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Theory  
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vBF H $\rightarrow$ WW  
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Discussion  
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Conclusion  
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# ggF+jj Analysis

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DESY

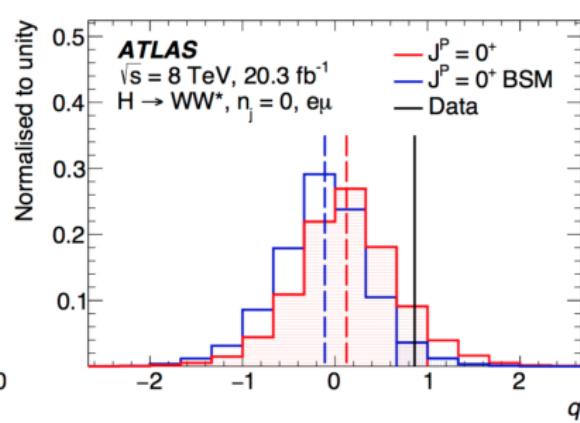
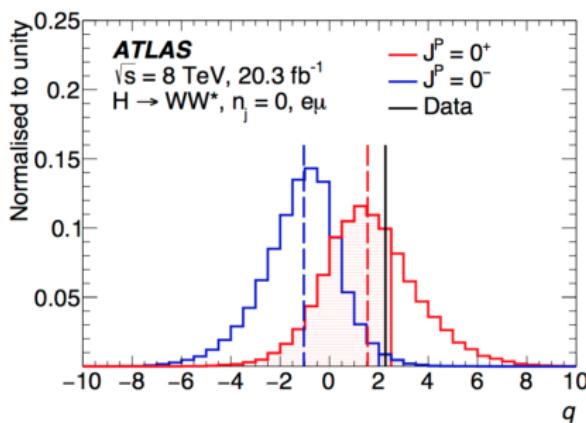
11 January 2018

# Introduction

What did we measure in Run 1?

- cross sections
- couplings
- properties → based on hypothesis testing: Spin and CP

Always 0 or 1 jet



# Introduction

What do we want to measure?

- cross sections
- couplings
- properties: such as CP

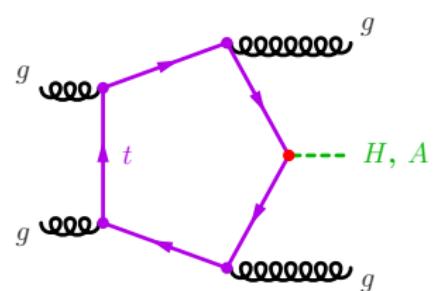
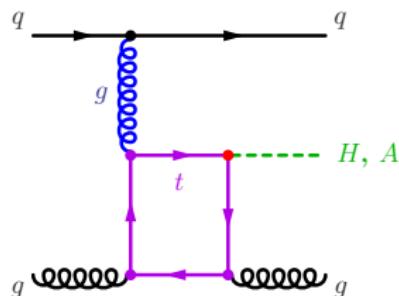
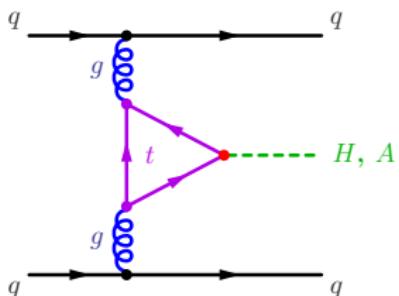
Use effective Lagrangian as an example, but can apply same techniques to many other BSM models with large sets of parameters

# ggF+jj

Study in the  $H \rightarrow WW \rightarrow l\nu/\nu$  channel.

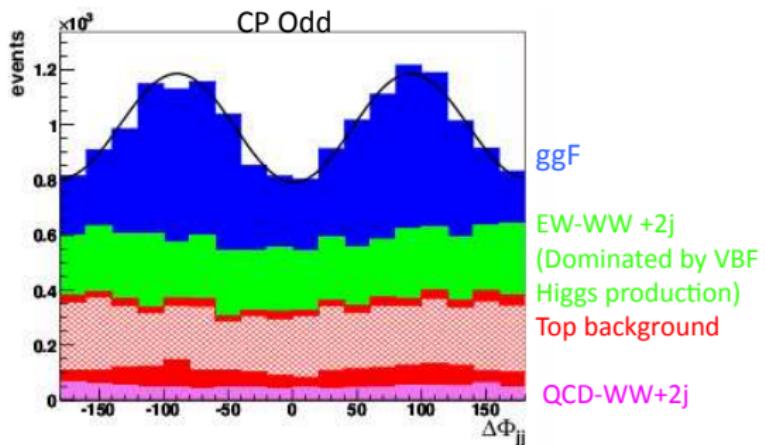
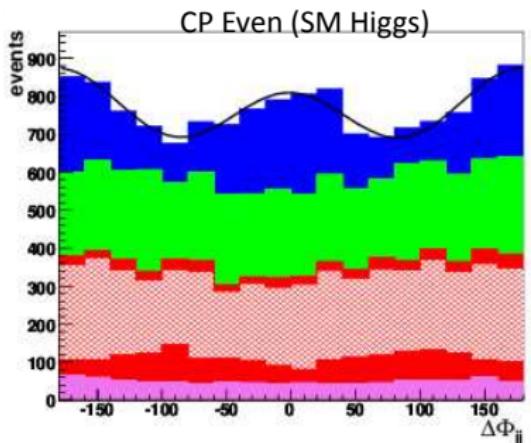
Looking at gluon gluon fusion (ggF) with two jets.

Feynman graphs contributing to  $pp \rightarrow Hjj$



# ggF+jj

- The SM CP even Higgs shows a modulation in  $\Delta\phi_{jj}$   
the backgrounds and the VBF process are flat
- In the cases for a CP Odd or a CP mixed stat there is a different modulation
  - G. Klämke and D. Zeppenfeld <http://arxiv.org/pdf/hep-ph/0703202.pdf>



# Effective field theory framework implemented in Higgs Characterisation model

- Effective Lagrangian for the interaction of scalar and pseudo-scalar states with vector bosons

$$\mathcal{L}_0^V = \left\{ c_\alpha \kappa_{SM} \left[ \frac{1}{2} \tilde{g}_{HZZ} Z_\mu Z^\mu + \tilde{g}_{HWW} W_\mu^+ W^{-\mu} \right] \right.$$

Used in Run 1

$$- \frac{1}{4} [c_\alpha \kappa_{H\gamma\gamma} \tilde{g}_{H\gamma\gamma} A_{\mu\nu} A^{\mu\nu} + s_\alpha \kappa_{A\gamma\gamma} \tilde{g}_{A\gamma\gamma} A_{\mu\nu} \tilde{A}^{\mu\nu}]$$

Plan Run 2

$$- \frac{1}{2} [c_\alpha \kappa_{HZ\gamma} \tilde{g}_{HZ\gamma} Z_{\mu\nu} A^{\mu\nu} + s_\alpha \kappa_{AZ\gamma} \tilde{g}_{AZ\gamma} Z_{\mu\nu} \tilde{A}^{\mu\nu}]$$

$$- \frac{1}{4} [c_\alpha \kappa_{Hgg} \tilde{g}_{Hgg} G_{\mu\nu}^a G^{a,\mu\nu} + s_\alpha \kappa_{Agg} \tilde{g}_{Agg} G_{\mu\nu}^a \tilde{G}^{a,\mu\nu}]$$

$$- \frac{1}{4} \frac{1}{\Lambda} [c_\alpha \kappa_{HZZ} Z_{\mu\nu} Z^{\mu\nu} + s_\alpha \kappa_{AZZ} Z_{\mu\nu} \tilde{Z}^{\mu\nu}]$$

$$- \frac{1}{2} \frac{1}{\Lambda} [c_\alpha \kappa_{HWW} W_\mu^+ W^{-\mu\nu} + s_\alpha \kappa_{AWW} W_\mu^+ \tilde{W}^{-\mu\nu}]$$

$$\left. - \frac{1}{\Lambda} c_\alpha [\kappa_{H\partial\gamma} Z_\nu \partial_\mu A^{\mu\nu} + \kappa_{H\partial Z} Z_\nu \partial_\mu Z^{\mu\nu} + \kappa_{H\partial W} (W_\nu^+ \partial_\mu W^{-\mu\nu} + h.c.)] \right\} \mathcal{X}_0$$

- Implemented in MADGRAPH5\_AMC@NLO
- $\Lambda = 1 \text{ TeV}$ ,  $\cos \alpha = \frac{1}{\sqrt{2}}$  fixed
- Define full coupling parameter as  $g_x$  (e.g.  $g_{AWW} = s_\alpha \kappa_{AWW}/\Lambda$ )

# Analyses overview and plans in ATLAS

## Plans for Run 2

- Perform combined studies of **many (all) parameters** in the matrix element
  - Take **all correlations** between different operators into account
  - Use constraining power from **rate & shape information**
  - Combine results from different channels
- Challenge: **large parameter space** (e.g. VBF H $\rightarrow$ VV 13 free parameters)
- New method to construct predictions for signal cross section and distributions

### Morphing

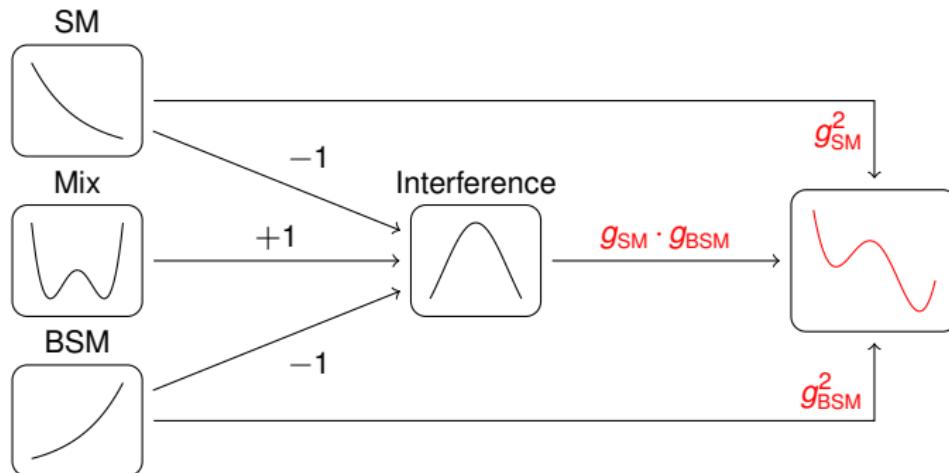
→ ggF+jj in H  $\rightarrow$  WW: 2 free parameters

## Signal model construction in Run 2: Morphing

- **Morphing function** for an observable  $T_{out}$  at any coupling point  $\vec{g}_{target}$  constructed from weighted sum of input samples  $T_{in}$  at fixed coupling points  $\vec{g}_i$

$$T_{out}(\vec{g}_{target}) = \sum_{i=1}^{N_{input}} w_i(\vec{g}_{target}; \vec{g}_i) \cdot T_{in}(\vec{g}_i)$$

e.g.  $T = \Delta\phi_{jj}$



## Example for 2 free parameters in one vertex

- Process with **two parameters** applied in **one vertex**:  $g_{\text{SM}}$  and  $g_{\text{BSM}}$
- Matrix element can be **factorized**:

$$\mathcal{M}(g_{\text{SM}}, g_{\text{BSM}}) = g_{\text{SM}} \mathcal{O}_{\text{SM}} + g_{\text{BSM}} \mathcal{O}_{\text{BSM}}$$

$$|\mathcal{M}(g_{\text{SM}}, g_{\text{BSM}})|^2 = g_{\text{SM}}^2 |\mathcal{O}_{\text{SM}}|^2 + g_{\text{BSM}}^2 |\mathcal{O}_{\text{BSM}}|^2 + 2g_{\text{SM}}g_{\text{BSM}} \mathcal{R}(\mathcal{O}_{\text{SM}}^* \mathcal{O}_{\text{BSM}})$$

- Distribution** of a kinematic observable **proportional to the matrix element squared**

$$T(g_{\text{SM}}, g_{\text{BSM}}) \propto |\mathcal{M}(g_{\text{SM}}, g_{\text{BSM}})|^2$$

- 3 generated distributions** needed to obtain distribution with arbitrary parameters
- E.g. generate MC events for  $T(1,0)$ ,  $T(0,1)$ ,  $T(1,1)$

$$T_{in}(1,0) \propto |\mathcal{O}_{\text{SM}}|^2$$

$$T_{in}(0,1) \propto |\mathcal{O}_{\text{BSM}}|^2$$

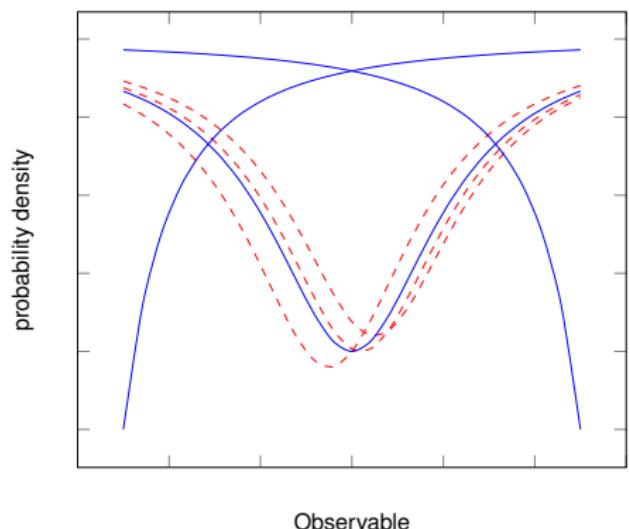
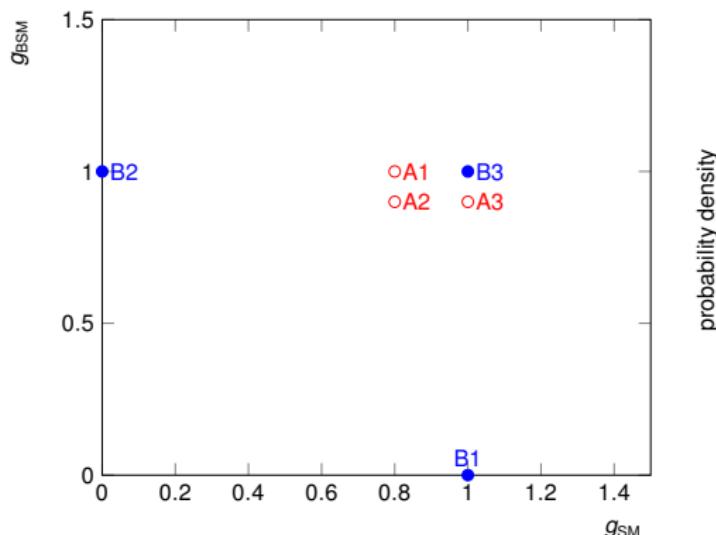
$$T_{in}(1,1) \propto |\mathcal{O}_{\text{SM}}|^2 + |\mathcal{O}_{\text{BSM}}|^2 + 2\mathcal{R}(\mathcal{O}_{\text{SM}}^* \mathcal{O}_{\text{BSM}})$$

- Distribution with **arbitrary parameters** ( $g_{\text{SM}}$ ,  $g_{\text{BSM}}$ )

$$T_{out}(g_{\text{SM}}, g_{\text{BSM}}) = \underbrace{(g_{\text{SM}}^2 - g_{\text{SM}}g_{\text{BSM}})}_{\text{Term 1}} T_{in}(1,0) + \underbrace{(g_{\text{BSM}}^2 - g_{\text{SM}}g_{\text{BSM}})}_{\text{Term 2}} T_{in}(0,1) + \underbrace{g_{\text{SM}}g_{\text{BSM}}}_{\text{Term 3}} T_{in}(1,1)$$

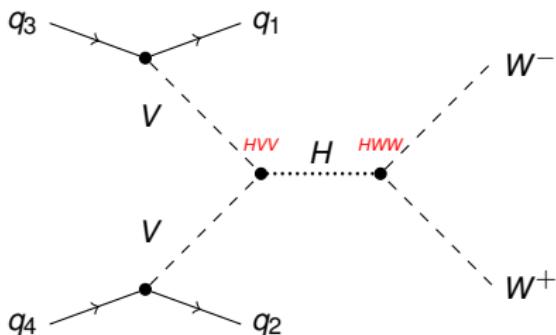
## Choice of input parameters

- So far fixed parameters for input distributions:  $T_{in}(1,0)$ ,  $T_{in}(0,1)$ ,  $T_{in}(1,1)$
  - Aim to **generalise morphing** to have arbitrary  $g_i$
- Can be chosen to **reduce statistical uncertainty**



Example: 13 free parameters for VBF H $\rightarrow$ ZZ process: 1605 samples

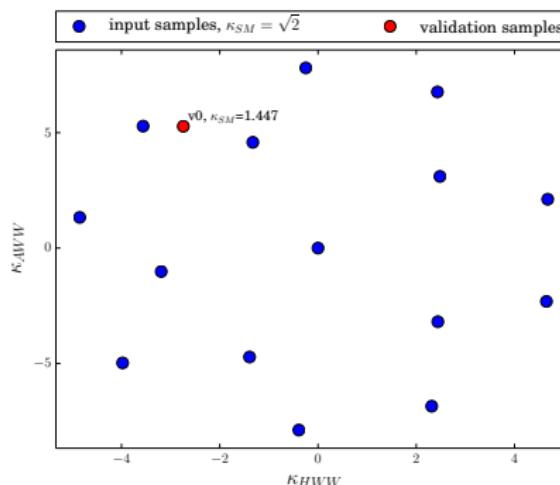
## VBF H $\rightarrow$ WW example



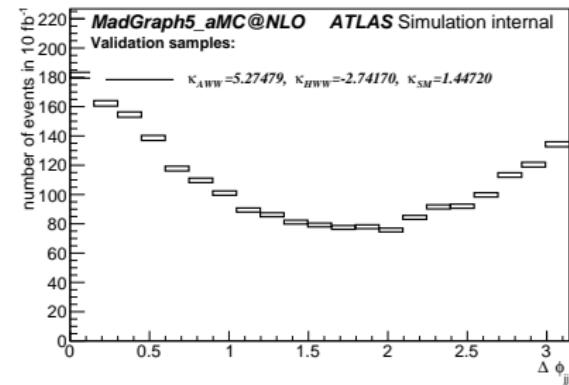
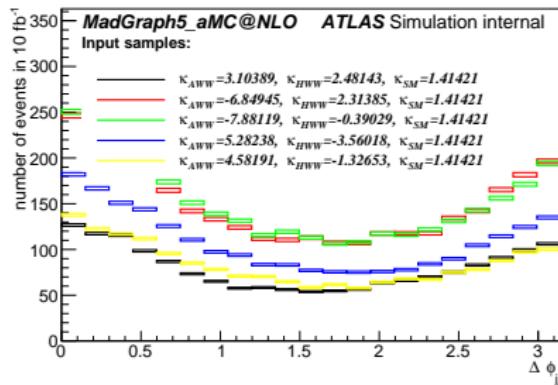
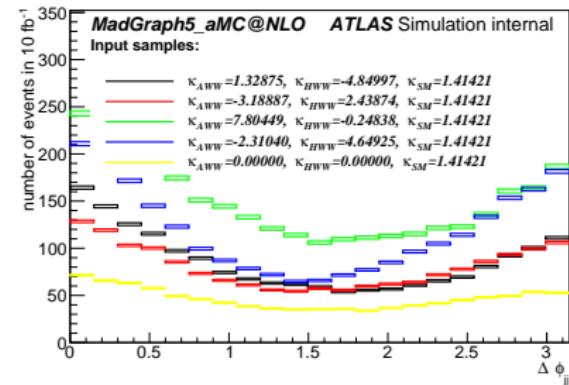
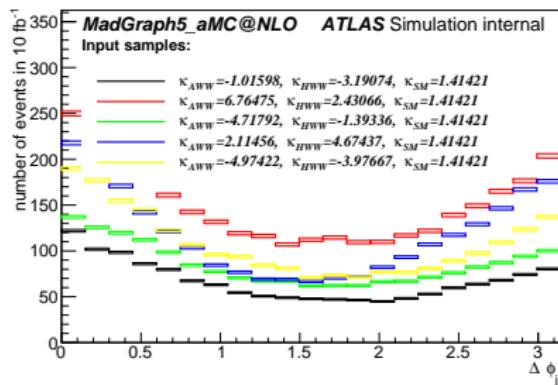
- VBF H $\rightarrow$ WW process with **SM** ( $g_{\text{SM}}$ ) and **2 BSM** operators ( $g_{\text{HWW}}$ ,  $g_{\text{AWW}}$ )
- **15 samples** with different parameters needed
- 50k events generated for each sample
- Kinematic observable used:  $\Delta\phi_{jj}$
- Only signal considered

## VBF H $\rightarrow$ WW example: Samples

- Expect only **small deviations from SM**
  - $g_{SM} = 1$  for all input samples ( $\Lambda = 1 \text{ TeV}$ ,  $\cos \alpha = \frac{1}{\sqrt{2}}$ )
  - BSM parameter limits chosen such that  $\sigma_{\text{pure BSM}} \sim \sigma_{\text{SM}}$
  - all other BSM parameters set to 0
- Scatter plot shows **blue** points in  $(g_{AWW}, g_{HWW})$  space used to generate **input samples**
- A **validation sample** is produced at the **red** point for cross-check
  - **morphing** can reproduce the distribution there
  - **fit** can reproduce the parameters from the validation sample



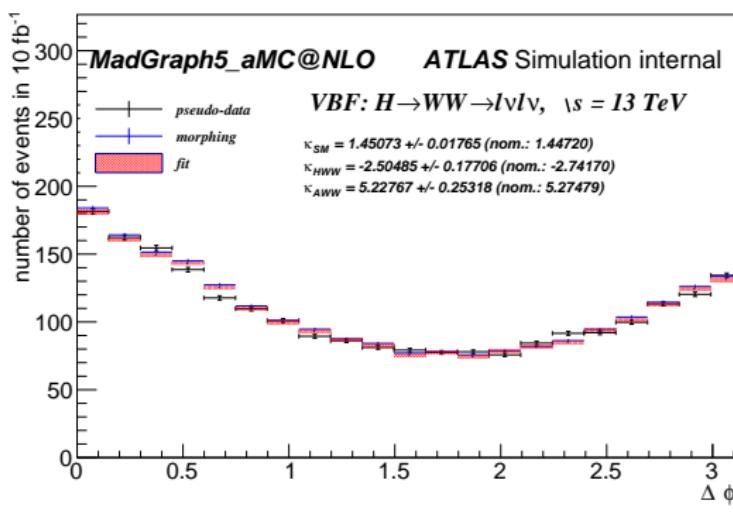
# VBF H $\rightarrow$ WW example: Input and validation distributions



## VBF H $\rightarrow$ WW example: Morphing and fit to validation sample

- **Morphing** and **fit** to validation distr. (pseudo-data)
- Validation and morphed distribution stat. independent
  - Agreement in morphing within MC stat. uncertainty
  - Fit results match nominal values within fit uncertainties
- **Sensitivity** on parameters shown in fit uncert.
- **Correlations** vary at different parameter point

	$\kappa_{SM}$	$\kappa_{HWW}$	$\kappa_{AWW}$
$\kappa_{SM}$	1.00	0.20	-0.95
$\kappa_{HWW}$	0.20	1.00	0.09
$\kappa_{AWW}$	-0.95	0.09	1.00



## Generality of the method

- Morphing only requires that any differential cross section can be expressed as **polynomial in BSM couplings**
- Method can be used on **any generator** that allows one to vary input couplings
- Works on **truth** and **reco-level** distributions
- **Independent of physics process**
- Works on distributions and cross sections

## Difficulties

From a theoretical viewpoint:

- Method in Effective Lagrangian: terms  $\sim \frac{1}{\Lambda^2}$  from dim 6 operators included, but not from dim 8 operators
- Problematic to include dim-8 operators:
  - No generator available
  - Additional large set of coupling parameters
- Neglecting of quadratic terms not possible due to negative cross sections

From a experimental viewpoint:

- Separating ggF+jj from VBF
  - does not seem to interfere in a deconstructive way
- Reduction of backgrounds without changing the shape of  $\Delta\phi_{jj}$ 
  - Careful checks necessary

## Summary

- Plan for Run 2: **Higgs coupling and properties measurements**
- Combine **rate and shape information** within effective Lagrangian framework
- New method for modelling BSM effects
  - continuous
  - analytical
  - fast

# Backup

## Comparison of methods

- **Needed:** MC samples covering wide range of values for coupling parameters
- Run 1 HWW and HZZ analyses: **Matrix Element Reweighting**  
(Event by event matrix element reweighting of one source MC sample with large statistics)

$$w(\vec{g}_{\text{target}}) = w(\vec{g}_i) \frac{|\mathcal{M}(\vec{g}_{\text{target}})|^2}{|\mathcal{M}(\vec{g}_{\text{source}})|^2}$$

### ME Reweighting

For every configuration point

- rerun analysis
- write event weights to disk
- additional interpolation

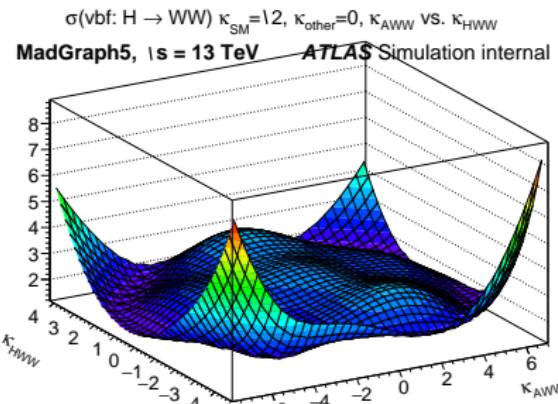
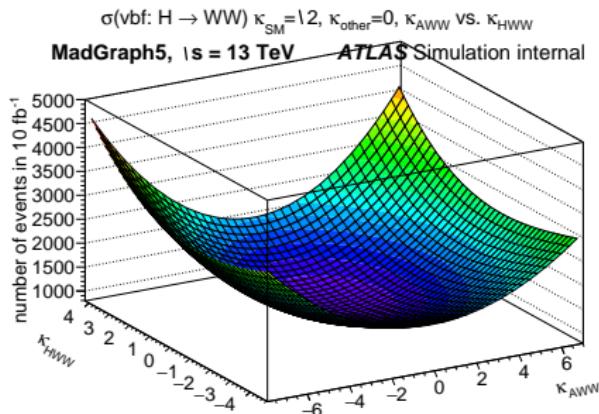
### Morphing

- only calculates linear sums of coefficients
- all other inputs are pre-computed once
- computationally fast & convenient tool

- **Morphing function:** Instead of “matrix element reweighting” use morphing to obtain a distribution with arbitrary coupling parameters
- Can be applied directly and without change to
  - Cross sections
  - Distributions (before or after detector simulation)
  - MC events
- **Exact continuous analytical description of rates and shapes**
- Even possible to **fit** coupling parameters to data & derive limits

## VBF H $\rightarrow$ WW example: Rel. uncertainty on number of expected events

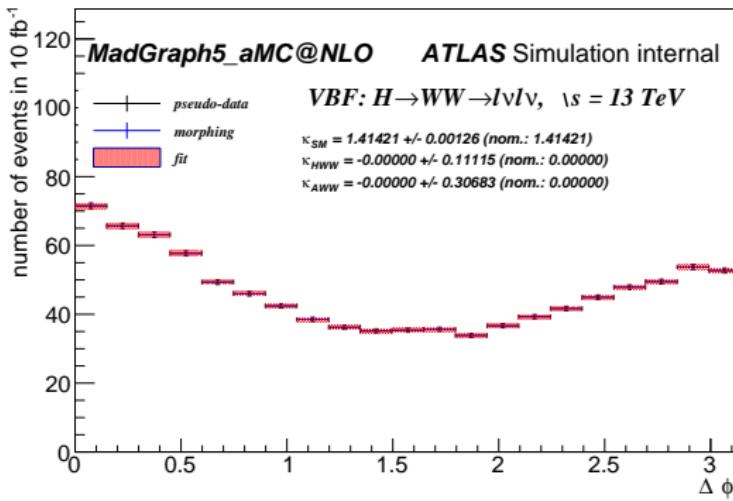
- Dependence of **stat. uncertainty** propagated in morphing function on generated input parameter grid
- Distribution of samples in parameter space **reduces** stat. uncertainty



## VBF H $\rightarrow$ WW example: Morphing and fit to SM input sample

- **Morphing** and **fit** to SM input distribution (pseudo-data)
- MC stat. uncertainty used
- Input and morphed distribution stat. dependent
  - perfect agreement in morphing
  - Post-fit parameters match exact nominal values
- **Sensitivity** on parameters shown in fit uncert.
- **Correlations** at SM point in table

	$\kappa_{SM}$	$\kappa_{HWW}$	$\kappa_{AWW}$
$\kappa_{SM}$	1.00	0.15	-0.23
$\kappa_{HWW}$	0.15	1.00	0.36
$\kappa_{AWW}$	-0.23	0.36	1.00



Example for 2 free parameters in one vertex: generalisation of input parameter

- Generalize to **arbitrary input parameters**  $\vec{g}_i$  used to generate input distributions  $T_{in}(\vec{g}_i)$

$$T_{in}(g_{SM,i}, g_{BSM,i}) \propto g_{SM,i}^2 |\mathcal{O}_{SM}|^2 + g_{BSM,i}^2 |\mathcal{O}_{BSM}|^2 + 2g_{SM,i}g_{BSM,i} \mathcal{R}(\mathcal{O}_{SM}^* \mathcal{O}_{BSM}),$$
$$i = 1, \dots, 3$$

- Ansatz for **output distribution**

$$\begin{aligned} T_{out}(g_{SM}, g_{BSM}) &= \underbrace{(a_{11}g_{SM}^2 + a_{12}g_{BSM}^2 + a_{13}g_{SM}g_{BSM})}_{w_1} T_{in}(g_{SM,1}, g_{BSM,1}) \\ &\quad + \underbrace{(a_{21}g_{SM}^2 + a_{22}g_{BSM}^2 + a_{23}g_{SM}g_{BSM})}_{w_2} T_{in}(g_{SM,2}, g_{BSM,2}) \\ &\quad + \underbrace{(a_{31}g_{SM}^2 + a_{32}g_{BSM}^2 + a_{33}g_{SM}g_{BSM})}_{w_3} T_{in}(g_{SM,3}, g_{BSM,3}) \end{aligned}$$

## Example for 2 operators in one vertex

- $T_{out}$  should be equal to  $T_{in}$  for  $\vec{g}_{target} = \vec{g}_i$

$$1 = a_{11} g_{SM,1}^2 + a_{12} g_{BSM,1}^2 + a_{13} g_{SM,1} g_{BSM,1}$$

$$0 = a_{21} g_{SM,1}^2 + a_{22} g_{BSM,1}^2 + a_{23} g_{SM,1} g_{BSM,1}$$

...

- Constraints in **matrix form**

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \cdot \begin{pmatrix} g_{SM,1}^2 & g_{SM,2}^2 & g_{SM,3}^2 \\ g_{BSM,1}^2 & g_{BSM,2}^2 & g_{BSM,3}^2 \\ g_{SM,1} g_{BSM,1} & g_{SM,2} g_{BSM,2} & g_{SM,3} g_{BSM,3} \end{pmatrix} = \mathbb{1}$$
$$\Leftrightarrow A \cdot G = \mathbb{1}$$

- **Definite solution**  $A = G^{-1}$  requires the samples to have parameters such that  $\det(G) \neq 0$
- Very flexible in choosing the parameters for the input distributions
- Can be chosen to **reduce statistical uncertainty** in considered parameter space

## General morphing and number of input distributions

- More complicated when processes share amplitudes between **production and decay**, for example VBF  $H \rightarrow VV$
- General matrix element squared at **LO** & assuming **narrow-width-approximation** (ignoring the effect on the total width)  
⇒ **polynomials** of 2nd order in production and 2nd order in decay

$$T(\vec{g}) \propto |\mathcal{M}(\vec{g})|^2 = \underbrace{\left( \sum_{i=1}^{n_p+n_s} g_i \mathcal{O}_i \right)^2}_{\text{production vertex}} \cdot \underbrace{\left( \sum_{j=1}^{n_d+n_s} g_j \mathcal{O}_j \right)^2}_{\text{decay vertex}}$$

with number of parameters in **production vertex** ( $n_p$ ), **decay vertex** ( $n_d$ ) and **shared in vertices** ( $n_s$ )

- Number of required input distributions** equal to  
number of different terms in expanded matrix element squared  
→ dependent on process and considered parameters  
→  $N_{\text{input}}$  function of  $n_p$ ,  $n_d$  and  $n_s$
  - Example: 13 free parameters for VBF  $H \rightarrow ZZ$  process:
    - $n_p = 4$  operators in production:  $g_{HWW}$ ,  $g_{AWW}$ ,  $g_{H\partial W}$ ,  $g_{H\partial W}^*$
    - $n_s = 9$  operators in both vertices:  $g_{SM}$ ,  $g_{HZZ}$ ,  $g_{AZZ}$ ,  $g_{H\partial Z}$ ,  $g_{H\gamma\gamma}$ ,  $g_{A\gamma\gamma}$ ,  $g_{HZ\gamma}$ ,  $g_{AZ\gamma}$ ,  $g_{H\partial\gamma}$
    - $n_d = 0$ , no operators only in decay
- **1605 samples** needed!
- Reduction of considered operators favourable → see VBF study

## Number of input distributions

$$\begin{aligned}N_{input} = & \frac{n_p(n_p+1)}{2} \cdot \frac{n_d(n_d+1)}{2} + \binom{4+n_s-1}{4} \\& + \left( n_p \cdot n_s + \frac{n_s(n_s+1)}{2} \right) \cdot \frac{n_d(n_d+1)}{2} \\& + \left( n_d \cdot n_s + \frac{n_s(n_s+1)}{2} \right) \cdot \frac{n_p(n_p+1)}{2} \\& + \frac{n_s(n_s+1)}{2} \cdot n_p \cdot n_d + (n_p + n_d) \binom{3+n_s-1}{3}\end{aligned}$$

with number of parameters in **production vertex** ( $n_p$ ), **decay vertex** ( $n_d$ ) and **shared in vertices** ( $n_s$ )

# Propagation of statistical uncertainties

[noframenumbering]

- Morphing function for a bin in distribution

$$T_{out}^{bin}(\vec{g}_{target}) = \sum_i w_i(\vec{g}_{target}; \vec{g}_i) T_{in}^{bin}(\vec{g}_i)$$

- For one input distribution, the bin content is calculated as follows

$$T_{in}^{bin}(\vec{g}_i) = N_{MC,in}^{bin}(\vec{g}_i) \cdot \sigma_{in}(\vec{g}_i) \mathcal{L} / N_{MC,in}$$

- The uncertainty on that bin is  $\sqrt{N_{MC,in}^{bin}(\vec{g}_i)}$
- The propagated statistical uncertainty is

$$\Delta T_{out}^{bin} = \sqrt{\sum_i w_i^2(\vec{g}_{target}; \vec{g}_i) N_{MC,in}^{bin}(\vec{g}_i) \cdot (\sigma_{in}(\vec{g}_i) \mathcal{L} / N_{MC,in})^2}$$

- Highly **dependent** on
  - **input parameters**  $\vec{g}_i$
  - desired **target parameters**  $\vec{g}_{target}$

