



A CASE STUDY ON $b\bar{b}h$ ASSOCIATED PRODUCTION

its physics implication, and machine interpretation

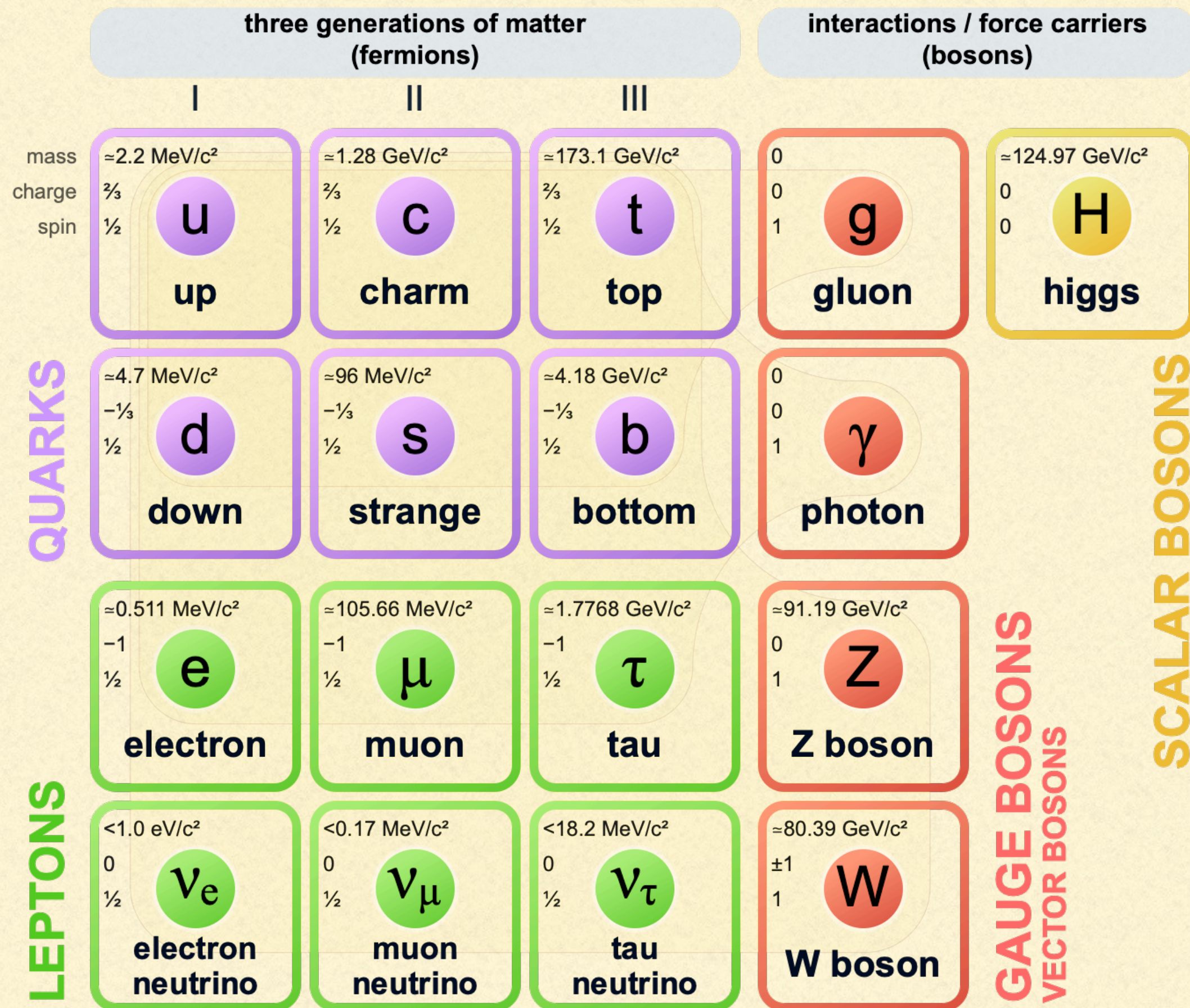
HPNP, March 25th 2021

Zhuoni Qian

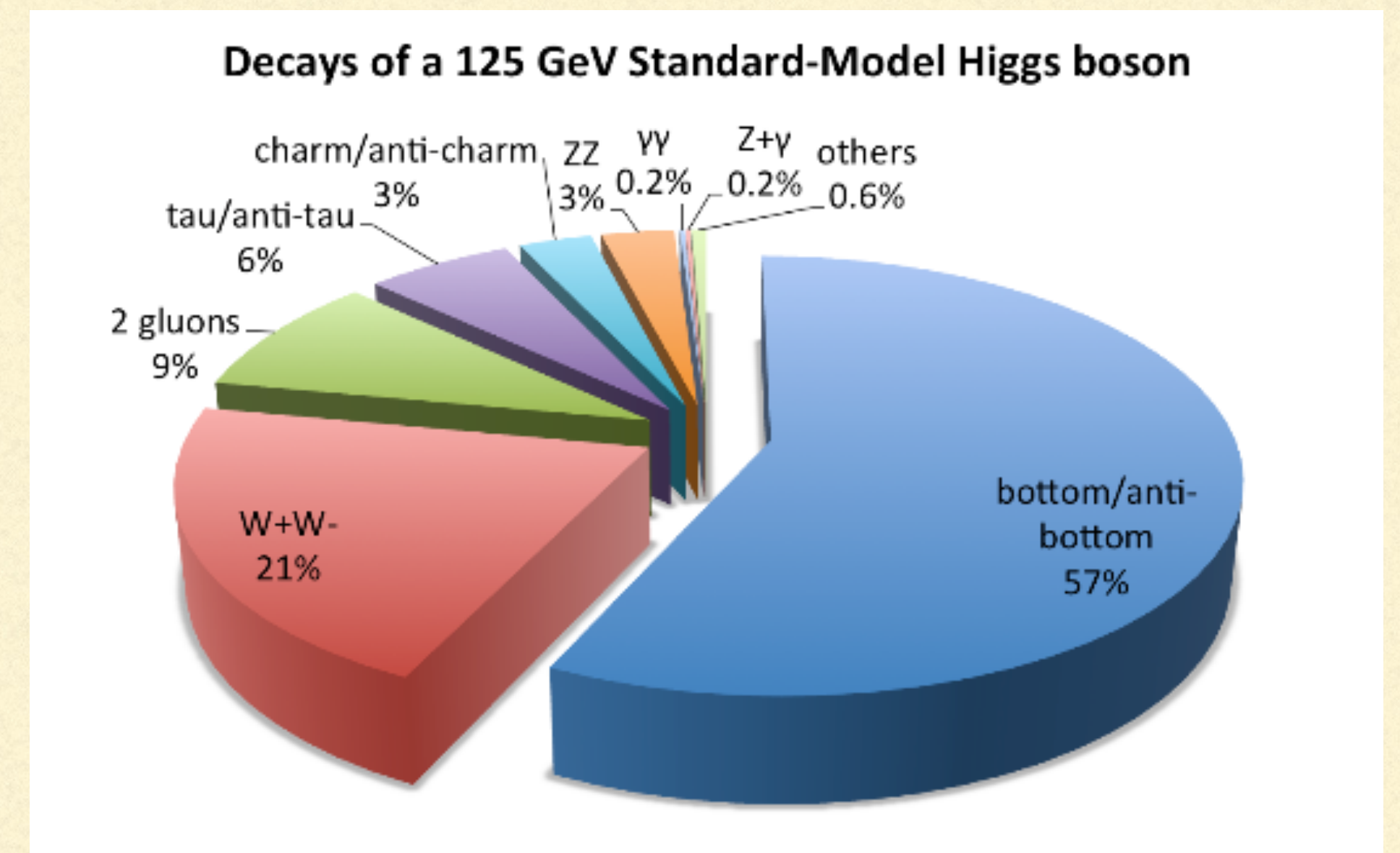
Based on work with Christophe Grojean, Ayan Paul (arXiv: 2011.13945)

Higgs couplings and $b\bar{b}h$

Standard Model of Elementary Particles

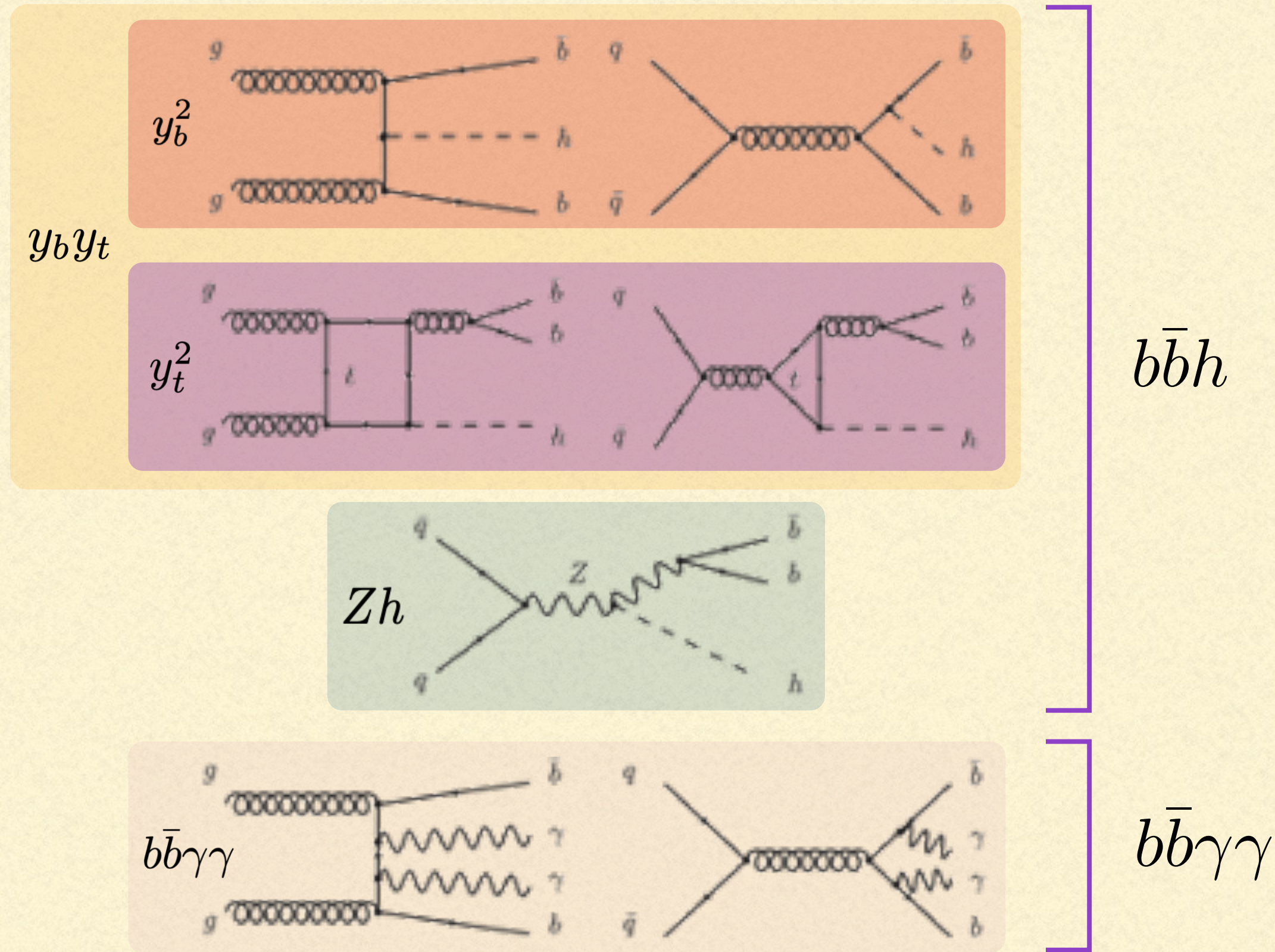


- Bottom Yukawa measurement is a recent achievement:
 $Vh, h \rightarrow b\bar{b}$
- The sign (or phase) of the Yukawa couplings have not been well measured
- There are possible interplays between Yukawa phases of various couplings in EDM measurements and collider physics



(Multi-channel) Signal embedded in large backgrounds

Goal: measure bottom-Yukawa couplings



Traditional cut-based analysis cannot separate the different $b\bar{b}h$ contributions – no y_b sensitivity at HL-LHC

Basic selection (14 TeV HL-LHC): **signals**

| Channel | LO σ (fb) | NLO-k-fact | 6 ab ⁻¹ [#evt] | 2b-jets[%] |
|------------------------|------------------|------------|---------------------------|------------|
| y_b^2 | 0.0648 | 1.5 | 583 | 7.7% |
| $y_b y_t$ | -0.00829 | 1.9 | -95 | 4.0% |
| y_t^2 | 0.123 | 2.5 | 1,840 | 12% |
| Zh | 0.0827 | 1.3 | 645 | 21% |
| $\sum b\bar{b}h$ | 0.262 | - | 2,970 | - |
| $b\bar{b}\gamma\gamma$ | 12.9 | 1.5 | 116,000 | 14% |

$b\bar{b}h$ background

QCD-QED background

$$p_T^{bjet} > 30 \text{ GeV}, p_T^{\gamma jet} > 20 \text{ GeV},$$

$$\eta_{bjet, \gamma jet} < 2.5, 110 < m_{\gamma\gamma} \text{ (GeV)} < 140.$$

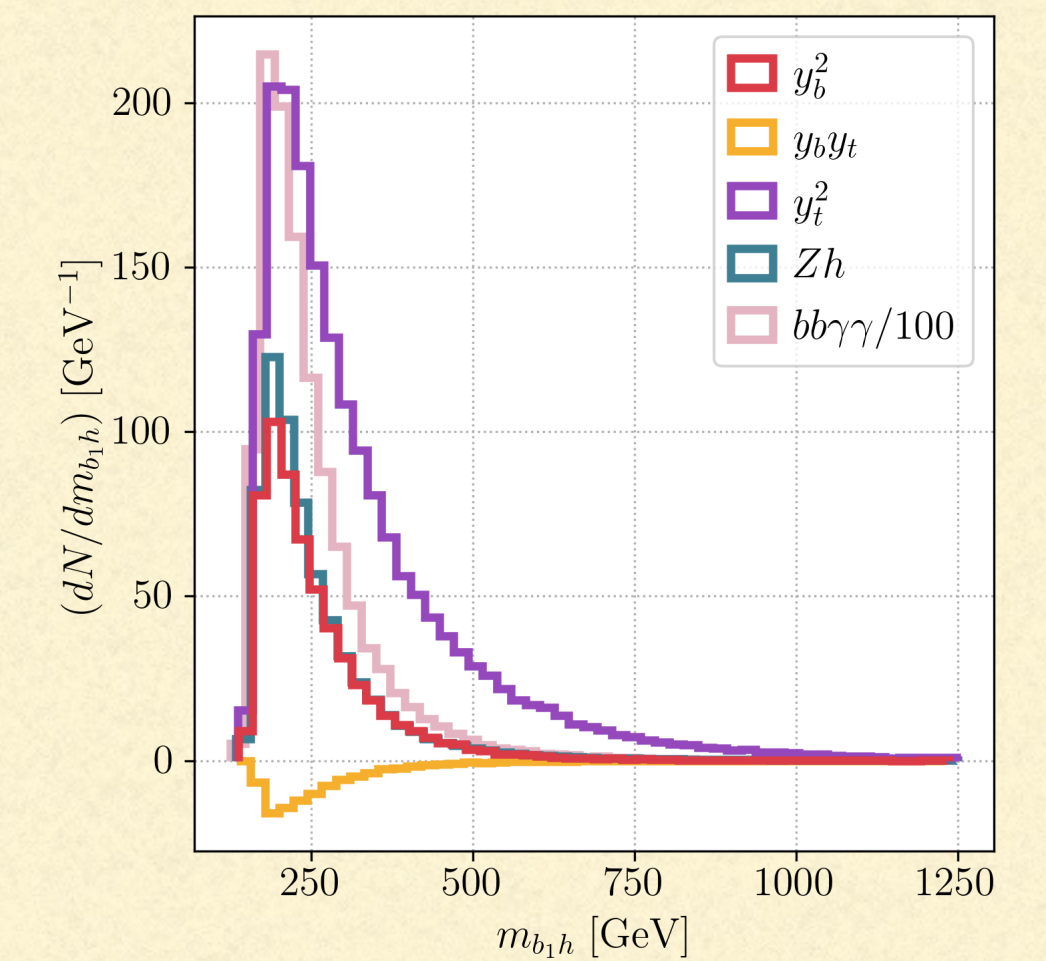
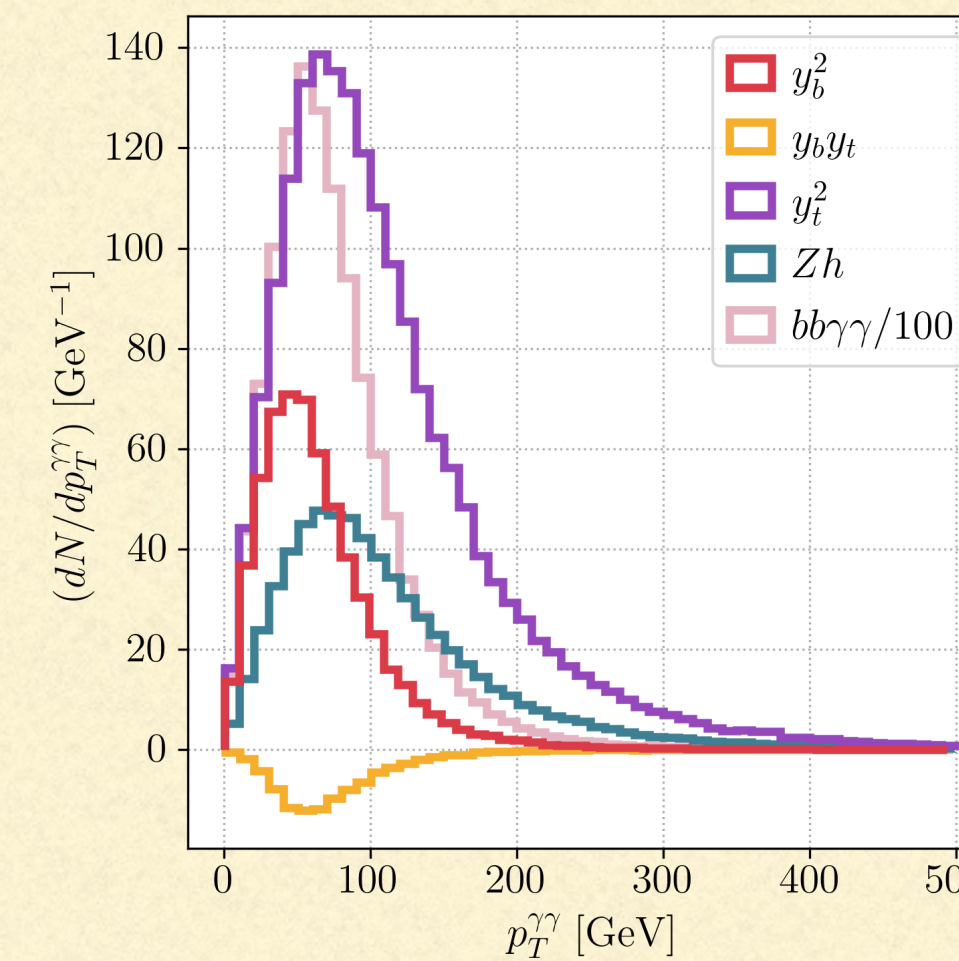
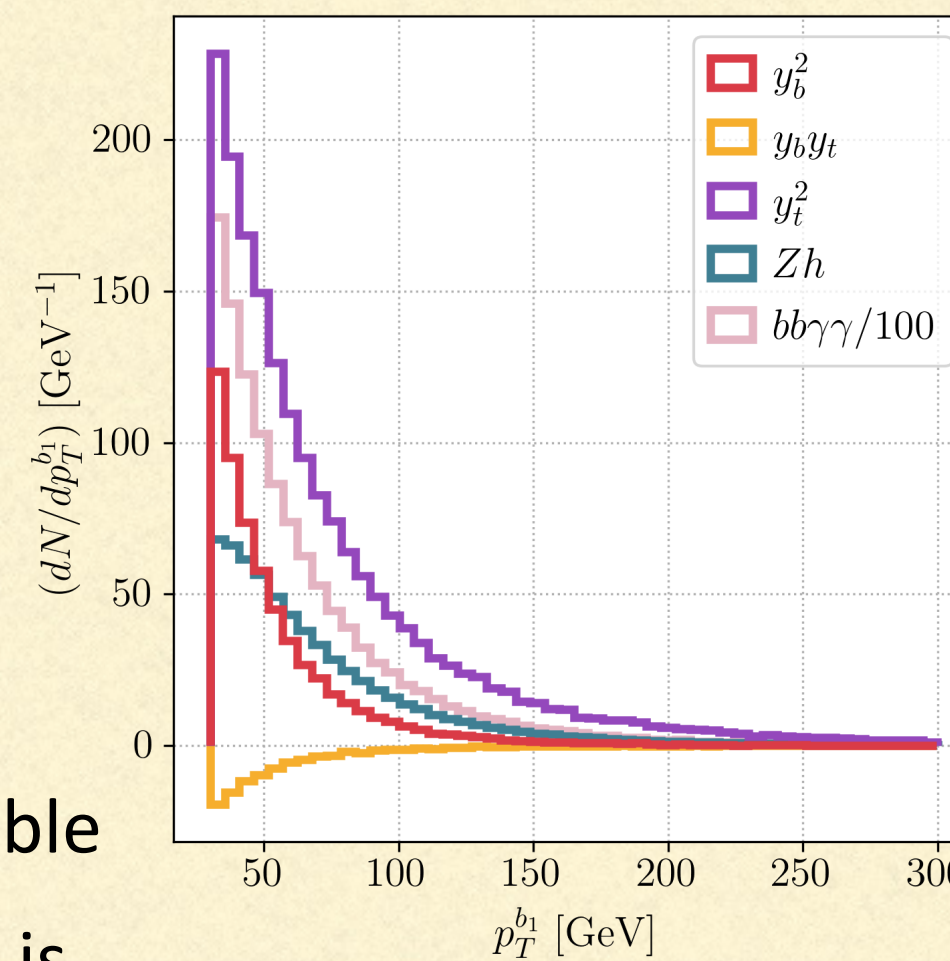
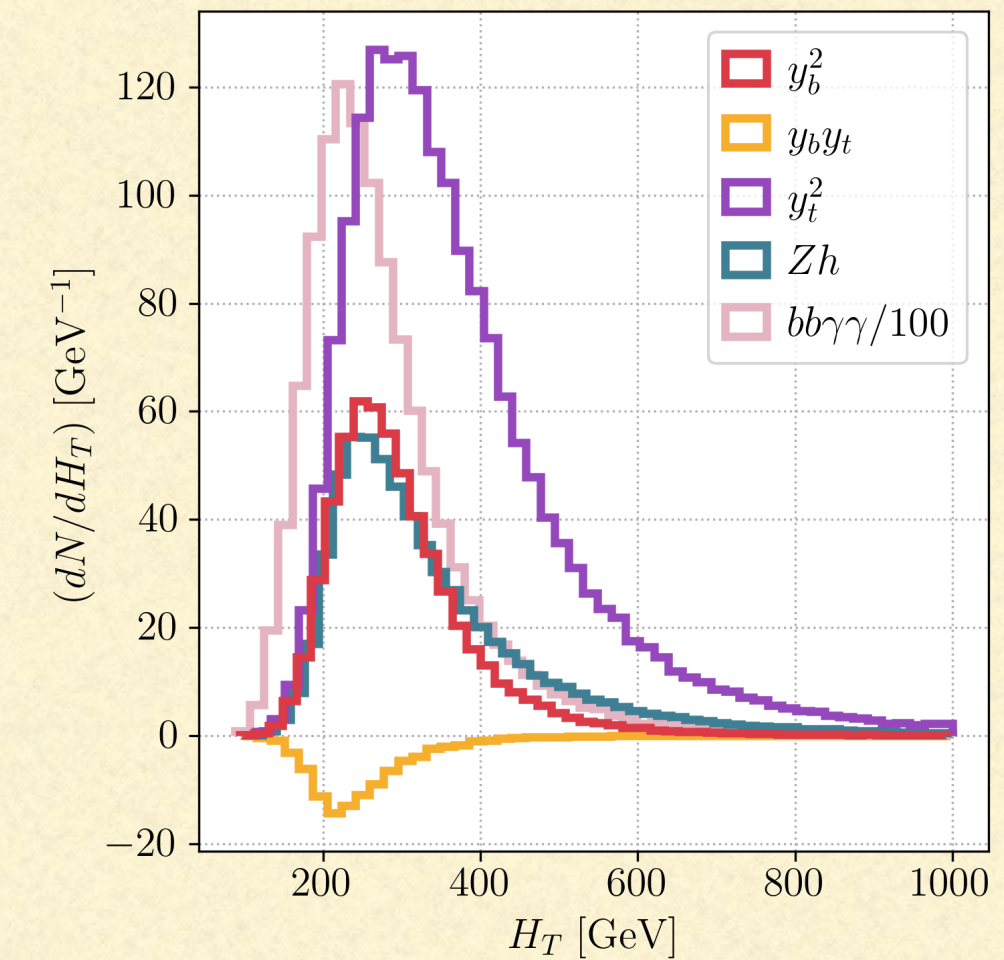
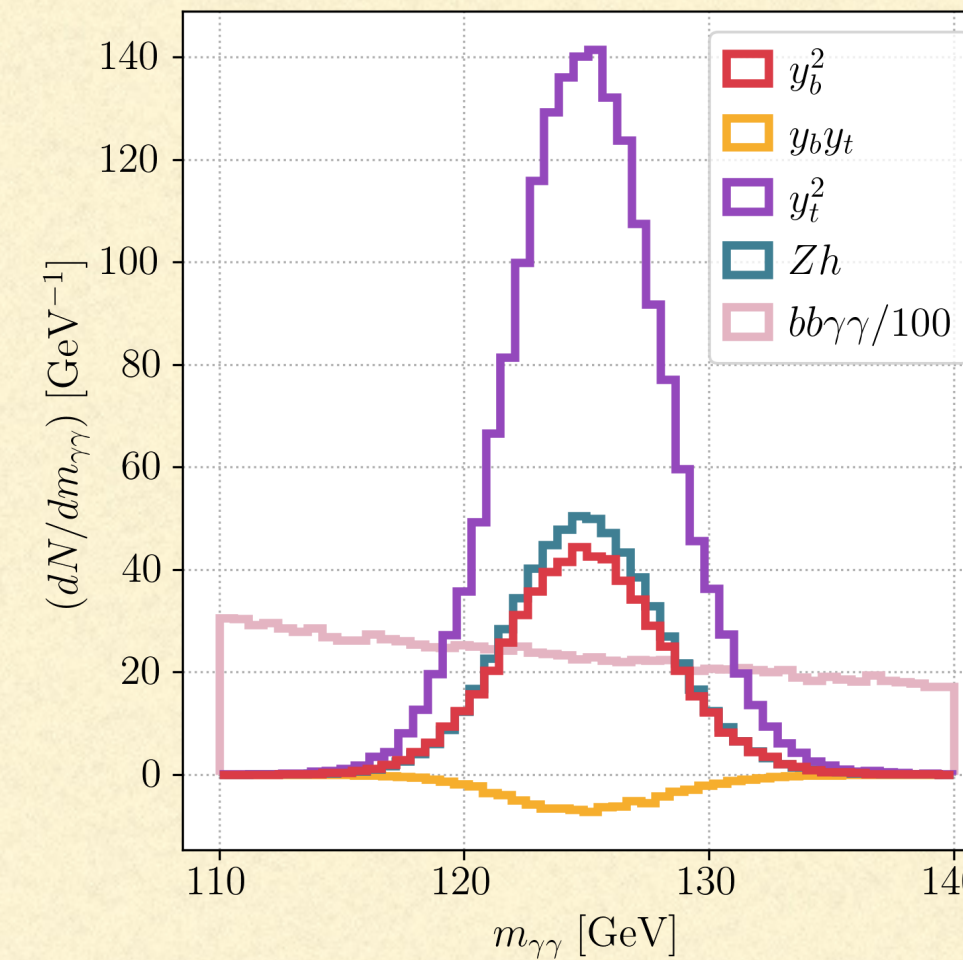
Observable and distributions:

Understanding differences in shapes

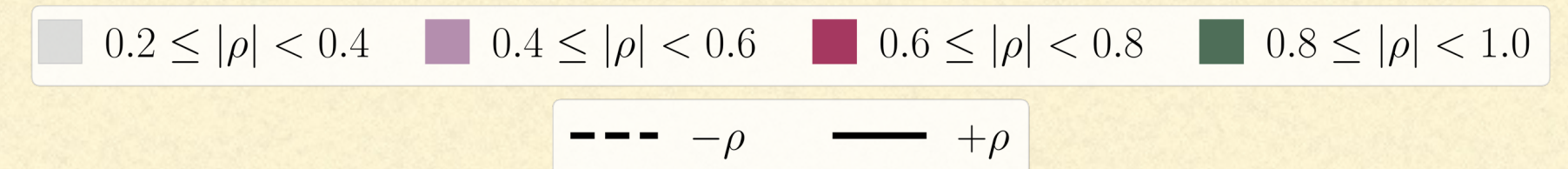
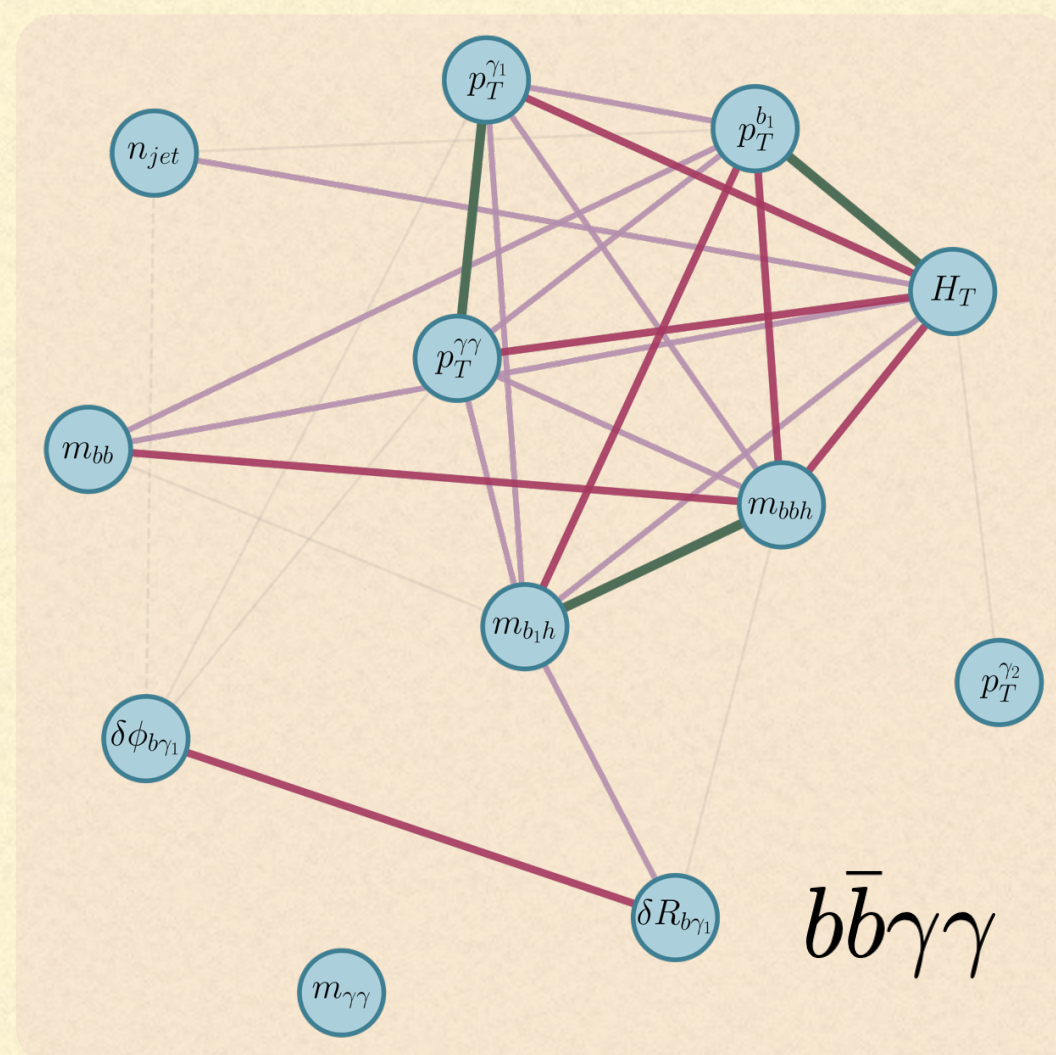
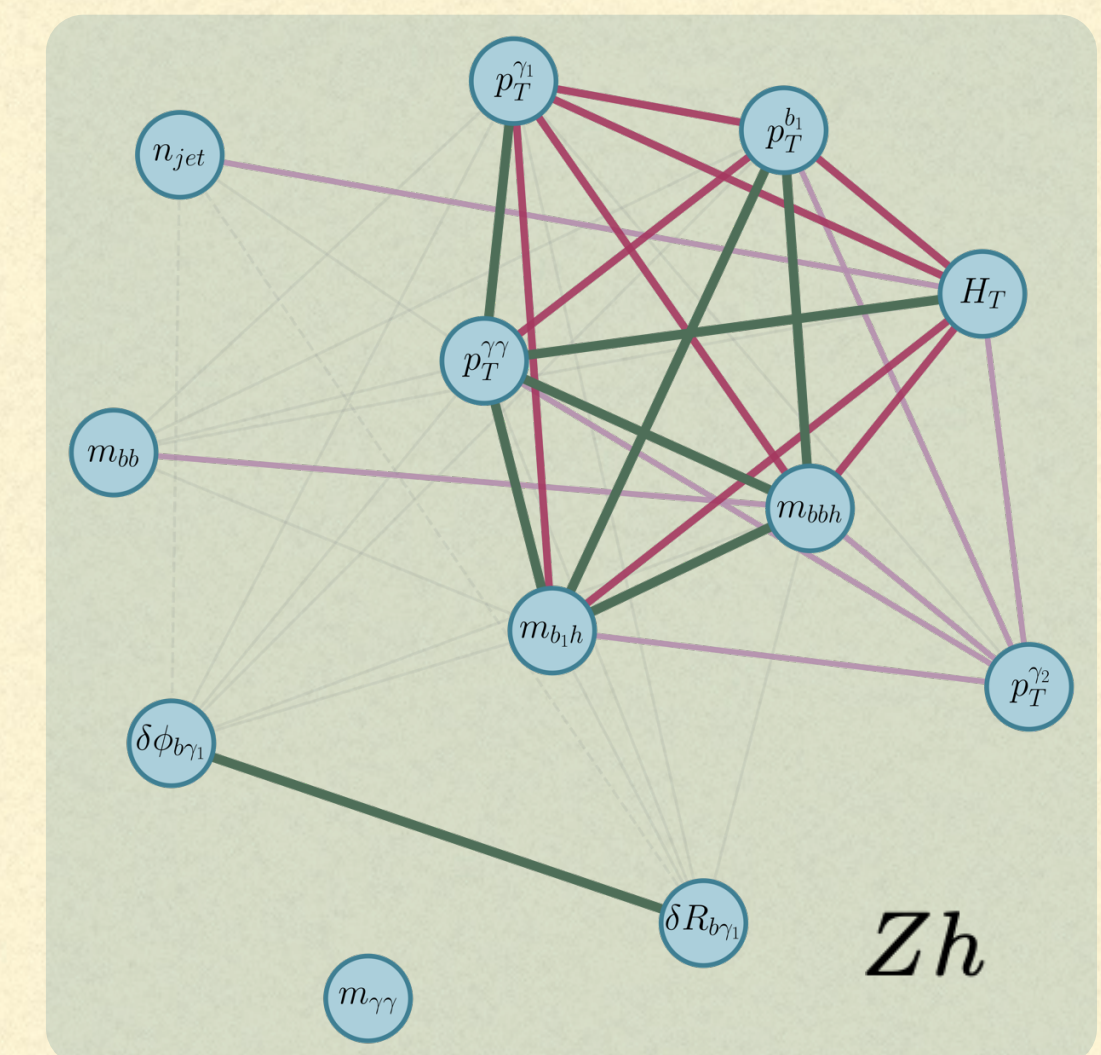
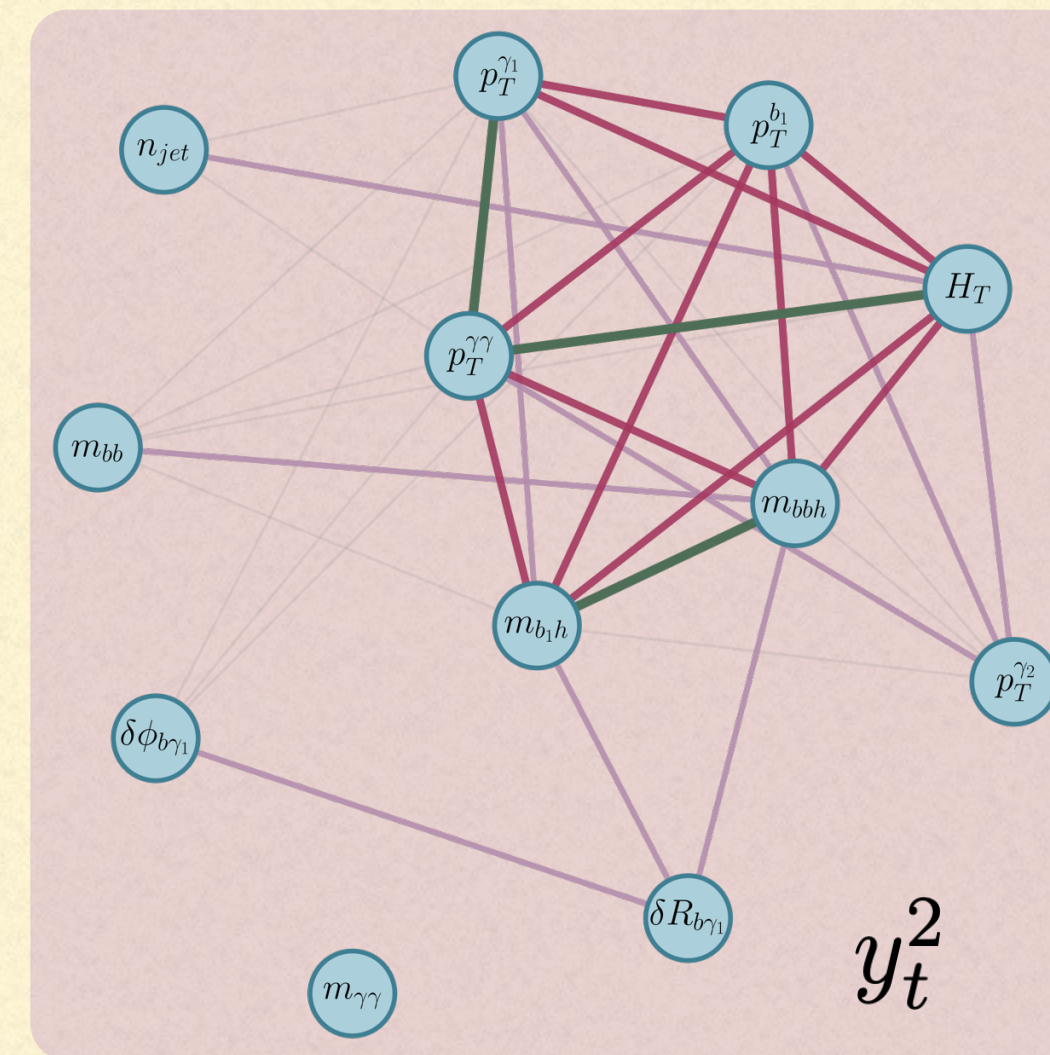
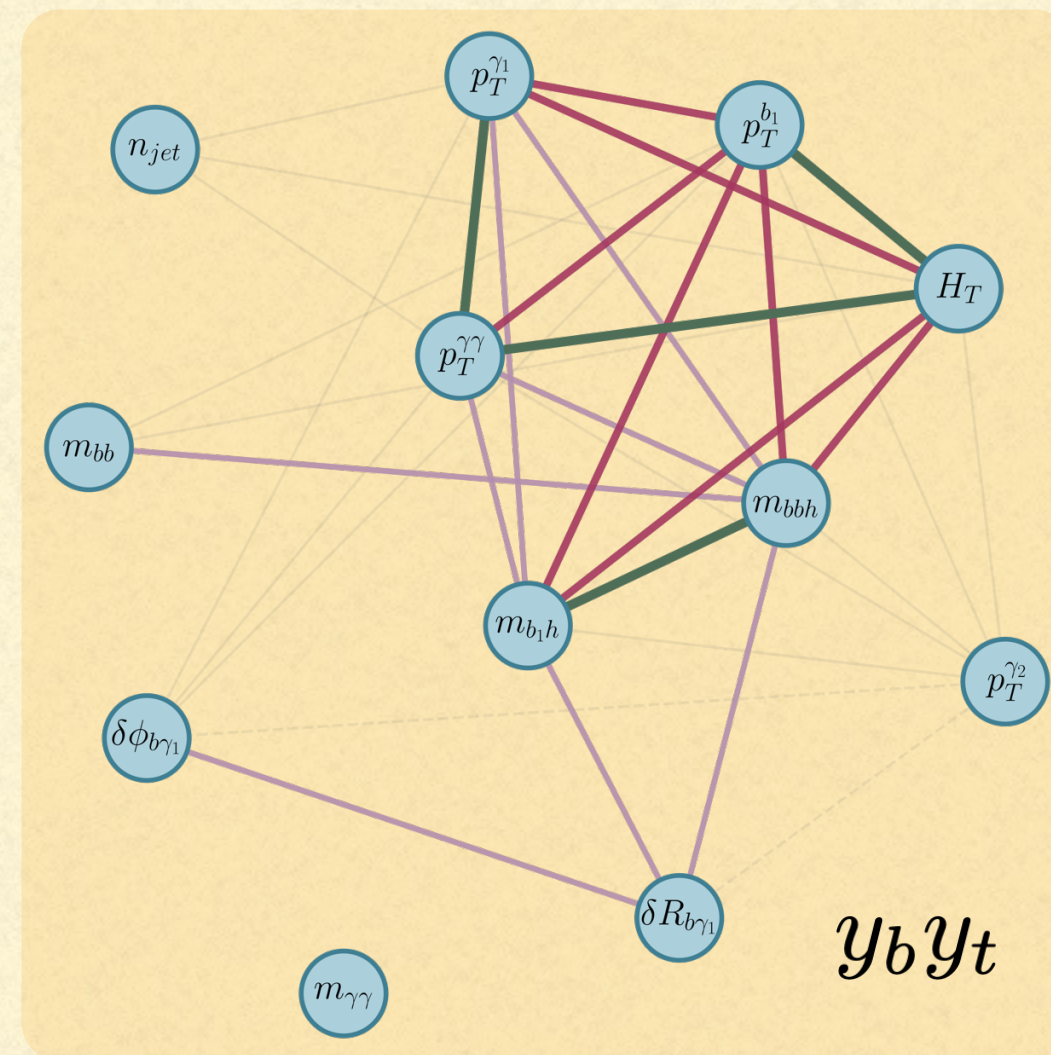
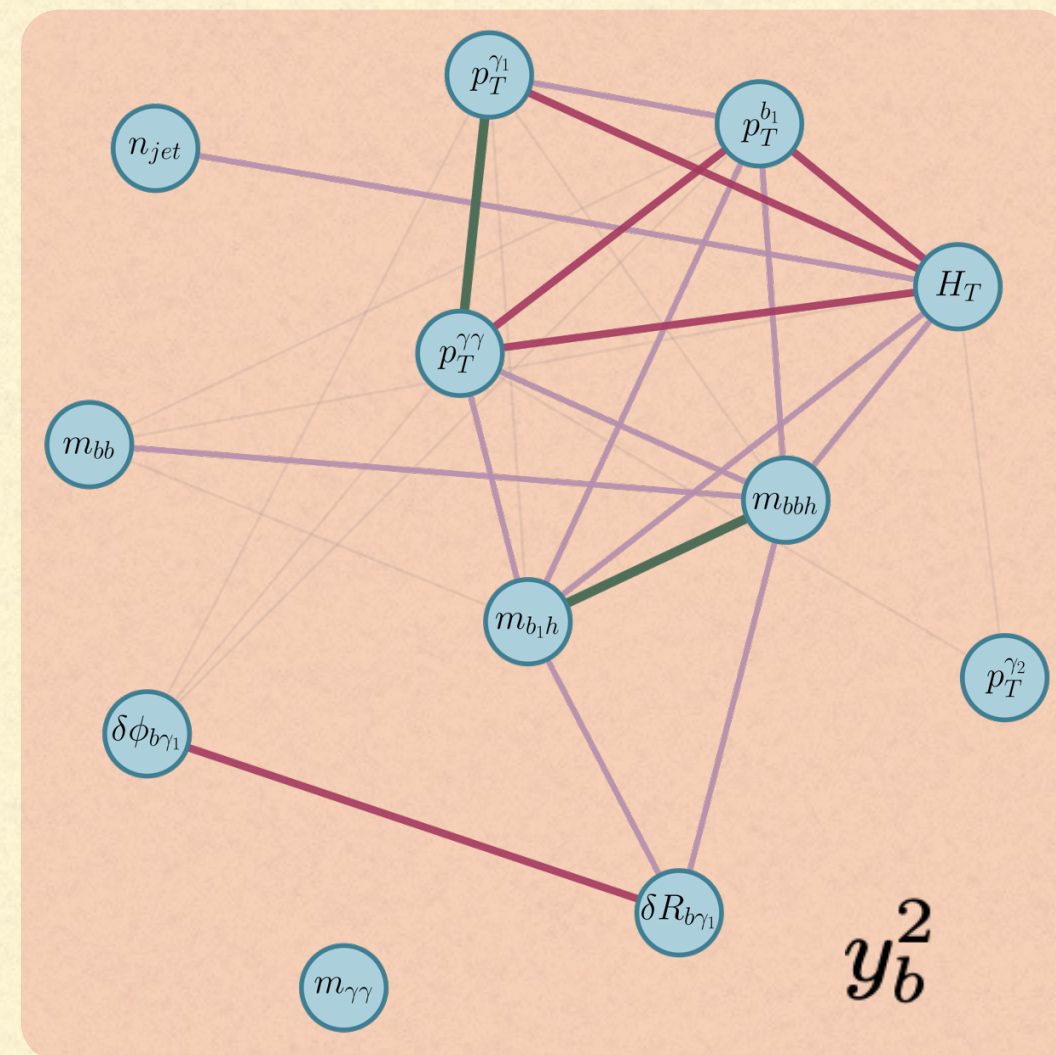
- $p_T^{b_1}, p_T^{b_2}, p_T^{\gamma_1}, p_T^{\gamma\gamma},$
- $\eta_{bj_1}, \eta_{bj_2}, \eta_{\gamma_1}, \eta_{\gamma\gamma},$
- $n_{bjet}, n_{jet}, \Delta R_{\min}^{b\gamma}, \Delta\phi_{\min}^{bb},$
- $m_{\gamma\gamma}, m_{bb}, m_{b_1h}, m_{b\bar{b}h}, H_T.$

The choice of variables is important:

- Momenta four vectors are not easily interpretable
- Kinematic variables are interpretable but there is no clear “complete set”



Into higher dimensions (the correlation):



- The multi-channel multivariable correlation pattern.
- MVAs (BDT, NN) > ID cuts <= higher order correlation
- Importance of observables measure

Analysis optimised with BDT classification:

Predicted no. of events at HL-LHC

| Actual no. of events | Channel | y_b^2 | $y_b y_t$ | y_t^2 | Zh | $bb\gamma\gamma$ | total |
|----------------------|---------|---------|-----------|---------|-------|------------------|---------|
| y_b^2 | | 170 | 54 | 51 | 122 | 189 | 586 |
| $y_b y_t$ | | -7 | -24 | -4 | -20 | -40 | -95 |
| y_t^2 | | 238 | 112 | 452 | 546 | 487 | 1,835 |
| Zh | | 22 | 28 | 21 | 416 | 161 | 648 |
| $bb\gamma\gamma$ | | 2,183 | 2,450 | 151 | 8,045 | 101,591 | 115,779 |
| Z_j | | 3.33 | 0.47 | 10. | 4.36 | 317 | |

$$Z_j = \frac{|N_{jj}|}{\sqrt{\sum_i N_{ij}}}$$

About ~60% gain in significance over traditional cut-based analyses (2σ).

Predicted no. of events at FCC-hh

| Actual no. of events | | y_b^2 | $y_b y_t$ | y_t^2 | Zh | $bb\gamma\gamma$ | total |
|----------------------|--|---------|-----------|---------|---------|------------------|-----------|
| y_b^2 | | 32,074 | 15,112 | 10,966 | 6,579 | 8,959 | 73,690 |
| $y_b y_t$ | | -964 | -6,815 | -907 | -583 | -1,820 | -11,089 |
| y_t^2 | | 48,772 | 45,751 | 148,669 | 39,598 | 26,484 | 309,274 |
| Zh | | 1,860 | 4,498 | 2,280 | 12,661 | 2,282 | 23,581 |
| $bb\gamma\gamma$ | | 172,088 | 373,436 | 106,335 | 126,429 | 7,952,834 | 8,731,122 |
| Z_j | | 63.7 | 10.4 | 288 | 29.4 | 2,813 | |

$$Z_j = \frac{|N_{jj}|}{\sqrt{\sum_i N_{ij}}}$$

About ~60% gain in significance over traditional cut-based analyses.

Physics Interpretation: real bottom Yukawa κ -scheme $\mathcal{L} \supset -\kappa_b \frac{m_b}{v} \bar{b}b h$

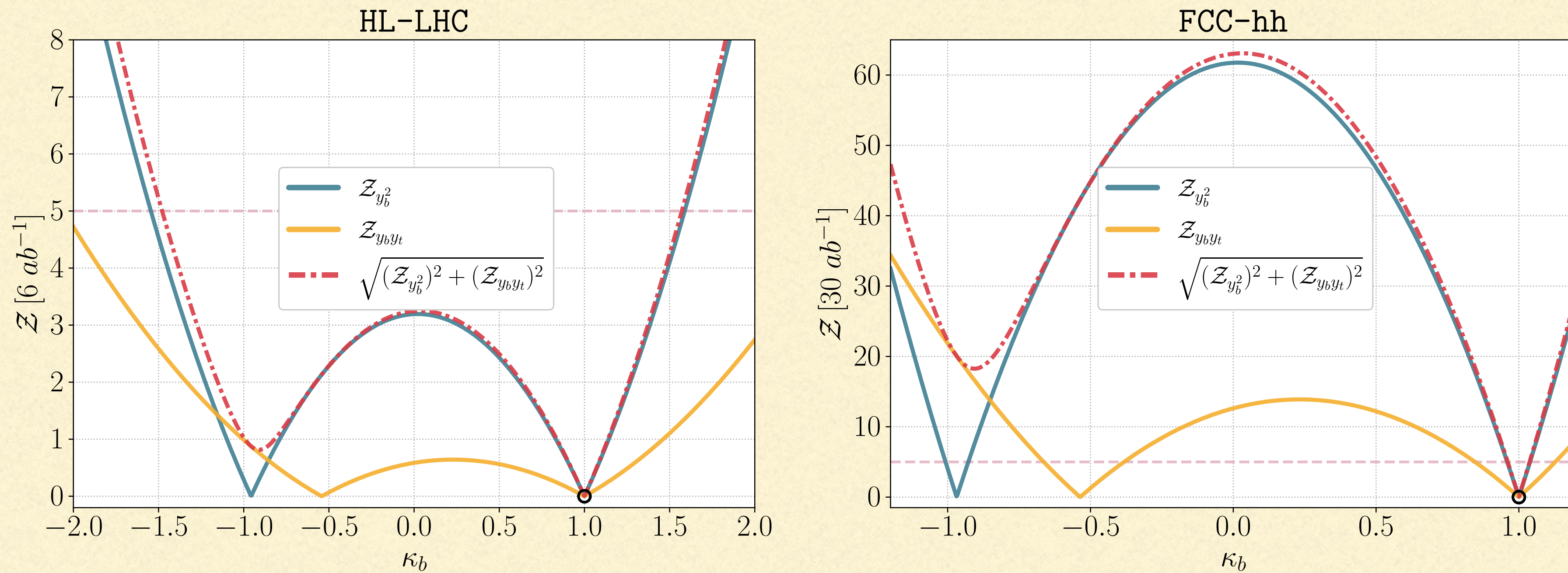
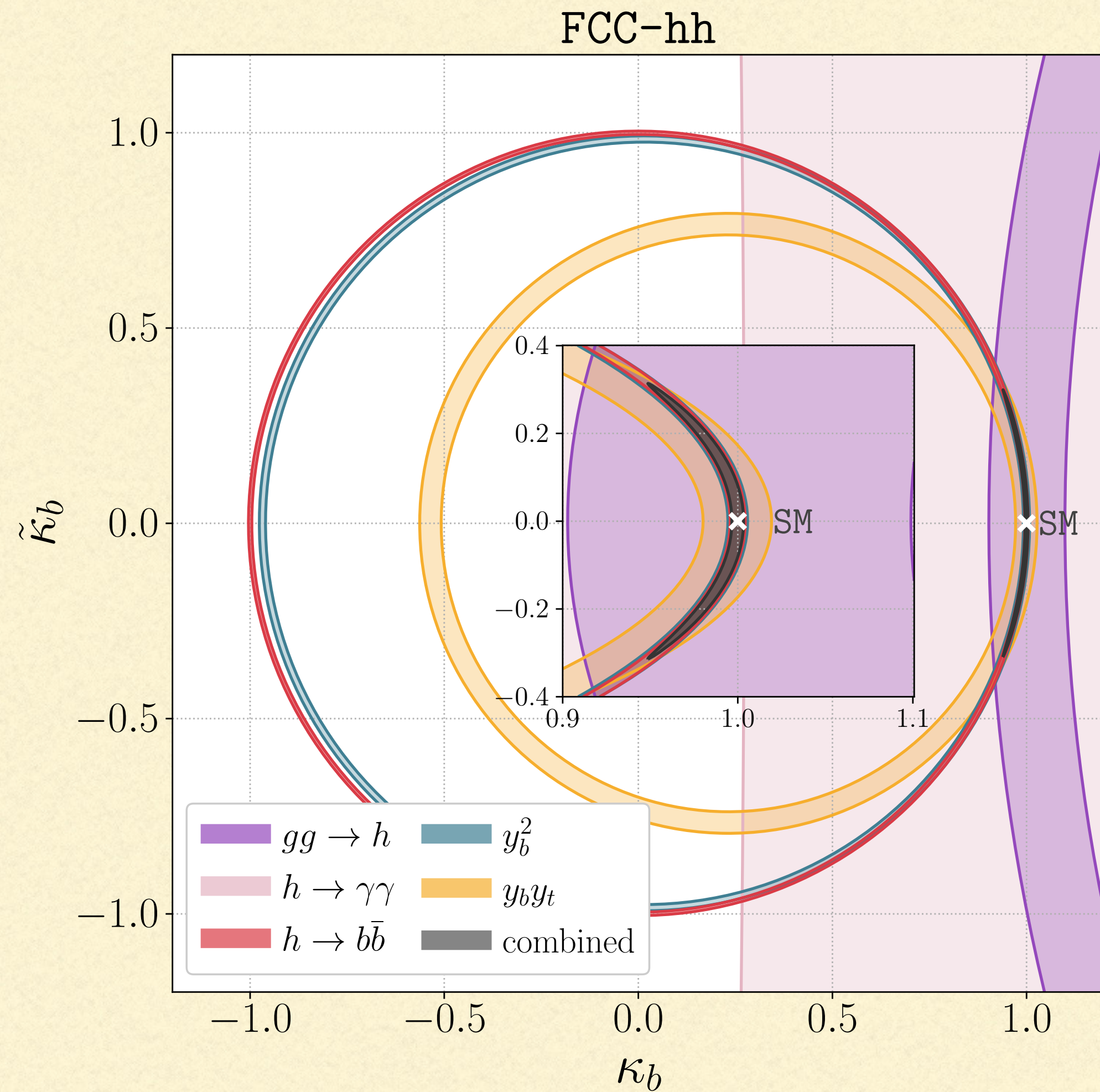
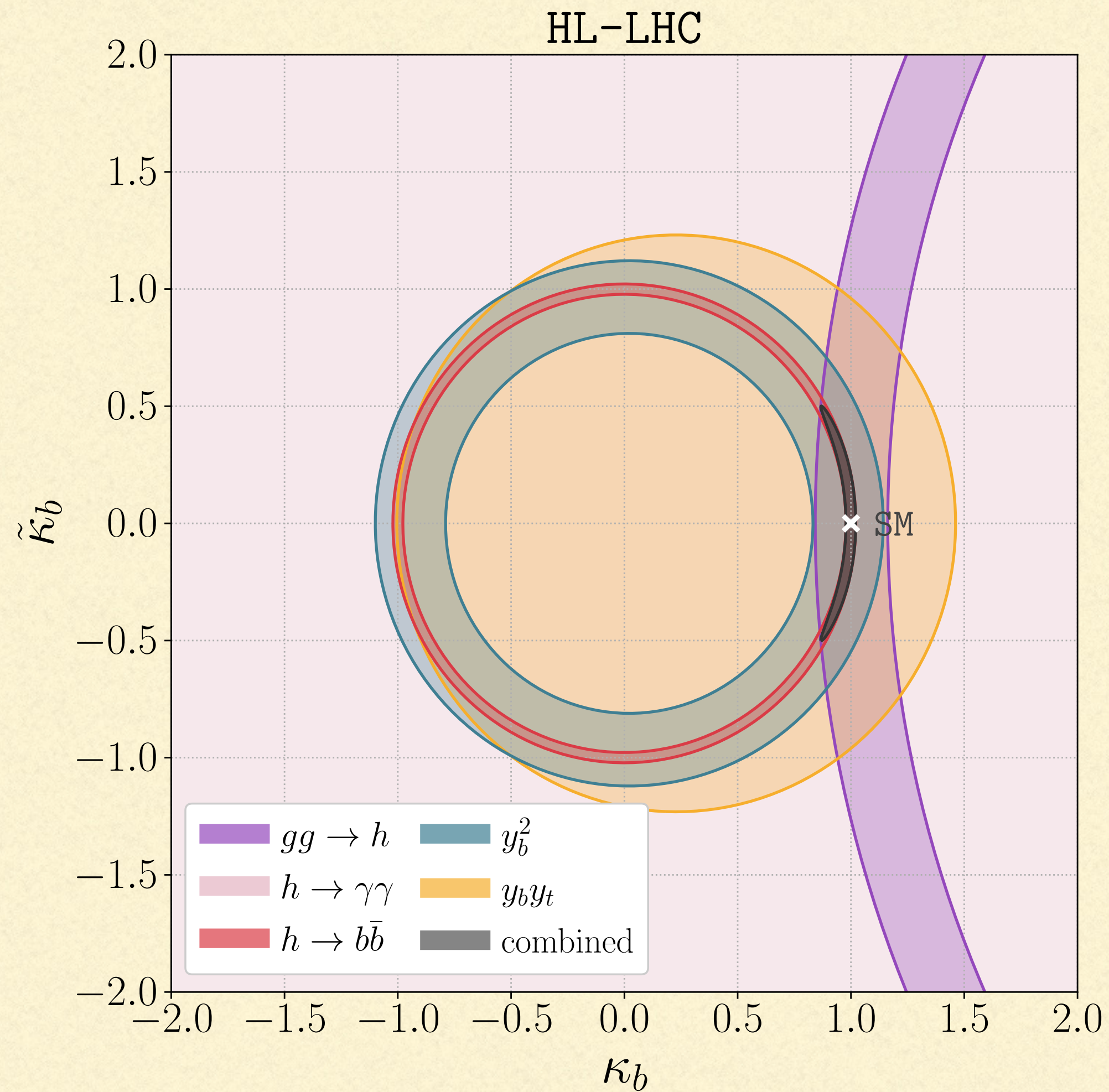


Figure 7. Significance, Z , as a function of κ_b at HL-LHC (ATLAS+CMS combined, $6 ab^{-1}$) and FCC-hh ($30 ab^{-1}$). A SM signal is injected.

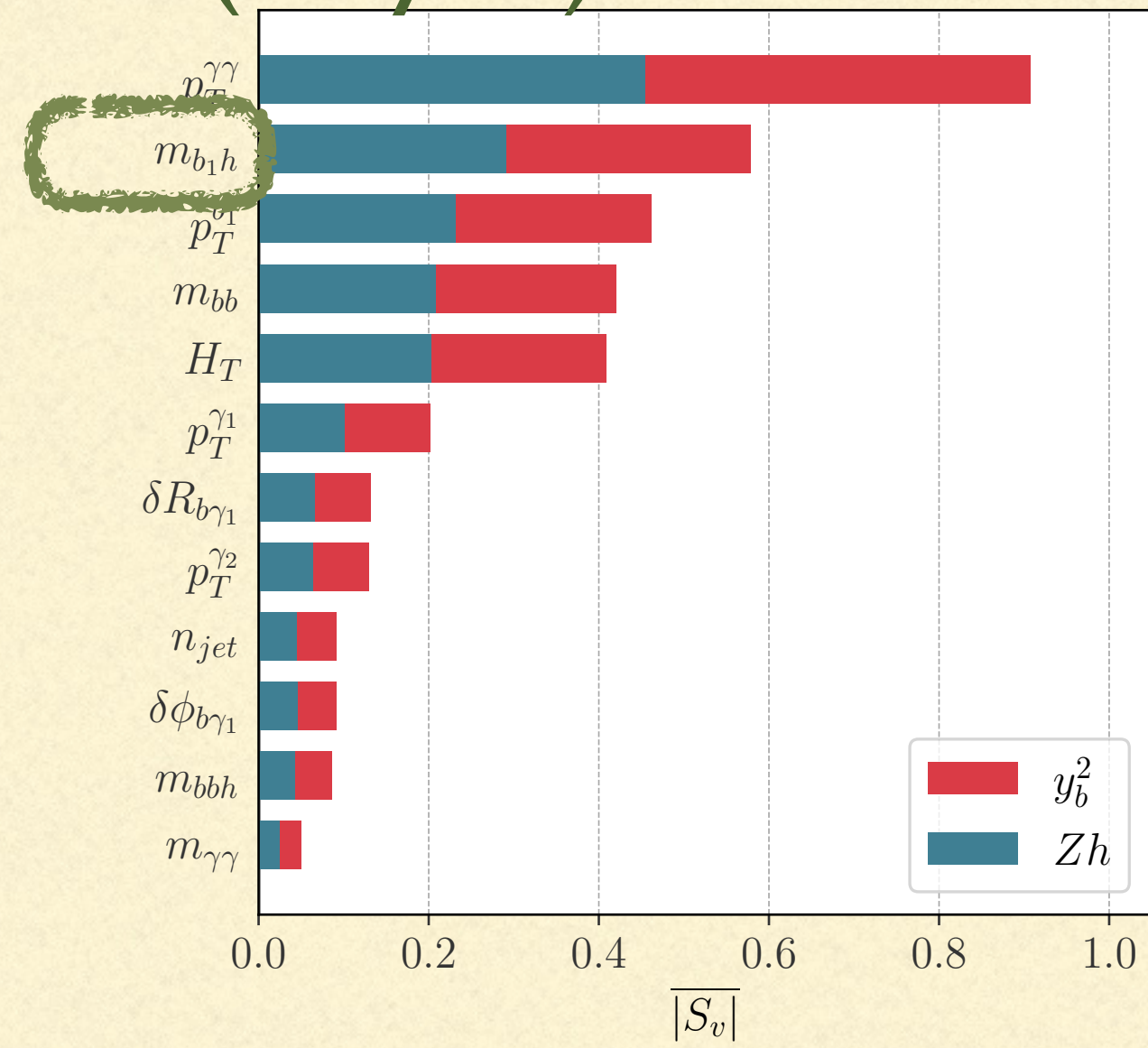
=> Unambiguous sign determination at FCC-hh.

Physics Interpretation: complex bottom Yukawa (CP-phase)

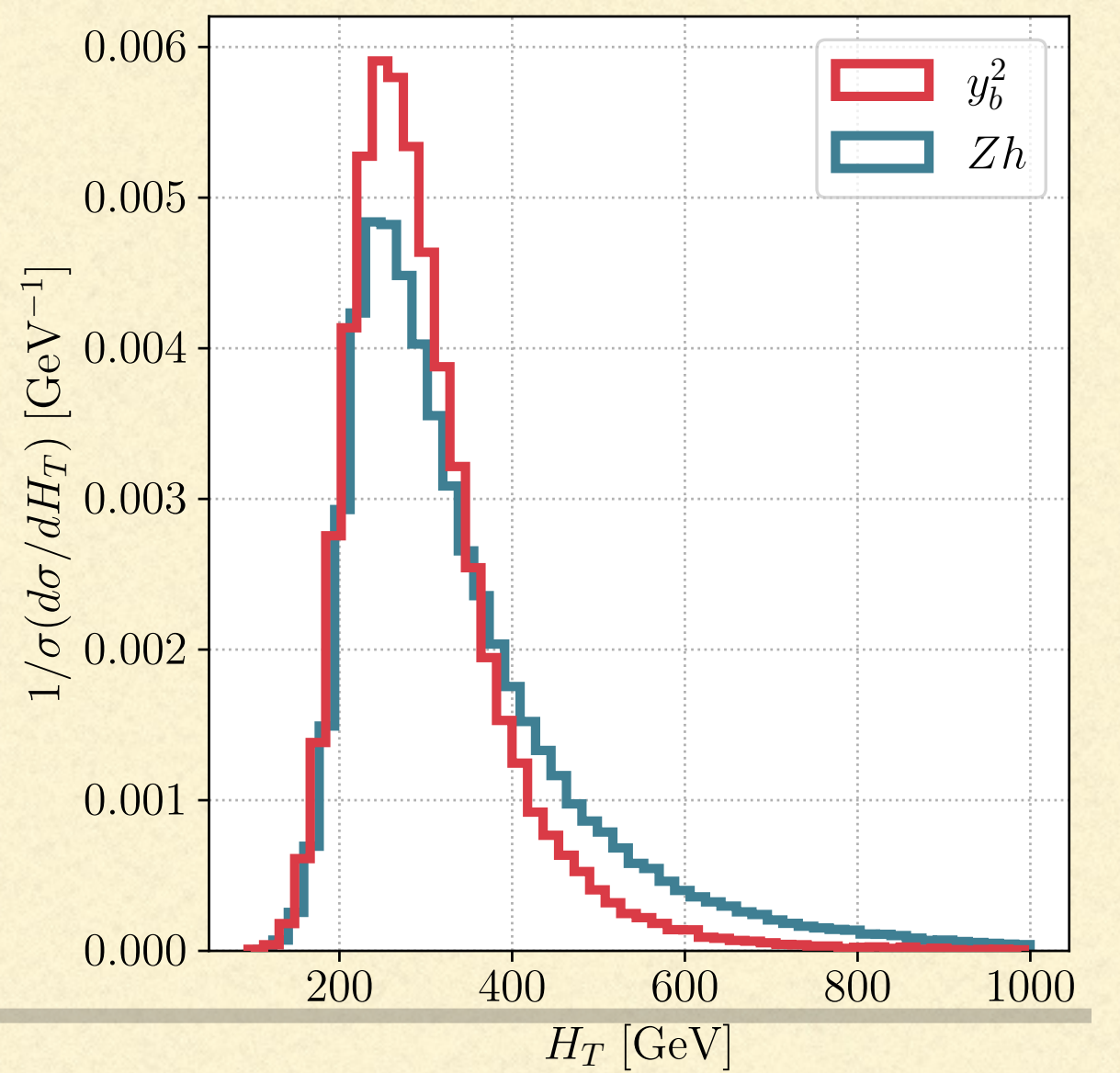
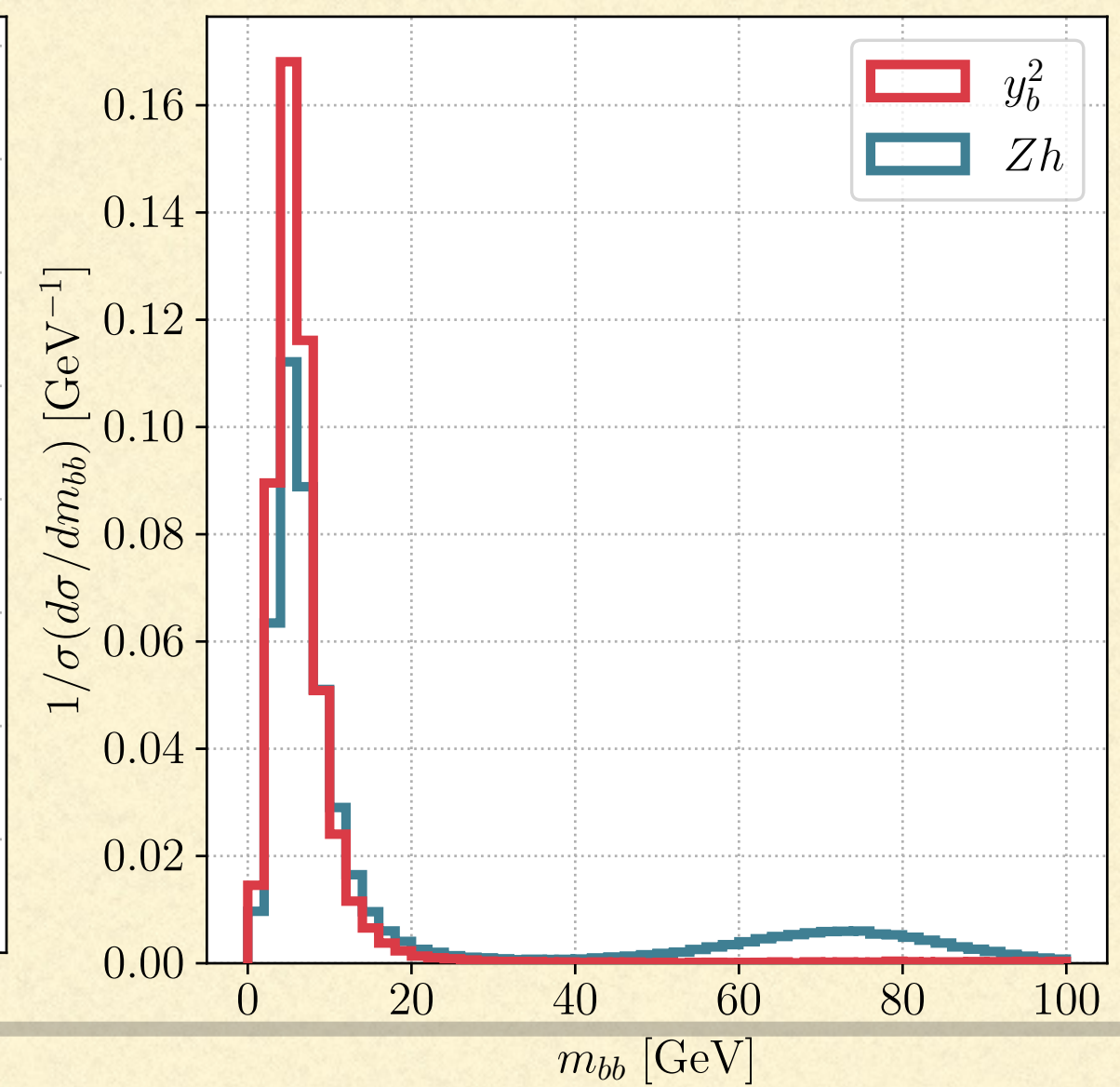
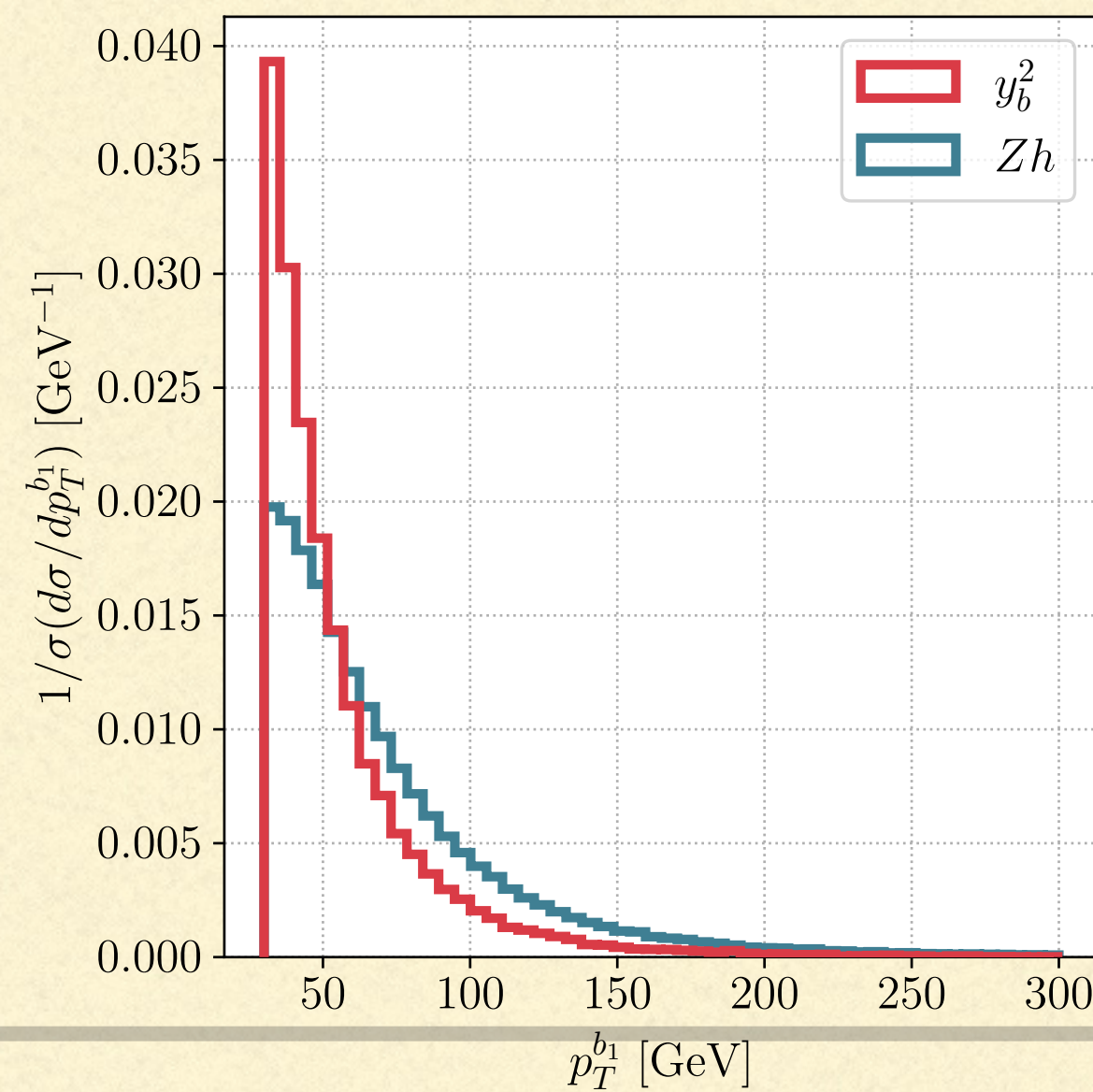
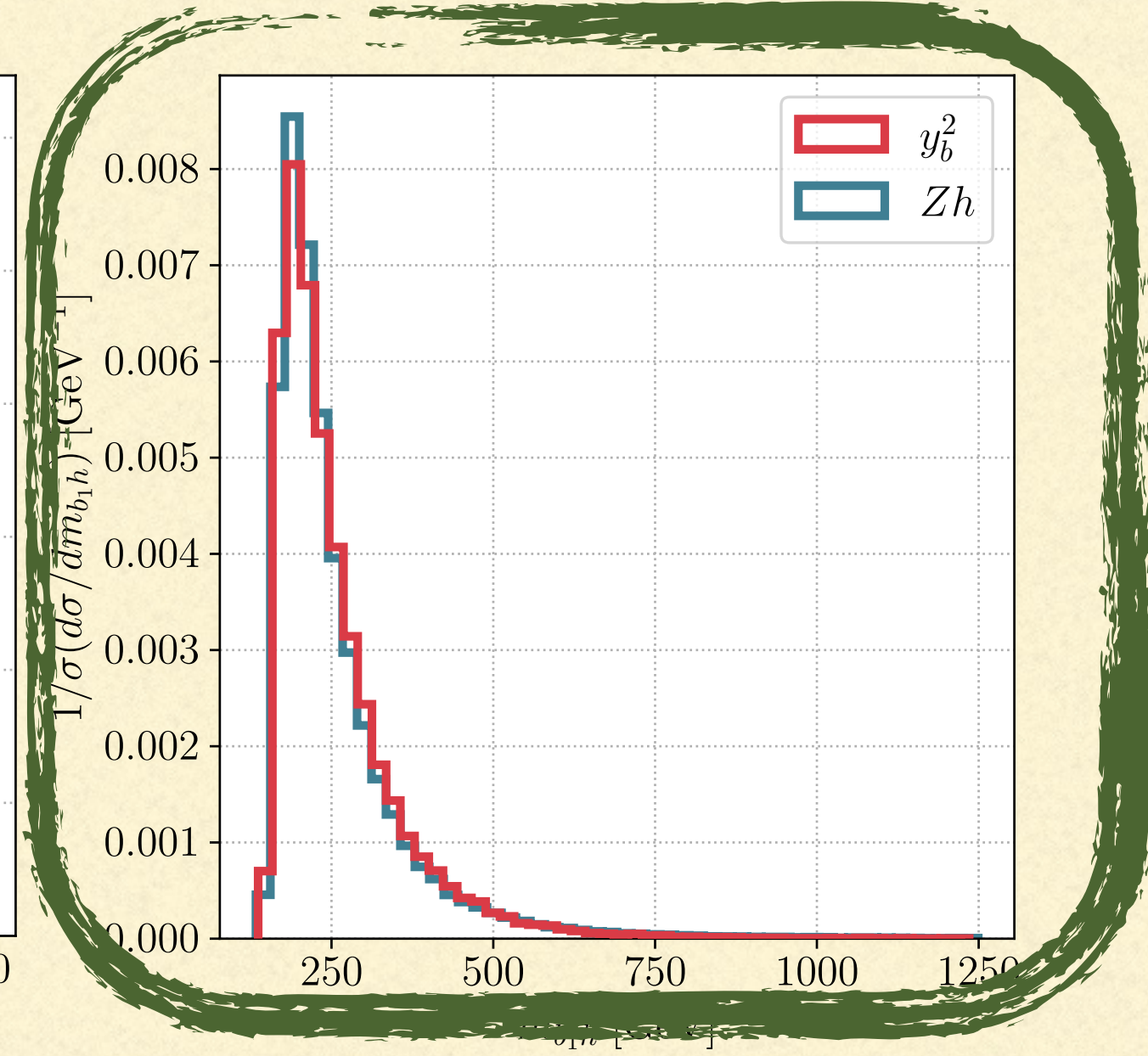
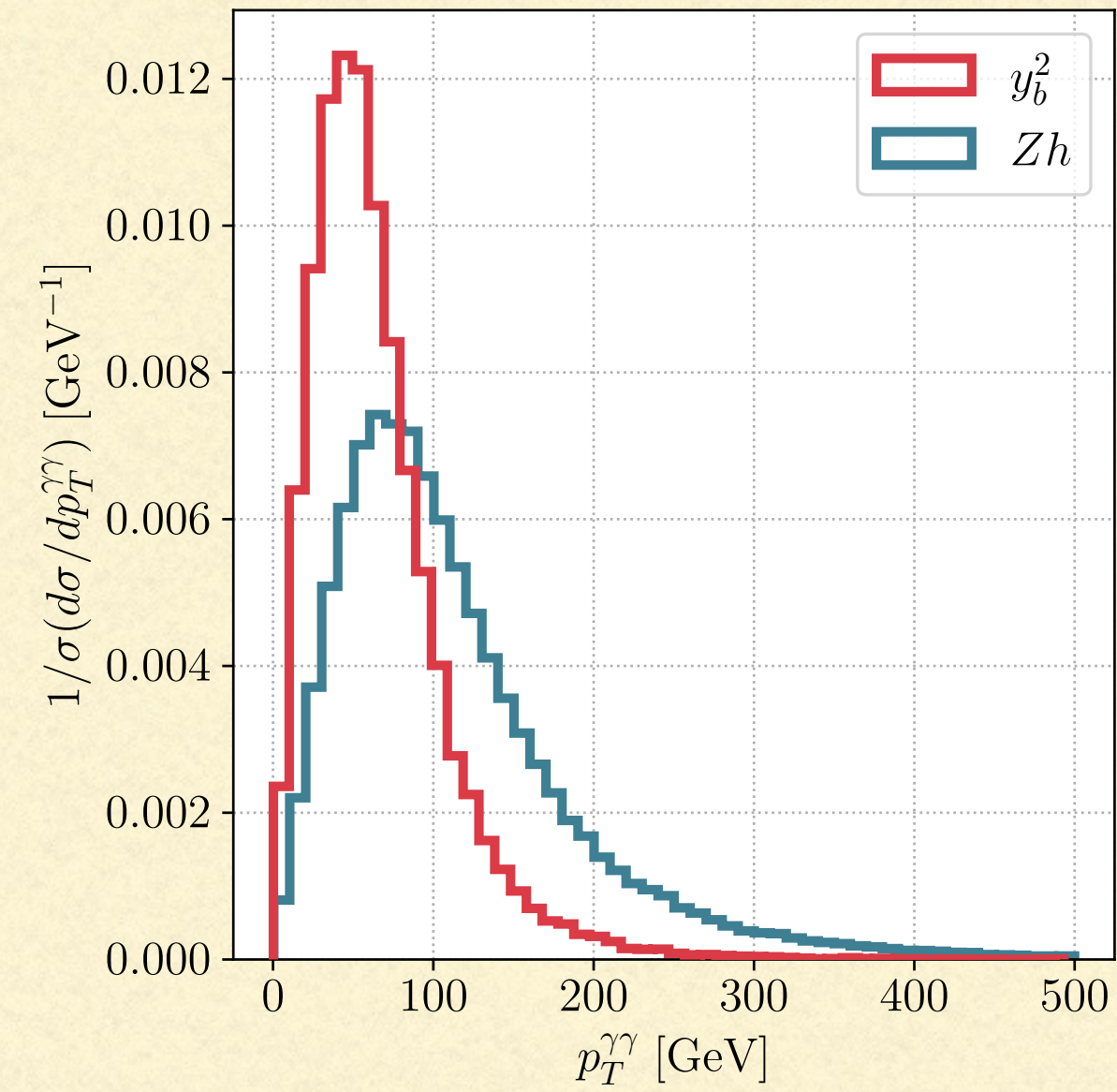
$$\mathcal{L} \supset -\frac{m_b}{v} (\kappa_b \bar{b}b + i\tilde{\kappa}_b \bar{b}\gamma_5 b)h$$



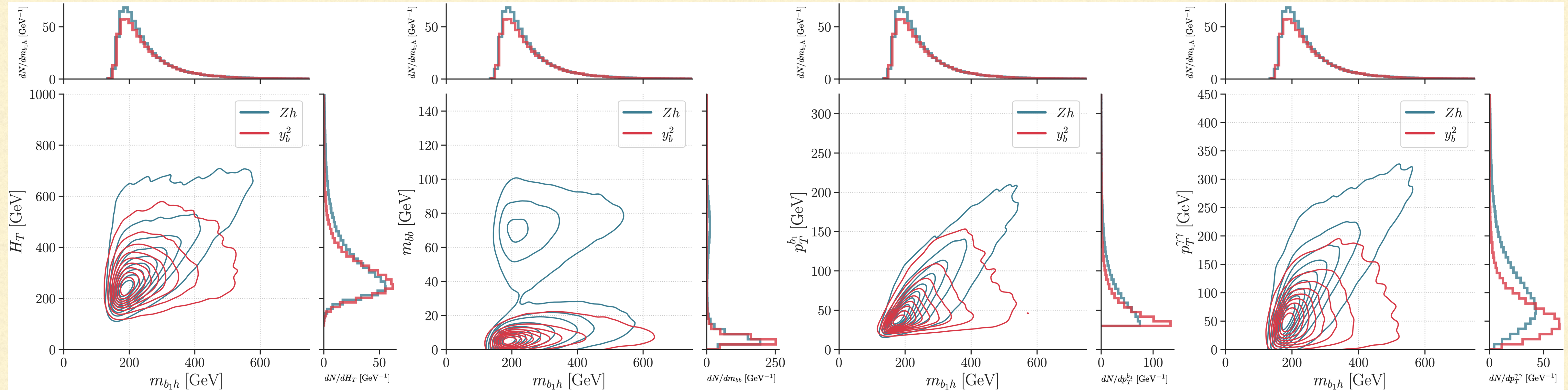
Machine Interpretation (zh-yb2):



HL-LHC



Machine Interpretation (zh-yb2):

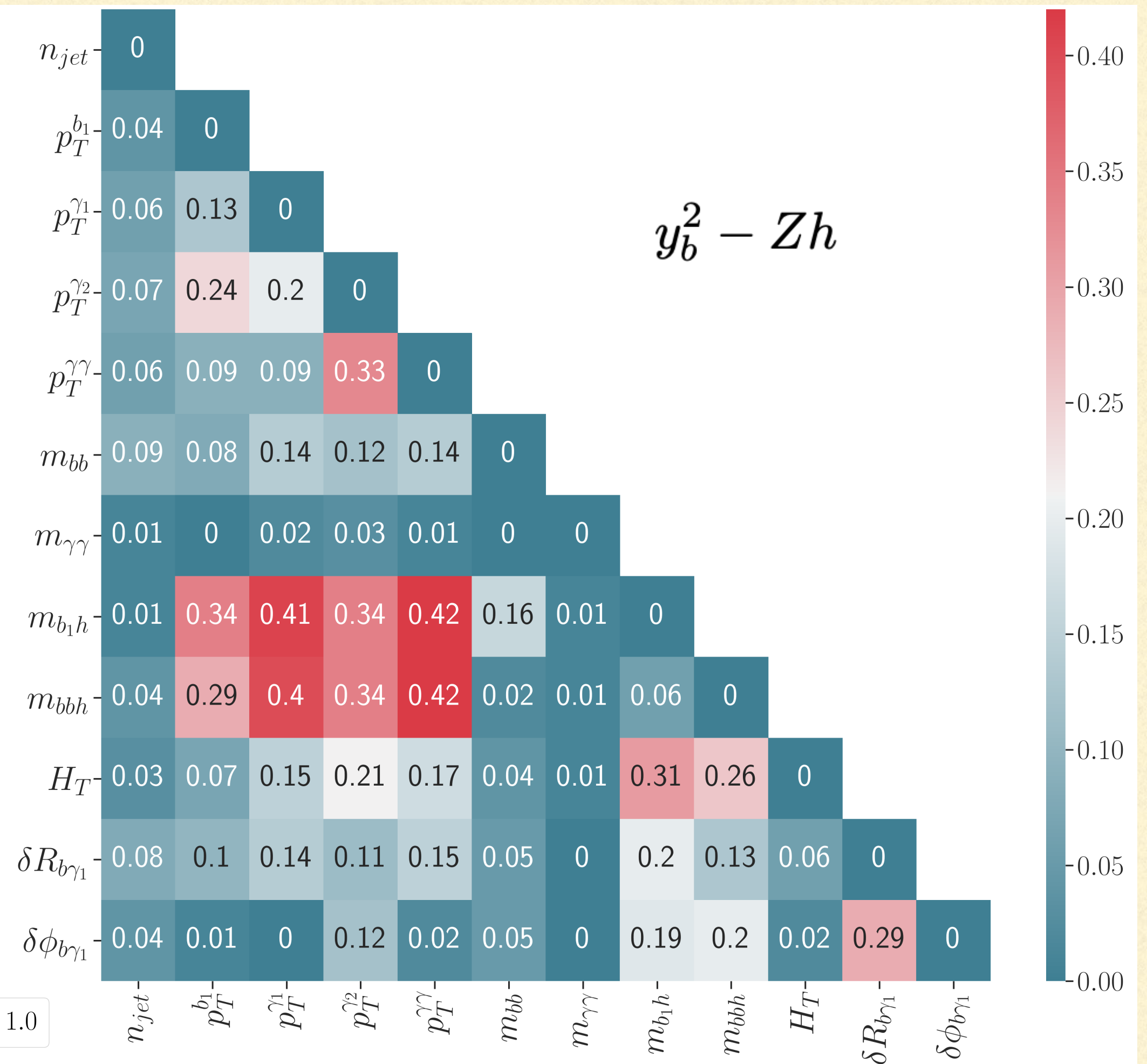
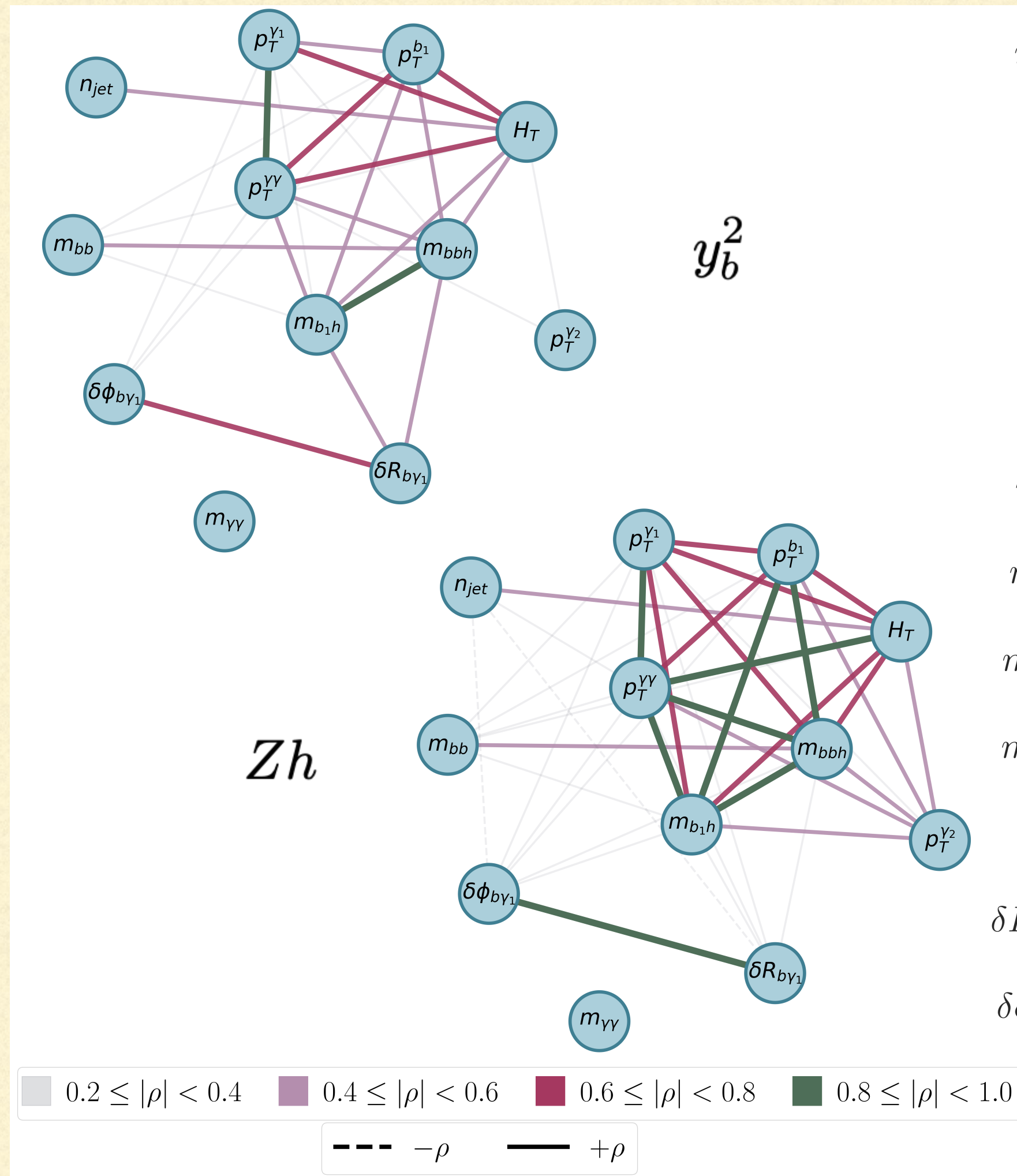


- Cut-based analyses start to falter with multivariate correlations – difficult to visualize and interpret
- Machine learning algorithms excel at multivariate analyses
- Machine learning algorithms are essentially black-boxes – not good for understanding the underlying dynamics

Machine Interpretation (zh-yb2):

“importance of m_{b_1h} variable visualised through correlation”

HL-LHC

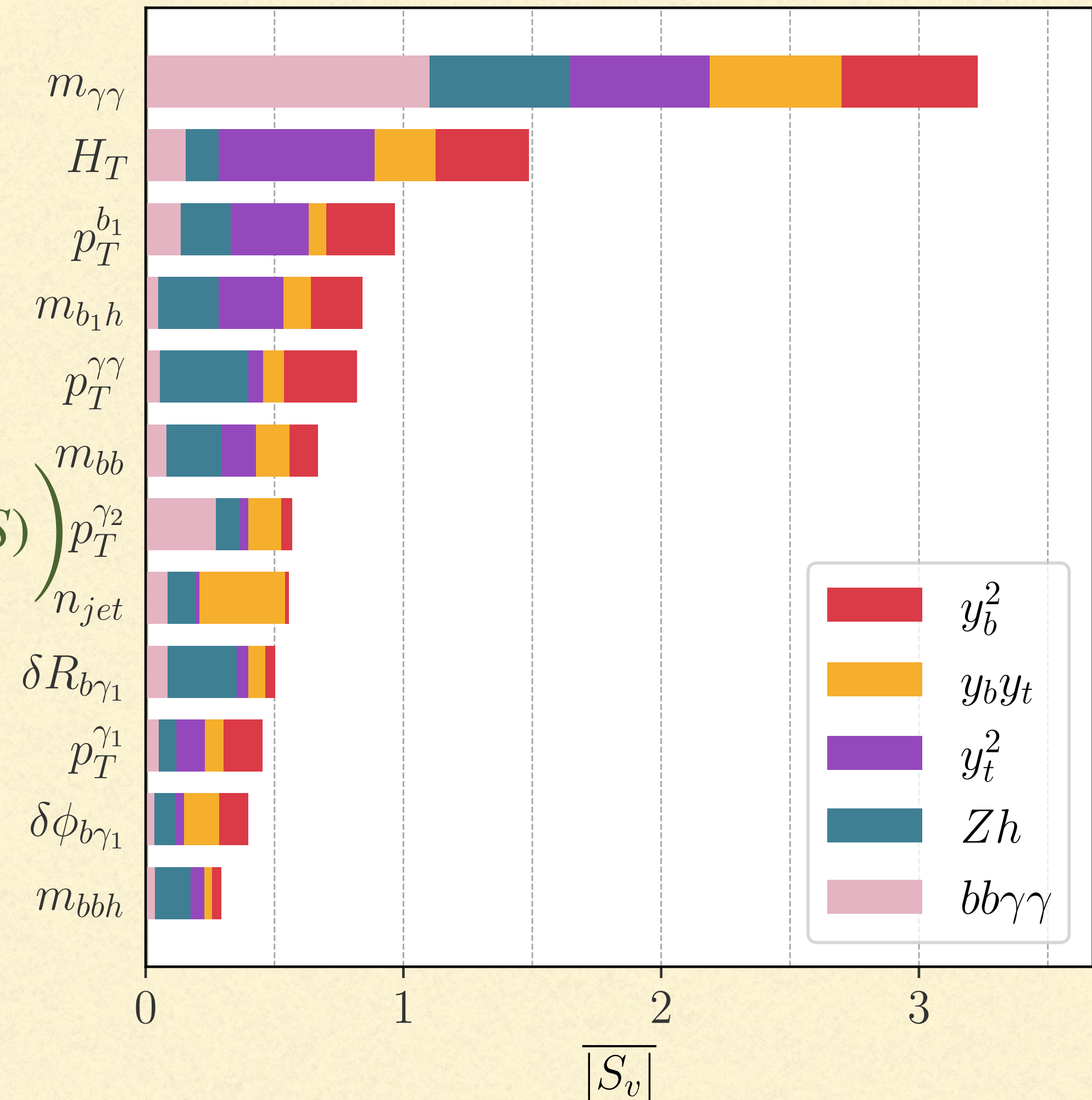


Machine Interpretation (full): Using shapley value:

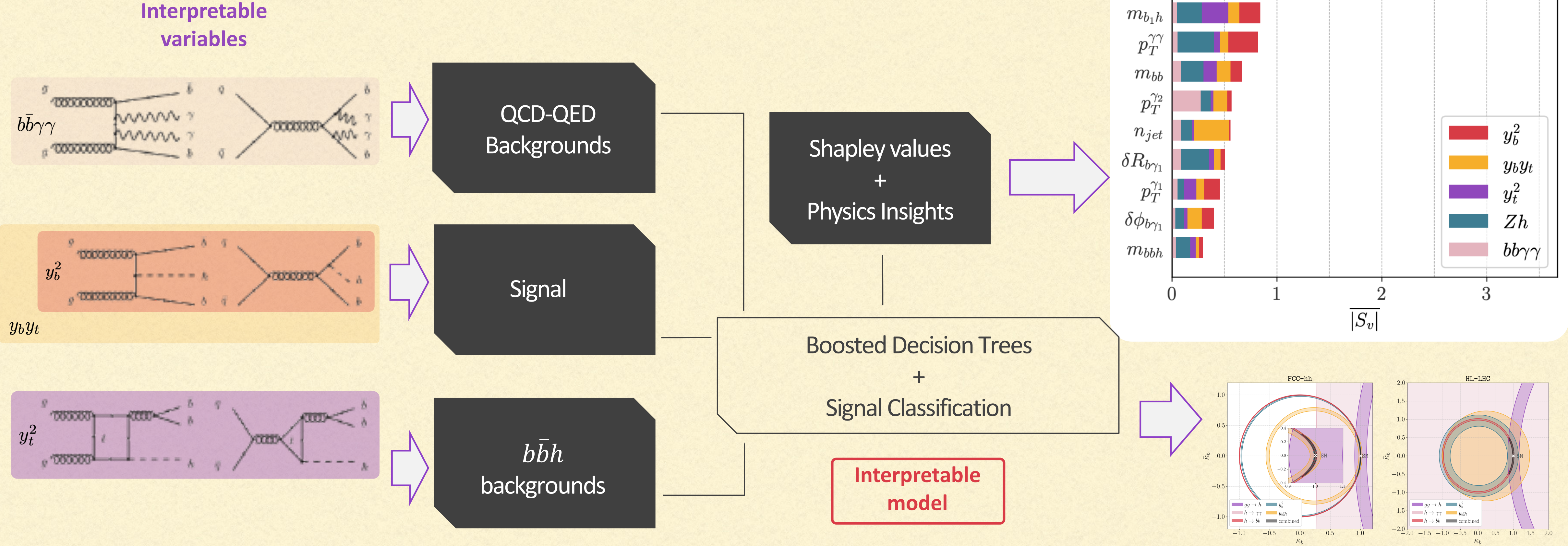
- Calculated by SHAP on BDT model
- Shapley value: an importance “measures” of given observable, through marginalising its contribution over the observable set:

$$\phi_j(val) = \sum_{S \subseteq \{x_1, \dots, x_p\} \setminus \{x_j\}} \frac{|S|!(p - |S| - 1)!}{p!} \left(val(S \cup \{x_j\}) - val(S) \right)$$

- Feature importance: the averaged absolute value of shapley value for a given observable: $I_j = \sum_{i=1}^n |\phi_j^{(i)}|$
- Reduction of observable d.o.f ; local attribution of importance with additivity



An interpretable framework:



Some Conclusions:

- Multivariate analysis are the key to distinguishing signals that cut-based analyses using only 1D or low-dimension info miserably fail at.
 - Multivariate methods can be better understood and supplemented with interpretable machine learning tools such as the Shapley values.
 - Associated production of $b\bar{b}h$ stands to gain at FCC as its production rate grows faster than backgrounds with rising energies. \Rightarrow sensitivity on a complex phase of y_b can be comparable to that from $h \rightarrow b\bar{b}$.
-

References

Measurement of $H \rightarrow b\bar{b}$

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- ATLAS collaboration, M. Aaboud et al., *Observation of $H \rightarrow b\bar{b}$ decays and VH production with the ATLAS detector*, [Phys. Lett. B 786 \(2018\) 59–86](#), [[arXiv:1808.08238](#)].
- CMS collaboration, A. M. Sirunyan et al., *Observation of Higgs boson decay to bottom quarks*, [Phys. Rev. Lett. 121 \(2018\) 121801](#), [[arXiv:1808.08242](#)].

Recent theory papers on $b\bar{b}h$

- N. Deutschmann, F. Maltoni, M. Wiesemann and M. Zaro, *Top-Yukawa contributions to $b\bar{b}h$ production at the LHC*, [JHEP 07 \(2019\) 054](#), [[arXiv:1808.01660](#)].
- D. Pagani, H.-S. Shao and M. Zaro, *RIP $Hb\bar{b}$: How other Higgs production modes conspire to kill a rare signal at the LHC*, [[arXiv:2005.10277](#)].

Papers on Higgs couplings fits

- M. Cepeda et al., *Report from Working Group 2: Higgs Physics at the HL-LHC and HE-LHC*, vol. 7, pp. 221–584. 12, 2019. [[arXiv:1902.00134](#)].
- J. de Blas et al., *Higgs Boson Studies at Future Particle Colliders*, [JHEP 01 \(2020\) 139](#), [[arXiv:1905.03764](#)].

Shapley values and interpretable machine learning

- L. S. Shapley, *Notes on the n -Person Game-II: The Value of an n -Person Game*, Rand Corporation (1951).
 - L. S. Shapley, *A Value for n -person Games*. Contributions to the Theory of Games 2.28 (1953): 307-317.
 - C. Molnar, *Interpretable Machine Learning*. Lulu, 2020. [[Link](#)]
 - S. M. Lundberg and S.-I. Lee, *A unified approach to interpreting model predictions*, in Advances in Neural Information Processing Systems (I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan et al., eds.), vol. 30, pp. 4765–4774, Curran Associates, Inc., 2017. [[arXiv:1705.07874](#)].
 - S. M. Lundberg, G. G. Erion and S.-I. Lee, Consistent Individualized Feature Attribution for Tree Ensembles, arXiv e-prints (Feb. 2018) , [[arXiv:1802.03888](#)].
 - S. M. Lundberg, G. Erion, H. Chen, A. DeGrave, J. M. Prutkin, B. Nair et al., *From local explanations to global understanding with explainable AI for trees*, [Nature Machine Intelligence 2 \(2020\) 56–67](#).
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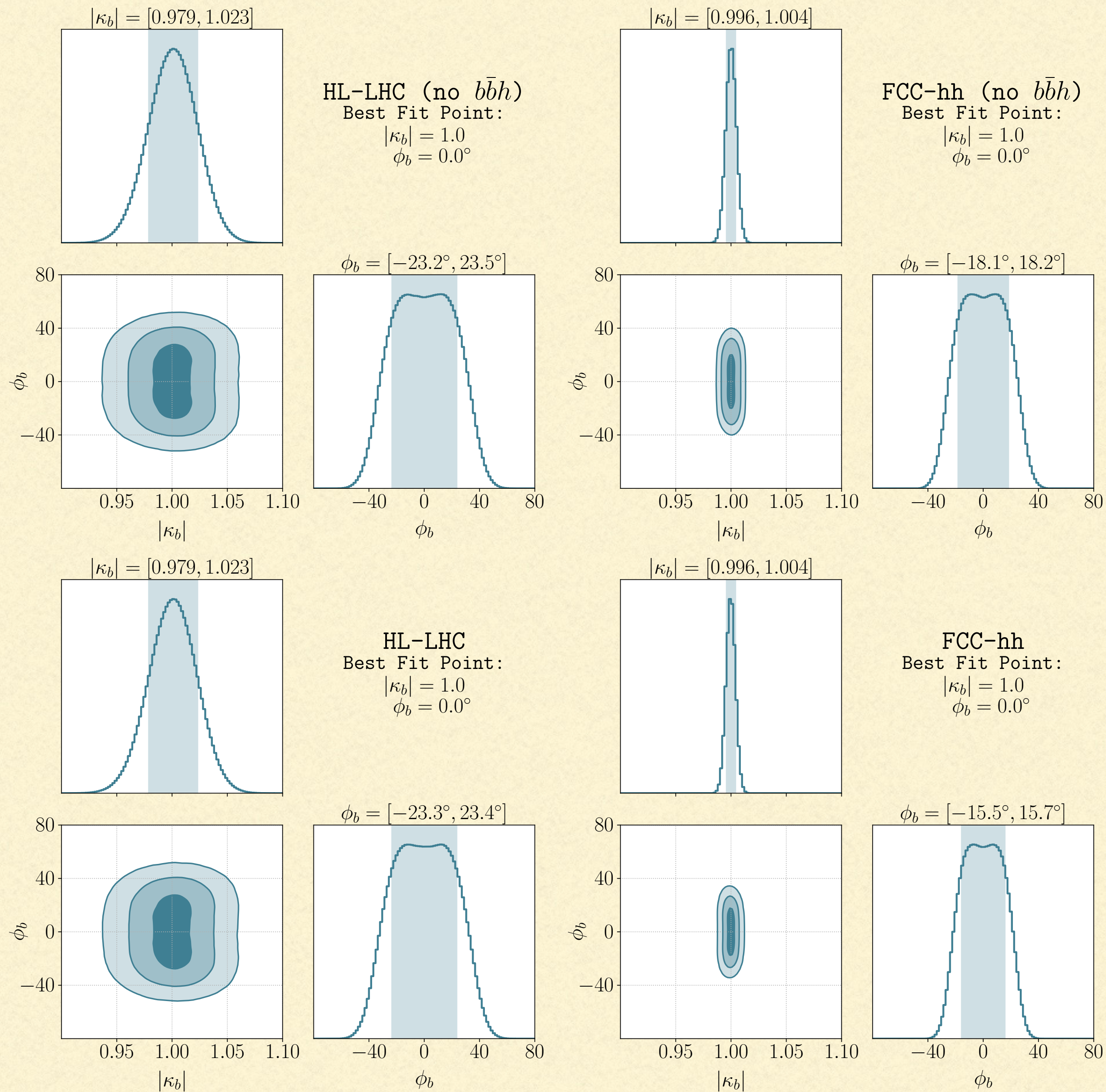
Backup

Additional backgrounds and discussion :

- VBF: light-jet veto kills the VBF while careful simulation is further needed.
 - di-Higgs: both m_{bb} and $m_{\gamma\gamma}$ clustered around the Higgs-mass peak, distinct final state shape to be separate
 - $gg \rightarrow Zh$: small at HL-LHC, but grows rapidly with s , and comparable but subdominant to the $q\bar{q}$ -sensitive channels at FCC-hh. Can be further distinguished as the case of $q\bar{q} \rightarrow Zh$.
 - Fakes: $ccxaa$, $jjxaa$, caa , $jjja$, etc.: subdominant yet comparable to $bbxaa$. Needs attention and study in future for better control
-

Systematics estimates:

| systematics | HL-LHC (6 ab ⁻¹) | | FCC-hh (30 ab ⁻¹) | |
|-------------|------------------------------|-----------|-------------------------------|-----------|
| | y_b^2 | $y_b y_t$ | y_b^2 | $y_b y_t$ |
| 0% | 3.33 | 0.47 | 63.7 | 10.4 |
| 0.5% | 3.26 | 0.46 | 32.2 | 3.44 |
| 1% | 3.06 | 0.42 | 17.9 | 1.80 |
| 5% | 1.41 | 0.18 | 3.72 | 0.36 |



HL-LHC: $\phi_b = [-23.2^\circ, 23.5^\circ] \Rightarrow \tilde{\kappa}_b \lesssim 0.4$

Negligible improvement from b \bar{b} xh study

FCC-hh: $\phi_b = [-15.5^\circ, 15.7^\circ] \Rightarrow \tilde{\kappa}_b \lesssim 0.3$

~15% improvement from b \bar{b} xh study

Comparison to:

Hadronic EDM (free of electron EDM assumption):

$$\text{nEDM: } \sum A \kappa_q \tilde{\kappa}_q + B \tilde{\kappa}_q \kappa_q \Rightarrow \tilde{\kappa}_b \lesssim 5.$$

Electron EDM:

$$\text{eEDM: } \sum A \kappa_e \tilde{\kappa}_q + B \tilde{\kappa}_e \kappa_q \Rightarrow \tilde{\kappa}_b \lesssim 0.5$$

One slide on Shapley value:

The Shapley value is defined via a value function val of players in S .

The Shapley value of a feature value is its contribution to the payout, weighted and summed over all possible feature value combinations:

$$\phi_j(val) = \sum_{S \subseteq \{x_1, \dots, x_p\} \setminus \{x_j\}} \frac{|S|! (p - |S| - 1)!}{p!} (val(S \cup \{x_j\}) - val(S))$$

where S is a subset of the features used in the model, x is the vector of feature values of the instance to be explained and p the number of features. $val_x(S)$ is the prediction for feature values in set S that are marginalized over features that are not included in set S :

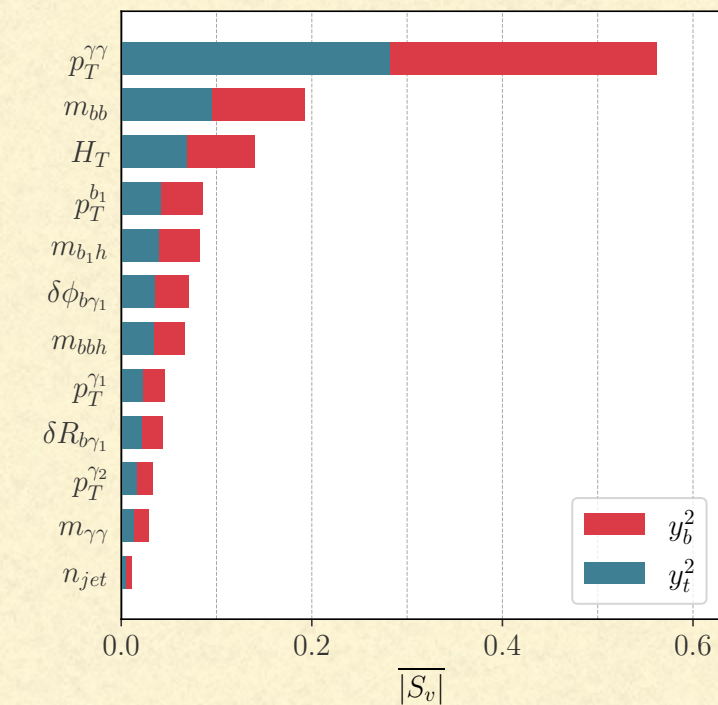
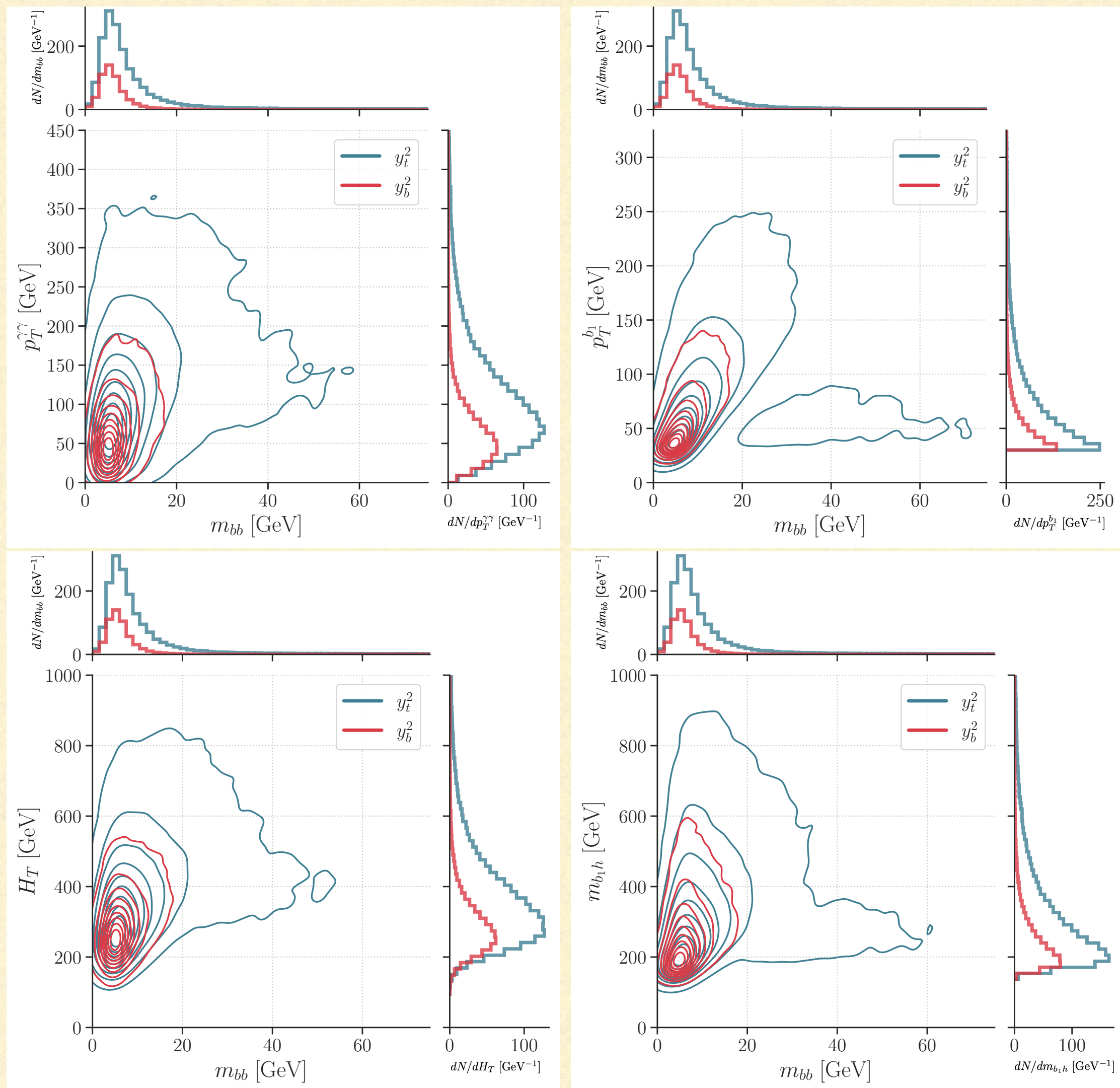
$$val_x(S) = \int \hat{f}(x_1, \dots, x_p) d\mathbb{P}_{x \notin S} - E_X(\hat{f}(X))$$

You actually perform multiple integrations for each feature that is not contained S . A concrete example: The machine learning model works with 4 features x_1 , x_2 , x_3 and x_4 and we evaluate the prediction for the coalition S consisting of feature values x_1 and x_3 :

$$val_x(S) = val_x(\{x_1, x_3\}) = \int_{\mathbb{R}} \int_{\mathbb{R}} \hat{f}(x_1, X_2, x_3, X_4) d\mathbb{P}_{X_2 X_4} - E_X(\hat{f}(X))$$

yt2-yb2

HL-LHC



HL-LHC

