



# Extending $hh \rightarrow b\bar{b}b\bar{b}$ searches into the HL-LHC era

**ULB**

UNIVERSITÉ  
LIBRE  
DE BRUXELLES

Jacob Amacker, William Balunas, Lydia Beresford, Daniela Bortoletto, James Frost, Cigdem Issever, Jesse Liu, James McKee, Alessandro Micheli, **Santiago Paredes Saenz**, Michael Spannowsky, and Beojan Stanislaus

[santiago.paredes@cern.ch](mailto:santiago.paredes@cern.ch)

**EOS be.h** Equinox Meeting  
September 2021



# This Talk

- Introduction & **Motivation**
- **Signal & Background** Modelling
- Analysis **Strategies**
- **Self-Coupling** Constraints
- Conclusion

Based on [arXiv:2004.04240](https://arxiv.org/abs/2004.04240)

## High Energy Physics – Phenomenology

[Submitted on 8 Apr 2020 (v1), last revised 12 Oct 2020 (this version, v3)]

### Higgs self-coupling measurements using deep learning in the $b\bar{b}b\bar{b}$ final state

Jacob Amacker, William Balunas, Lydia Beresford, Daniela Bortoletto, James Frost, Cigdem Issever, Jesse Liu, James McKee, Alessandro Micheli, Santiago Paredes Saenz, Michael Spannowsky, Beojan Stanislaus

Measuring the Higgs trilinear self-coupling  $\lambda_{hhh}$  is experimentally demanding but fundamental for understanding the shape of the Higgs potential. We present a comprehensive analysis strategy for the HL-LHC using di-Higgs events in the four  $b$ -quark channel ( $hh \rightarrow 4b$ ), extending current methods in several directions. We perform deep learning to suppress the formidable multijet background with dedicated optimisation for BSM  $\lambda_{hhh}$  scenarios. We compare the  $\lambda_{hhh}$  constraining power of events using different multiplicities of large radius jets with a two-prong structure that reconstruct boosted  $h \rightarrow b\bar{b}$  decays. We show that current uncertainties in the SM top Yukawa coupling  $y_t$  can modify  $\lambda_{hhh}$  constraints by  $\sim 20\%$ . For SM  $y_t$ , we find prospects of  $-0.8 < \lambda_{hhh}/\lambda_{hhh}^{\text{SM}} < 6.6$  at 68% CL under simplified assumptions for  $3000\text{-fb}^{-1}$  of HL-LHC data. Our results provide a careful assessment of di-Higgs identification and machine learning techniques for all-hadronic measurements of the Higgs self-coupling and sharpens the requirements for future improvement.

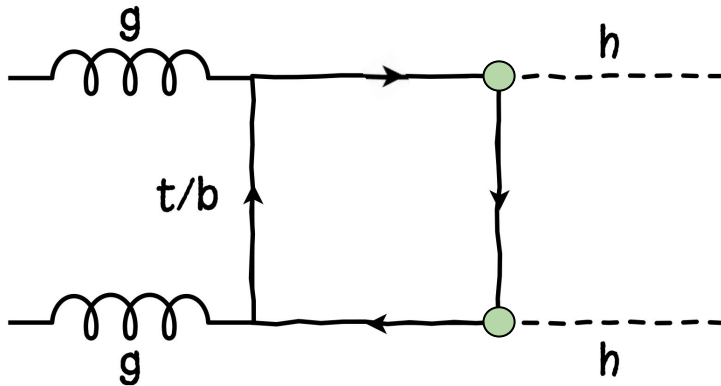
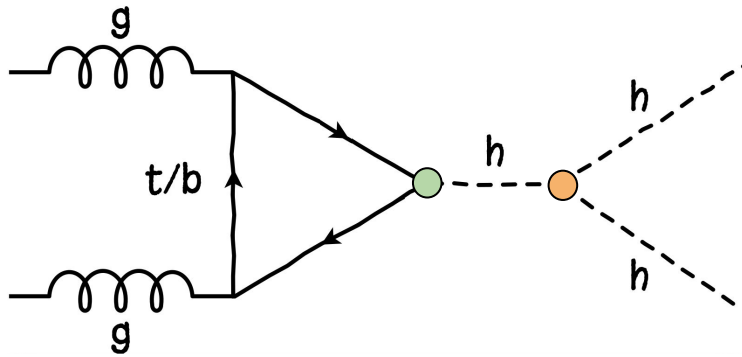
Comments: 36 pages, 15 figures + bibliography and appendices  
Subjects: **High Energy Physics – Phenomenology (hep-ph)**; High Energy Physics – Experiment (hep-ex)  
Journal reference: JHEP 12 (2020) 115  
DOI: [10.1007/JHEP12\(2020\)115](https://doi.org/10.1007/JHEP12(2020)115)  
Report number: IPPP/20/11  
Cite as: arXiv:2004.04240 [hep-ph]  
(or [arXiv:2004.04240v3](https://arxiv.org/abs/2004.04240v3) [hep-ph] for this version)

# Introduction & Motivation

---

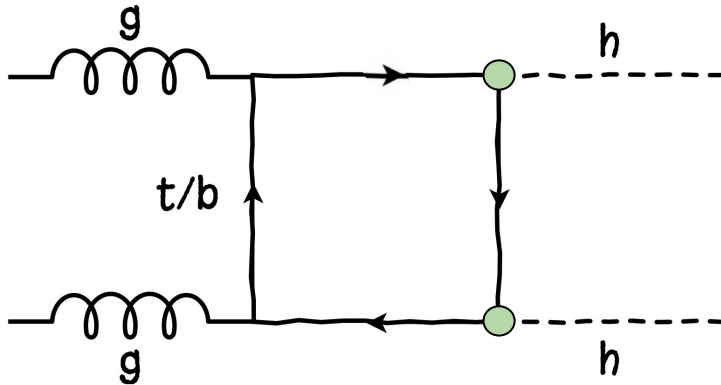
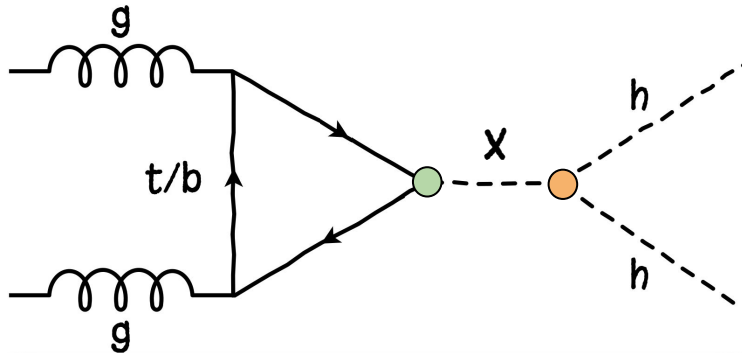


# Why hh?



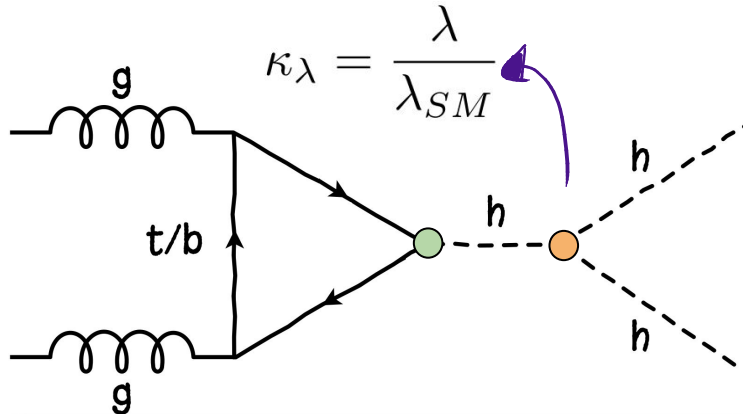
- Standard Model
  - ⇒ Sensitive to the higgs **self-coupling** ●
  - ⇒ Also to the **tth** ● vertex
- Beyond the SM
  - ⇒ New physics effects in ● & loops
  - ⇒ Heavy resonances (X) decaying to di-higgs

# Why hh?



- Standard Model
  - ⇒ Sensitive to the higgs **self-coupling** ●
  - ⇒ Also to the **tth** ● vertex
- Beyond the SM
  - ⇒ **New physics** effects in ● & ● loops
  - ⇒ **Heavy resonances** ( $X$ ) decaying to di-higgs

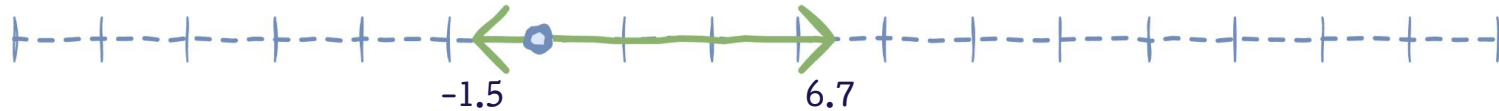
# Why hh?



- **Key parameter** in the standard model  
↳ **Not only** for collider physics
- **hh the only way to directly** measure self-coupling!



full Run II data -  $bb\gamma\gamma$  - 95% C.L.  $\kappa_\lambda$  constraints\*

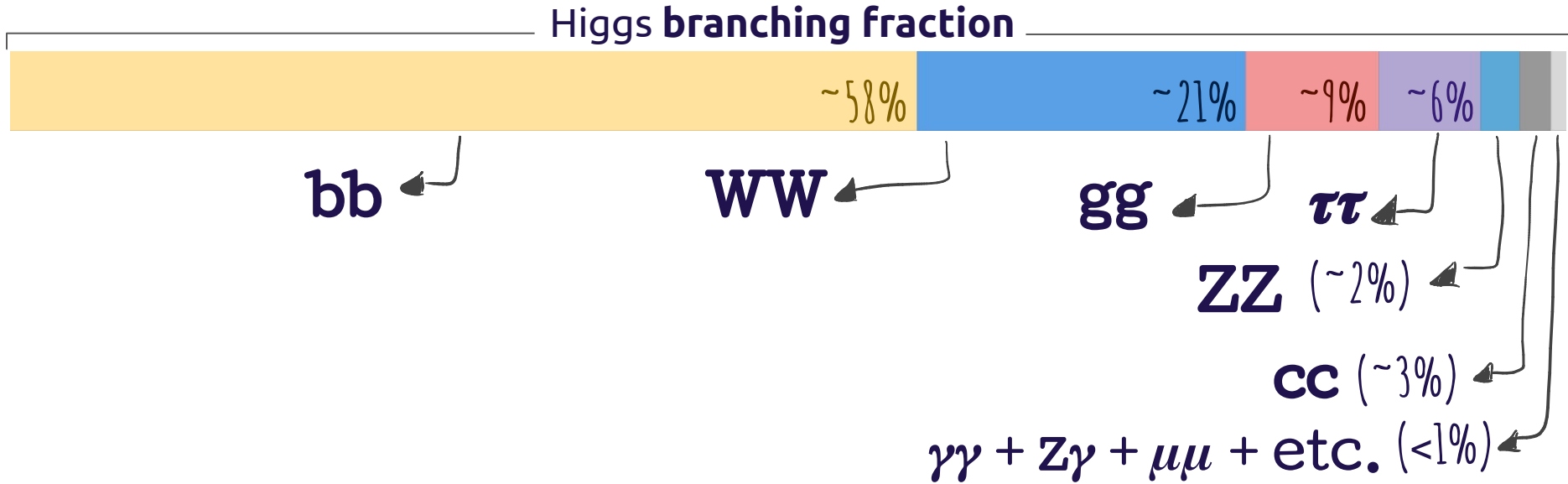


[ATLAS-CONF-2021-016](#)

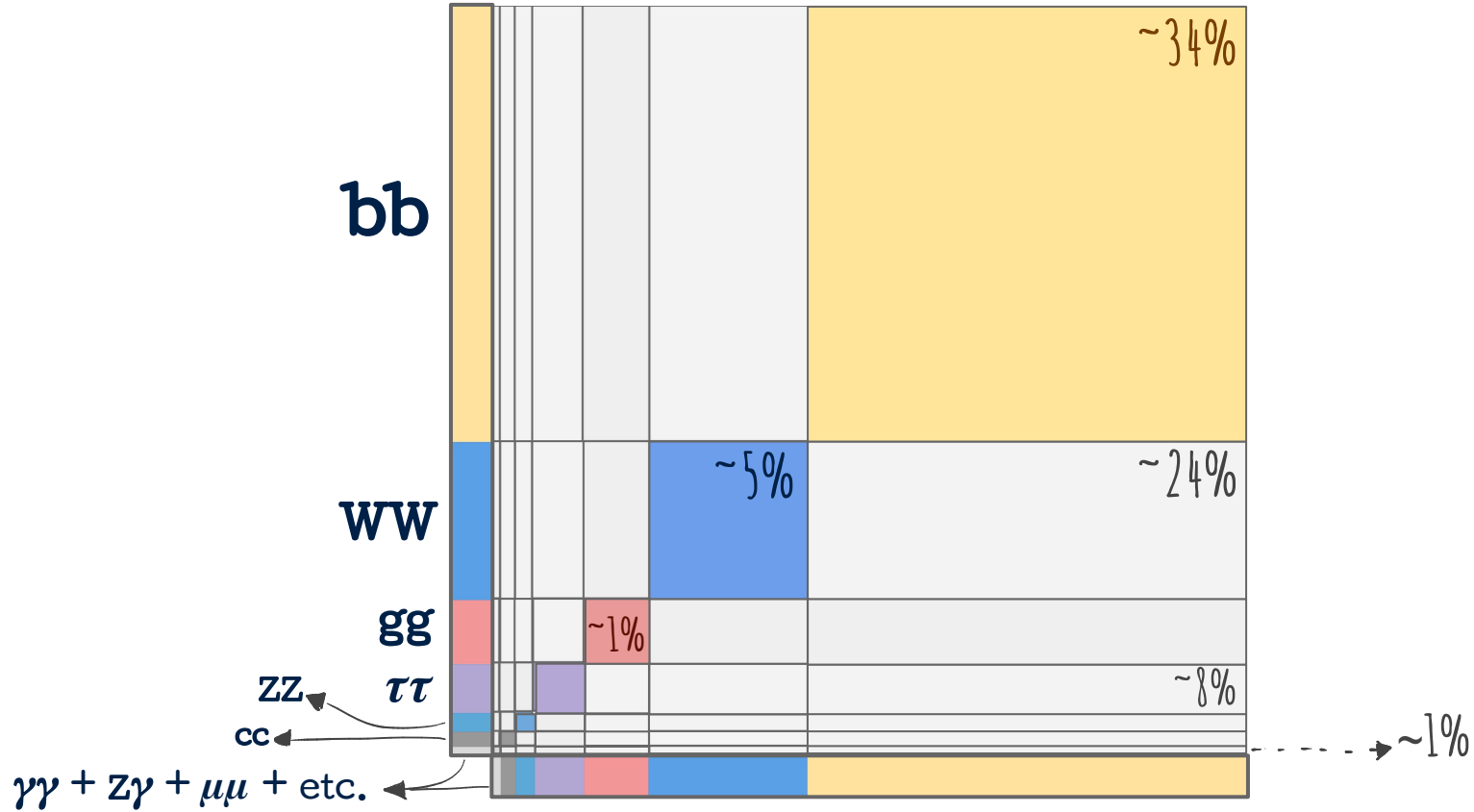


[JHEP03\(2021\)257](#)

# Why $hh \rightarrow 4b$ ?



# Why $hh \rightarrow 4b$ ?



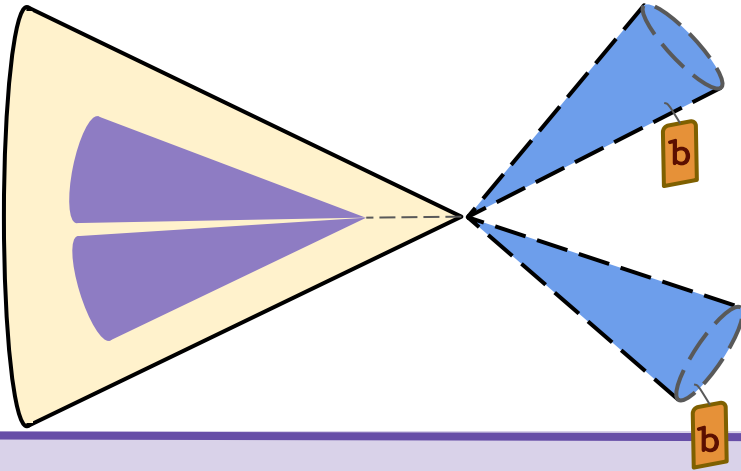
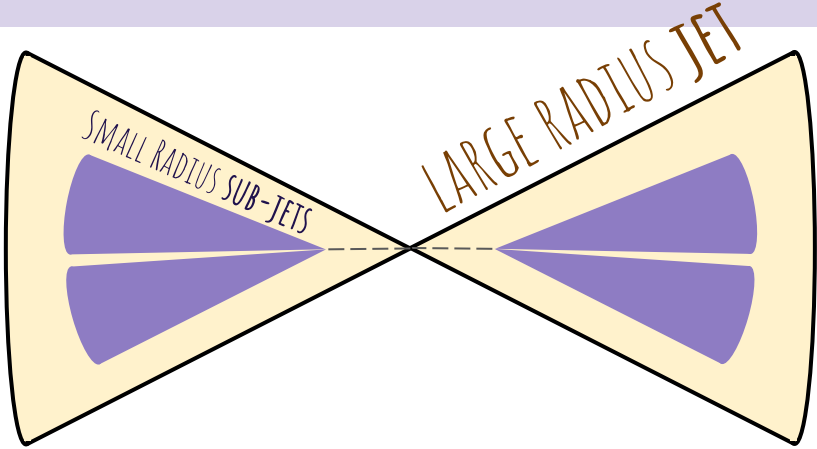
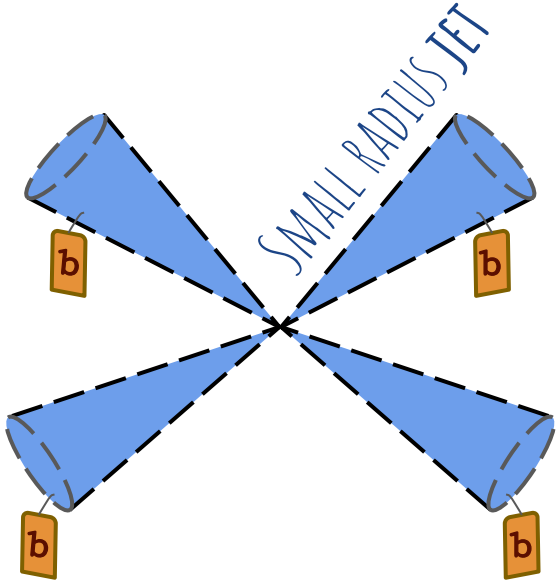


# Signal & Background Modelling

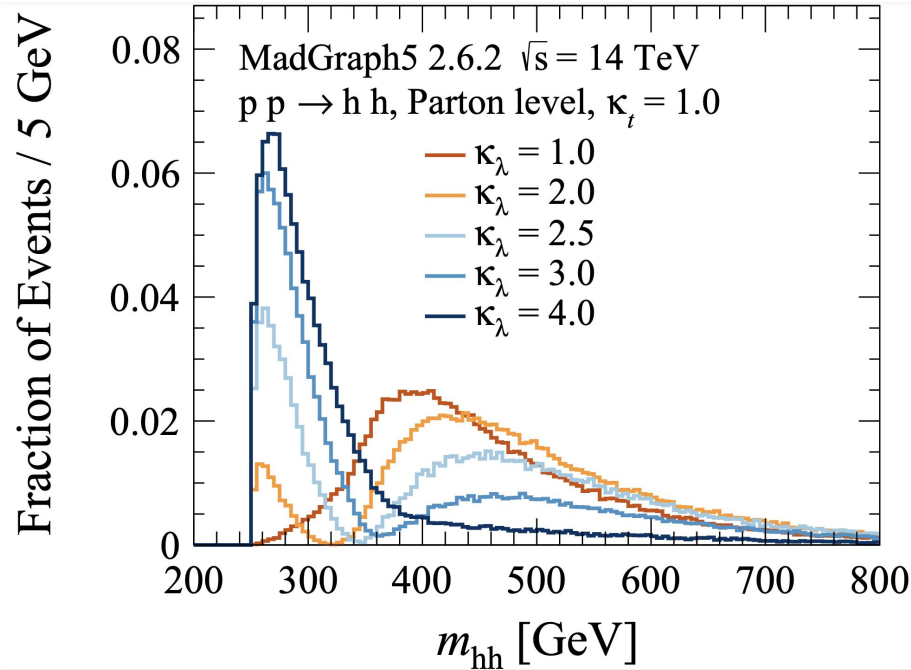
---



# Signal Topology



# Signal Samples

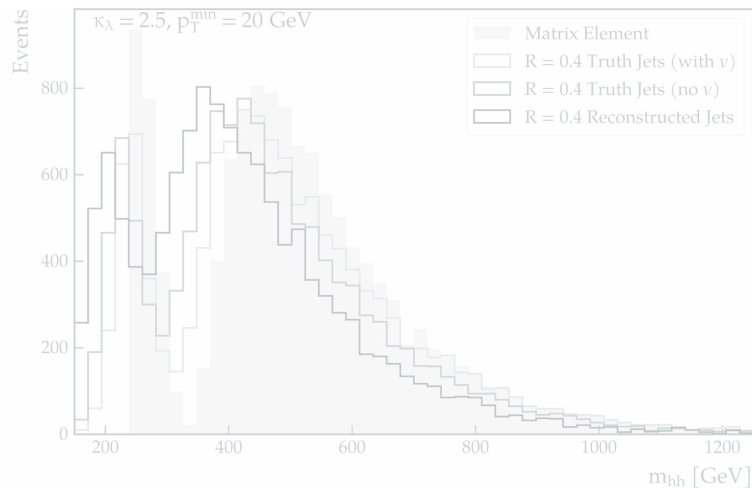
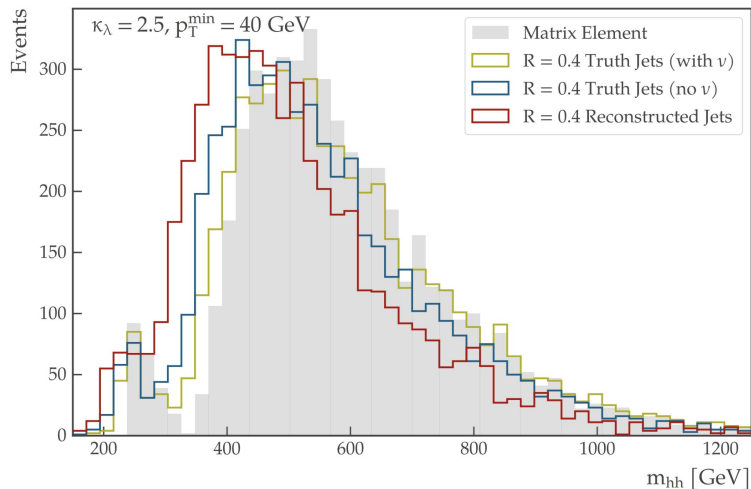


- $gg \rightarrow hh$  production
  - ↪ **Inclusive h decay**
- Points with **varied** coupling to **top** quark and **self couplings**
- Extra  $\kappa_t=1$  samples for **training**
  - ↪ **More** events per point
  - ↪ **Exclusive** decay **h**  $\rightarrow$  **bb**

# Parentheses - $m_{hh}$ shape degradation

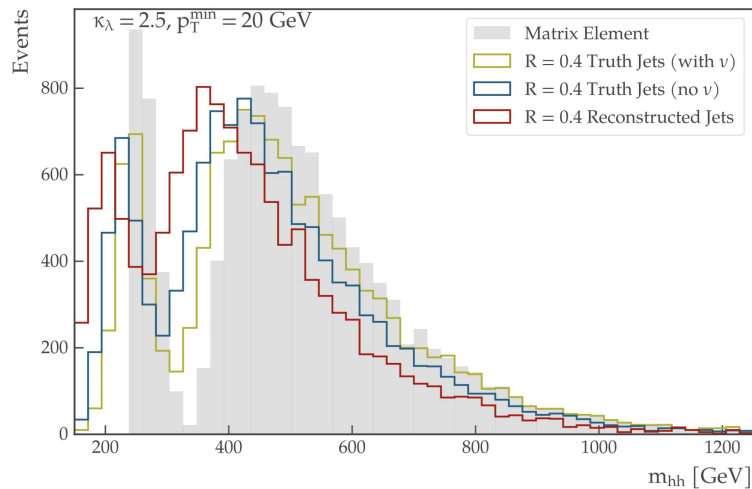
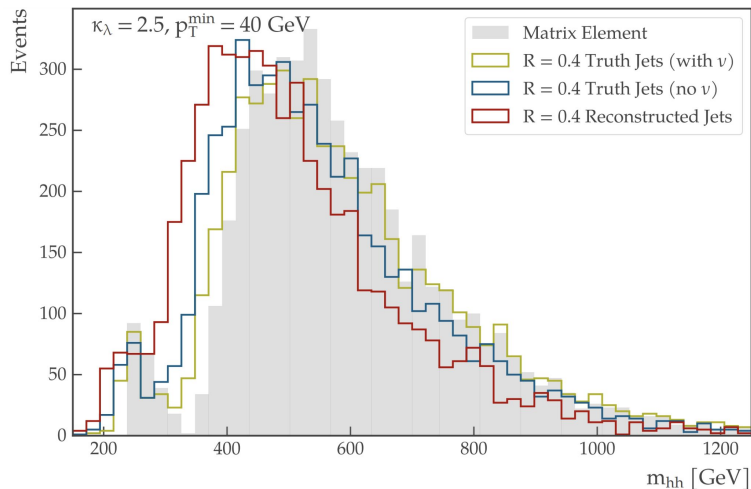
- $m_{hh}$  spectrum, various jets
  - ↪  $p_T > 40 \text{ GeV}$  → Same as analysis
  - ↪  $\kappa_\lambda = 2.5$  → Max. interference
- **Double-peak is degraded**

- Same plot, except:
  - ↪  $p_T > 20 \text{ GeV}$
- **Recover double peak**



# Parentheses - $m_{hh}$ shape degradation

- $m_{hh}$  spectrum, various jets
    - ↪  $p_T > 40 \text{ GeV}$  → Same as analysis
    - ↪  $\kappa_\lambda = 2.5$  → Max. interference
  - **Double-peak is degraded**
- Same plot, except:
    - ↪  $p_T > 20 \text{ GeV}$
  - **Recover double peak**



# Background Samples

- Similar generation process to signals
- **Main** backgrounds:
  - ↪ **Multijet** → 4b and 2b-2j
  - ↪ **Top quark backgrounds** →  $t\bar{t}$  (+ $b\bar{b}$ ) and  $t\bar{t}h$
- Other backgrounds:
  - ↪  $b\bar{b}h$
  - ↪ ZZ
  - ↪ Zh
  - ↪ Wh

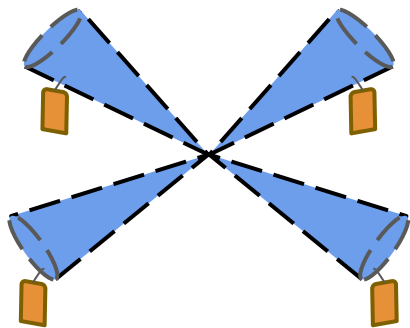
# Analysis Strategies

---



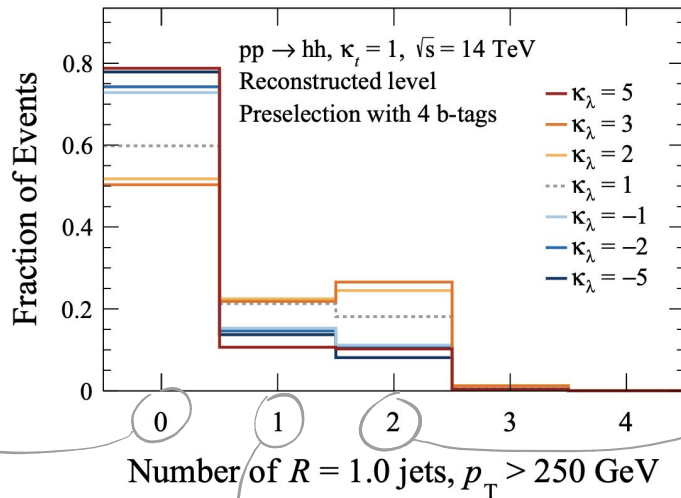
# Channels

**Resolved**

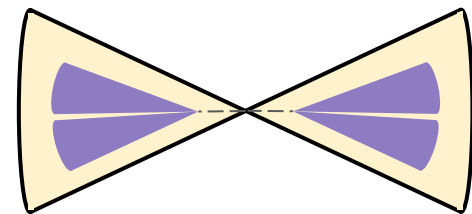


$$j_s \left| \begin{array}{l} R = 0.4 \\ p_T > 40 \text{ GeV} \\ |\eta| < 2.5 \end{array} \right.$$

$$\frac{j_T}{\Delta R(j_i, j_j) < 1.0} \left| \begin{array}{l} R = 0.2 \\ p_T > 20 \text{ GeV} \\ |\eta| < 2.5 \end{array} \right.$$

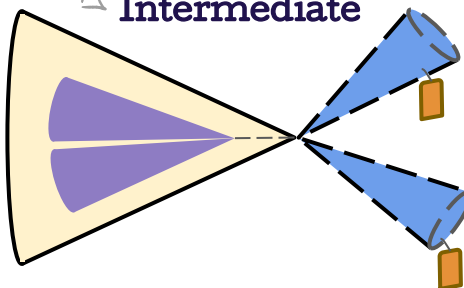


**Boosted**



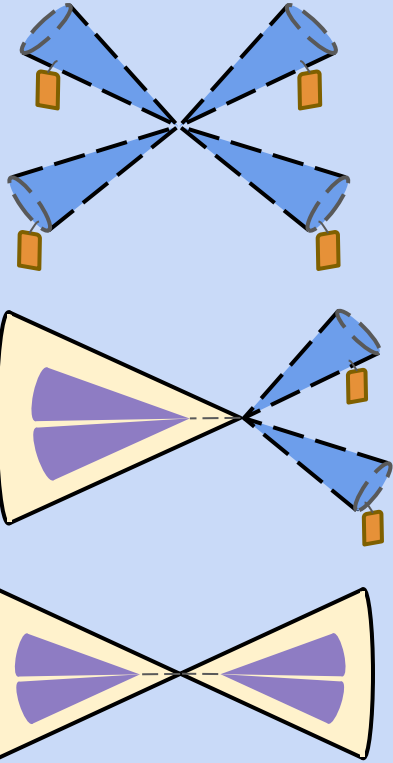
$$p_T > 250 \text{ GeV} \left| \begin{array}{l} R = 1.0 \\ |\eta| < 2.0 \end{array} \right. j_L$$

**Intermediate**



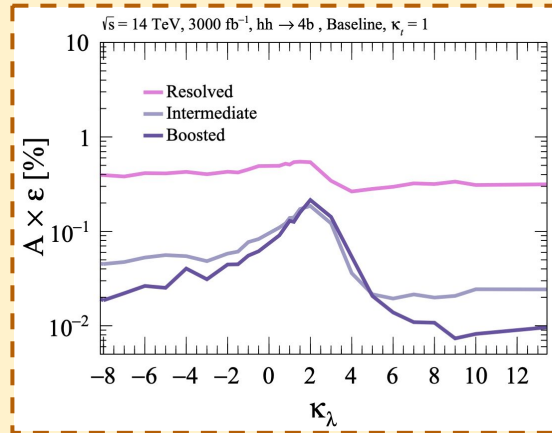


# Analysis Strategy



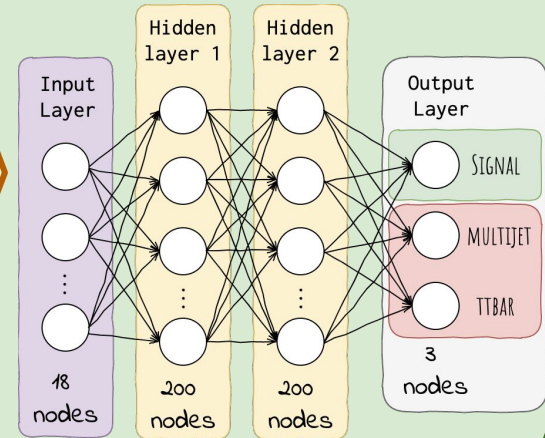
## Baseline Analysis

- **Cut Based**
- **ATLAS/CMS-inspired**

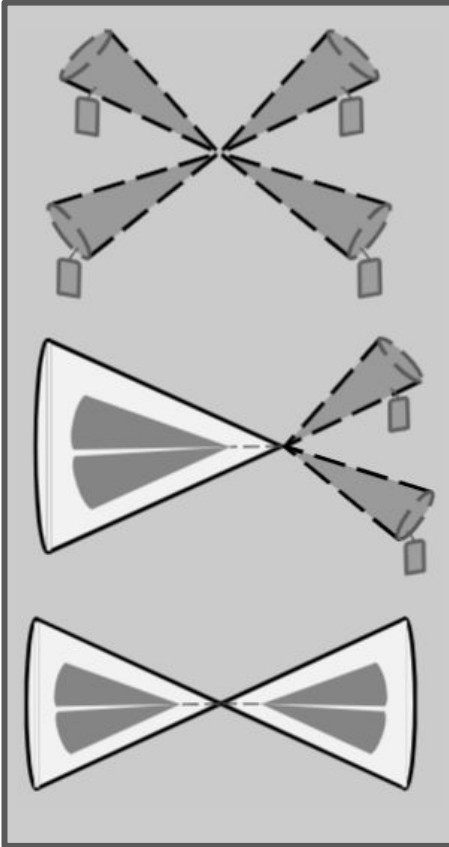


## DNN Analysis

- Trained NN **classifier**
- **Cut on NN score**

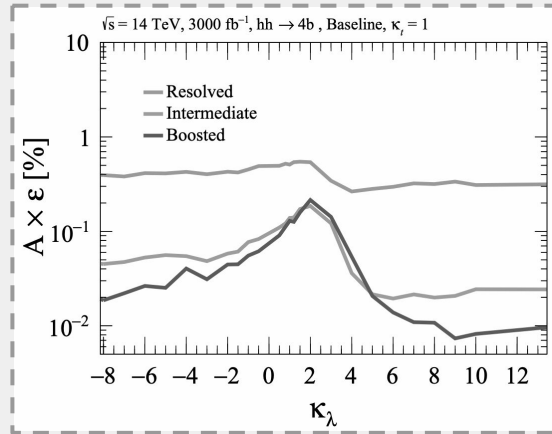


# Analysis Strategy



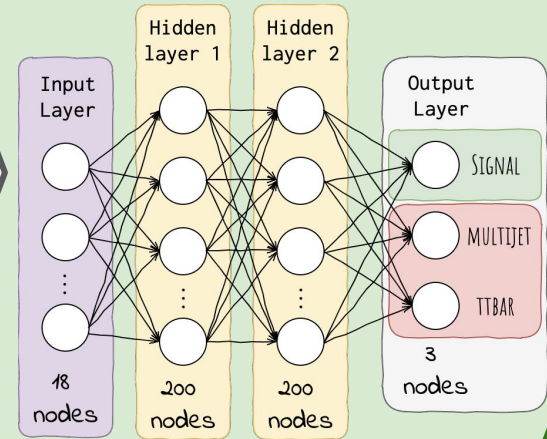
## Baseline Analysis

- **Cut Based**
- ATLAS/CMS-inspired



## DNN Analysis

- Trained NN **classifier**
- **Cut on NN score**



# Baseline Analysis

- Analysis-specific cuts  $\Rightarrow$  define Signal Region (**SR**) in  $m_{hh}$

$\hookrightarrow N(j_L \triangle) = 0$

$\hookrightarrow N(j_S \triangle) \geq 4$

$\hookrightarrow$  Lepton, MET veto

$\hookrightarrow$  4 b-tags

$\hookrightarrow \Delta R(j_S^1, j_S^2)$  cut

$\hookrightarrow N(j_L \triangle) = 1$

$\hookrightarrow N(j_S \triangle) \geq 2$

$\hookrightarrow$  Lepton, MET veto

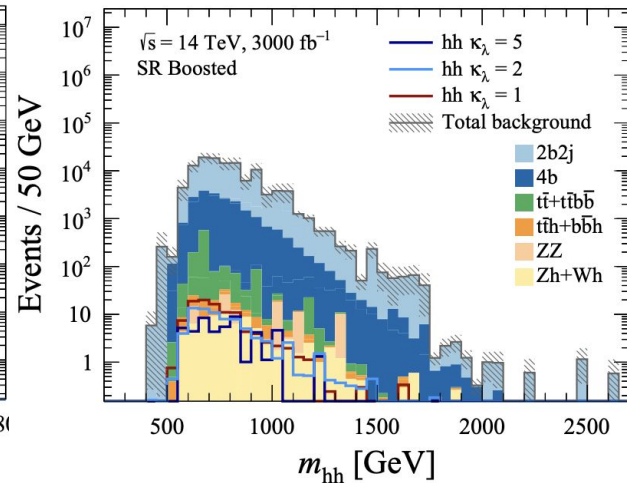
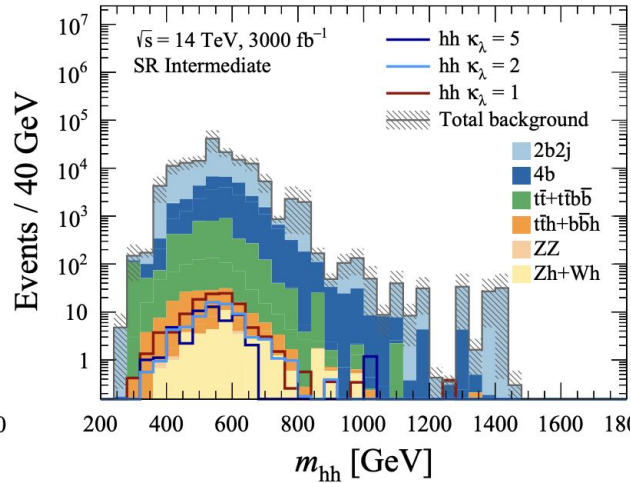
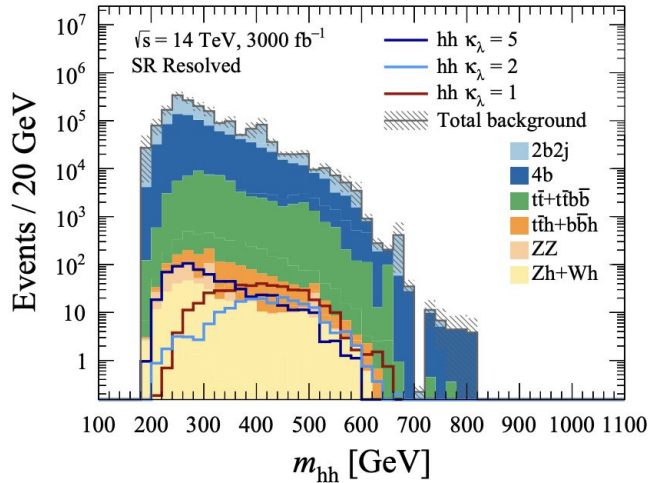
$\hookrightarrow$  4 b-tags

$\hookrightarrow N(j_L \triangle) = 2$

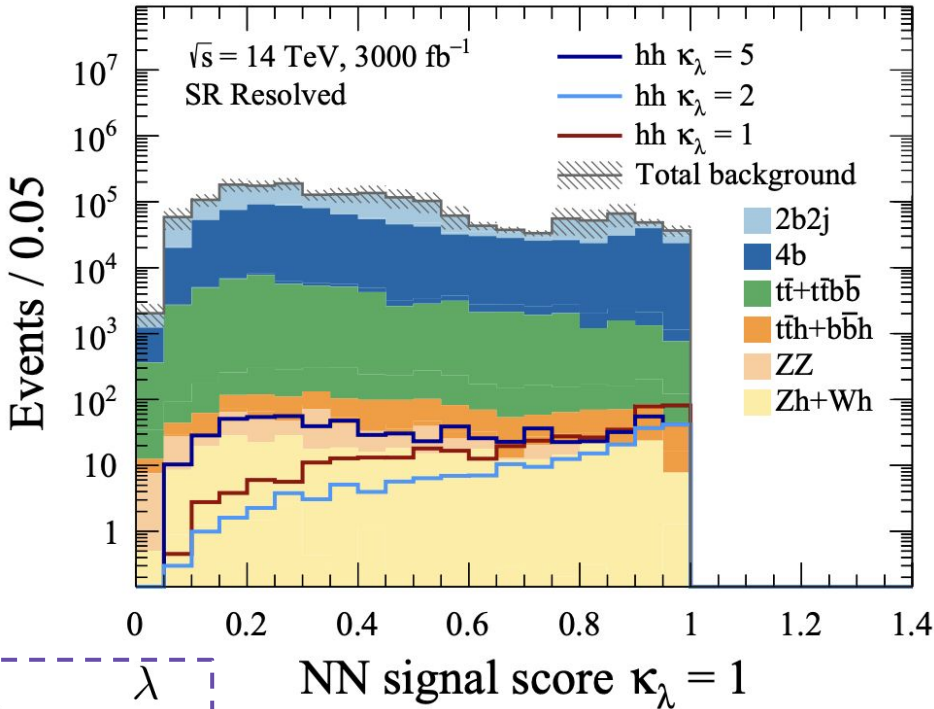
$\hookrightarrow N(j_S \triangle) \geq 0$

$\hookrightarrow$  Lepton, MET veto

$\hookrightarrow$  4 b-tags



# DNN Analysis



$$\kappa_\lambda = \frac{\lambda}{\lambda_{SM}}$$

- **Multi-class** classifier  
 ↪ Signal vs multijet vs  $t\bar{t}$

**TRAINING VARIABLES**

↪ $p_T^{HH}$	↪ MET	↪ SUB-JET $\eta$
↪ $M^{HH}$	↪ MET $\phi$	↪ SUB-JET $\phi$
↪ #MUONS	↪ SUB-JET MASS	↪ SUB-JETS $\Delta R$
↪ #ELEC	↪ SUB-JET $p_T$	↪ SUB-JETS B-TAG

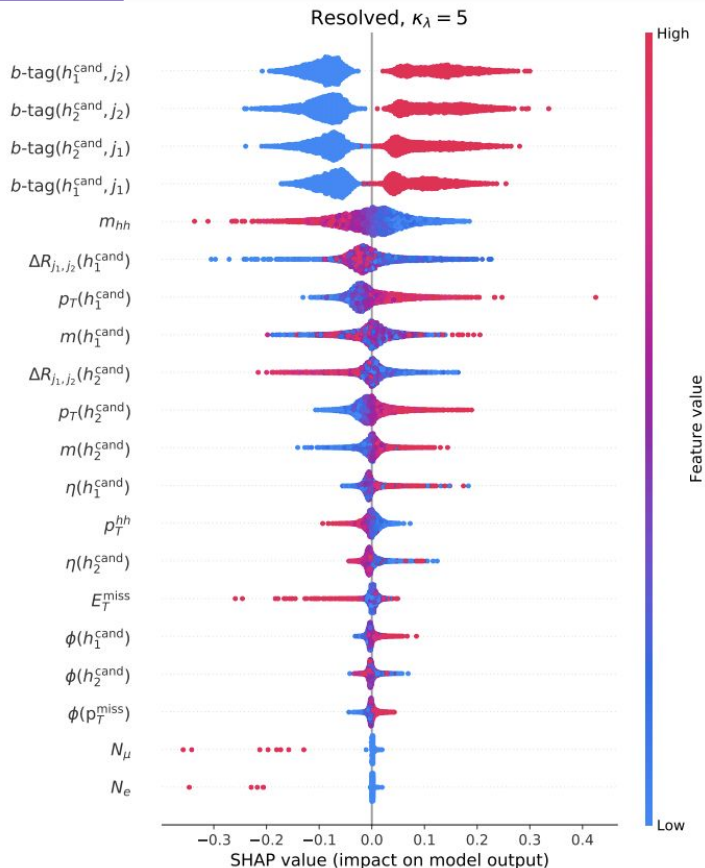
- Cut  $\Rightarrow$  NN signal score  $> 0.75$
- Trained with **multiple  $\kappa_\lambda$**  signals  
 ↪ **Use  $\kappa_\lambda = 5$**  network

# Parentheses - What did our machine learn?

- SHAP value framework  
→ Shapley values for ML interpretability

NN variables

Ranked by impact on NN score

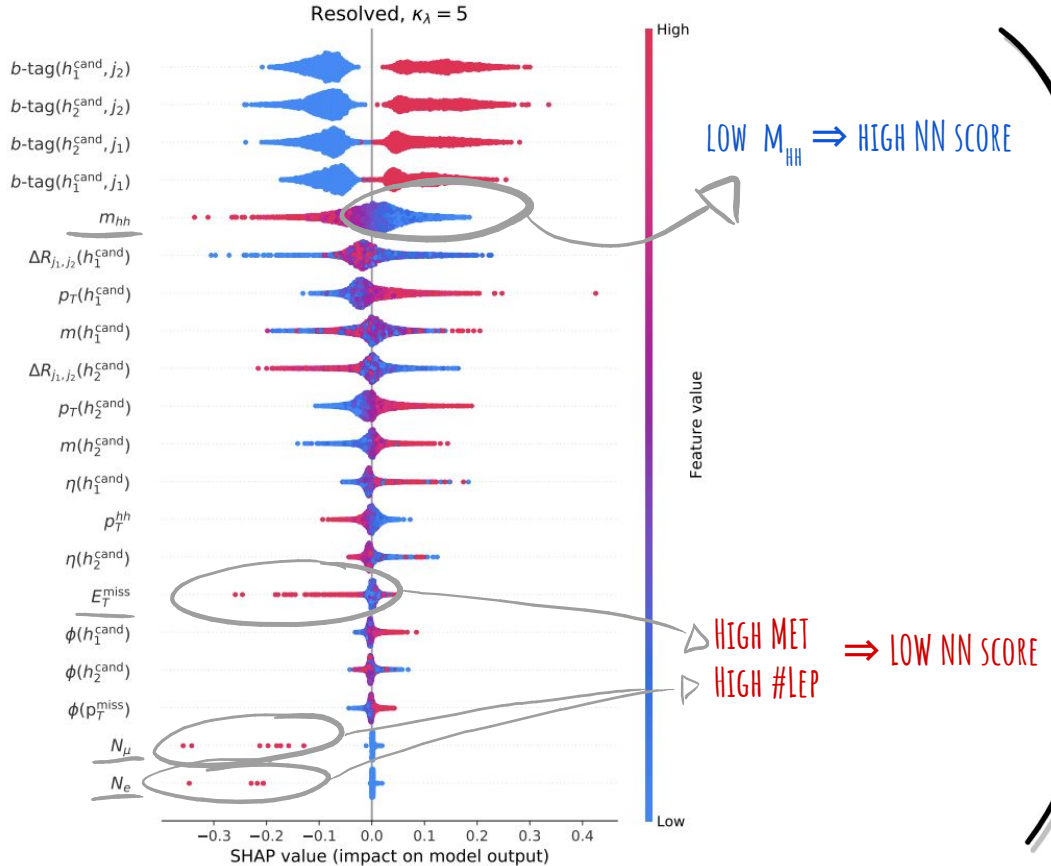


# Parentheses - What did our machine learn?

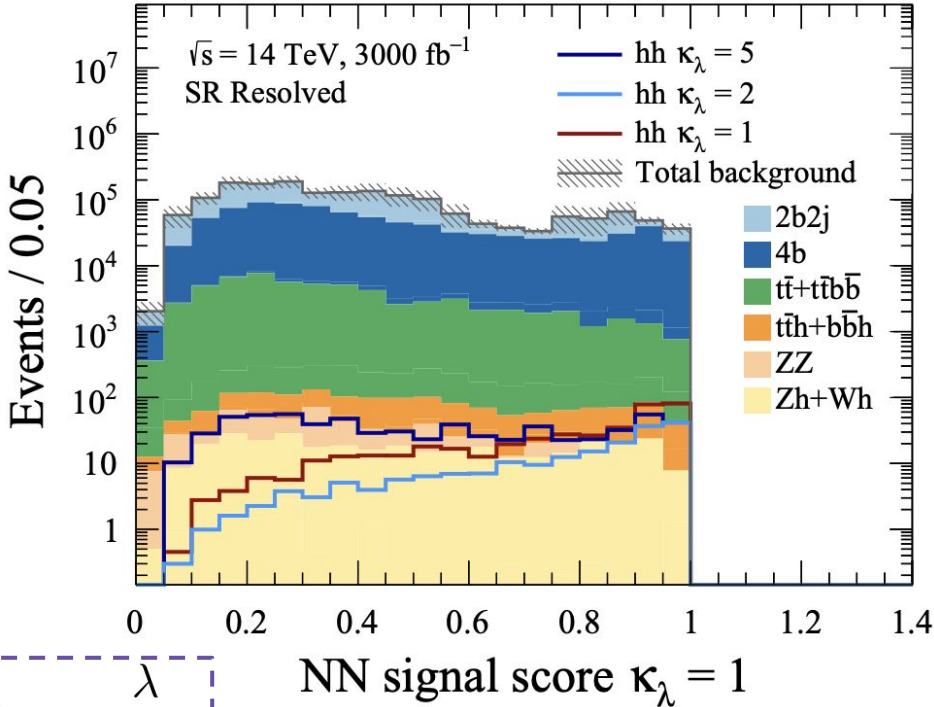
• SHAP value framework  
 ↪ Shapley values for ML interpretability

NN variables

Ranked by impact on NN score



# DNN Analysis



$$\kappa_\lambda = \frac{\lambda}{\lambda_{SM}}$$

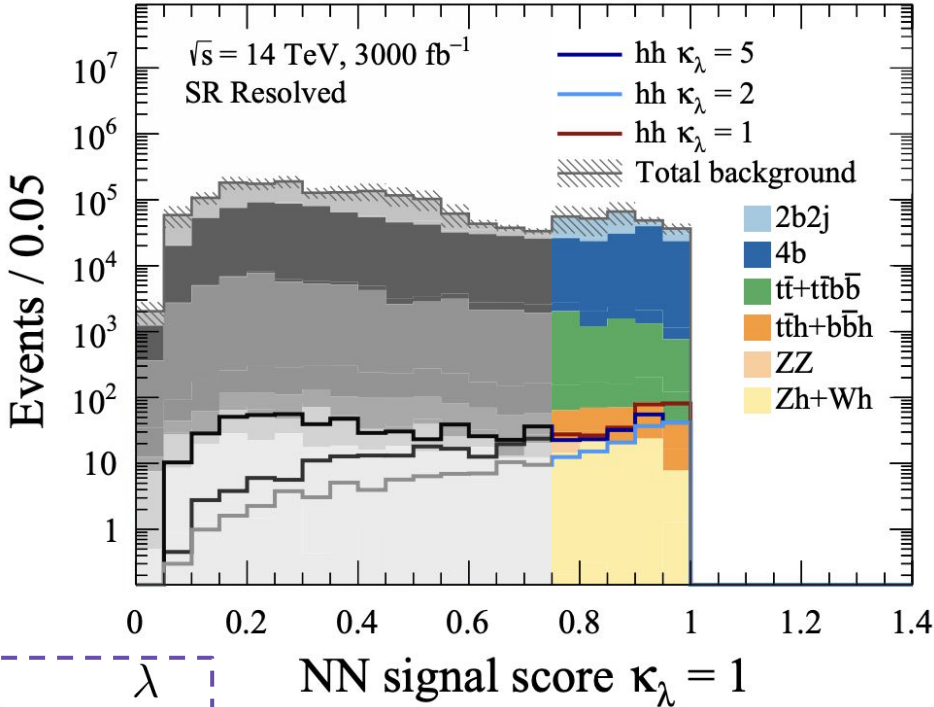
- **Multi-class** classifier  
 ↪ Signal vs multijet vs  $t\bar{t}$

**TRAINING VARIABLES**

↪ $p_T^{HH}$	↪ MET	↪ SUB-JET $\eta$
↪ $M^{HH}$	↪ MET $\phi$	↪ SUB-JET $\phi$
↪ #MUONS	↪ SUB-JET MASS	↪ SUB-JETS $\Delta R$
↪ #ELEC	↪ SUB-JET $p_T$	↪ SUB-JETS B-TAG

- Cut  $\Rightarrow$  NN signal score  $> 0.75$
- Trained with **multiple  $\kappa_\lambda$**  signals  
 ↪ **Use  $\kappa_\lambda = 5$**  network

# DNN Analysis



$$\kappa_\lambda = \frac{\lambda}{\lambda_{SM}}$$

- **Multi-class** classifier  
 ↪ Signal vs multijet vs  $t\bar{t}$

**TRAINING VARIABLES**

↪ $p_T^{HH}$	↪ MET	↪ SUB-JET $\eta$
↪ $M^{HH}$	↪ MET $\phi$	↪ SUB-JET $\phi$
↪ #MUONS	↪ SUB-JET MASS	↪ SUB-JETS $\Delta R$
↪ #ELEC	↪ SUB-JET $p_T$	↪ SUB-JETS B-TAG

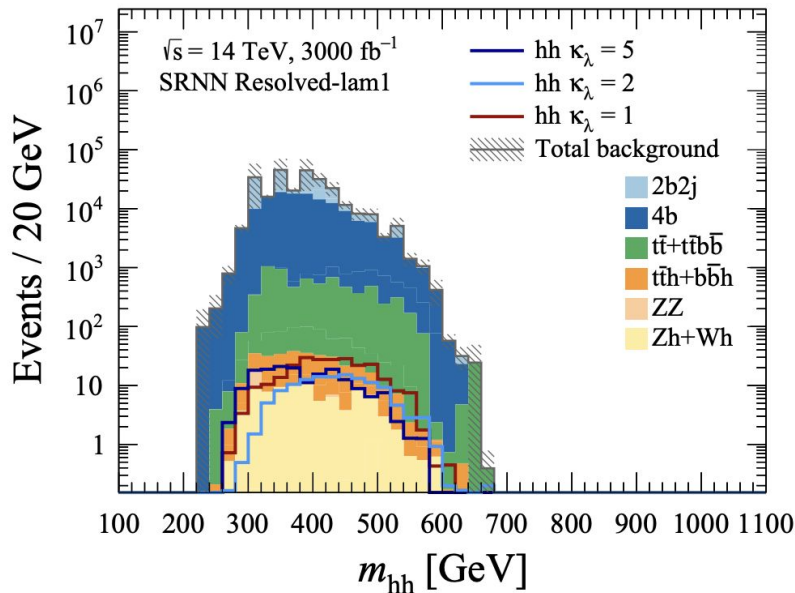
- Cut  $\Rightarrow$  NN signal score  $> 0.75$
- Trained with **multiple  $\kappa_\lambda$**  signals  
 ↪ **Use  $\kappa_\lambda = 5$**  network



# Parentheses - BSM $\kappa_\lambda$ training

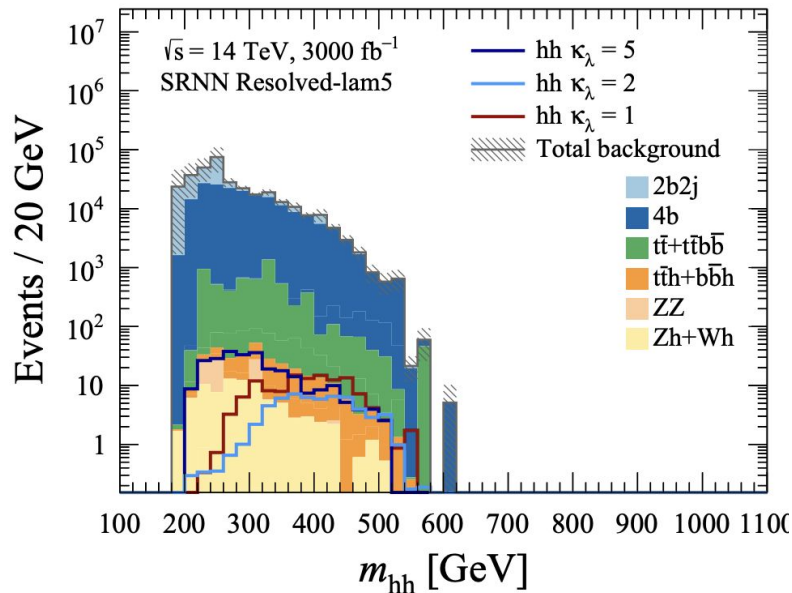
$\kappa_\lambda = 1$  NN cut

- **Background rejection** ✓
- **Signal characterization** ✗

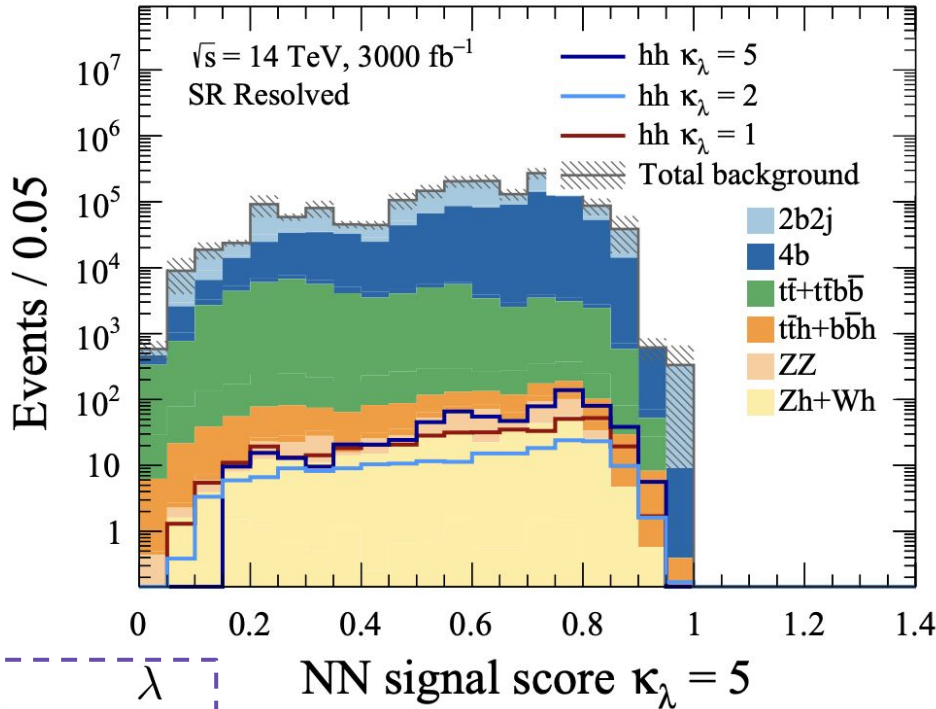


$\kappa_\lambda = 5$  NN cut

- **Background rejection** ✓
- **Signal characterization** ✓



# DNN Analysis



$$\kappa_\lambda = \frac{\lambda}{\lambda_{SM}}$$

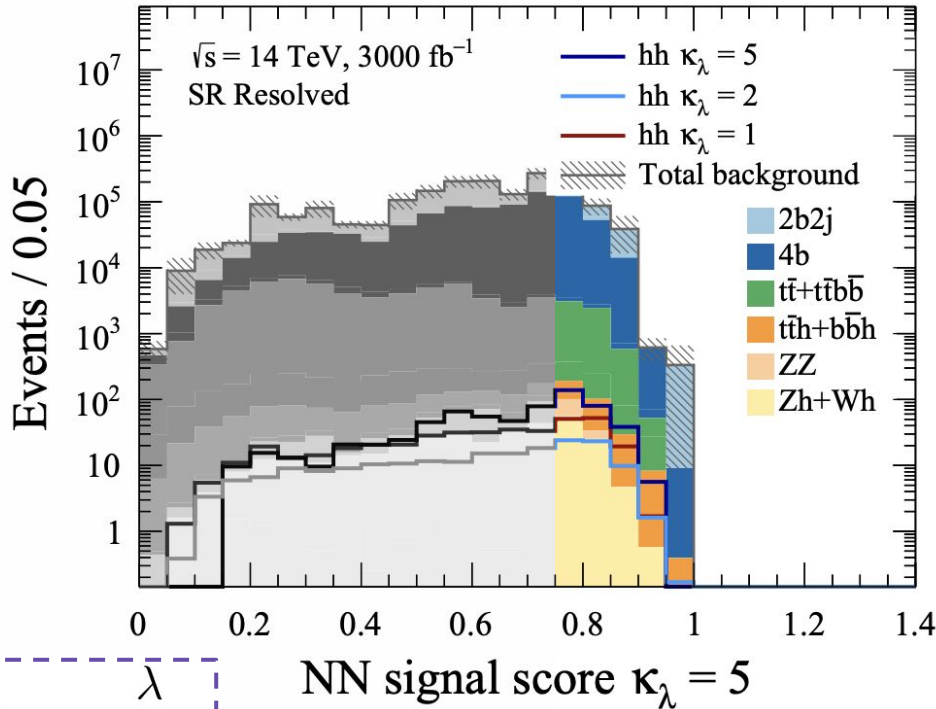
- **Multi-class** classifier  
 ↪ Signal vs multijet vs  $t\bar{t}$

**TRAINING VARIABLES**

↪ $p_T^{HH}$	↪ MET	↪ SUB-JET $\eta$
↪ $M^{HH}$	↪ MET $\phi$	↪ SUB-JET $\phi$
↪ #MUONS	↪ SUB-JET MASS	↪ SUB-JETS $\Delta R$
↪ #ELEC	↪ SUB-JET $p_T$	↪ SUB-JETS B-TAG

- Cut  $\Rightarrow$  NN signal score  $> 0.75$
- Trained with **multiple  $\kappa_\lambda$**  signals  
 ↪ **Use  $\kappa_\lambda = 5$**  network

# DNN Analysis



- **Multi-class** classifier  
 ↪ Signal vs multijet vs  $t\bar{t}$

**TRAINING VARIABLES**

↪ $p_T^{HH}$	↪ MET	↪ SUB-JET $\eta$
↪ $M^{HH}$	↪ MET $\phi$	↪ SUB-JET $\phi$
↪ #MUONS	↪ SUB-JET MASS	↪ SUB-JETS $\Delta R$
↪ #ELEC	↪ SUB-JET $p_T$	↪ SUB-JETS B-TAG

- Cut  $\Rightarrow$  NN signal score  $> 0.75$
- Trained with **multiple  $\kappa_\lambda$**  signals  
 ↪ **Use  $\kappa_\lambda = 5$**  network

$$\kappa_\lambda = \frac{\lambda}{\lambda_{SM}}$$

# Self-Coupling Constraints

---



# Constraints on $\kappa_\lambda - \kappa_t$ Plane

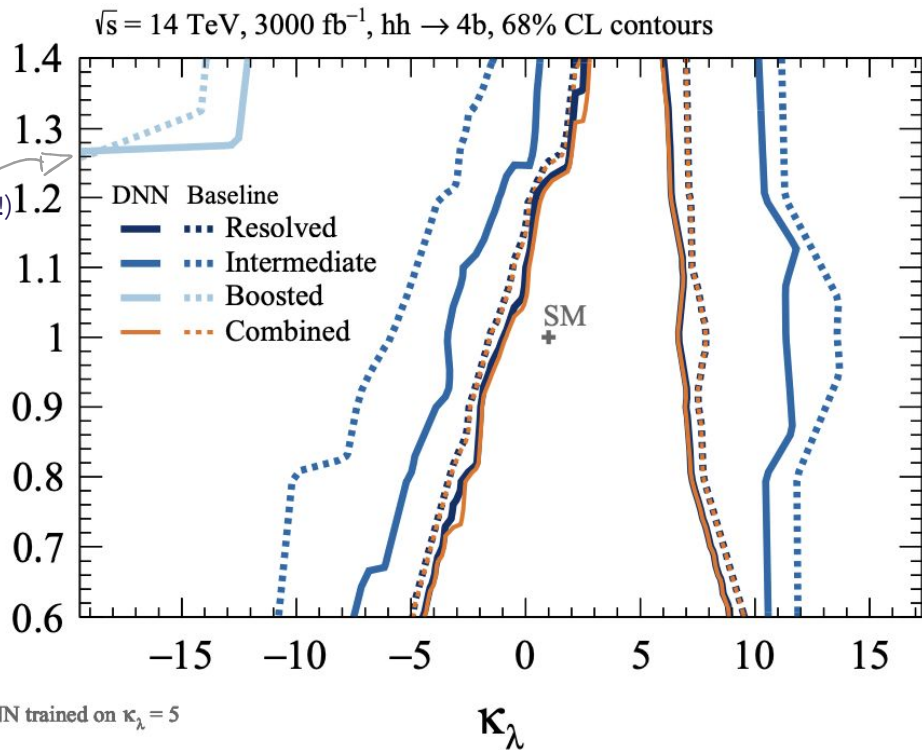
- Resolved  $\rightarrow$  **most powerful**
- $\hookrightarrow$  Intermediate  $\rightarrow$  **non-negligible**
- $\hookrightarrow$  Boosted  $\rightarrow$  **negligible\*** (but made it in the plot!)
- Strong dependence** on  $\kappa_t$

## Parentheses - Upper Bound for $\kappa_t$

- Assuming  $\kappa_\lambda = 1 \rightarrow \kappa_t < 1.22!$
- $\hookrightarrow$  (Not really a **safe** assumption)
- Independent** of current methods
- Possible in **any hh process**
- $\hookrightarrow$  **Likely better** in **other decay modes**

S. Paredes Saenz

HH



\*Note that this does not necessarily apply to analyses optimized for discovery of SM hh production - only those aiming to constrain  $\kappa_\lambda$ .

# Constraints on $\kappa_\lambda$ - $\kappa_t$ Plane

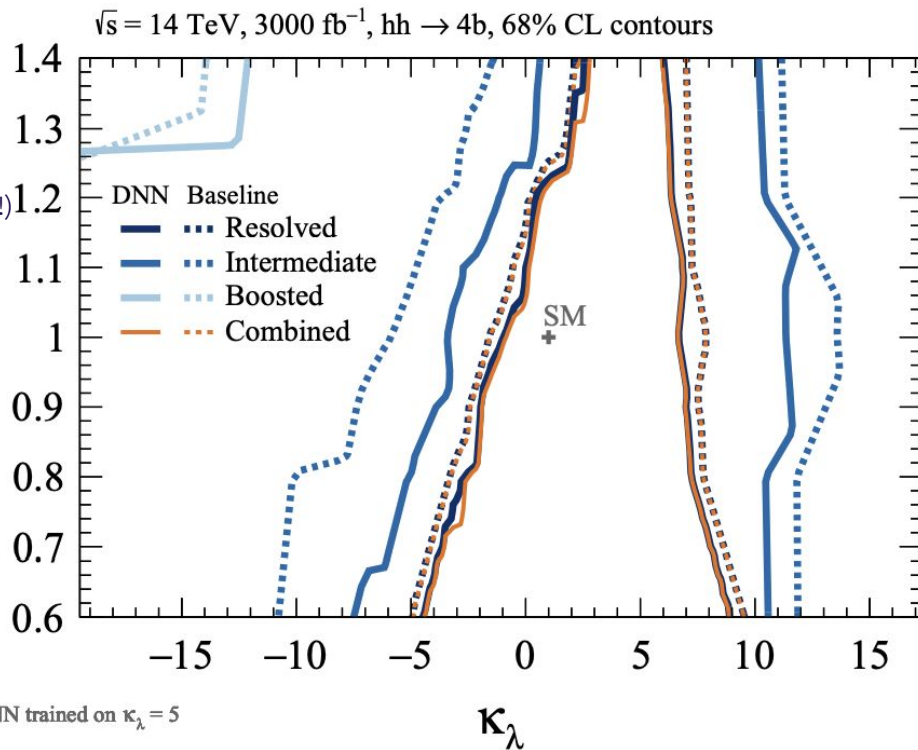
- Resolved  $\rightarrow$  **most powerful**
- $\hookrightarrow$  Intermediate  $\rightarrow$  **non-negligible**
- $\hookrightarrow$  Boosted  $\rightarrow$  **negligible\*** (but made it in the plot!)
- Strong dependence on  $\kappa_t$**

## Parentheses - Upper Bound for $\kappa_t$

- Assuming  $\kappa_\lambda = 1 \rightarrow \kappa_t < 1.22!$   
 $\hookrightarrow$  (Not really a **safe** assumption)
- Independent** of current methods
- Possible in **any hh process**  
 $\hookrightarrow$  **Likely better** in **other decay modes**

S. Paredes Saenz

HH



\*Note that this does not necessarily apply to analyses optimized for discovery of SM hh production - only those aiming to constrain  $\kappa_\lambda$ .

# Conclusion

---



# Conclusions

- **First detailed comparison** of  $\lambda_{hh\bar{h}}$  **constraints** in  $hh \rightarrow 4b$  resolved, intermediate and boosted channels, in the context of HL-LHC.
  - ↪ **Resolved most constraining**, then intermediate and then boosted
- A basic **DNN analysis** provided **noticeable improvement** over the cut based baseline analysis
- Best constraints came from NN trained on BSM signal
  - ↪  $hh \rightarrow 4b$  analyses **optimized** for **discovery of SM hh** may be **suboptimal**



# Conclusions

---

- **Experimental limitations**, triggering and jet reconstruction, **affect** the reconstruction of the **main discriminating variable  $m_{hh}$**
- **Uncertainty** on  $k_t$  has a strong impact on sensitivity to  $k_\lambda$ 
  - ↪ Same applies for **uncertainty multijet BKG estimates**
- This  $hh \rightarrow 4b$  search has **some sensitivity** to constrain  $k_t$  despite no dedicated optimization
- $4b$  is a **challenging**  $hh$  channel for  $\lambda_{hhh}$  constraints, but can provide important **independent information** for statistical **combinations**



# Thanks!

The logo for the Université Libre de Bruxelles (ULB). It consists of the letters 'ULB' in a large, bold, white, uppercase sans-serif font, set against a dark grey rectangular background.

UNIVERSITÉ  
LIBRE  
DE BRUXELLES

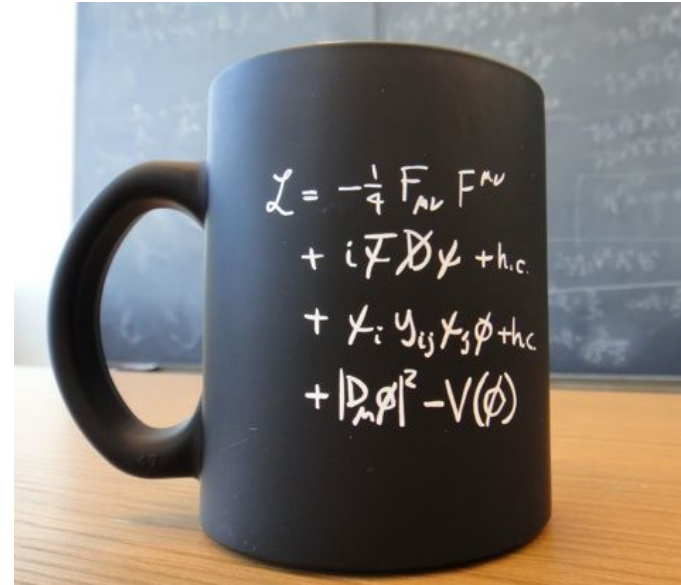
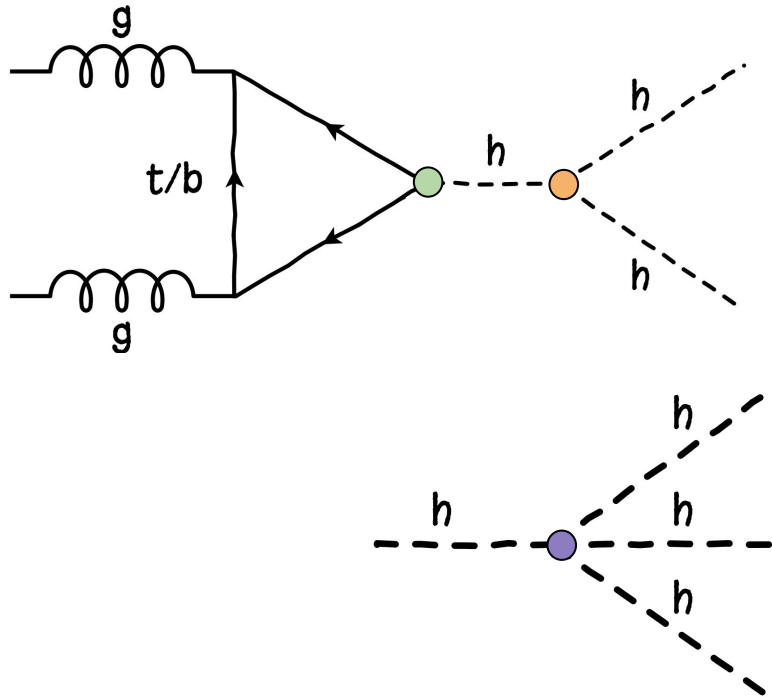
Jacob Amacker, William Balunas, Lydia Beresford, Daniela Bortoletto, James Frost, Cigdem Issever, Jesse Liu, James McKee, Alessandro Micheli, **Santiago Paredes Saenz**, Michael Spannowsky, and Beojan Stanislaus

[santiago.paredes@cern.ch](mailto:santiago.paredes@cern.ch)

**EOS be.h** Equinox Meeting  
September 2021

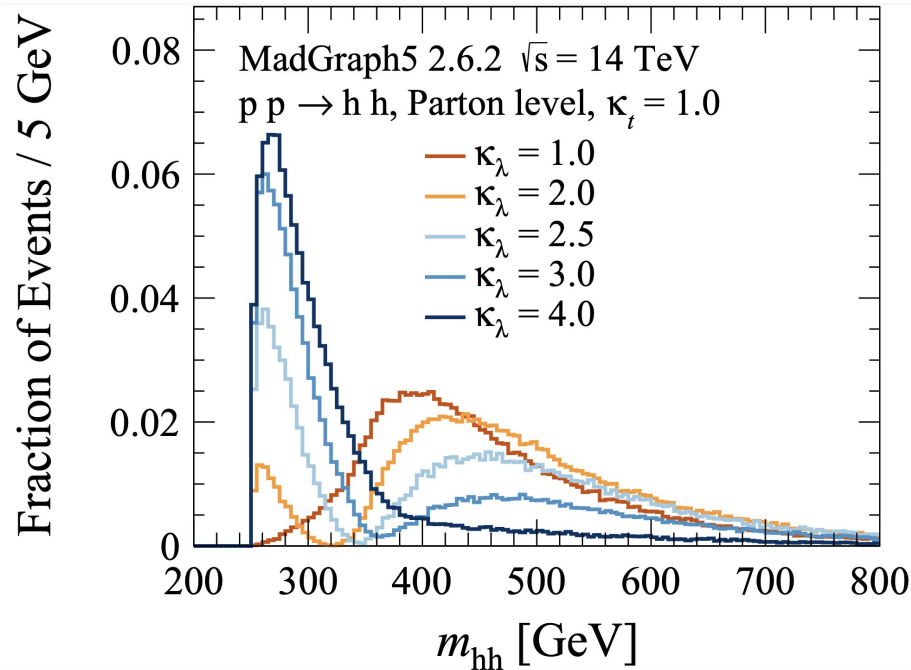


# Why di-higgs?



$$\lambda v^2 h^2 + \lambda v h^3 + \frac{\lambda}{4} h^4$$

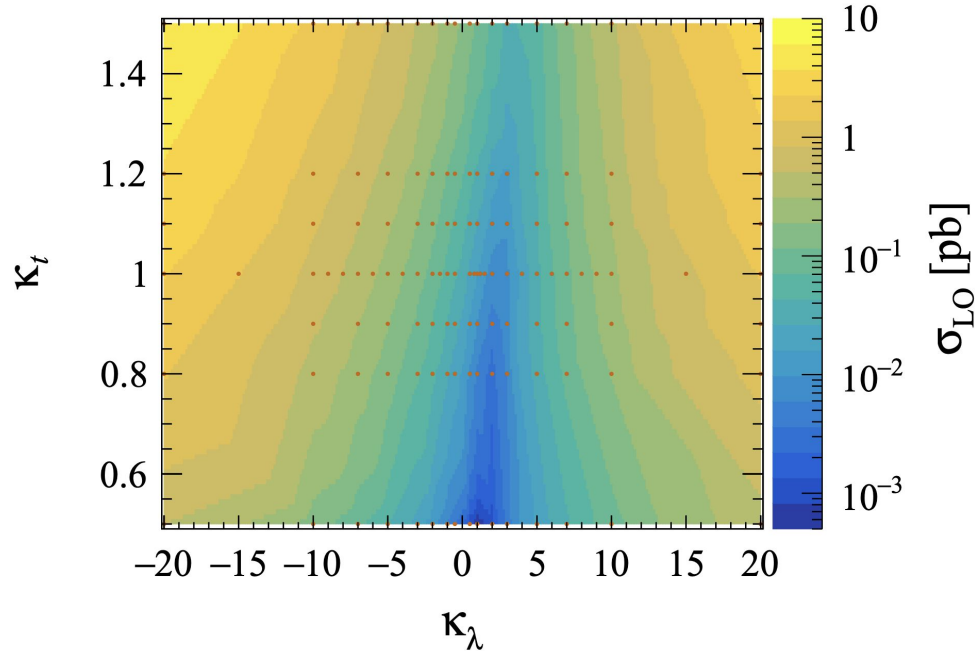
# Signal Samples



- $gg \rightarrow hh$  production
  - ↪ **100k events** per point
  - ↪ MadGraph 2.6.2
  - ↪ **Inclusive h decay**
- Decay, parton shower, hadronization, and underlying event  $\rightarrow$  Pythia 8.230
- **Varied** coupling to **top** quark and **self couplings**
  - ↪ All **BSM couplings** set to **0**
- Extra  $\kappa_t=1$  samples for **ML training**
  - ↪ **250k** events per point
  - ↪ Exclusive decay  $h \rightarrow b\bar{b}$

# Signal Samples

MadGraph5 2.6.2  $\sqrt{s} = 14$  TeV,  $pp \rightarrow hh$  • Points sampled



- $gg \rightarrow hh$  production
  - ↪ **100k events** per point
  - ↪ MadGraph 2.6.2
  - ↪ **Inclusive h decay**
- Decay, parton shower, hadronization, and underlying event
  - ↪ Pythia 8.230
- **Varied** coupling to **top** quark and **self couplings**
  - ↪ All **BSM couplings** set to **0**
- Extra  $\kappa_t=1$  samples for **ML training**
  - ↪ **250k** events per point
  - ↪ Exclusive decay  $h \rightarrow b\bar{b}$

# Event and Object Selection

Observable	Preselection		
Large jet $j_L$	$R = 1.0, p_T > 250 \text{ GeV},  \eta  < 2.0$		
Small jet $j_S$	$R = 0.4, p_T > 40 \text{ GeV},  \eta  < 2.5$		
Track jet $j_T$	$R = 0.2, p_T > 20 \text{ GeV},  \eta  < 2.5$		
$j_T \in j_L$	$\Delta R(j_T, j_L) < 1.0$		
	Resolved	Intermediate	Boosted
$N(j_L)$	$= 0$	$= 1$	$= 2$
$N(j_S)$	$\geq 4$	$\geq 2$	$\geq 0$
$h_1^{\text{cand}}$	$j_S^{(i)}$ pair	$j_L$	$j_L^{(1)}$
$h_2^{\text{cand}}$	$j_S^{(i)}$ pair	$j_S^{(i)}$ pair, $\Delta R(j_S^{(i)}, j_L) > 1.2$	$j_L^{(2)}$
$\Delta R_{jj}$	See Eqs. 3.2, 3.3	—	—

# Signal region definitions

Signal region			
$j_T \in h_1^{\text{cand}}$	—	$\geq 2$	$\geq 2$
$j_T \in h_2^{\text{cand}}$	—	—	$\geq 2$
$b$ -tagging	Two $b$ -tags for each $h_i^{\text{cand}}$		
$ \Delta\eta(h_1, h_2) $	$< 1.5$		
$E_T^{\text{miss}}$	$< 150$ GeV		
$p_T^\ell,  \eta_\ell $	$> 10$ GeV, $< 2.5$		
$N_\ell$	$= 0$		
$p_{\text{signal}}^{\text{DNN}}$	$> 0.75$ ( <i>neural network analysis only</i> )		
	Resolved	Intermediate	Boosted
$m(h_1)$ [GeV]	[90, 140]	[90, 140]	[90, 140]
$m(h_2)$ [GeV]	[90, 140]	[90, 140]	[90, 140]
Lower bin edges for $m_{hh}$ binning [GeV]			
Resolved	[200, 250, 300, 350, 400, 500]		
Intermediate	[200, 500, 600]		
Boosted	[500, 800]		

# Fixed $k_t=1$

BSM  $k_\lambda$   
yield

SM  $k_\lambda$   
yield

Category	Systematic $\zeta_b$
Resolved	0.3%
Intermediate	1%
Boosted	5%

$$\chi^2 = \sum_i \left[ \frac{(S - S_{\text{SM}})^2}{S + B + (\zeta_b B)^2 + (\zeta_s S)^2} \right]_i$$

$m_{hh}$   
bins

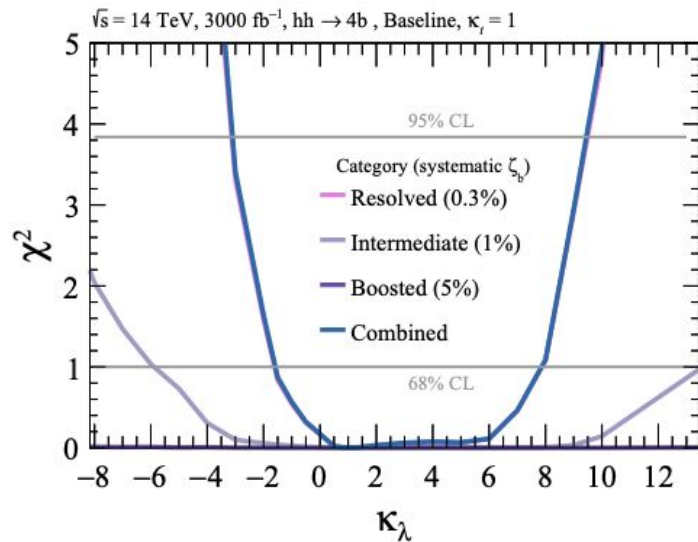
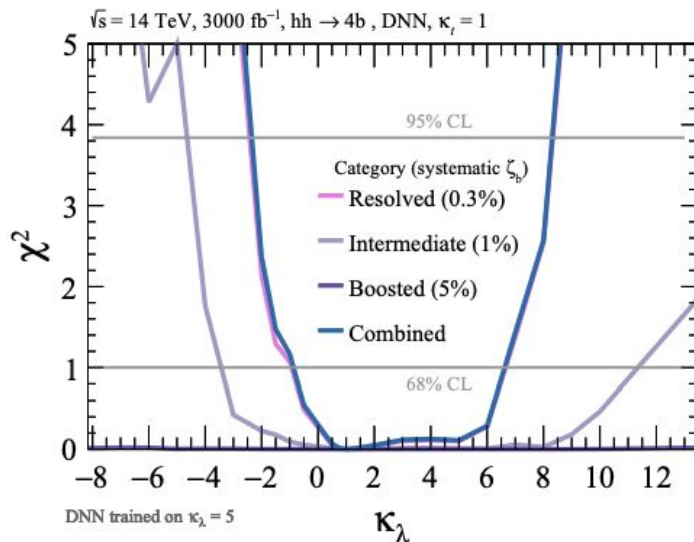
background  
uncertainty

signal  
uncertainty



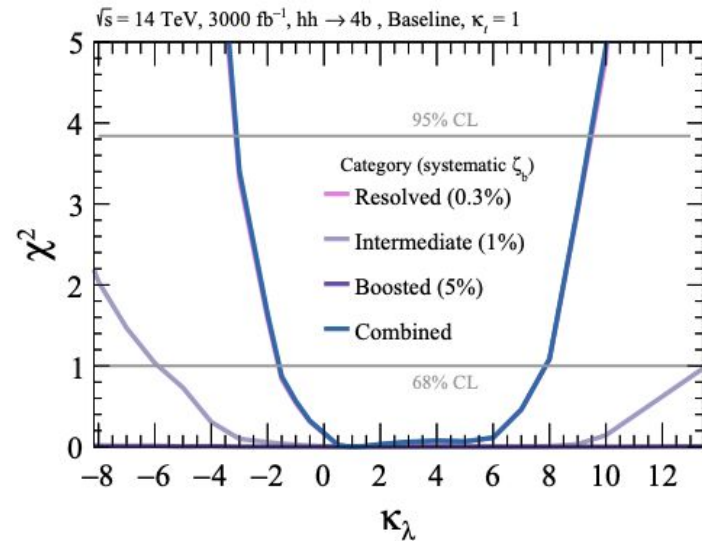
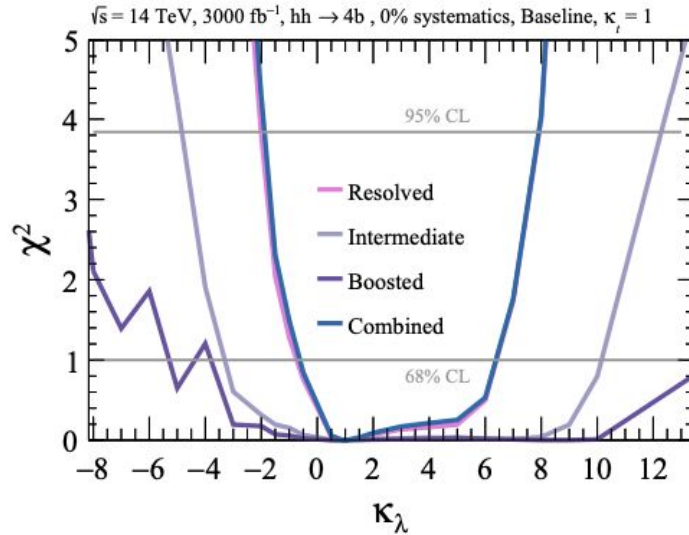
# Constraints on $\kappa_\lambda$ - Fixed $\kappa_t=1$

- Resolved  $\rightarrow$  **most powerful**
  - $\hookrightarrow$  Intermediate  $\rightarrow$  **non-negligible**
  - $\hookrightarrow$  Boosted  $\rightarrow$  **negligible\***
- Basic DNN analysis improved sensitivity**



# Parentheses - Impact of BKG Uncertainty

- **Background uncertainty** has **large impact** on sensitivity  
↳ **Often a large uncertainty** in  $hh \rightarrow 4b$  searches

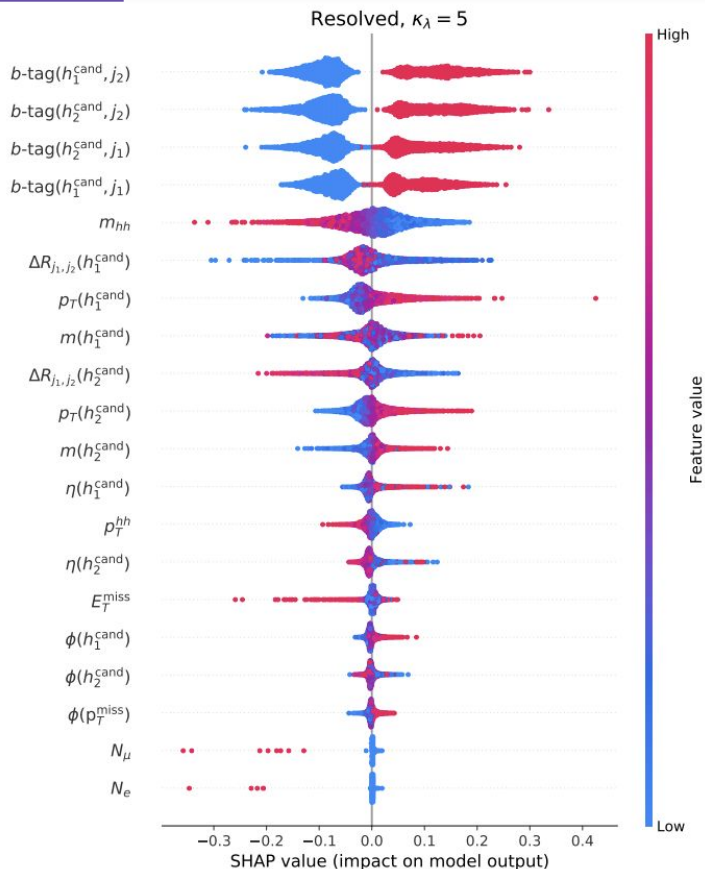


# Parentheses - What did our machine learn?

- SHAP value framework  
→ Shapley values for ML interpretability

NN variables

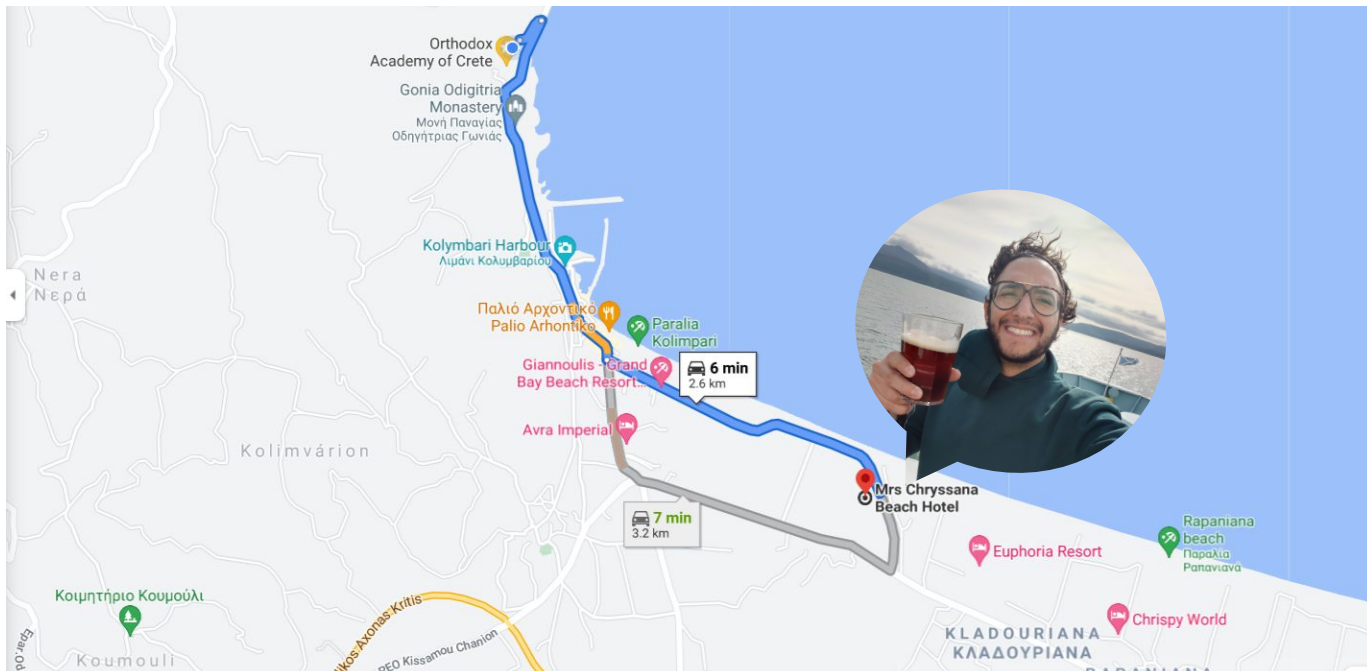
Ranked  
by impact on  
NN score



# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

## Parentheses - Shapley Values



-0.3 -0.2 -0.1 0.0 0.1 0.2 0.3 0.4 Low

SHAP value (impact on model output)

SHAP value

More signal-like impact on score

# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

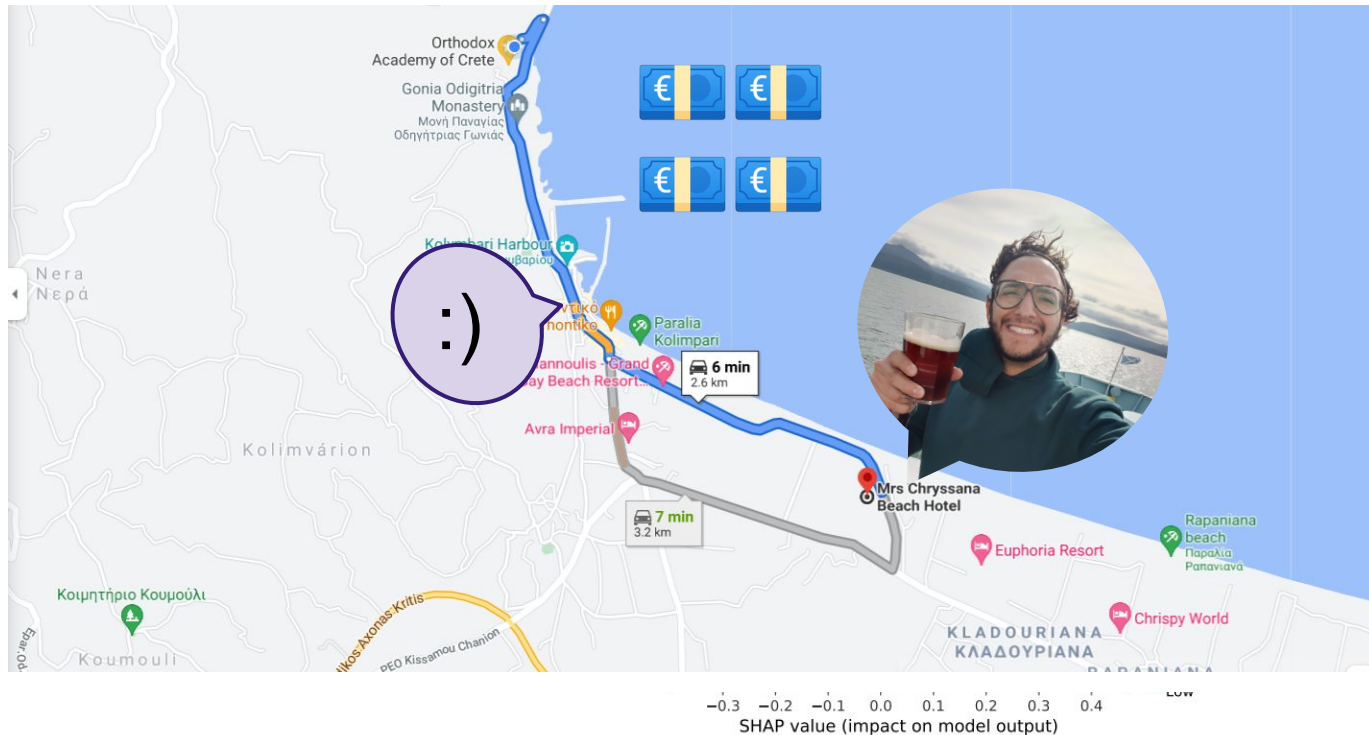
## Parentheses - Shapley Values



# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

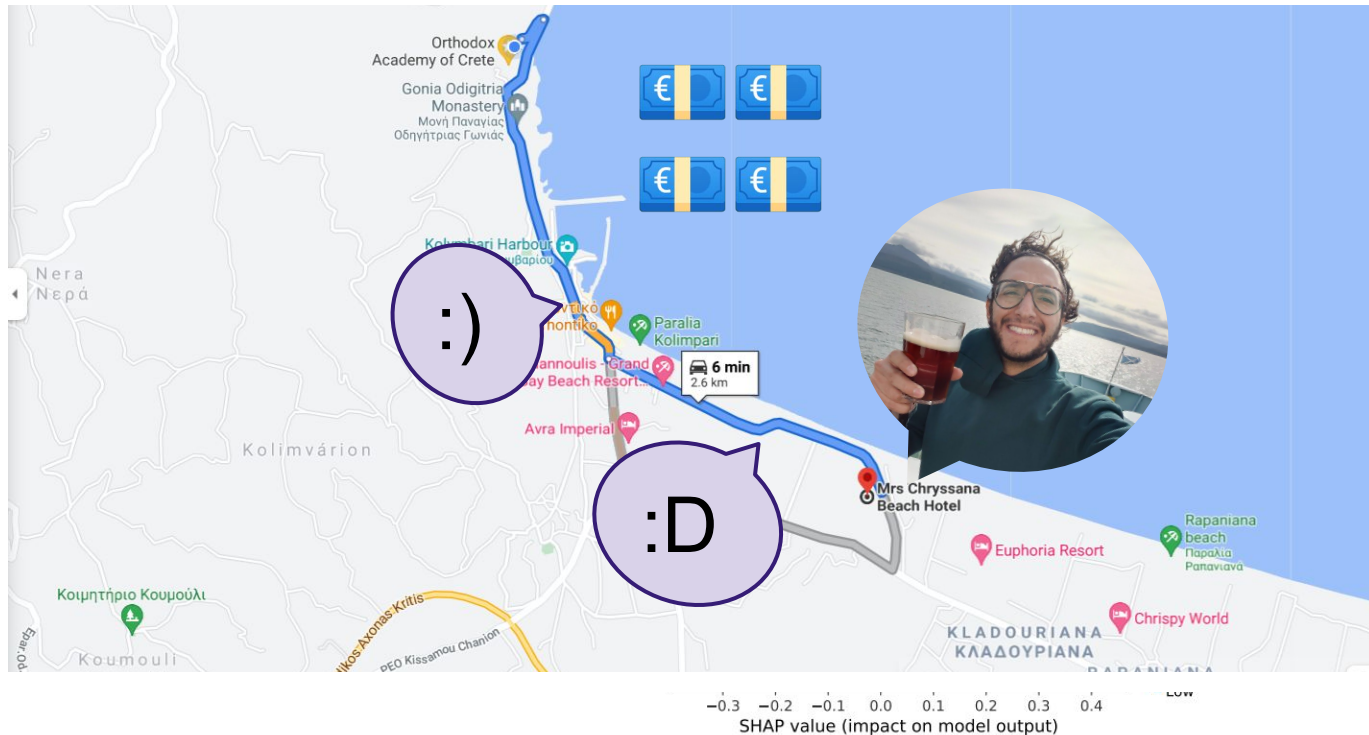
## Parentheses - Shapley Values



# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

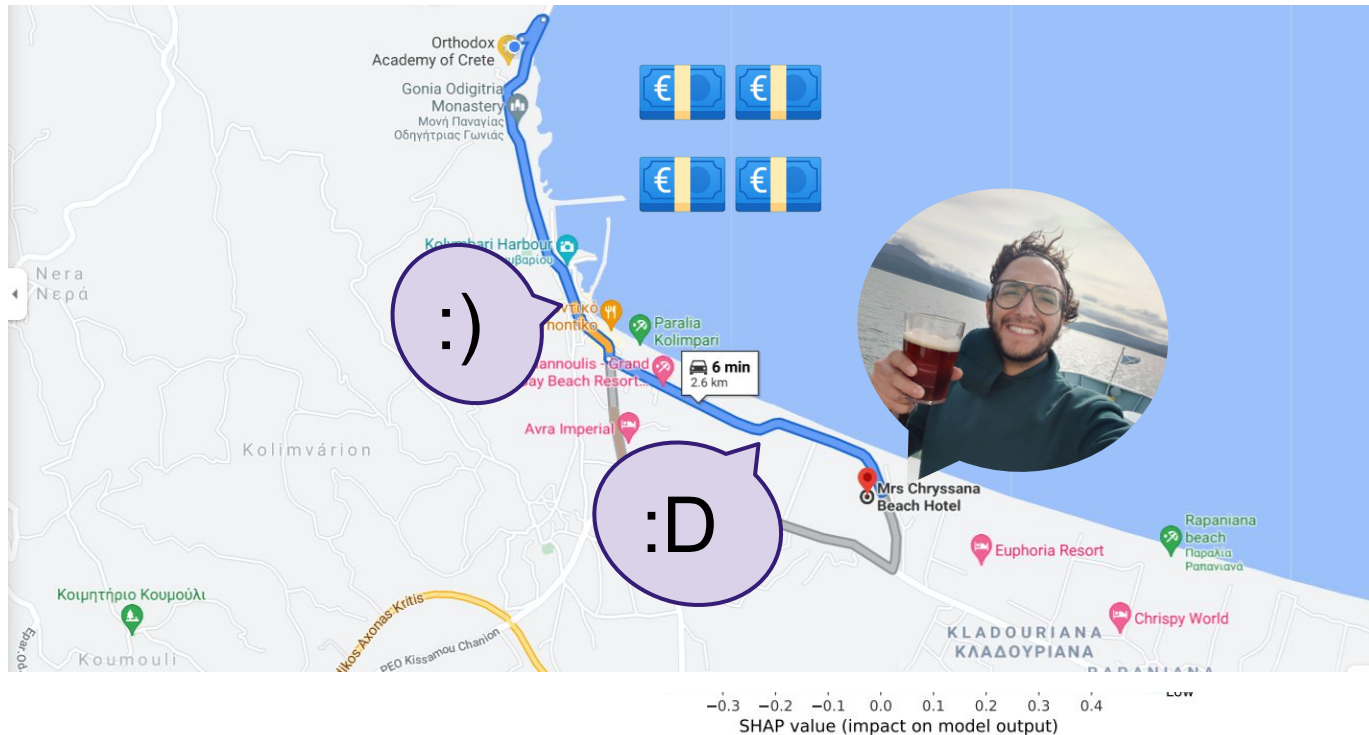
## Parentheses - Shapley Values



# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

## Parentheses - Shapley Values





# Parentheses - What did our machine learn?

Resolved,  $\kappa_\lambda = 5$

## Parentheses - Shapley Values

