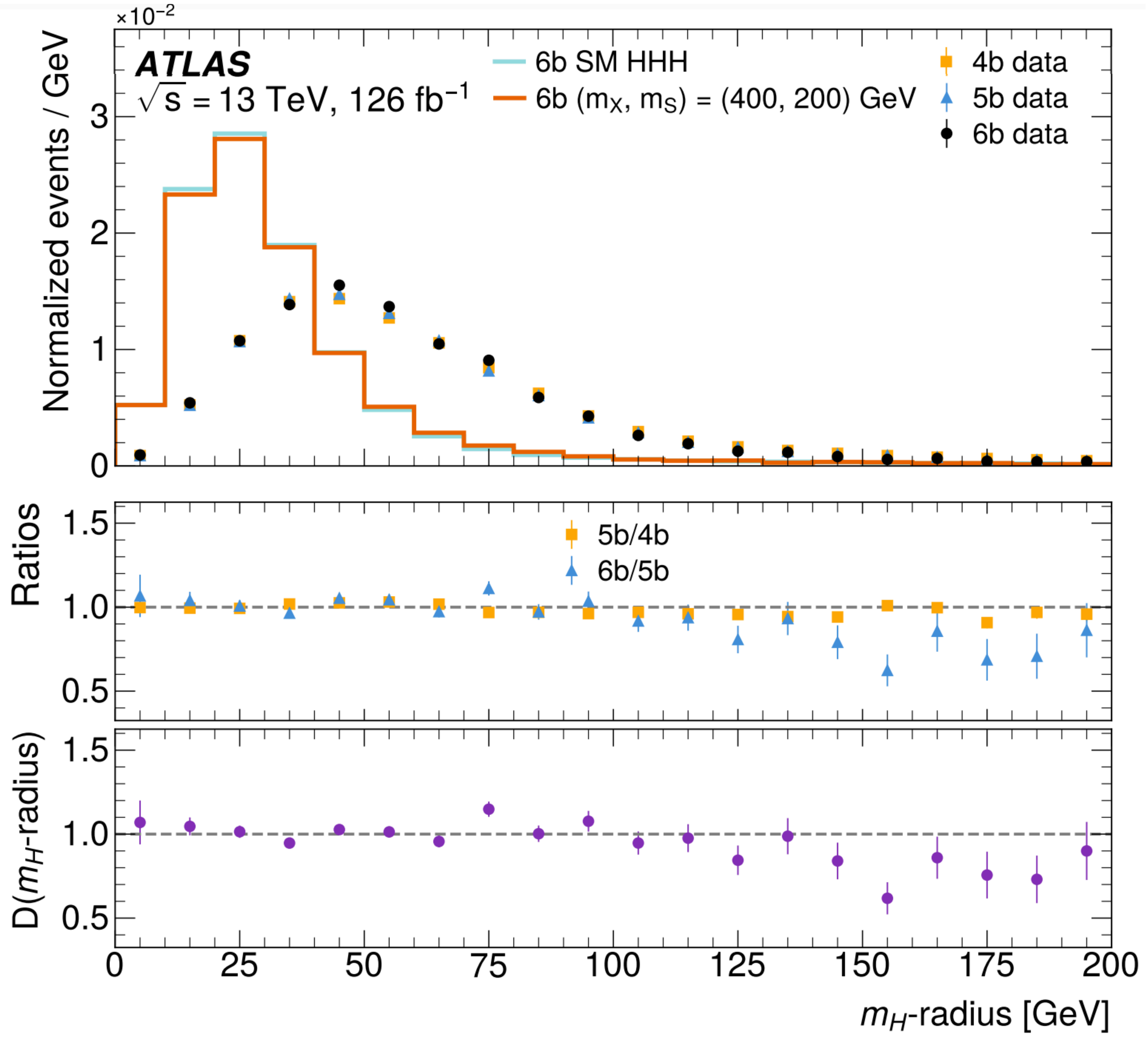
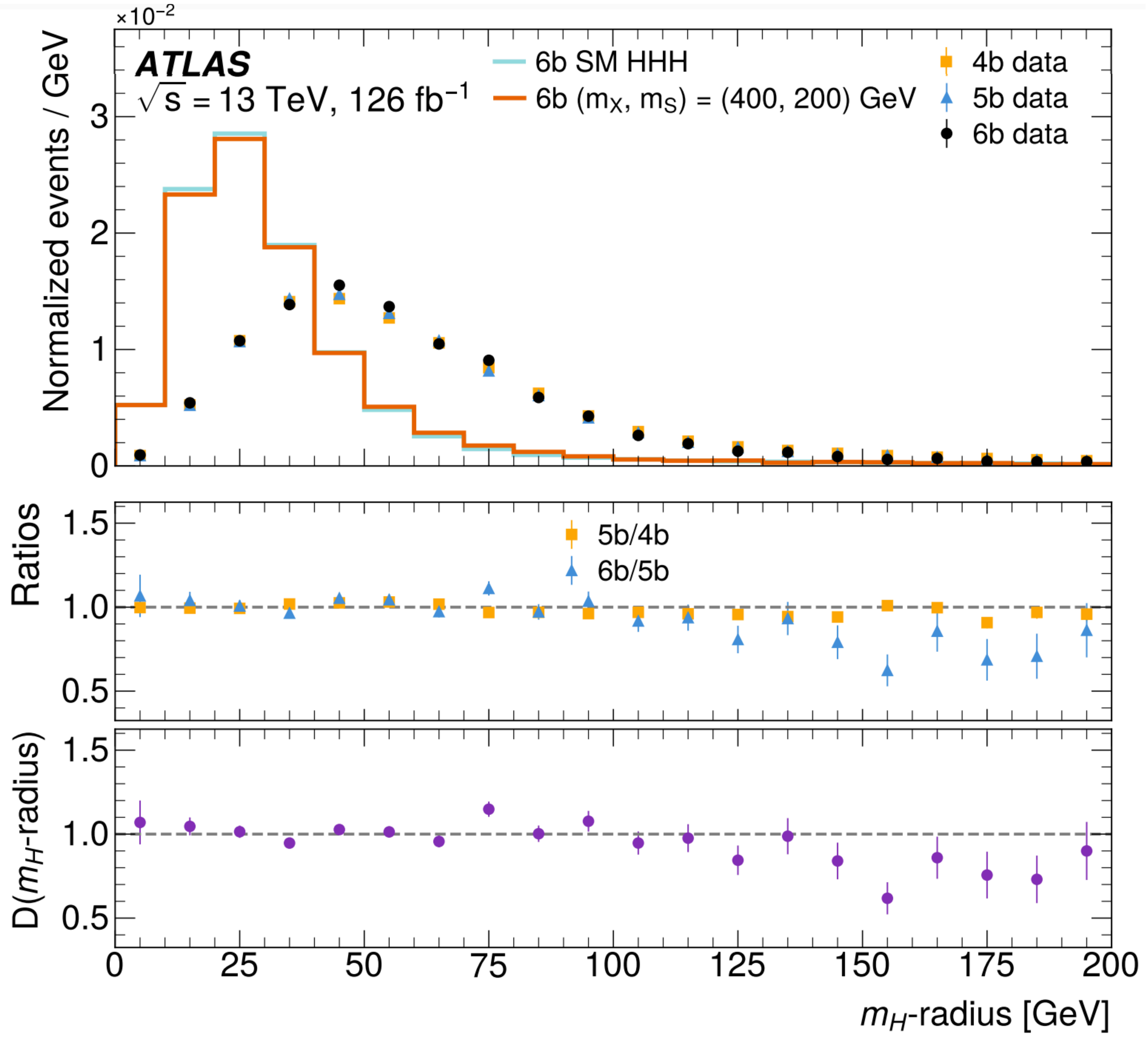


×10^{-2}
ATLAS
$\sqrt{s}$ = 13 TeV, 126 fb^{-1}
6b SM HHH
6b (m_X, m_S) = (400, 200) GeV
4b data
5b data
6b data
Normalized events / GeV
5b/4b
6b/5b
Ratios
D(m_H-radius)
m_H-radius [GeV]

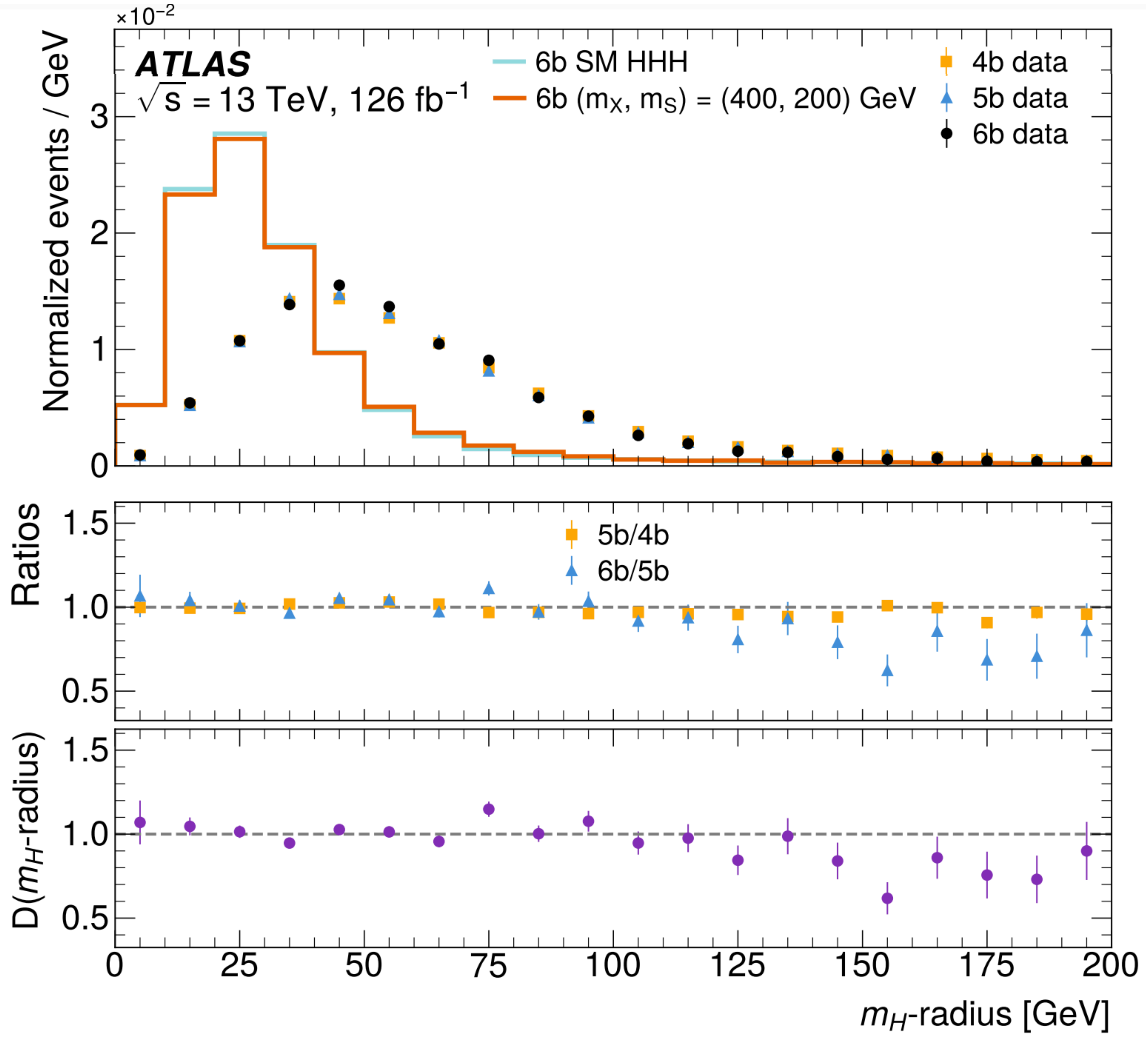
DNN inputs

- **Example of one DNN input shown.**
  - Distance from pairing center: (120, 115, 110) GeV
  - This is an example of a variable for which pairing matters



DNN inputs

- **Example of one DNN input shown.**
  - Distance from pairing center: (120, 115, 110) GeV
  - This is an example of a variable for which pairing matters
- **Also shown are 4b, 5b, 6b data and their ratios**
  - We limit ourselves to variables which have small shape difference vs. b-jet multiplicity.
  - This is a trade-off between using more discriminating variables vs. having larger systematic uncertainty on the b-jet extrapolation.



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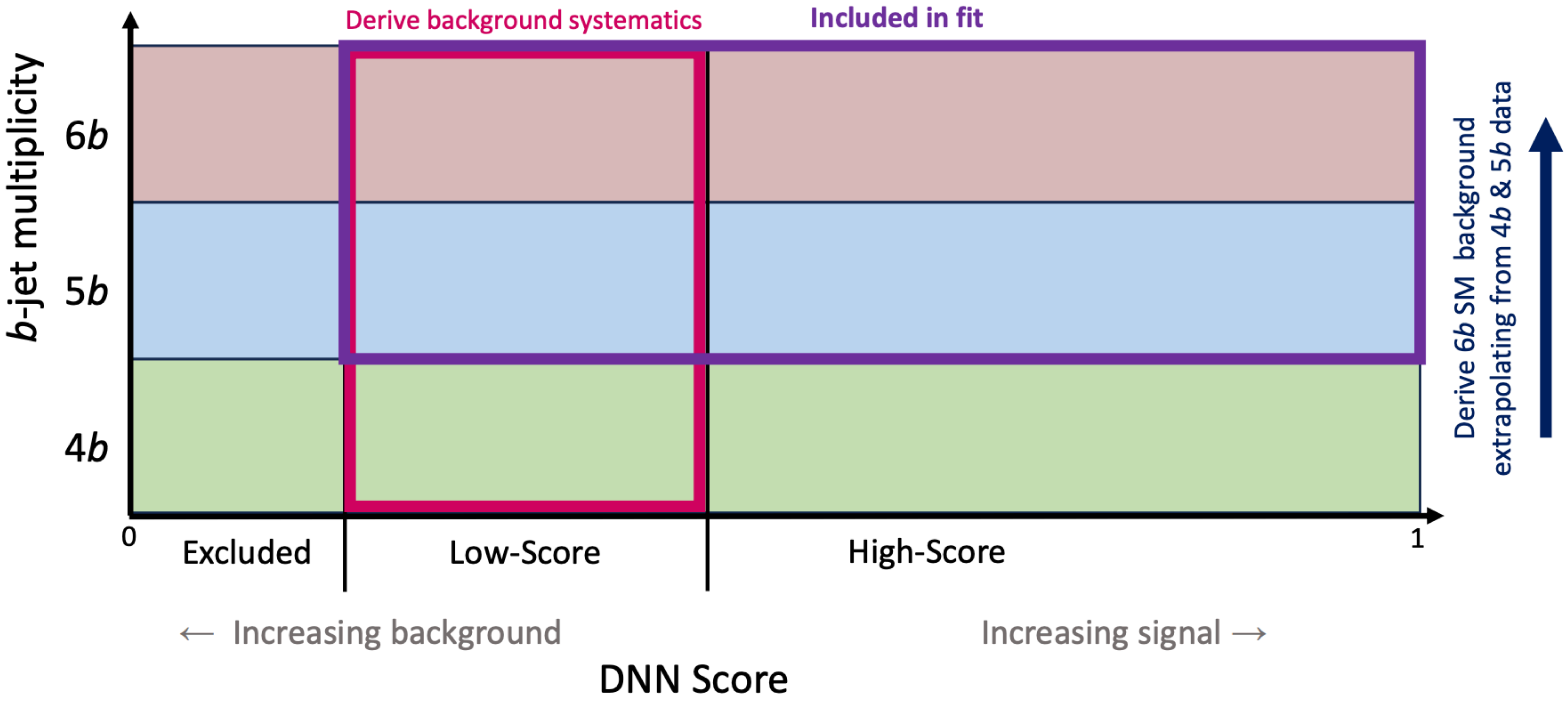

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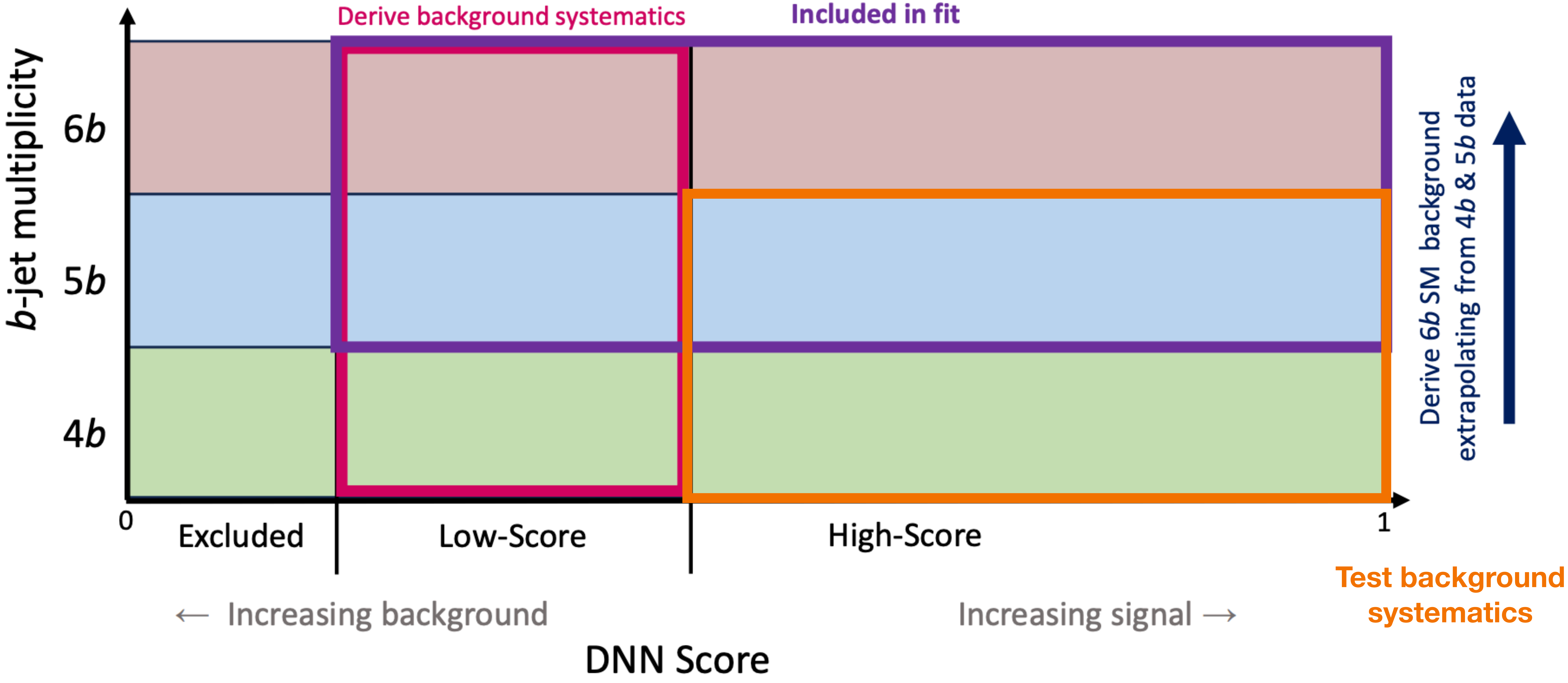

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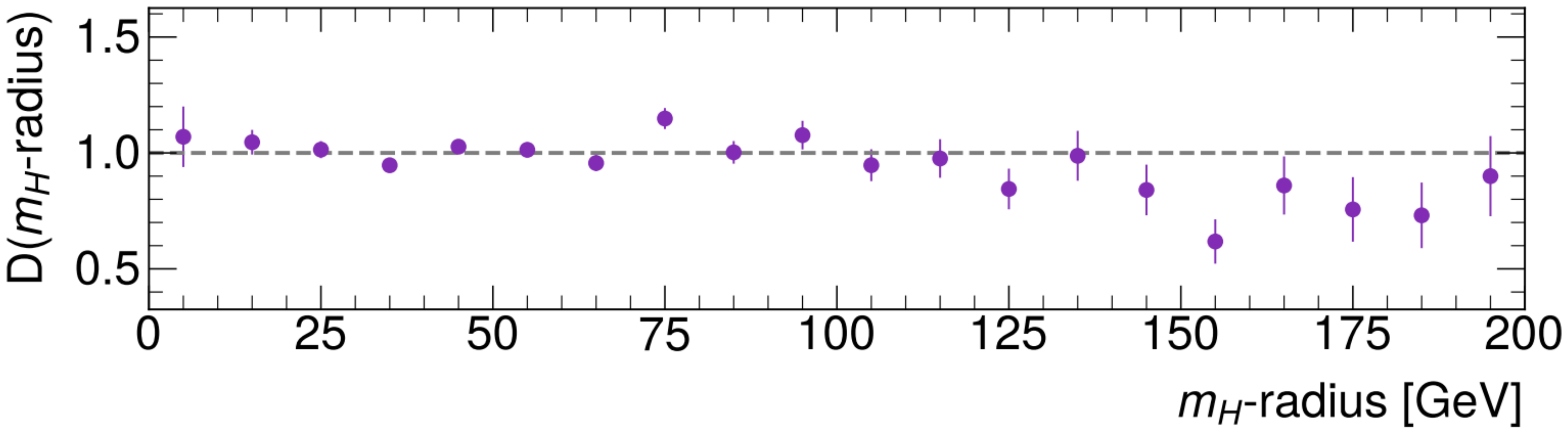

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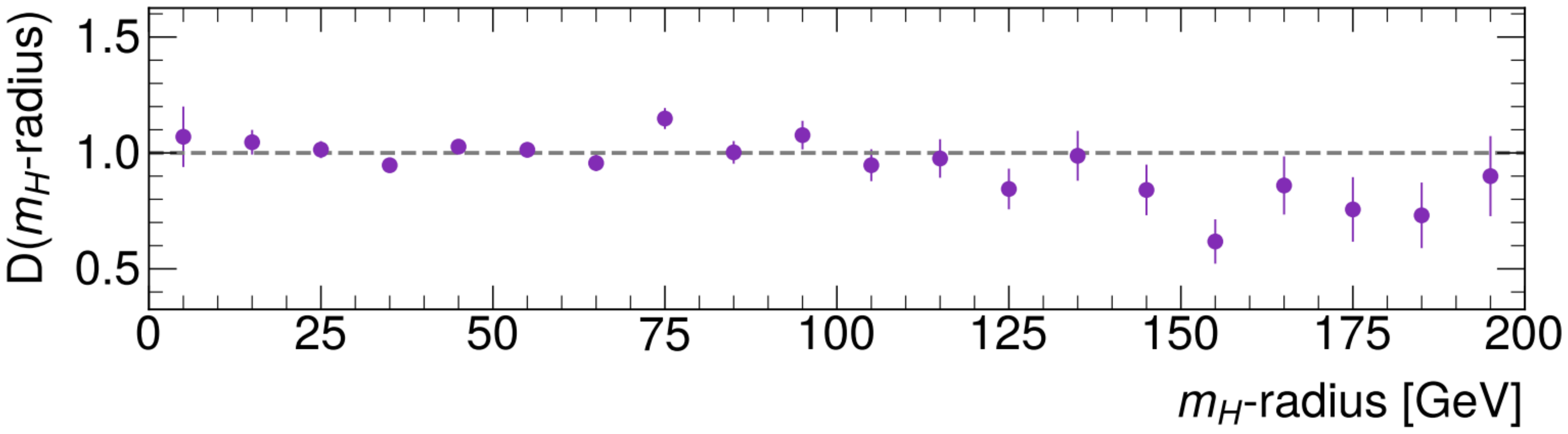
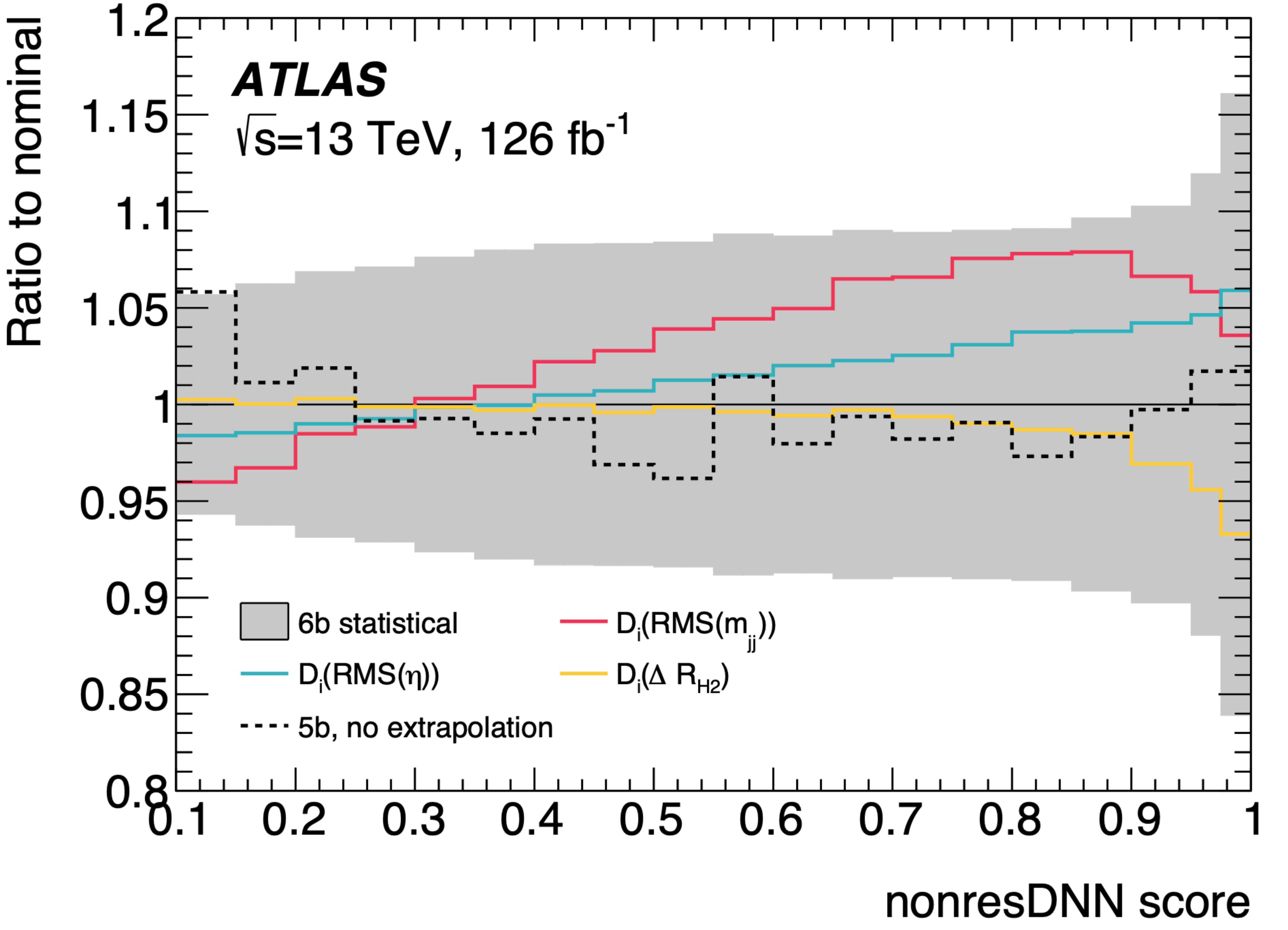
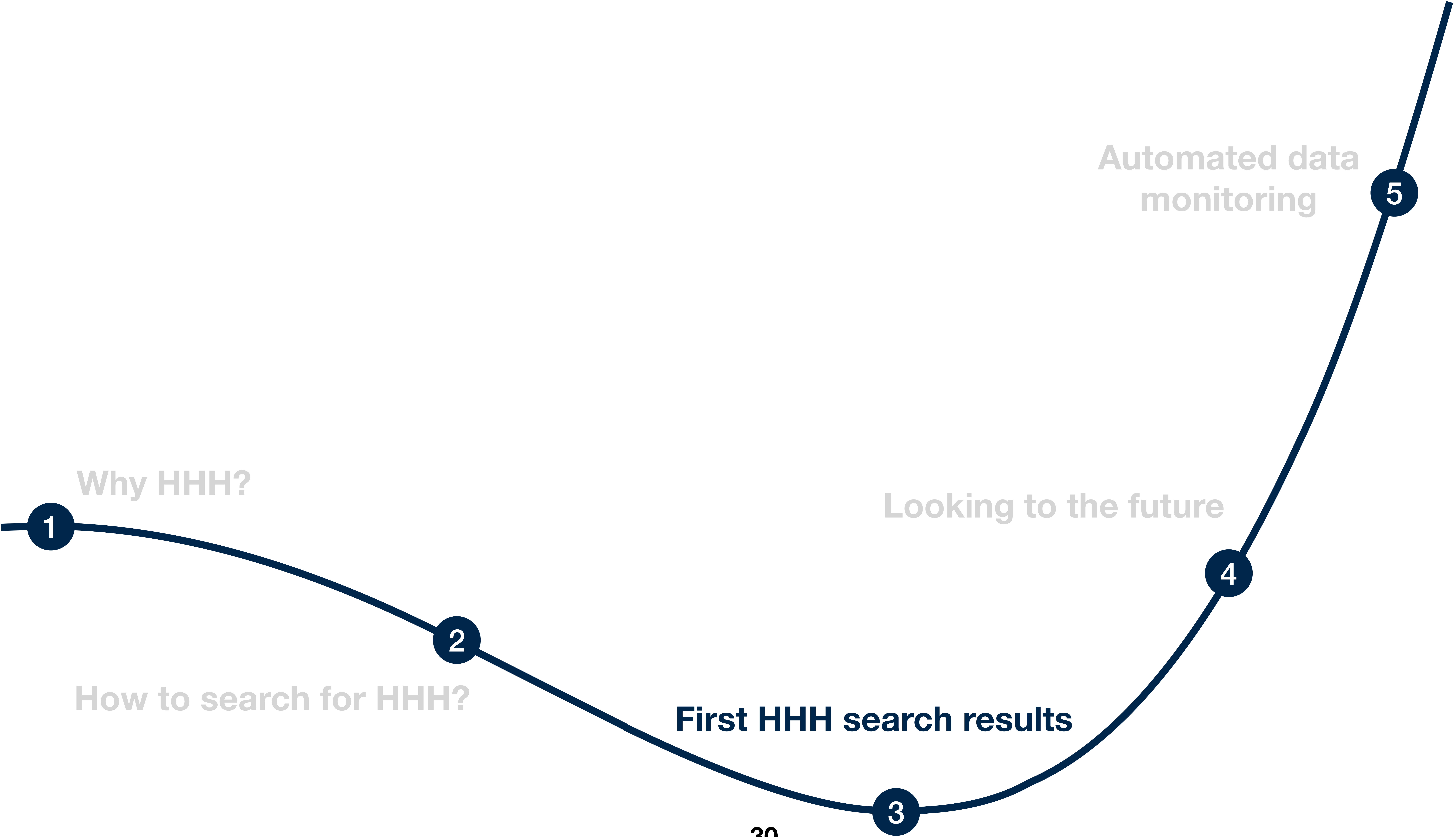


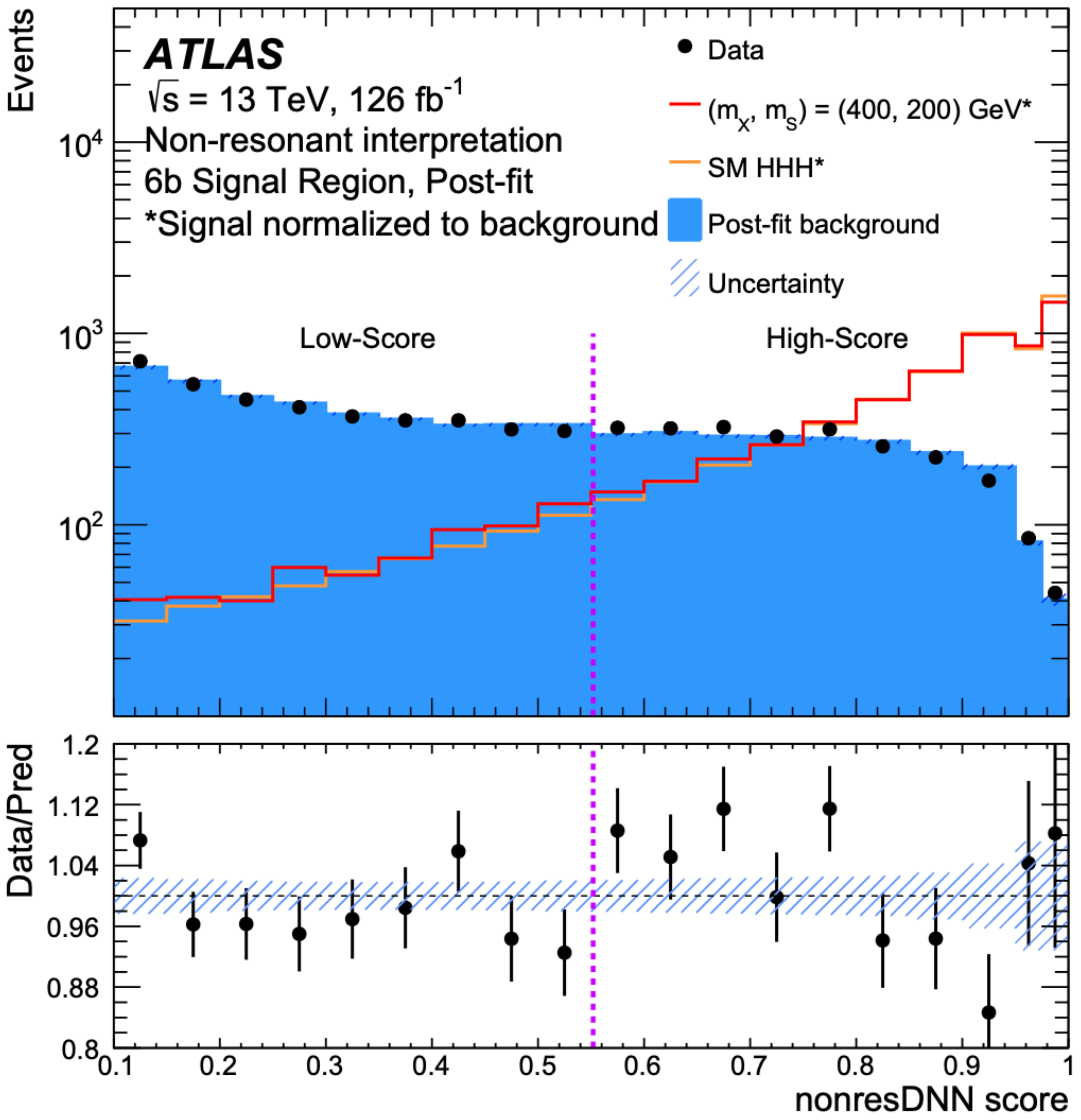
- **Reweight each event by this histogram. Select a linearly independent subset of alternate shapes.**




1
Why HHH?
2
How to search for HHH?
3
First HHH search results
4
Looking to the future
5
Automated data monitoring

Results

- **No evidence for non-resonant HHH production**
- **Set limit at $\mu = \sigma/\sigma_{SM} < 750$, or 59 fb**
- **Non-resonant BSM modes can have nearly identical signature to SM HHH.**



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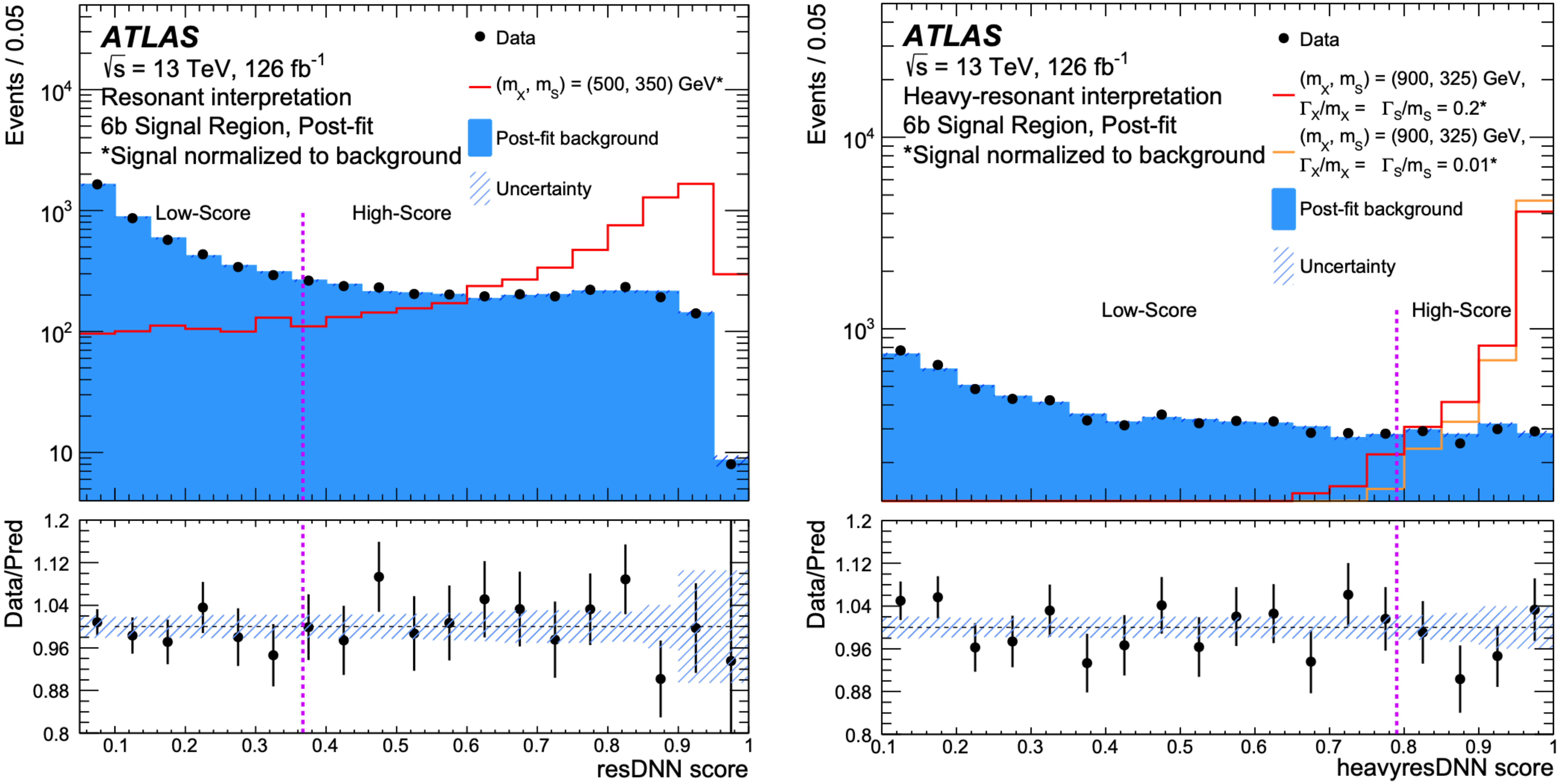
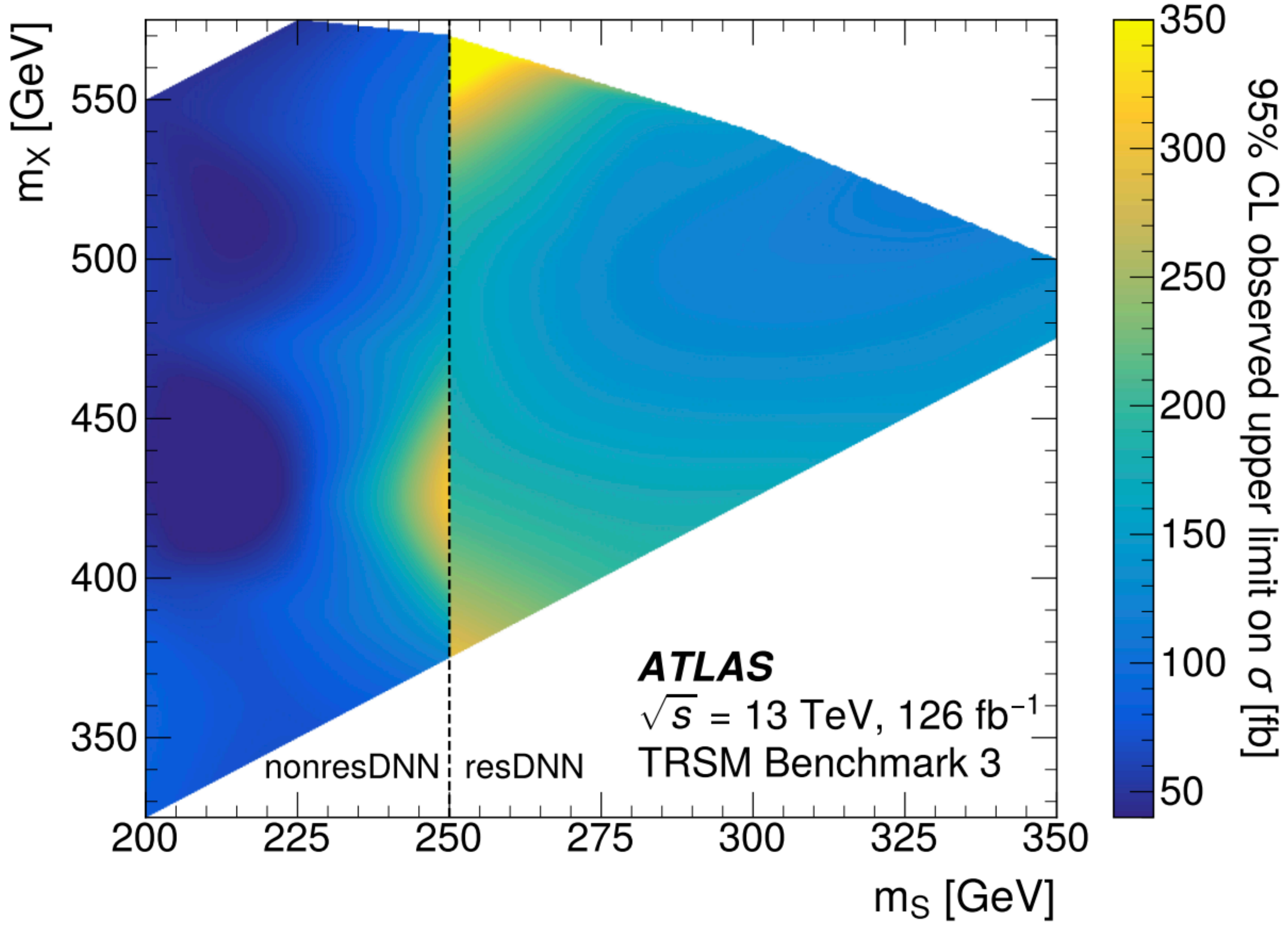


- **No evidence for resonant HHH production**

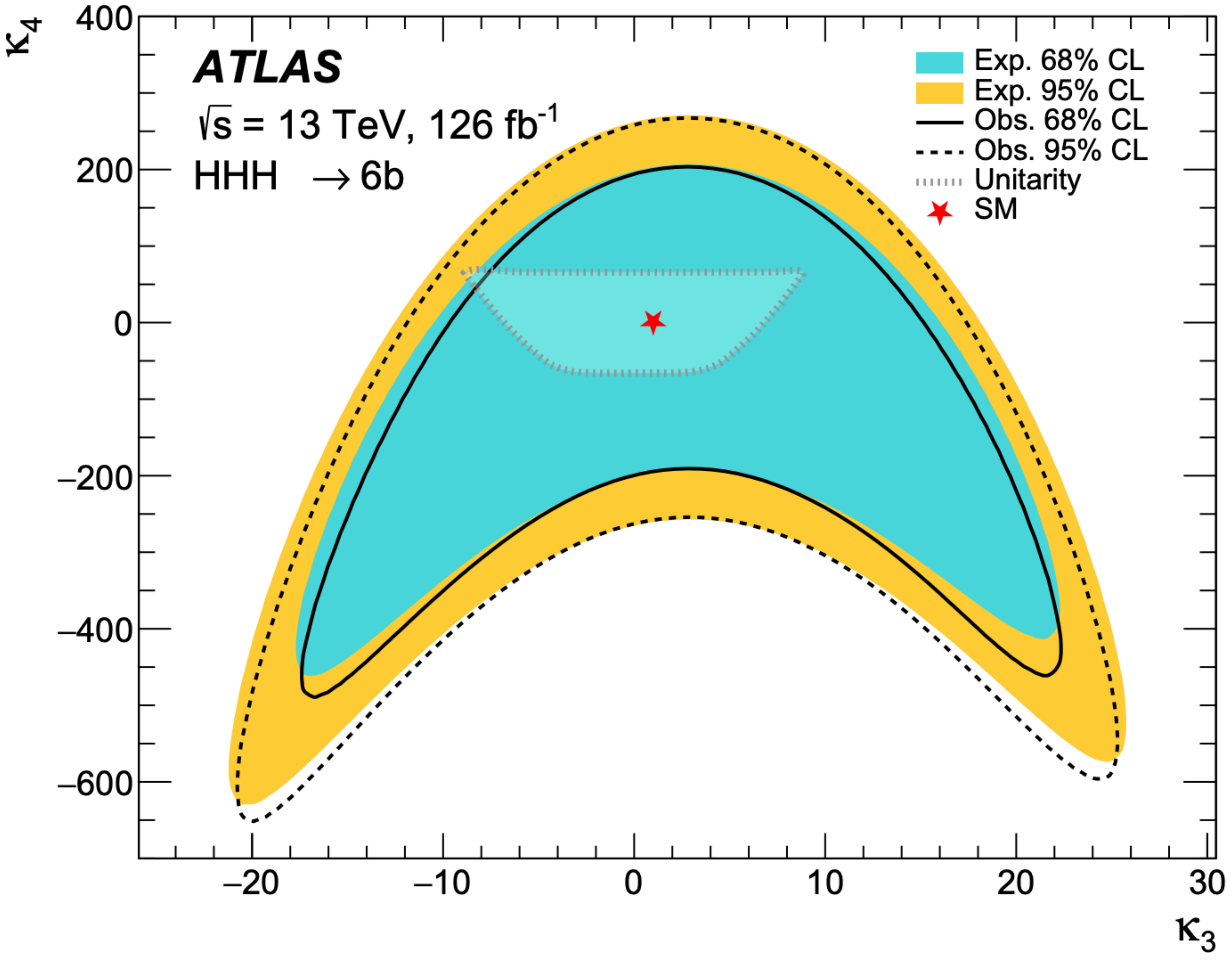
Conclusions: BSM searches

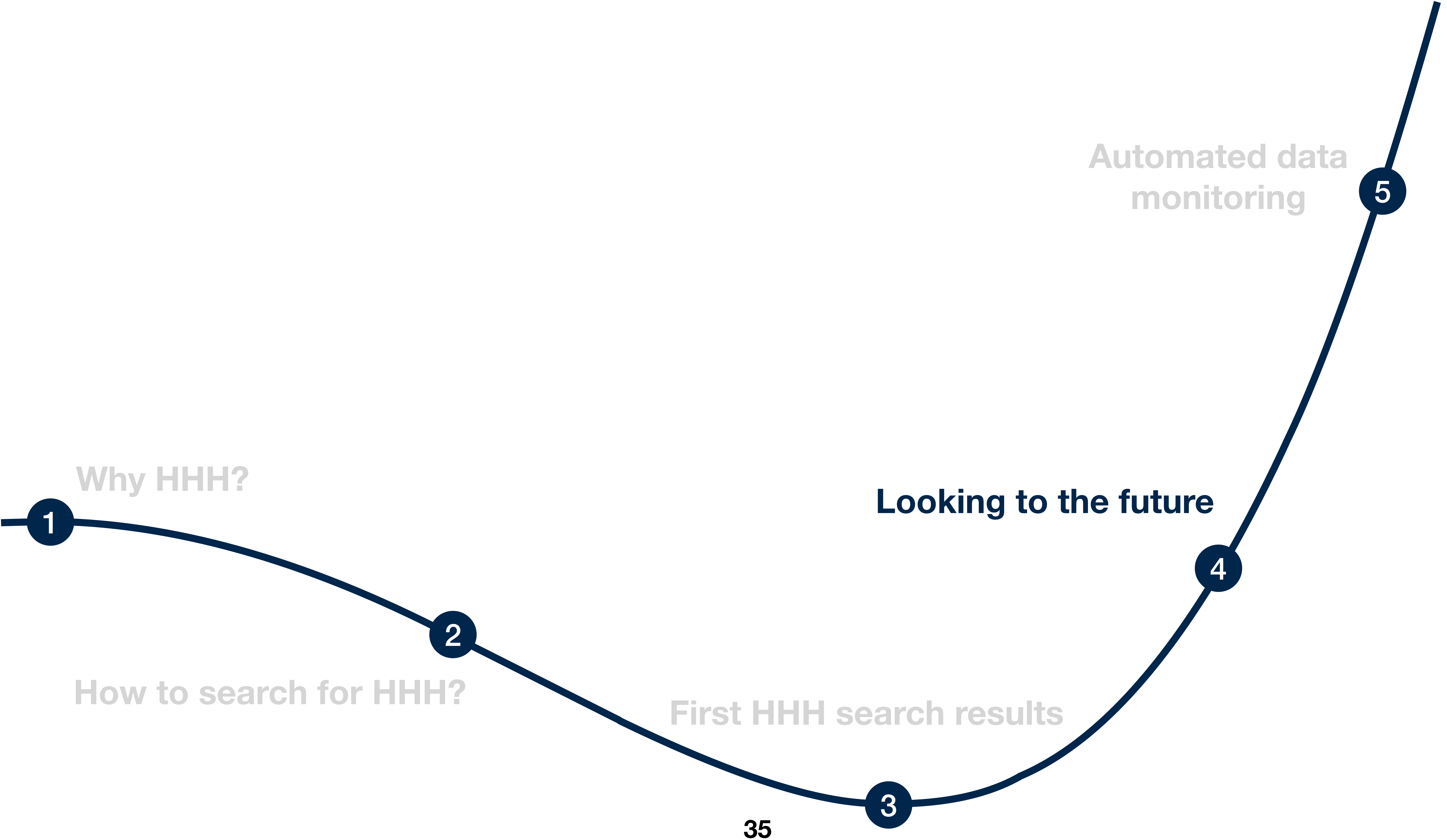
- **The first search for HHH production was recently published**
- **TRSM model predicts HHH production cross sections up to ~150 fb**
- **HHH production limits are on the same order as predicted cross section (50-350 fb as a function of m_X, m_S)**
- **Searches for BSM physics in HHH is relevant TODAY!**



Conclusions: SM-like interpretation

- **The first search for HHH production was recently published**
- **Results include first ever limits on κ_4, the quartic Higgs self-coupling**
- **Current results suggest $\kappa_4 = 1 \pm 30$ is an ambitious target at the HL-LHC.**
  - ATLAS projects in progress. This is back of envelope math
  - Need 10x improvement on top of lumi (6 ab^{-1}).
    - With no improvement other than lumi, more like $\kappa_4 = 1 \pm 100$
  - Some improvement expected from:
    - Multiple channels
    - Reduction of theoretical uncertainties
- **HHH may be especially suited to AI/ML due to the complicated final state.**

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  - A HHH cross-section at 13 TeV was not available in the literature.
  - We computed a quadratic fit to the 14 TeV, 27 TeV, 100 TeV cross-sections and added an additional 20% uncertainty.
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- **Exploration of more channels**
  - There is slight tension in phenomenological studies with respect to which channel is best
  - This is suggestive that in a HHH combination many channels would contribute

Decay Mode	Branching Fraction
bbbbbb	19.5%
bbbb+1 lepton*	15.2%
bbbb+yy	0.2%
bbbb+taus(had)	2.5%
bb+SS leptons	1.9%

HHH as an AI laboratory

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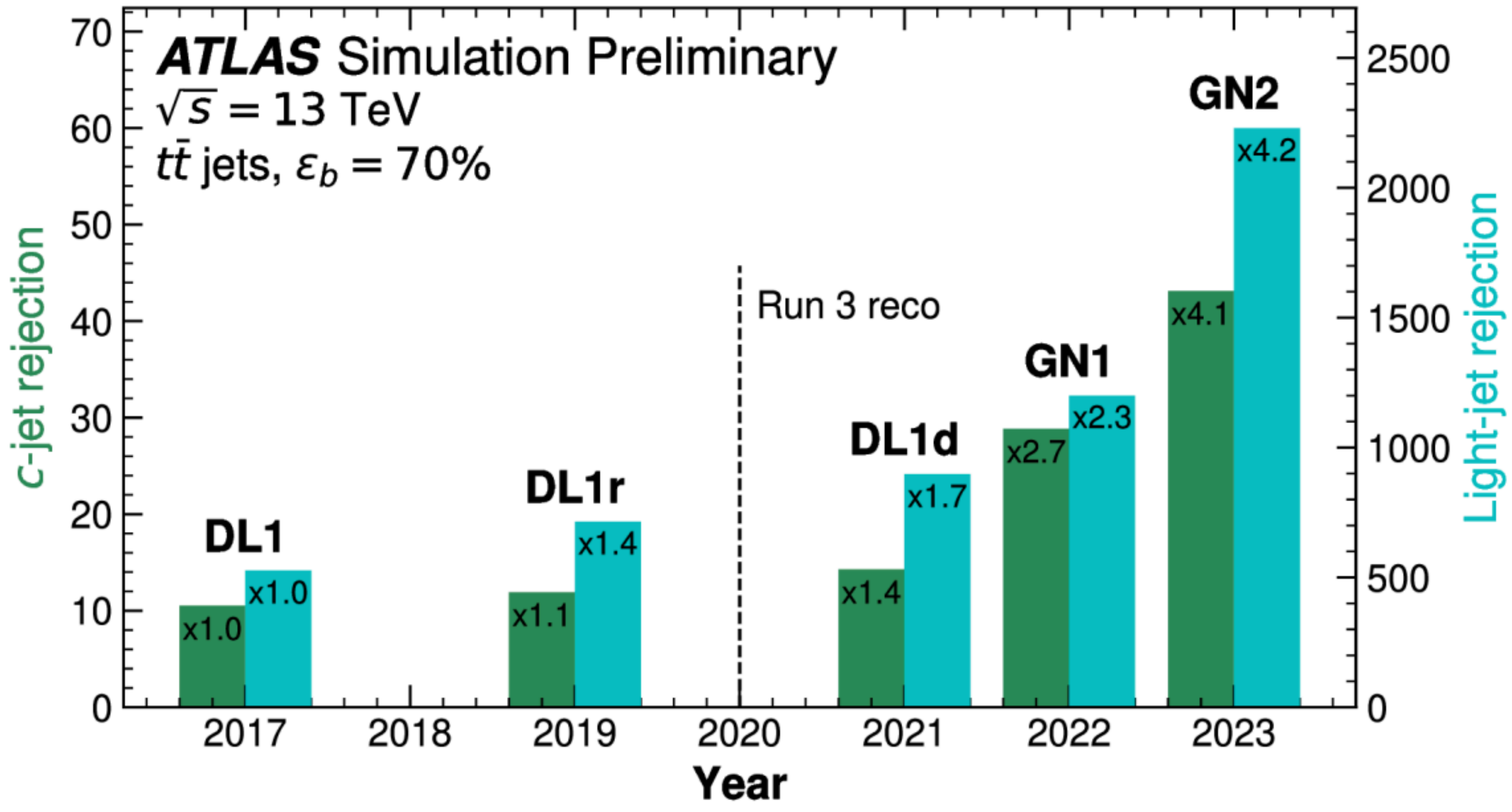

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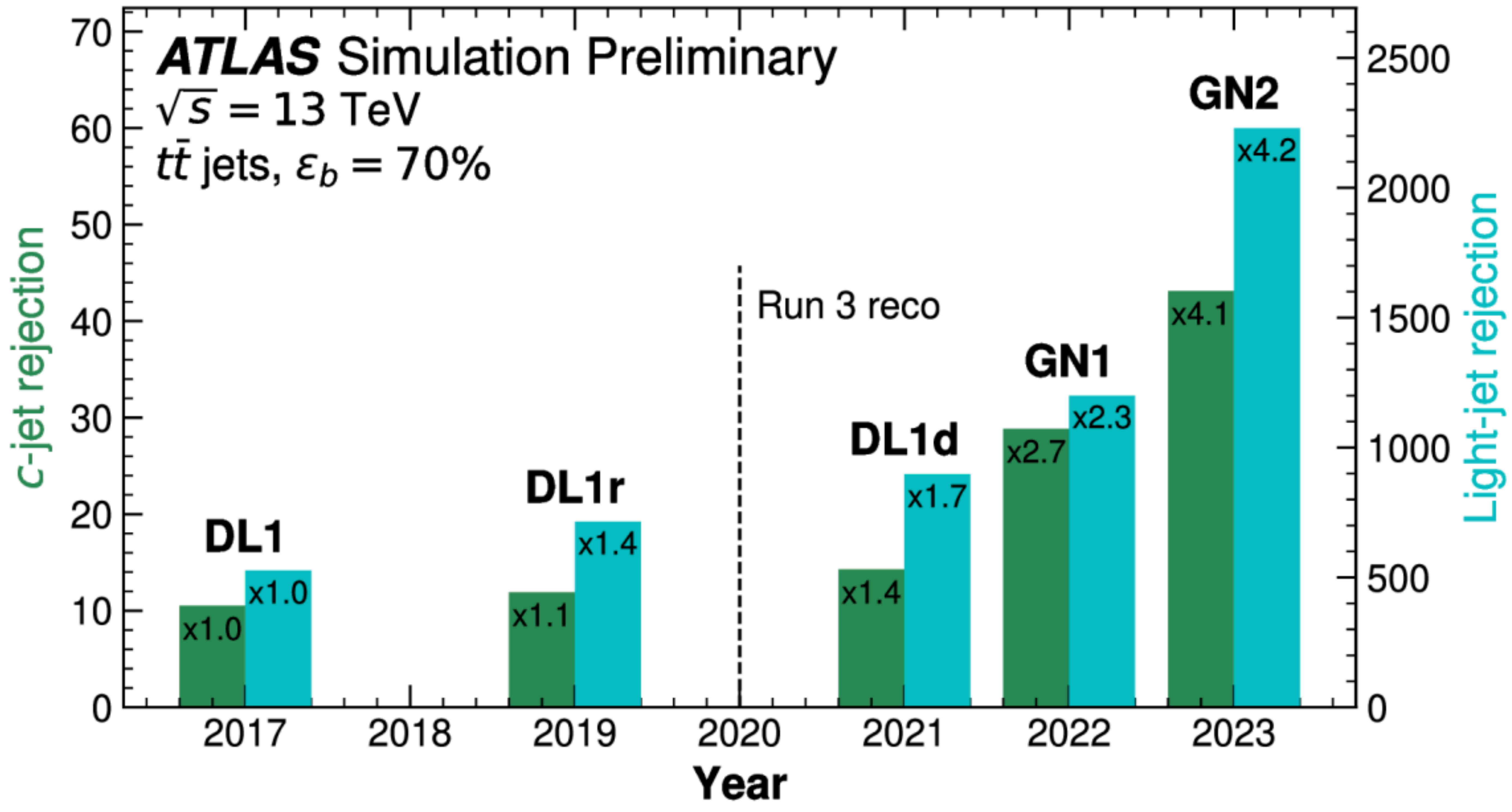

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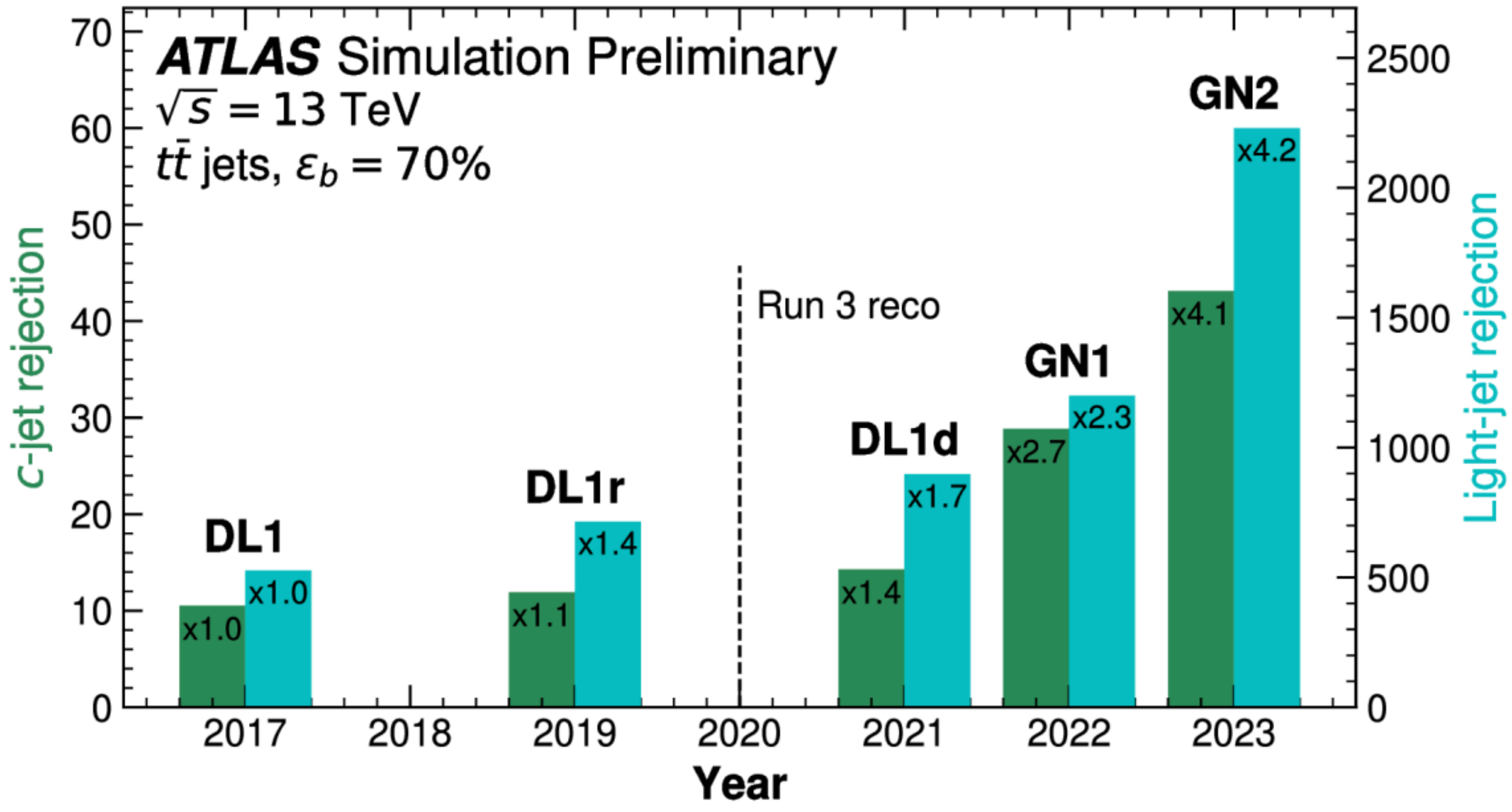

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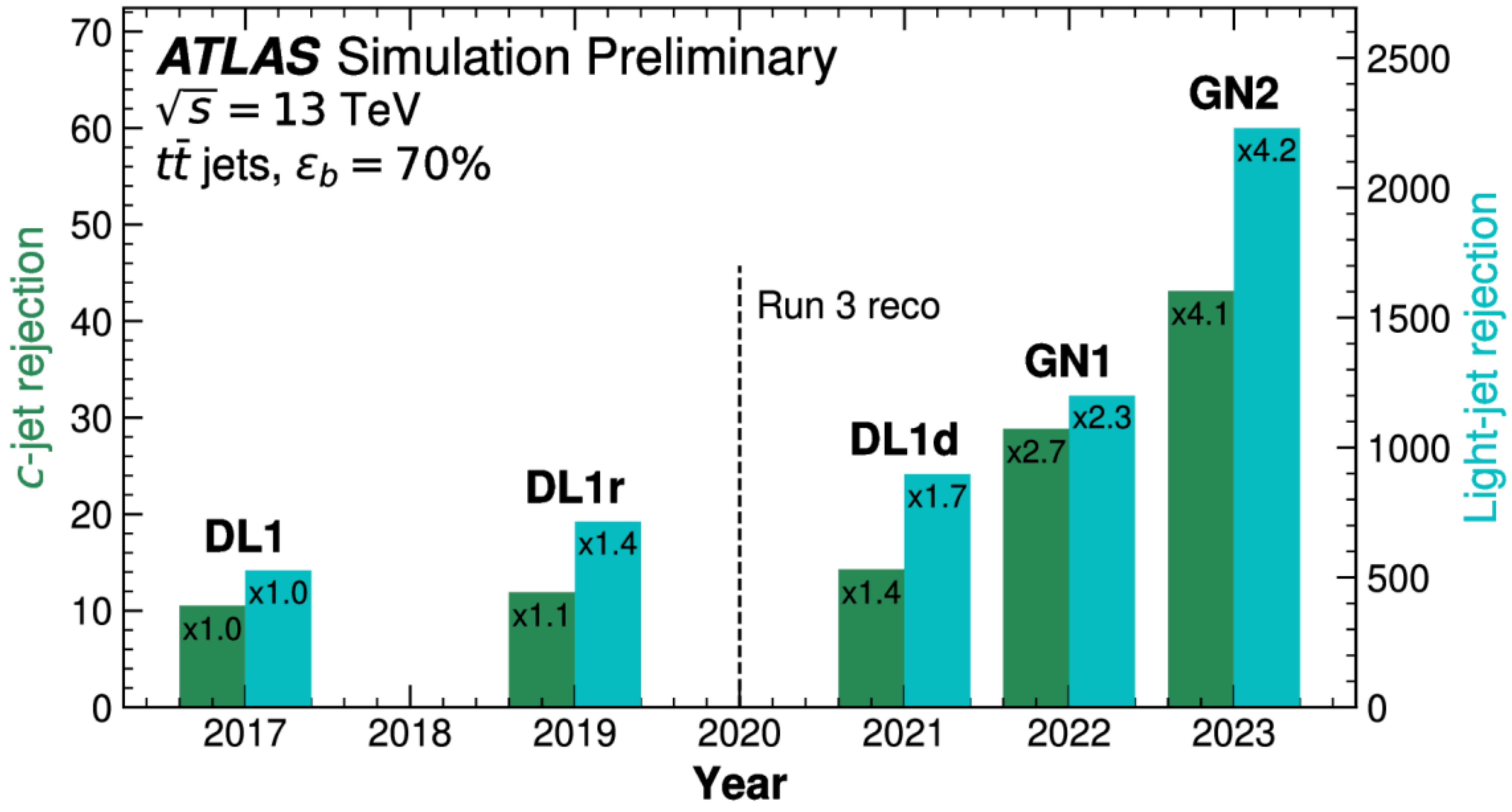

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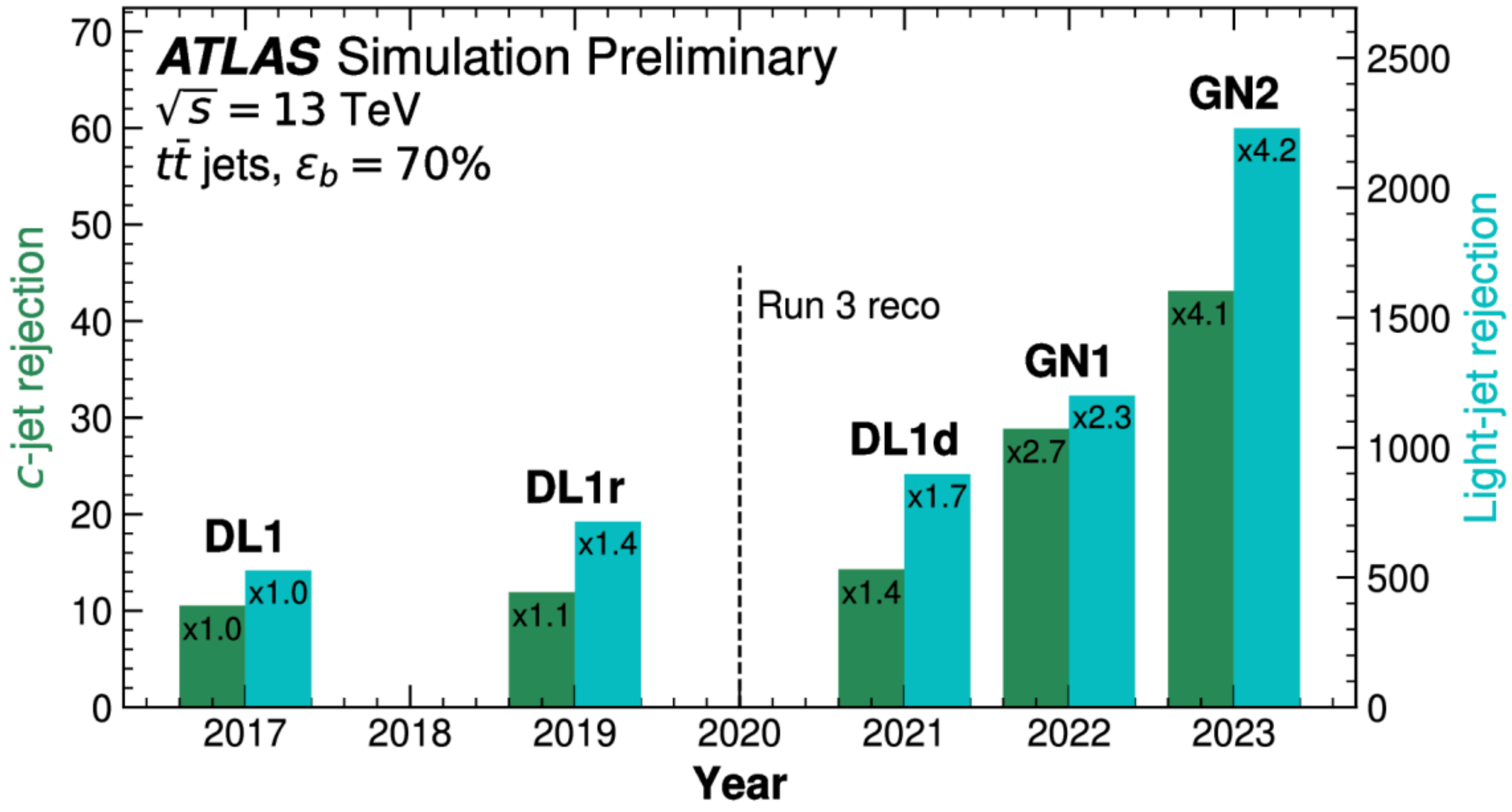

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- **Need some classic datasets "MNIST of ATLAS/LHC" for ML challenges**

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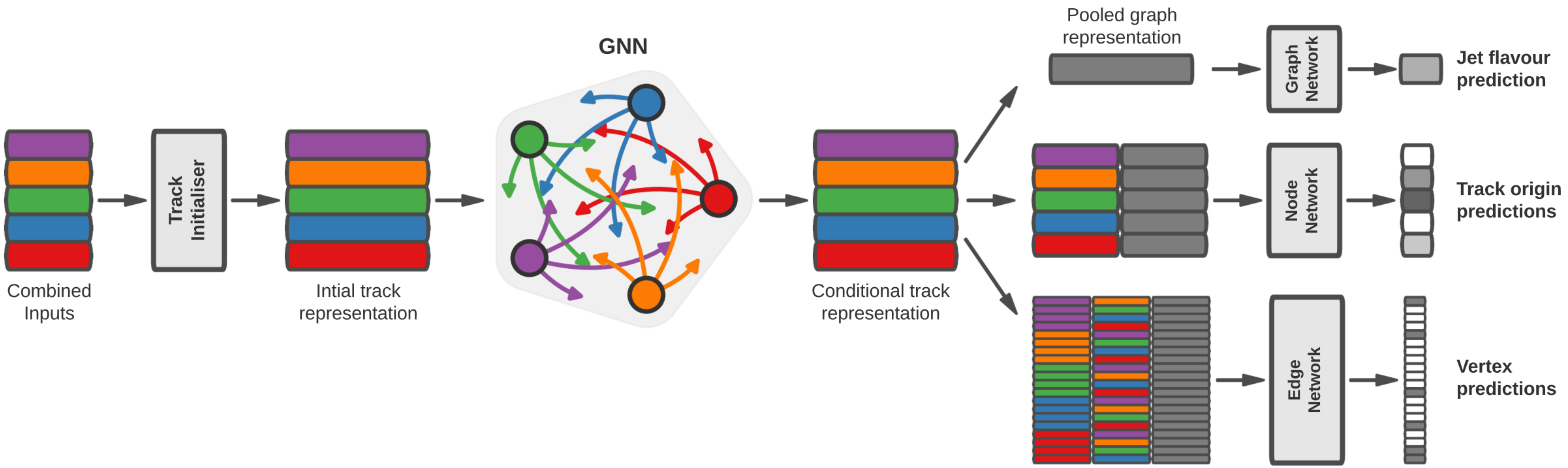

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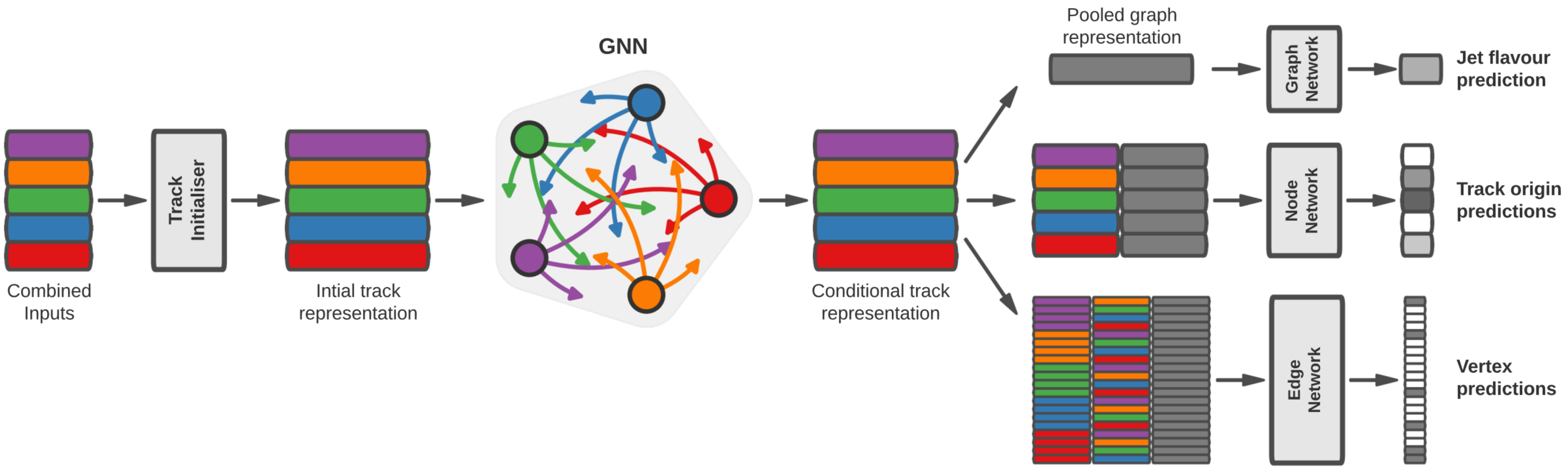

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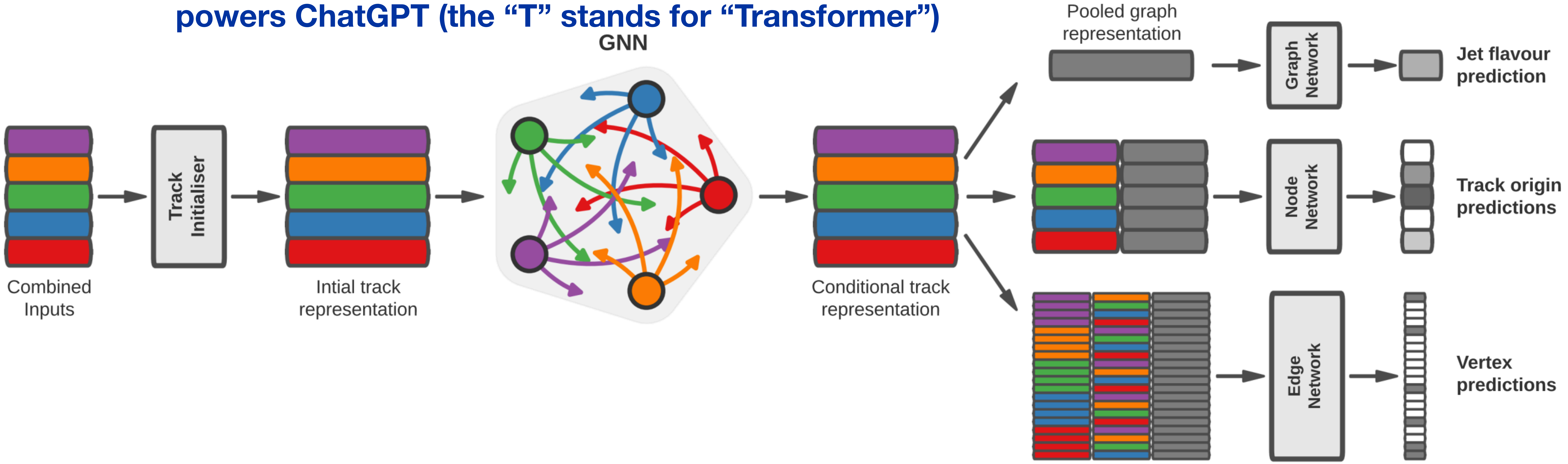

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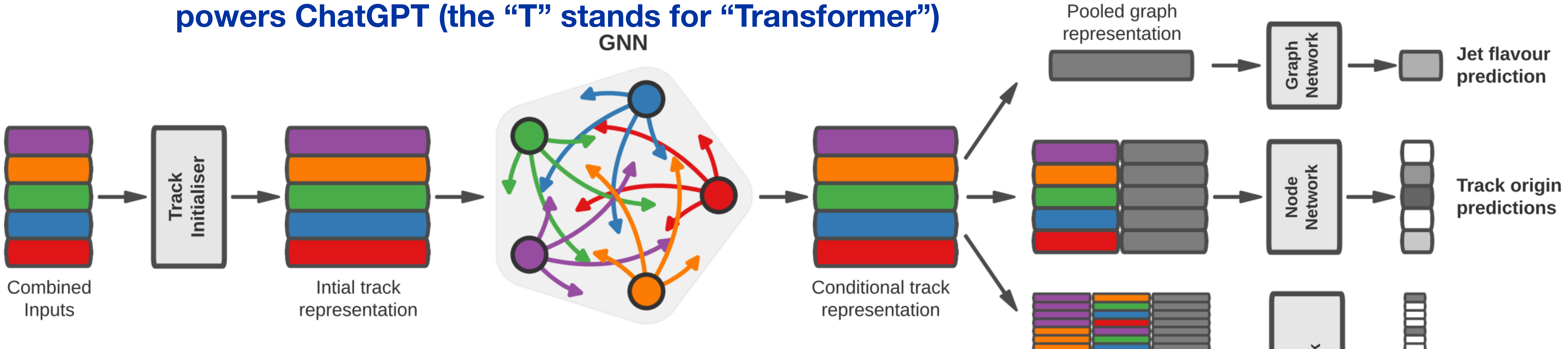

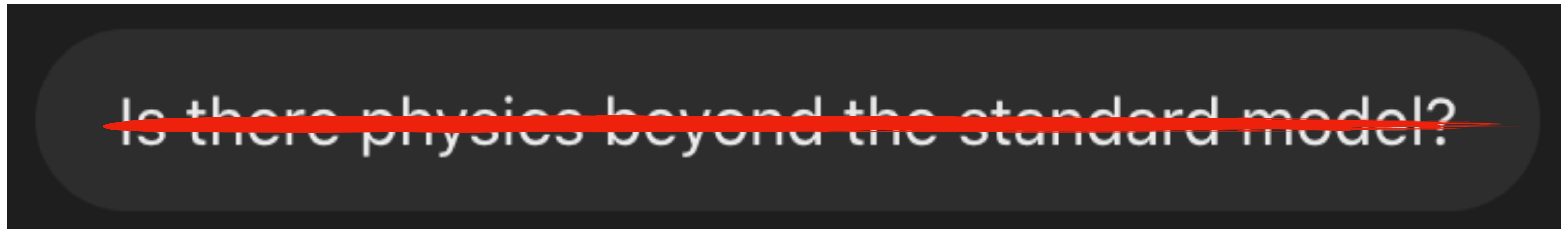

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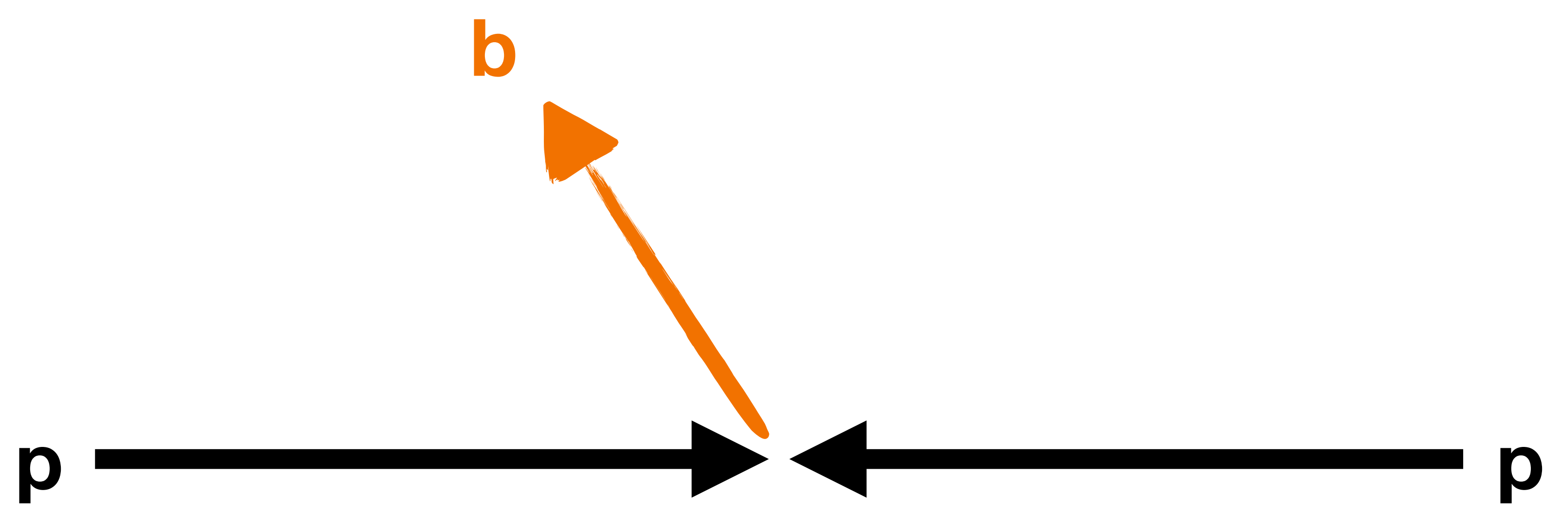

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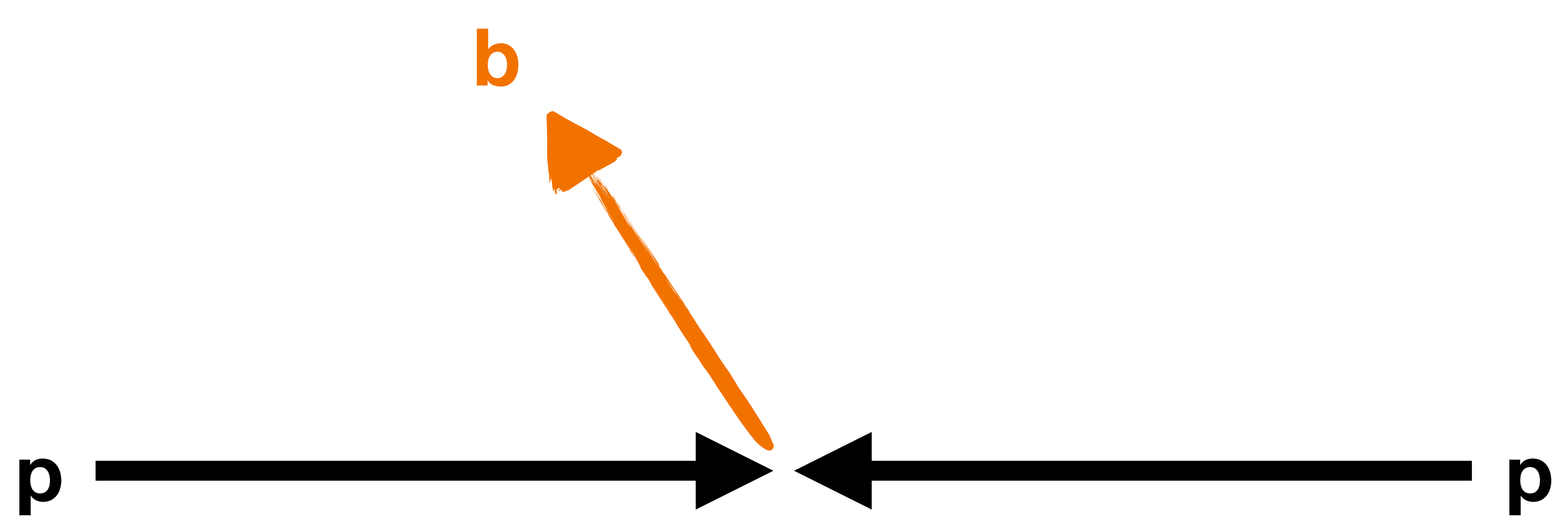

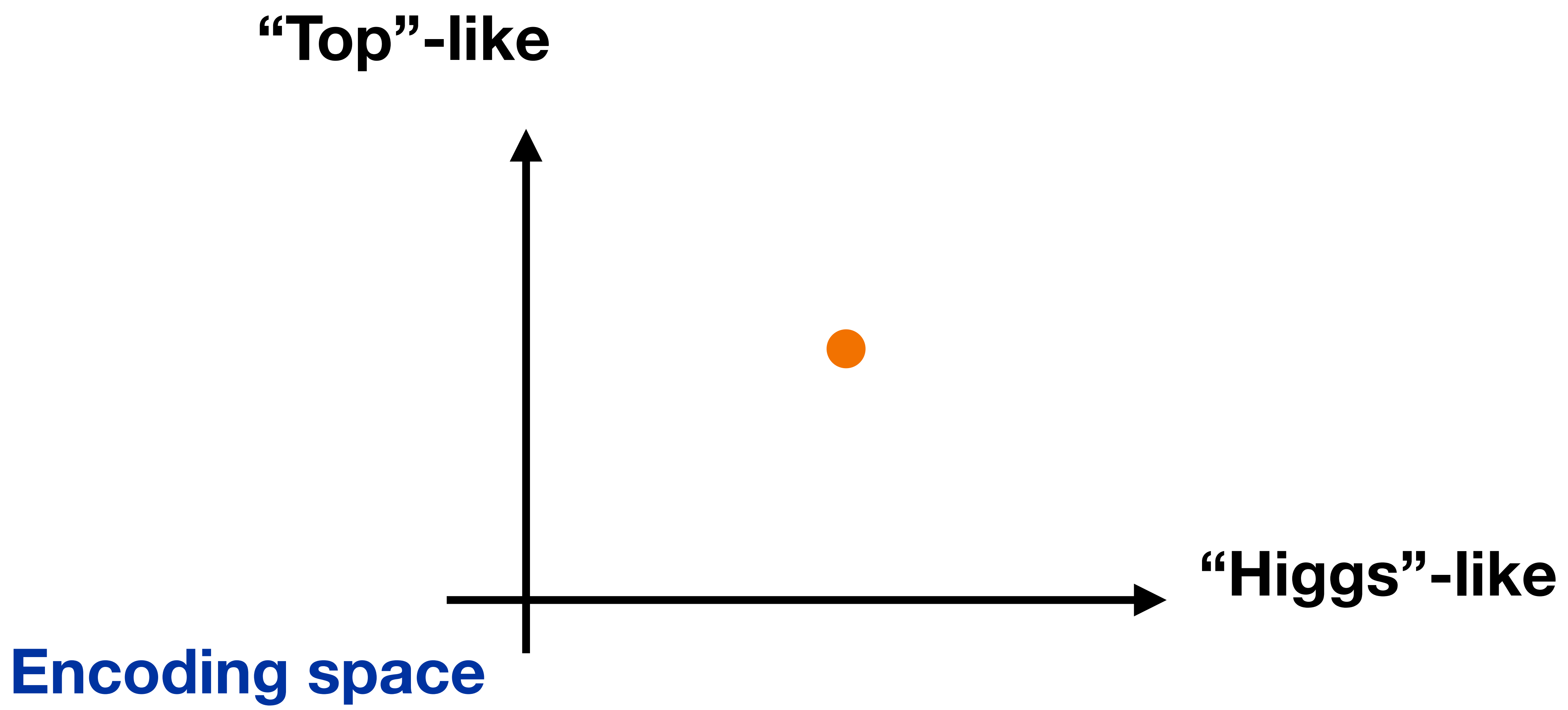

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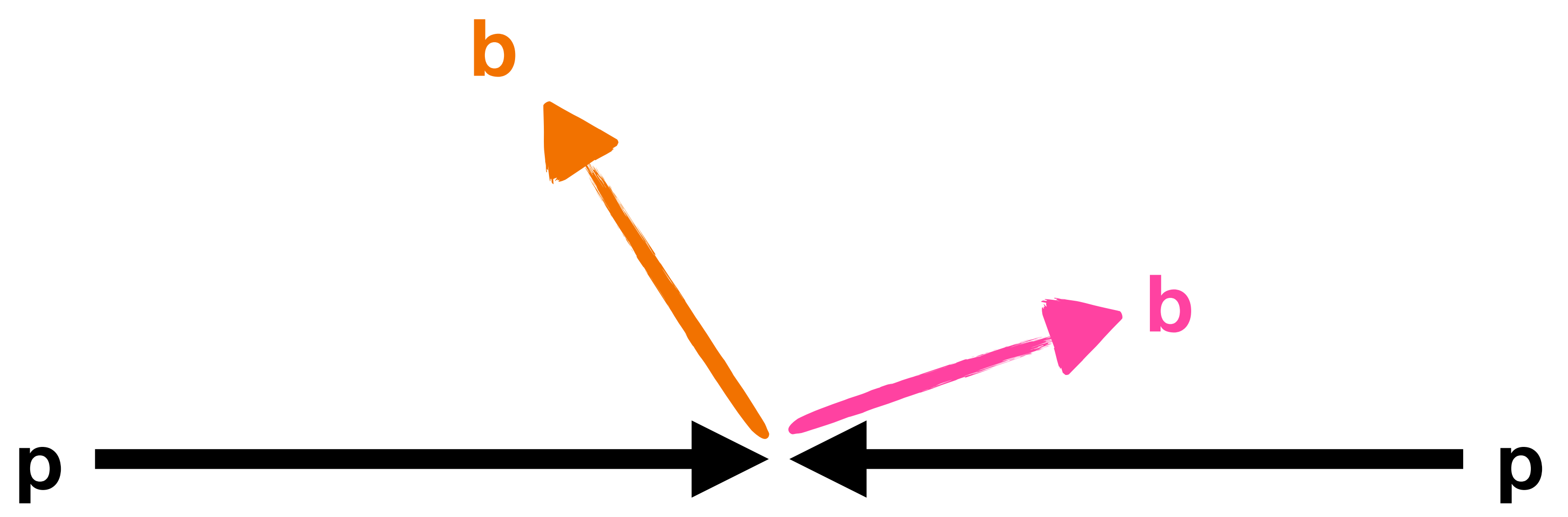

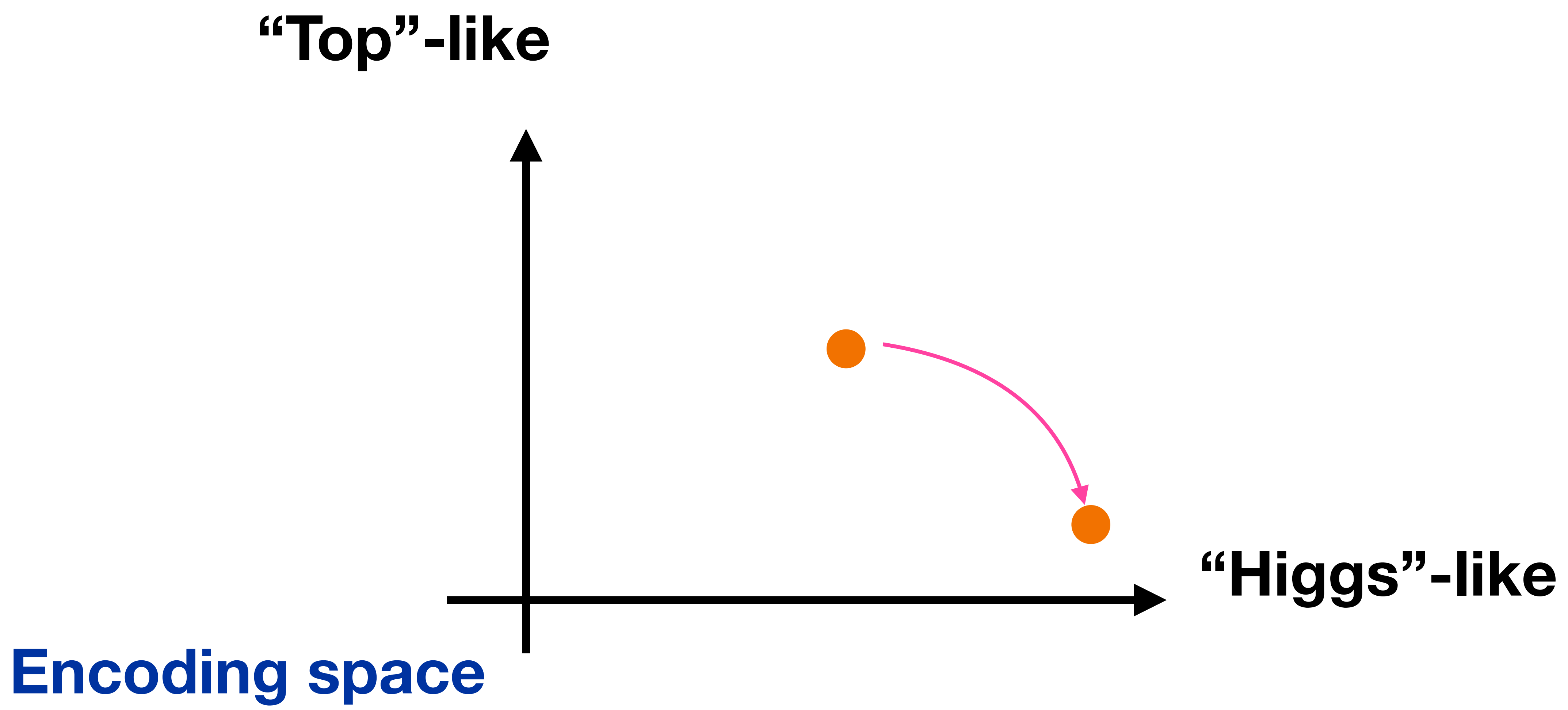

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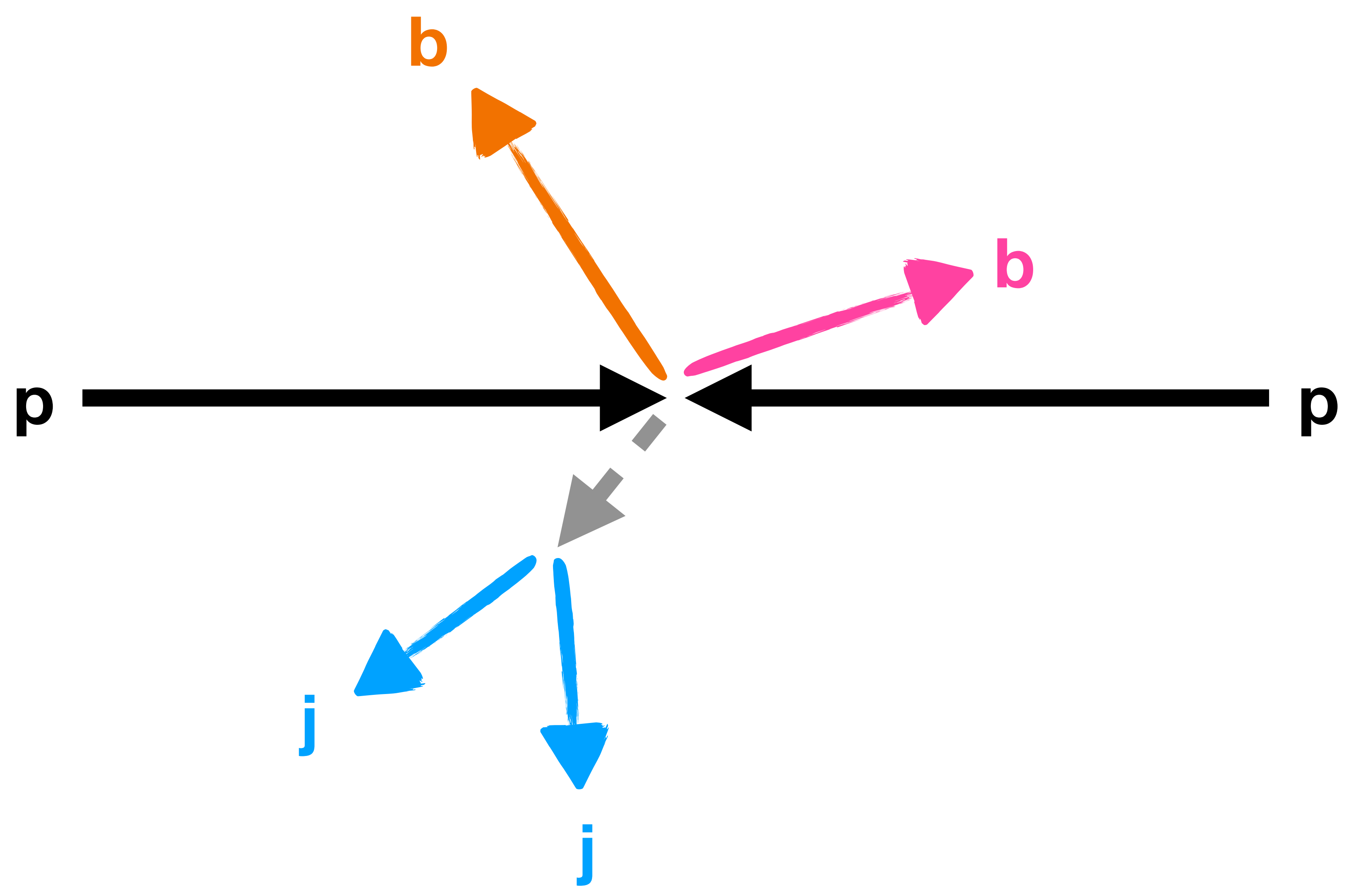

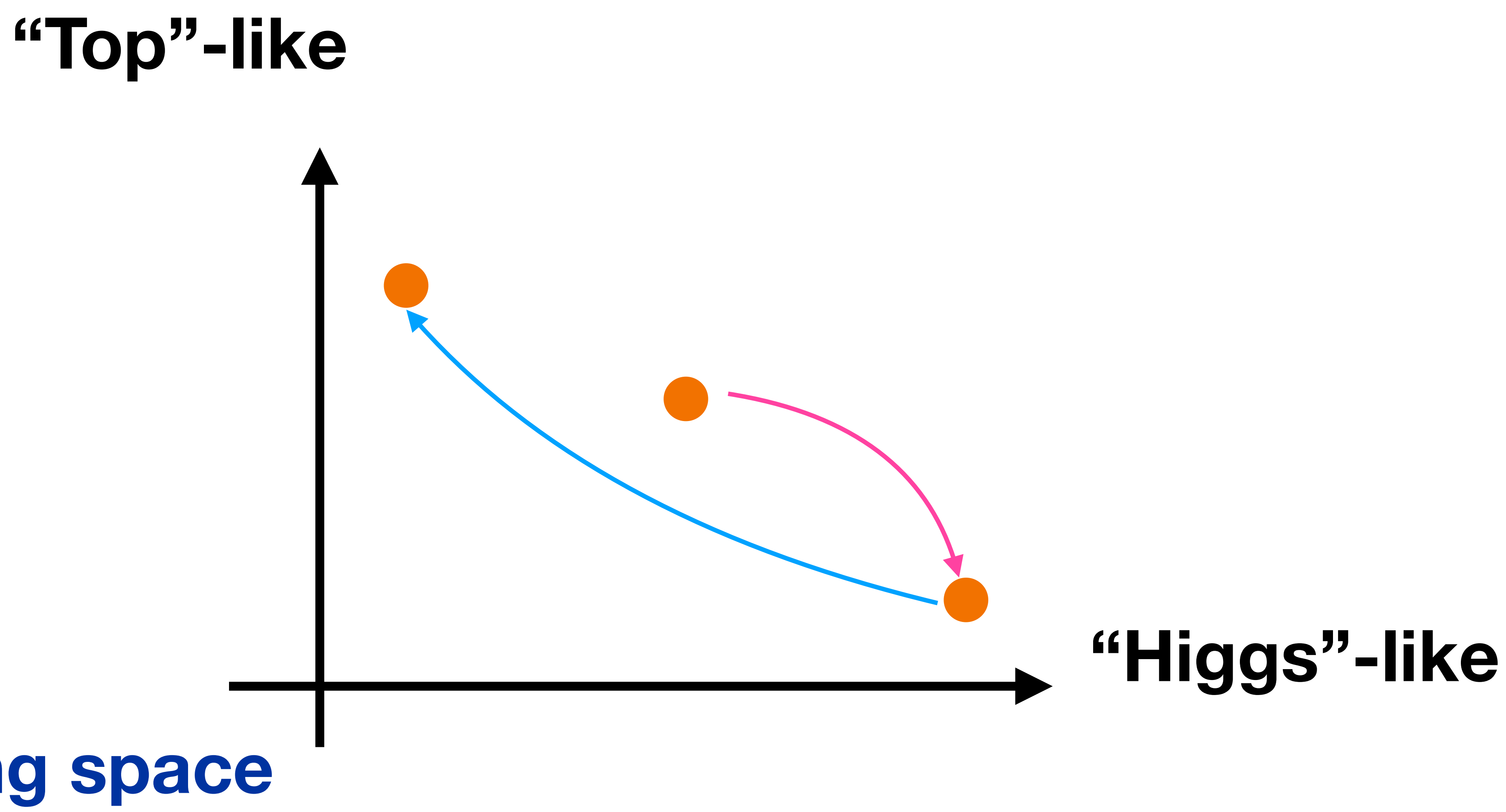

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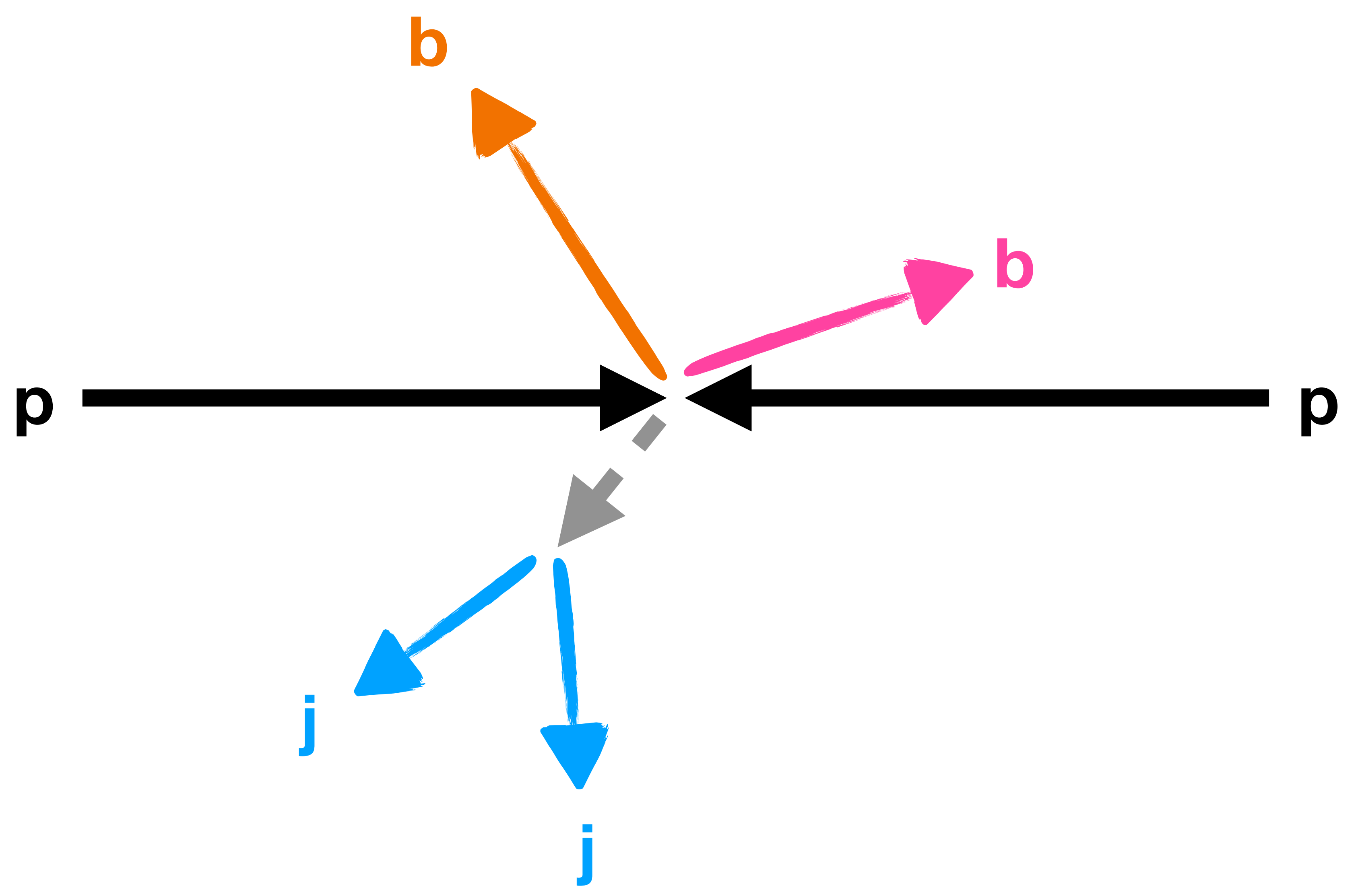
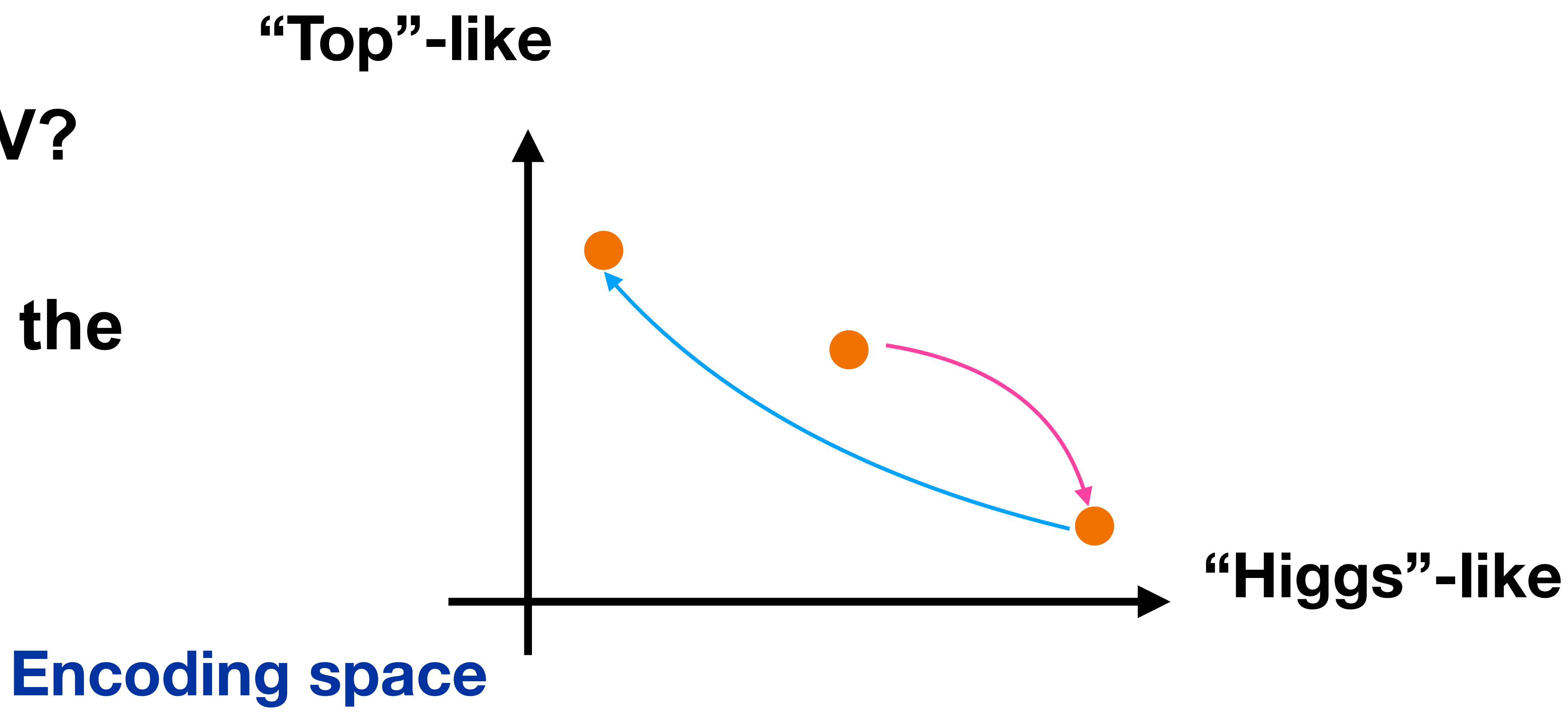
- **Transformers can add these conflicting contexts in the embedding space and pair in auxiliary tasks**





Domain adaptation

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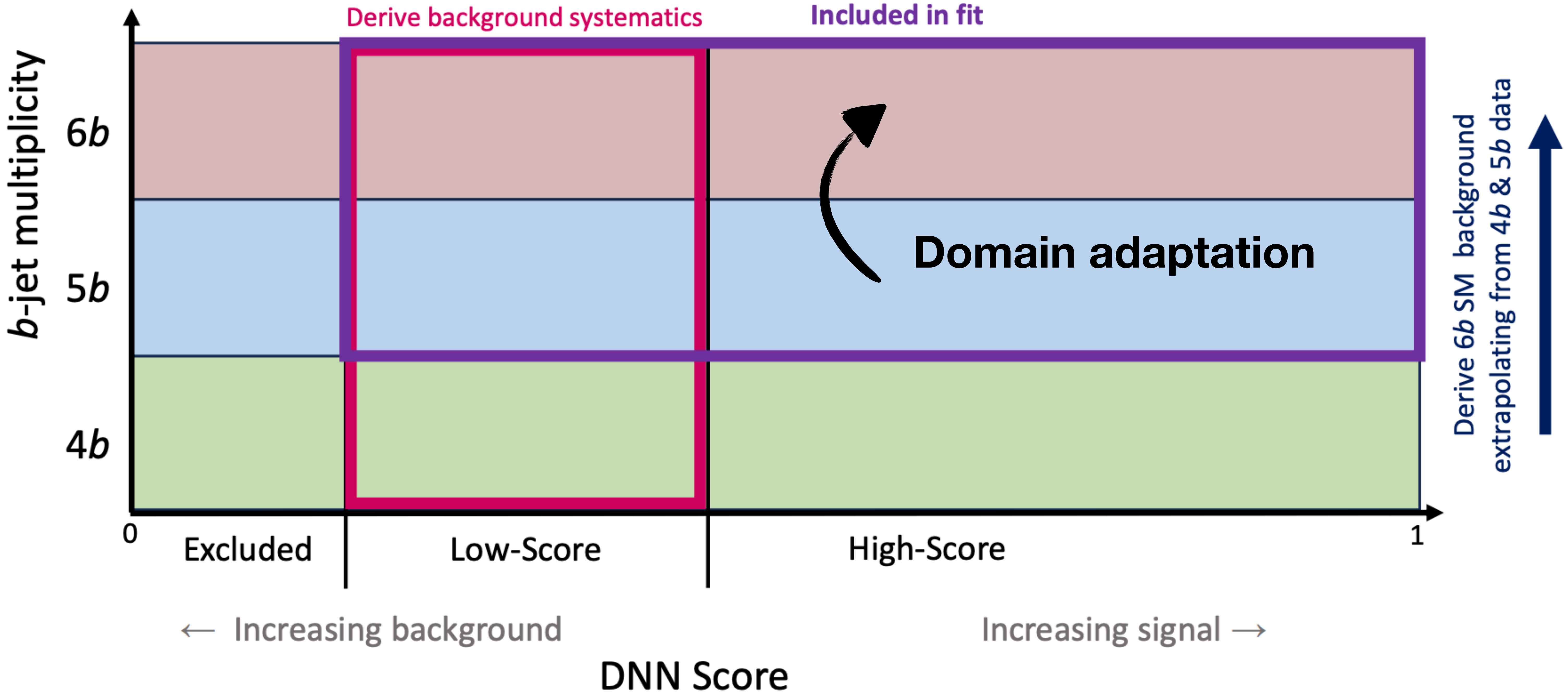

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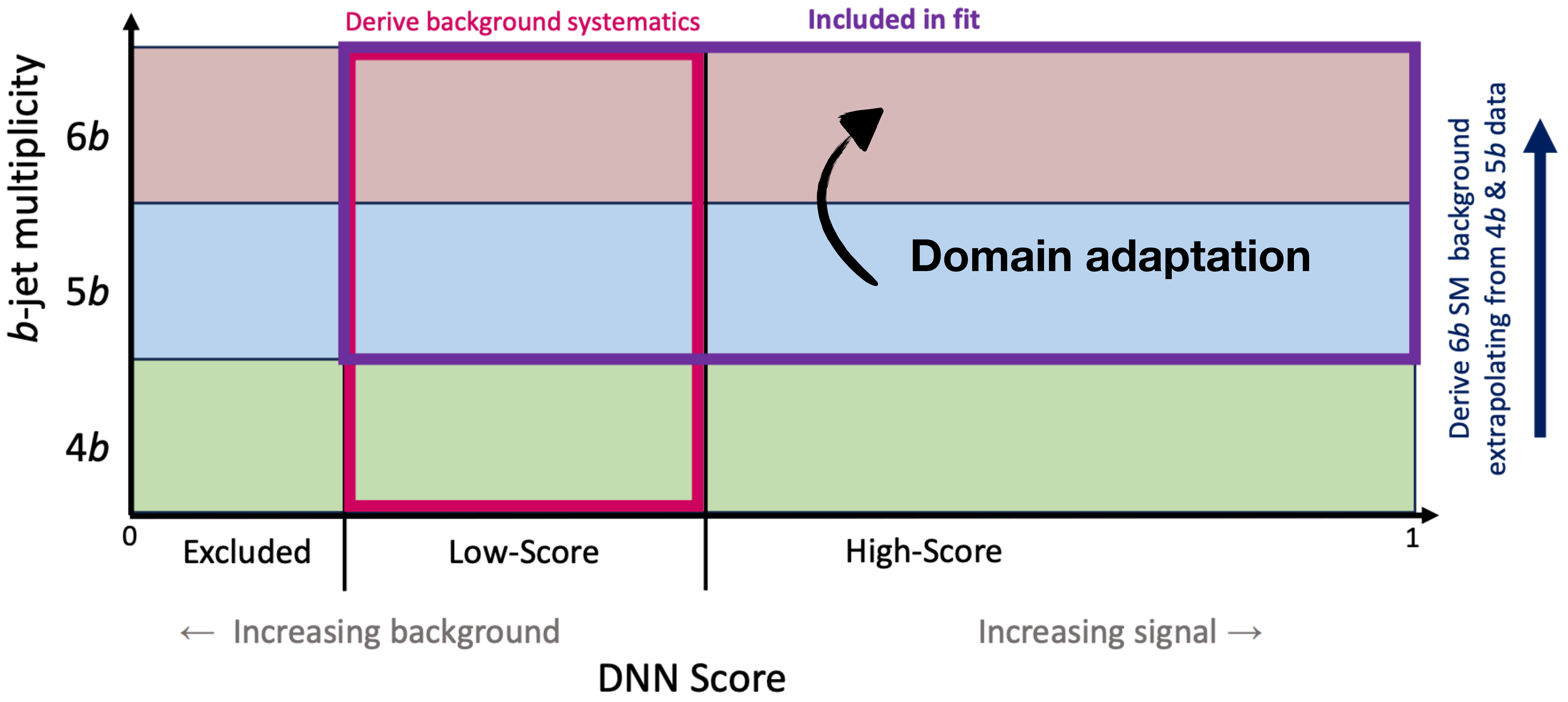
- **The problem of training on 5b and applying the NN on 6b is referred to as "domain adaptation"**
- **We selected input features which minimized difference between 5b and 6b data**
  - But this may have left us with a non-optimal DNN



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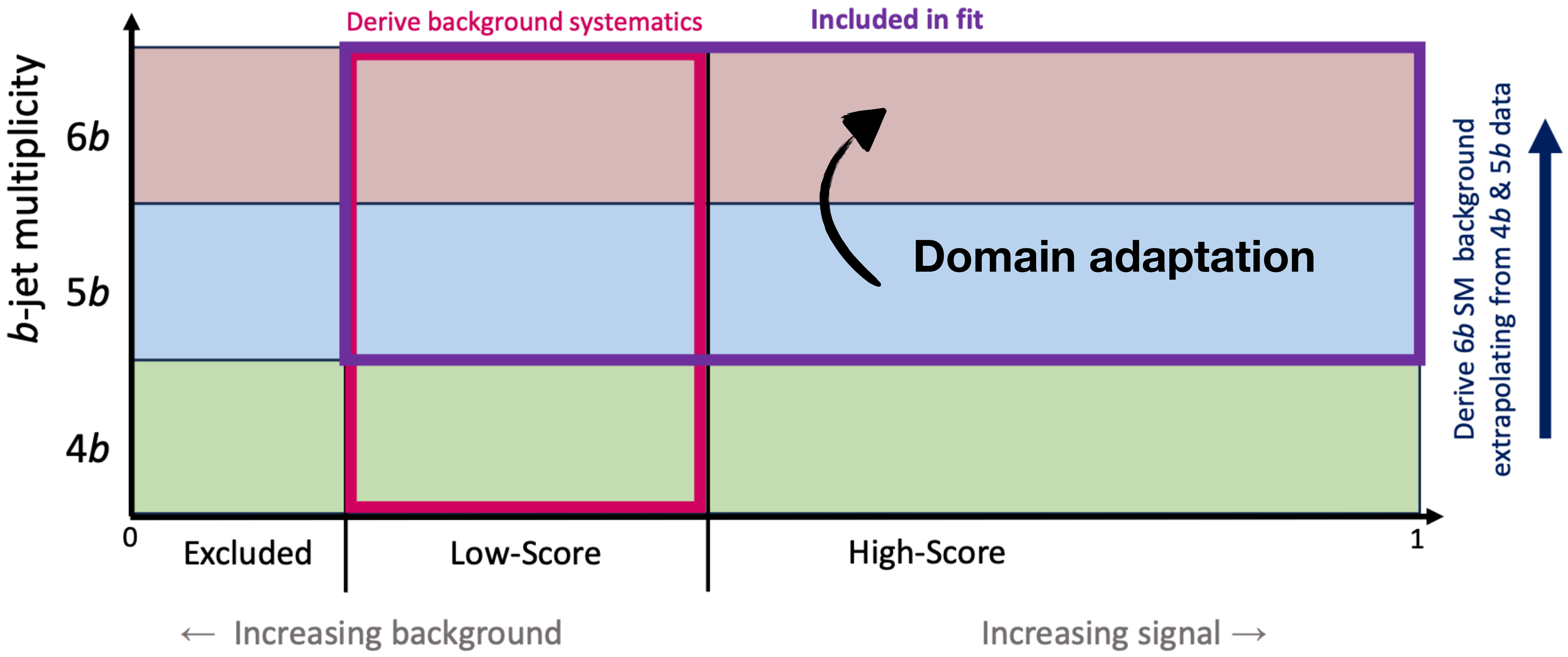

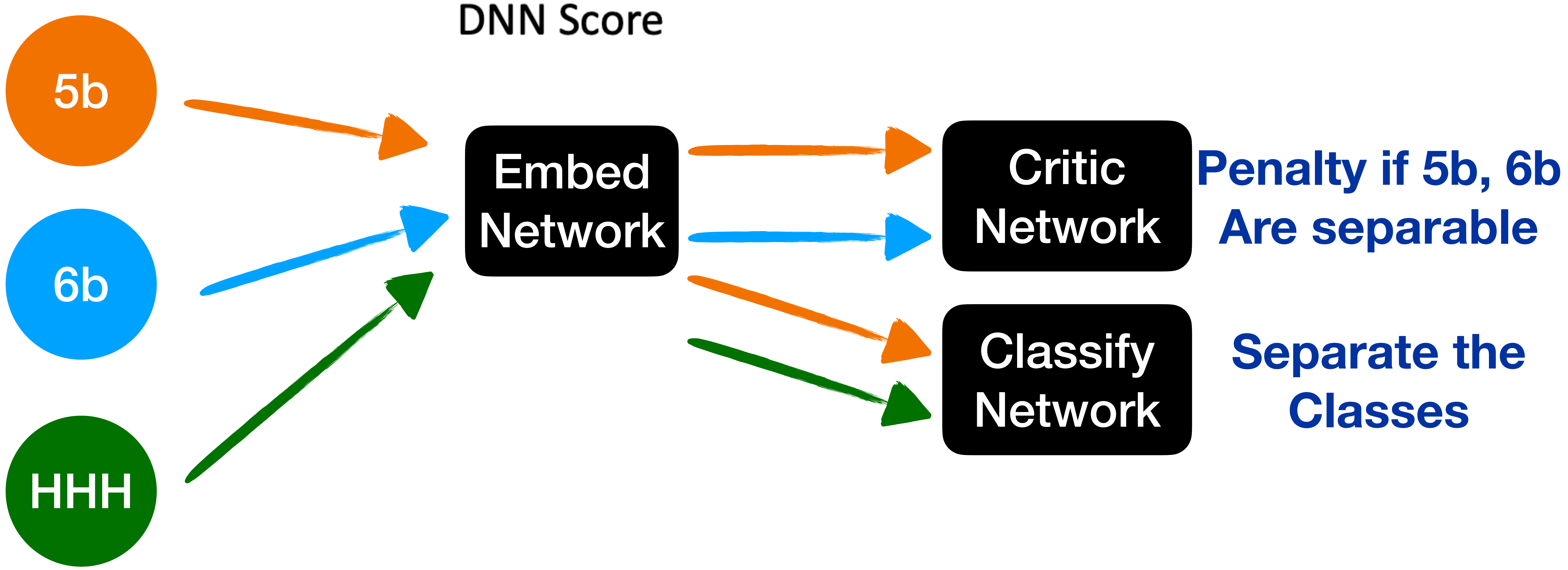

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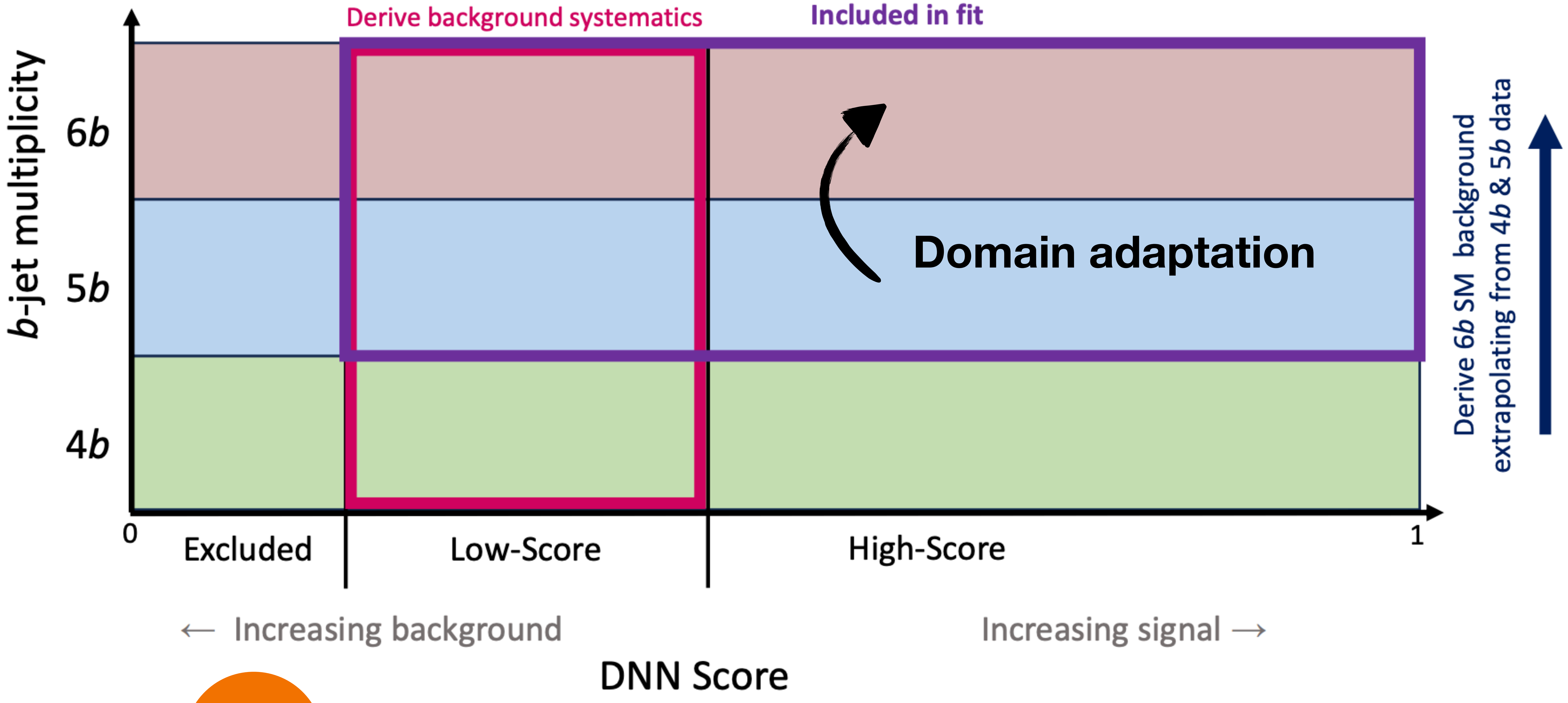

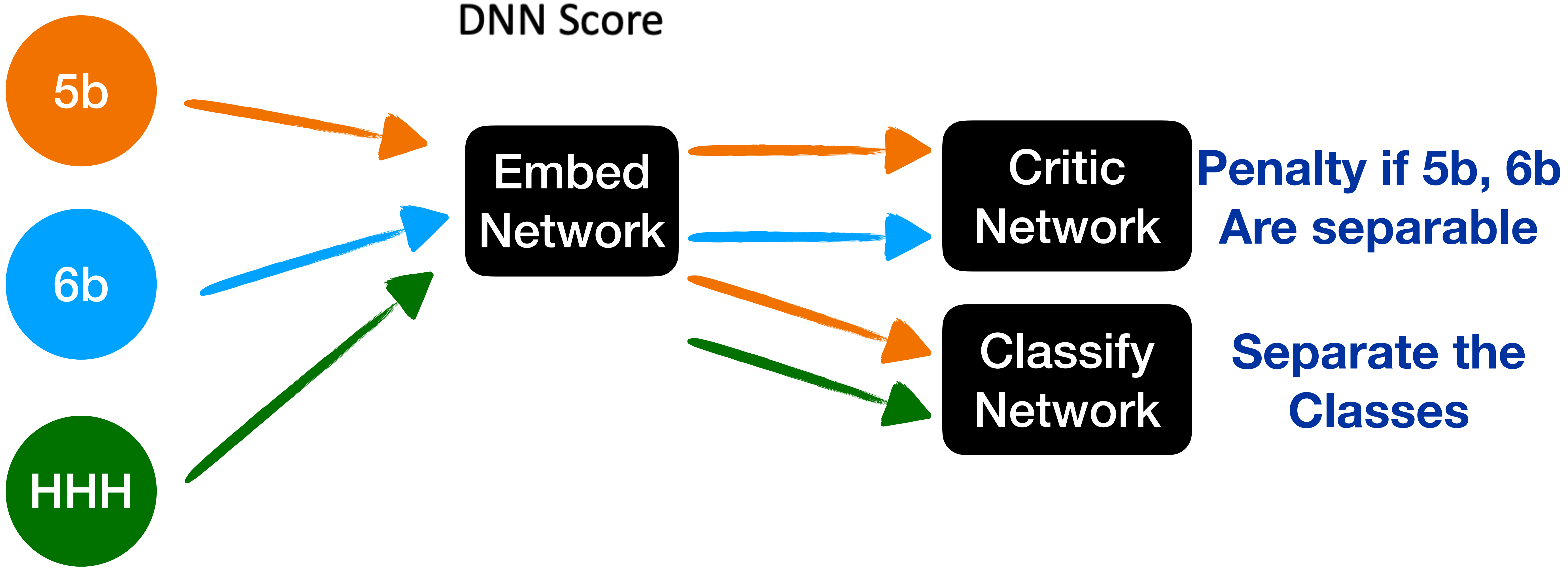

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Uncertainty source	SM-like
All uncertainties	24
Experimental	22
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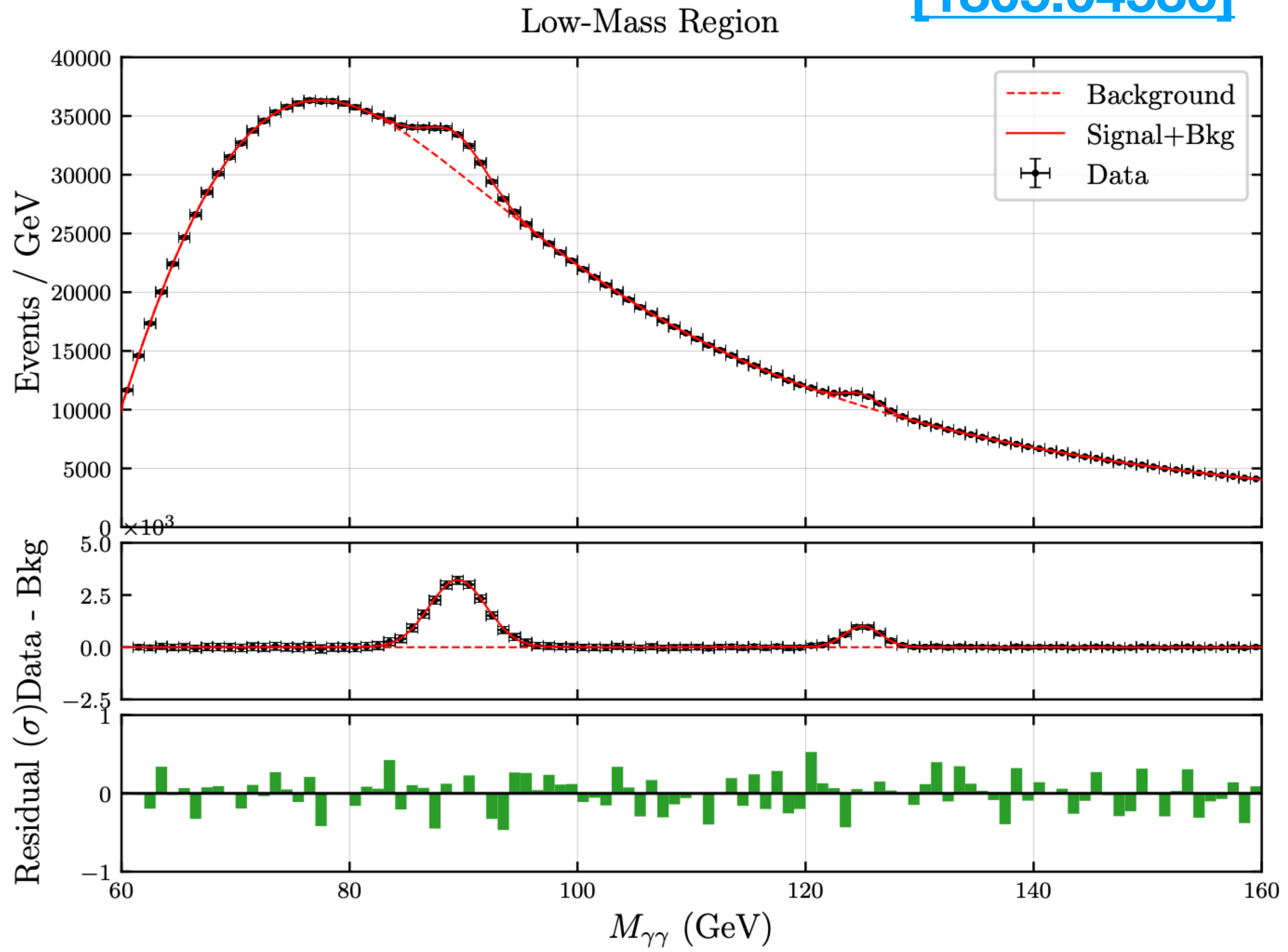

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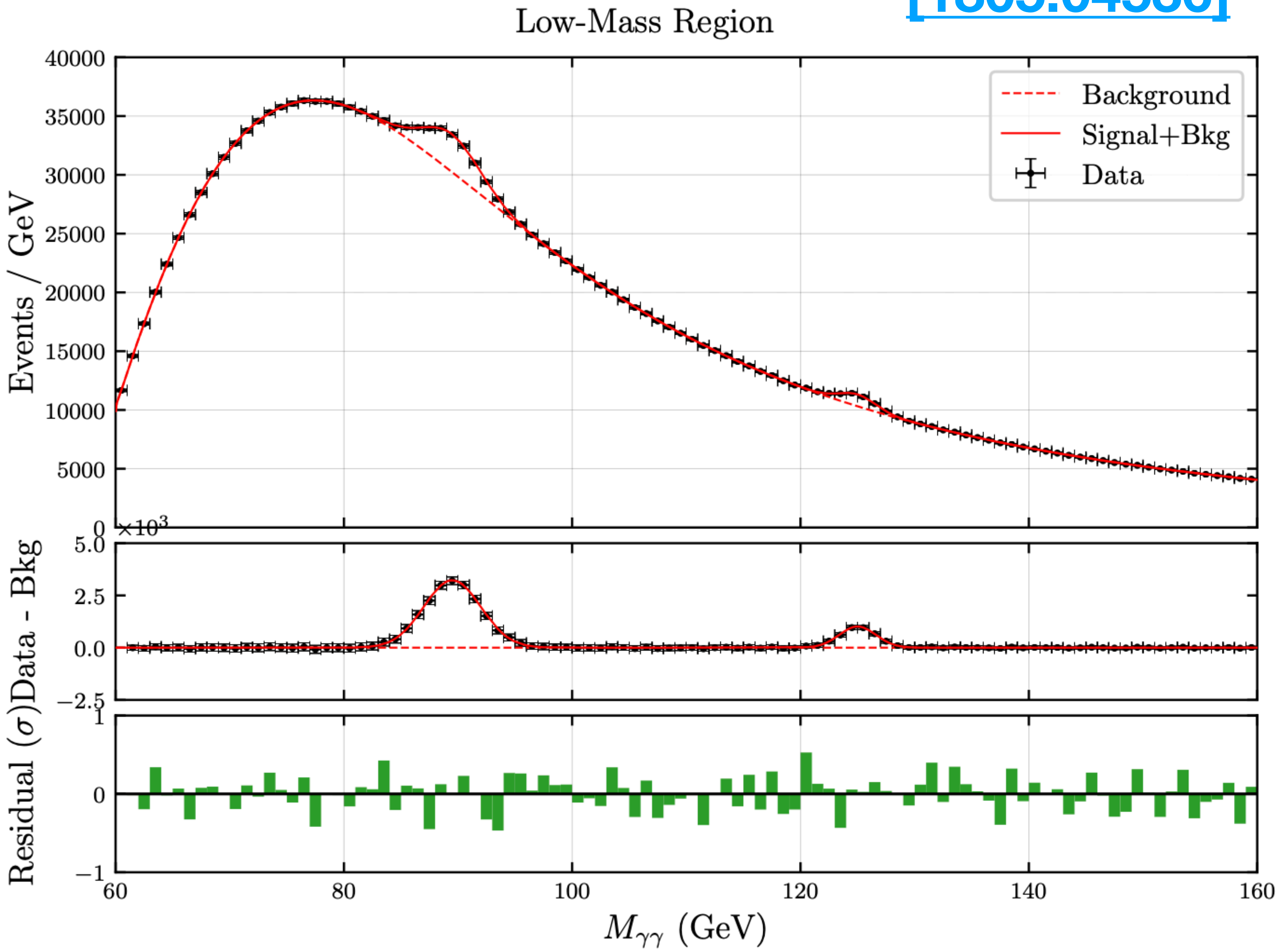
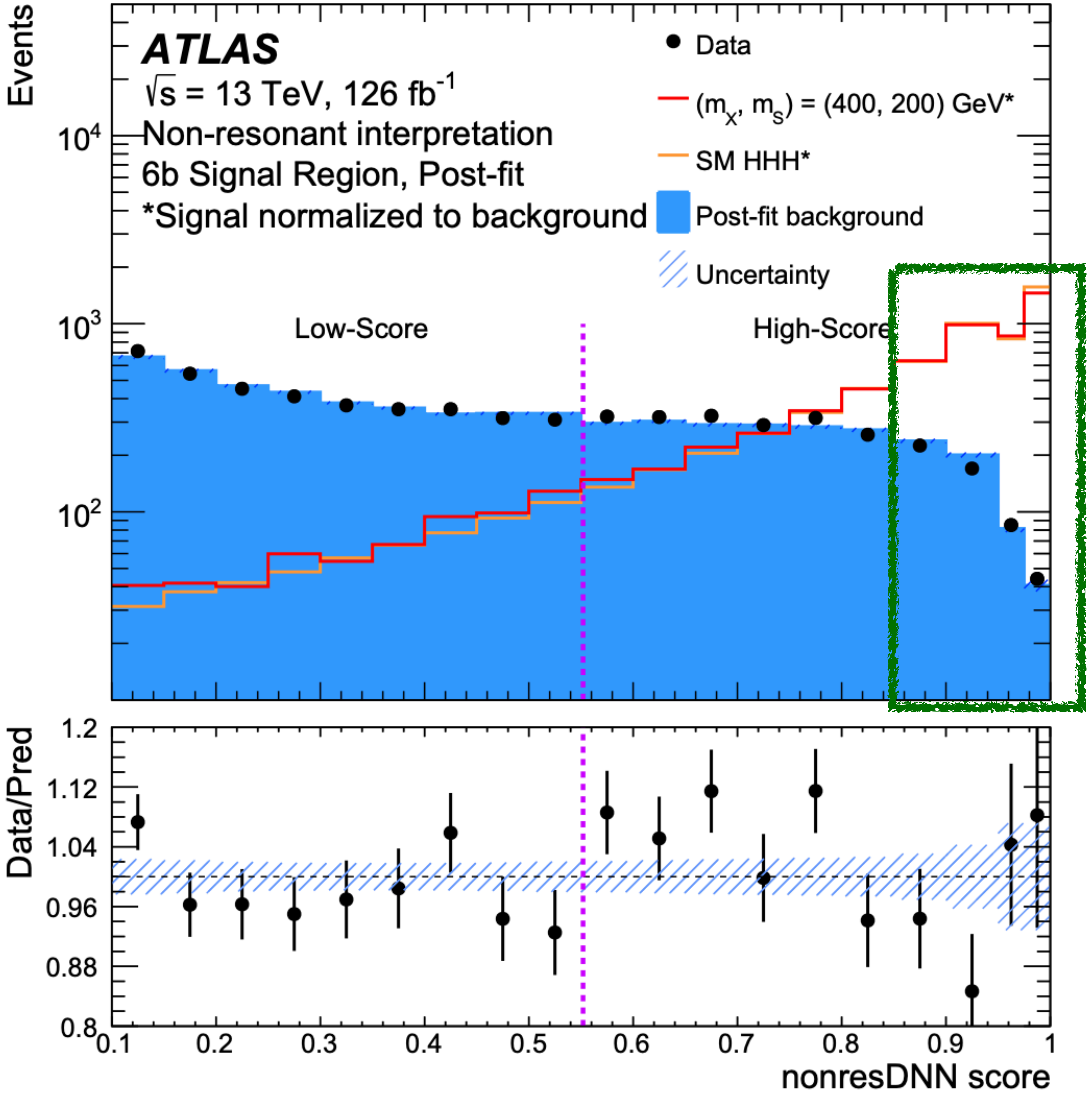


Differentiable p-values with FD



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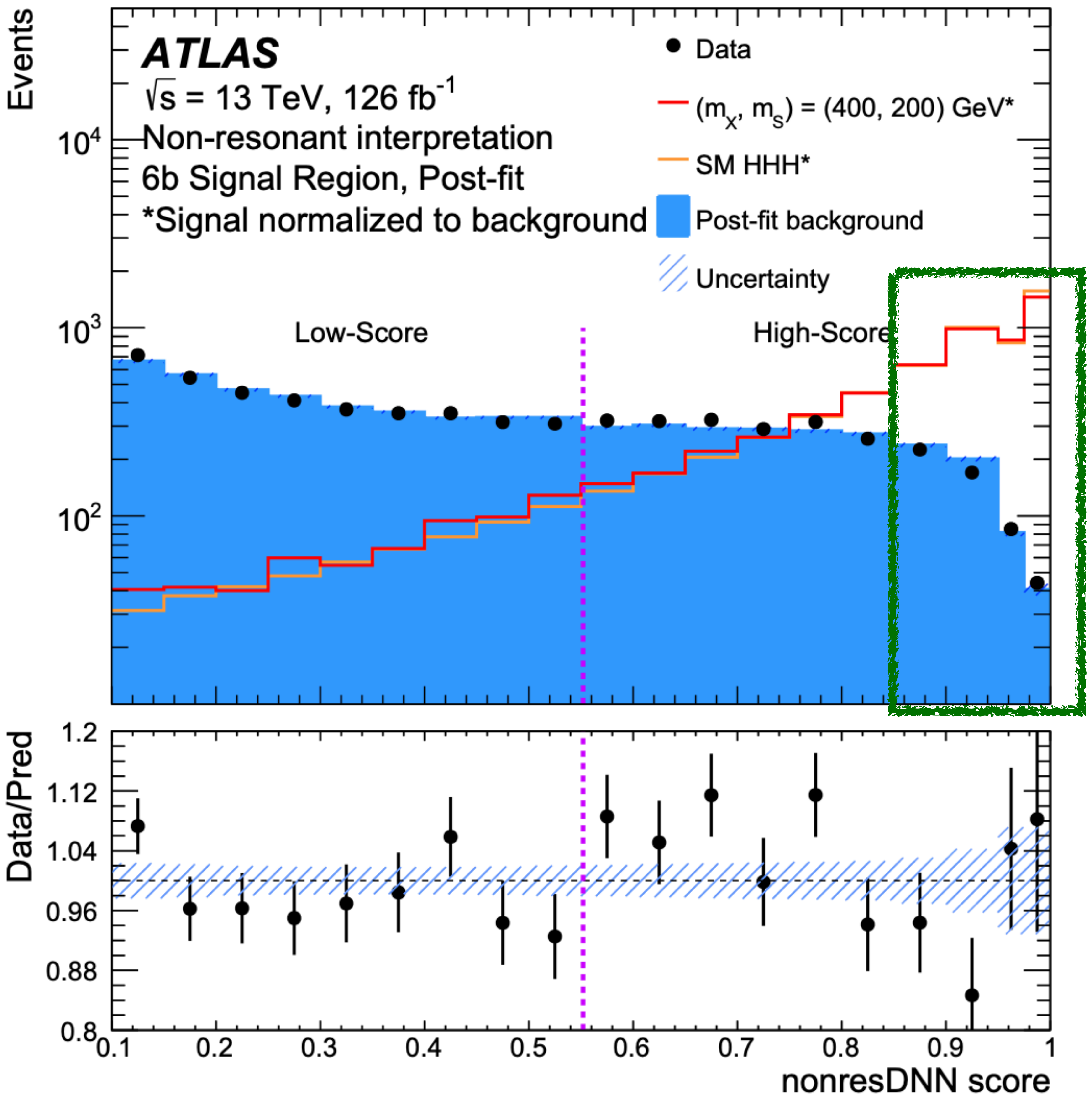

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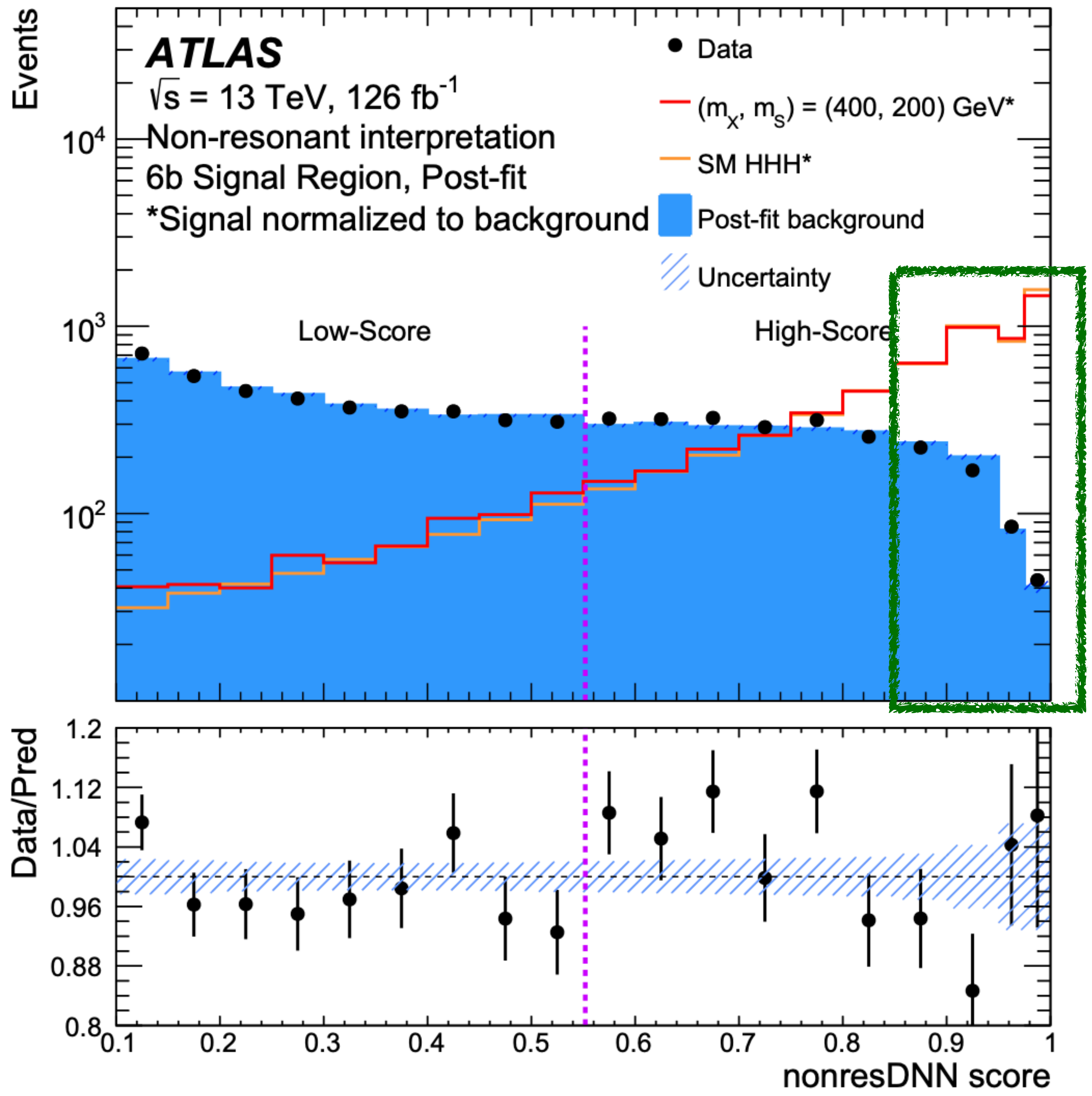

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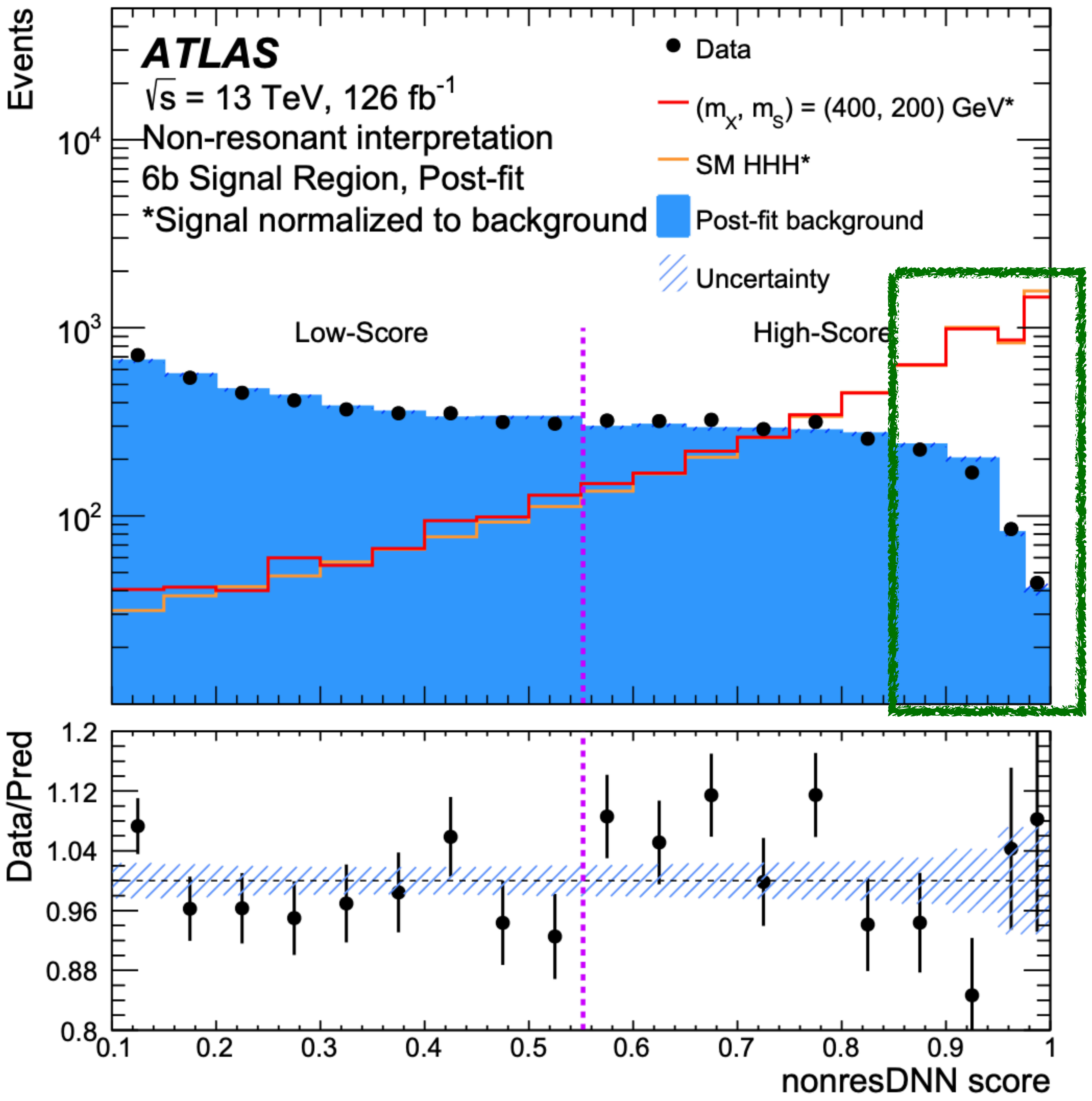

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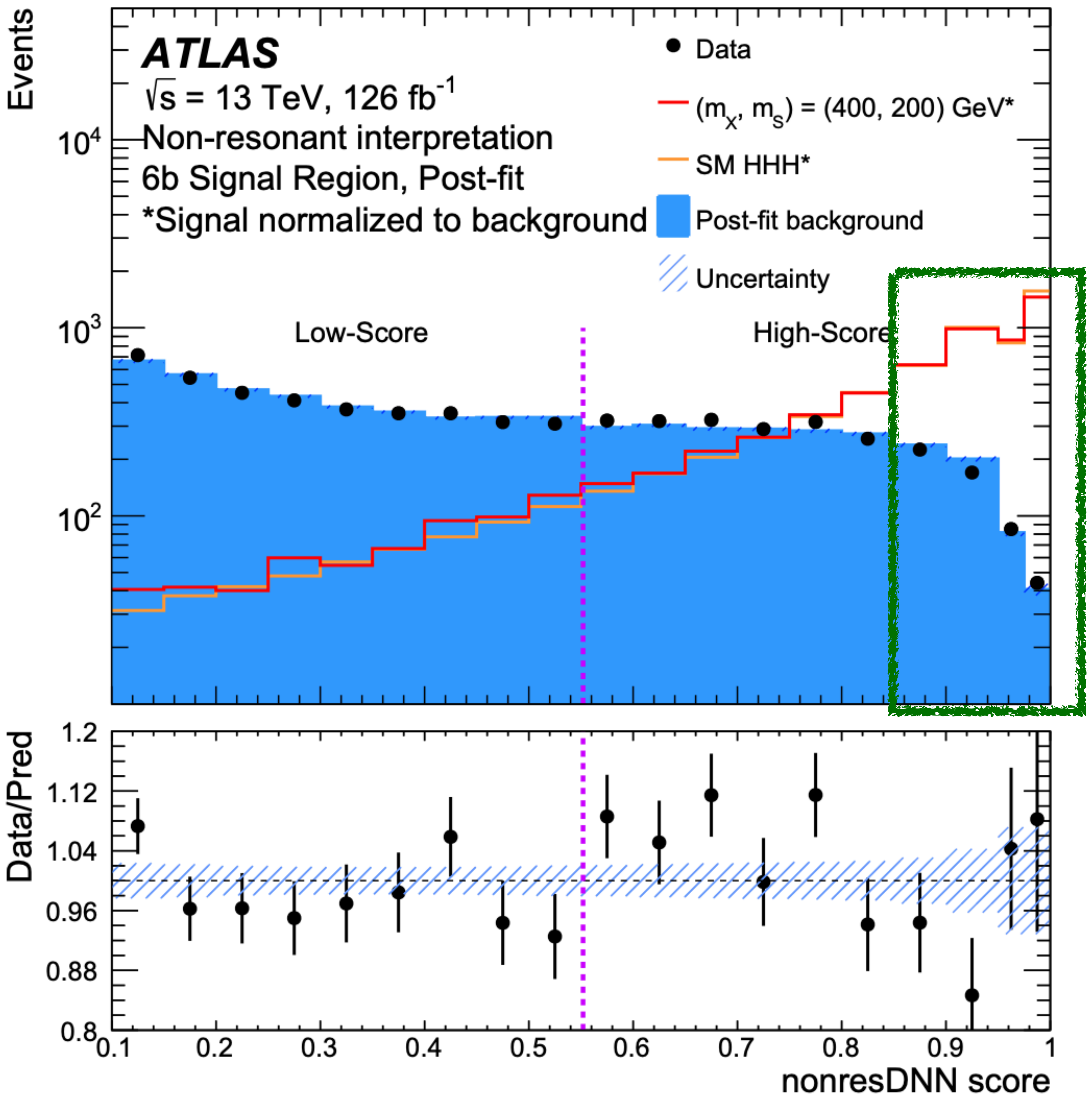

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Kevin Nelson

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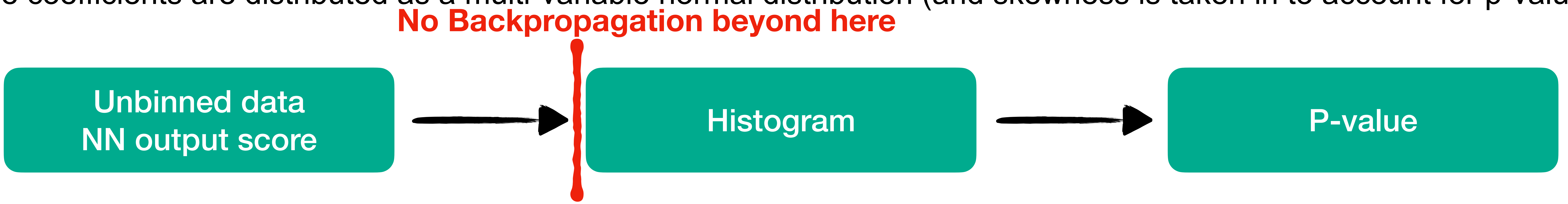

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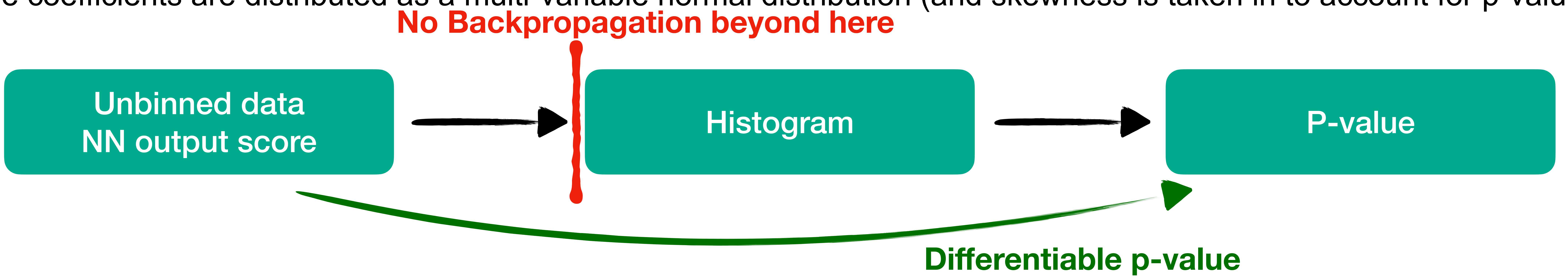

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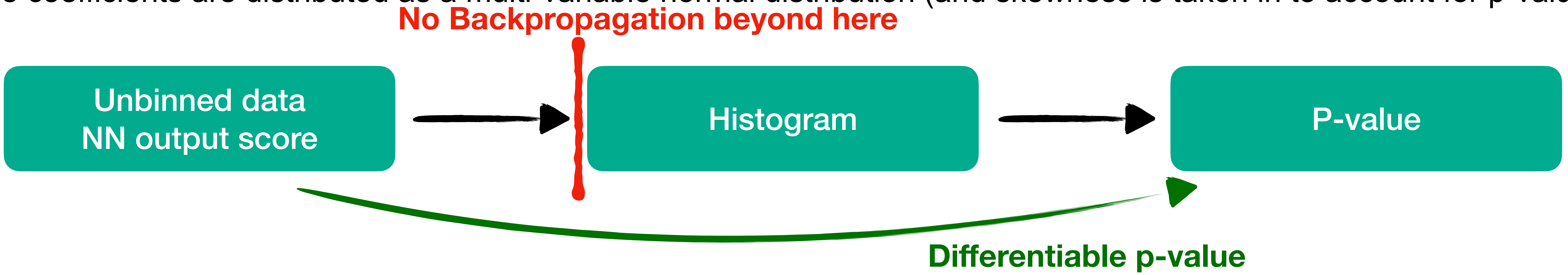

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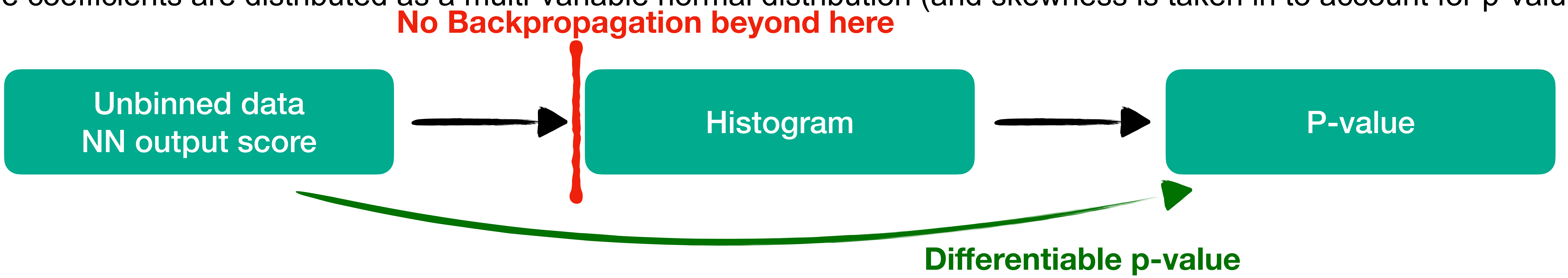

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- **Another benefit: with FD background model is learned in a semi-supervised manner**

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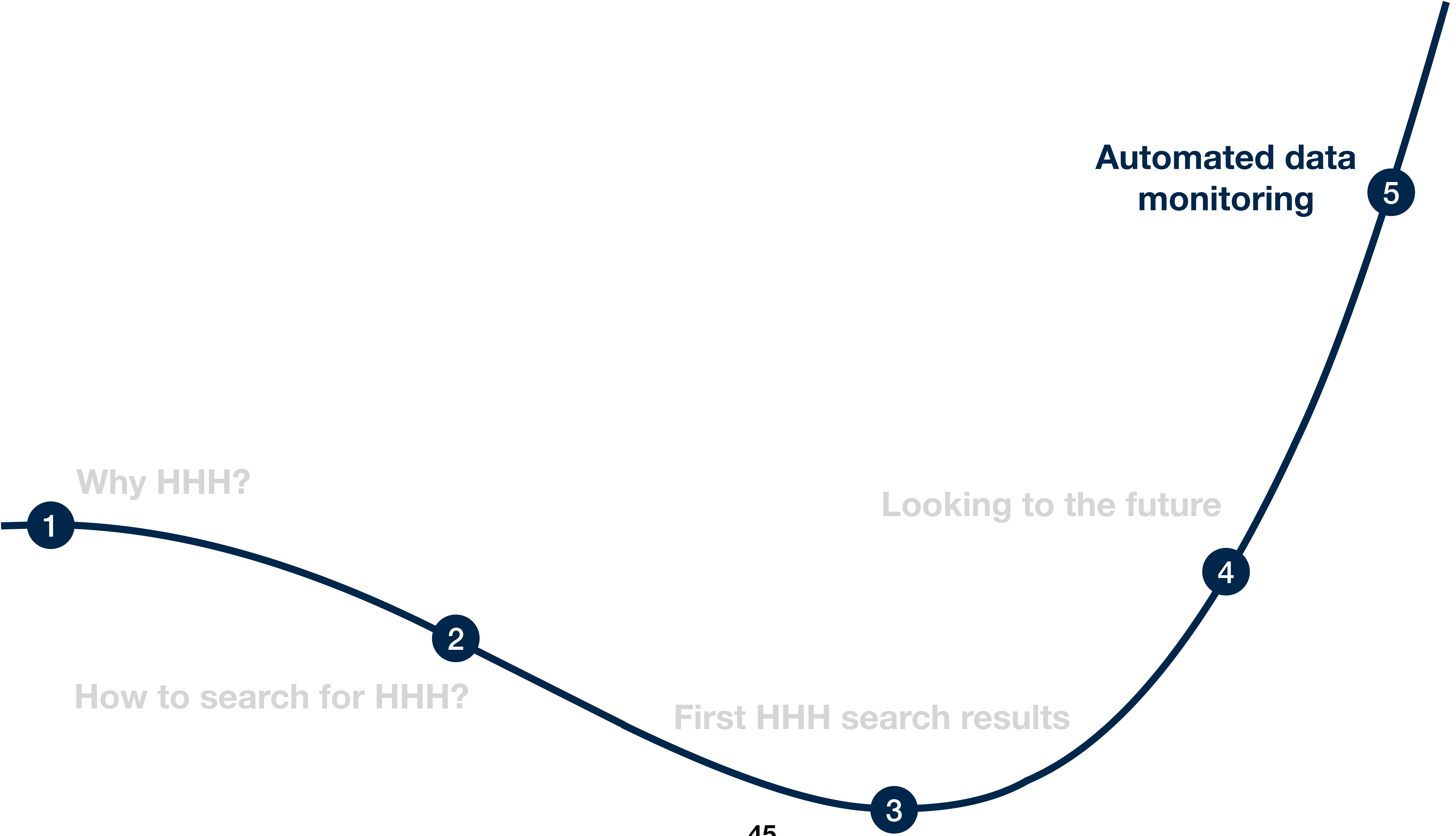
1
Why HHH?
2
How to search for HHH?
3
First HHH search results
4
Looking to the future
5
Automated data monitoring

Muon performance studies

Muon performance studies

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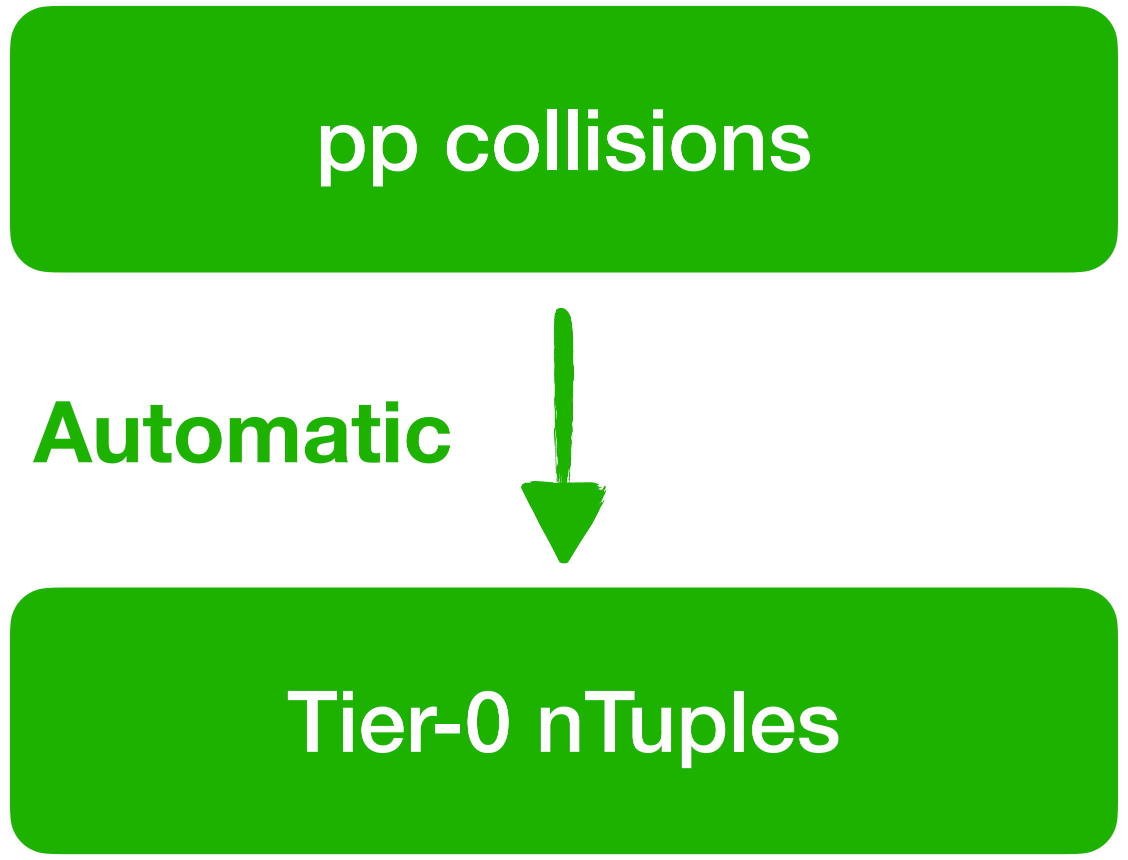

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pp collisions

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Muon performance analysis toolkit

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pp collisions

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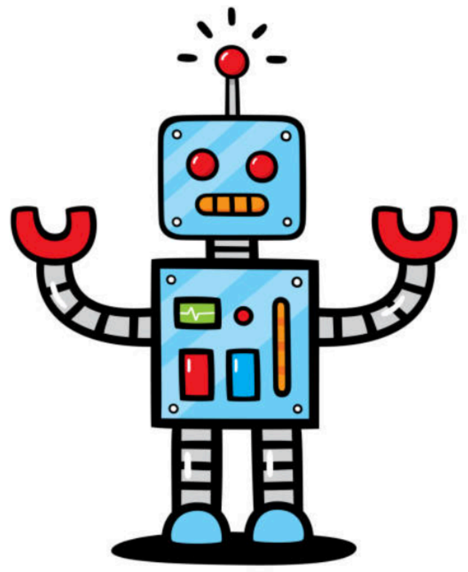

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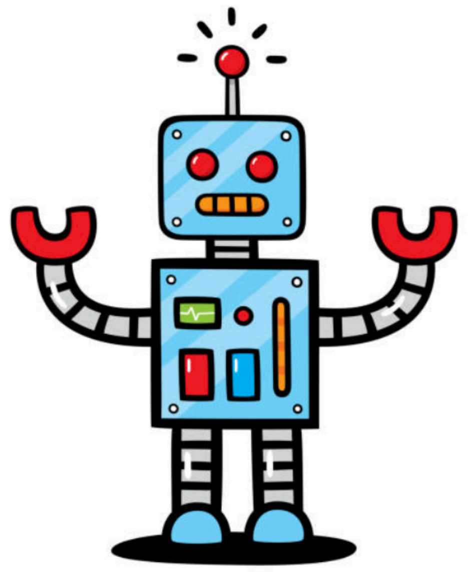

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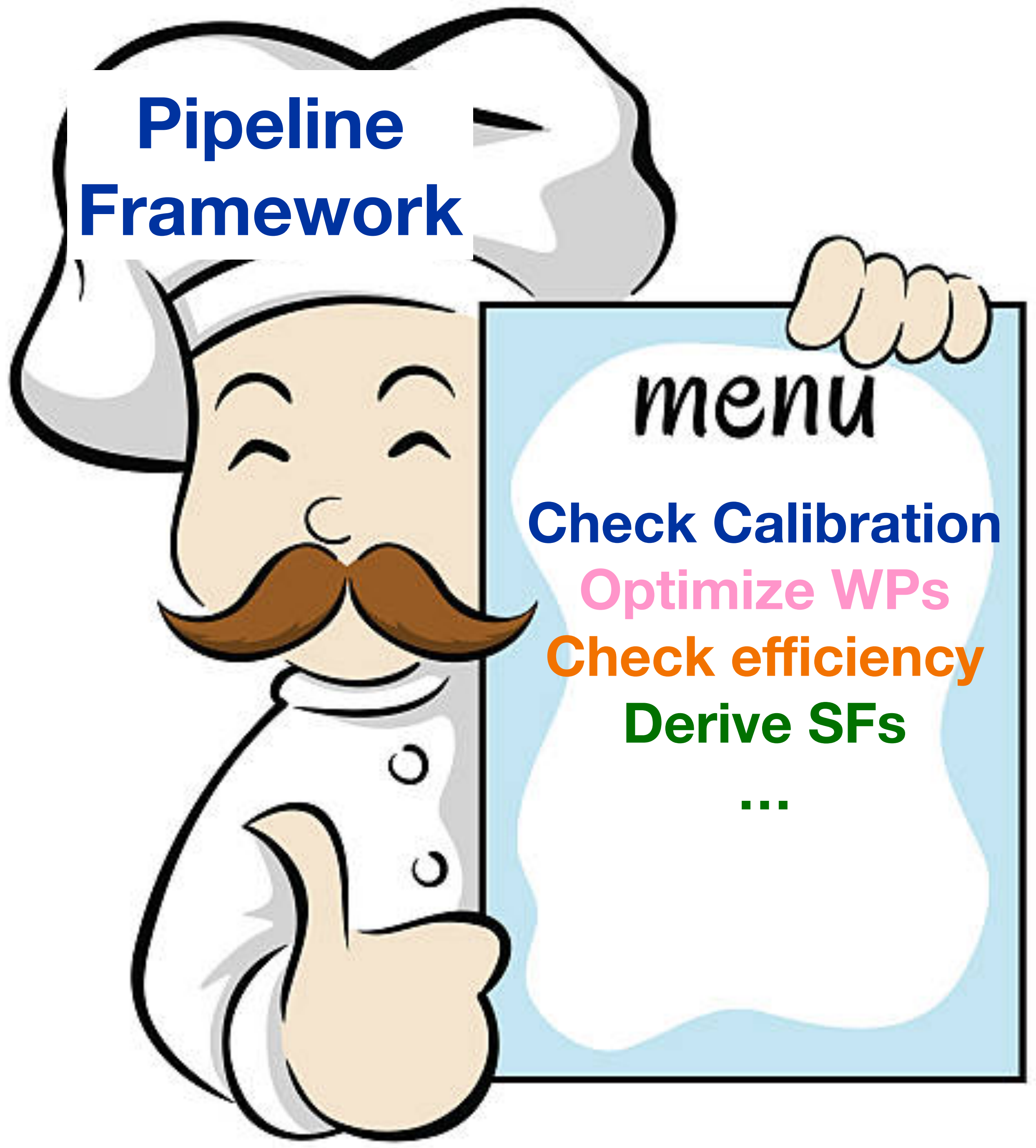

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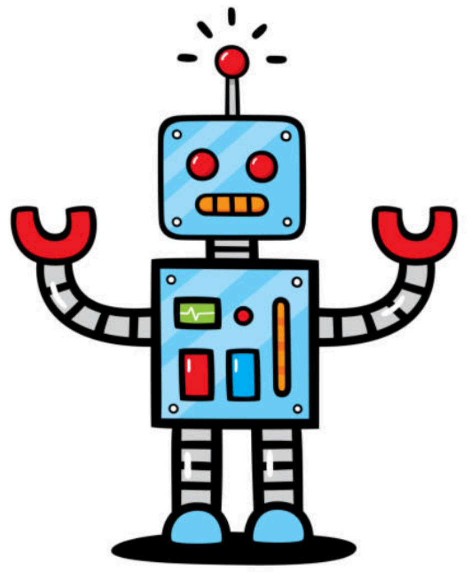

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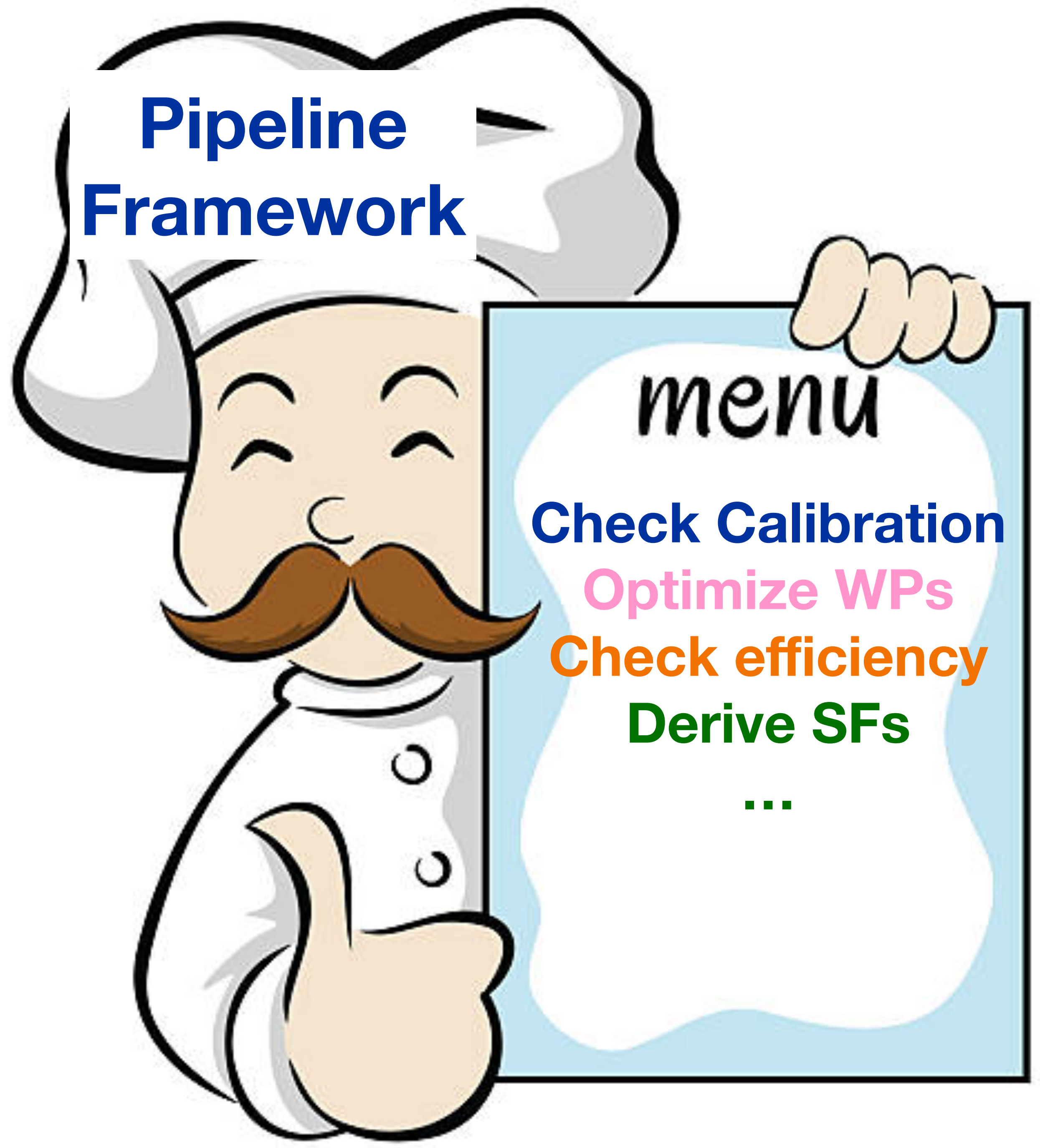

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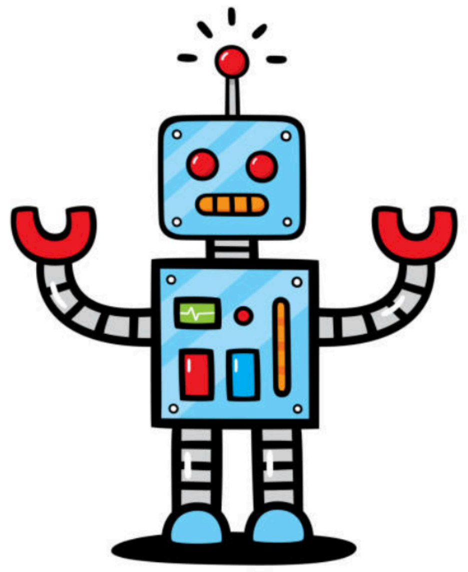
Muon performance analysis toolkit
Packaged into docker images



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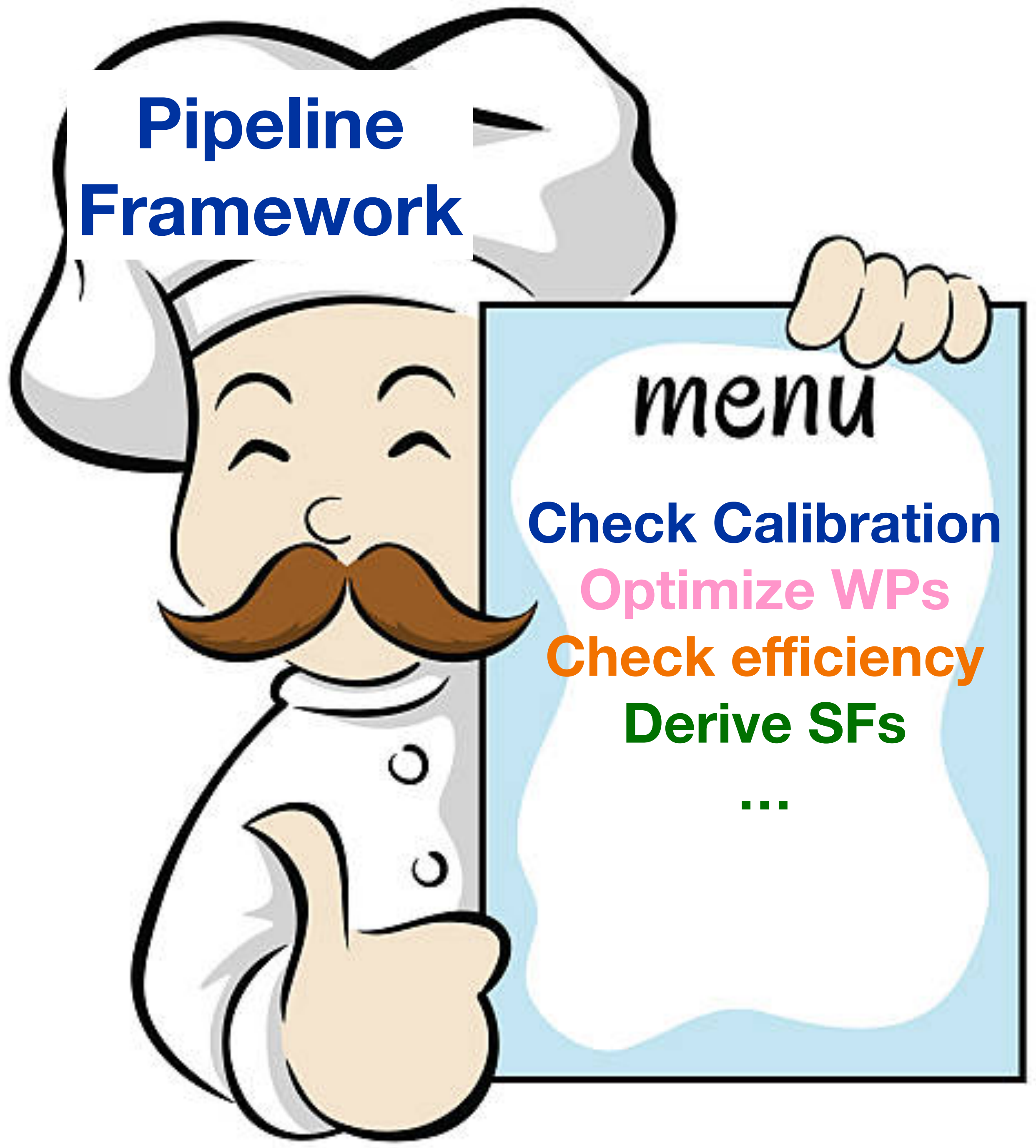

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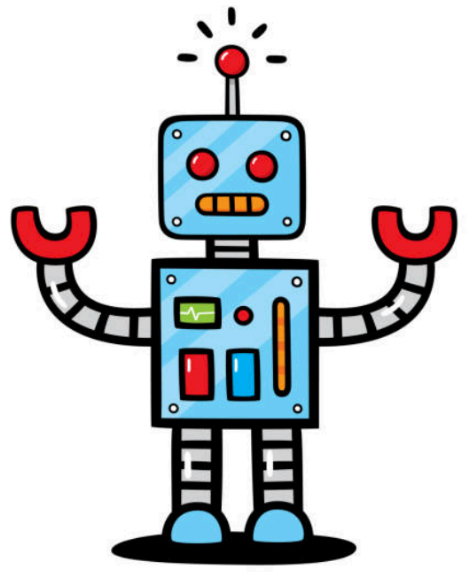

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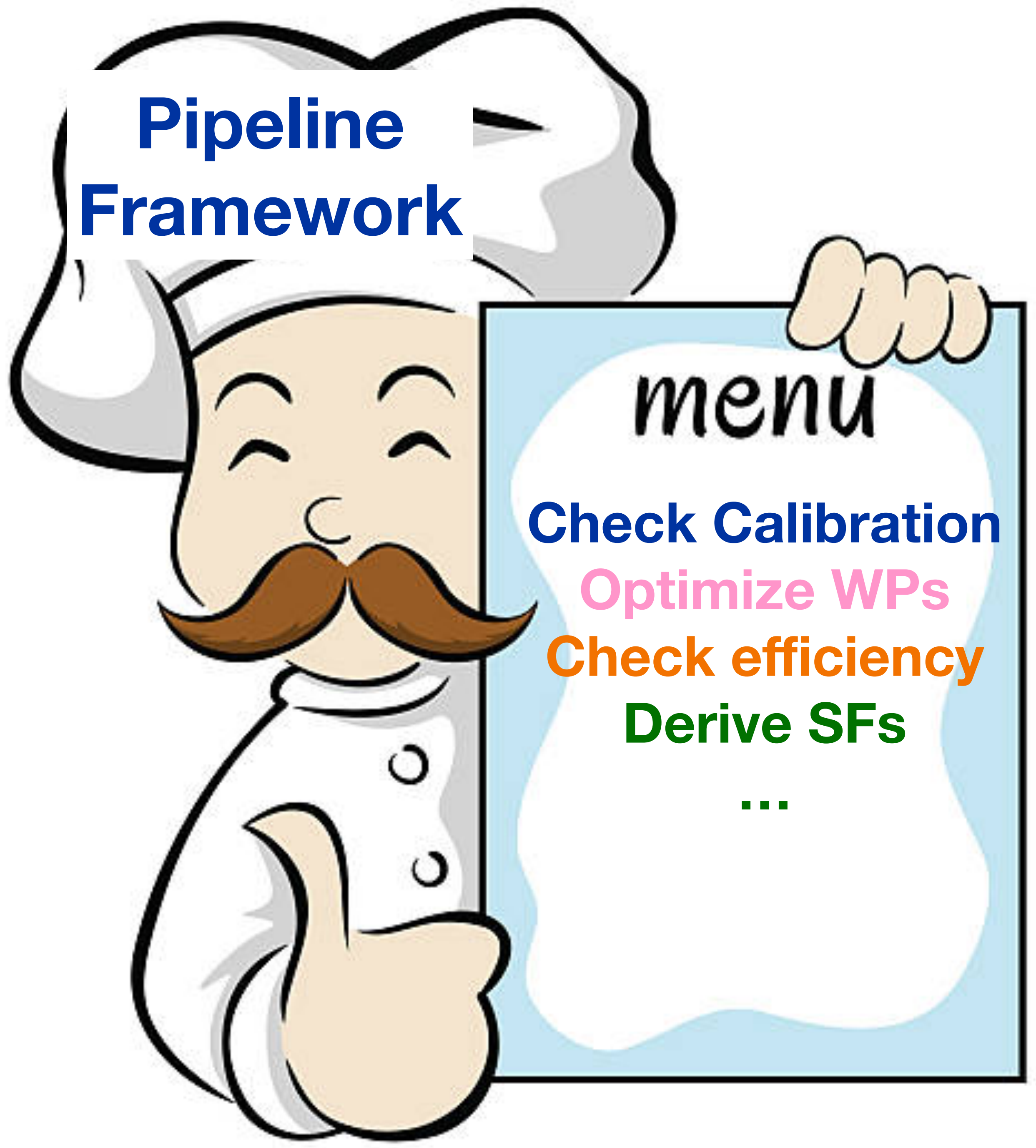

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Muon performance analysis toolkit
Packaged into docker images

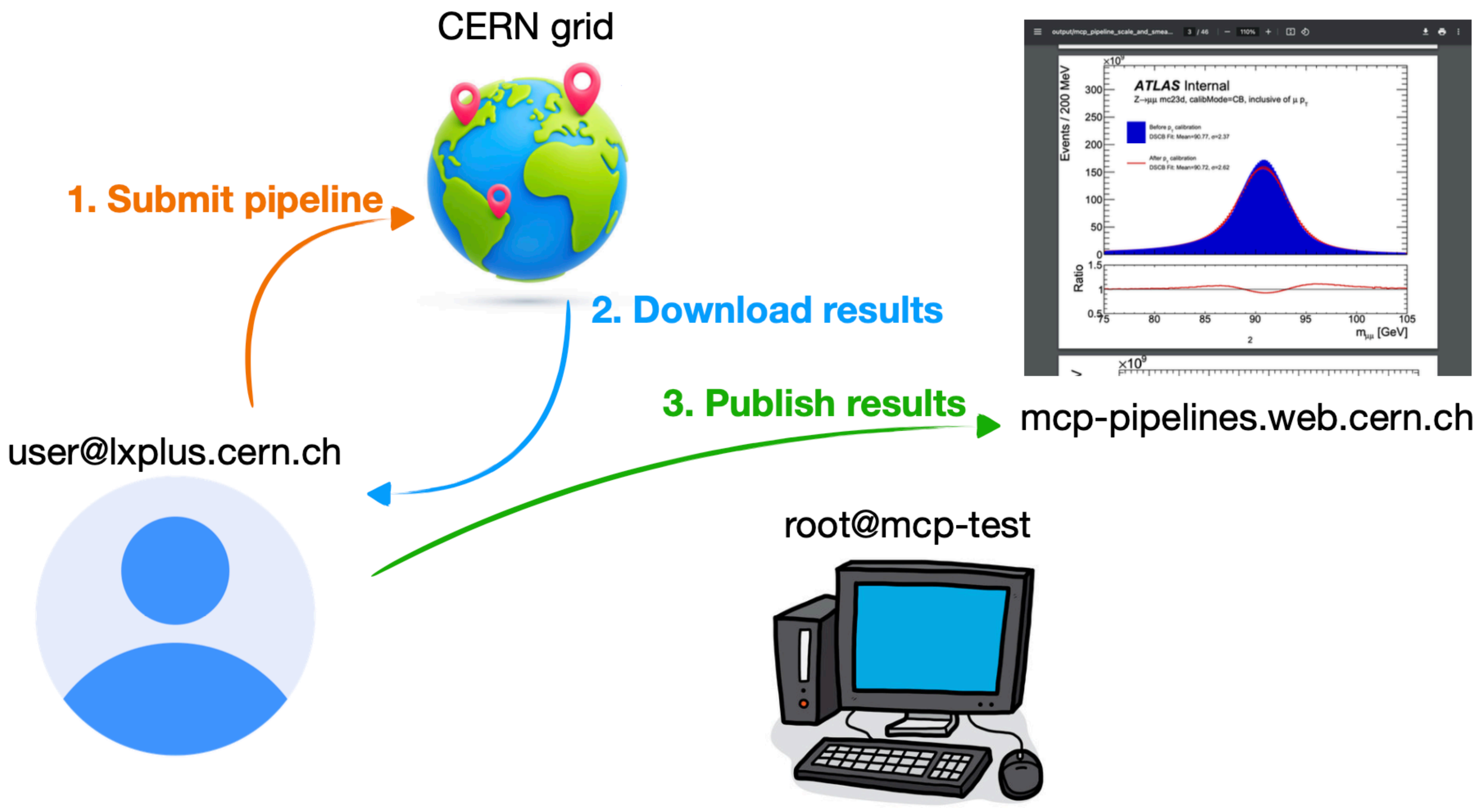
.pdf, .root output files
Published to the web
Can compare previous runs of the same workflow and check consistency

Automation

- **The typical workflow in the pipeline framework**

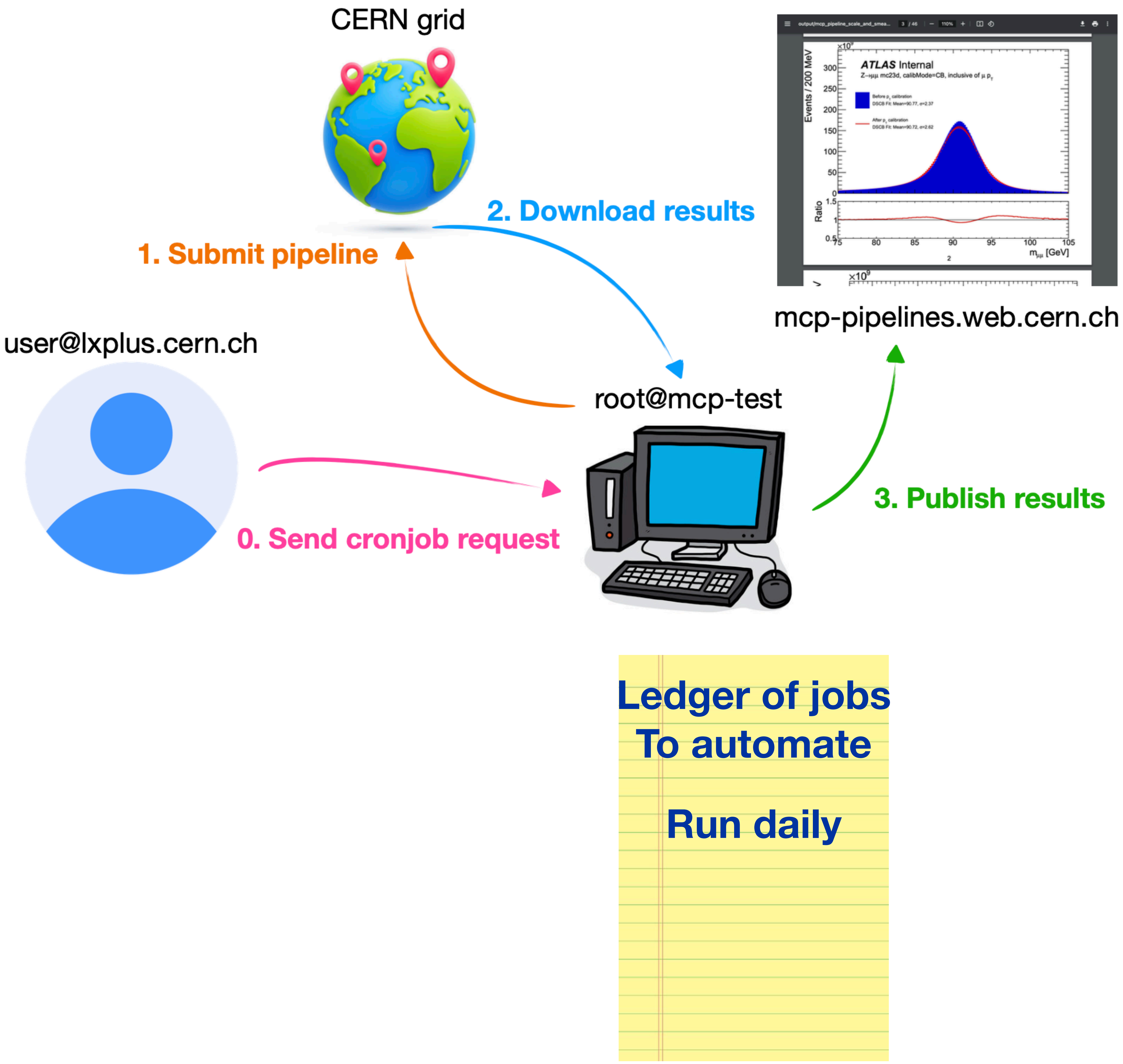
- **A lot is already automatic, as a full workflow is encapsulated into a single interaction with the grid**
  - Ntuple creation, histogram creation, plot creation all happens in a single “chain” of grid jobs.

- **But, what if we could remove the user entirely??**



Automation

- The workflow of an automated job is similar
- The user can modify the jobs.txt file on the remote server at any time with a command line interface
- Whenever new data is taken, nTuples are automatically created at Tier0 computing center
- Previously, we did very little with these nTuples!
- Now, we analyze them automatically and check for changes in muon performance on a regular basis.
- This automated method will be deployed in 2025!



Conclusion

- **The first search for HHH has been performed**
  - Unique sensitivity to κ_4, which is the limiting factor on our knowledge of the Higgs potential shape for large deviations from VeV
  - Relevant *today* because of possible HHH enhancement in models with extra scalars (TRSM, DM-CPV)

- **HHH is a suitable laboratory for AI studies**
  - Statistics limited, simple data-driven method.
  - Applications of modern AI methods can be studied:
    - Domain adaptation
    - Functional decomposition
    - Transformers and object pairing

- **Muon performance studies are *accelerated* via *preservation* and *automation* in a new framework**

Google image FX’s interpretation of “discovering new physics”

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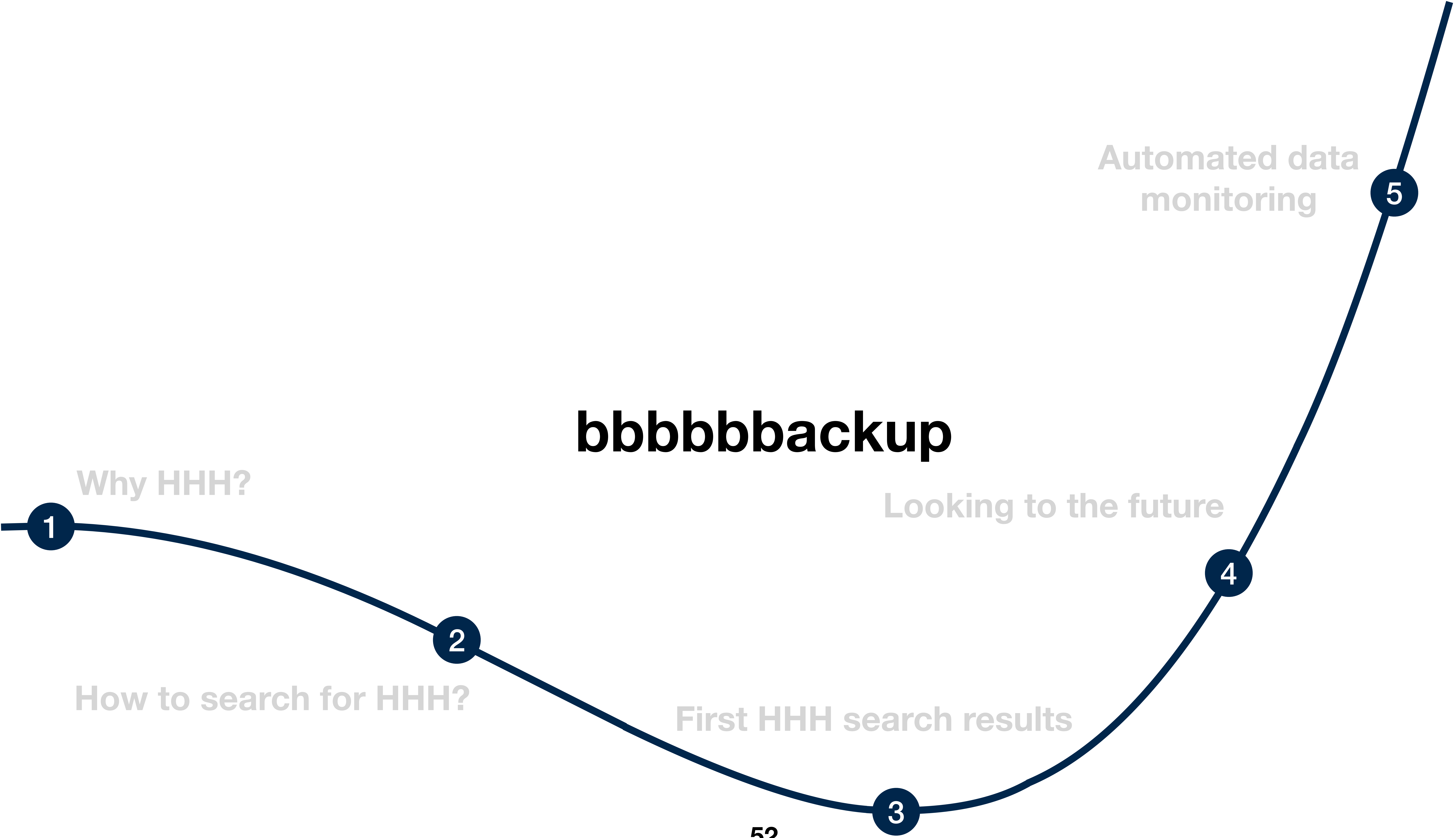
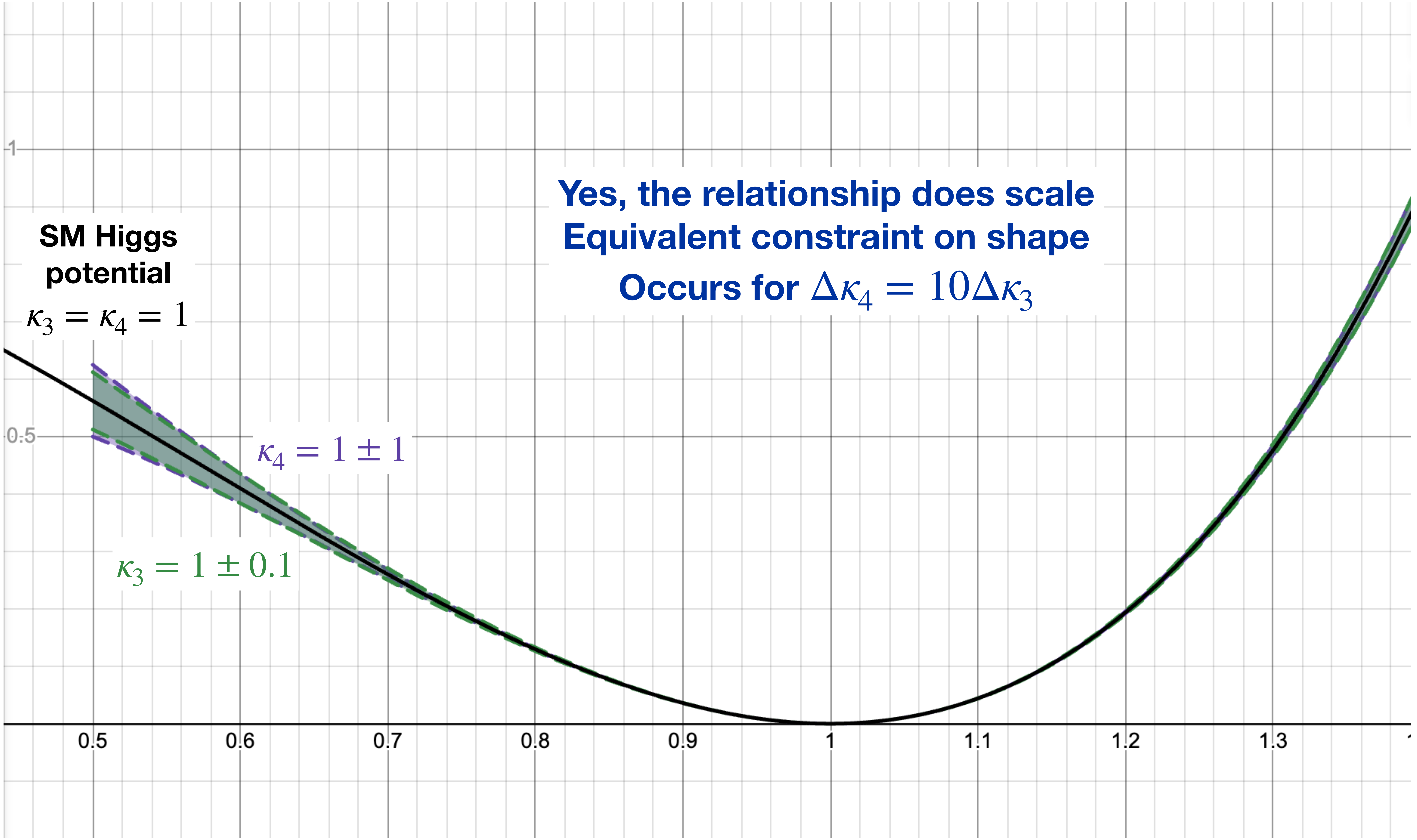
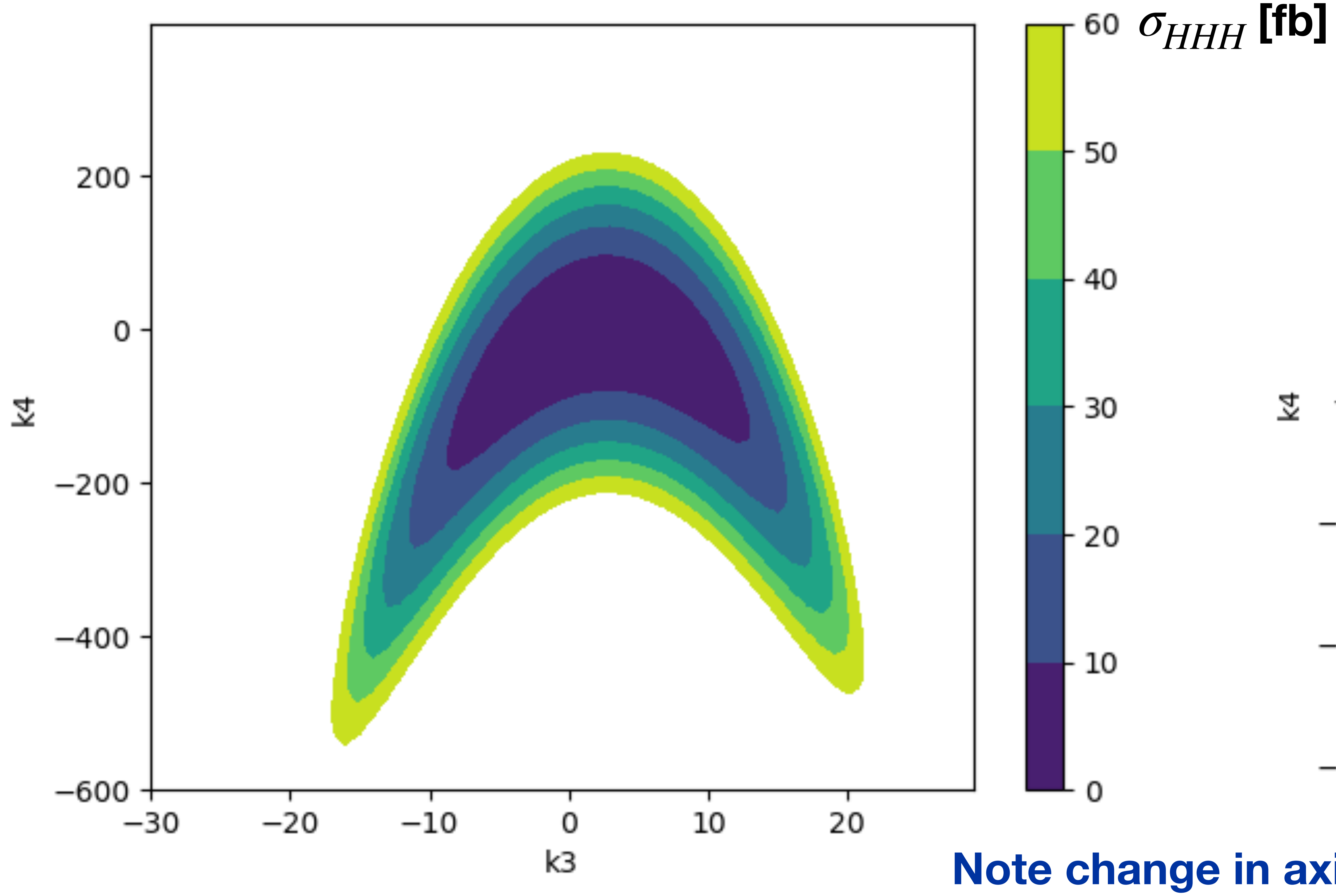
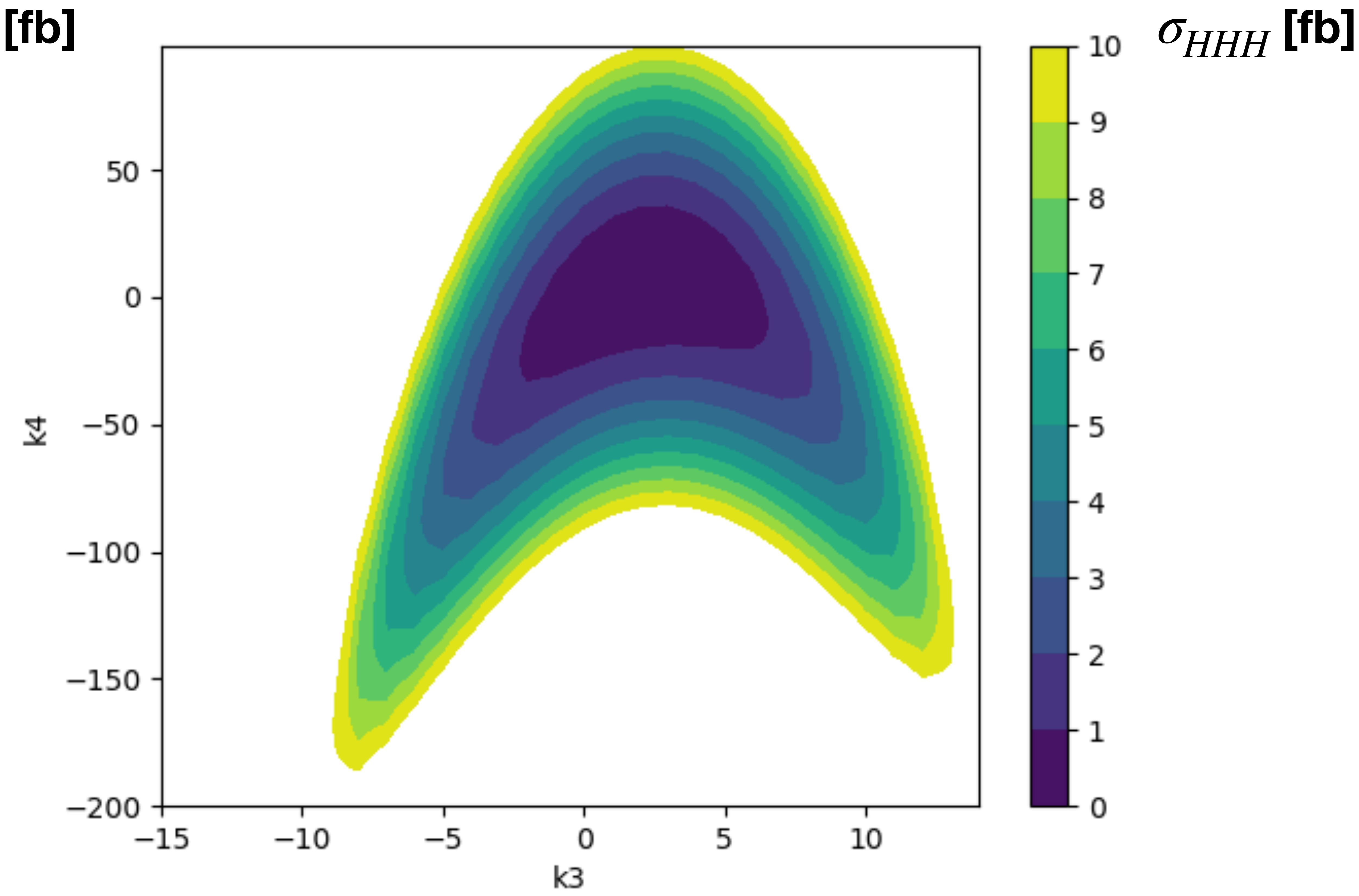


Scaling of κ_3 vs κ_4



HHH production cross section



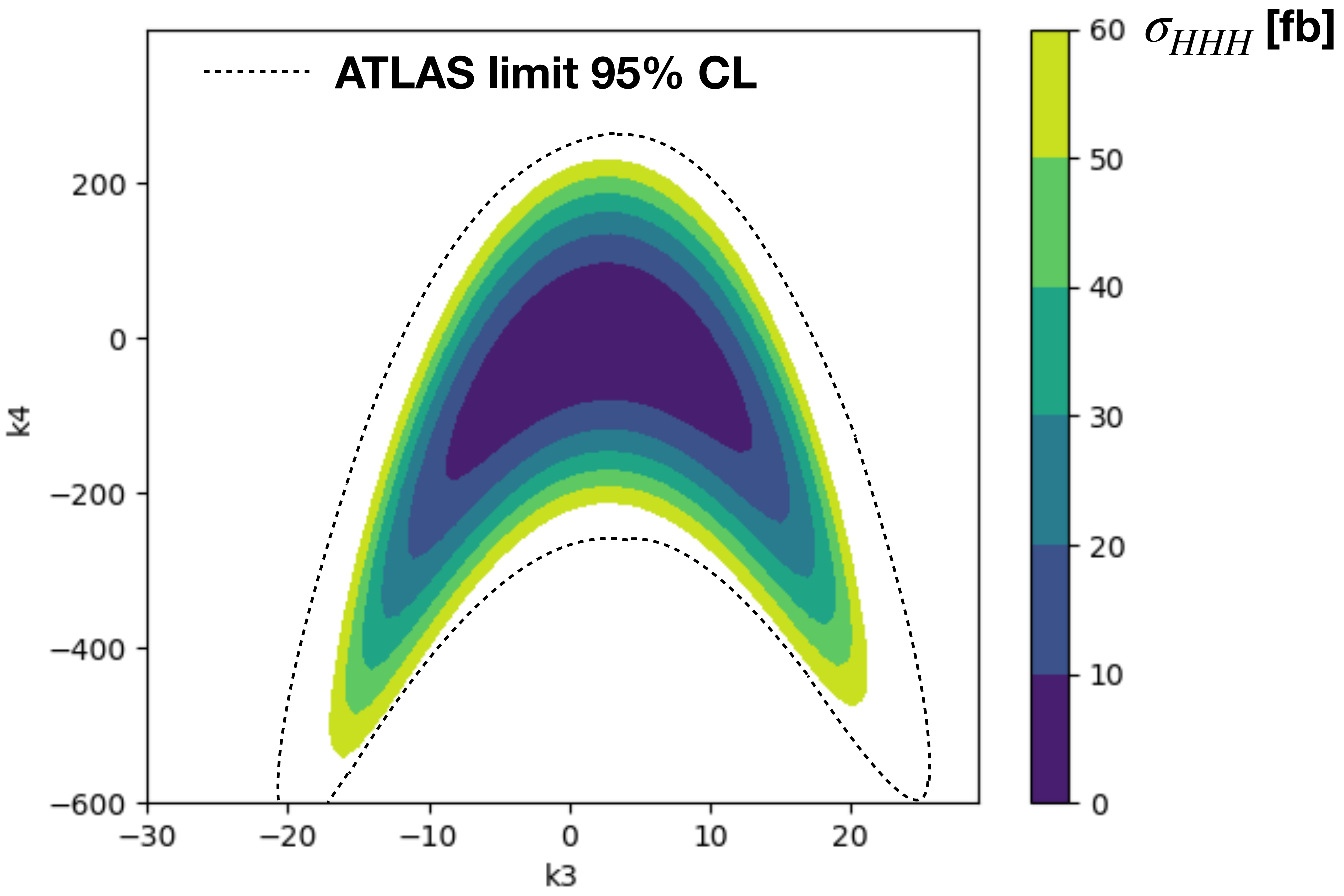


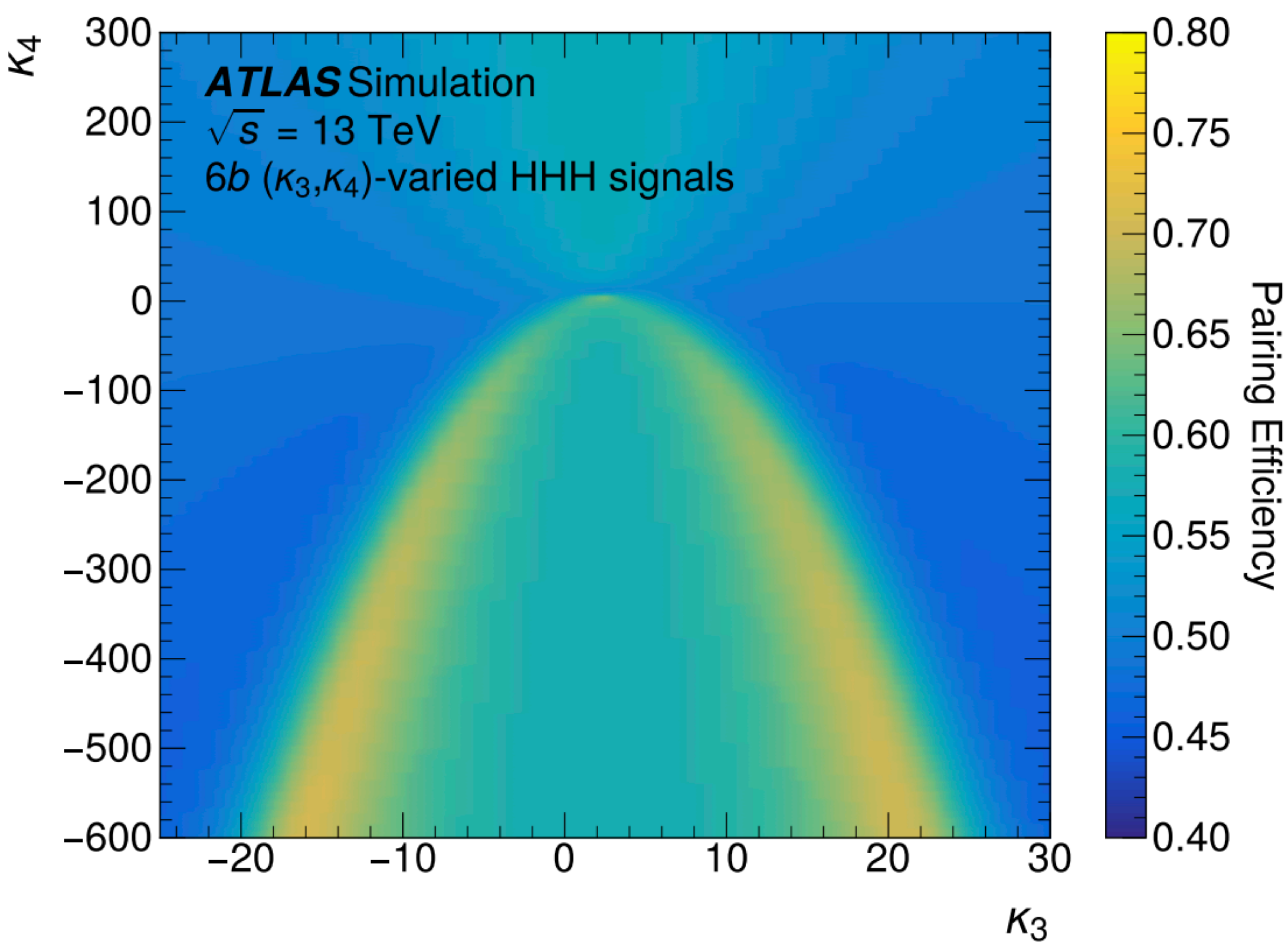
Note change in axis scales

- **Constraint of $\kappa_4 = 1 \pm 30$ roughly translates to a constraint $\sigma_{HHH} \leq$ 1 fb**
- **Luminosity-only scaling for HL-LHC should get us to around $\sigma_{HHH} \leq$ 10 fb**

Kevin Nelson

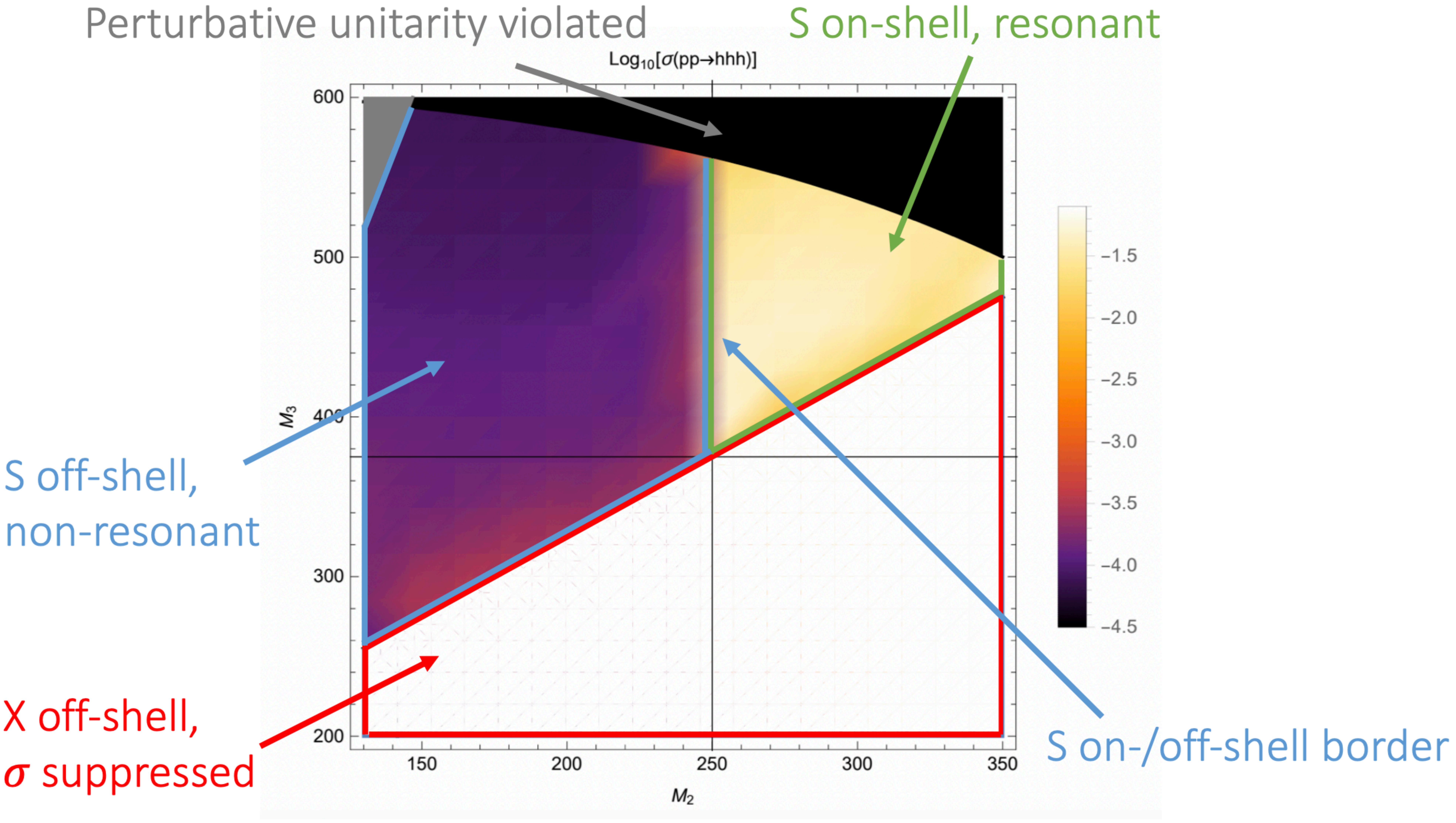
Shape of ATLAS limits



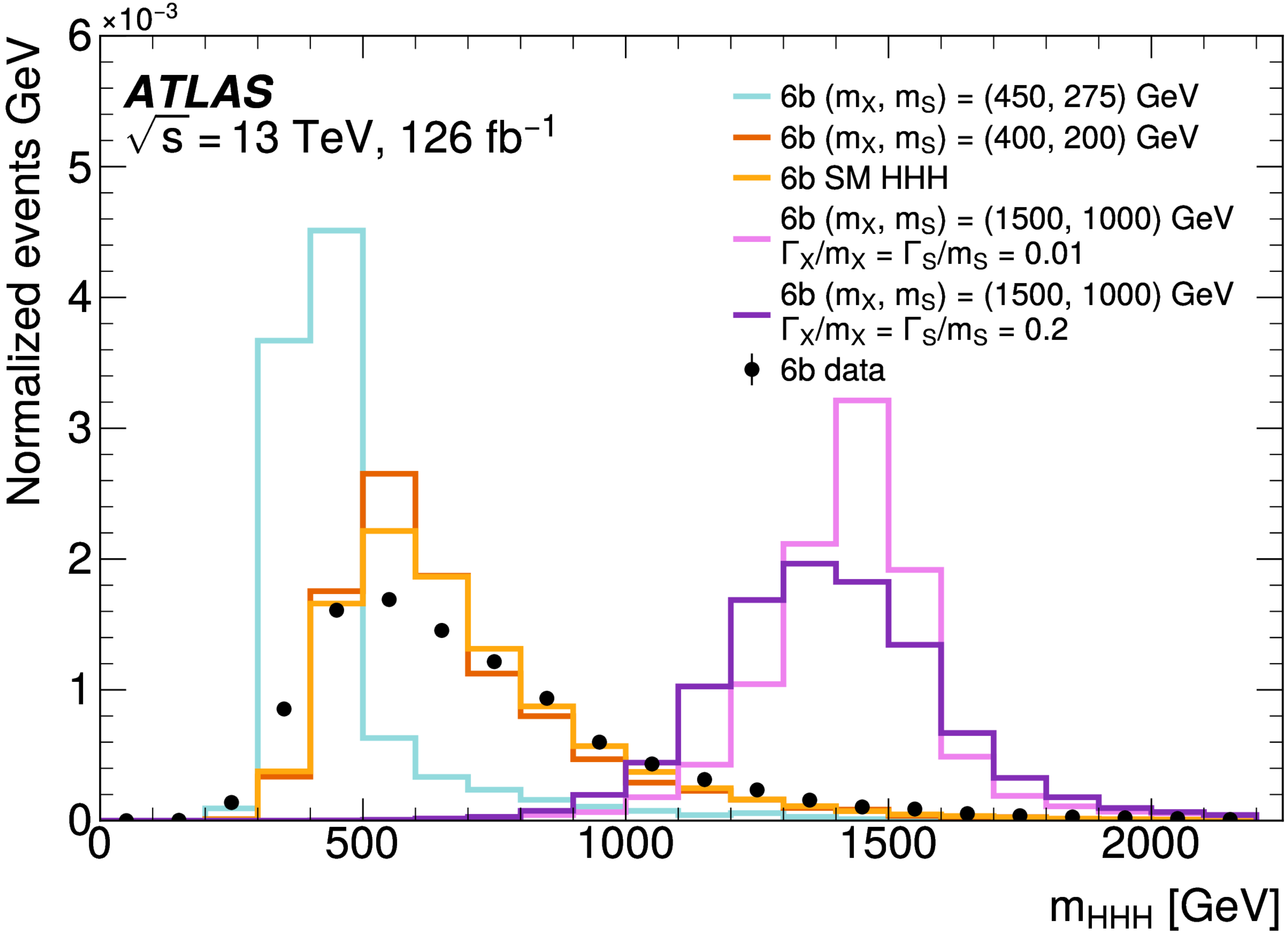


- **ATLAS limit inherits its shape from the contours of constant σ_{HHH}**
- **Slight modulations in shape come from how boosted the Higgses are, and therefore how well we pair the jets.**
- **In regions of higher pairing efficiency, we set a more strict limit**

TRSM perturbative unitarity



Signal kinematics



Trigger strategy

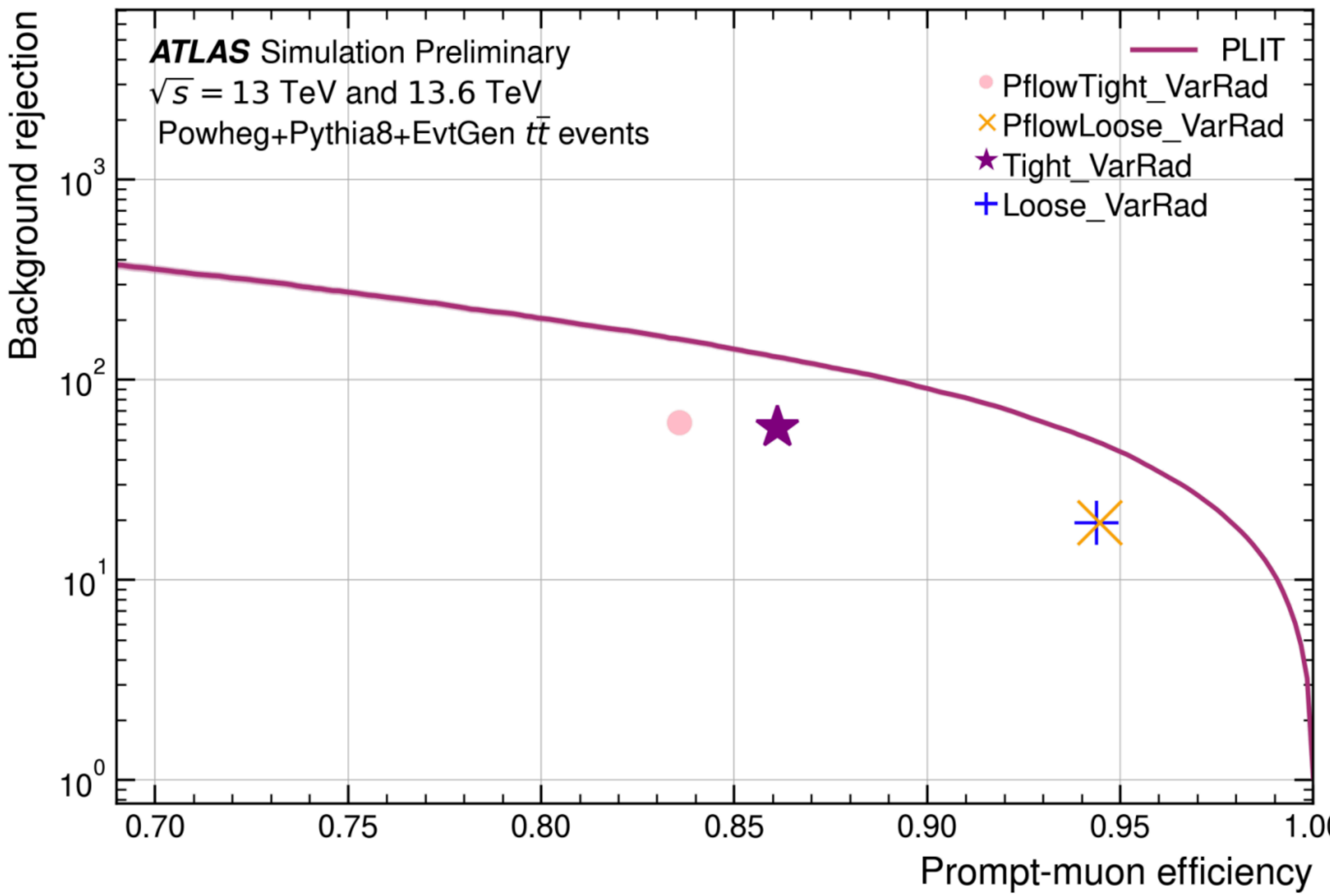
- Using multi-*b*-jet triggers for a 6b final state – similar to the resolved HH4b analysis
  - Omitting 2015 data due to lack of jet trigger-matching information
- 2b2j triggers in 2016, 2018
- 3b1j triggers in 2017
  - Due to very tight online *b*-tagging working point in 2017 2b2j triggers

Table 5.1: List of *b*-jet triggers selected for efficiency study.

Year	Type	Trigger Name
2016	2b+2j	HLT_2j35_bmv2c2060_split_2j35_L14J15.0ETA25
2017	3b+1j	HLT_3j15_gsc35_bmv2c1070_split_j15_gsc35_boffperf_split_L14J15.0ETA25
2018	2b+2j	HLT_2j35_bmv2c1060_split_2j35_L14J15.0ETA25

Other applications of transformers

- **Factor of 2 improvement in lepton isolation from transformer architecture**



Differentiable p-values with FD

- **Transformation from physical to frequency domain is fast:**
  - Recursion relationships for the orthonormal functions
  - Use unbinned data: inner product with Dirac delta functions is simple to compute

- **In the frequency domain background and signal are separable by a cut**