

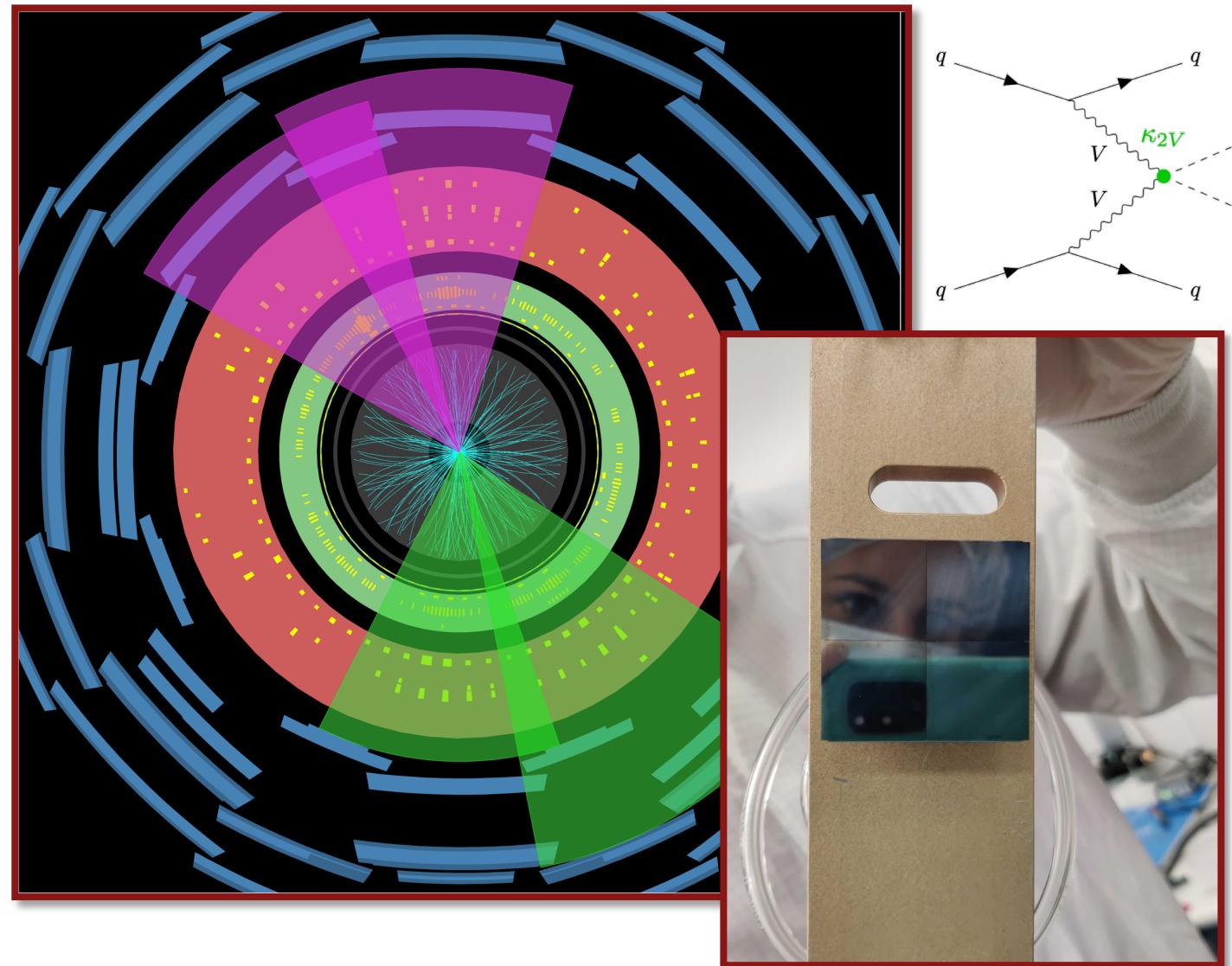
Studying Higgs Boson Self-Interactions at the ATLAS Experiment

Fermilab - Physics Forum

Rachel Hyneman, Fundamental Physics Directorate - ATLAS
07 September 2023

Outline

- Why do we care about Higgs Boson self-interactions?
- How do we measure Higgs Boson self-interactions?
- A measurement probing Higgs Boson self-interactions
- How does this result fit into the broader ATLAS Higgs Boson Self-Interactions Program?

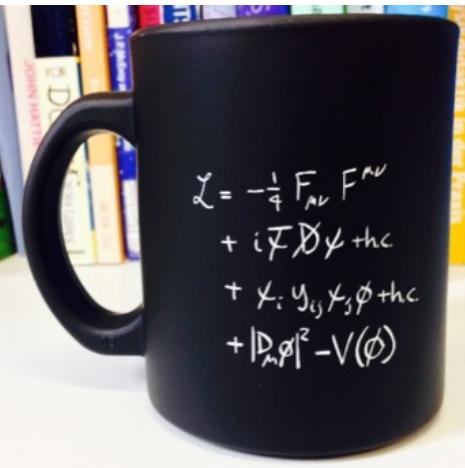
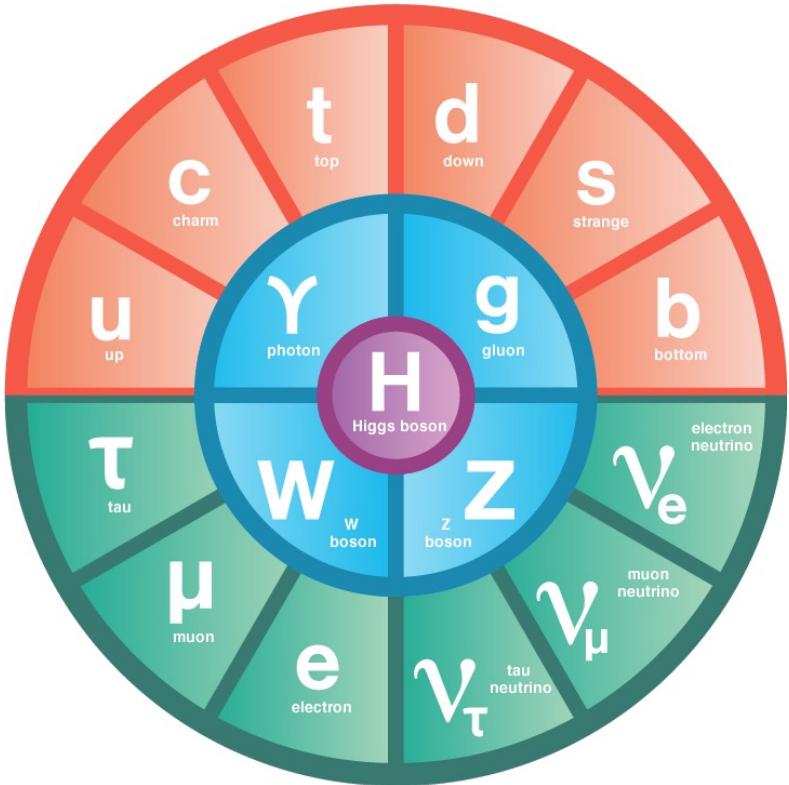


Why do we care about Higgs Boson self-interactions?

Introduction

The Standard Model of Particle Physics

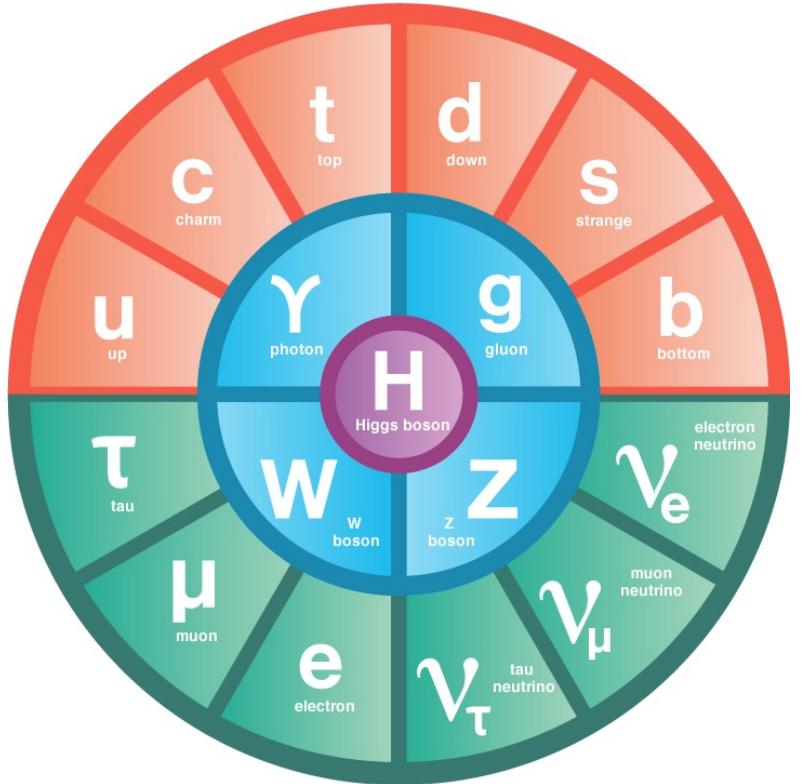
A theory of fundamental particles and how they interact



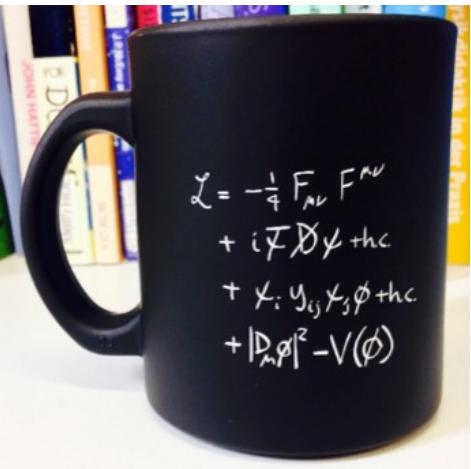
[Symmetry Magazine](#)

The Standard Model of Particle Physics

A theory of fundamental particles and how they interact

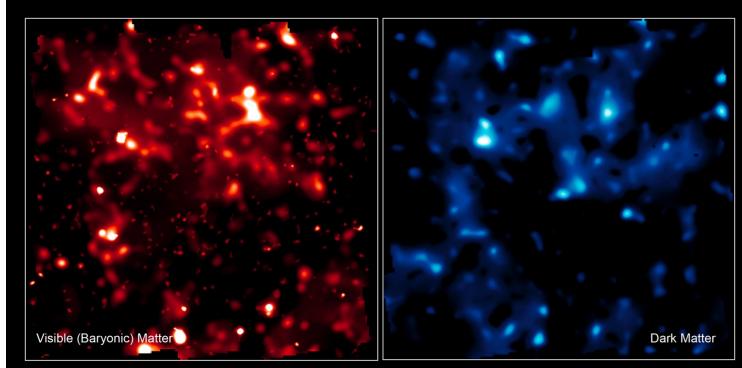


[Symmetry Magazine](#)

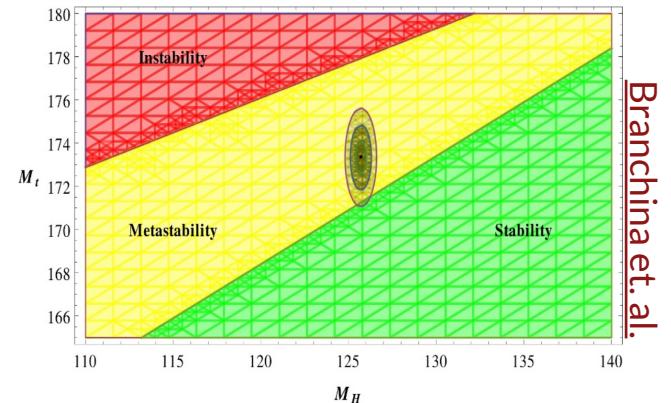


Why is there
more Matter than
Anti-Matter?

ESA What is Dark Matter?

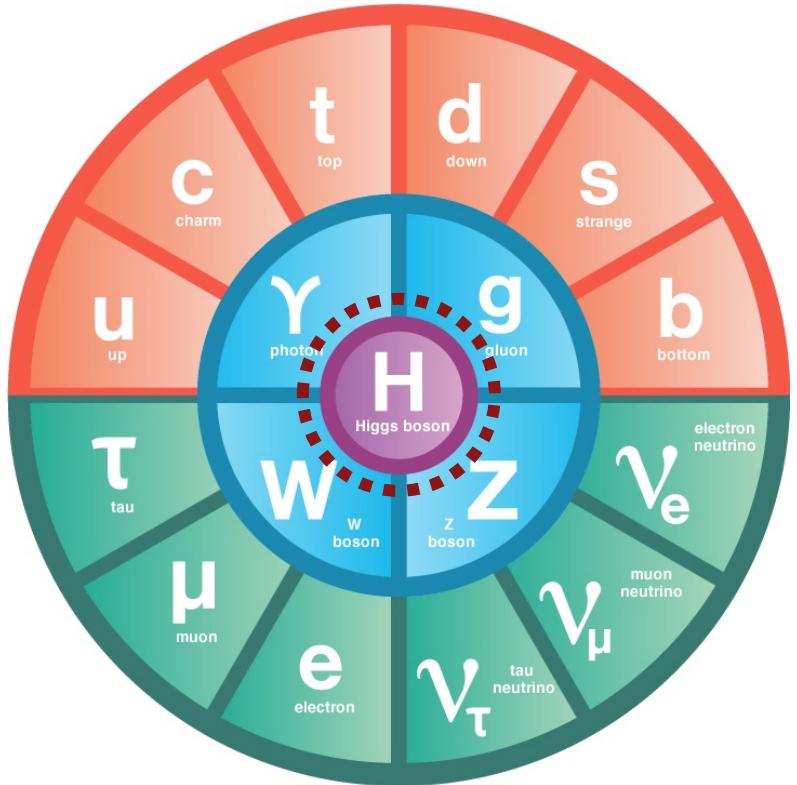


Is our universe stable?

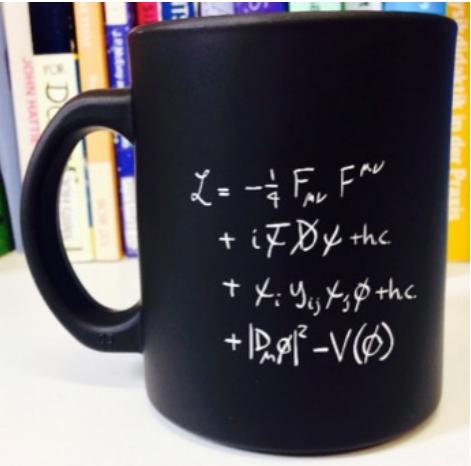


The Standard Model of Particle Physics

A theory of fundamental particles and how they interact

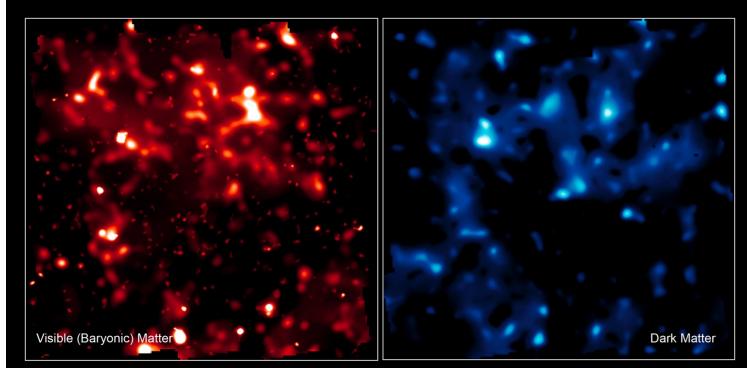


[Symmetry Magazine](#)

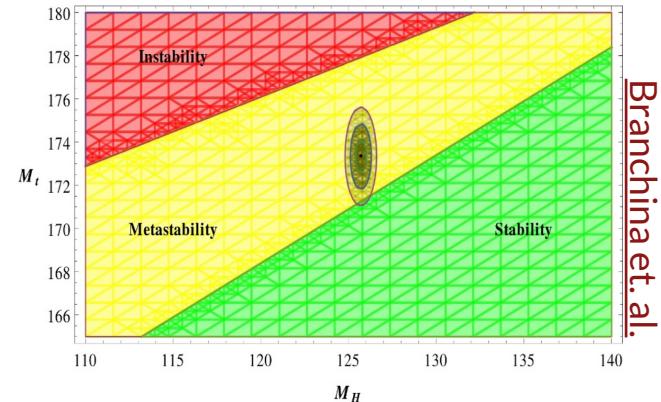


Why is there
more Matter than
Anti-Matter?

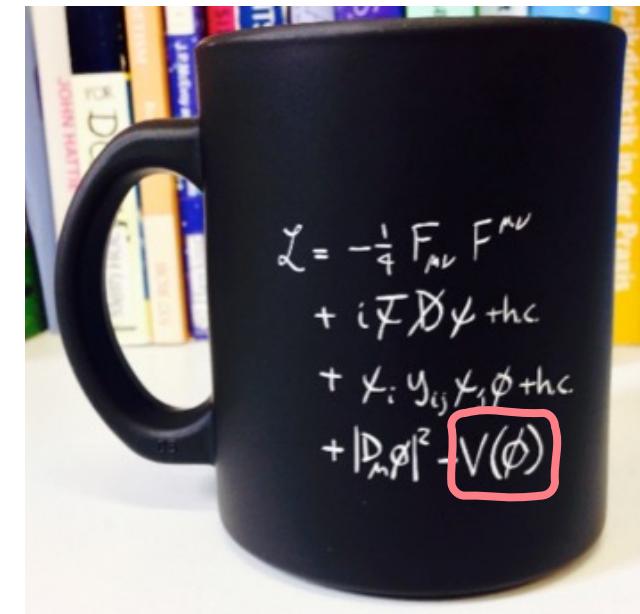
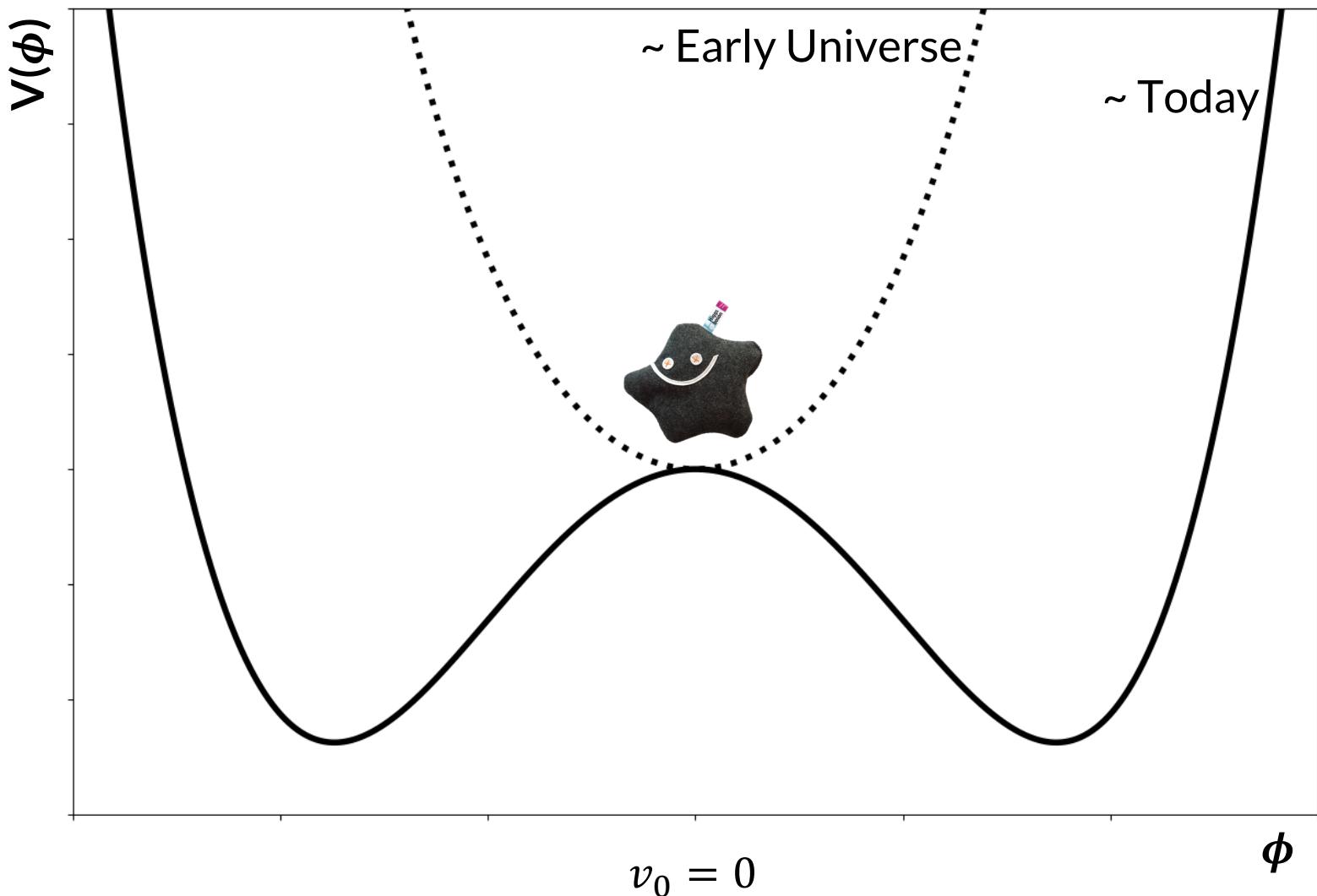
ESA What is Dark Matter?



Is our universe stable?

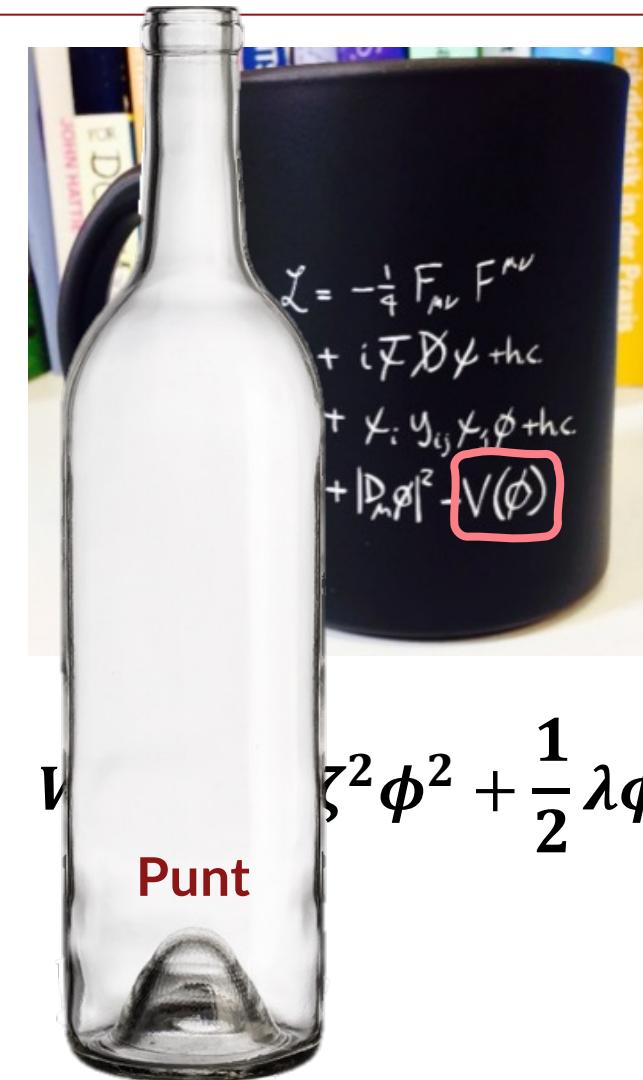
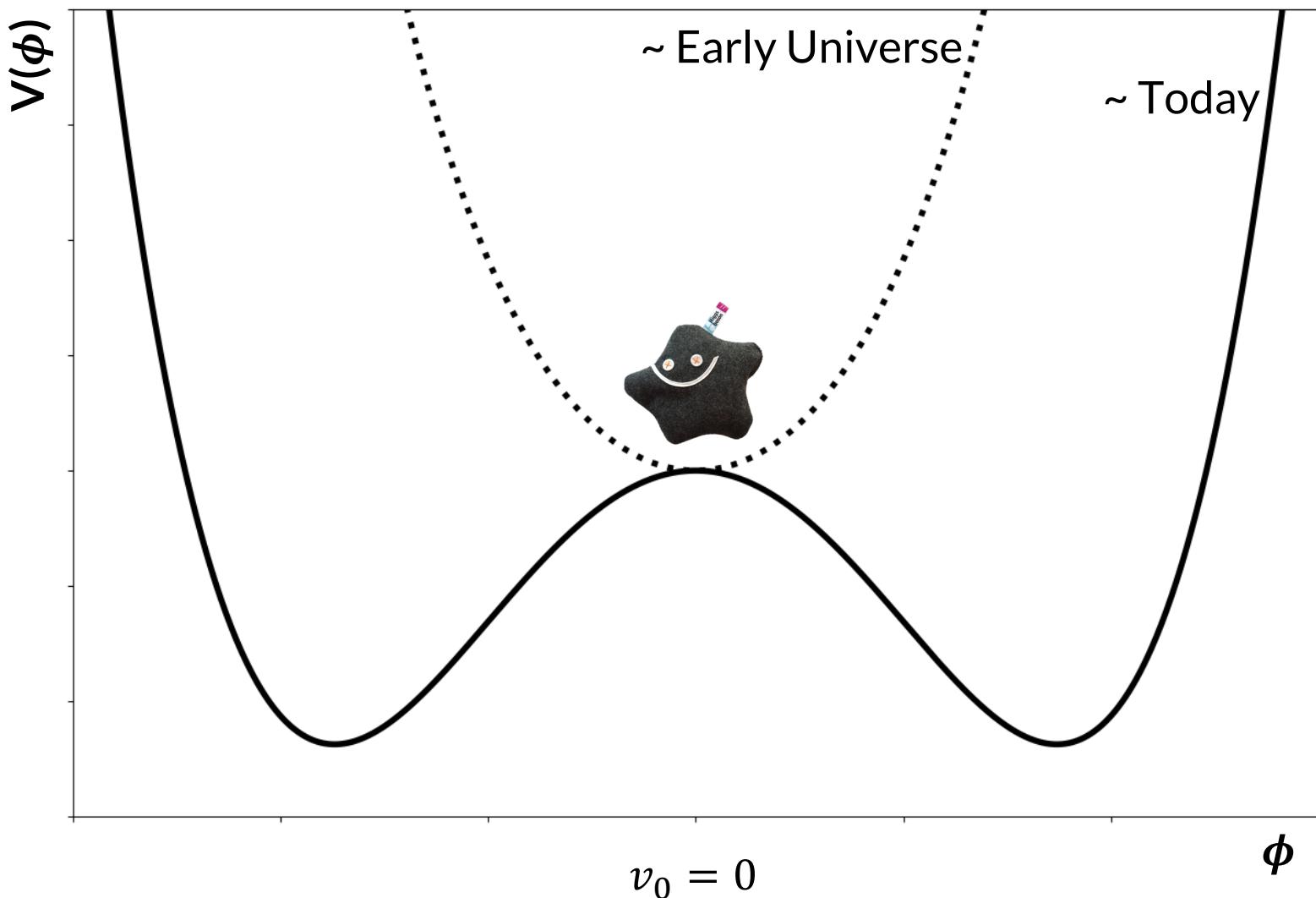


The Higgs Boson and its Potential



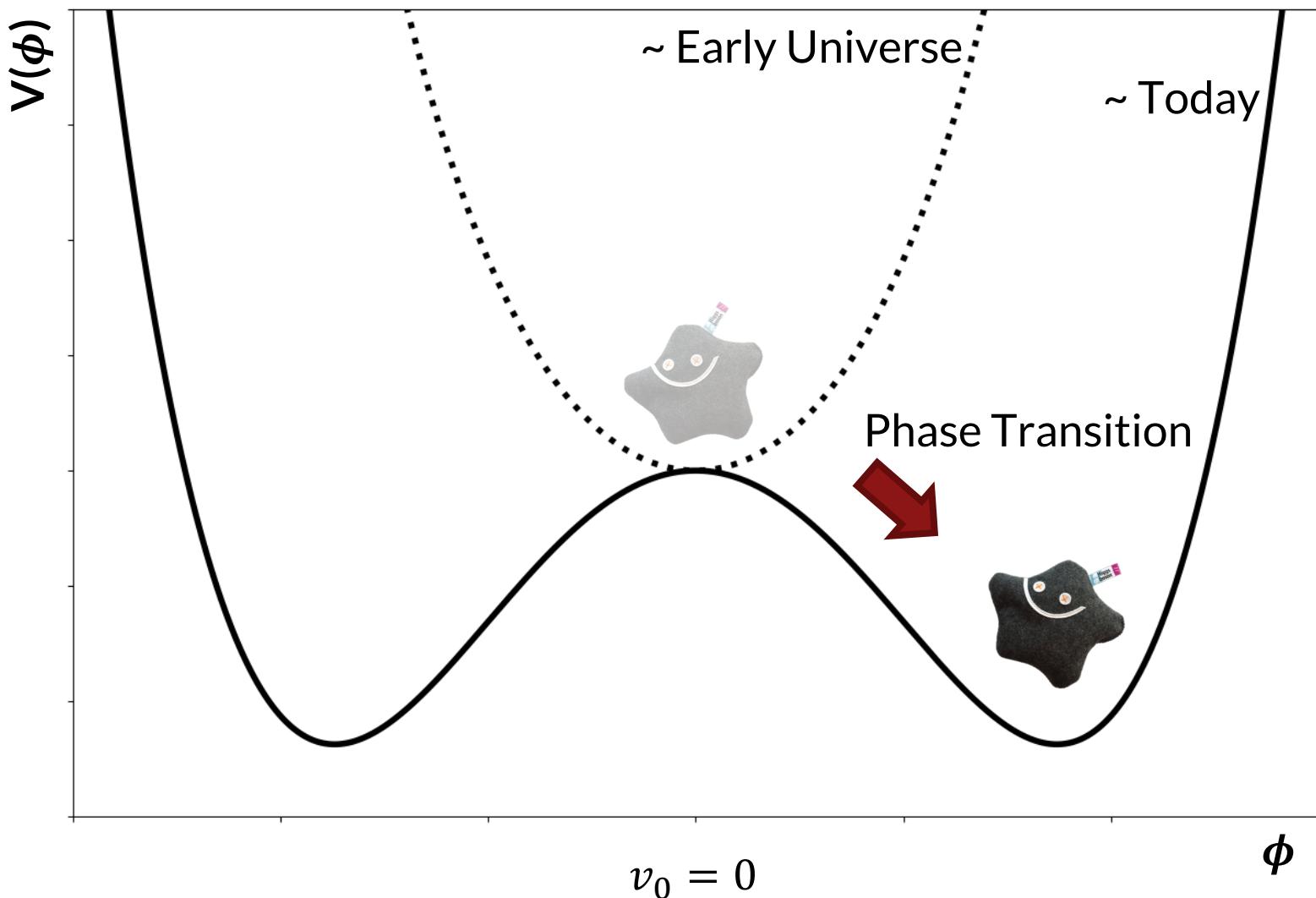
$$V(\phi) = \frac{1}{2} \zeta^2 \phi^2 + \frac{1}{2} \lambda \phi^4$$

The Higgs Boson and its Potential



$$\zeta^2 \phi^2 + \frac{1}{2} \lambda \phi^4$$

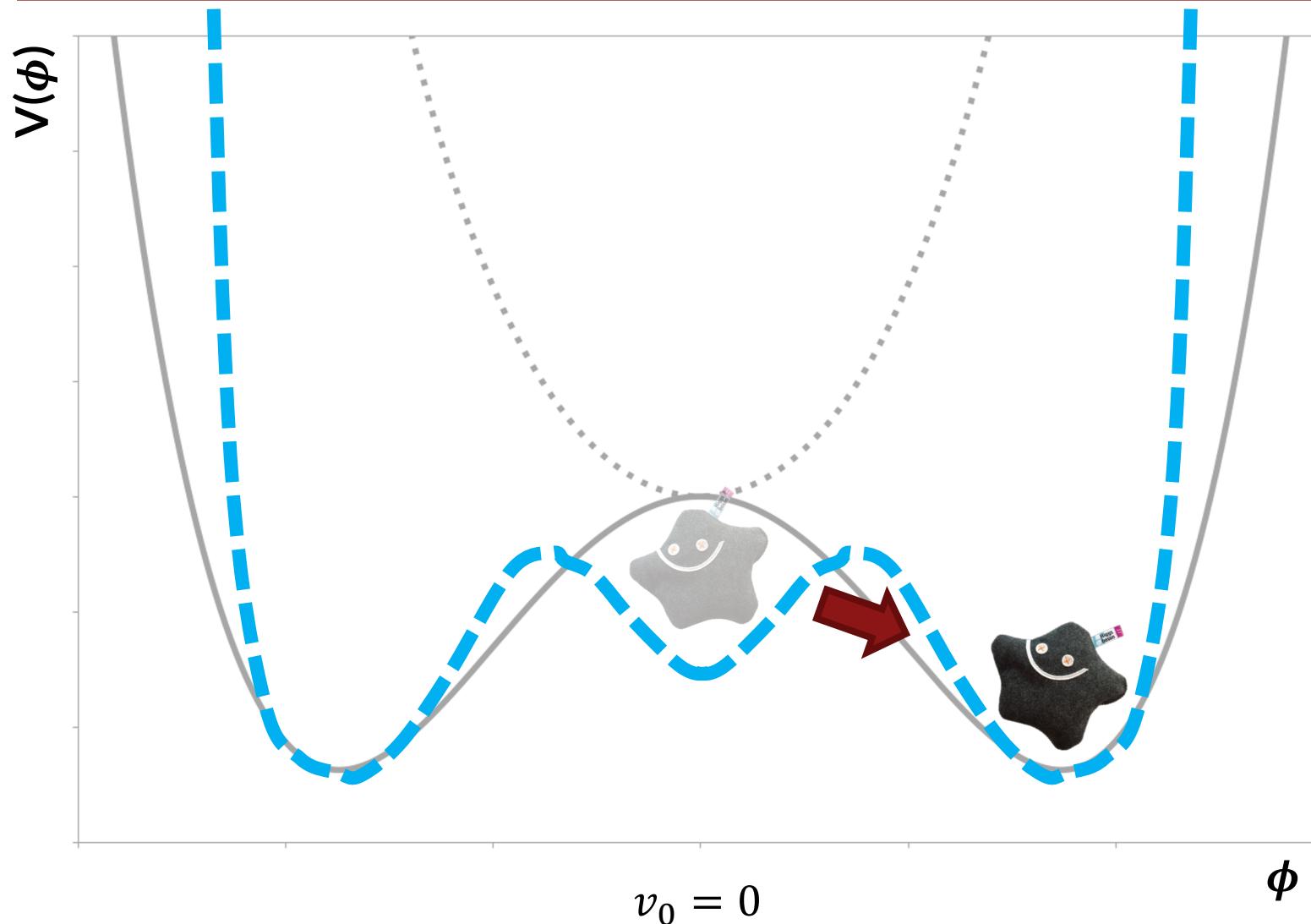
The Higgs Boson and its Potential



$$V(h) \sim \lambda v h^3 + \frac{1}{4} \lambda h^4$$

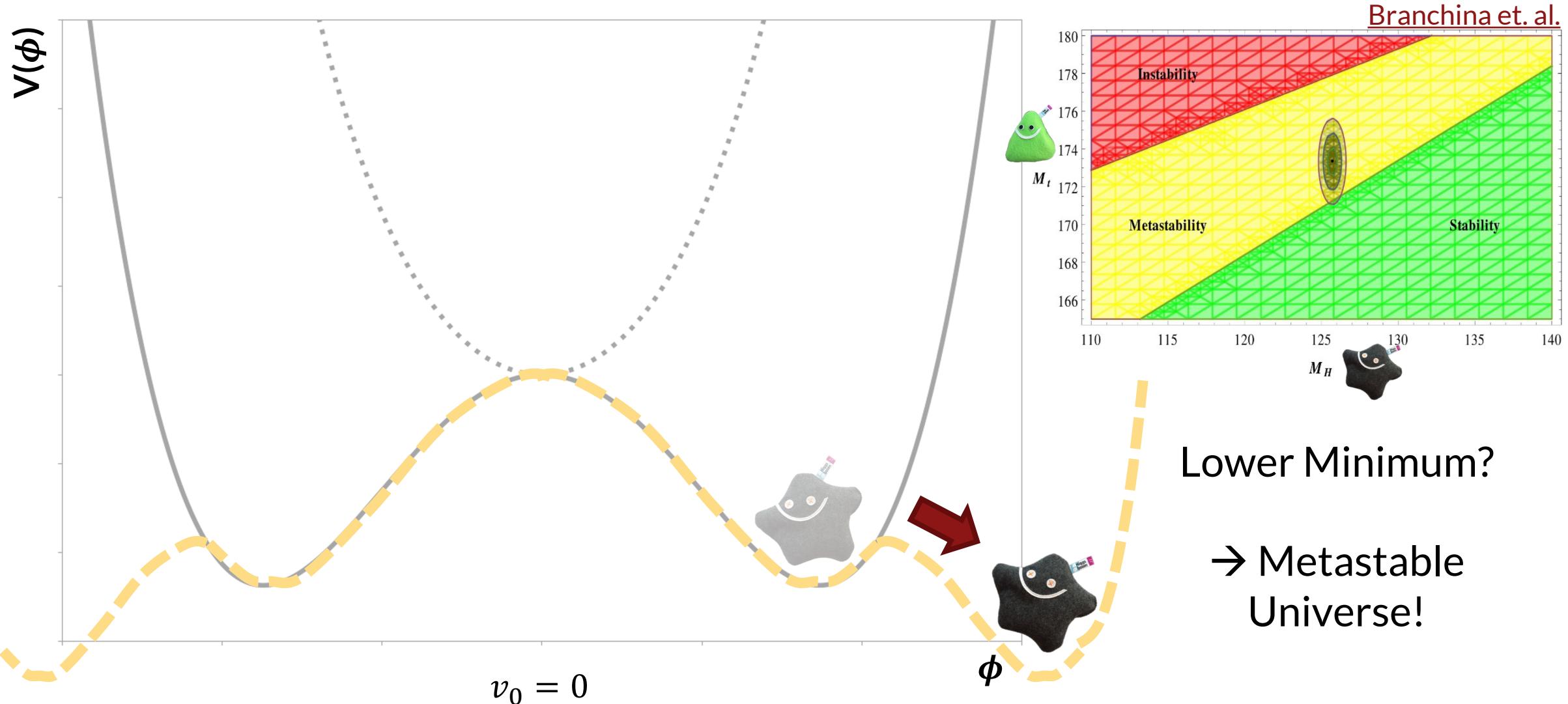
What if the potential looks a little different?

New Physics and the Higgs Potential

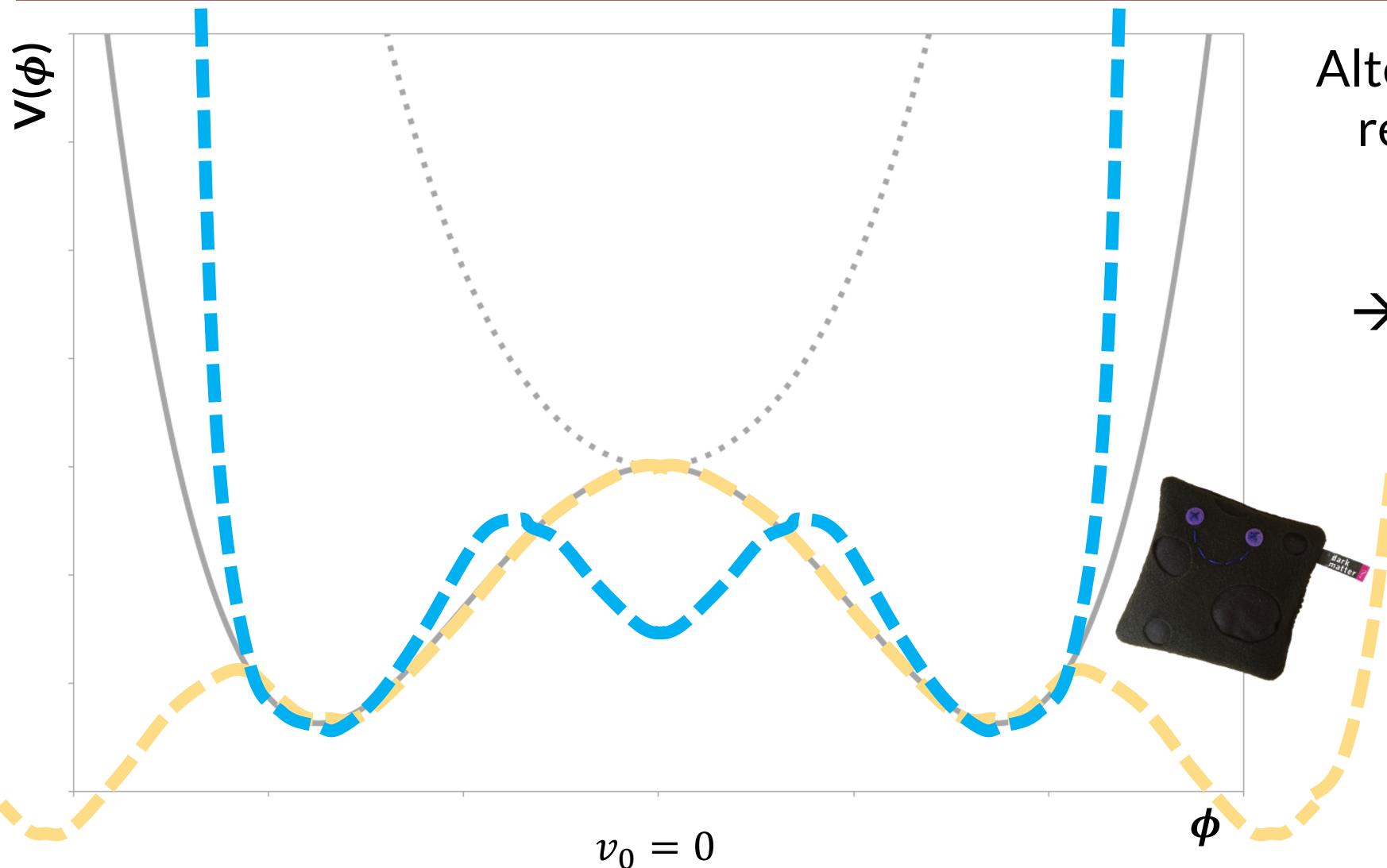


“Second Order” phase transition in early universe
→ required for “Electroweak Baryogenesis”
(= Electroweak Phase Transition as the source of Matter-Antimatter Asymmetry)

New Physics and the Higgs Potential



New Physics and the Higgs Potential



Alternative potentials
require new Higgs
interactions

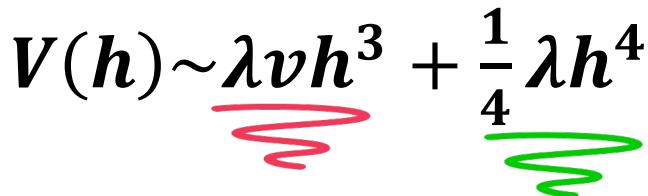
→ from a new dark
sector particle?

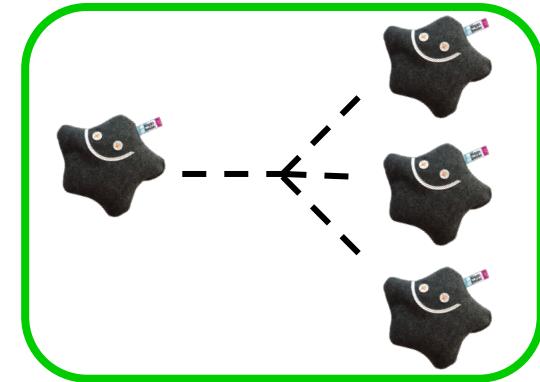
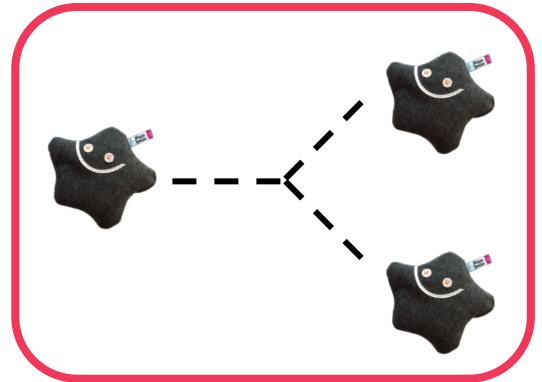
How Do We Measure the Higgs Potential?

$$V(h) \sim \lambda v h^3 + \frac{1}{4} \lambda h^4$$



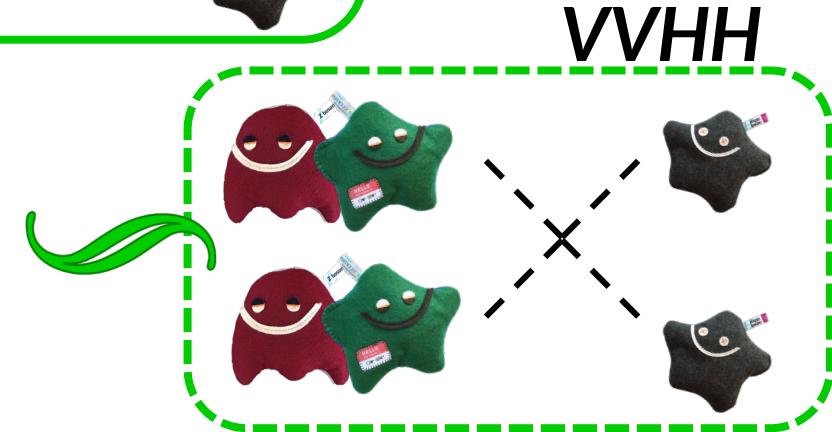
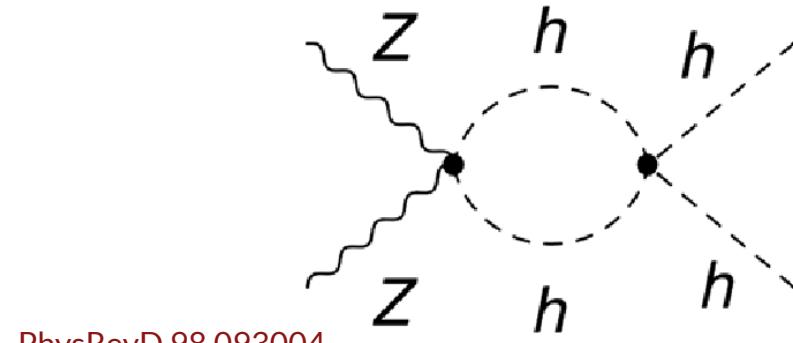

How Do We Measure the Higgs Potential?

$$V(h) \sim \lambda v h^3 + \frac{1}{4} \lambda h^4$$




Can constrain
coupling to within an
order of magnitude...
at 100 TeV Hadron
Collider!

[PhysRevD.93.013007](#)

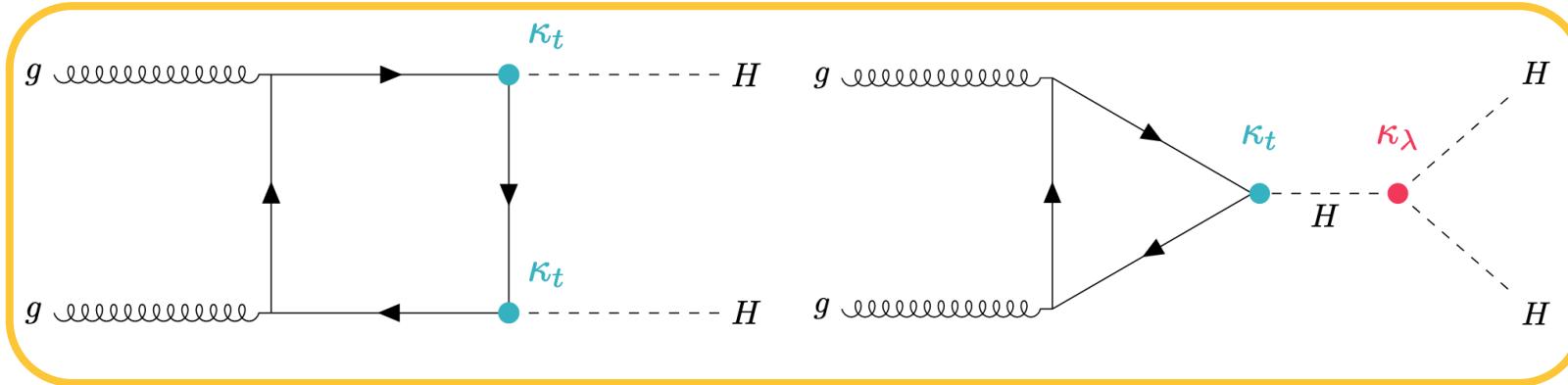


How Can We Study the Higgs Potential at Colliders?

Higgs boson pair production (HH)

gluon-gluon-Fusion

$$\sigma_{ggF} \sim 31 \text{ fb}^{[1]}$$

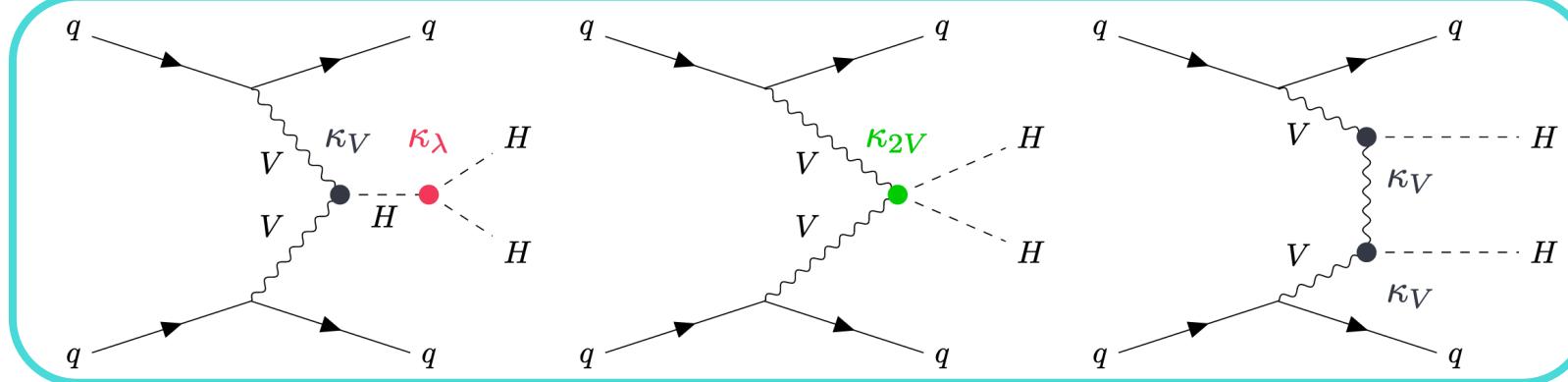


“Kappa framework”

$$\kappa_c = \frac{c}{c_{SM}}$$

Vector Boson Fusion

$$\sigma_{VBF} \sim 1.7 \text{ fb}^{[2]}$$



[1] [arxiv:1803.02463](https://arxiv.org/abs/1803.02463)

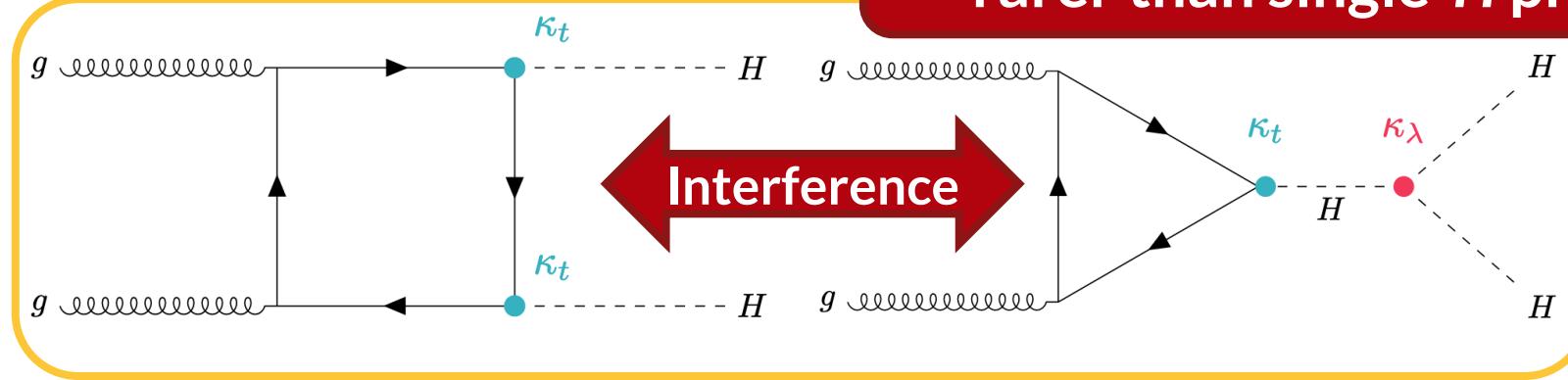
[2] [arxiv:1811.07906](https://arxiv.org/abs/1811.07906)

How Can We Study the Higgs Potential at Colliders?

Higgs boson pair production (HH)

gluon-gluon-Fusion

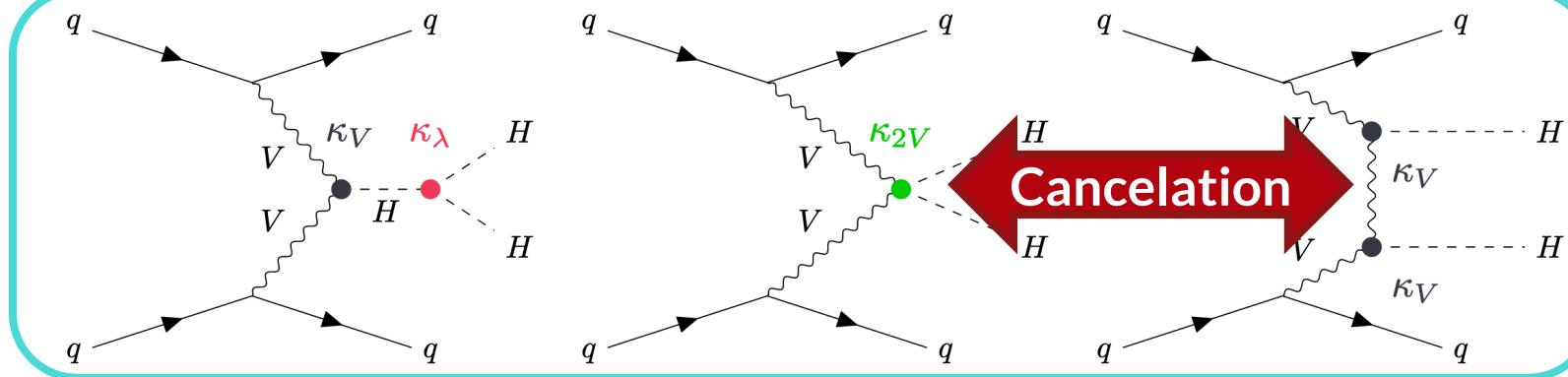
$\sigma_{ggF} \sim 31 \text{ fb}$ [1]



HH production is a factor of $\sim 1000\times$ rarer than single- H production!

Vector Boson Fusion

$\sigma_{VBF} \sim 1.7 \text{ fb}$ [2]

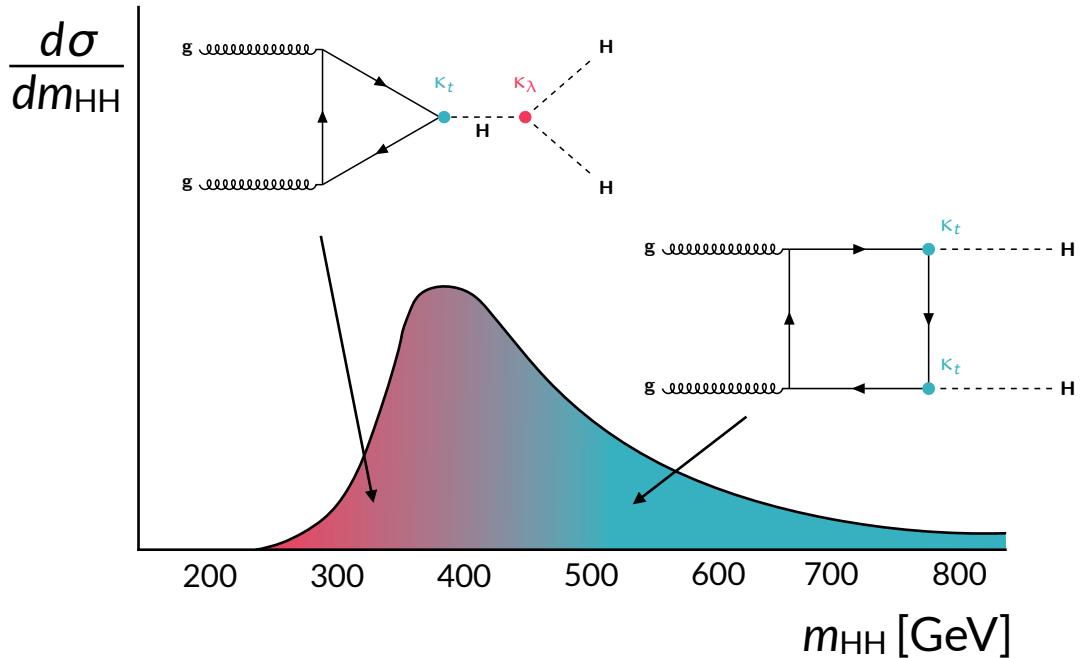


[1] [arxiv:1803.02463](https://arxiv.org/abs/1803.02463)

[2] [arxiv:1811.07906](https://arxiv.org/abs/1811.07906)

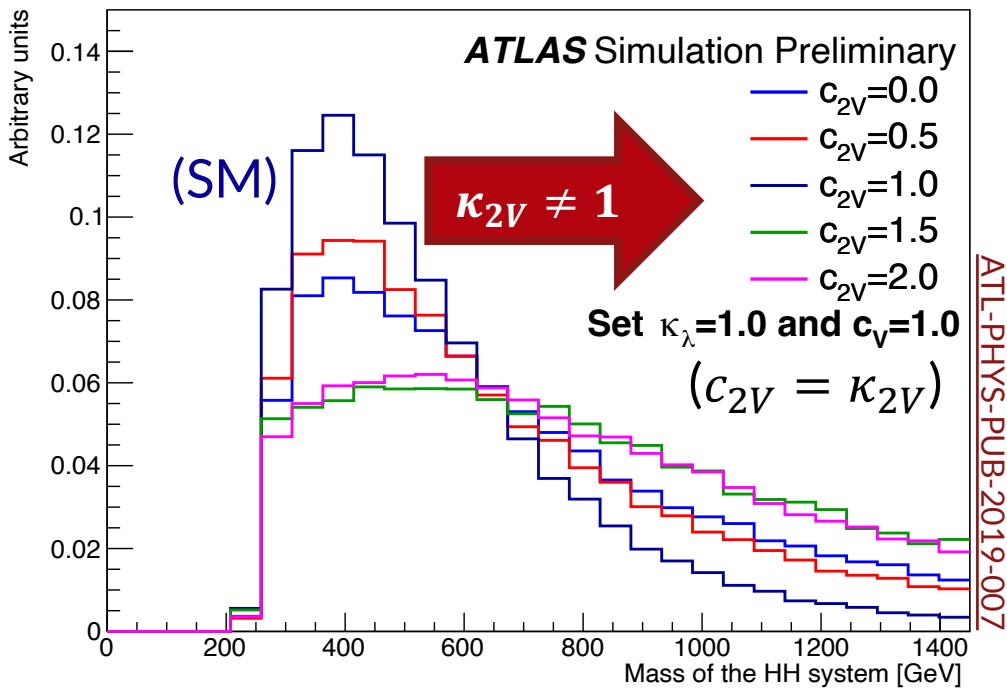
Sensitivity to New Physics in the Self-Couplings

Contribution of ggF diagrams to di-Higgs invariant mass spectrum (~energy)



ggF: disrupt interference
→ more signal, softer events

VBF Di-Higgs invariant mass spectrum (~energy) for various κ_{2V}

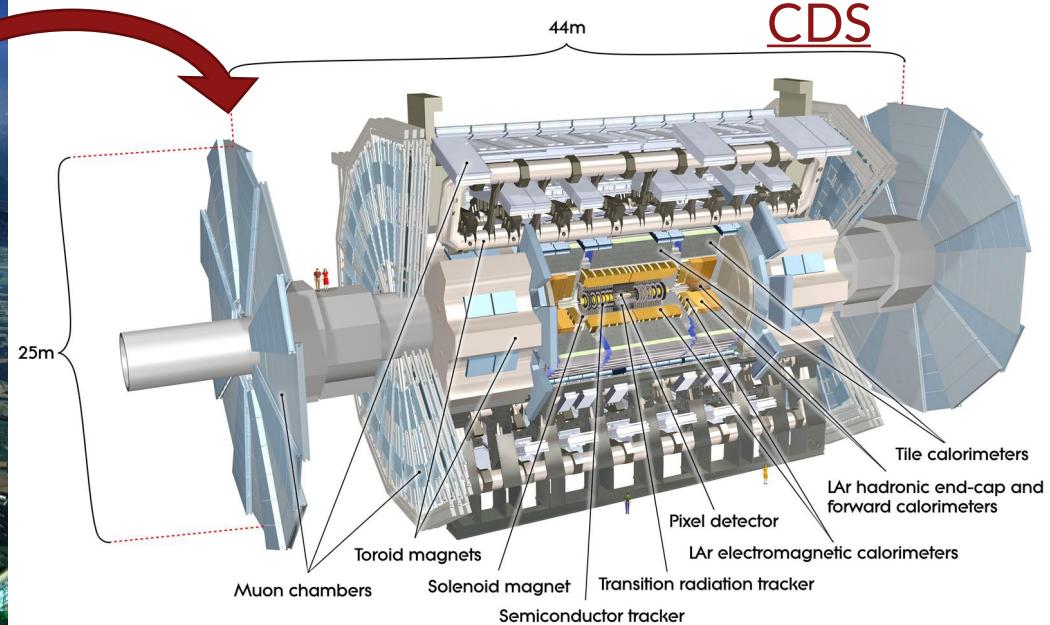
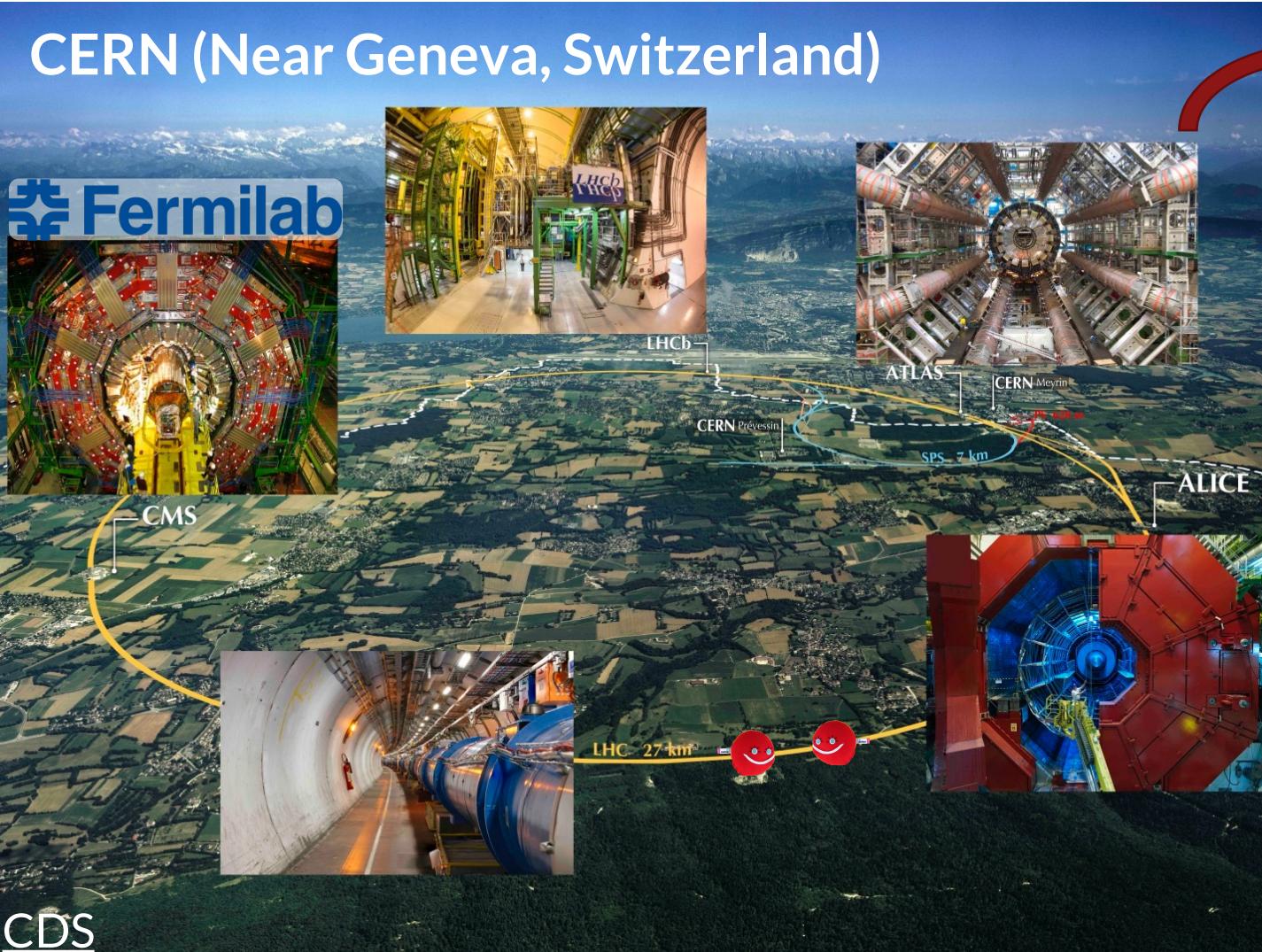


VBF: break cancellation
→ more signal, harder events

How do we measure Higgs Boson self-interactions?

The ATLAS Detector

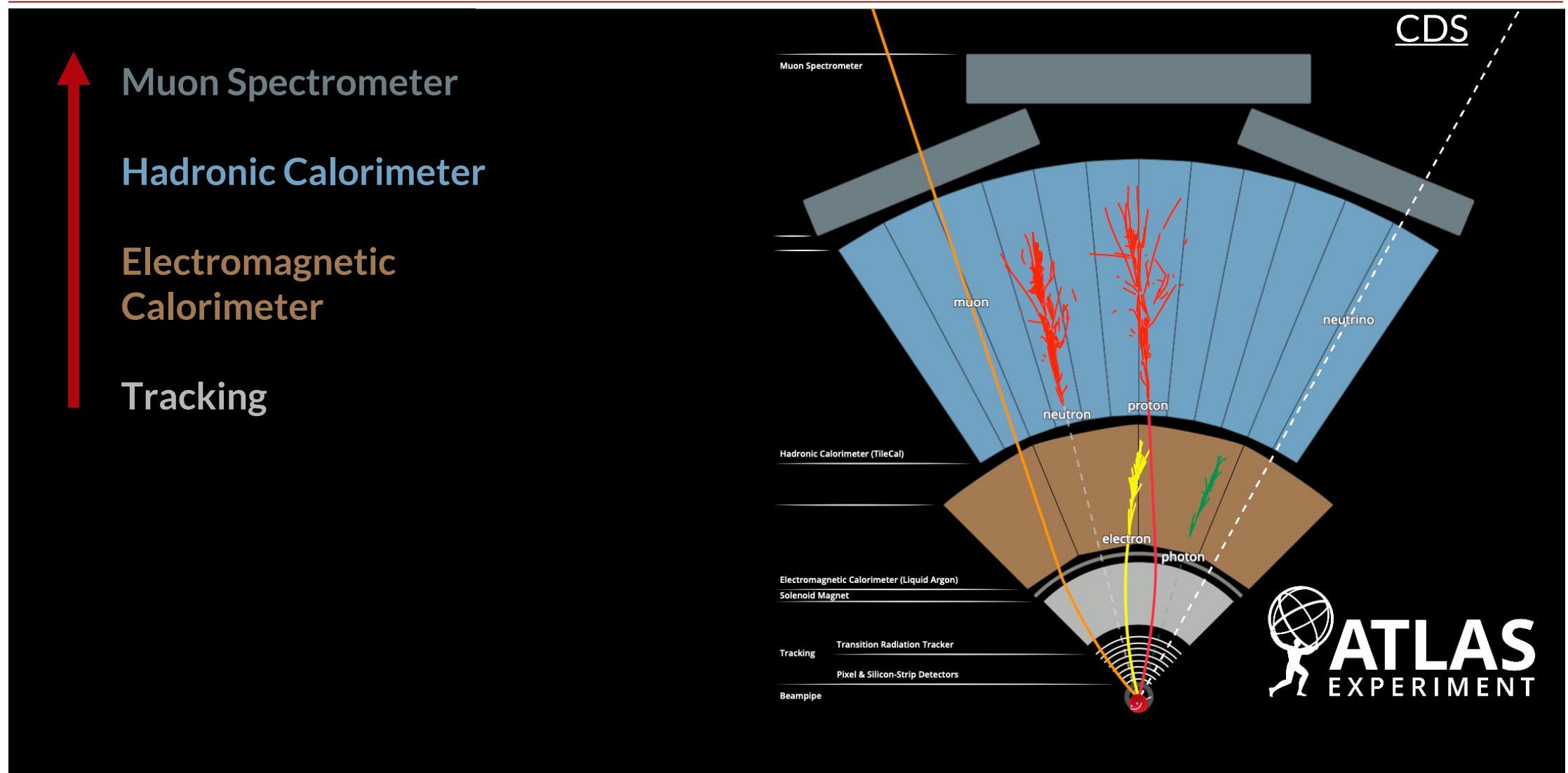
ATLAS and the Large Hadron Collider



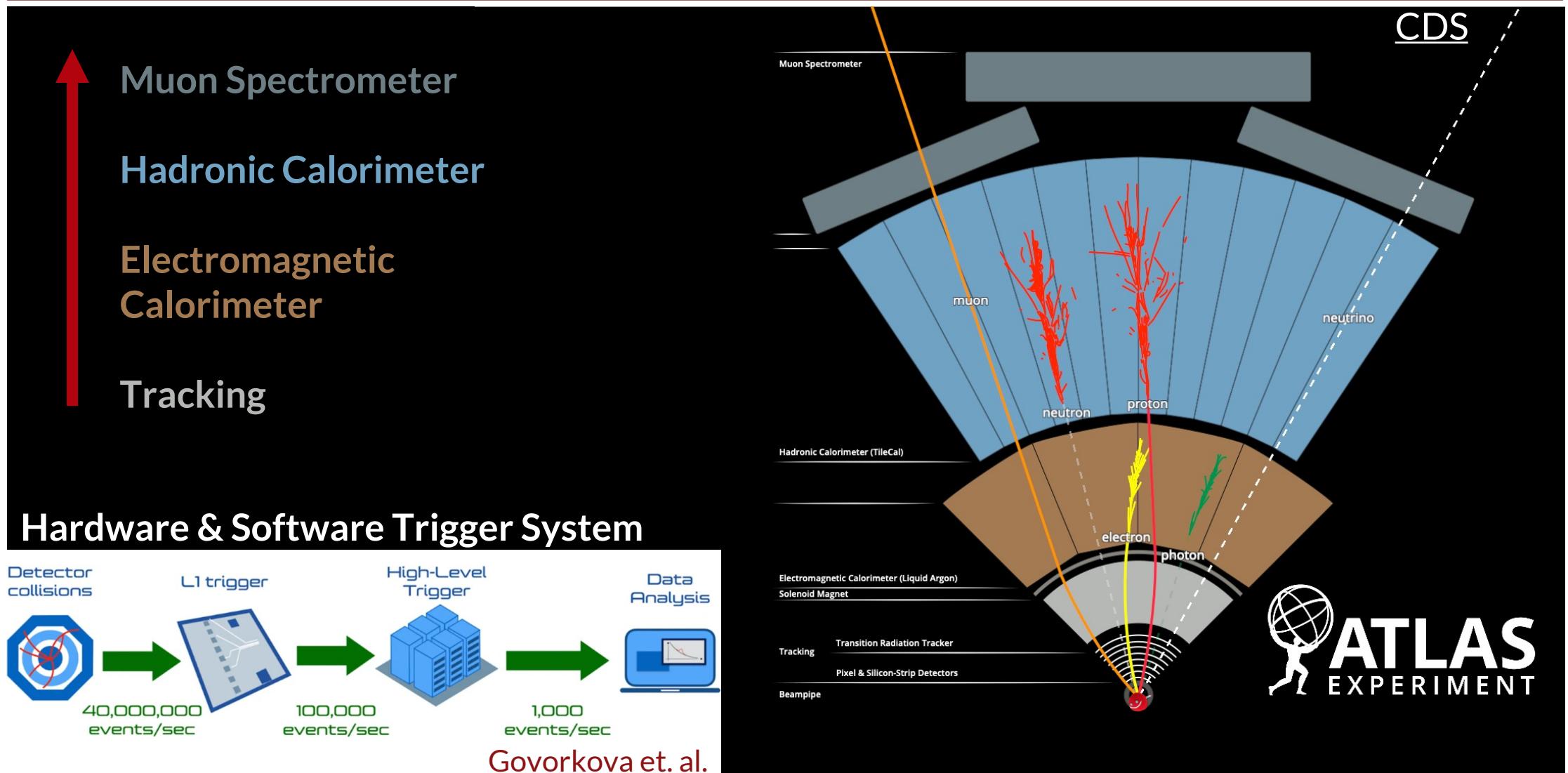
ATLAS
→ General purpose detector

Today: Run 2 (2015-2018)

The ATLAS Detector

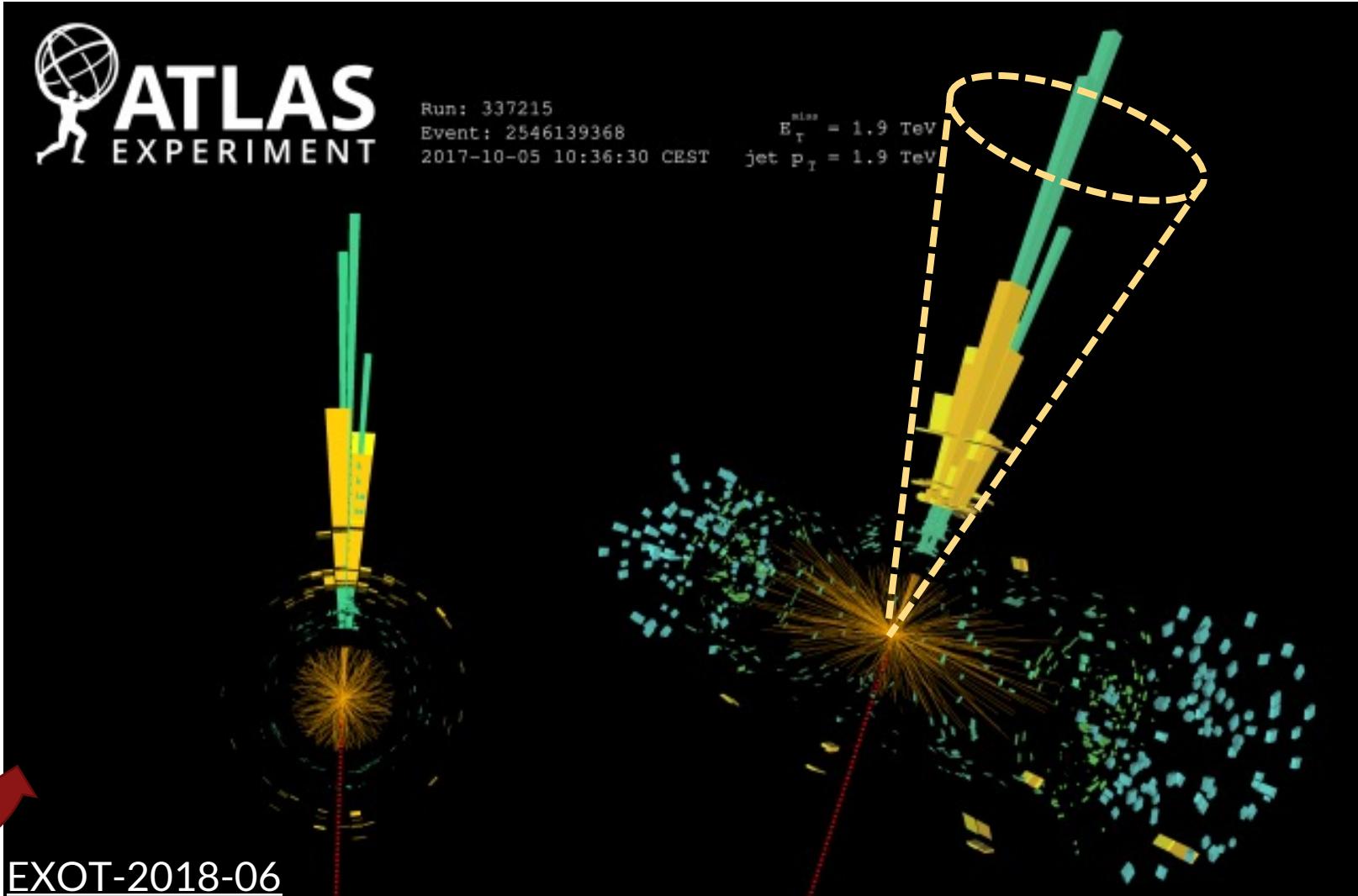
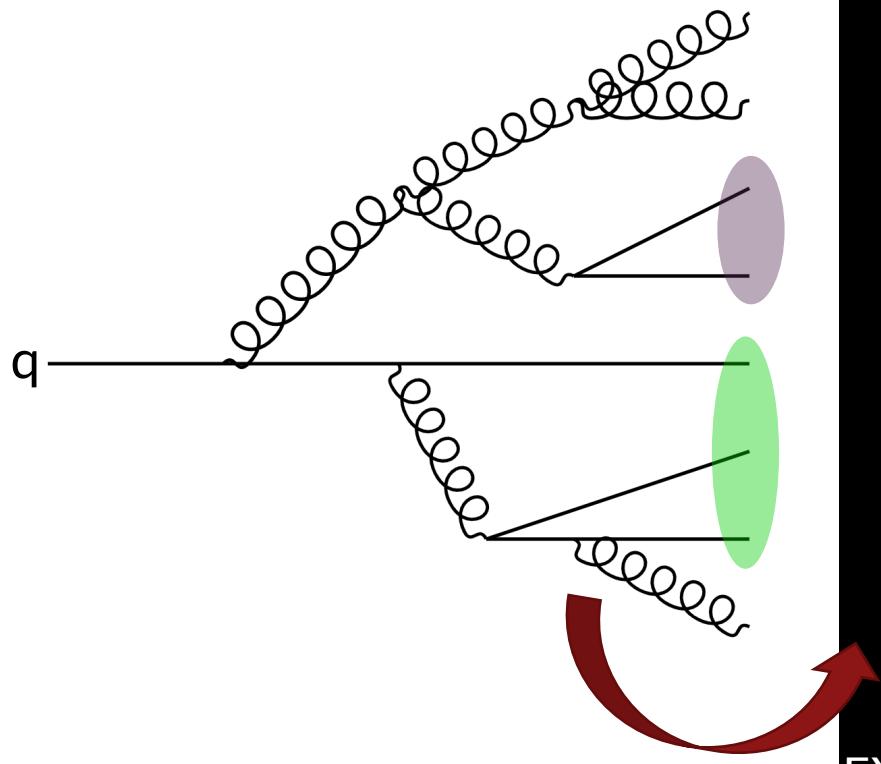


The ATLAS Detector



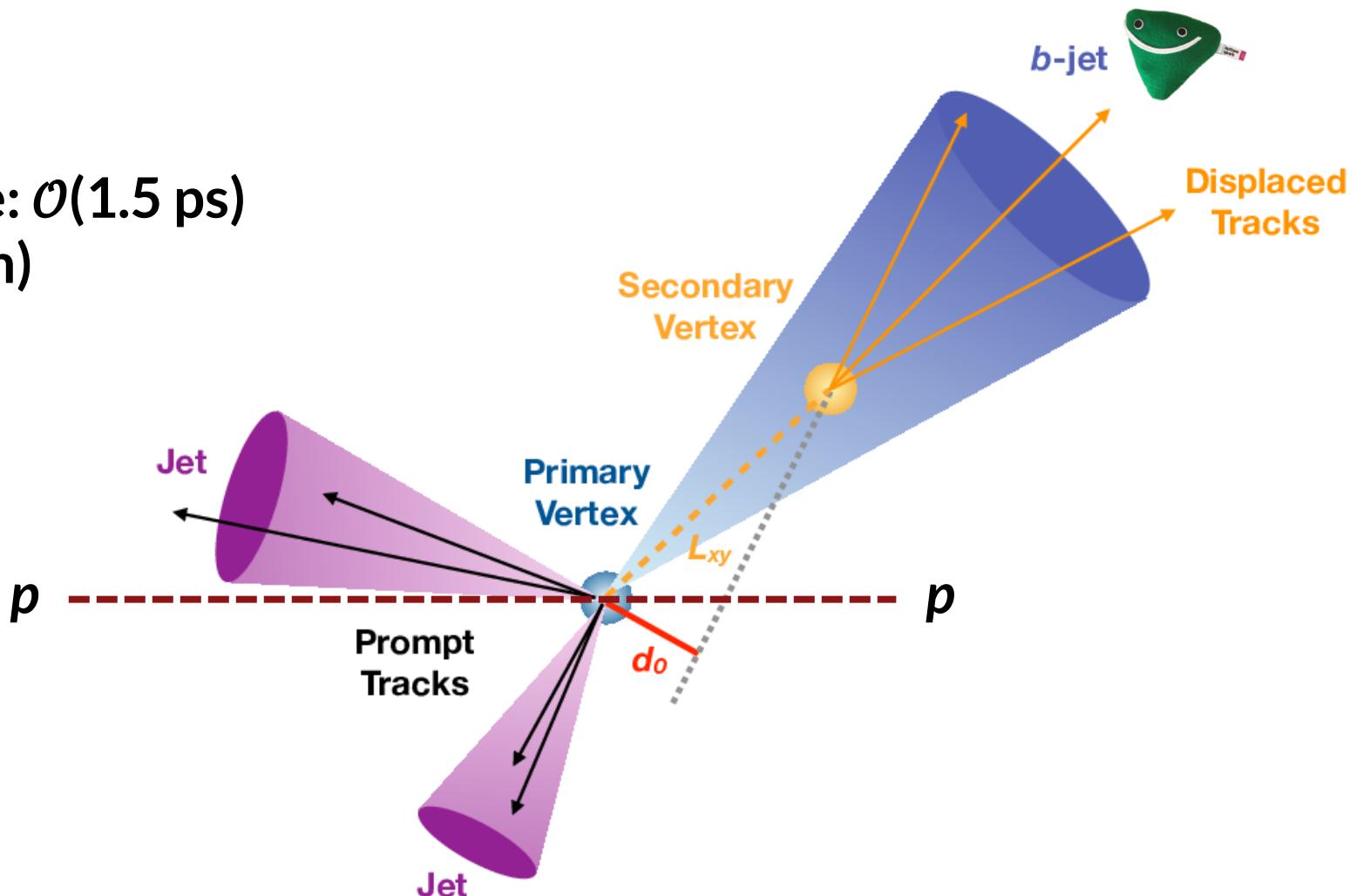
What is a Jet?

No single quarks →
Spray of high-energy
particles



Identifying jets from b -quarks

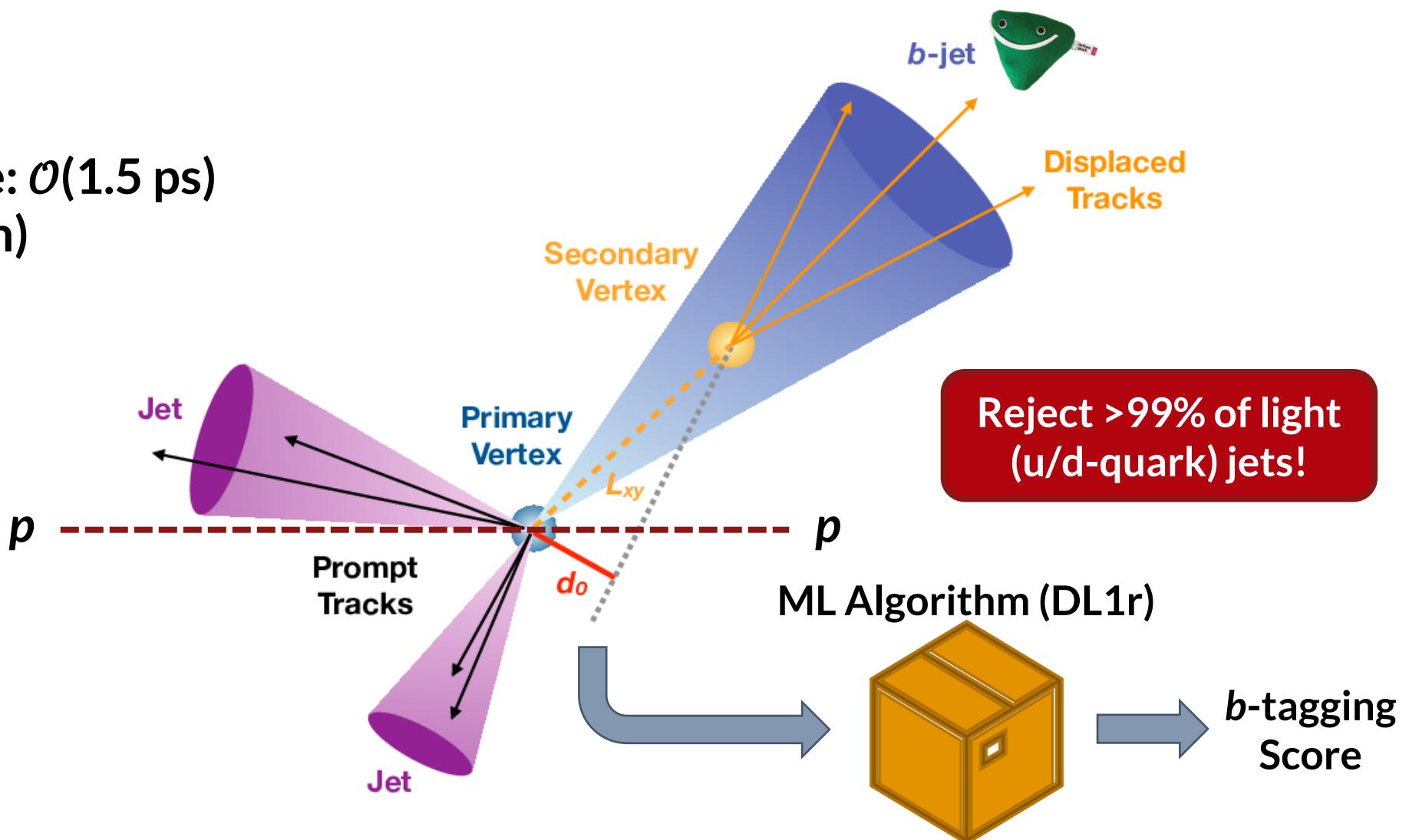
B-meson lifetime: $\mathcal{O}(1.5 \text{ ps})$
 $\rightarrow L: \mathcal{O}(\text{mm})$



TRIG-2018-08

Identifying jets from b -quarks

B-meson lifetime: $\mathcal{O}(1.5 \text{ ps})$
 $\rightarrow L: \mathcal{O}(\text{mm})$



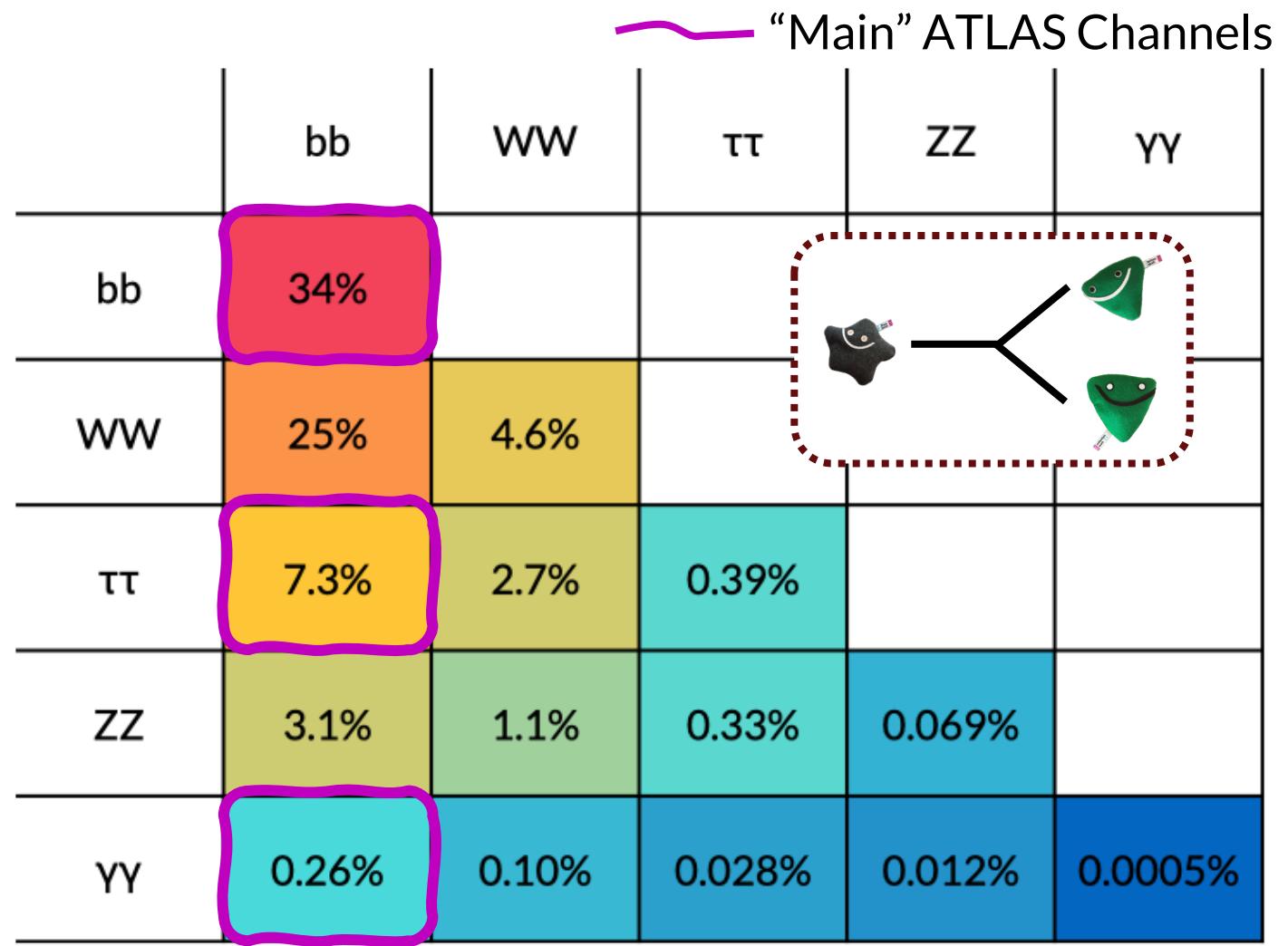
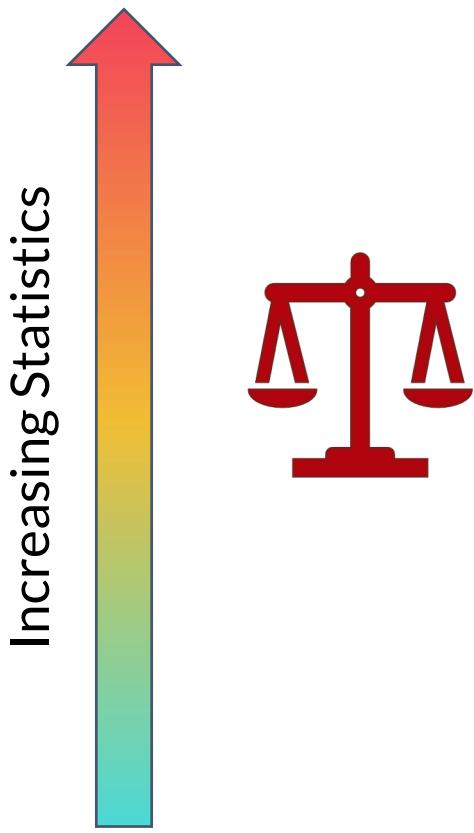
TRIG-2018-08

A measurement probing Higgs Boson self-interactions

[arxiv:2301.03212](https://arxiv.org/abs/2301.03212)

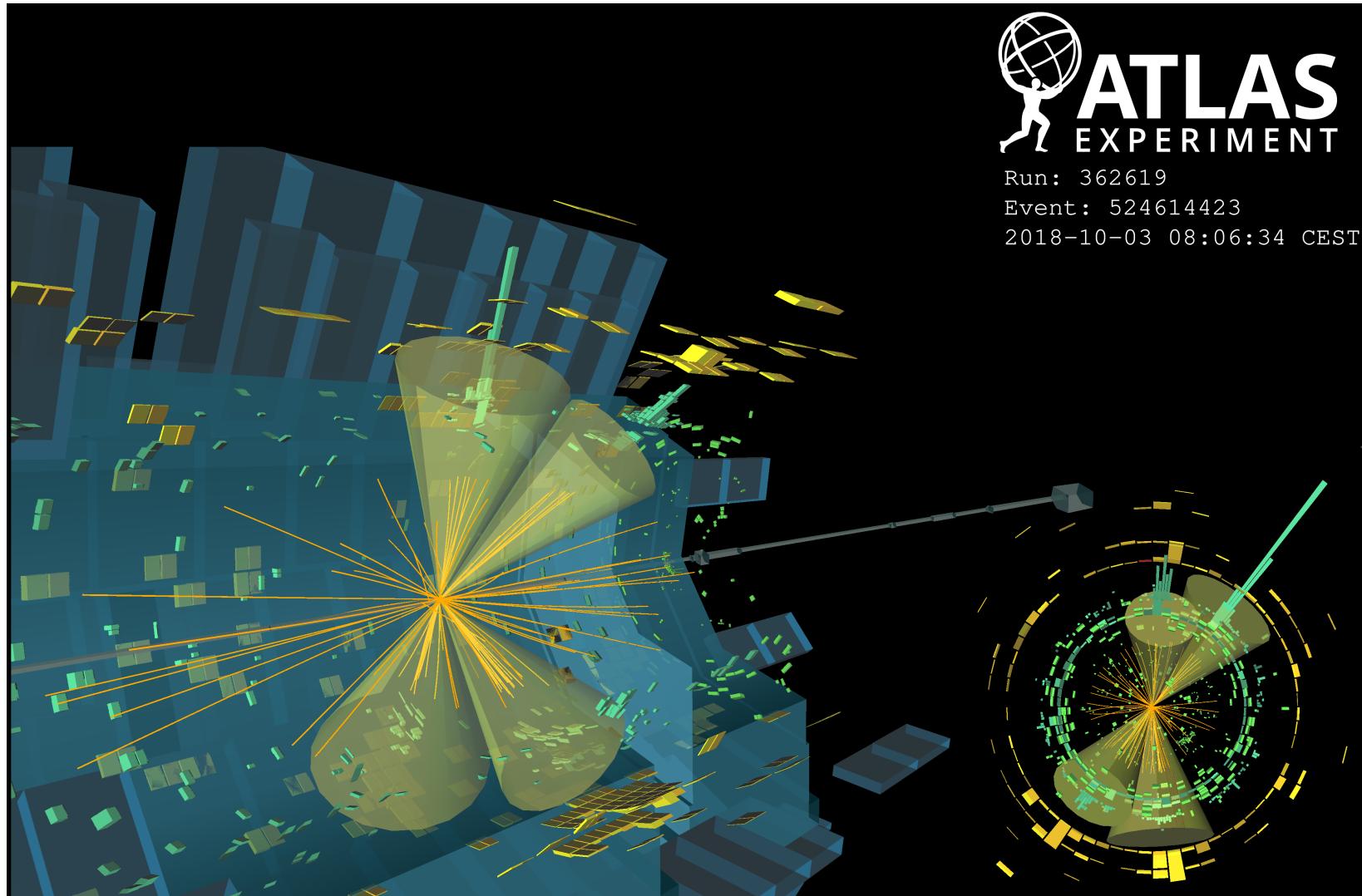
The ATLAS $HH \rightarrow b\bar{b}b\bar{b}$ Analysis

Di-Higgs Boson Decays



What Makes 4b a Challenging Final State?

~2400 HH Events
(ATLAS Run 2)



ATLAS
EXPERIMENT
Run: 362619
Event: 524614423
2018-10-03 08:06:34 CEST

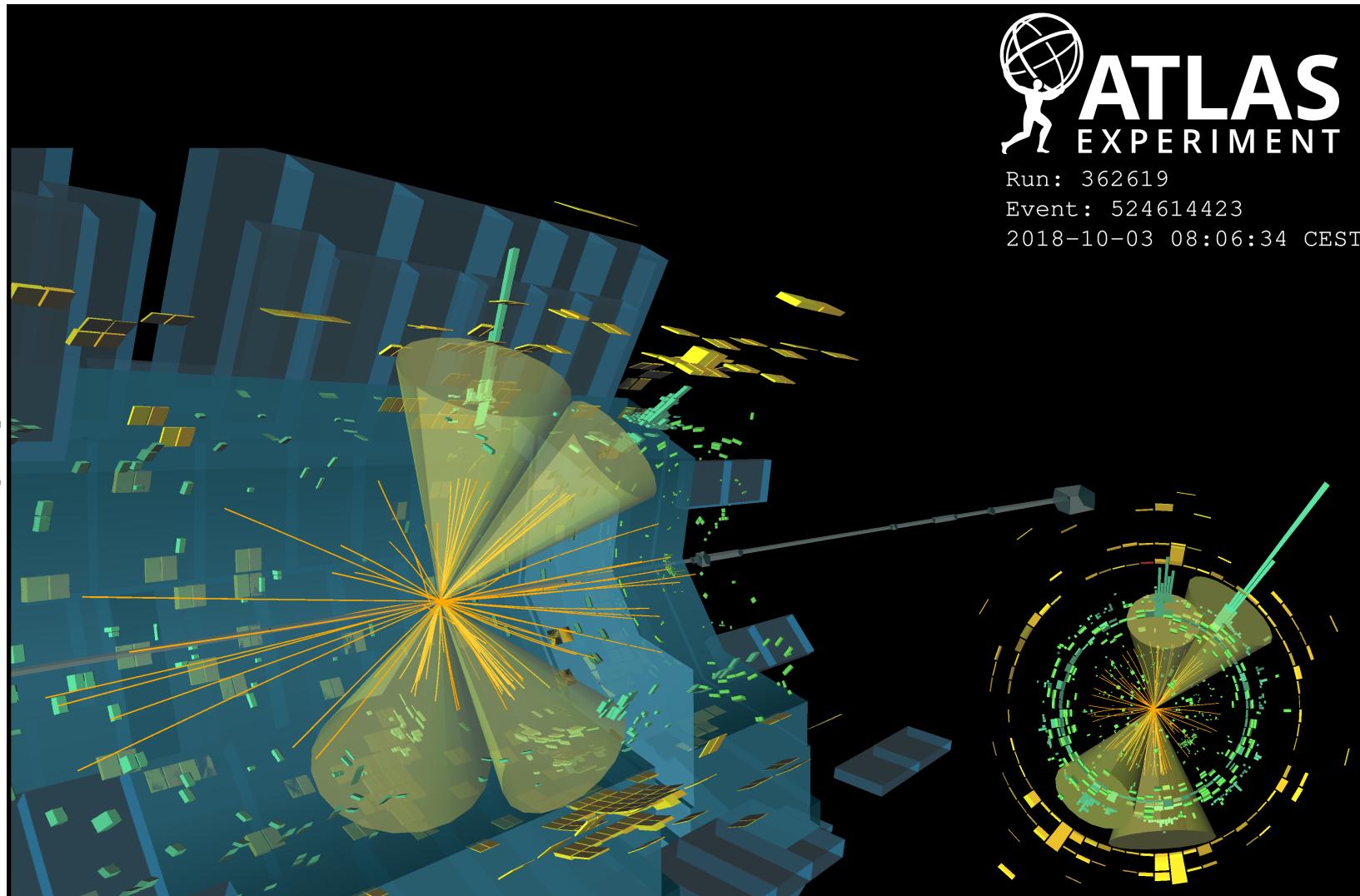
What Makes 4b a Challenging Final State?

~2400 HH Events
(ATLAS Run 2)



↓ $BR(HH \rightarrow b\bar{b}b\bar{b}) \sim \frac{1}{3}$

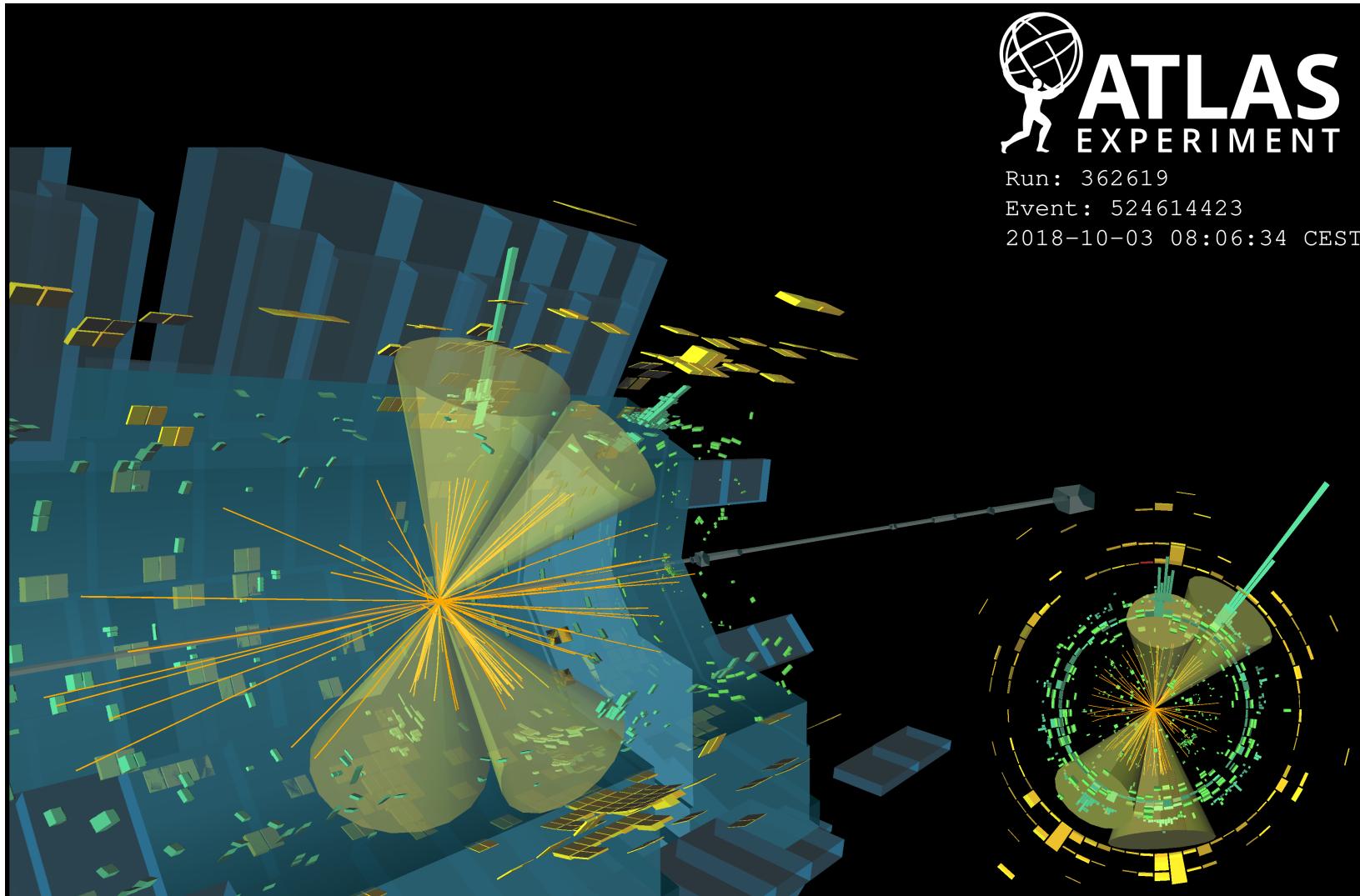
~800 $HH \rightarrow b\bar{b}b\bar{b}$ Events



ATLAS
EXPERIMENT
Run: 362619
Event: 524614423
2018-10-03 08:06:34 CEST

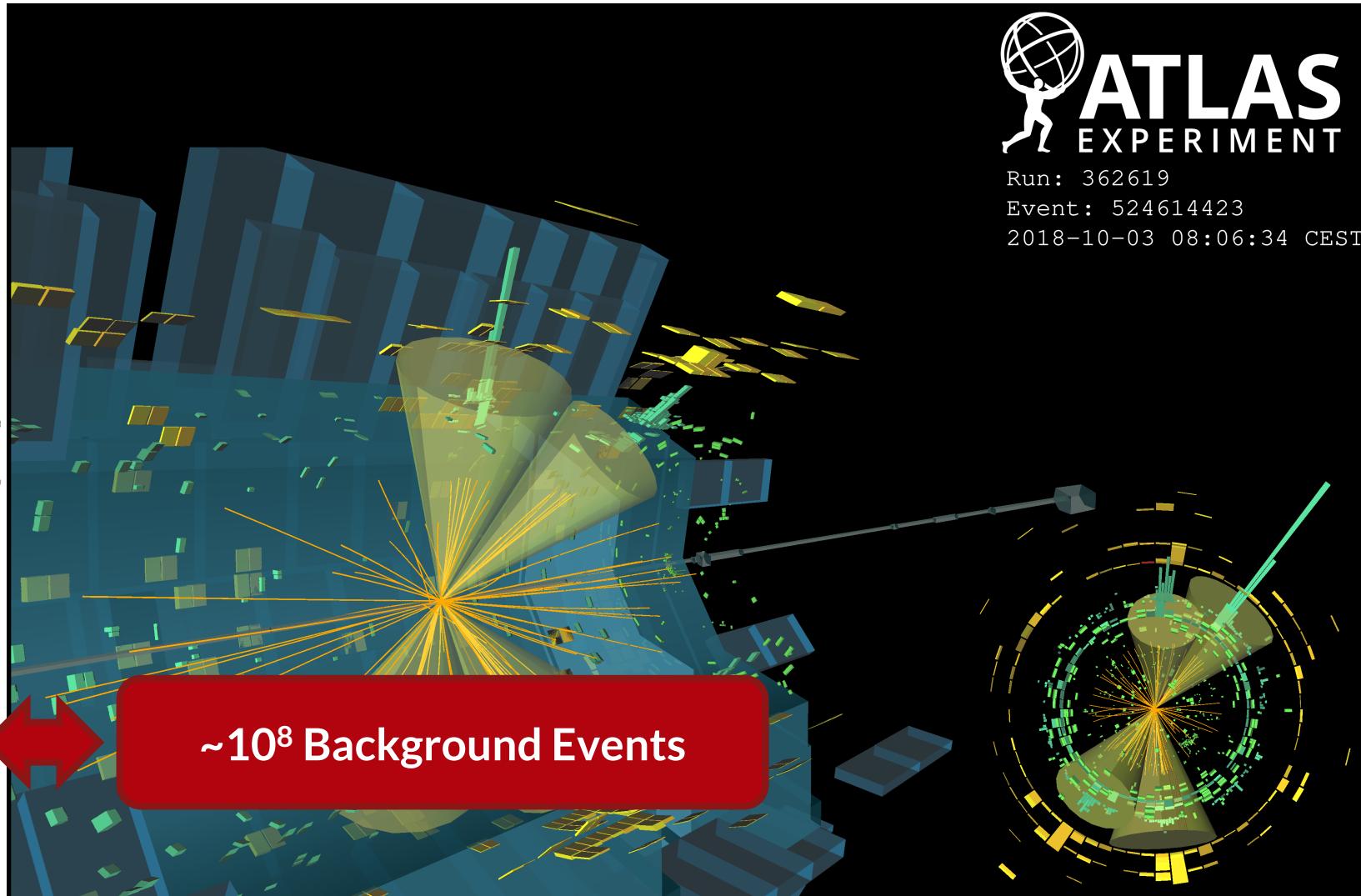
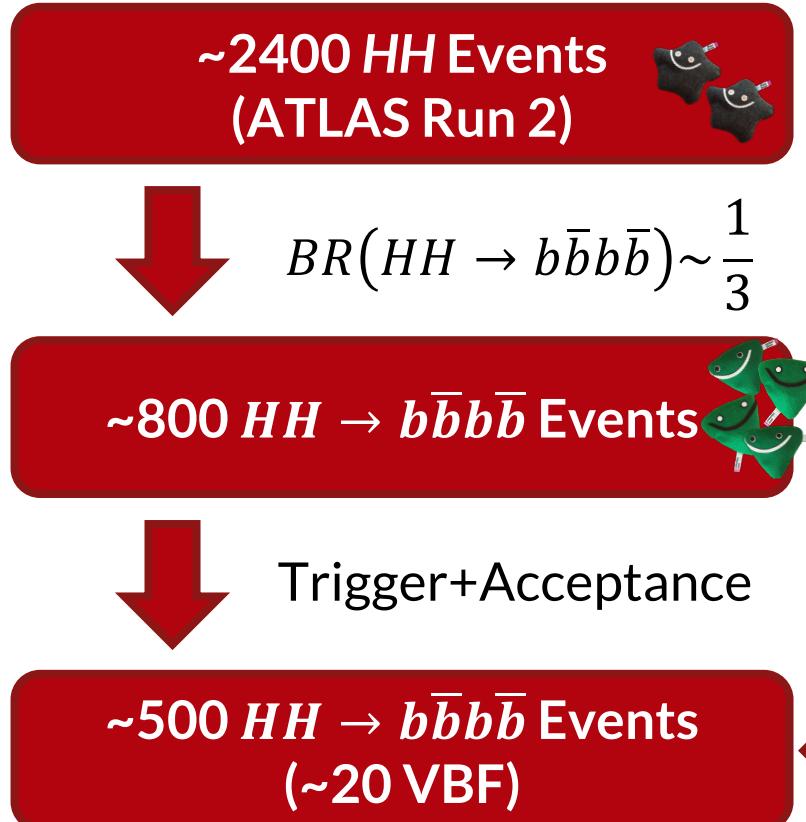
What Makes 4b a Challenging Final State?

- ~2400 HH Events
(ATLAS Run 2) 
- ↓ $BR(HH \rightarrow b\bar{b}b\bar{b}) \sim \frac{1}{3}$
- ~800 $HH \rightarrow b\bar{b}b\bar{b}$ Events 
- ↓ Trigger+Acceptance
- ~500 $HH \rightarrow b\bar{b}b\bar{b}$ Events
(~20 VBF)

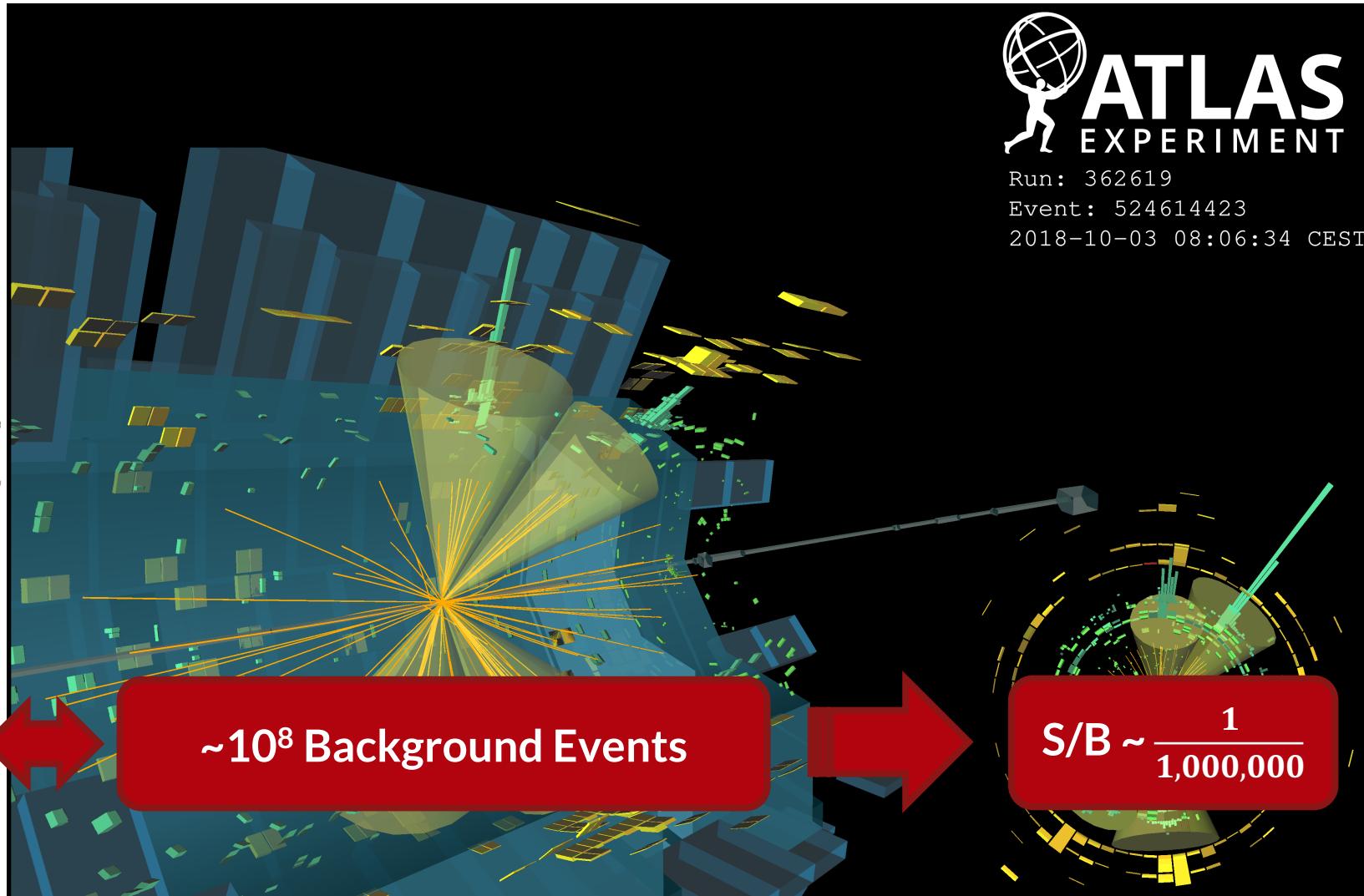
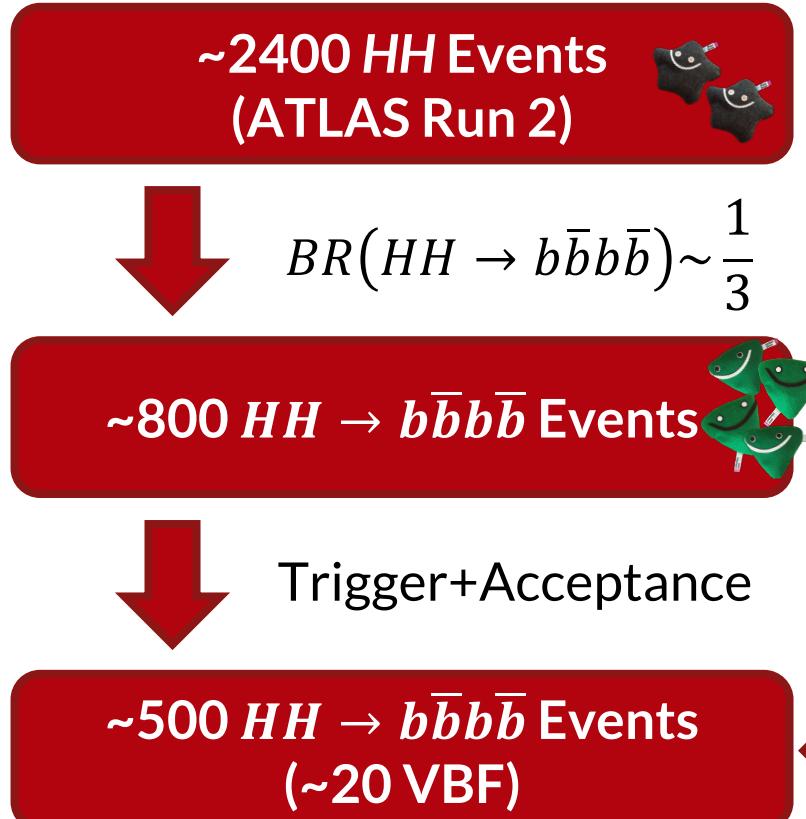


ATLAS
EXPERIMENT
Run: 362619
Event: 524614423
2018-10-03 08:06:34 CEST

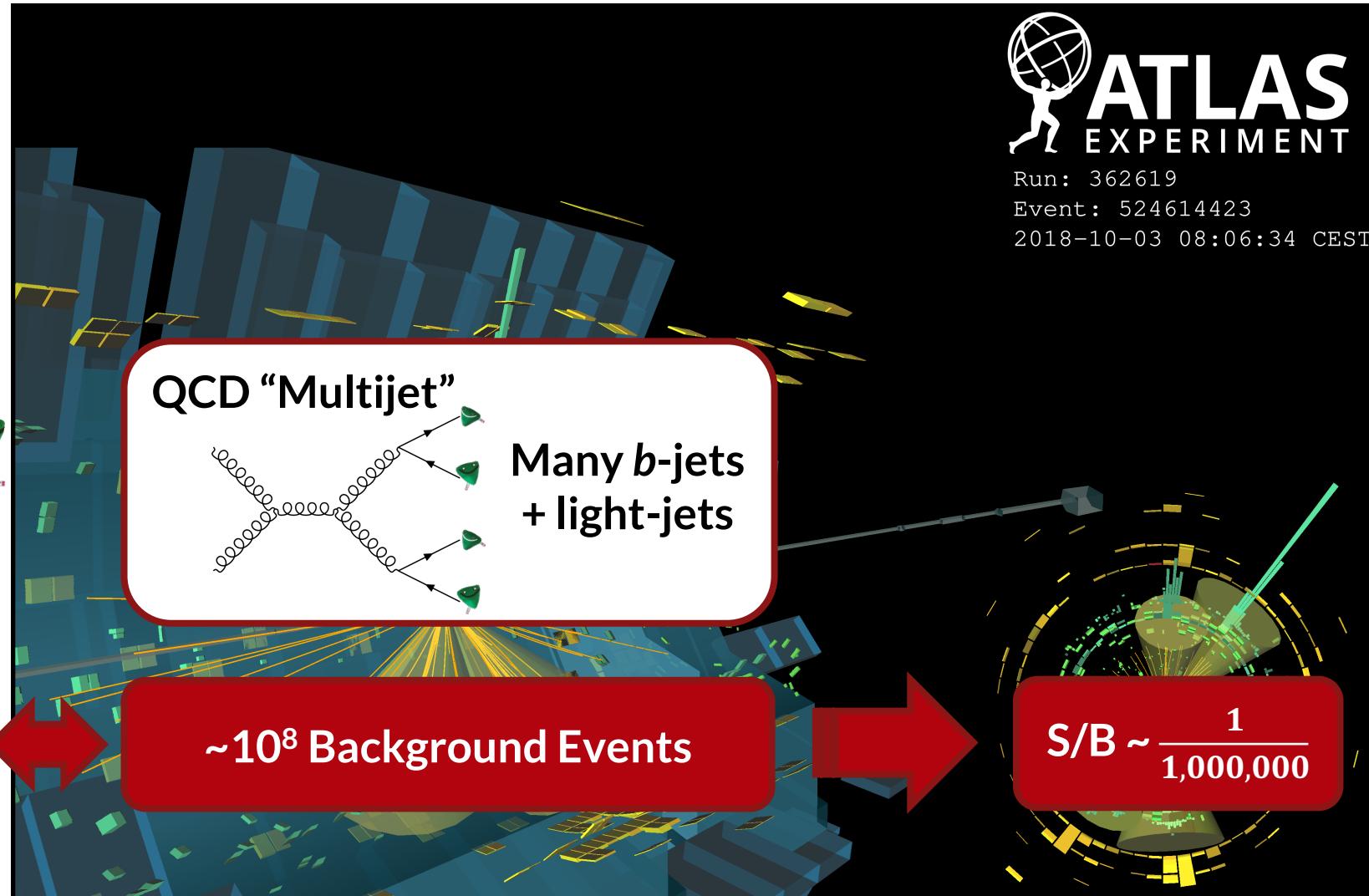
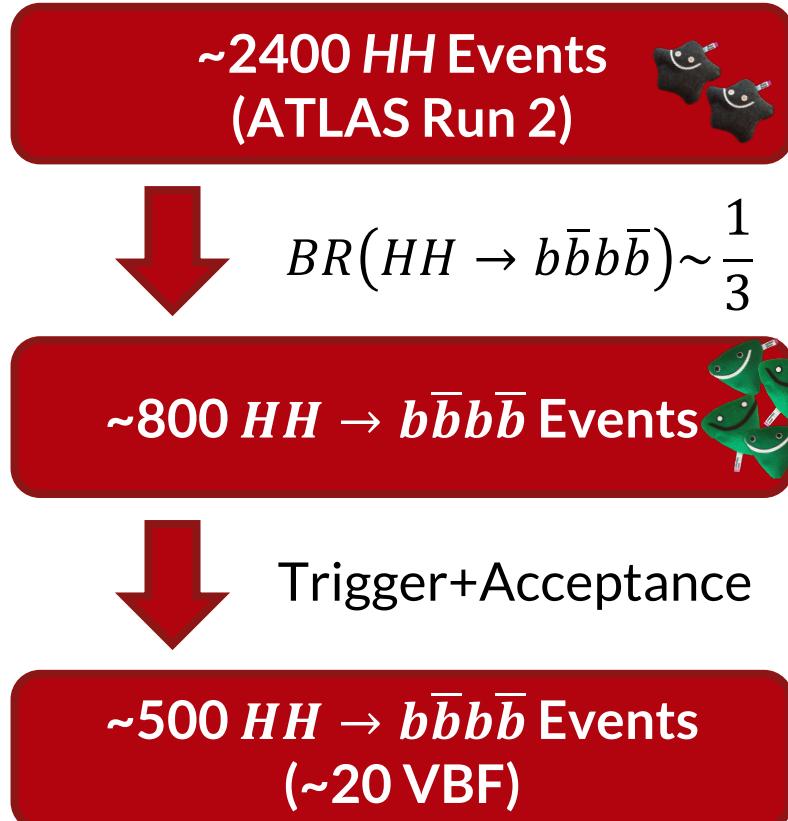
What Makes 4b a Challenging Final State?



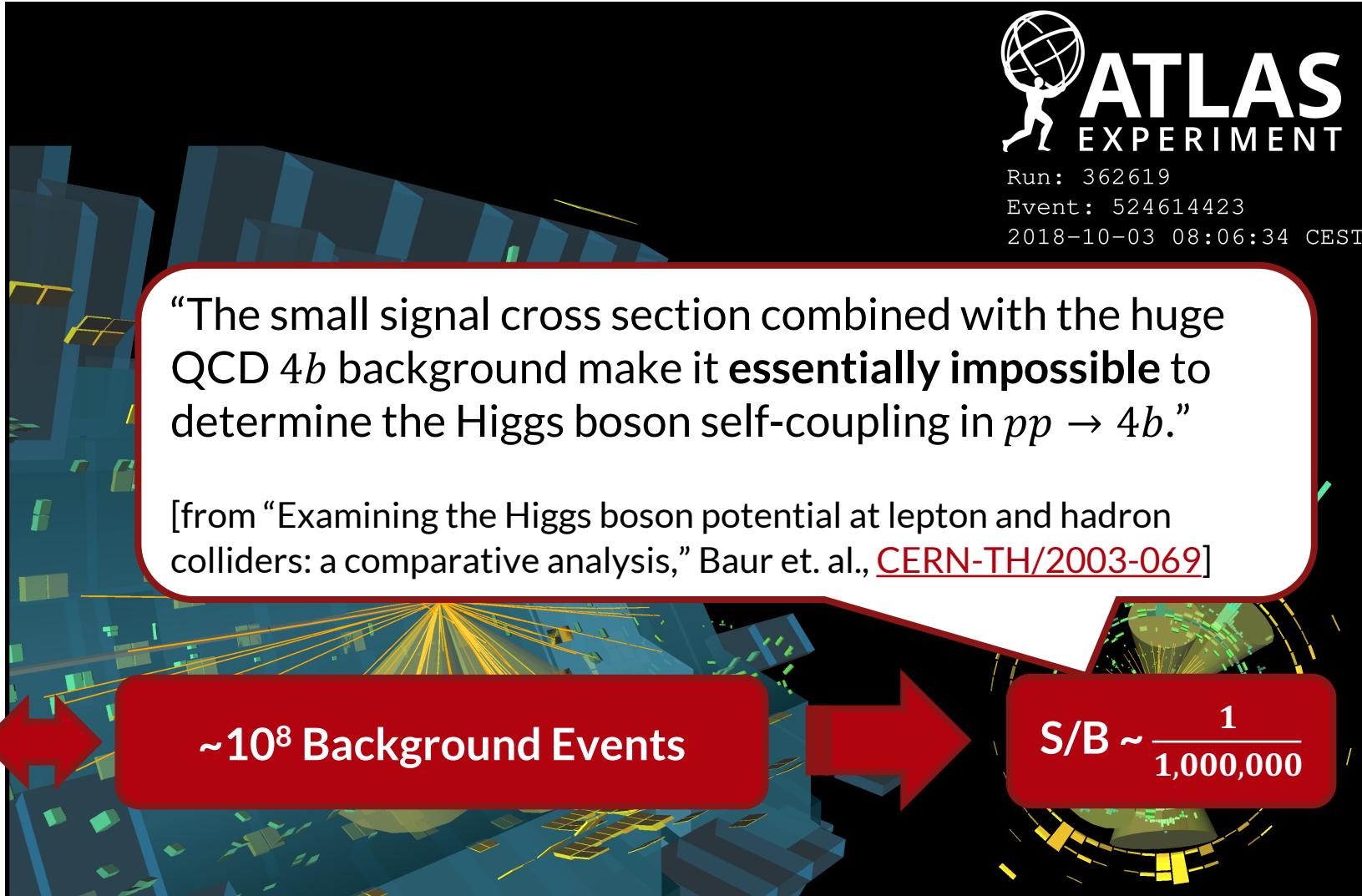
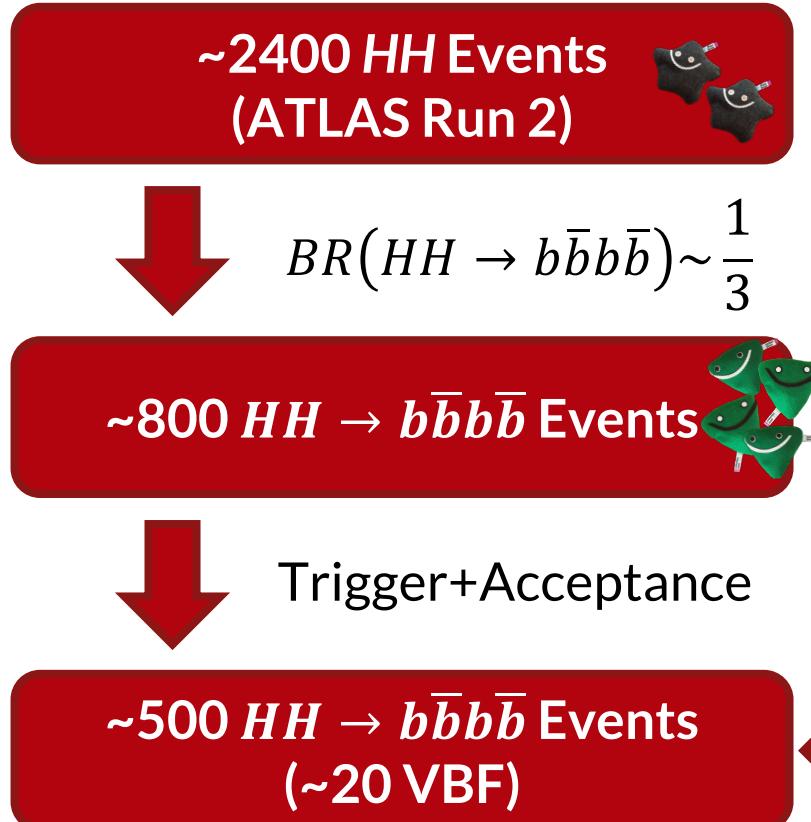
What Makes 4b a Challenging Final State?



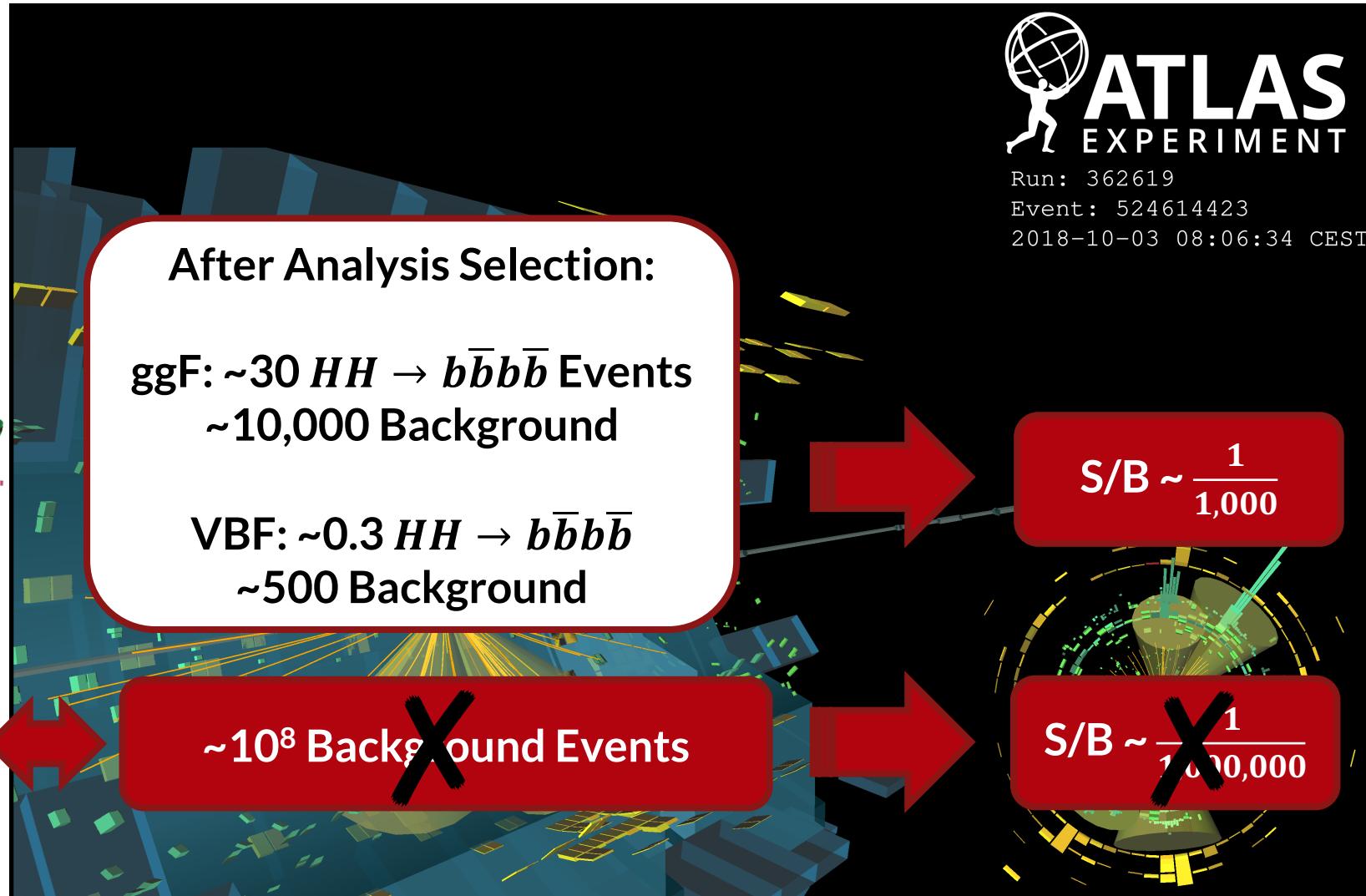
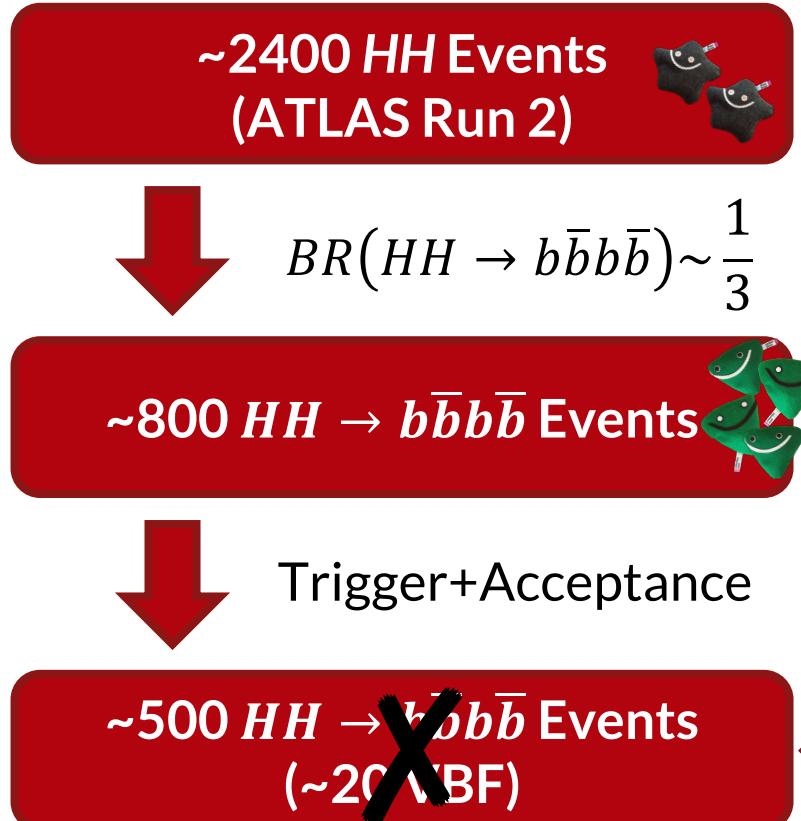
What Makes 4b a Challenging Final State?



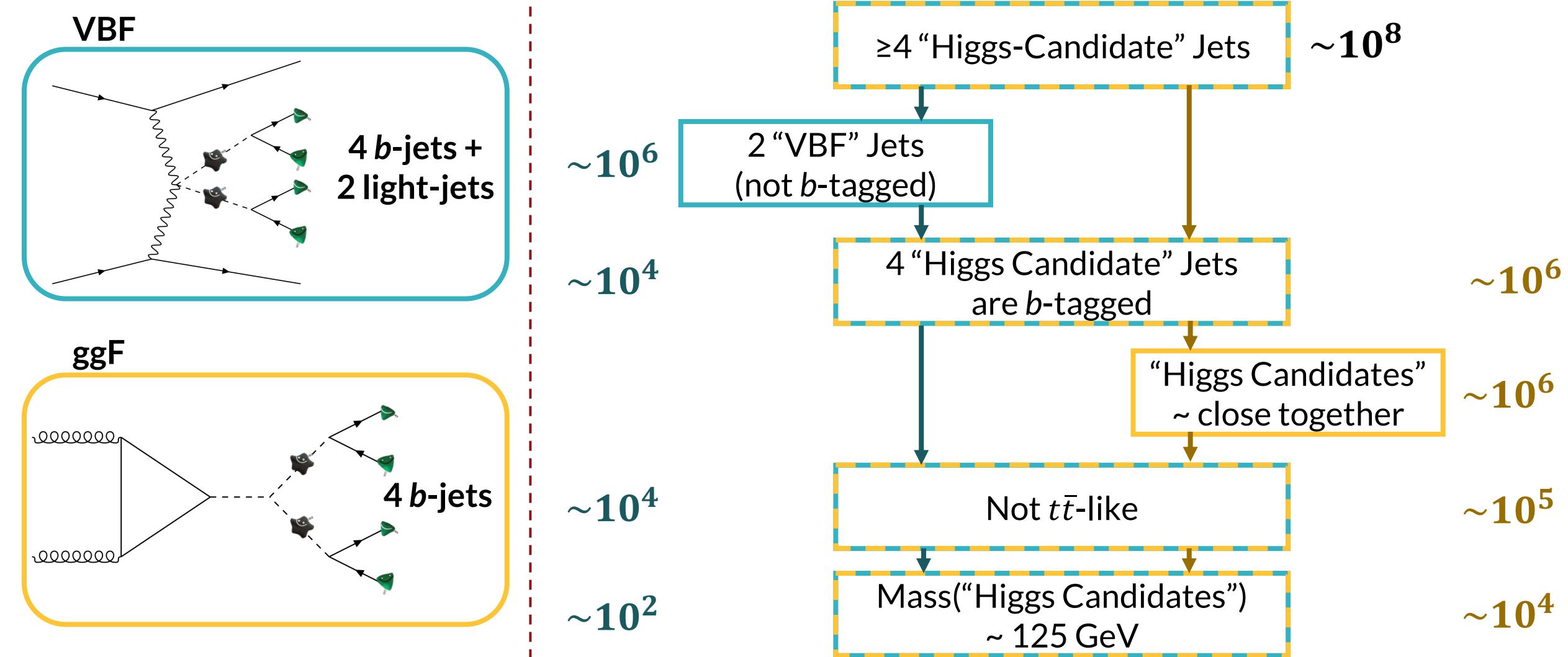
What Makes 4b a Challenging Final State?



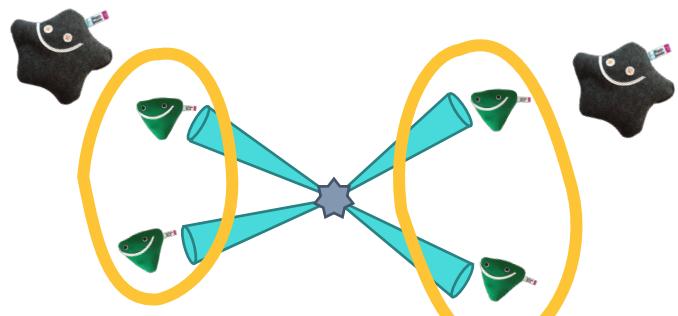
What Makes 4b a Challenging Final State?



Isolating $HH \rightarrow b\bar{b}b\bar{b}$ Events



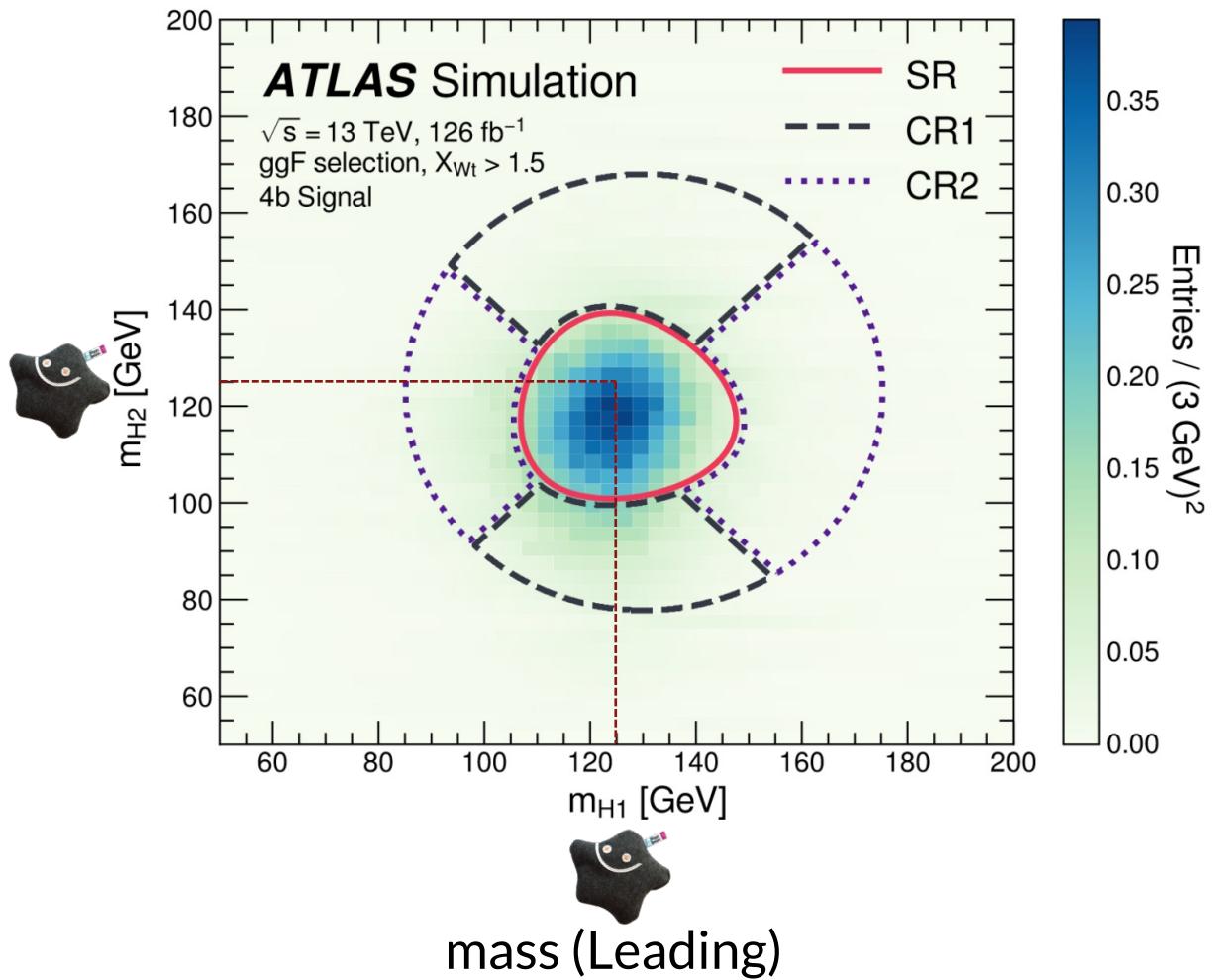
The “Mass-Plane”



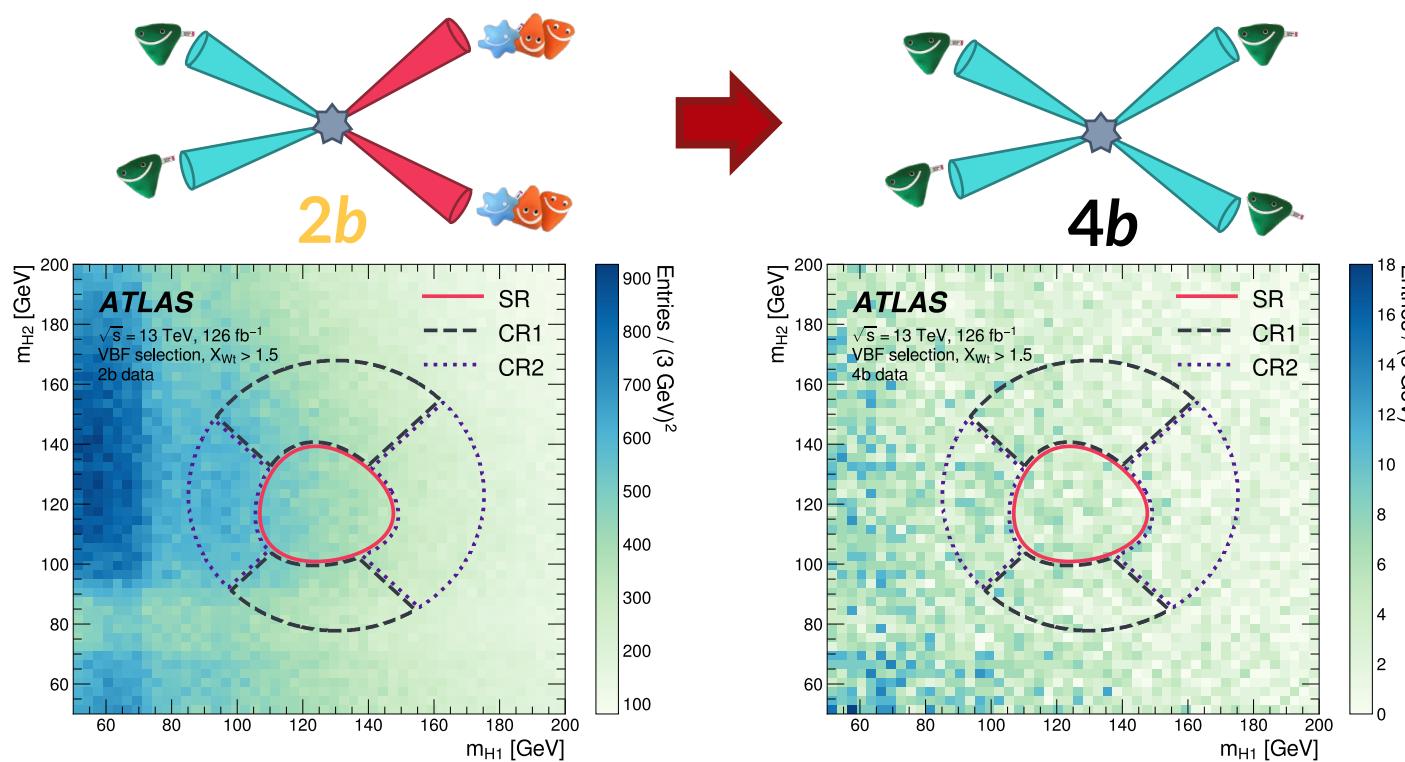
Require reconstructed Higgs Boson candidate masses ~ 125 GeV

→ Define “Signal Region”

mass (Subleading)



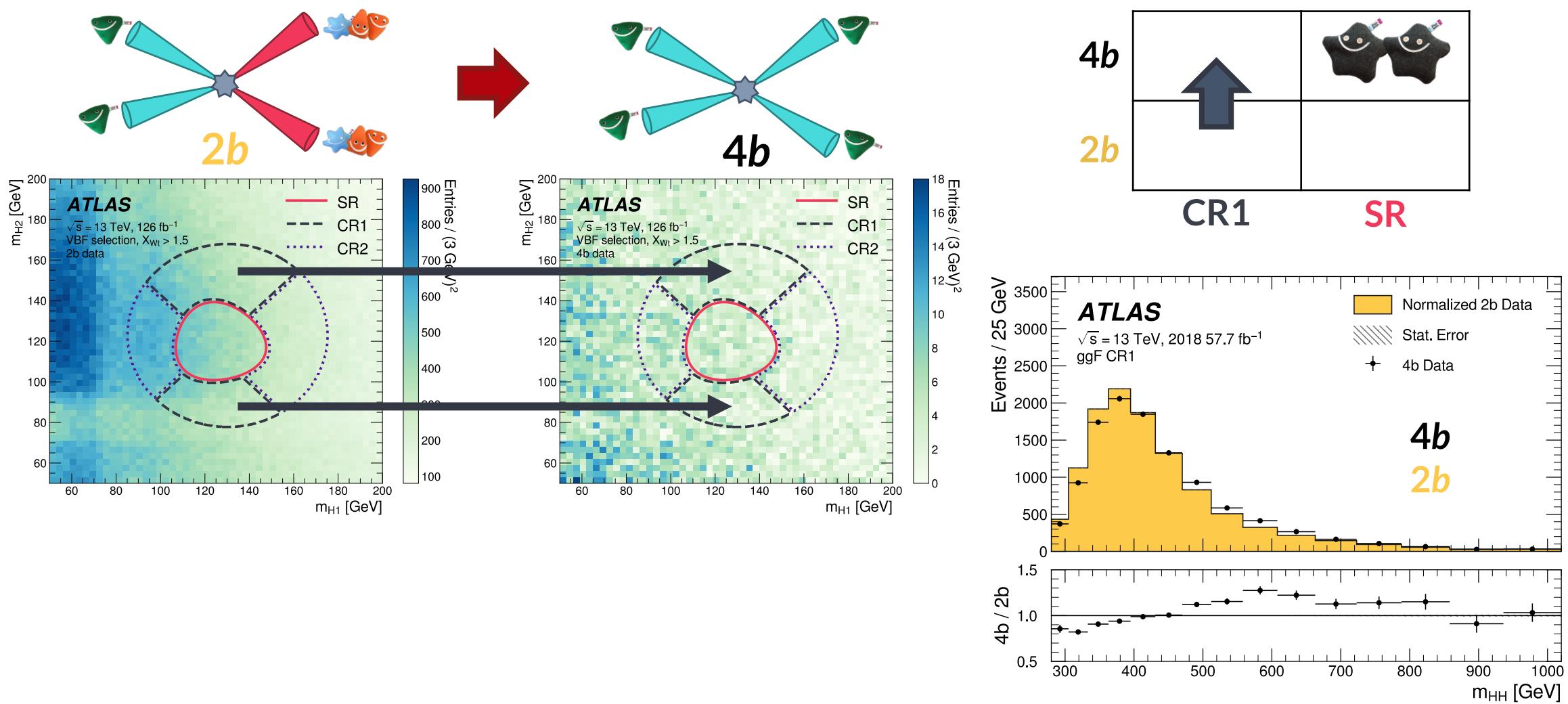
Background Modeling Strategy



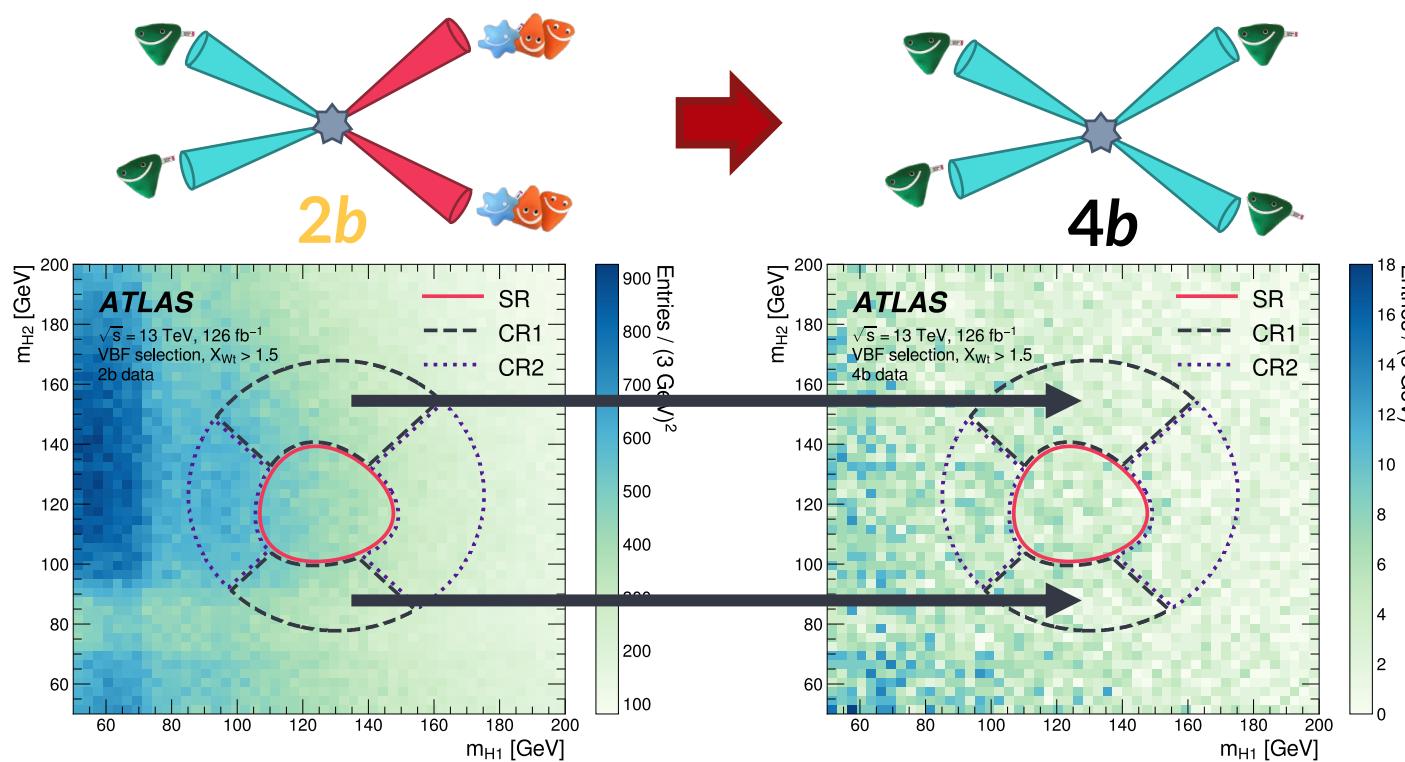
2b background processes
~ 4b background processes

→ use 2b data to estimate
backgrounds in the 4b region?

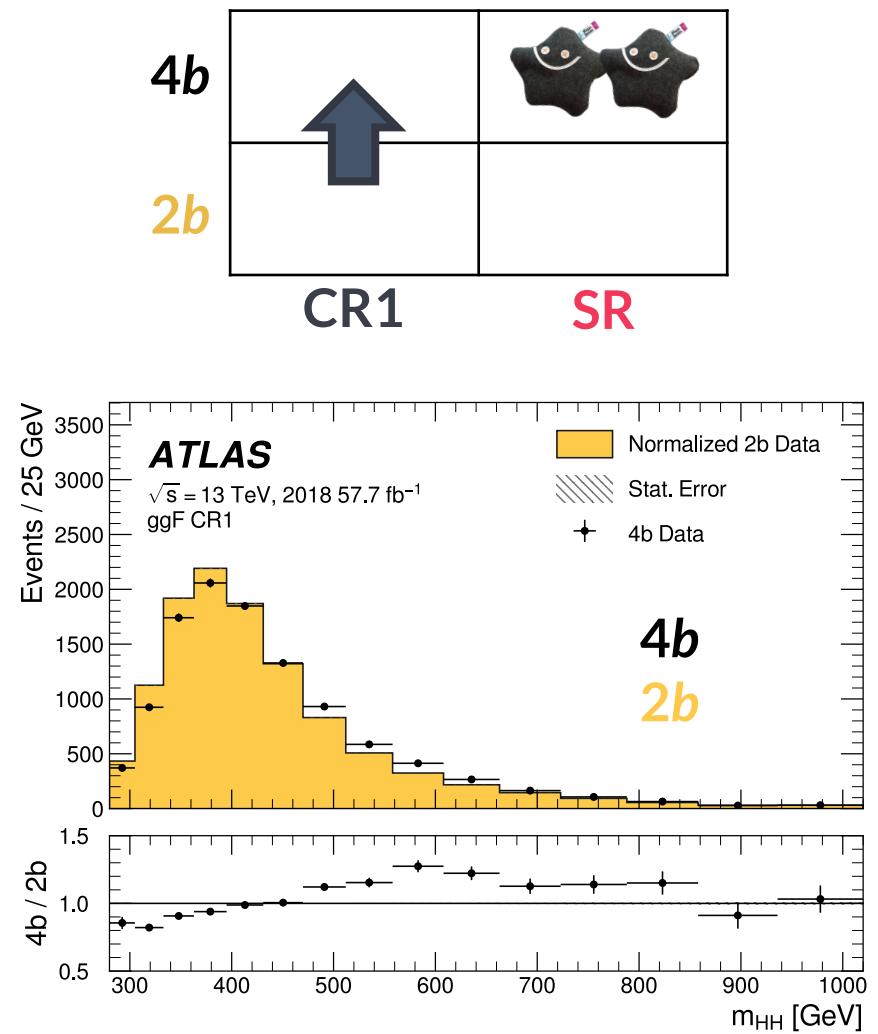
Background Modeling Strategy



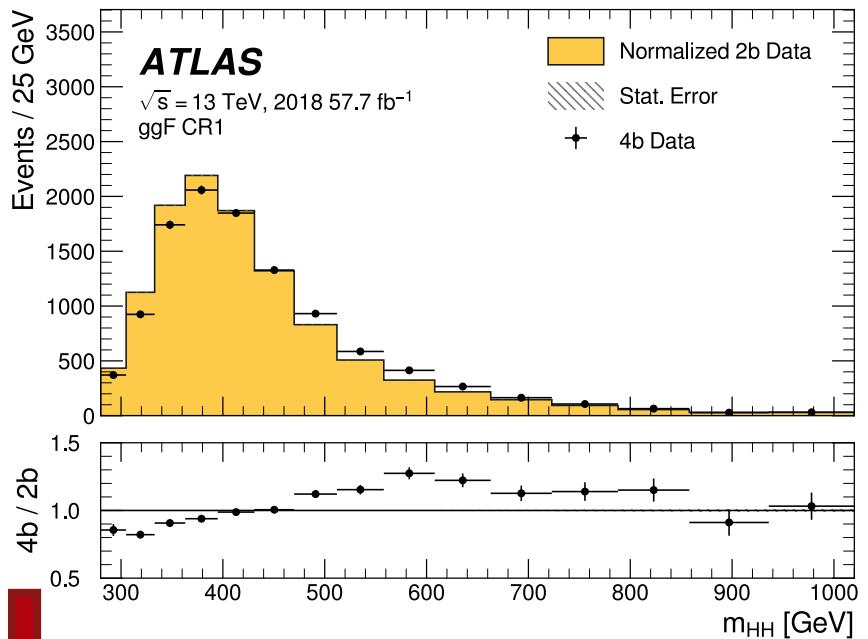
Background Modeling Strategy



1-Dimensional density ratio
 $w(x) = p_{4b}(x)/p_{2b}(x)$

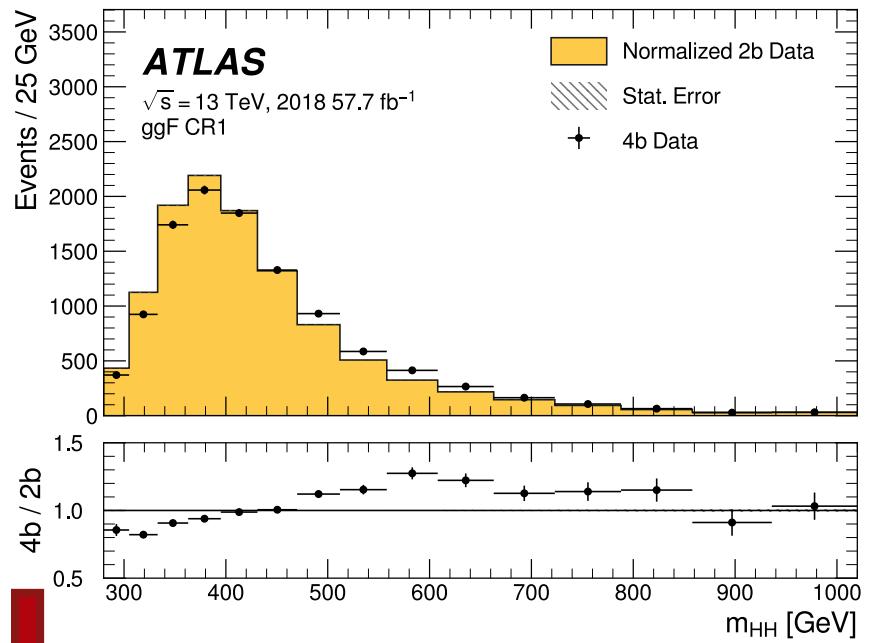


Density Ratio Estimation with Histograms



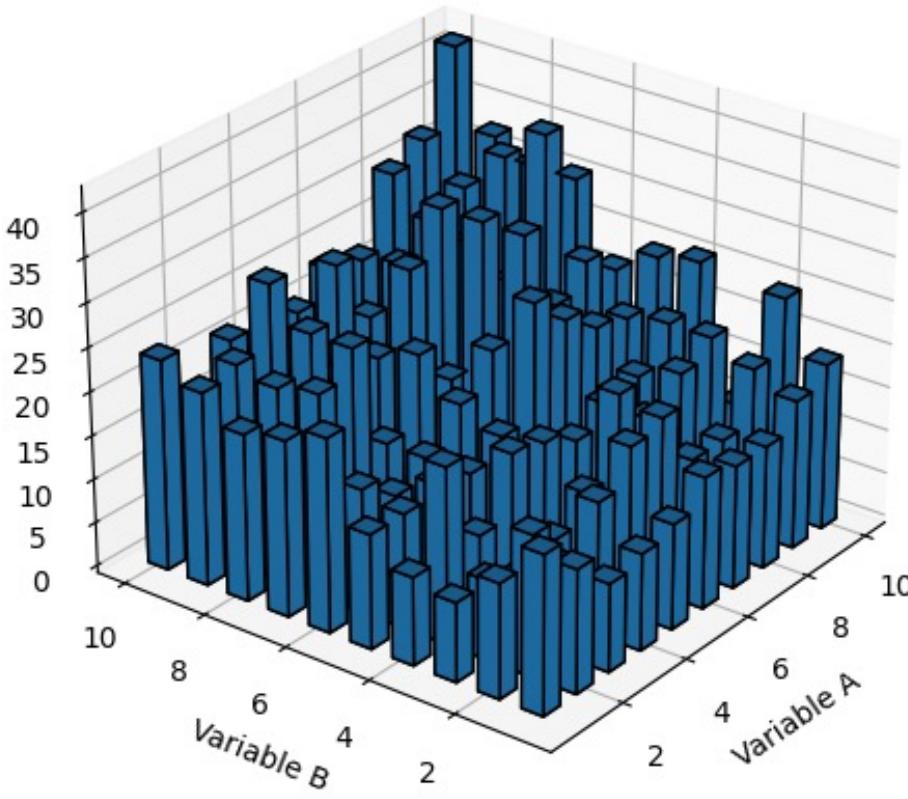
- 1-Dimensional Reweighting
 - Prone to statistical fluctuations
 - No correlation with other kinematics
(assumes similar domain $p_{2b}^{\text{CR}} \sim p_{2b}^{\text{SR}}$)

Density Ratio Estimation with Histograms



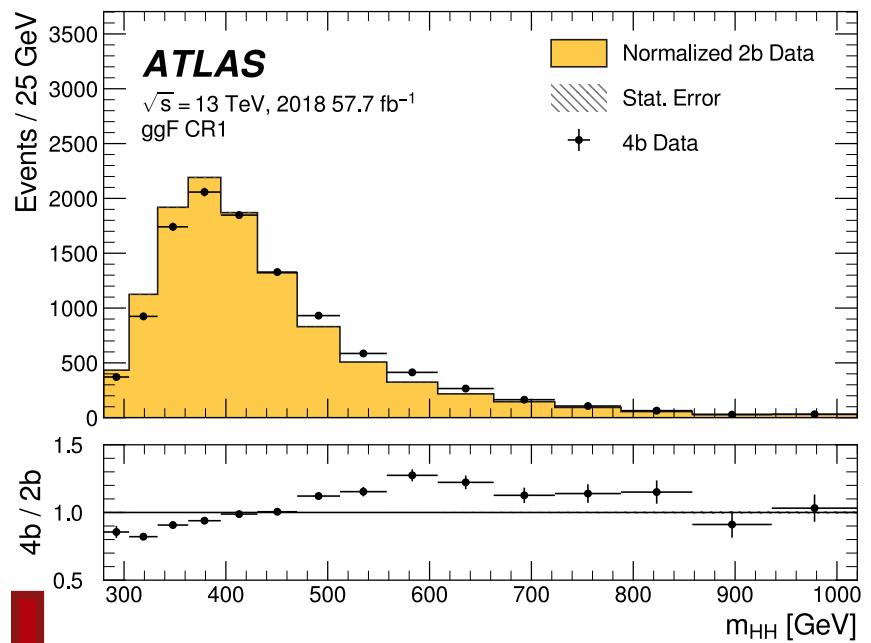
- 1-Dimensional Reweighting
 - Prone to statistical fluctuations
 - No correlation with other kinematics
(assumes similar domain $p_{2b}^{CR} \sim p_{2b}^{SR}$)

Multi-Dimensional Histogram Reweighting?



Curse of
Dimensionality

Density Ratio Estimation with Neural Networks



- 1-Dimensional Reweighting X
- Prone to statistical fluctuations
- No correlation with other kinematics
- (assume similar domain $p_{2b}^{\text{CR}} \sim p_{2b}^{\text{SR}}$)

$$w(\vec{x}) = p_{4b}(\vec{x}) / p_{2b}(\vec{x})$$

Train Neural Network with specific Loss function:

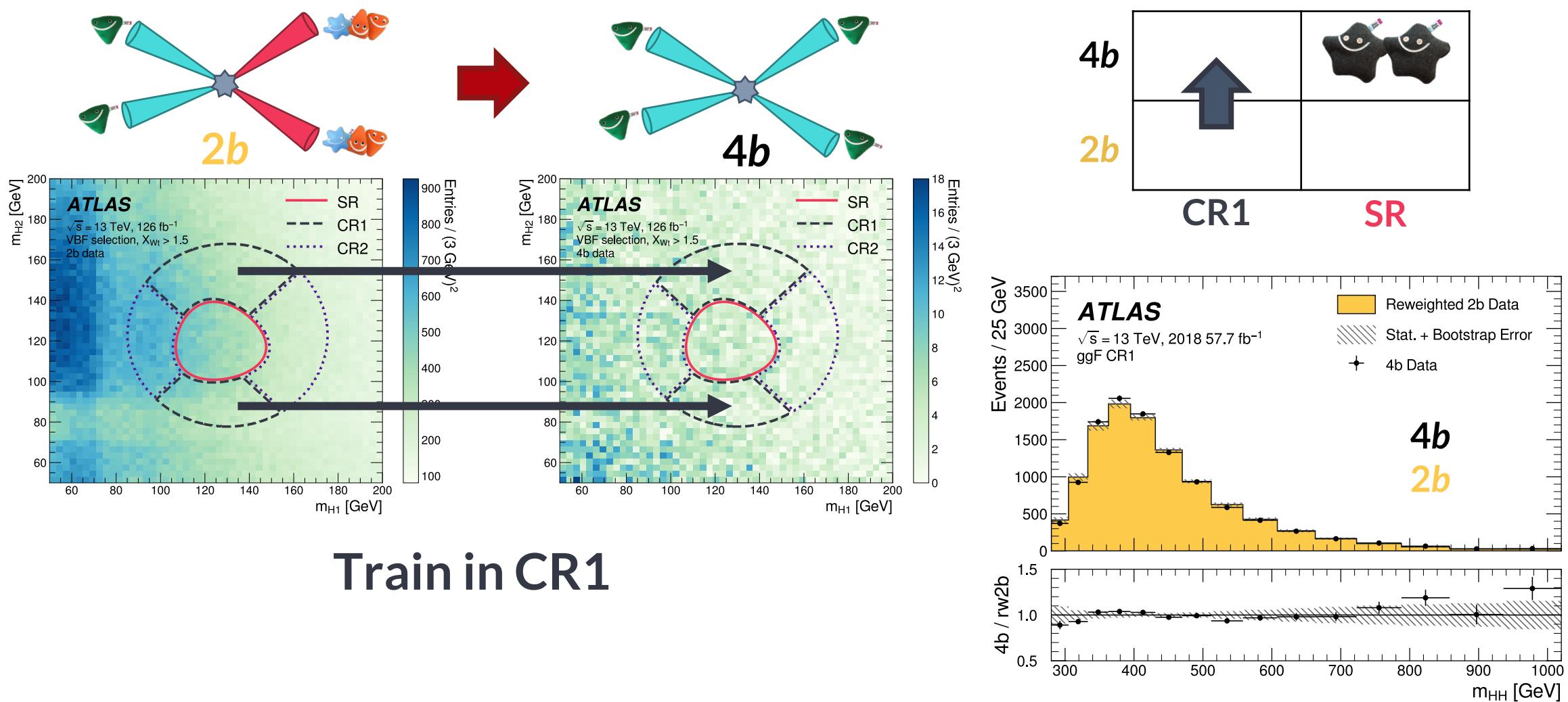
$$\mathcal{L}(R(\vec{x})) = \mathbb{E}_{x \sim p_{2b}} [\sqrt{R(\vec{x})}] + \mathbb{E}_{x \sim p_{4b}} \left[\frac{1}{\sqrt{R(\vec{x})}} \right]$$

$$\rightarrow \arg \min_R \mathcal{L}(R(\vec{x})) = w(\vec{x})$$

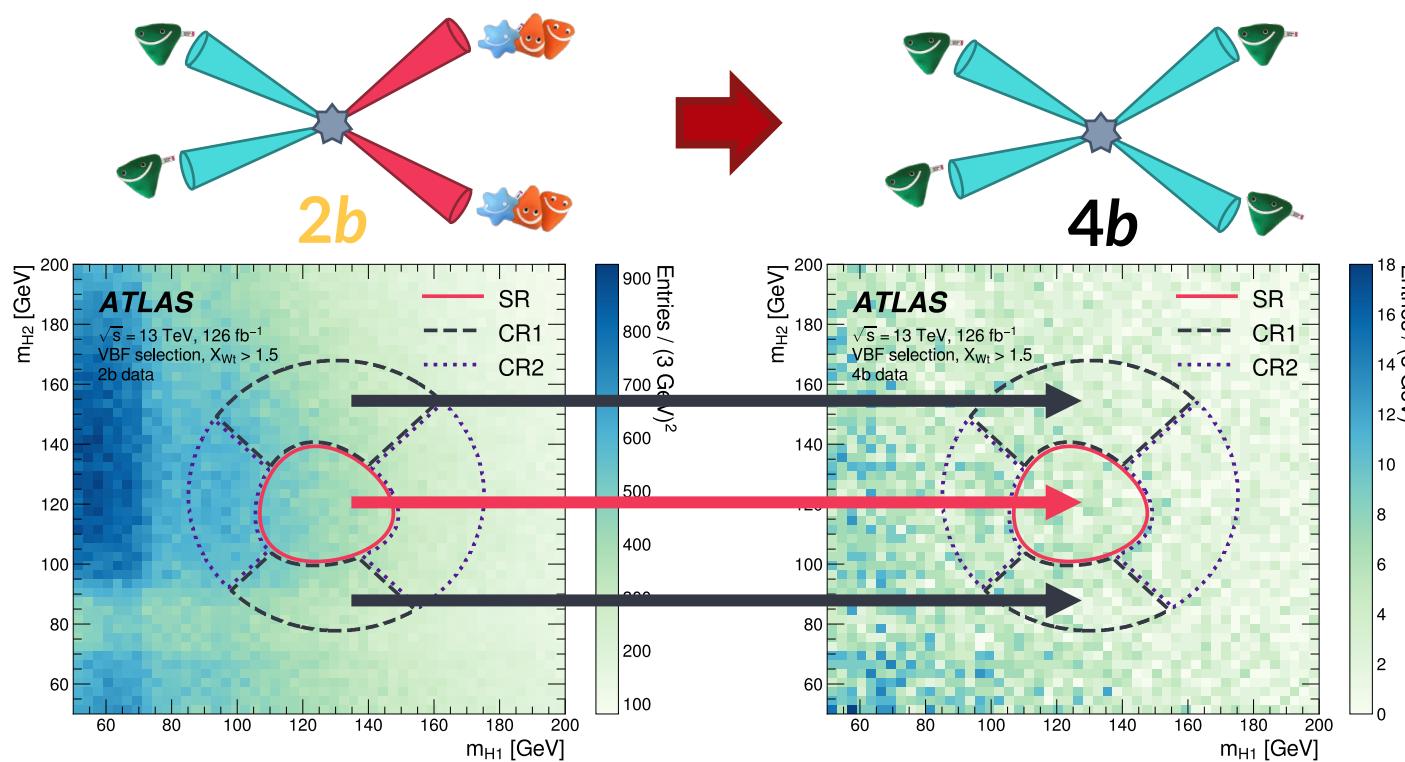
High-dimensional, “Event-level” reweighting!

[arxiv:1911.00405](https://arxiv.org/abs/1911.00405)
Kanamori et. al. (JMLR)

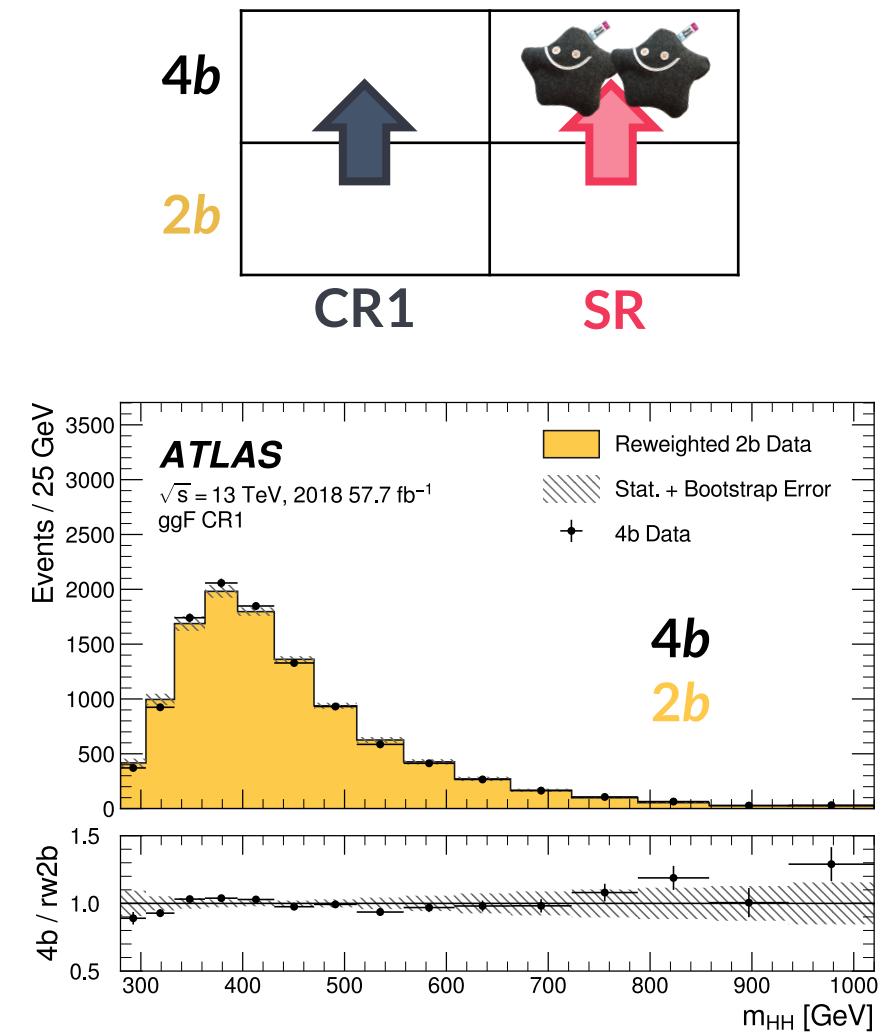
Background Modeling Strategy



Background Modeling Strategy

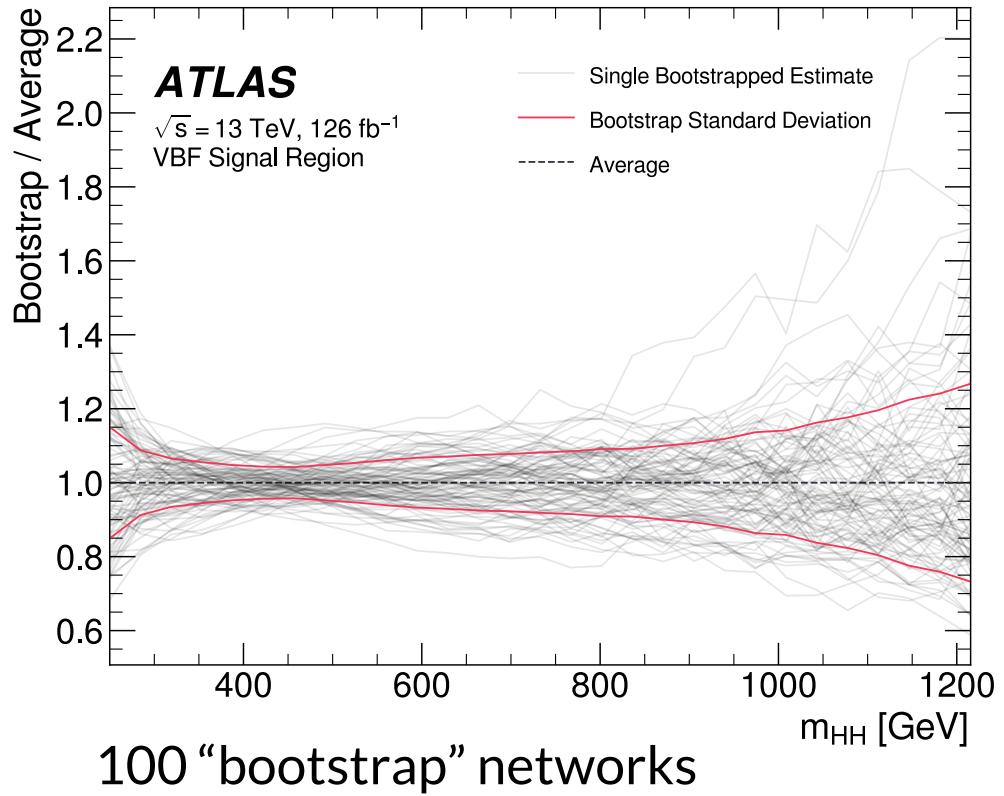


Train in CR1
Apply in SR

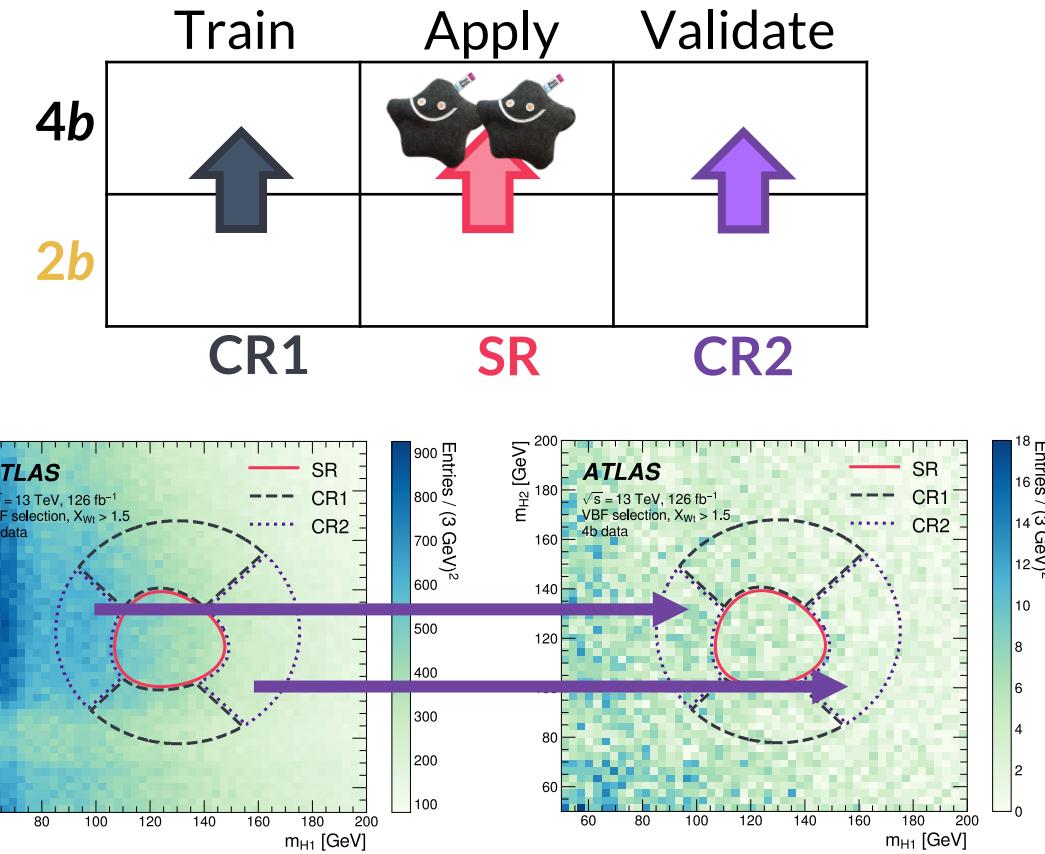


Background Modeling Strategy: Uncertainties

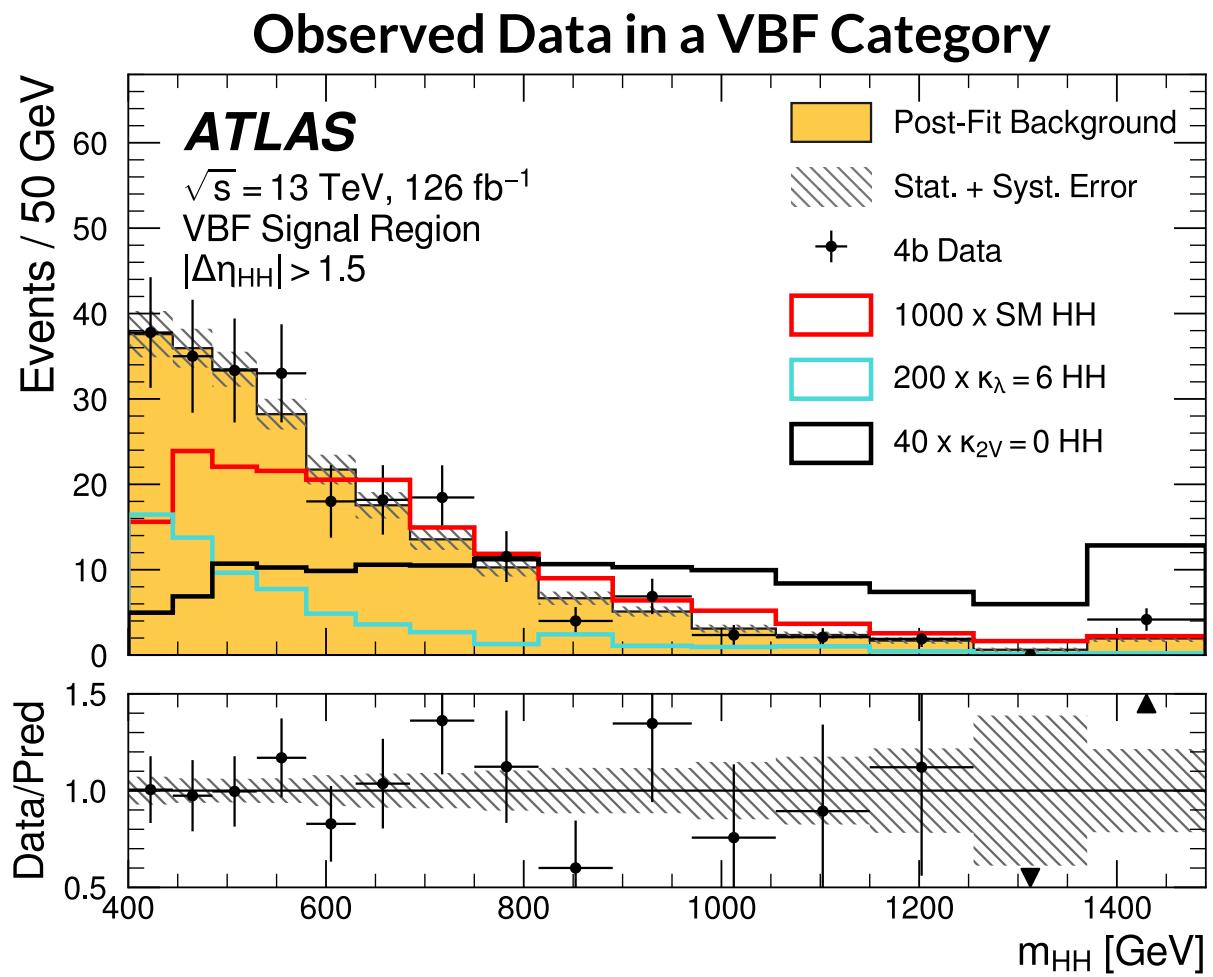
Uncertainty from limited training statistics/network initialization



Uncertainty from domain transfer



Observed Data

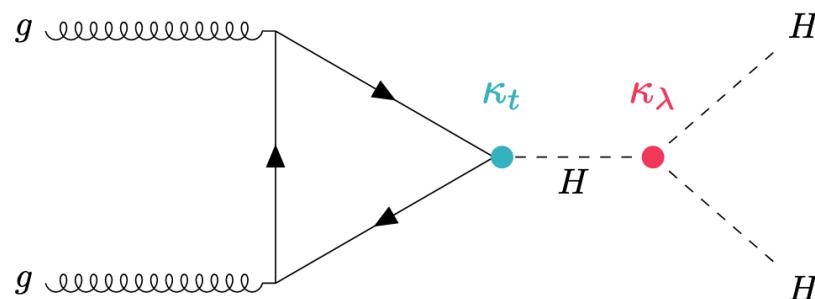


Standard Model ($\kappa_\lambda = \kappa_{2V} = 1$)
 $\kappa_\lambda = 10$ ($\kappa_{2V} = 1$)
 $\kappa_{2V} = 0$ ($\kappa_\lambda = 1$)

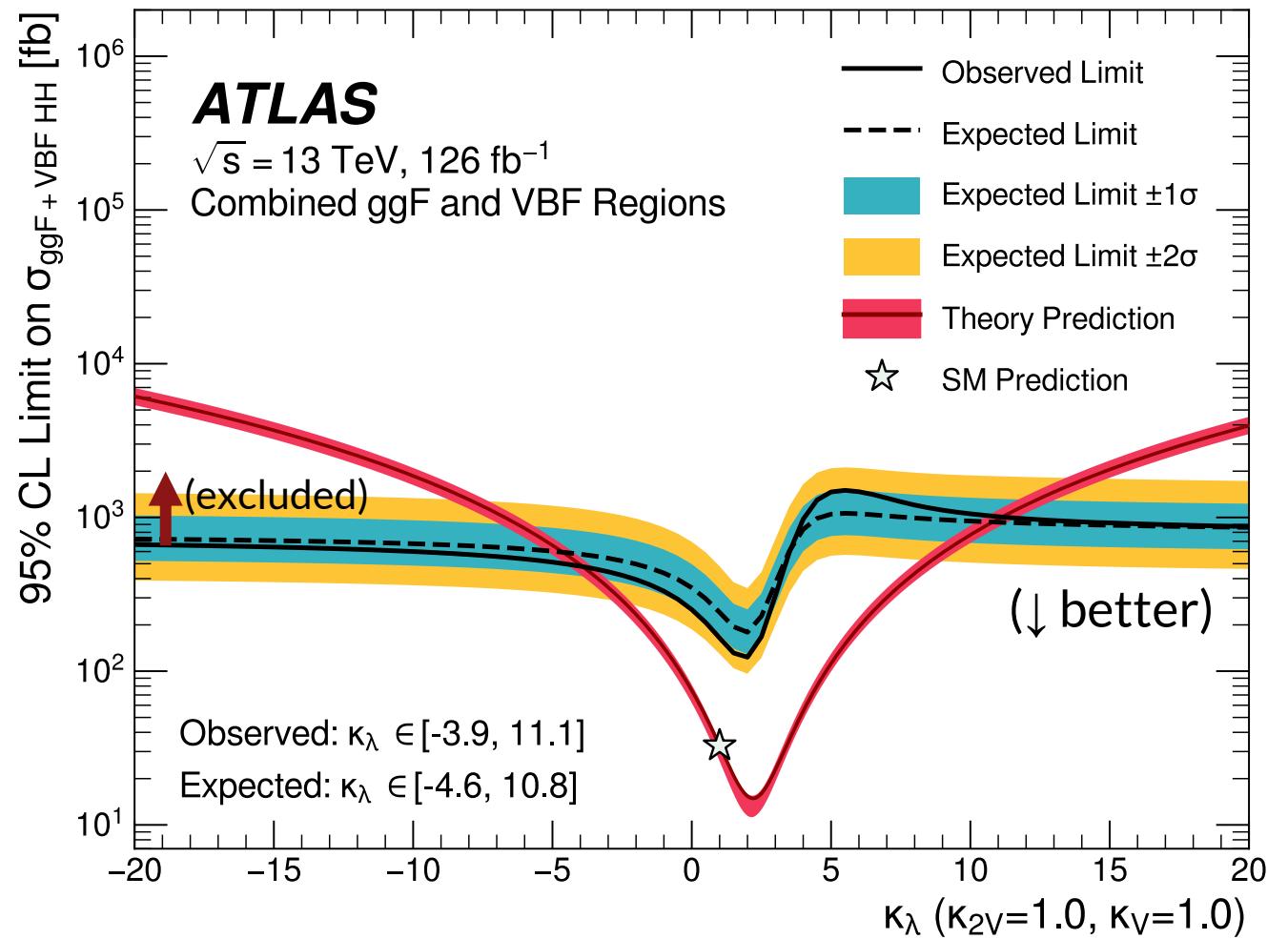
Neural-network
reweighted background
agrees well with
observed data

Results - κ_λ

Constraining the $H\bar{H}H$ coupling

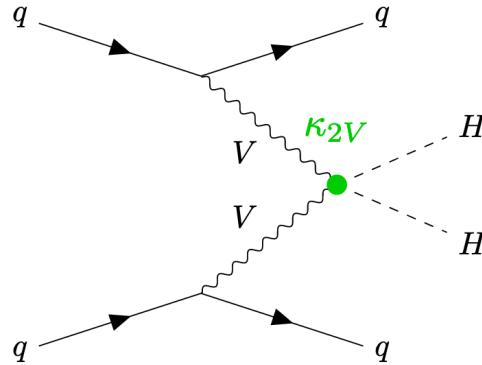


BSM softer \rightarrow less sensitive

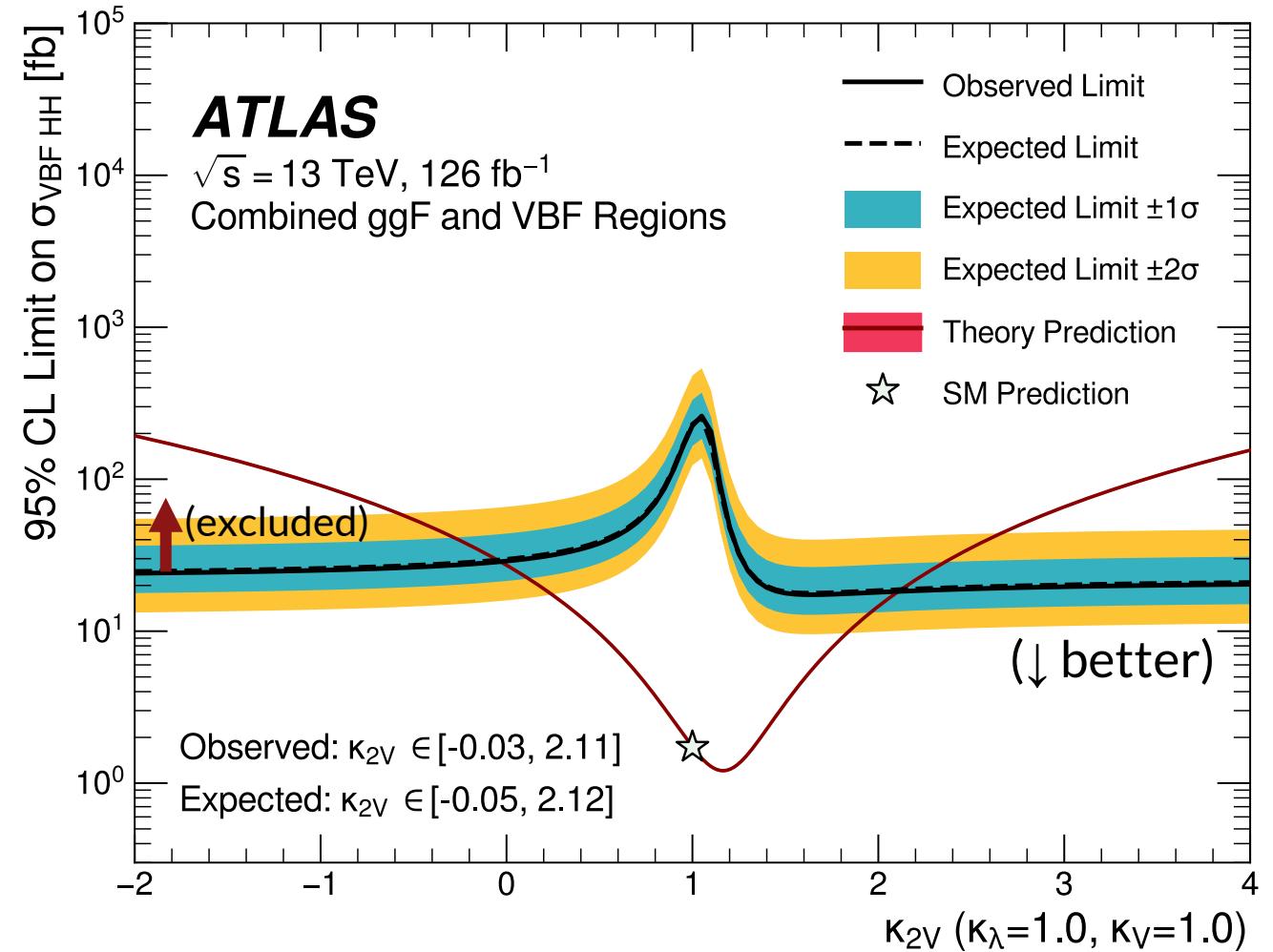


Results - κ_{2V}

Constraining the $HHVV$ coupling

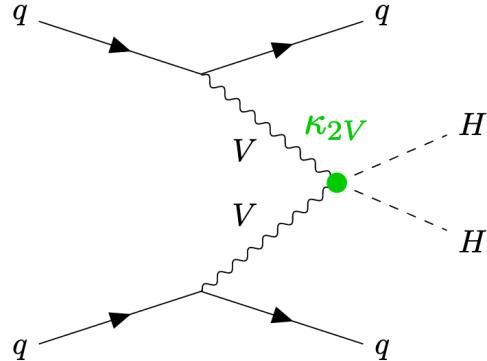


BSM harder → more sensitive



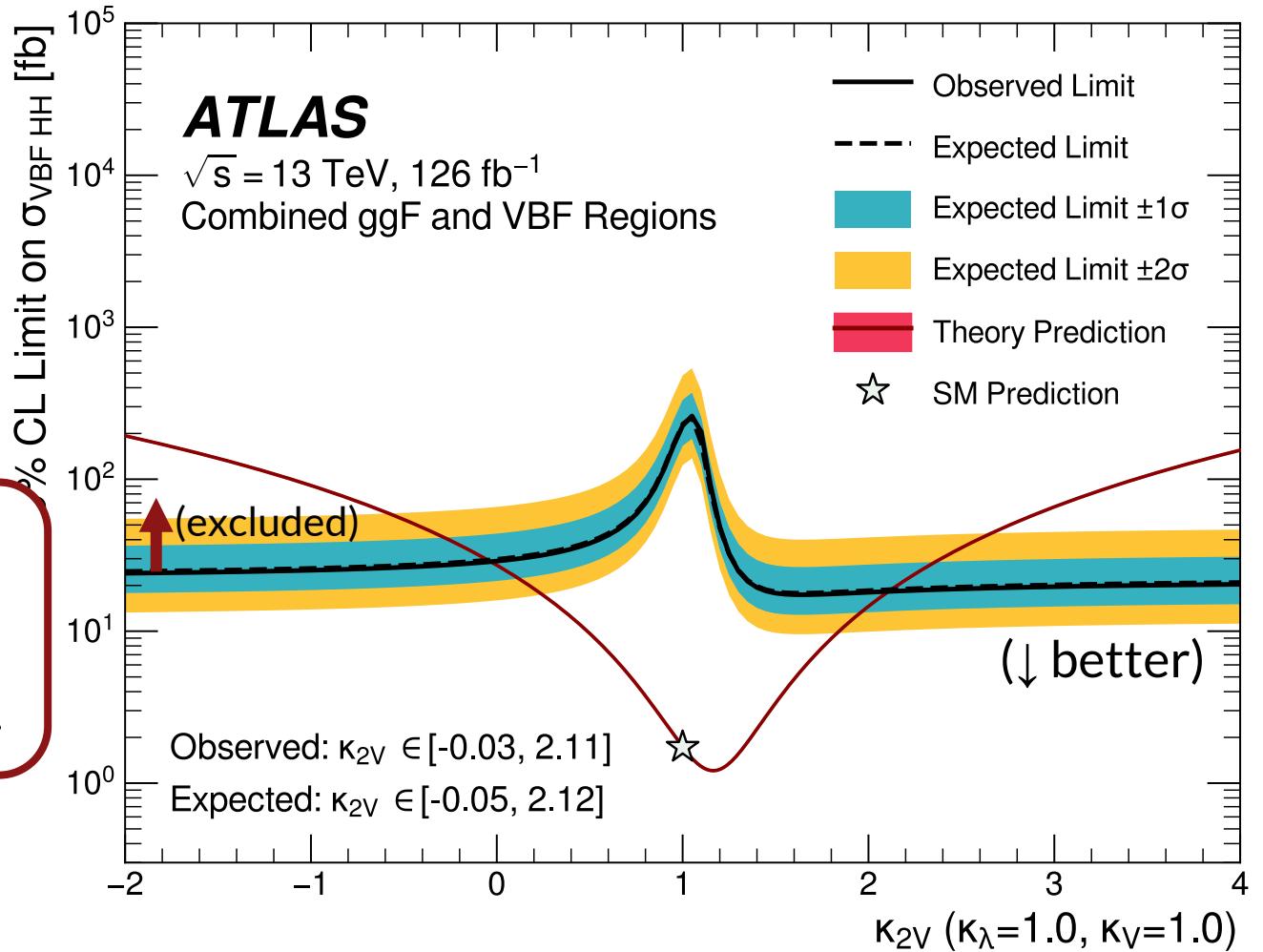
Results - κ_{2V}

Constraining the $HHVV$ coupling



Compared to previous ATLAS result:
~75% improvement on $\sigma_{\text{VBF}}^{\text{SM}}$ upper limit!
~30% improvement on allowed κ_{2V} range!

[arxiv:2001.05178](https://arxiv.org/abs/2001.05178)

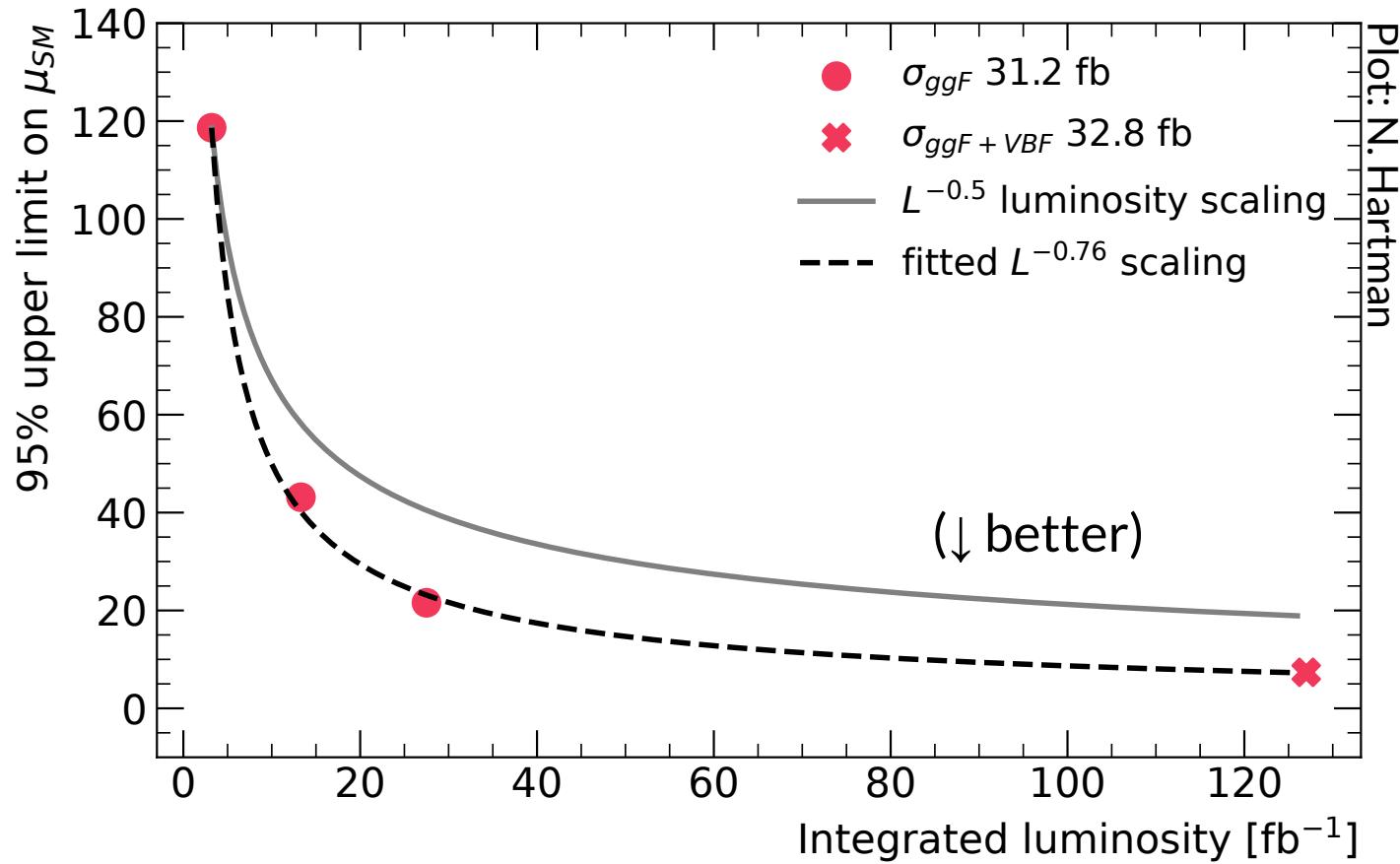


How Have We Been Improving HH Measurements?

More data
&
Better techniques to analyze data

Increasing dataset by factor
of x improves limits by $x^{-0.5}$

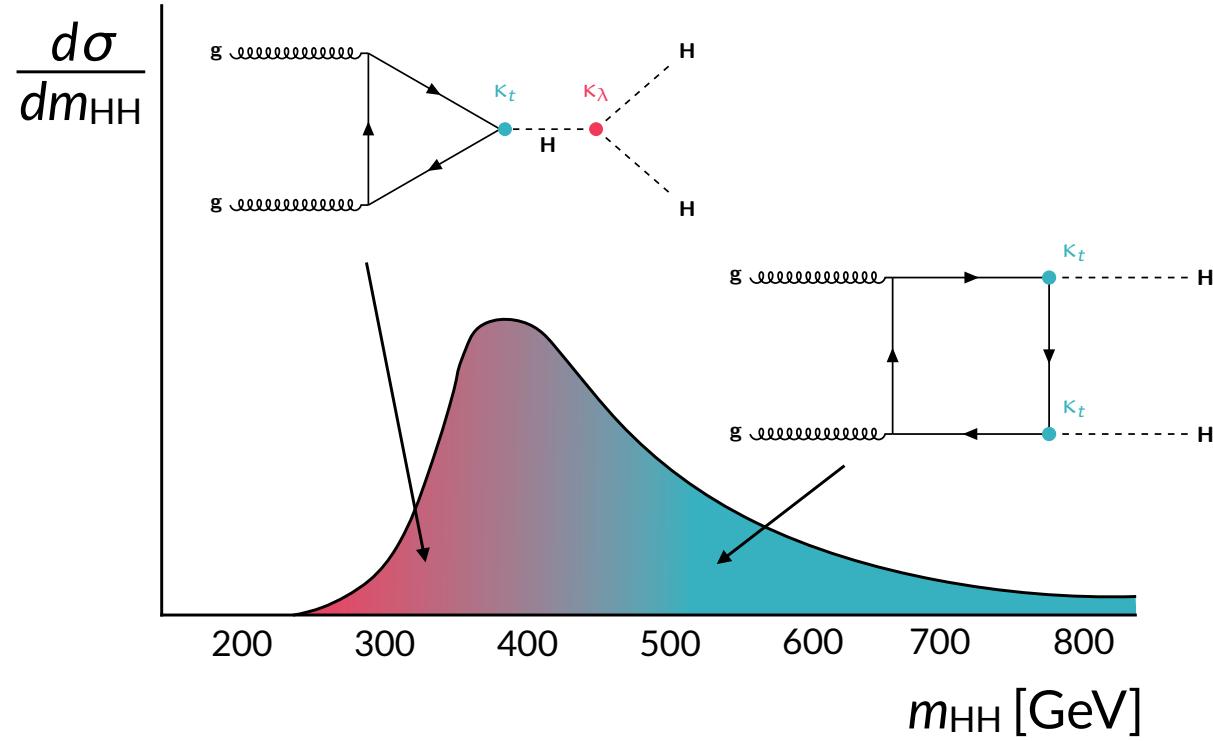
Results improving by factor
of $\sim x^{-0.76}$



How does this result fit into the broader ATLAS HH Program?

Combination and Future Prospects

Combination: $HH \rightarrow b\bar{b}b\bar{b}, b\bar{b}\tau\tau, b\bar{b}\gamma\gamma$

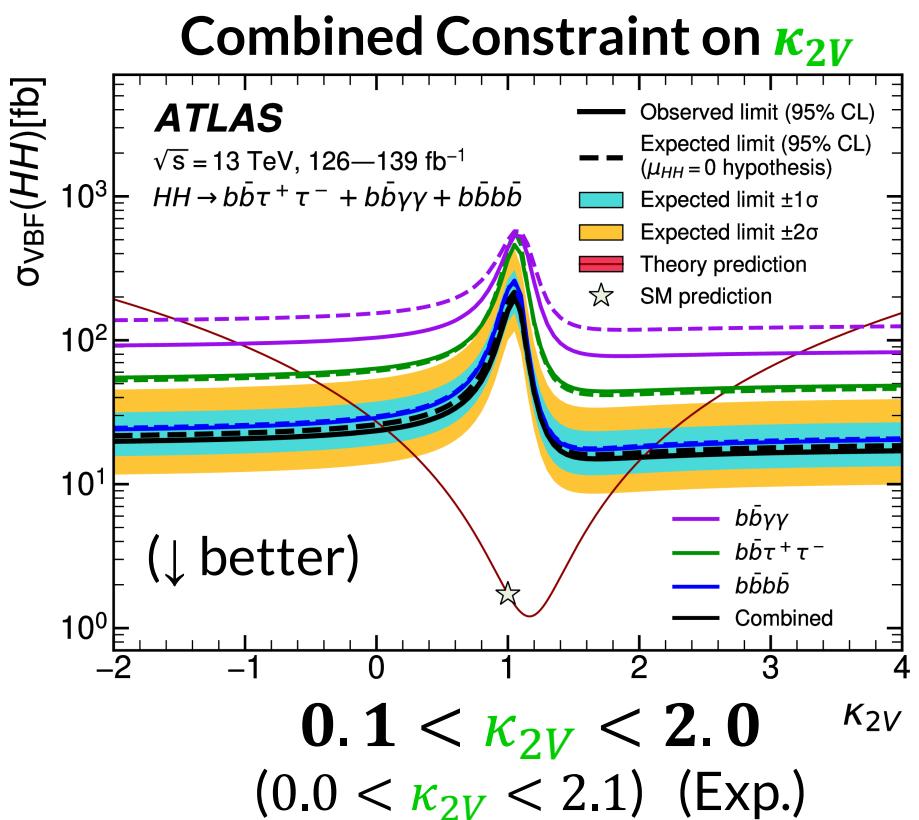
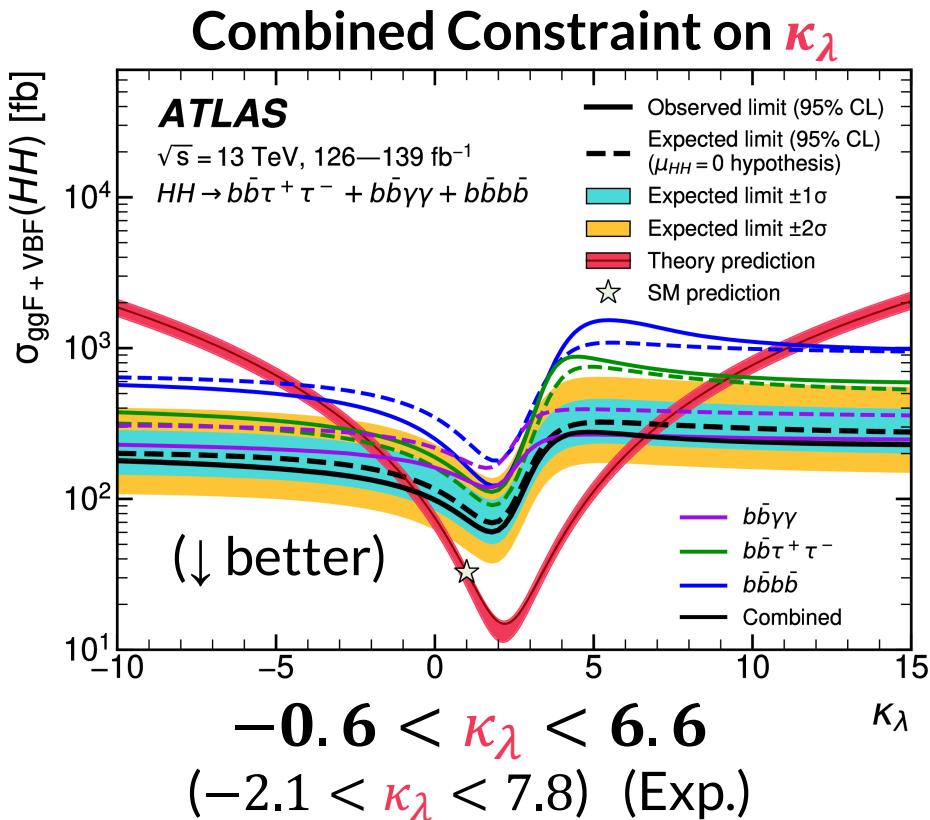


| | bb | WW | ττ | ZZ | γγ |
|----|-------|-------|--------|--------|---------|
| bb | 34% | | | | |
| WW | 25% | 4.6% | | | |
| ττ | 7.3% | 2.7% | 0.39% | | |
| ZZ | 3.1% | 1.1% | 0.33% | 0.069% | |
| γγ | 0.26% | 0.10% | 0.028% | 0.012% | 0.0005% |

← $b\bar{b}\gamma\gamma$ $b\bar{b}\tau\tau$ $b\bar{b}b\bar{b}$ →

~ Sensitive region by decay channel

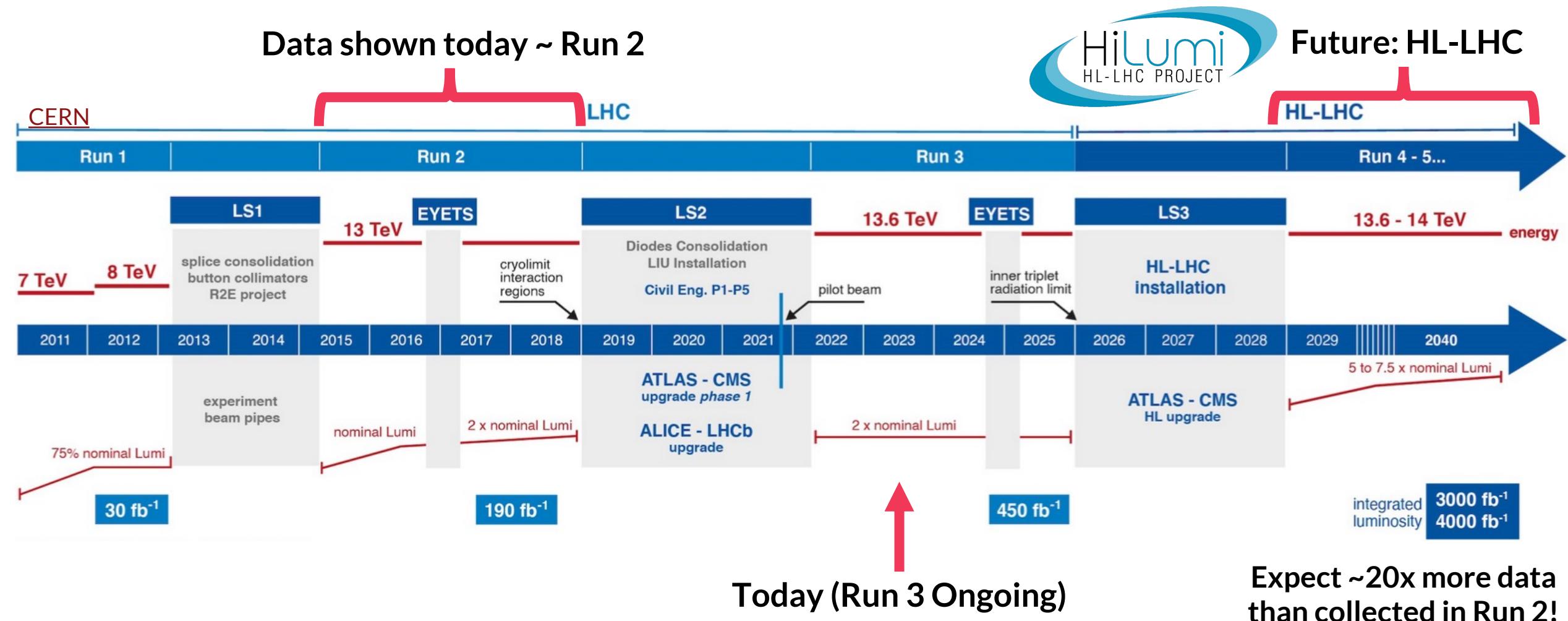
Combination: $HH \rightarrow b\bar{b}b\bar{b}, b\bar{b}\tau\tau, b\bar{b}\gamma\gamma$



| | bb | WW | tt | zz | yy |
|----|-------|-------|--------|--------|---------|
| bb | 34% | | | | |
| WW | 25% | 4.6% | | | |
| tt | 7.3% | 2.7% | 0.39% | | |
| zz | 3.1% | 1.1% | 0.33% | 0.069% | |
| yy | 0.26% | 0.10% | 0.028% | 0.012% | 0.0005% |

→ $b\bar{b}b\bar{b}$ final state less sensitive to BSM κ_λ , but most sensitive to BSM κ_{2V}

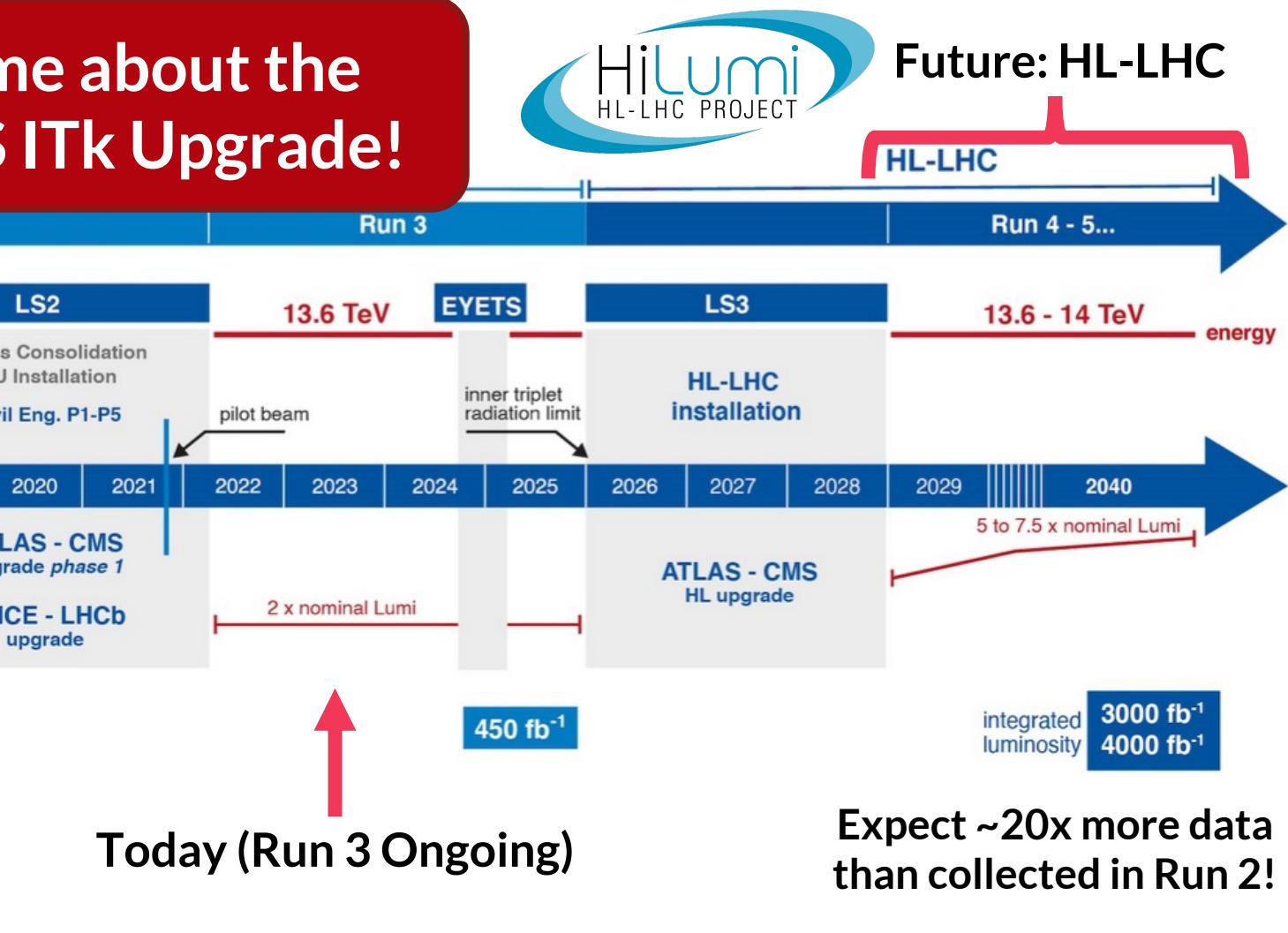
Looking to the Future: The High-Luminosity LHC



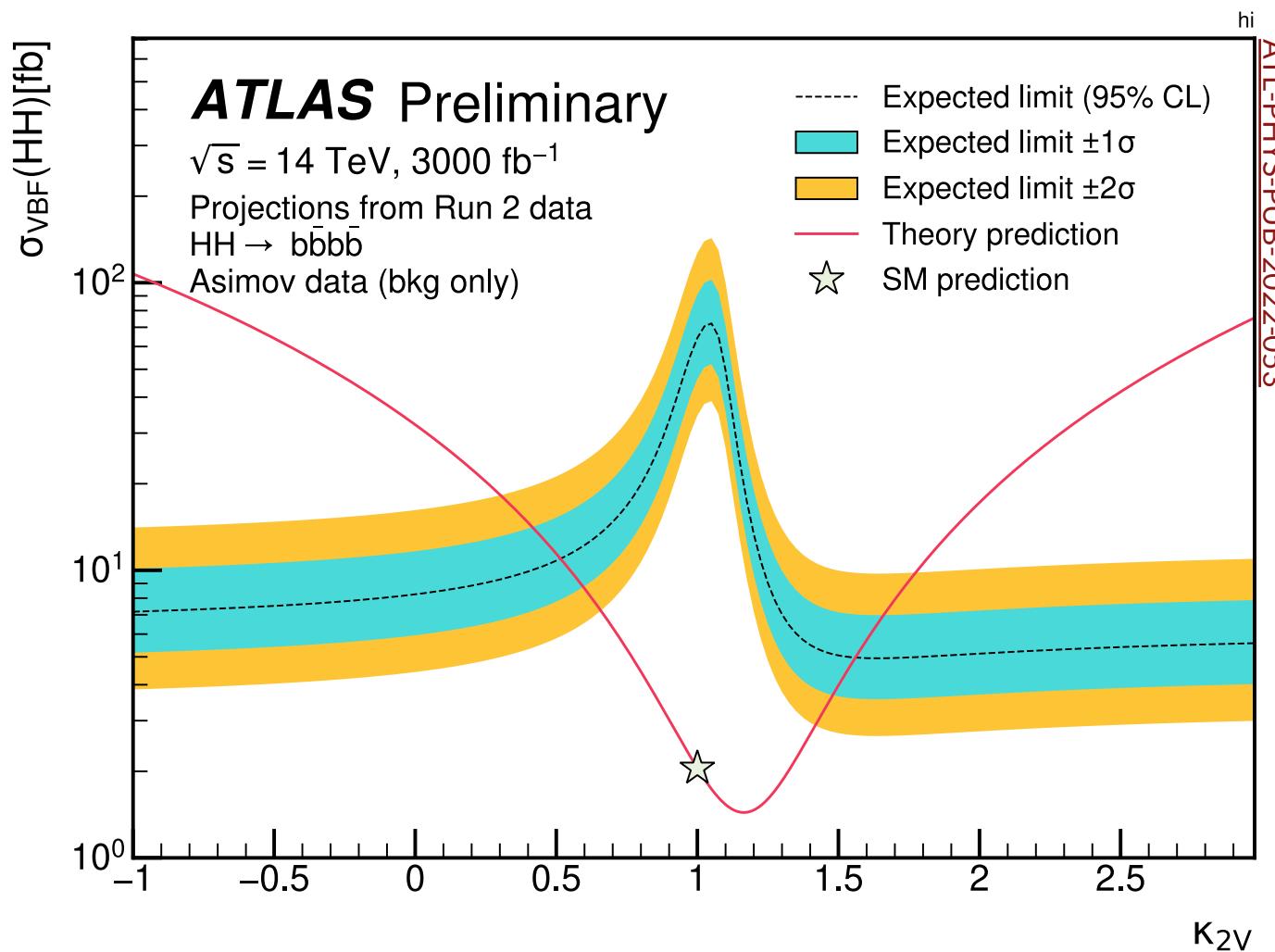
Looking to the Future: The High-Luminosity LHC



Ask me about the
ATLAS ITk Upgrade!



HH Prospects at the High-Luminosity LHC: κ_{2V}

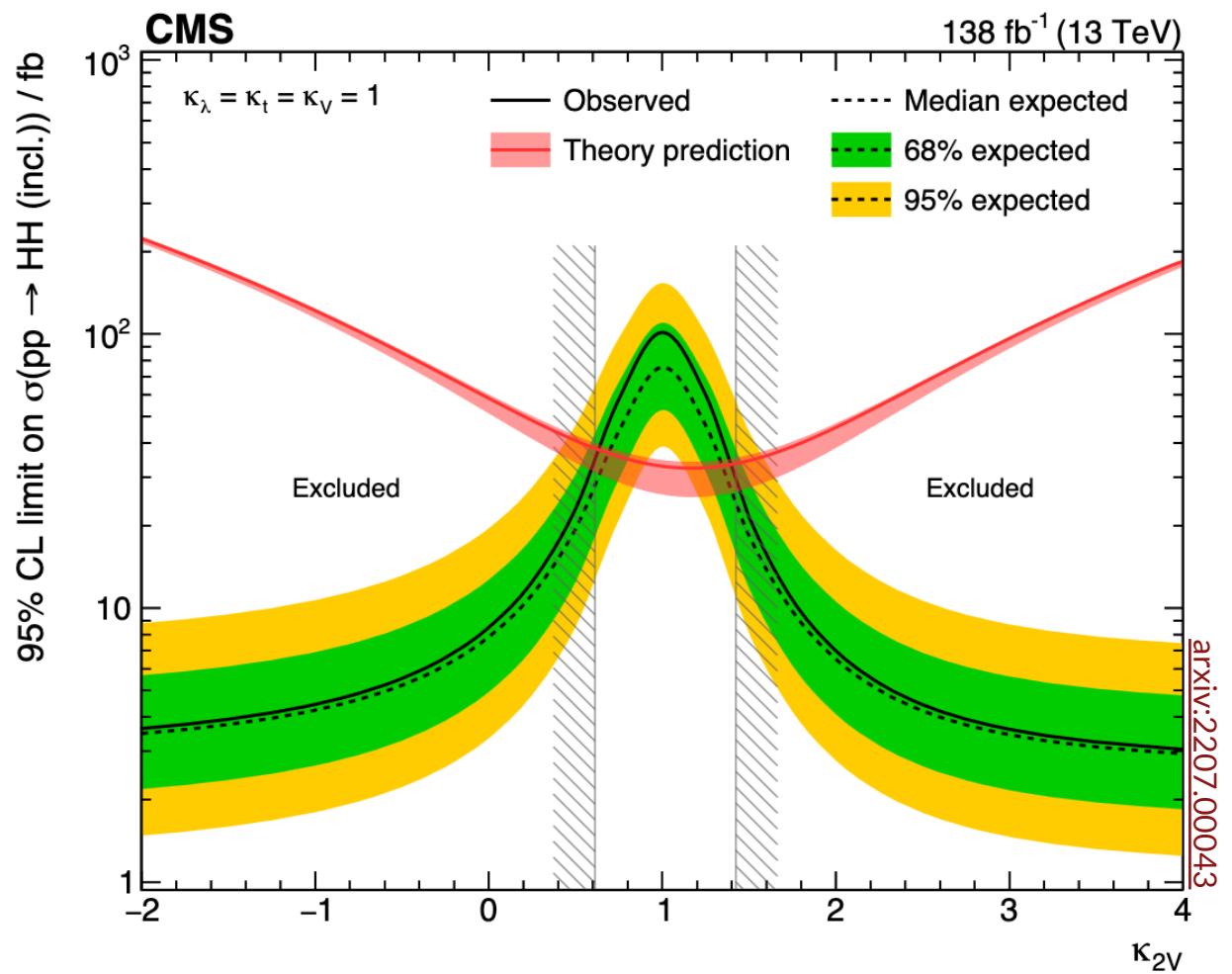


Full HL-LHC Dataset,
 $\text{HH} \rightarrow b\bar{b}b\bar{b}$ only:

$$0.5 < \kappa_{2V} < 1.6$$

→ Sensitive to $\mathcal{O}(\sim 50\%)$ effects

How is CMS Doing?

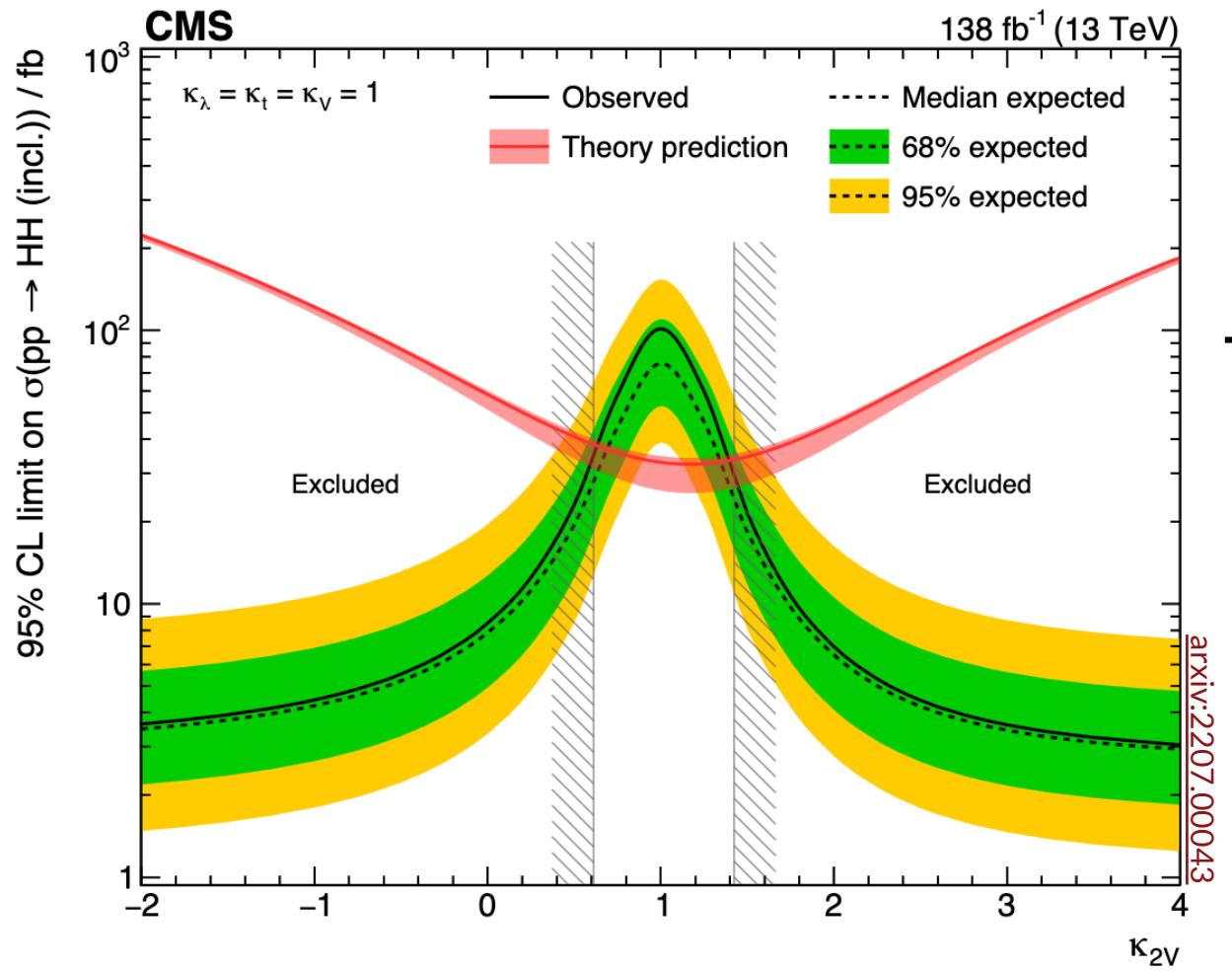


CMS HH Combination (Run 2):

$$0.67 < \kappa_{2V} < 1.38$$

... better than ATLAS HL-LHC
Projection??

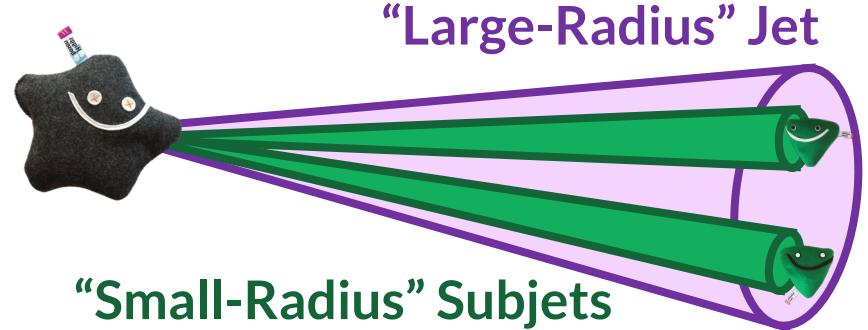
How is CMS Doing?



CMS HH Combination (Run 2):

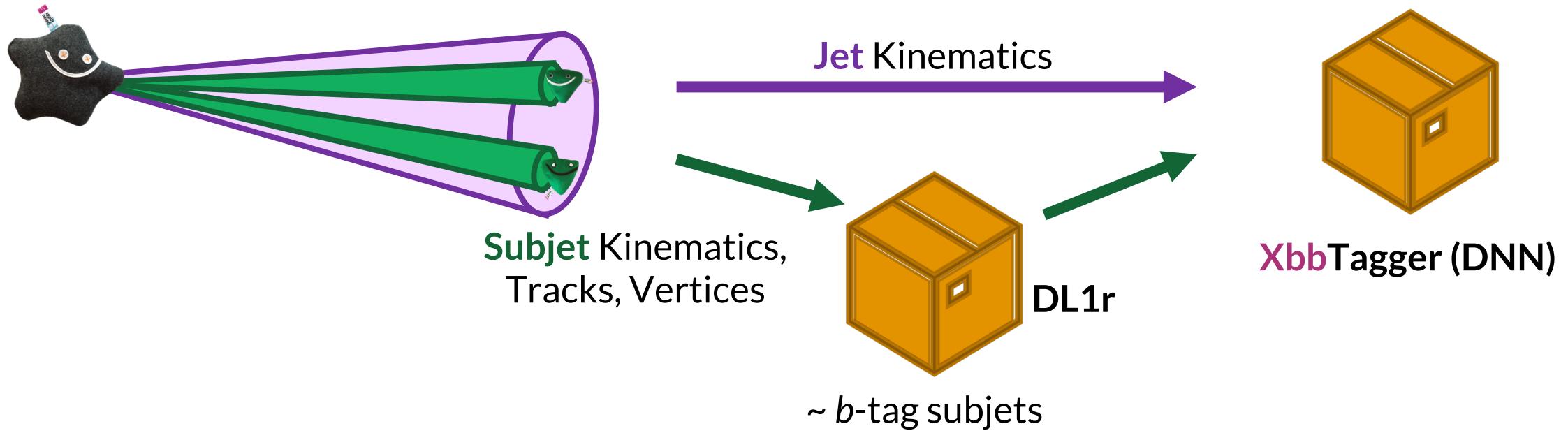
$$0.67 < \kappa_{2V} < 1.38$$

→ Driven by “boosted” $b\bar{b}b\bar{b}$ analysis!

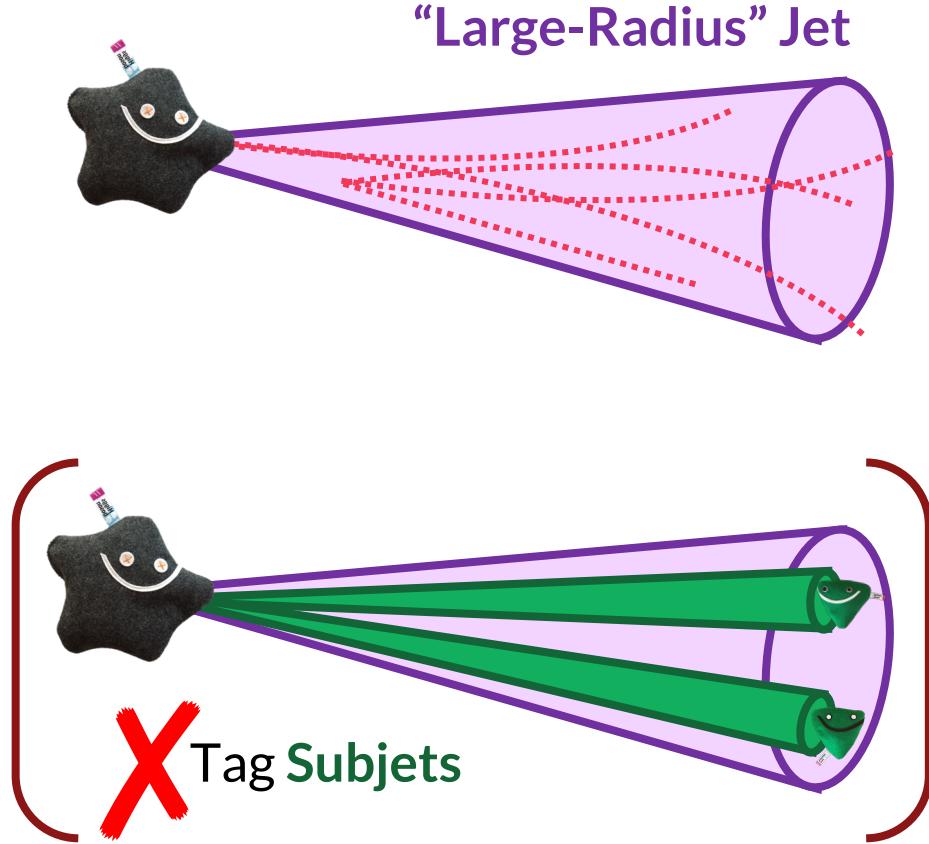


Less background at higher energy +
Dedicated ML-based $H \rightarrow b\bar{b}$ tagging

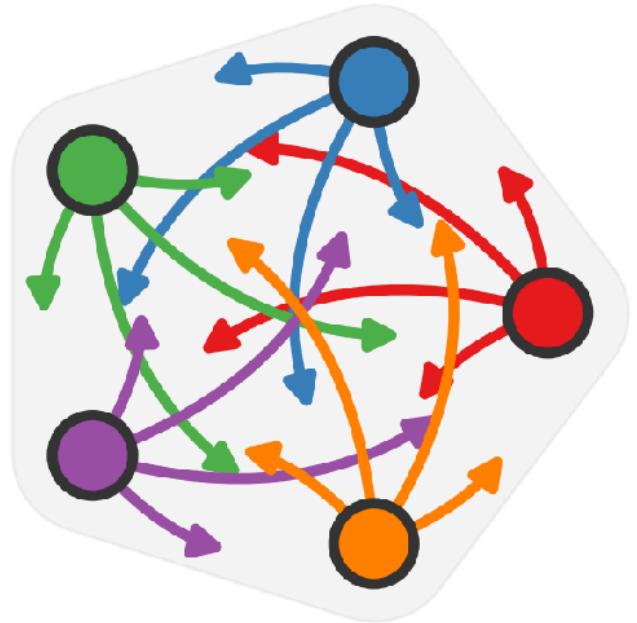
Boosted $X \rightarrow b\bar{b}$ Tagging in ATLAS



Boosted $X \rightarrow b\bar{b}$ Tagging in ATLAS



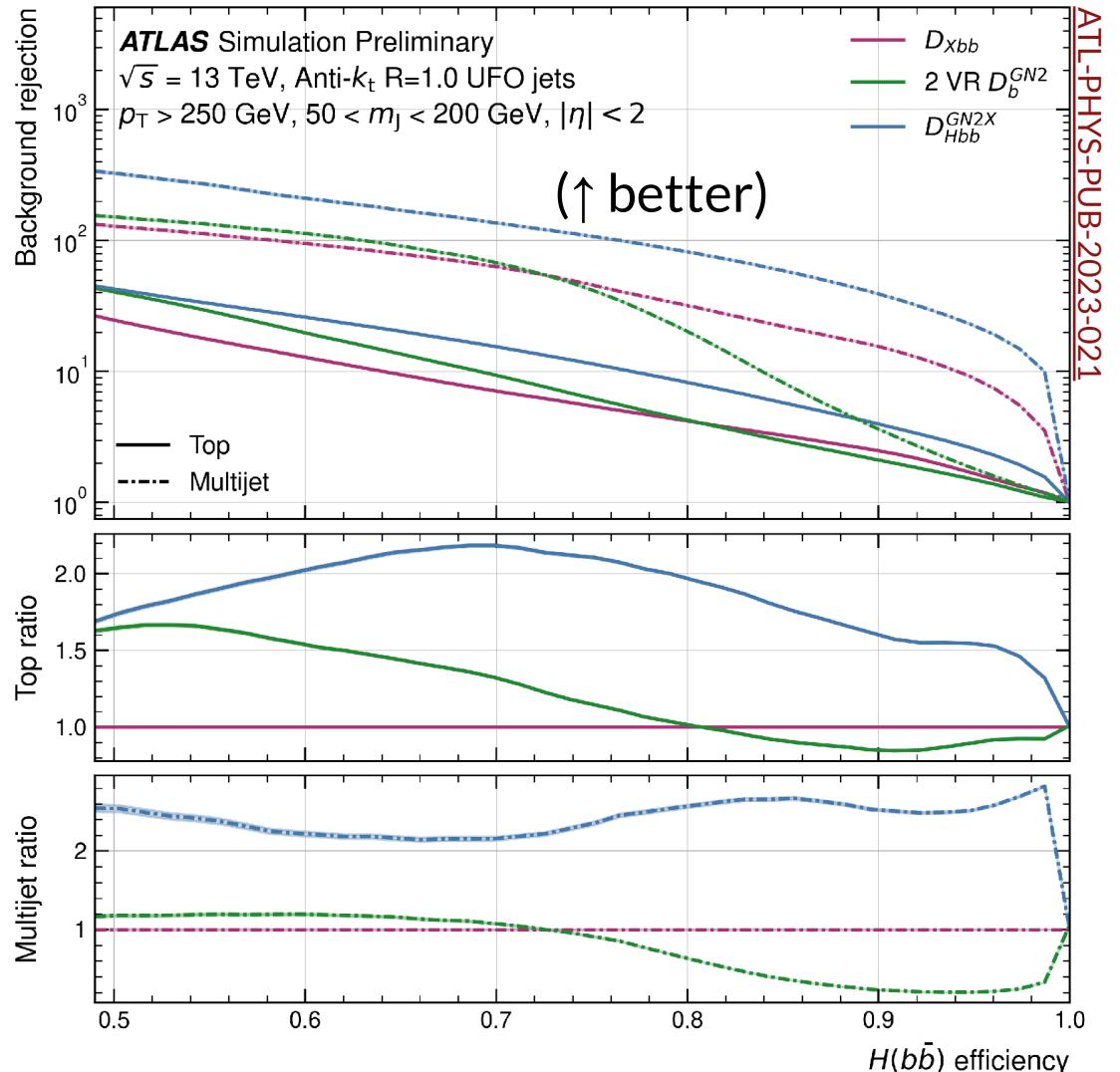
Jet Kinematics, Tracks, Vertices



GN2X Tagger
(Transformer Neural Network)

[ATL-PHYS-PUB-2023-021](#)

Boosted $b\bar{b}$ Tagging in ATLAS Today



Factor of $\sim 2x$ Improvement in **GN2X** compared to **Xbb**!

Significantly more correlations accessible to **GN2X**

Enabled by new architectures (GNNs/Transformers)

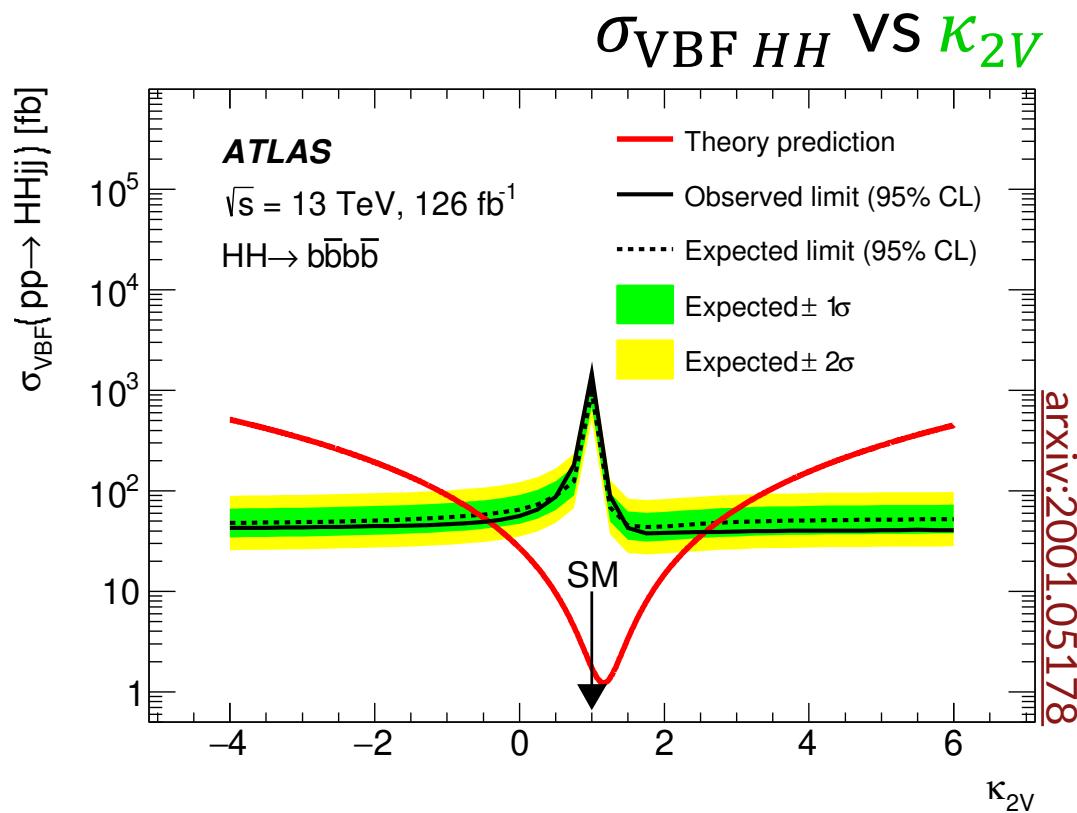
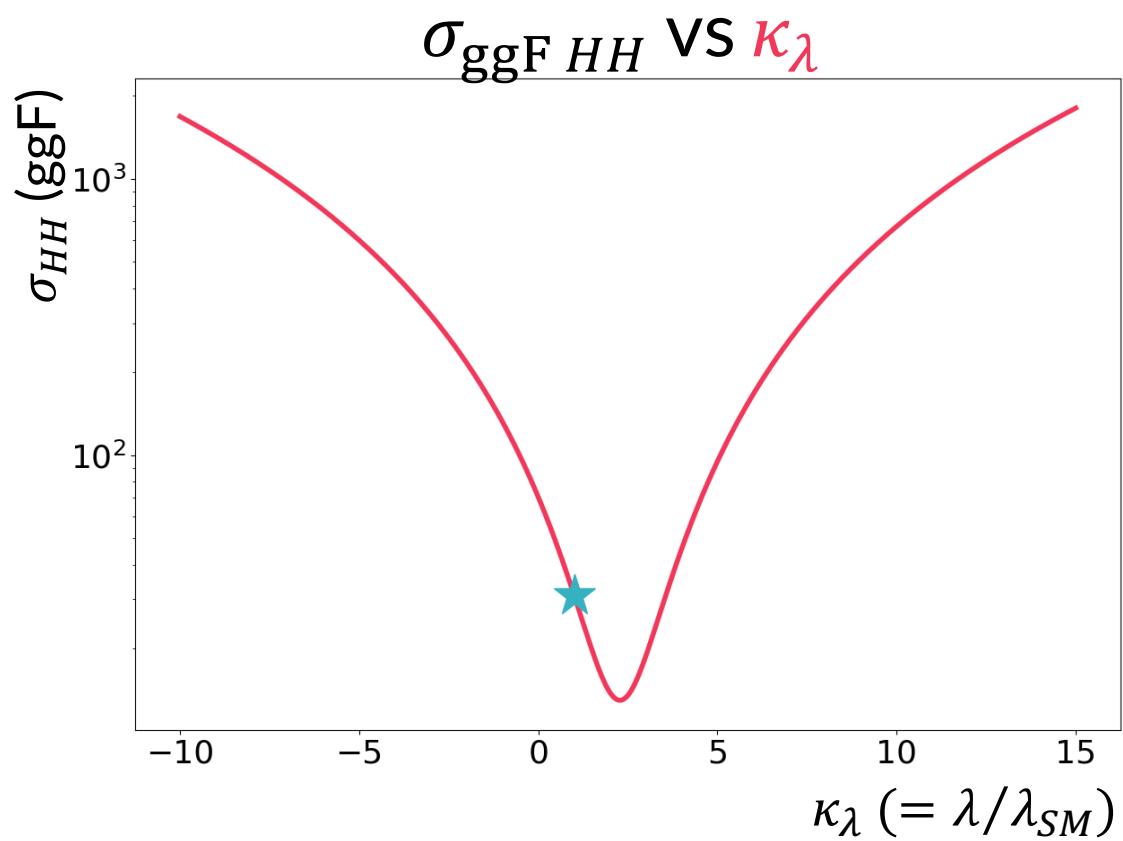
Conclusions

- Measuring HH production probes the Higgs boson potential, which could hold the key to big question left unanswered by the Standard Model
 - ... but, it's hard to measure!
- Machine learning is enabling measurements in “impossible” channels, like $b\bar{b}b\bar{b}$
- Clever analysis strategies will allow us to make the best use of upcoming data

Thanks for listening!

Additional Material

Sensitivity to New Physics in the $HHVV$ Coupling



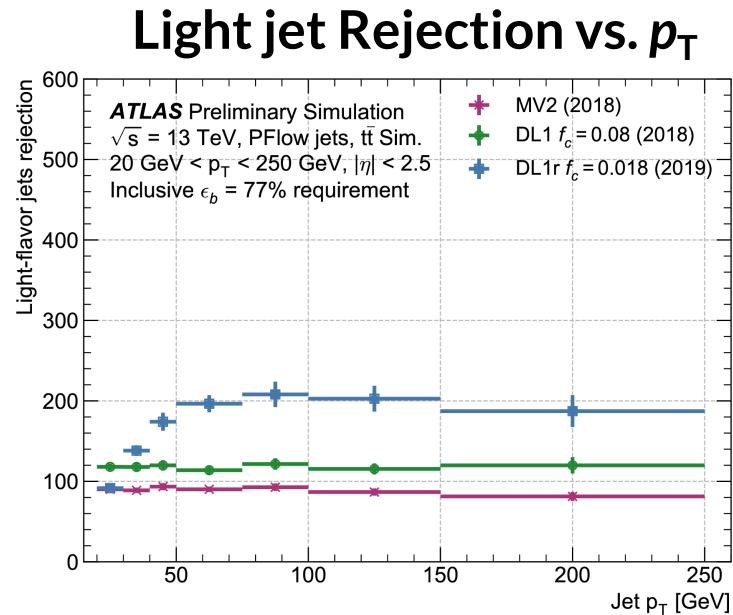
New physics \rightarrow more signal!

b-Tagging in ATLAS

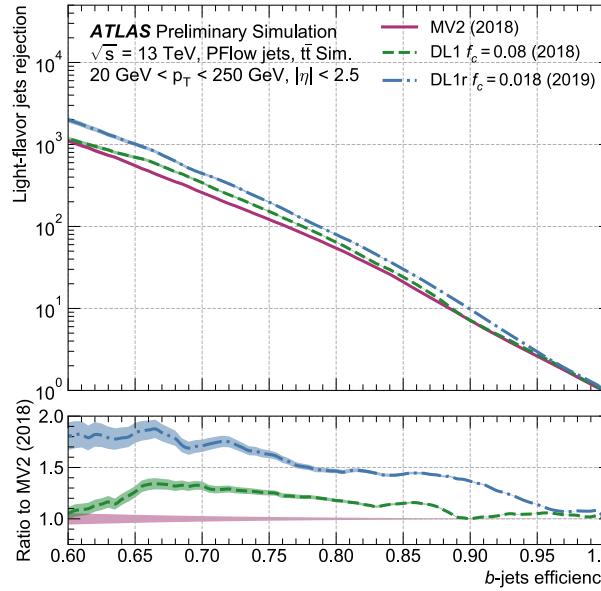
Improving ATLAS analyses through Machine Learning-based object identification

MV2C10: Boosted Decision Tree

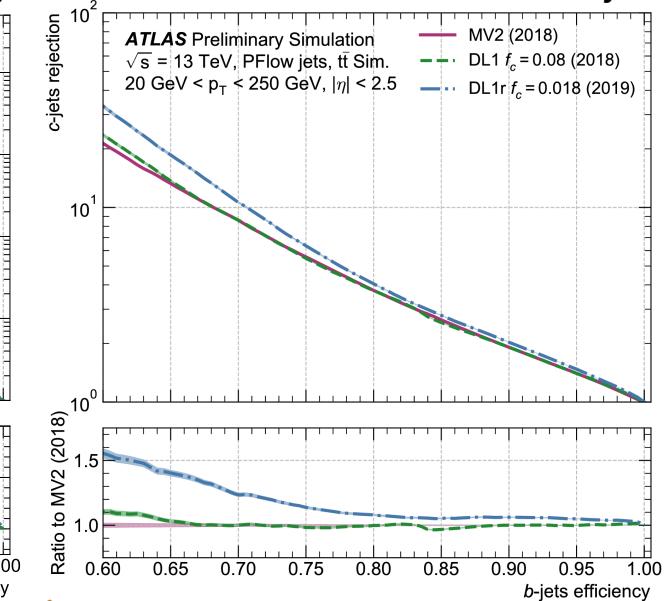
DL1r: Deep Neural Network
(FTAG-2019-005)



Light jet Rejection vs. $\epsilon_{b\text{-jet}}$



c-jet Rejection vs. $\epsilon_{b\text{-jet}}$

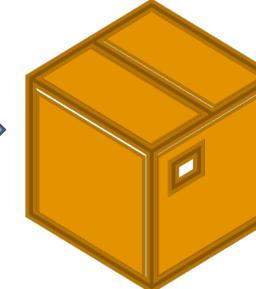


RNNIP (Recurrent NN)

JetFitter (Kalman Filter)

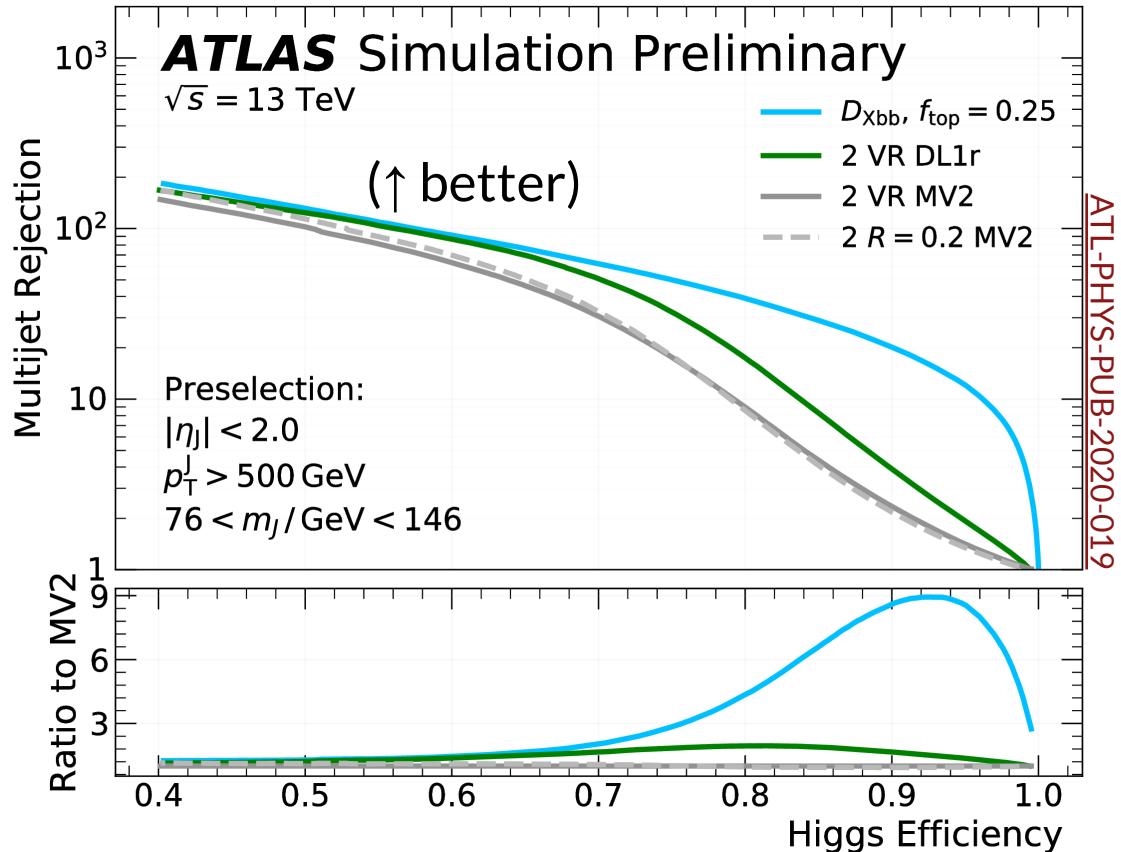
IP2D/IP3D (Impact Parameter)

SV1 (Secondary Vertex)



DL1r Score

The Evolution of Boosted $b\bar{b}$ Tagging in ATLAS



Unlike **subjet tagging**, **Xbb tagger** accounts for correlations between subjets

Jet Inputs
(Kinematics)

Subjet Inputs
(Tracks + Vertices)

Low-Level Algorithms:
Utilize Impact Parameter,
Secondary Vertices,
Reconstructed B decay

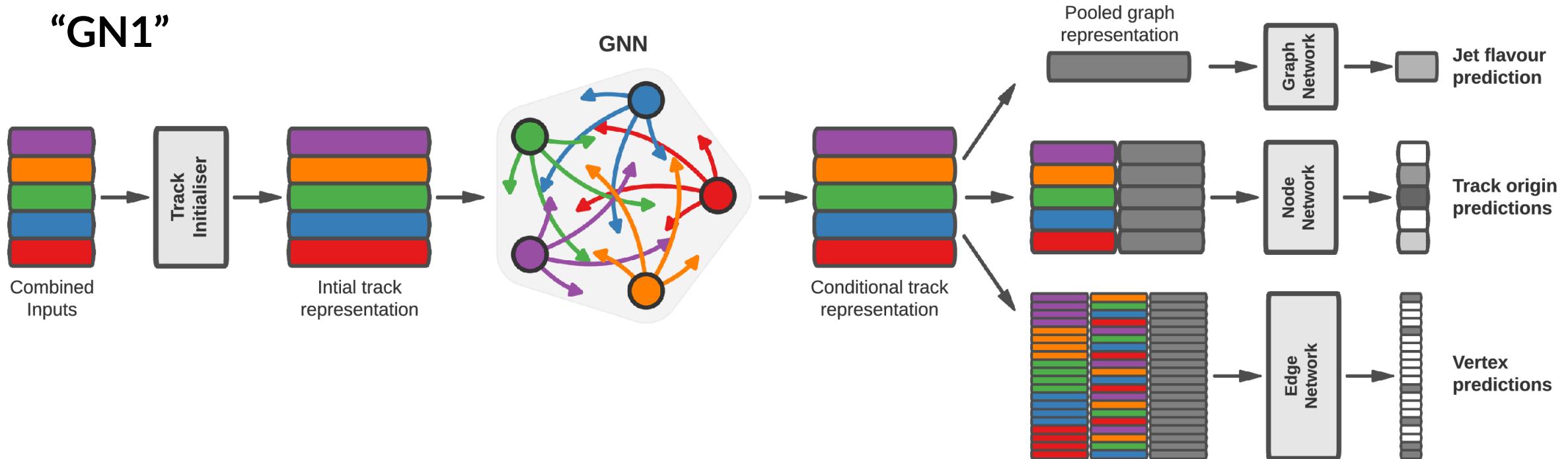
High-Level Algorithms:
Utilize Outputs from
Low-Level Algorithms

ML!

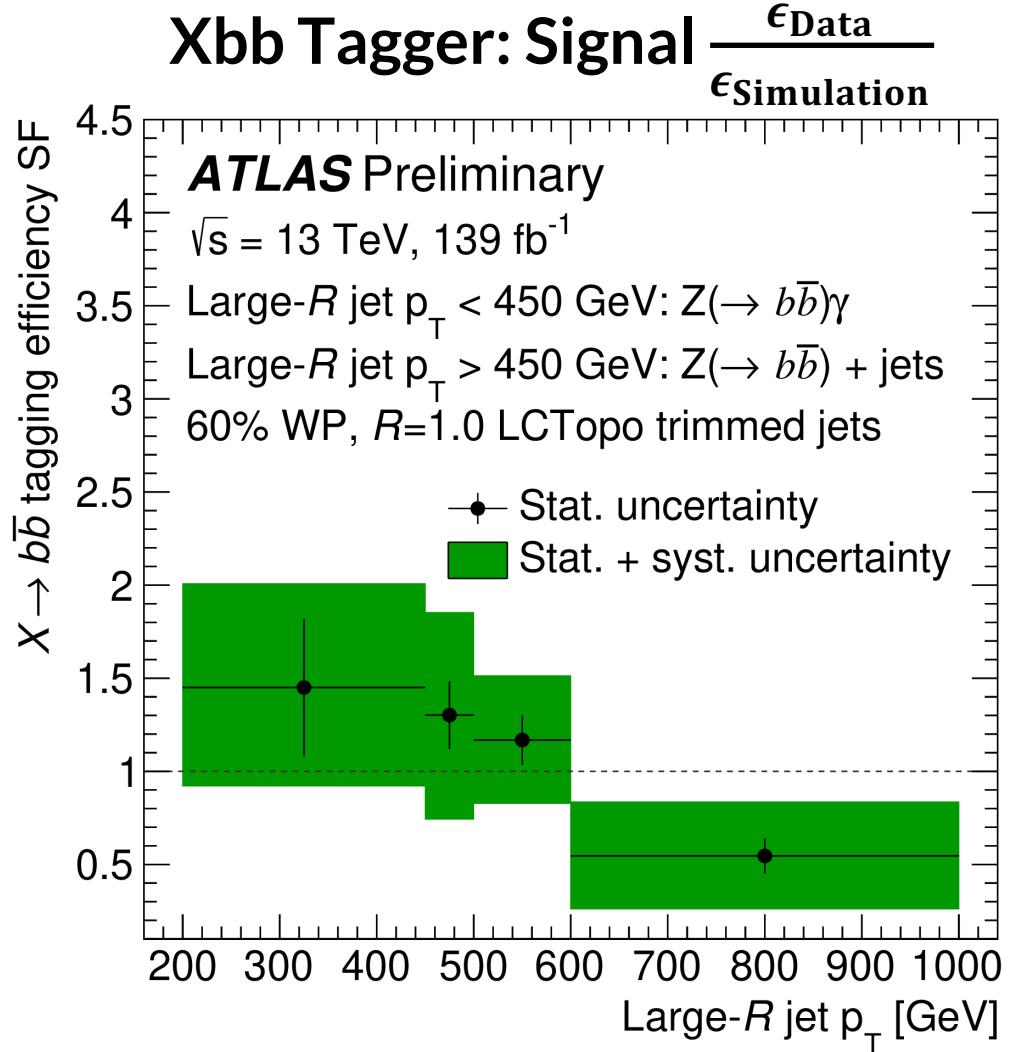
Xbb Tagger (Neural Network)

More ML!

GN1 Architecture



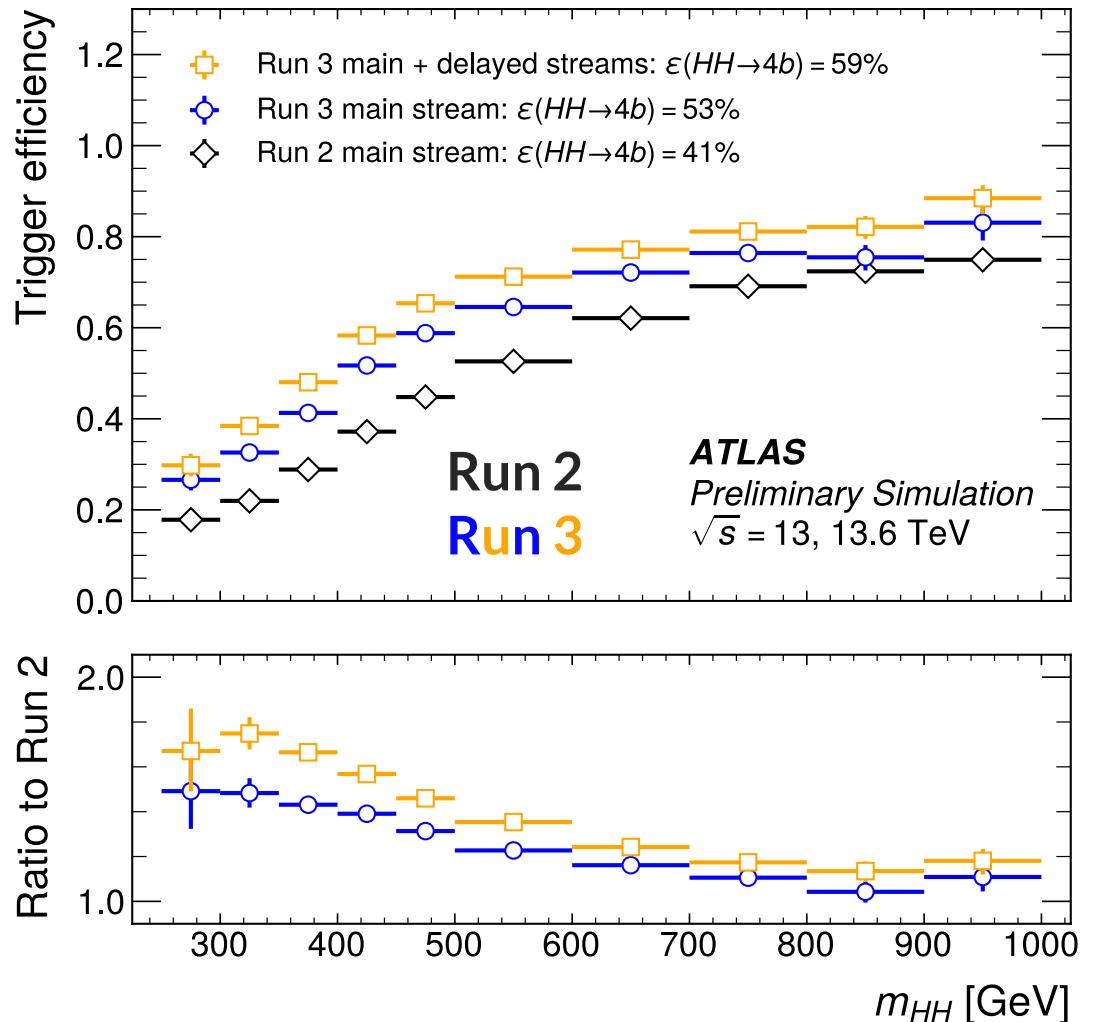
Performance is not the End of the Story



$\mathcal{O}(30\%)$ uncertainty on
the selection efficiency of
 $H \rightarrow b\bar{b}$ signal events by
the Xbb tagger

Precise calibration critical
for the future of GN2X!

Trigger Efficiency for ggF $HH \rightarrow b\bar{b}b\bar{b}$ Events



Combination of Triggers (Run 2):

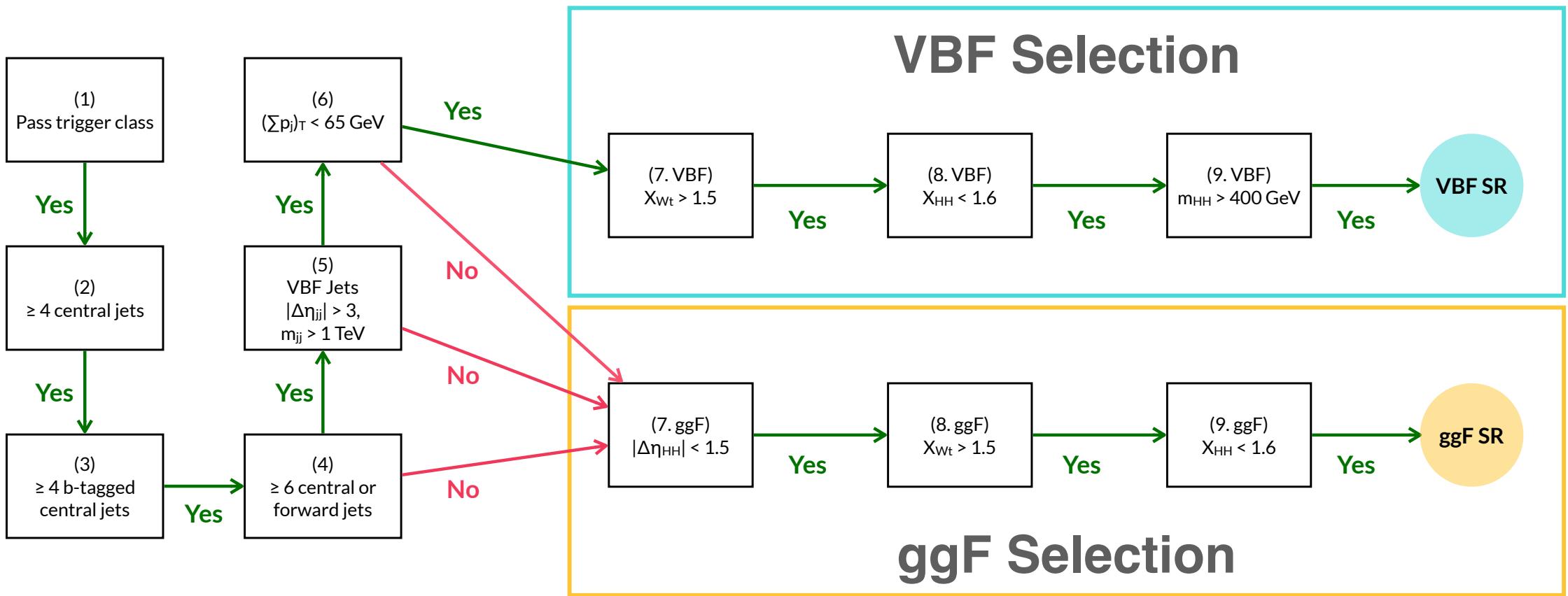
- 2 b -jet + 1 jet
- 2 b -jet + 2 jet

Run 3:

“Asymmetric” requirements on jet p_T

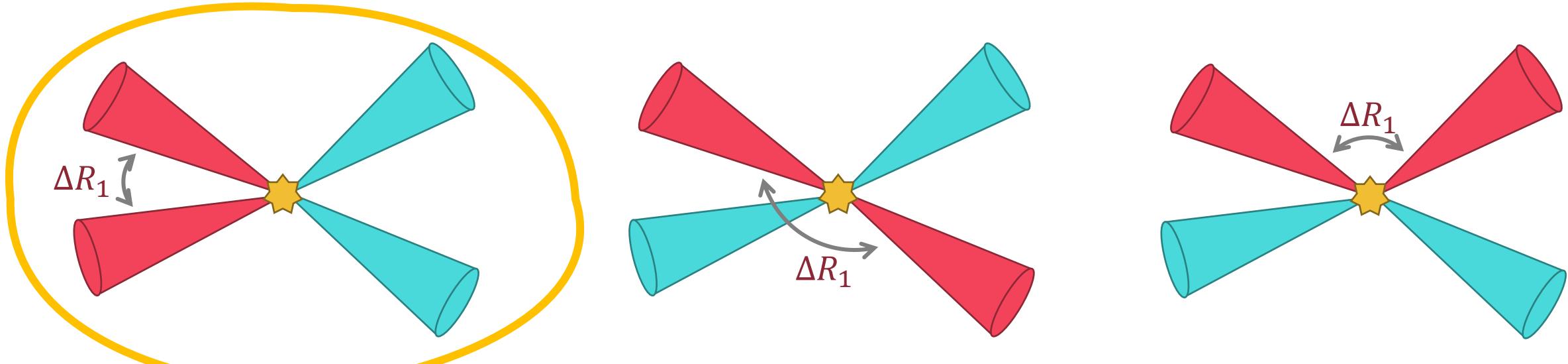
Full Analysis Selection

$$X_{Wt} = \min \left[\sqrt{\left(\frac{m_{jj} - m_W}{0.1m_{jj}} \right)^2 + \left(\frac{m_{jjb} - m_t}{0.1m_{jjb}} \right)^2} \right] \quad X_{HH} = \sqrt{\left(\frac{m_{H1} - 124 \text{ GeV}}{0.1m_{H1}} \right)^2 + \left(\frac{m_{H2} - 117 \text{ GeV}}{0.1m_{H2}} \right)^2}$$

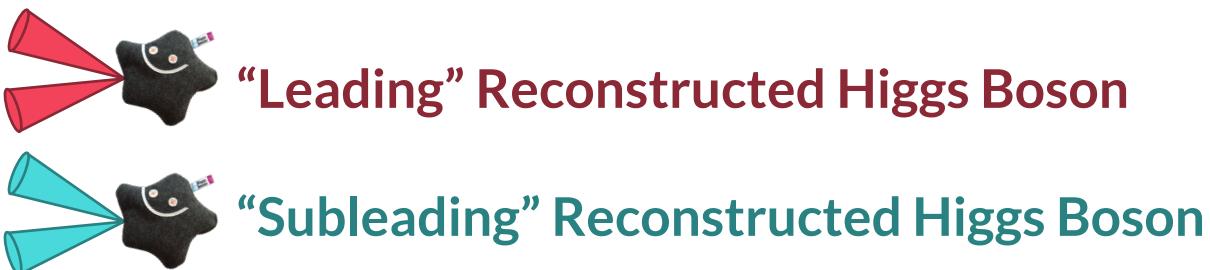


“Pairing” Higgs Bosons

Combinatorics: three possible pairings given four b -tagged jets



Pairing $\gtrsim 70\%$ accurate for VBF
($\gtrsim 90\%$ for κ_{2V} far from 1)

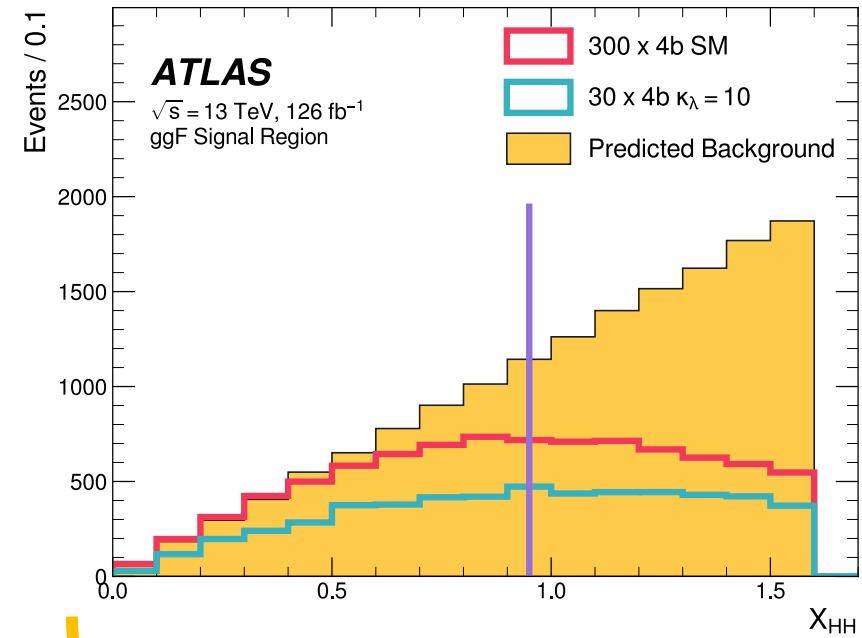


Categorization

Isolate different physics ($\kappa_\lambda, \kappa_{2V}$) scenarios

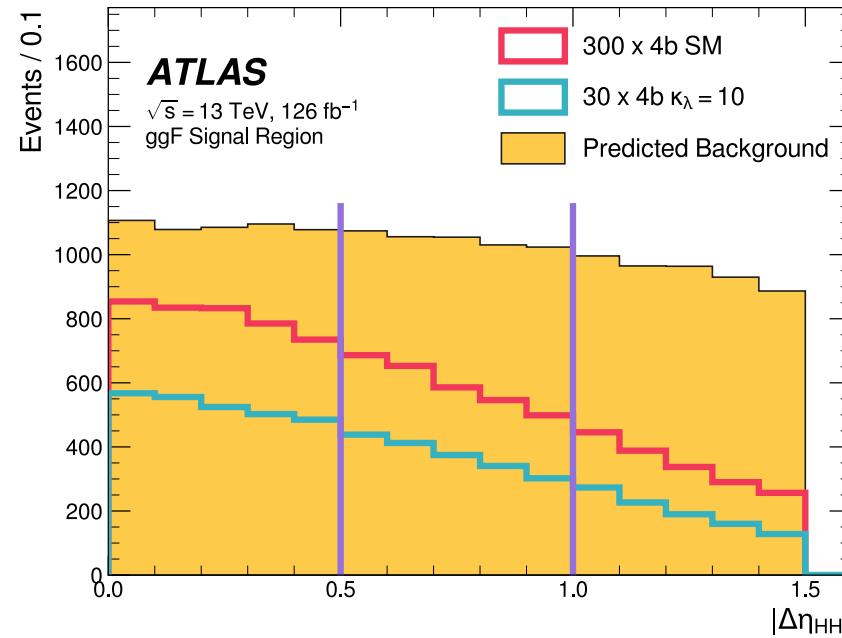
Standard Model ($\kappa_\lambda = \kappa_{2V} = 1$)
 $\kappa_\lambda = 10$ ($\kappa_{2V} = 1$)
 $\kappa_{2V} = 0$ ($\kappa_\lambda = 1$)

X_{HH}

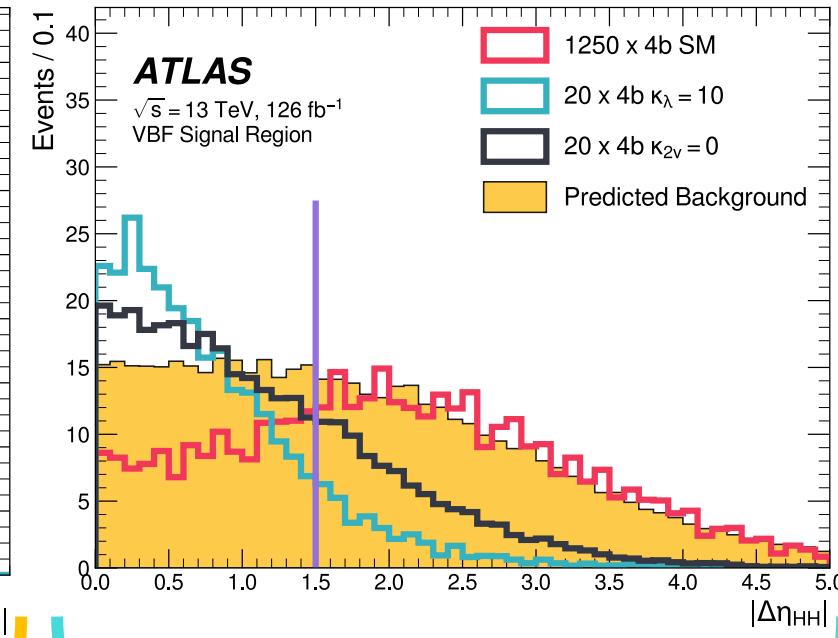


ggF

$|\Delta\eta_{HH}|$

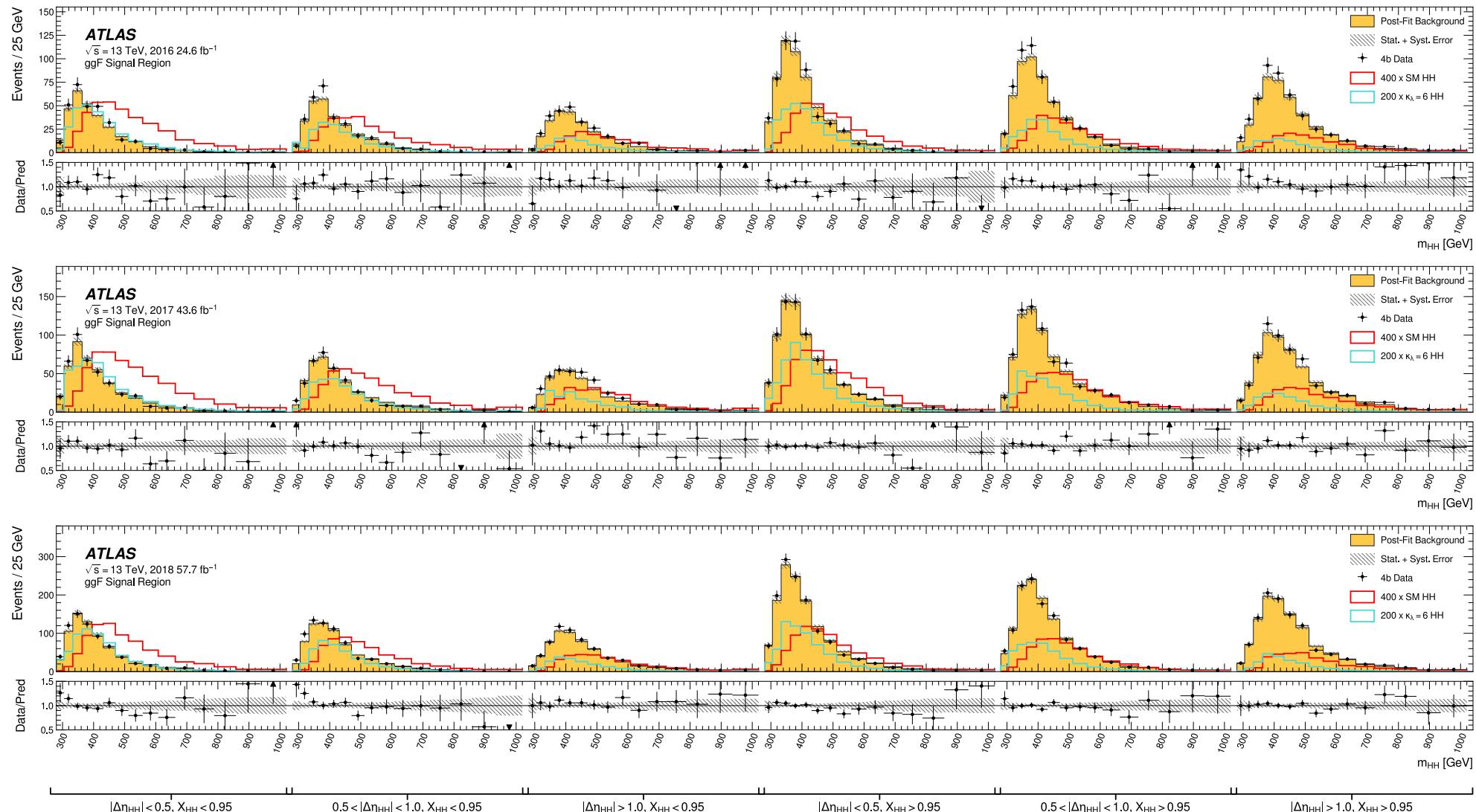


$|\Delta\eta_{HH}|$

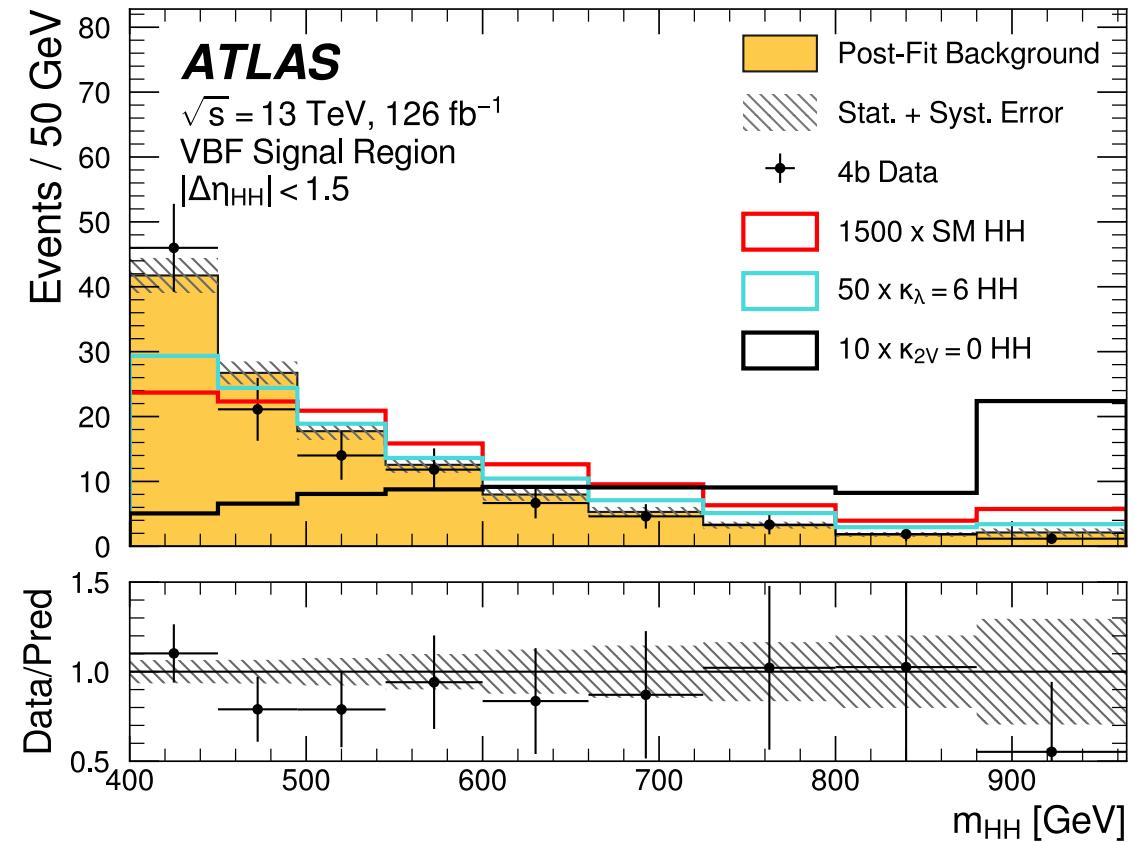
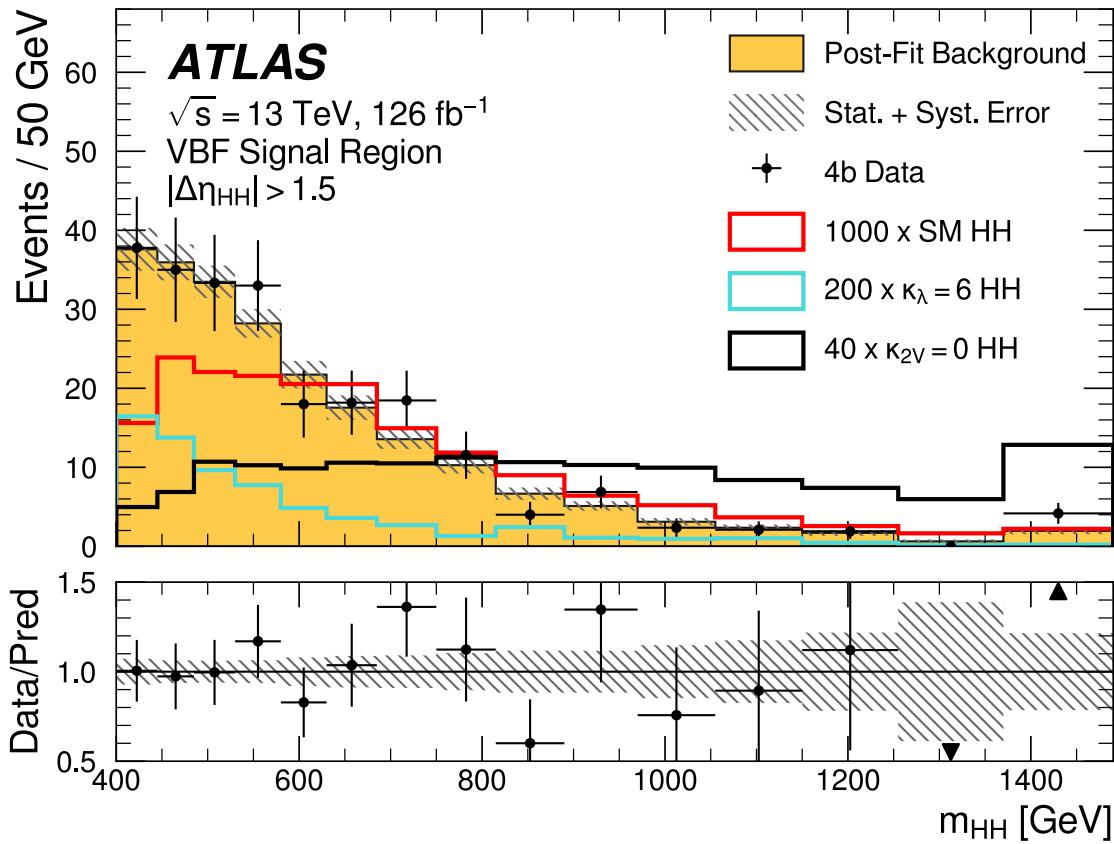


VBF

Observed m_{HH} Distributions in ggF Categories



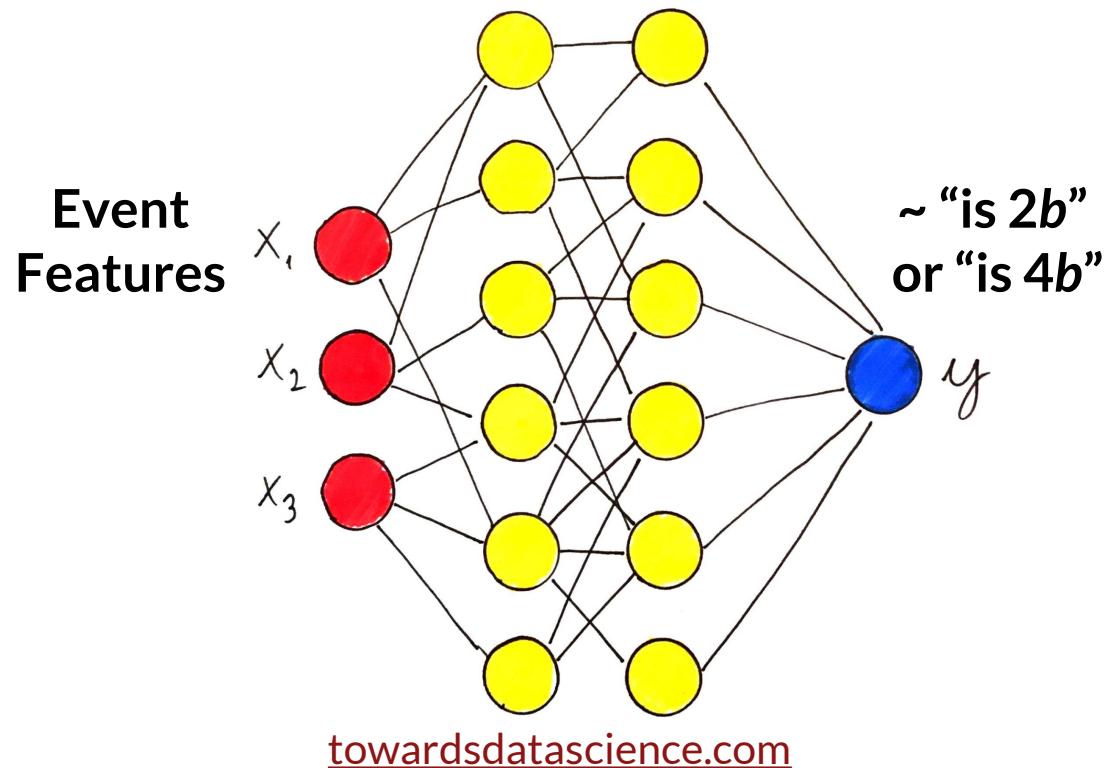
Observed m_{HH} Distributions in VBF Categories



Neural Networks for Density Estimation

(Lemma) best discriminator between two classes:

$$\lambda = \frac{p_A}{p_A + p_B}$$

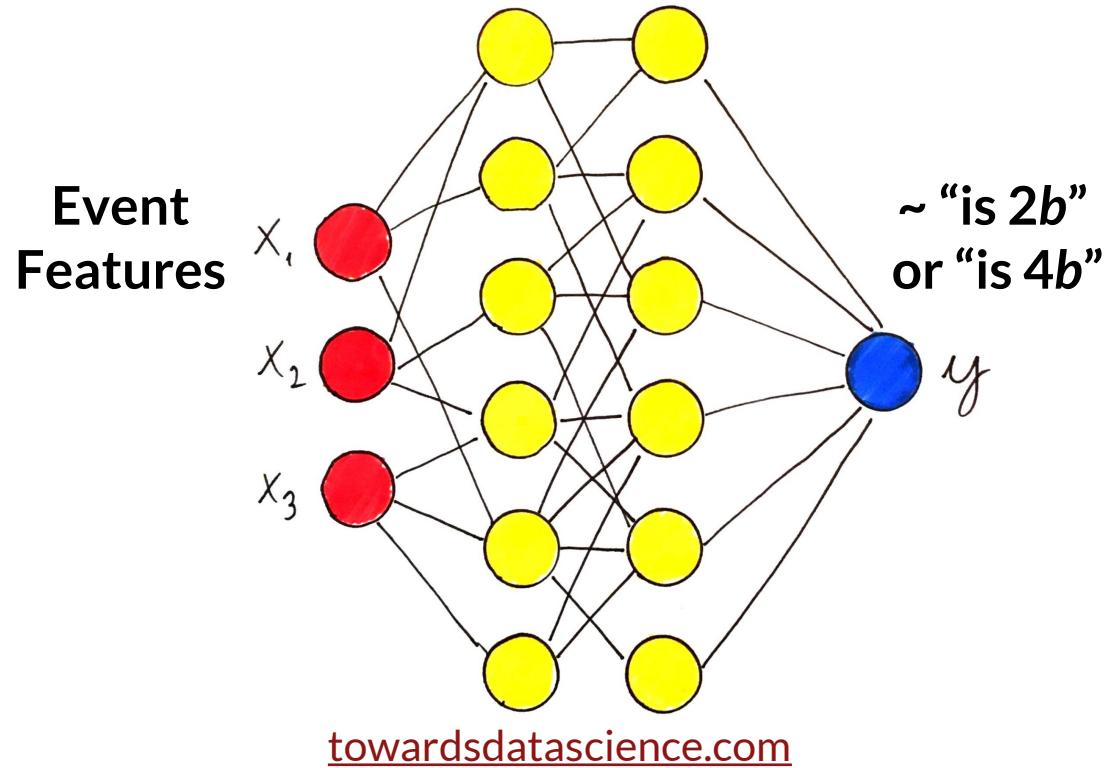


NNs classify data well → approximate λ

$$\frac{p_A}{p_B} = \frac{\lambda}{1 - \lambda}$$

→ a classification NN can approximate the density ratio!

Neural Networks for Density Estimation



$$p_{2b}(\vec{x}) \cdot w(\vec{x}) = p_{4b}(\vec{x})$$

Train NN with specific Loss function:

$$\mathcal{L}(R(\vec{x})) = \mathbb{E}_{x \sim p_{2b}} [\sqrt{R(\vec{x})}] + \mathbb{E}_{x \sim p_{4b}} \left[\frac{1}{\sqrt{R(\vec{x})}} \right]$$

$$\rightarrow \arg \min_R \mathcal{L}(R(\vec{x})) = w(\vec{x})$$

“Event-level” reweighting!

[arxiv:1911.00405](https://arxiv.org/abs/1911.00405)
Kanamori et. al. (JMLR)

Reweighting Neural Network – Details

Architecture and Input Variables

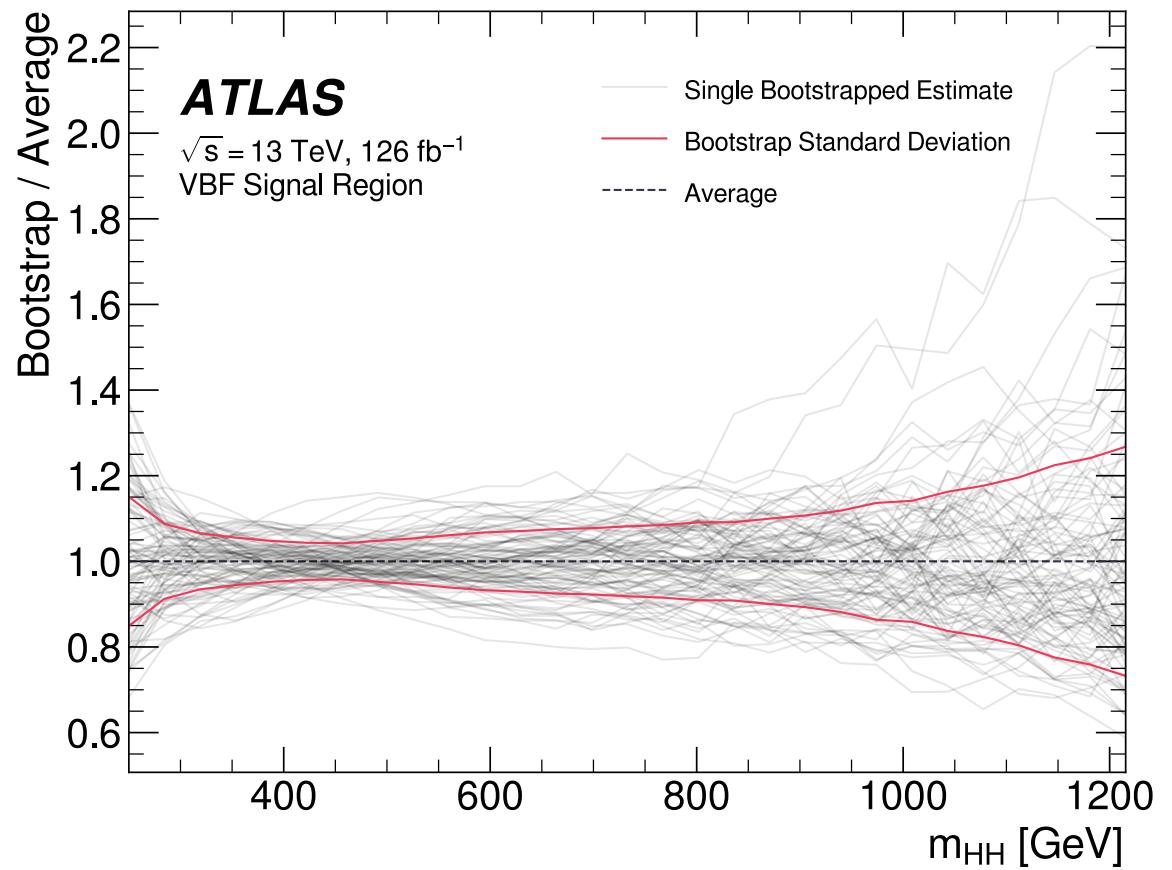
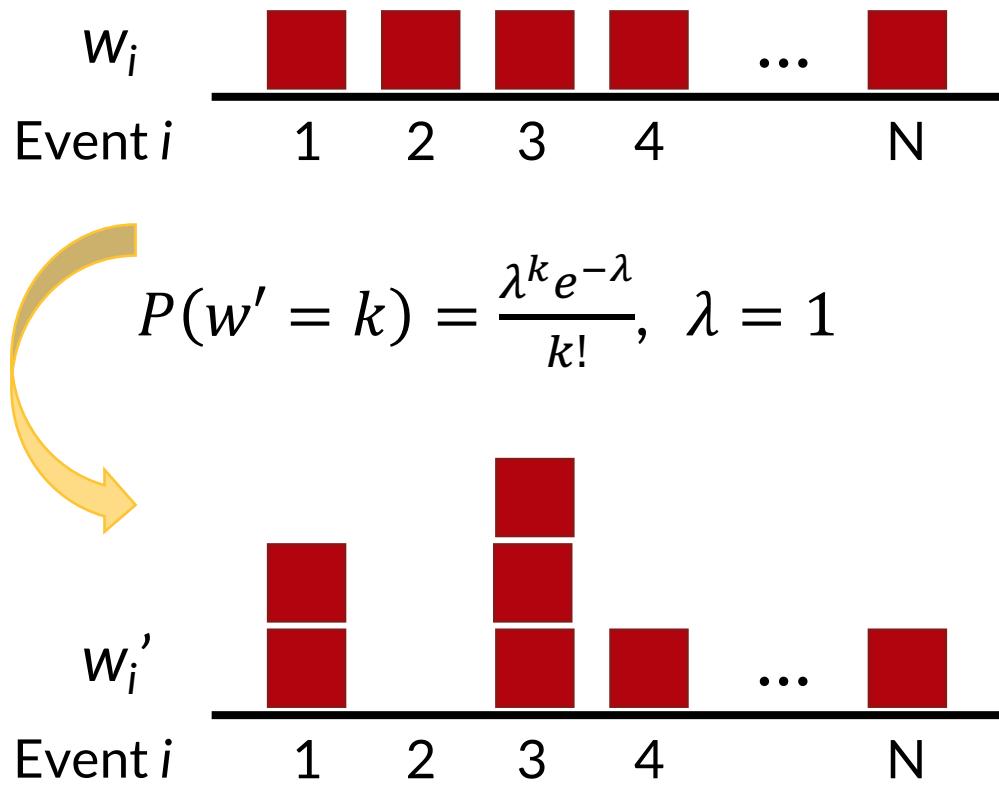
3 Densely-
Connected
Hidden Layers
(50 Nodes Each)

Single-Node
Output

| ggF | VBF | 3 Densely- Connected Hidden Layers (20 Nodes Each) | Single-Node Output |
|--|--|---|-----------------------|
| <ol style="list-style-type: none">1. $\log(p_T)$ of the 2nd leading Higgs boson candidate jet2. $\log(p_T)$ of the 4th leading Higgs boson candidate jet3. $\log(\Delta R)$ between the closest two Higgs boson candidate jets4. $\log(\Delta R)$ between the other two Higgs boson candidate jets5. Average absolute η value of the Higgs boson candidate jets6. $\log(p_T)$ of the di-Higgs system7. ΔR between the two Higgs boson candidates8. $\Delta\phi$ between jets in the leading Higgs boson candidate9. $\Delta\phi$ between jets in the subleading Higgs boson candidate10. $\log(X_{Wt})$11. Number of jets in the event12. Trigger class index as one-hot encoder | <ol style="list-style-type: none">1. Maximum dijet mass from the possible pairings of the four Higgs boson candidate jets2. Minimum dijet mass from the possible pairings of the four Higgs boson candidate jets3. Energy of the leading Higgs boson candidate4. Energy of the subleading Higgs boson candidate5. Second-smallest ΔR between the jets in the leading Higgs boson candidate (from the three possible pairings for the leading Higgs candidate)6. Average absolute η value of the four Higgs boson candidate jets7. $\log(X_{Wt})$8. Trigger class index as one-hot encoder9. Year index as one-hot encoder (for years inclusive training) | 3 Densely- Connected Hidden Layers (20 Nodes Each) | Single-Node Output |

Background Modeling – Uncertainties

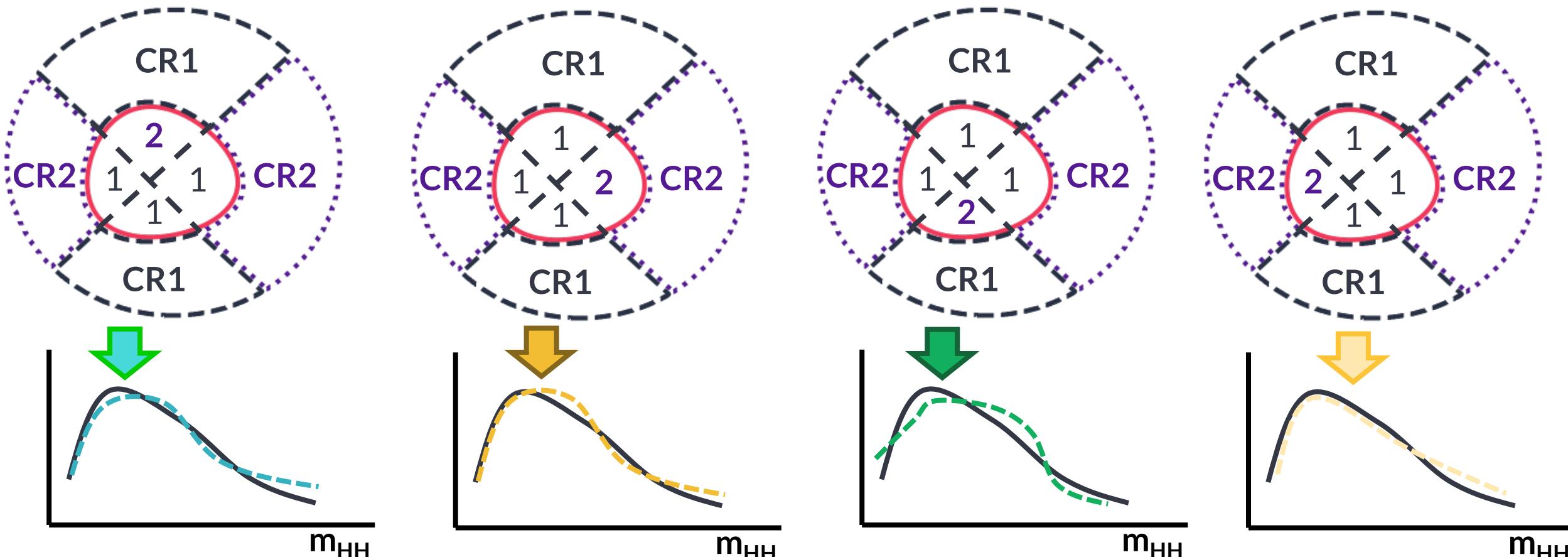
Bootstrap Uncertainty – quantifying “noise” in the neural network training



Background Modeling

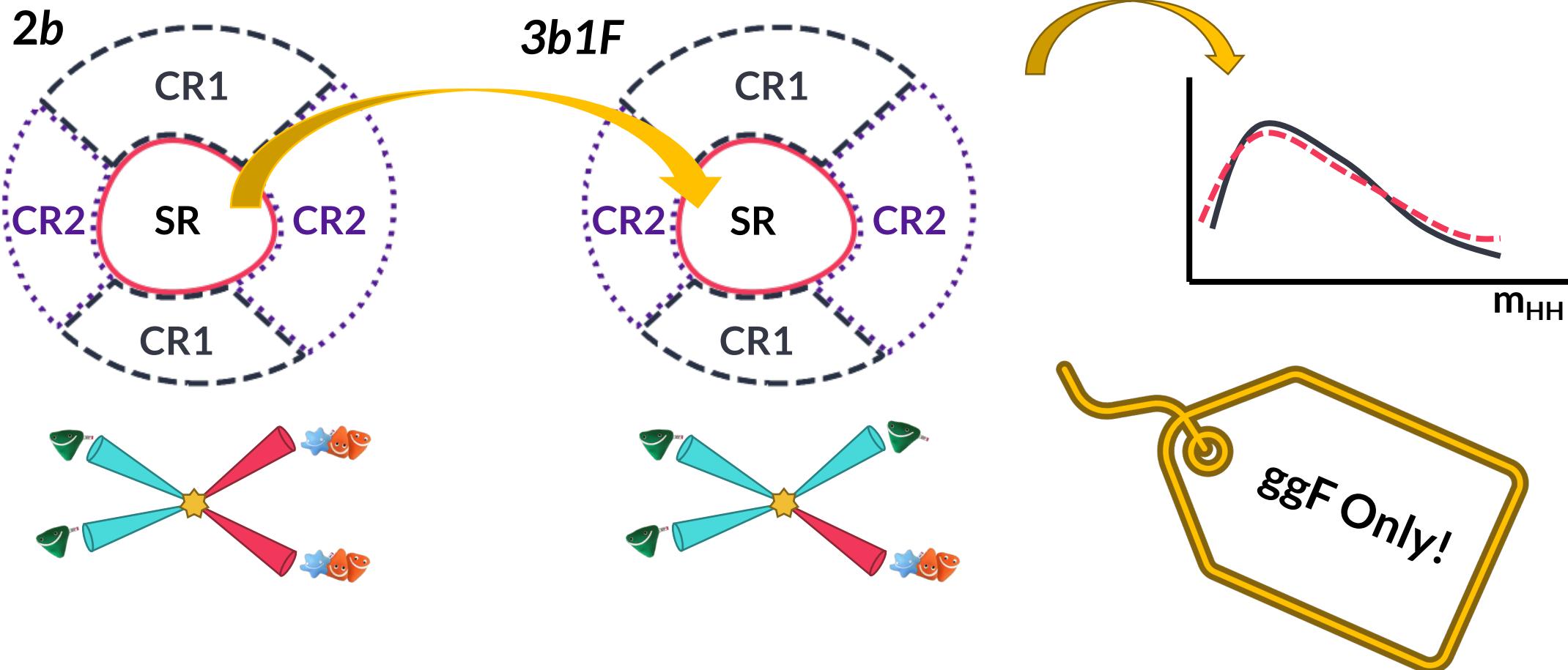
“Shape” Uncertainty – quantifying variations across the mass plane

Alternative Training in CR2 for each SR “Quadrant”



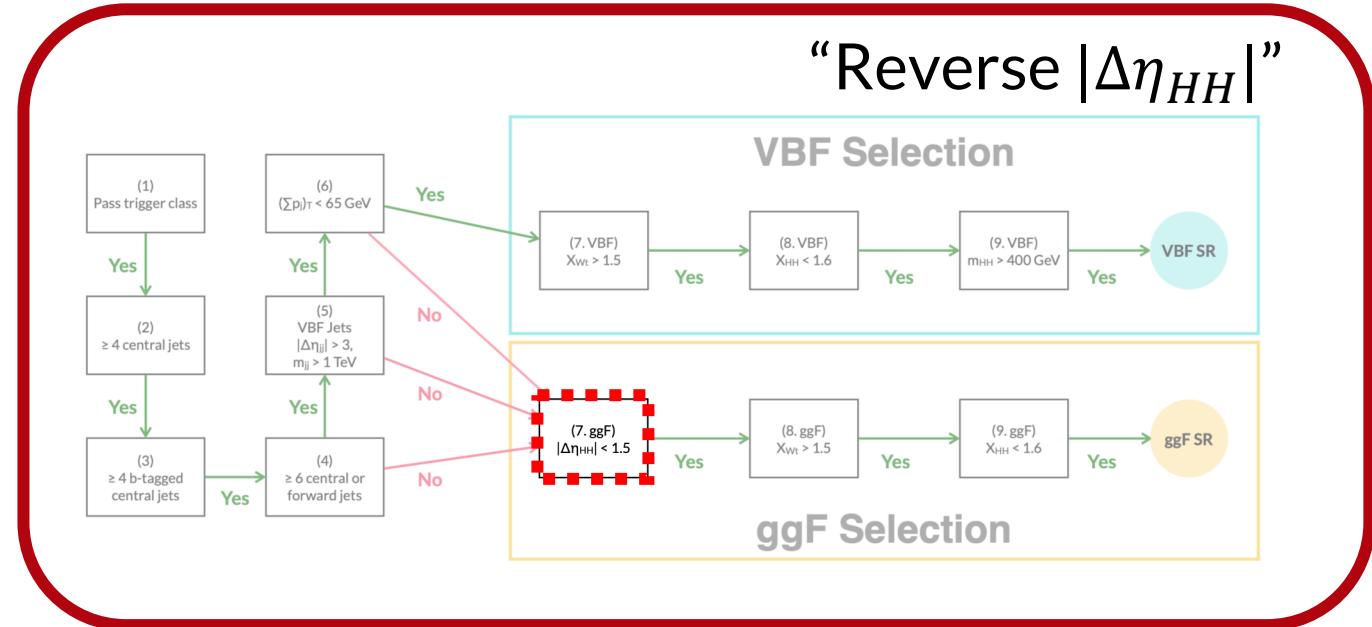
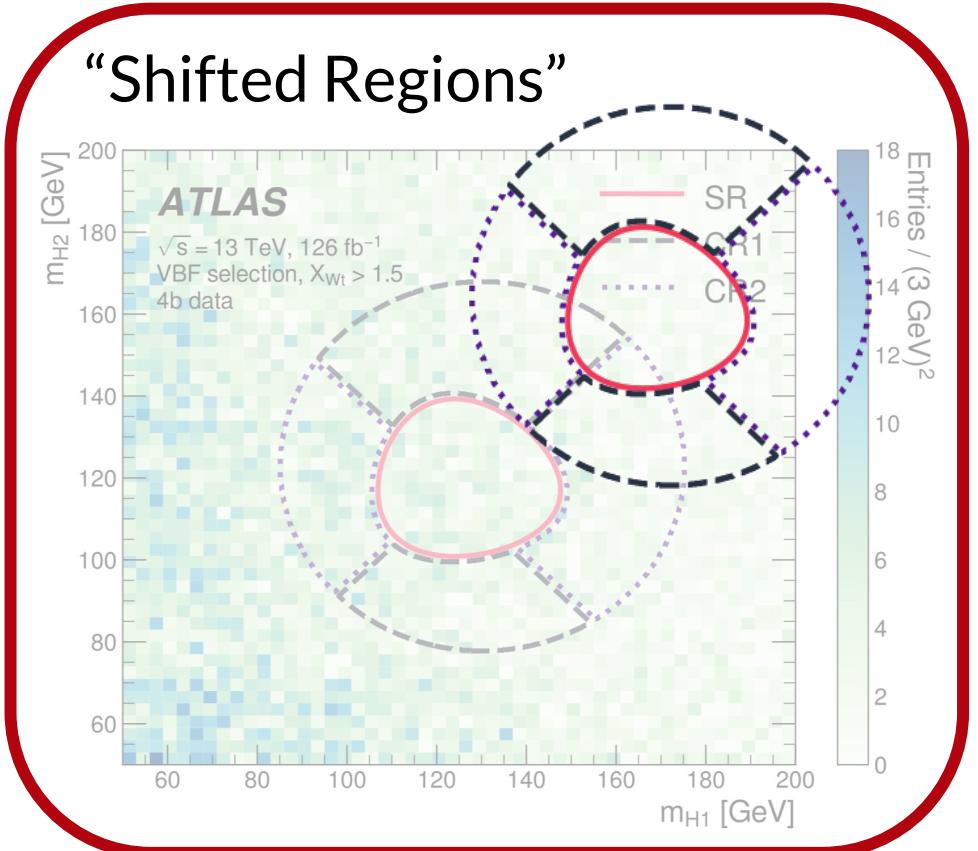
Background Modeling

“Non-closure” Uncertainty – testing the background modeling in an orthogonal dataset



Other Background Modeling Checks

Further validating the procedure



Simulated $t\bar{t}$ and multiple-b-jet events

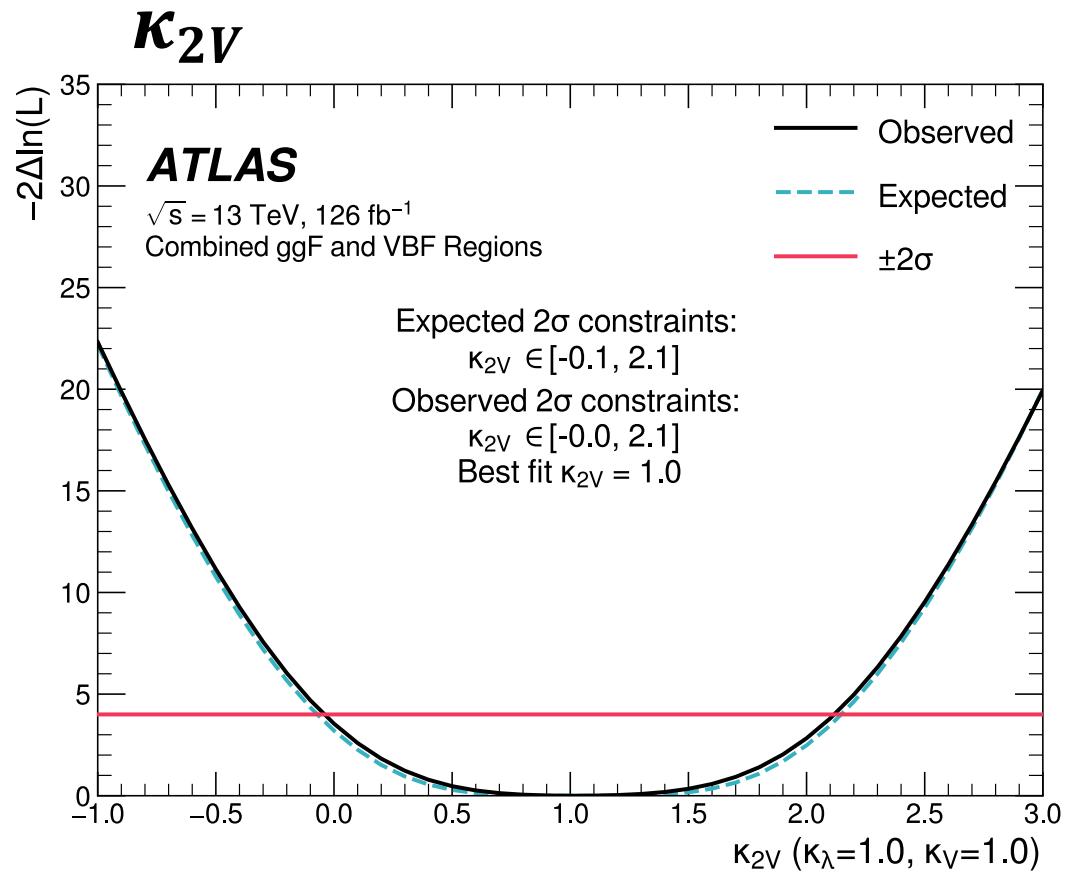
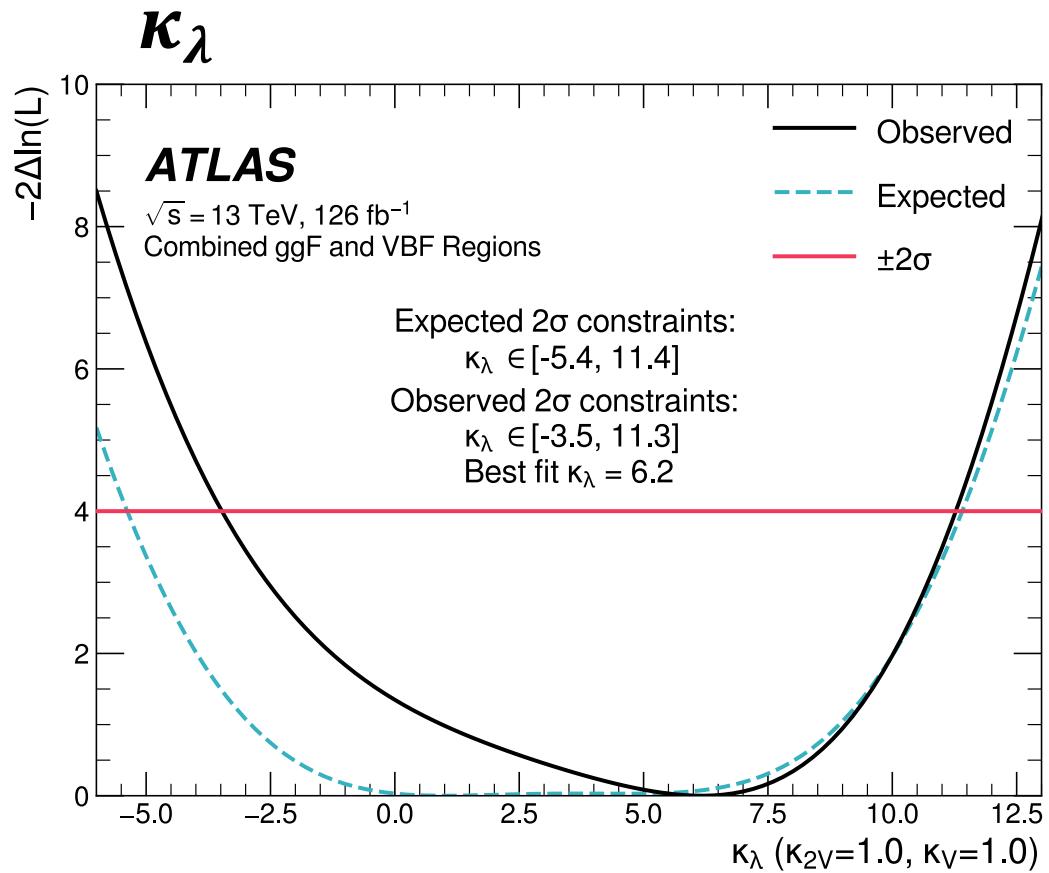


Table of Event Yields

Both ggF (top) and VBF (bottom) signal regions

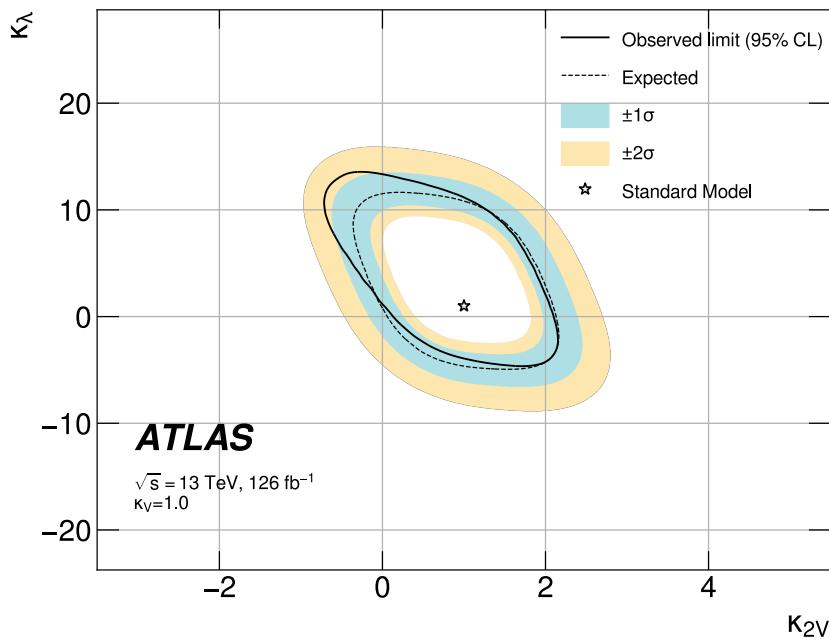
| Category | Data | Expected Background | ggF Signal SM | VBF Signal SM |
|--|------|------------------------|------------------|------------------|
| ggF signal region | | | | |
| $ \Delta\eta_{HH} < 0.5, X_{HH} < 0.95$ | 1940 | 1935(25) | 7.0 | 0.038 |
| $ \Delta\eta_{HH} < 0.5, X_{HH} > 0.95$ | 3602 | 3618(37) | 6.5 | 0.036 |
| $0.5 < \Delta\eta_{HH} < 1.0, X_{HH} < 0.95$ | 1924 | 1874(21) | 5.1 | 0.037 |
| $0.5 < \Delta\eta_{HH} < 1.0, X_{HH} > 0.95$ | 3540 | 3492(35) | 4.7 | 0.040 |
| $ \Delta\eta_{HH} > 1.0, X_{HH} < 0.95$ | 1880 | 1739(22) | 2.9 | 0.043 |
| $ \Delta\eta_{HH} > 1.0, X_{HH} > 0.95$ | 3285 | 3212(37) | 2.8 | 0.041 |
| VBF signal region | | | | |
| $ \Delta\eta_{HH} < 1.5$ | 116 | 125.3(44) | 0.37 | 0.090 |
| $ \Delta\eta_{HH} > 1.5$ | 241 | 230.6(53) | 0.06 | 0.21 |

More Results (Likelihood Scans)

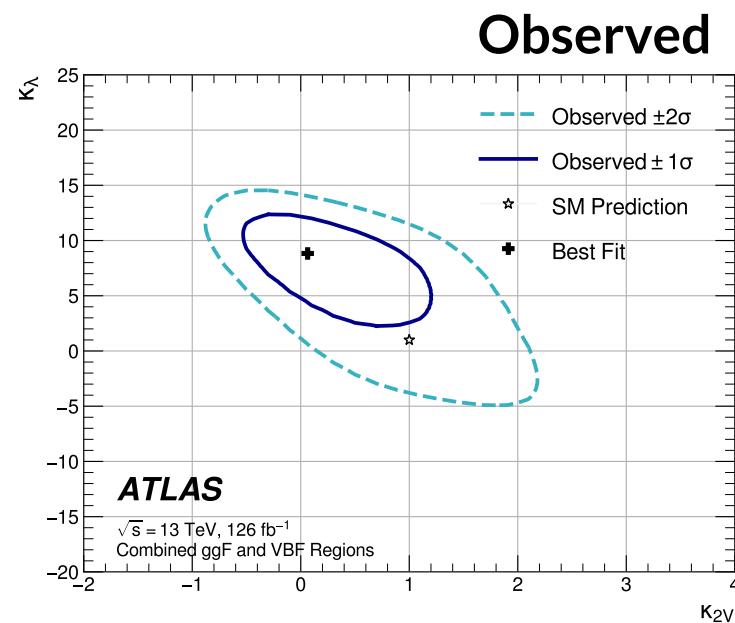


More Results (2D Limits)

“95% CL” (2D in κ_λ vs. κ_{2V})

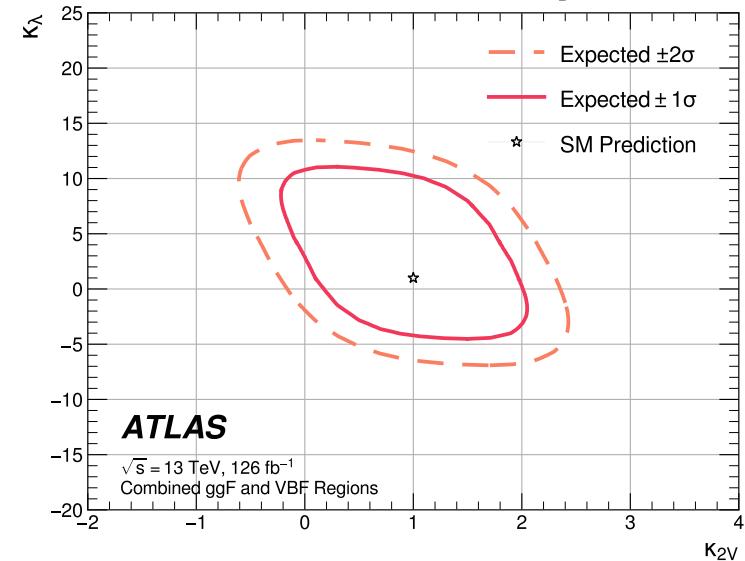


“Log Likelihood Scan” (2D in κ_λ vs. κ_{2V})



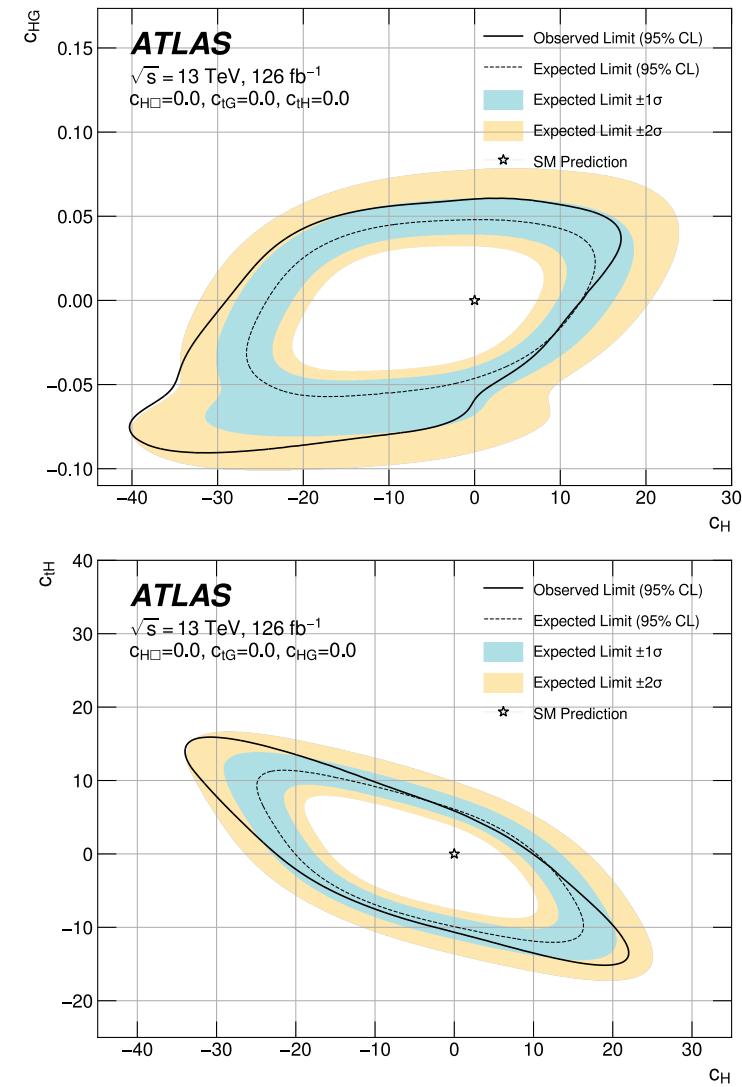
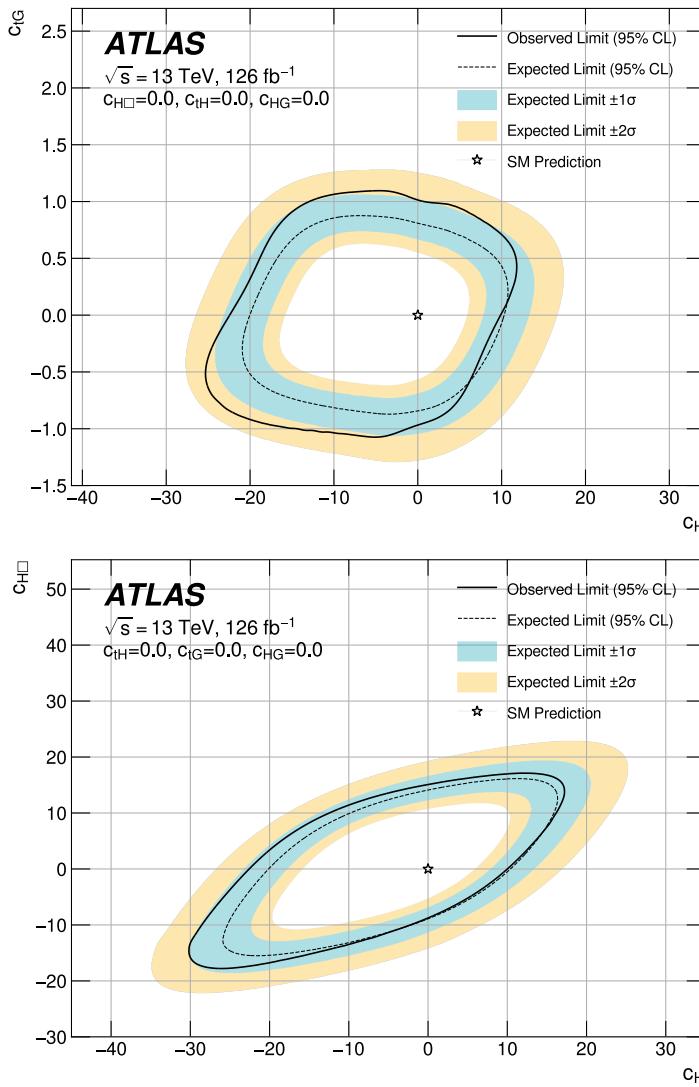
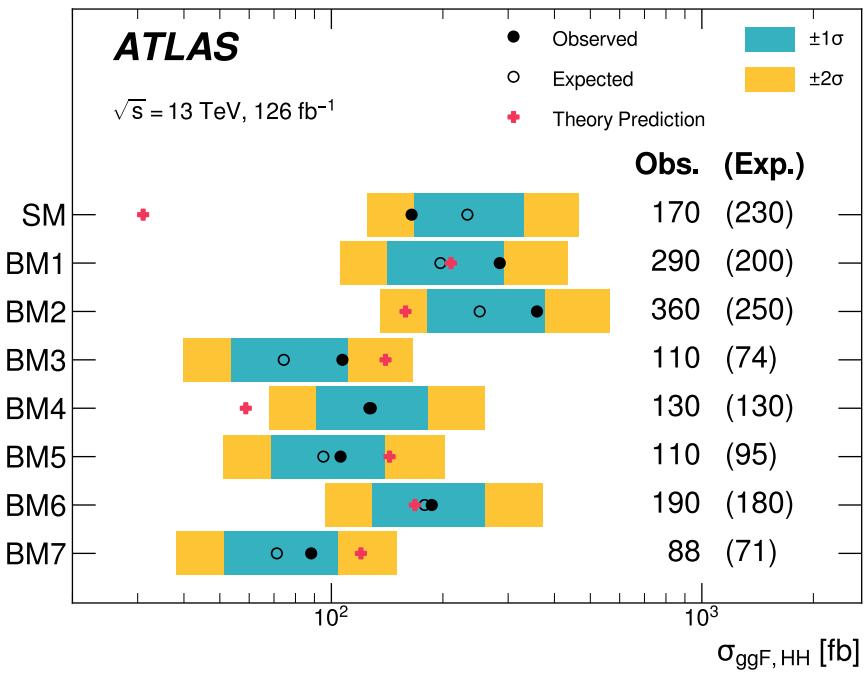
Observed

Expected



HEFT and SMEFT Constraints

ggF only



Uncertainties

Dominant uncertainties:

Theoretical signal modeling

Experimental background modeling

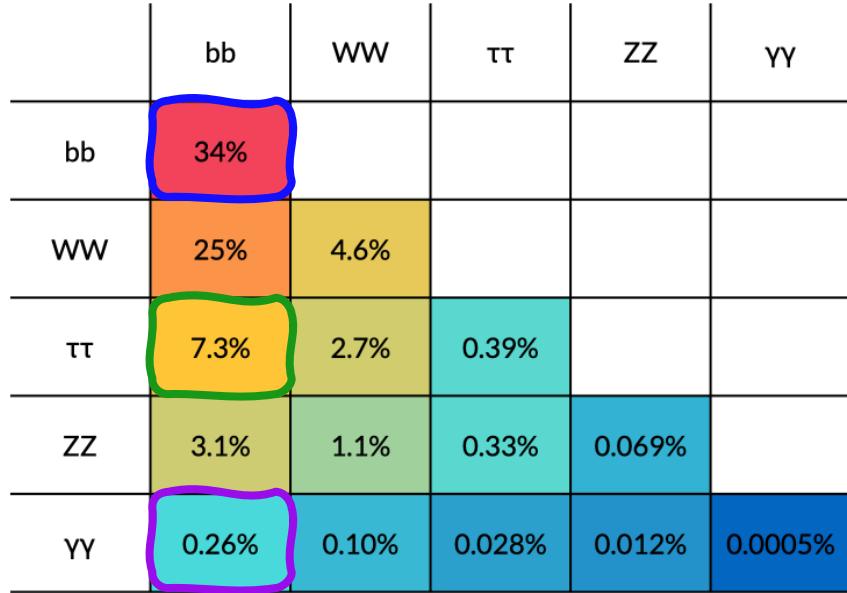
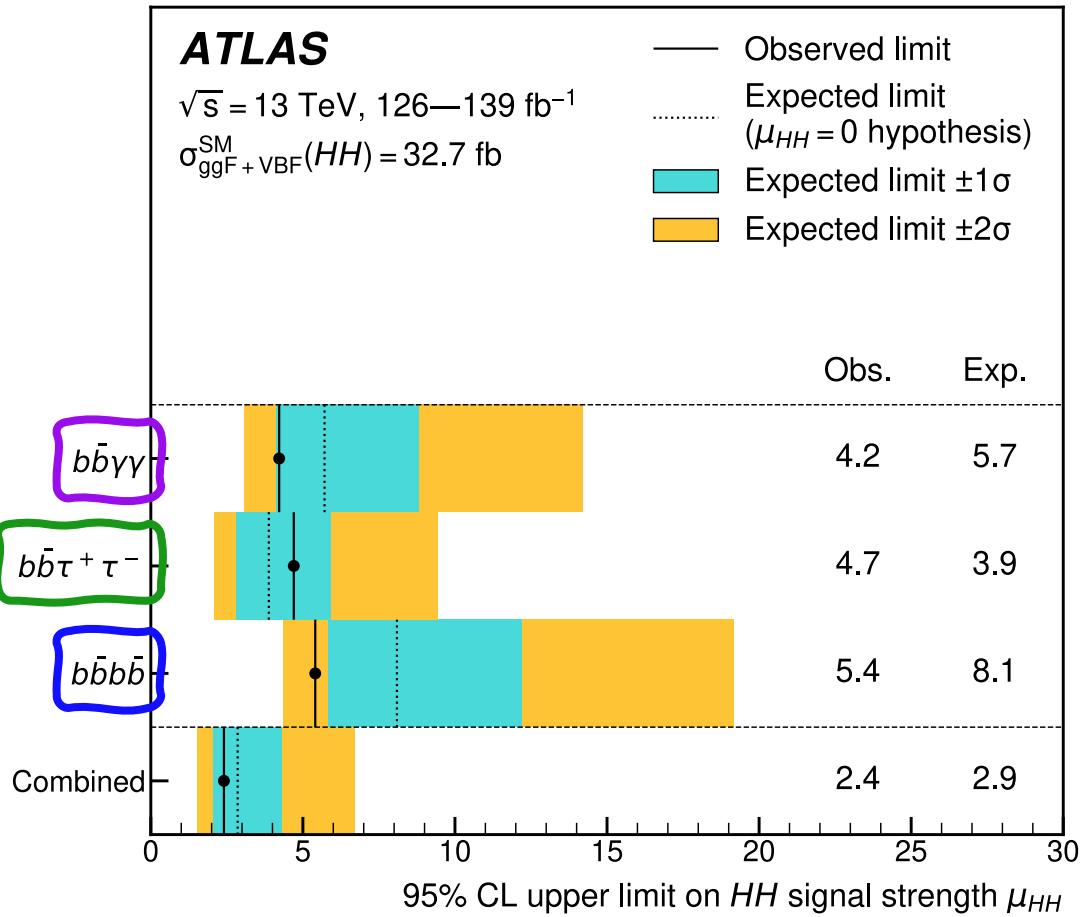
| Uncertainties | $\mu_{\text{ggF+VBF}}$ |
|-----------------------|------------------------|
| Statistical Only | 6.0 |
| + Background Modeling | 7.1 |
| + Theoretical | 8.1 |

$\mu_{\text{ggF+VBF}}$ (Upper limit on HH signal strength)

| Source of Uncertainty | $\Delta\mu/\mu$ |
|--|-----------------|
| Theory uncertainties | |
| Theory uncertainty in signal cross-section | -9.0% |
| All other theory uncertainties | -1.4% |
| Background modeling uncertainties | |
| Bootstrap uncertainty | -7.1% |
| CR to SR extrapolation uncertainty | -7.5% |
| 3b1f nonclosure uncertainty | -2.0% |

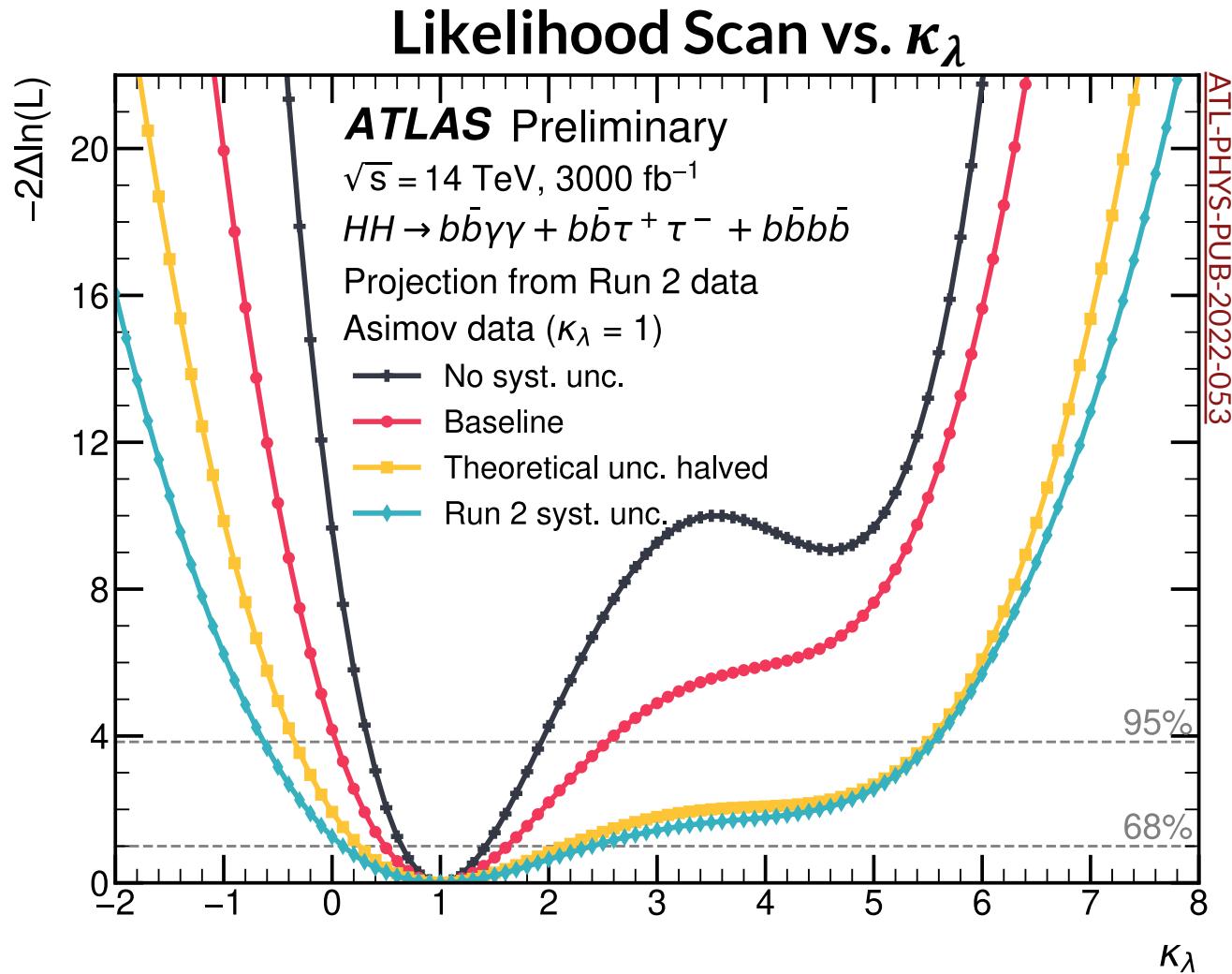


Combination: $HH \rightarrow b\bar{b}b\bar{b}, b\bar{b}\tau\tau, b\bar{b}\gamma\gamma$



Combined upper-limit on
SM HH Cross-Section:
 $2.4 \times \sigma_{SM}$ (2.9 Exp.)

HH Prospects at the High-Luminosity LHC: κ_λ



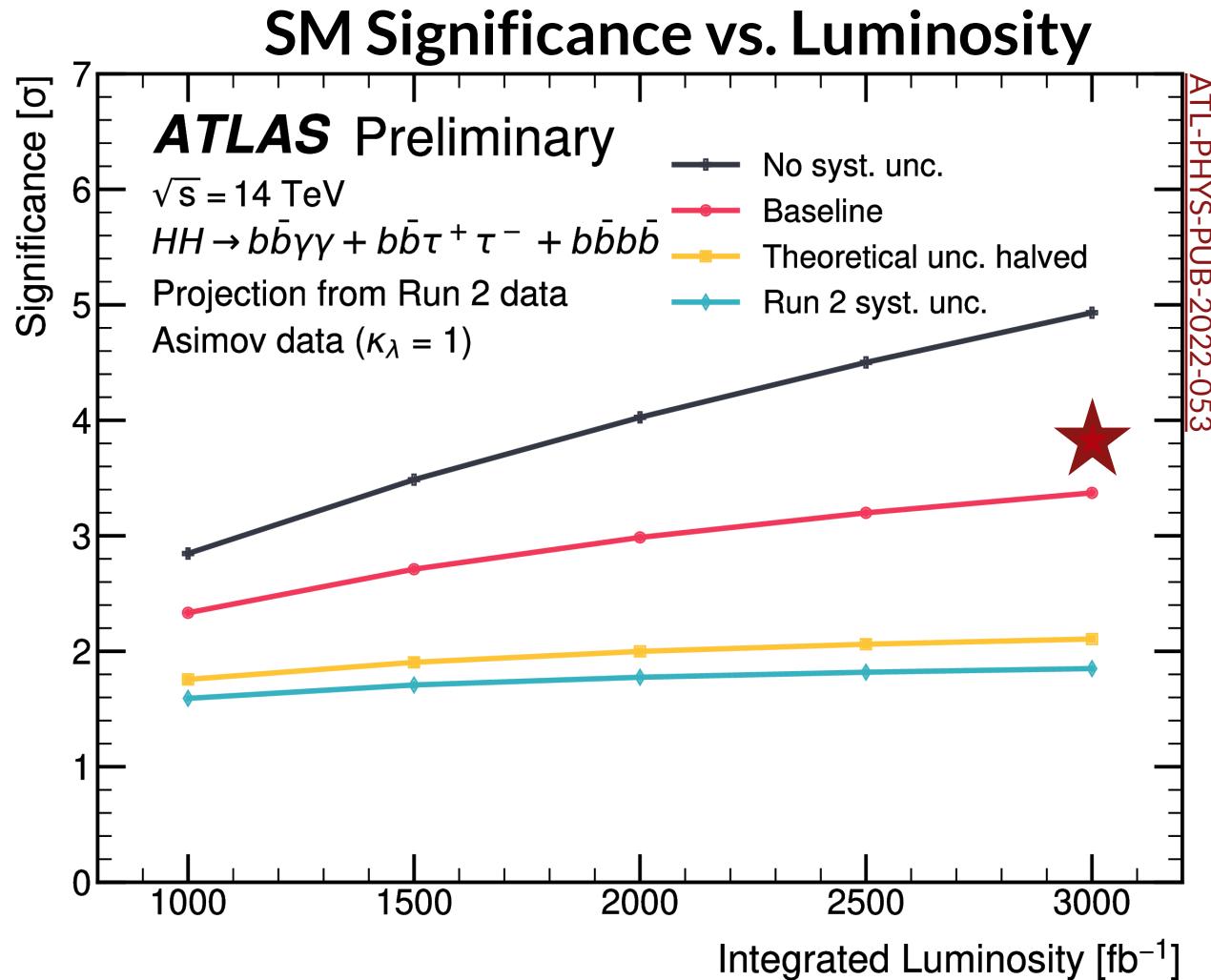
Full HL-LHC Dataset,
“Baseline” Uncertainty Scenario:

$$0.0 < \kappa_\lambda < 2.5$$

→ Move from probing $\mathcal{O}(\sim 10)$ effects to $\mathcal{O}(\sim 1)$ effects

★ “Log Likelihood Scan” limits utilize different assumptions (expected background includes SM HH signal)

HH Prospects at the High-Luminosity LHC



~ Observation sensitivity (3.4σ) to SM HH signal by end of HL-LHC!

→ If our understanding of the Higgs potential is roughly correct, we should be able to see a “bump”

HH Prospects @ HL-LHC: Uncertainty Scenarios

| Baseline Scenario | |
|----------------------------------|---|
| Systematic uncertainties | Scale factors for HL-LHC baseline scenario |
| Theoretical uncertainty | 0.5 |
| b-jet tagging efficiency | 0.5 |
| c-jet tagging efficiency | 0.5 |
| Light-jet tagging efficiency | 1.0 |
| Jet energy scale and resolution | 1.0 |
| Luminosity | 0.6 |
| Background bootstrap uncertainty | 0.5 |
| Background shape uncertainty | 1.0 |

Other Scenarios:

- No Systematic Uncertainties (Statistical Only)

- Run 2 Systematic Uncertainties

- Run 2 Systematic Uncertainties, with theoretical uncertainties halved