

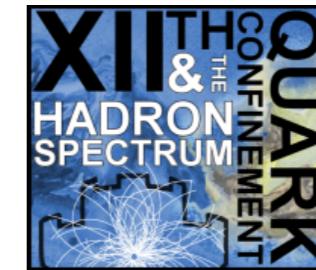
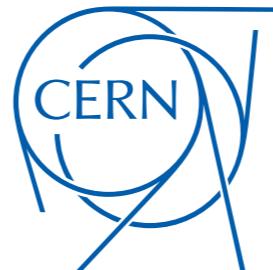
# Statistical combination of experimental results in ATLAS

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Stefan Gadatsch<sup>a</sup> on behalf of the ATLAS collaboration

2<sup>nd</sup> September, 2016

<sup>a</sup>CERN



# The role of combinations in HEP



- Combinations are **increasingly important** for HEP to perform the single most powerful test of a hypothesis, e.g. for a **measurement** or assessing the **compatibility** of measurements
- Dedicated analyses for each production and decay mode target specific properties
- Example: Higgs boson mass and couplings
- Searches are often performed more **inclusively**, complicating statistical combinations
- Many analyses perform combinations already **implicitly**
  - Example: data driven background estimates, subsidiary measurements, etc.

Channel	References for individual publications		Signal strength [ $\mu$ ] from results in this paper (Section 5.2)		Signal significance [ $\sigma$ ]	
	ATLAS	CMS	ATLAS	CMS	ATLAS	CMS
$H \rightarrow \gamma\gamma$	[91]	[92]	$1.14^{+0.27}_{-0.25}$ $(^{+0.26}_{-0.24})$	$1.11^{+0.25}_{-0.23}$ $(^{+0.23}_{-0.21})$	5.0 (4.6)	5.6 (5.1)
$H \rightarrow ZZ$	[93]	[94]	$1.52^{+0.40}_{-0.34}$ $(^{+0.32}_{-0.27})$	$1.04^{+0.32}_{-0.26}$ $(^{+0.30}_{-0.25})$	7.6 (5.6)	7.0 (6.8)
$H \rightarrow WW$	[95, 96]	[97]	$1.22^{+0.23}_{-0.21}$ $(^{+0.21}_{-0.20})$	$0.90^{+0.23}_{-0.21}$ $(^{+0.23}_{-0.20})$	6.8 (5.8)	4.8 (5.6)
$H \rightarrow \tau\tau$	[98]	[99]	$1.41^{+0.40}_{-0.36}$ $(^{+0.37}_{-0.33})$	$0.88^{+0.30}_{-0.28}$ $(^{+0.31}_{-0.29})$	4.4 (3.3)	3.4 (3.7)
$H \rightarrow bb$	[100]	[101]	$0.62^{+0.37}_{-0.37}$ $(^{+0.39}_{-0.37})$	$0.81^{+0.45}_{-0.43}$ $(^{+0.45}_{-0.43})$	1.7 (2.7)	2.0 (2.5)
$H \rightarrow \mu\mu$	[102]	[103]	$-0.6^{+3.6}_{-3.6}$ $(^{+3.6}_{-3.6})$	$0.9^{+3.6}_{-3.5}$ $(^{+3.3}_{-3.2})$		
$t\bar{t}H$ production	[77, 104, 105]	[107]	$1.9^{+0.8}_{-0.7}$ $(^{+0.7}_{-0.7})$	$2.9^{+1.0}_{-0.9}$ $(^{+0.9}_{-0.8})$	2.7 (1.6)	3.6 (1.3)

The work of many people

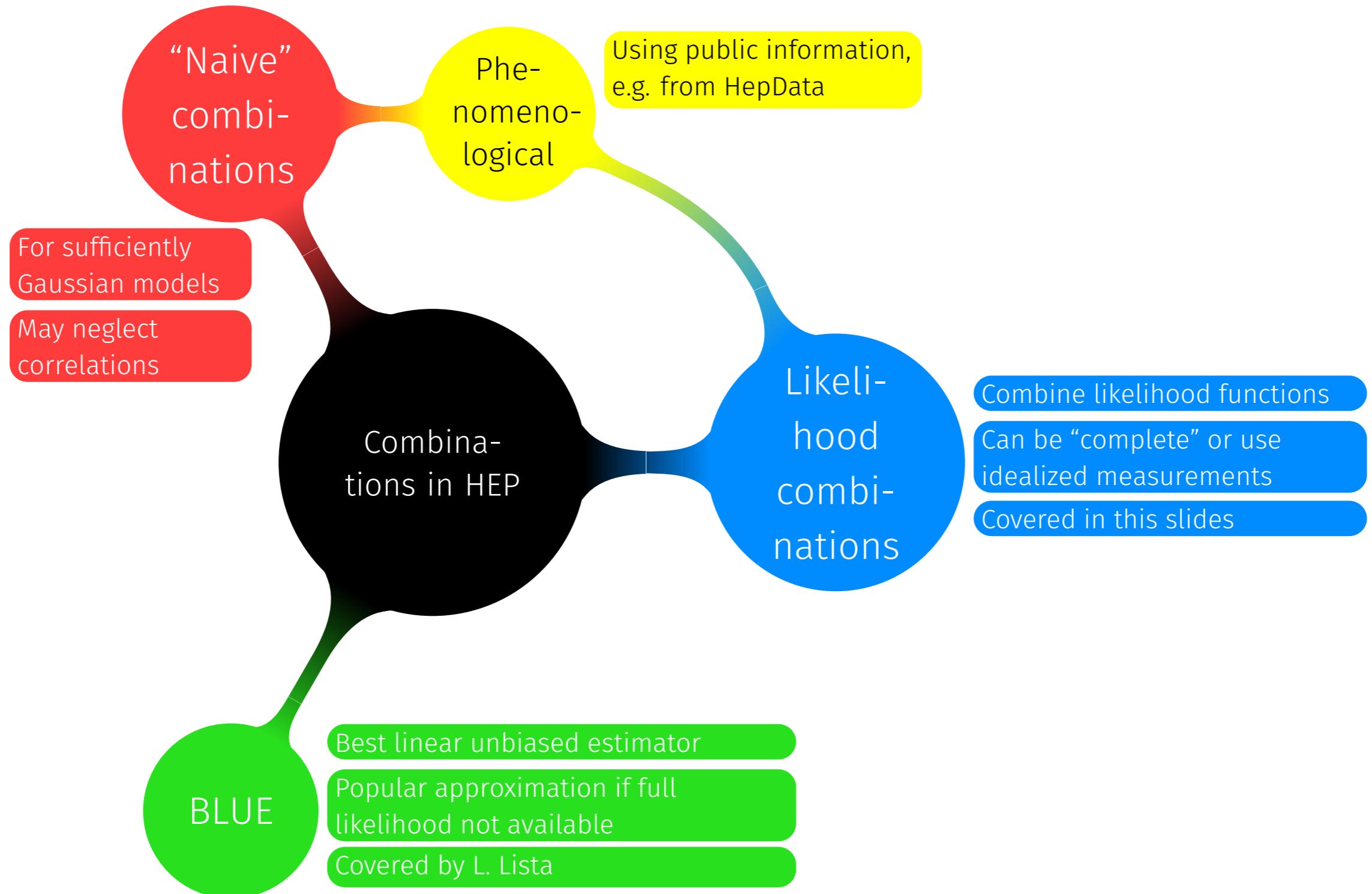
# Disclaimer



- This talk will be focussed on **likelihood combinations**
  - Other approaches, e.g. BLUE, will be covered in different talks  L. Lista
  - Key concepts will be explained with the Higgs coupling combination as an example
  - Statistical inference also covered by other speakers

 E. Gross, F. Matorras, S. Schmitt, S. Biondi, ...

# Approaches to perform combinations



# Likelihood combinations

- Given a set of **measurements** and a **hypothesis**, a **likelihood function** is defined as the probability of the data under this hypothesis, formulated as a **probability density function**
  - Simplest example: idealised measurement

$$\theta = \tilde{\theta} \pm \sigma \rightarrow \text{Gaussian}(\tilde{\theta} | \theta, \sigma)$$

- Disjoint selections of the data are simultaneously described by a **product over the respective likelihood functions**

$$L(\alpha) = \prod_{c=1}^{c_{\max}} L_c(\alpha)$$

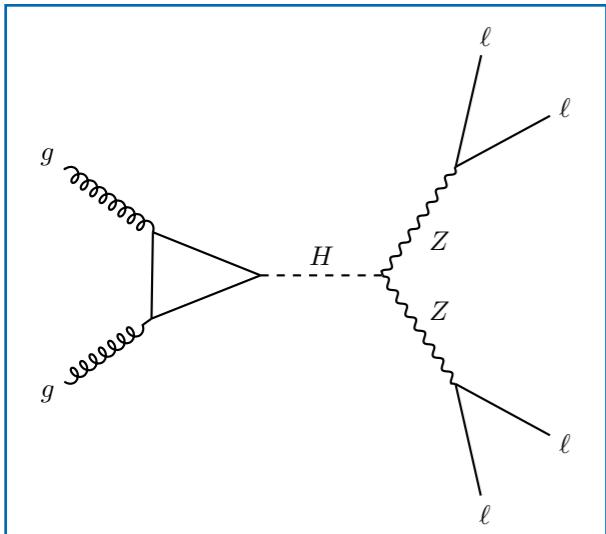
Diagram illustrating the joint likelihood model:

- Joint likelihood model**: Points to the overall product term  $\prod_{c=1}^{c_{\max}}$ .
- Hypothesis**: Points to the variable  $\alpha$  in the likelihood function  $L_c(\alpha)$ .
- Likelihood function for individual selections/analyses**: Points to the term  $L_c(\alpha)$ .

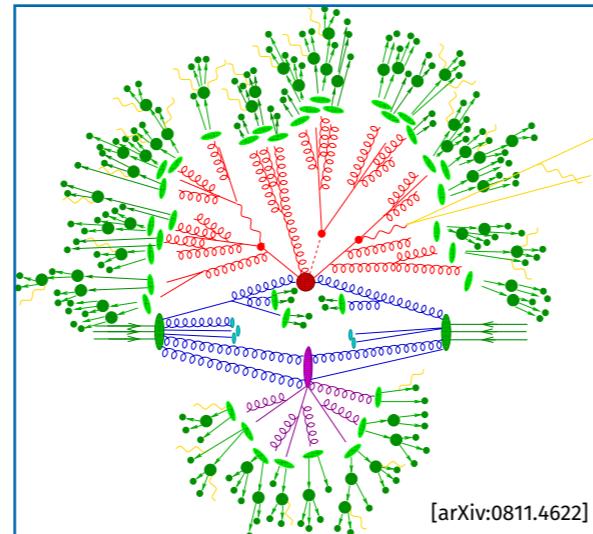
# HEP analysis chain



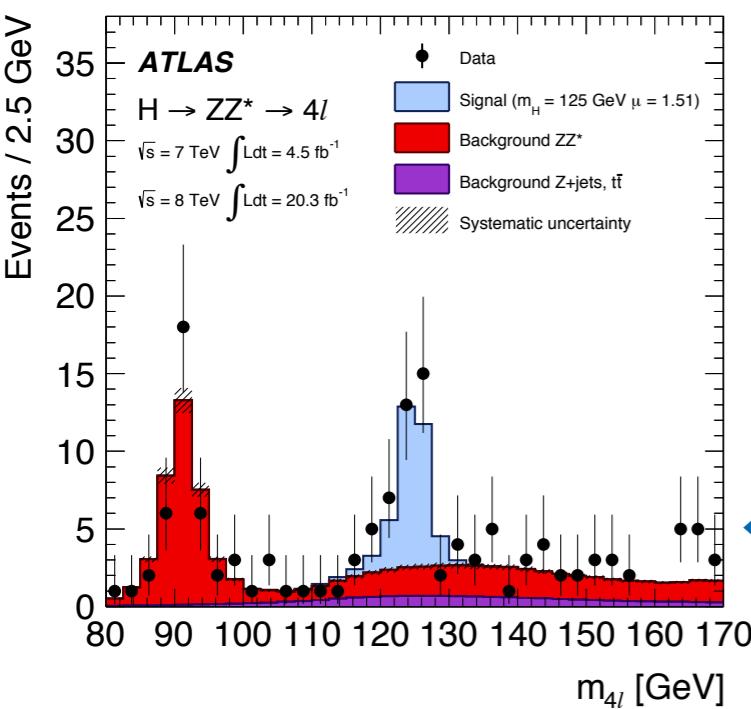
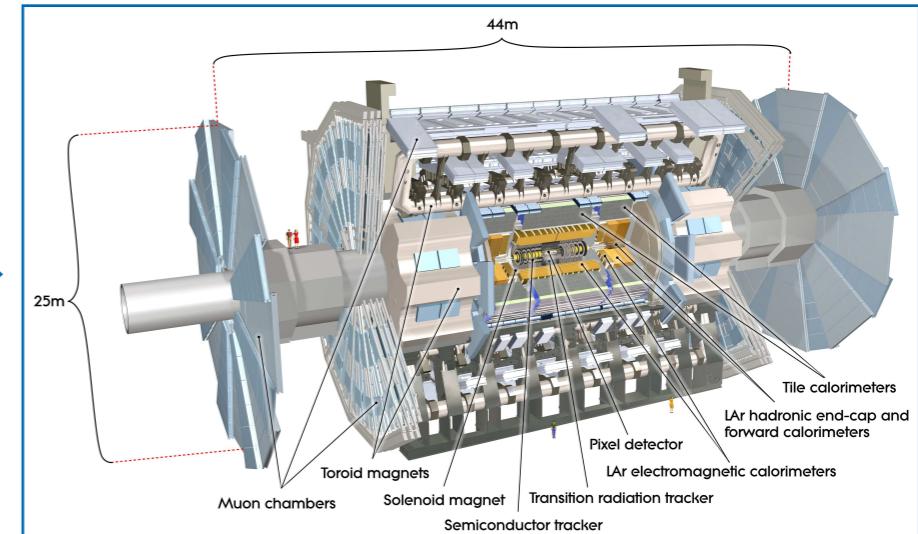
## Hard scatter



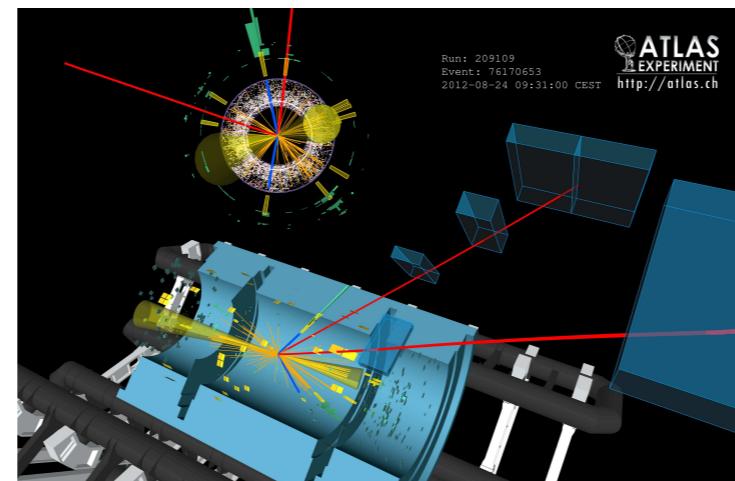
## Soft physics



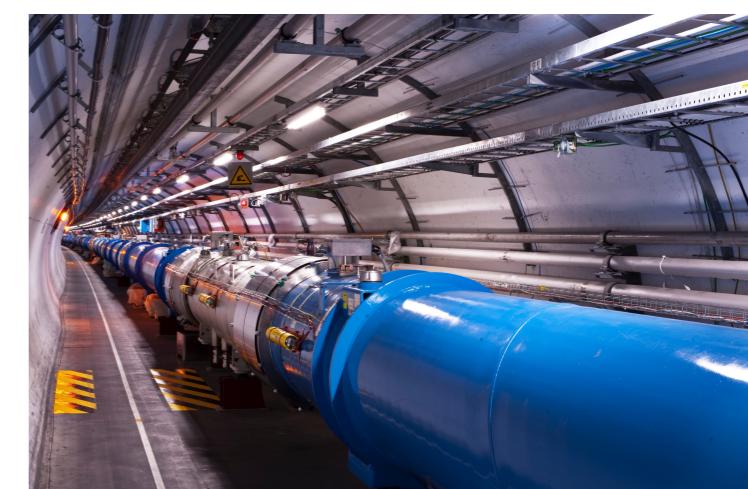
## Detector simulation



Selection



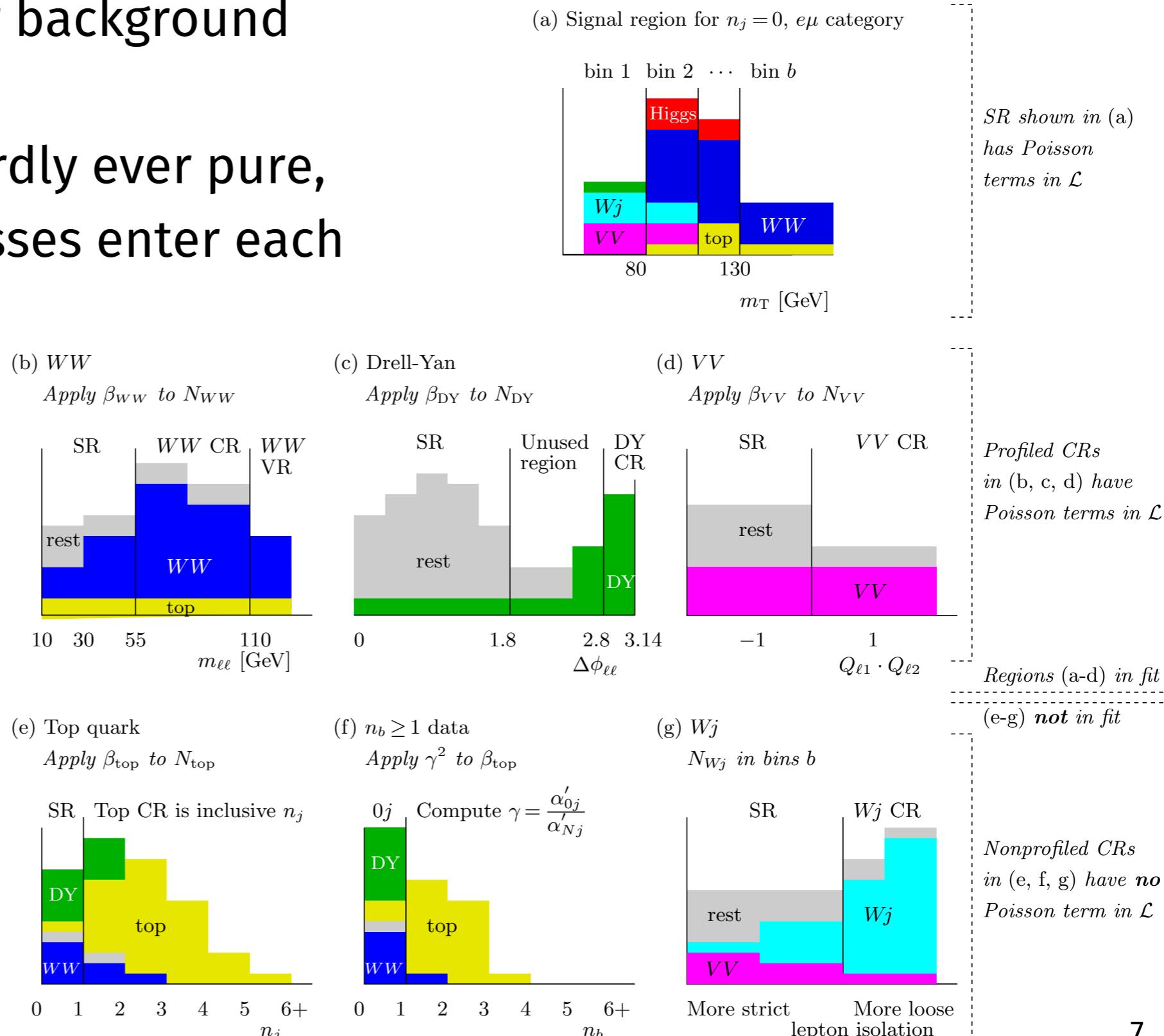
Reconstruction



LHC data

# Typical HEP measurements

- Typically analyses consist of one or more **disjoint selections** enriched in signal or background like events
  - Categories are hardly ever pure, i.e. various processes enter each selection
- The measurement can be a **single number** or the data can be augmented with one or more discriminating observables



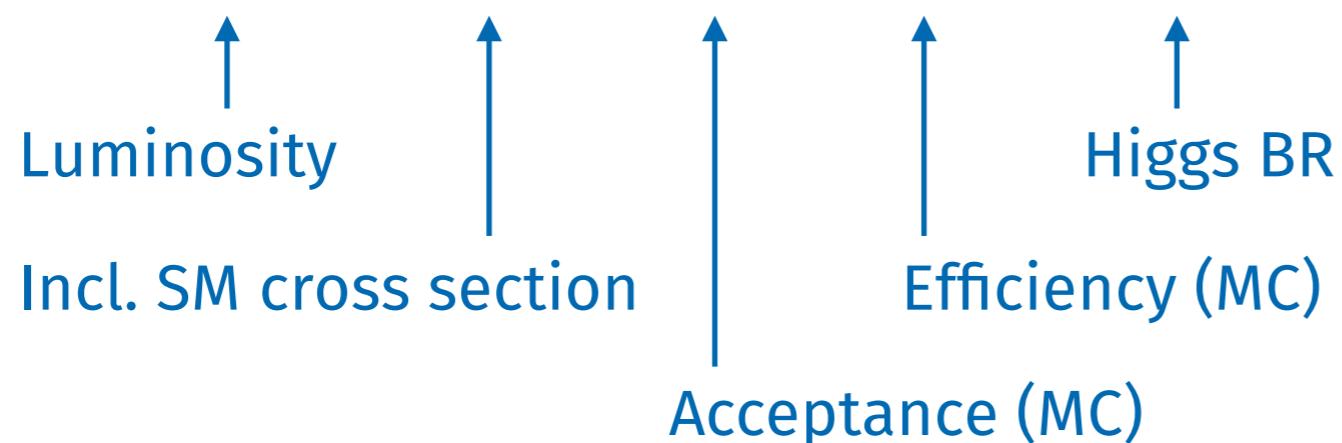
# Constructing a probability model

- Construct **likelihood** function for each event selection
  - At LHC, templates typically are derived from **histograms** with each bin effectively being a **Poisson counting experiment**

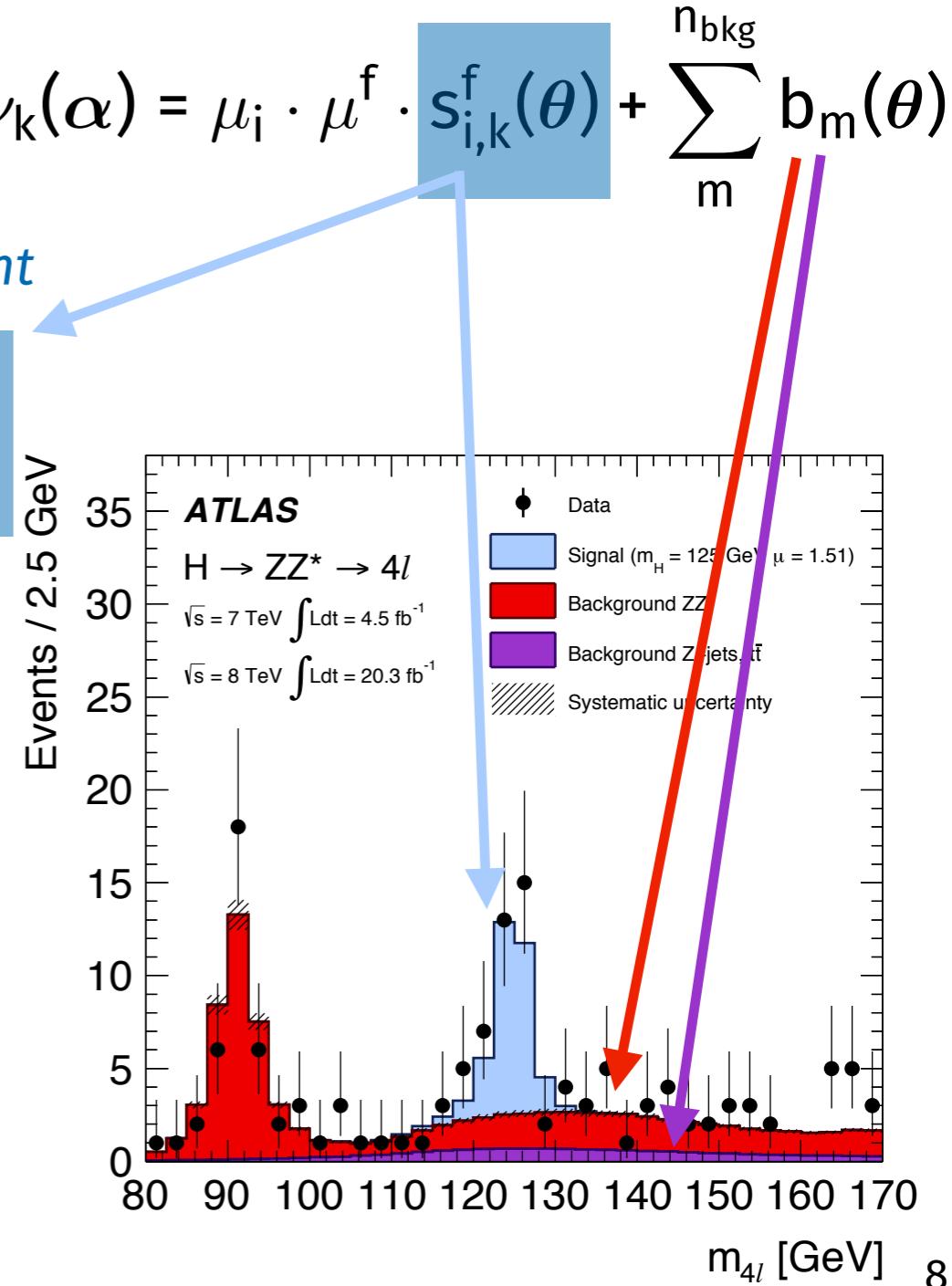
$$L(\mathcal{D}|\alpha) = \prod_{k=1}^{n_{\text{bins}}} \text{Poisson}(n_k | \nu_k(\alpha)), \quad \nu_k(\alpha) = \mu_i \cdot \mu^f \cdot s_{i,k}^f(\theta) + \sum_m b_m(\theta)$$

where

$$s_{i,k}^f = \mathcal{L}(k) \cdot \left\{ \sigma_i^{\text{SM}} \cdot A_i^f(k) \cdot \varepsilon_i^f(k) \cdot \text{BR}_{\text{SM}}^f \right\}$$

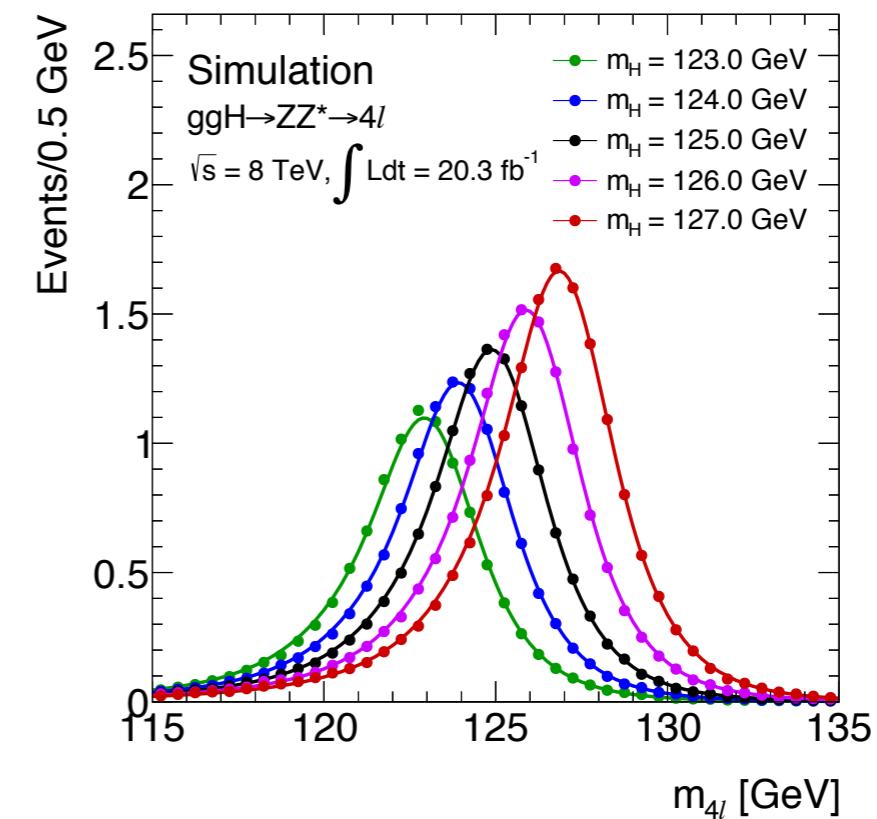
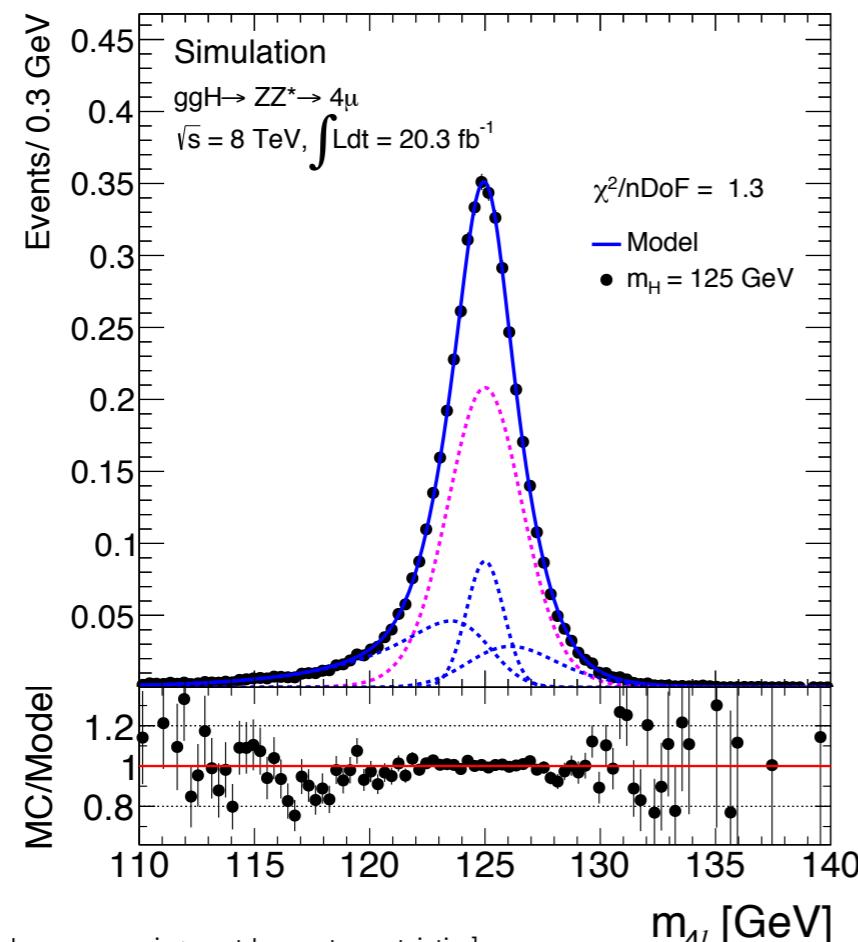


- Can generalise the approach to **continuous distributions** if analytical model is available



# Continuous probability density models

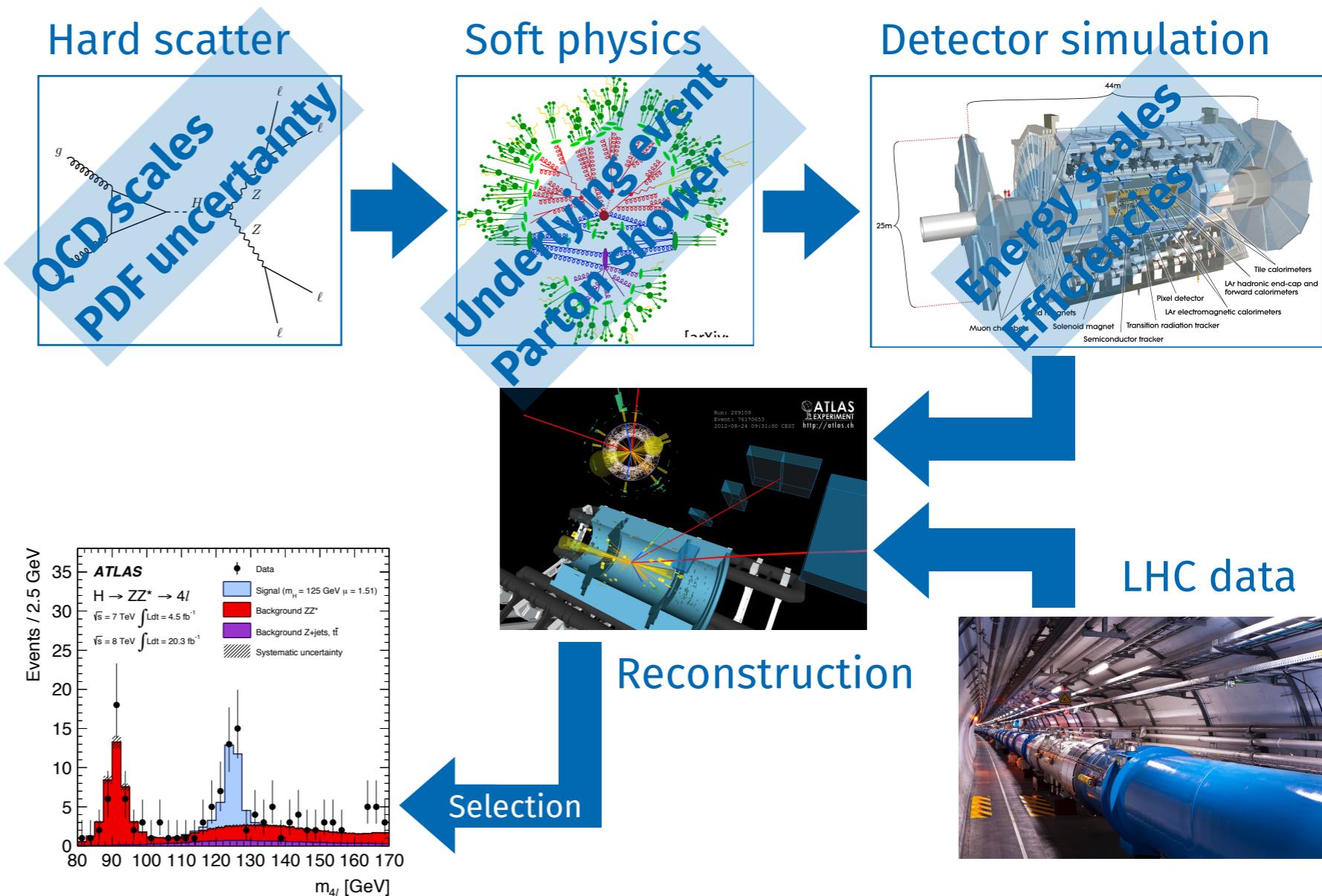
- In rare cases (e.g. measuring  $m_H$  in Higgs decays to four leptons) it is possible to construct an **analytical model**
- Requires **convolving** the predicted **detector response** with the truth **lineshape** per event (typically a Breit-Wigner for resonances)
- Response varies e.g. for different lepton flavours
- Can be extended to include per-event uncertainties



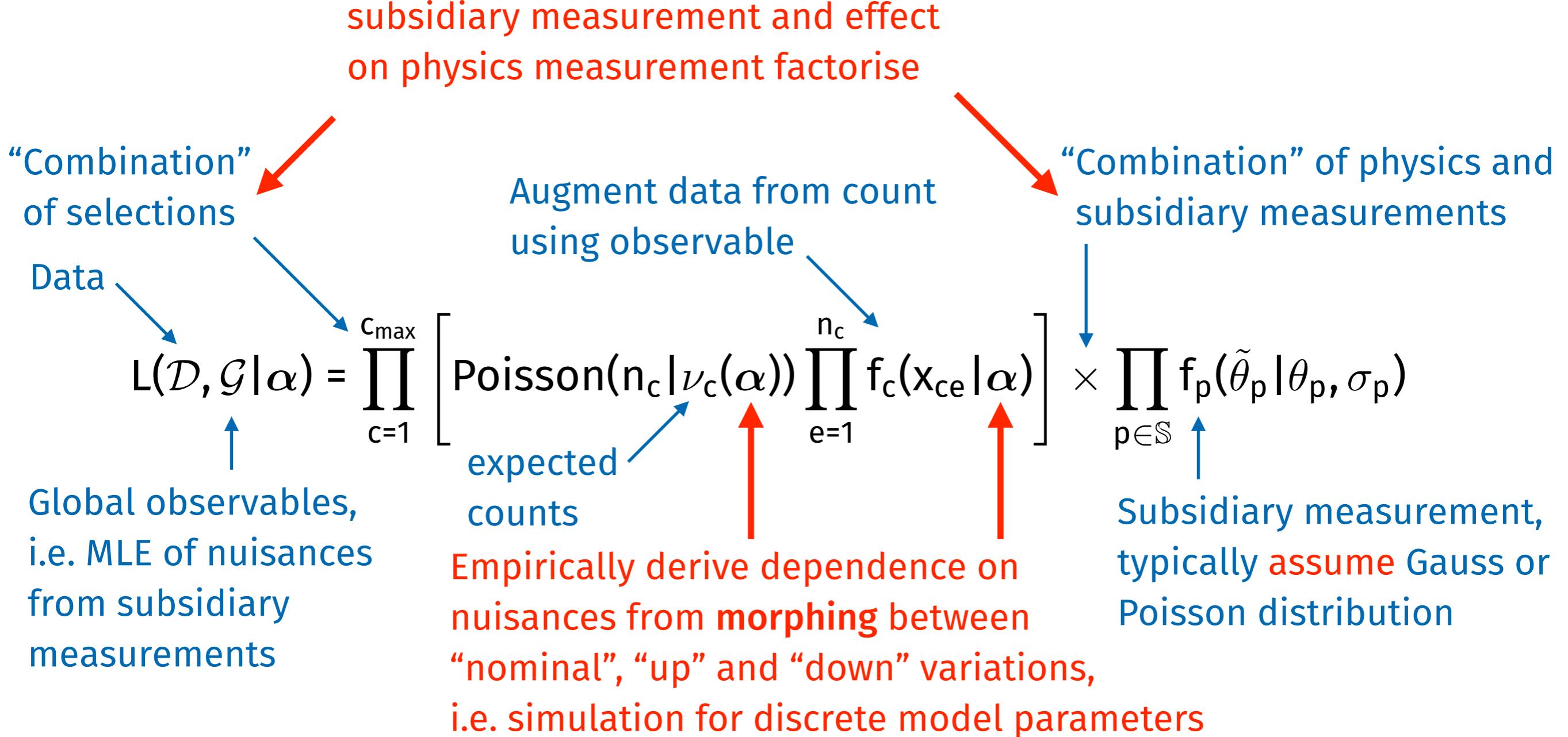
# Incorporating systematic uncertainties

- Counts and distributions are subject to many uncertainties
- Capture the effect of each by introducing **nuisance parameters**
- Often only the maximum likelihood estimate from **subsidiary measurements** known
  - Information not sufficient to construct full likelihood model
  - Empirically parametrise** effect of each nuisance from available simulation for discrete model parameters

💬 E. Gross

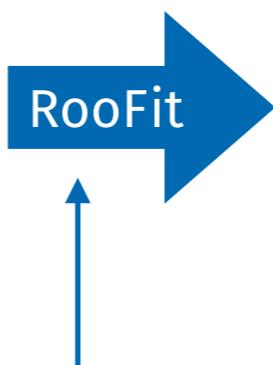
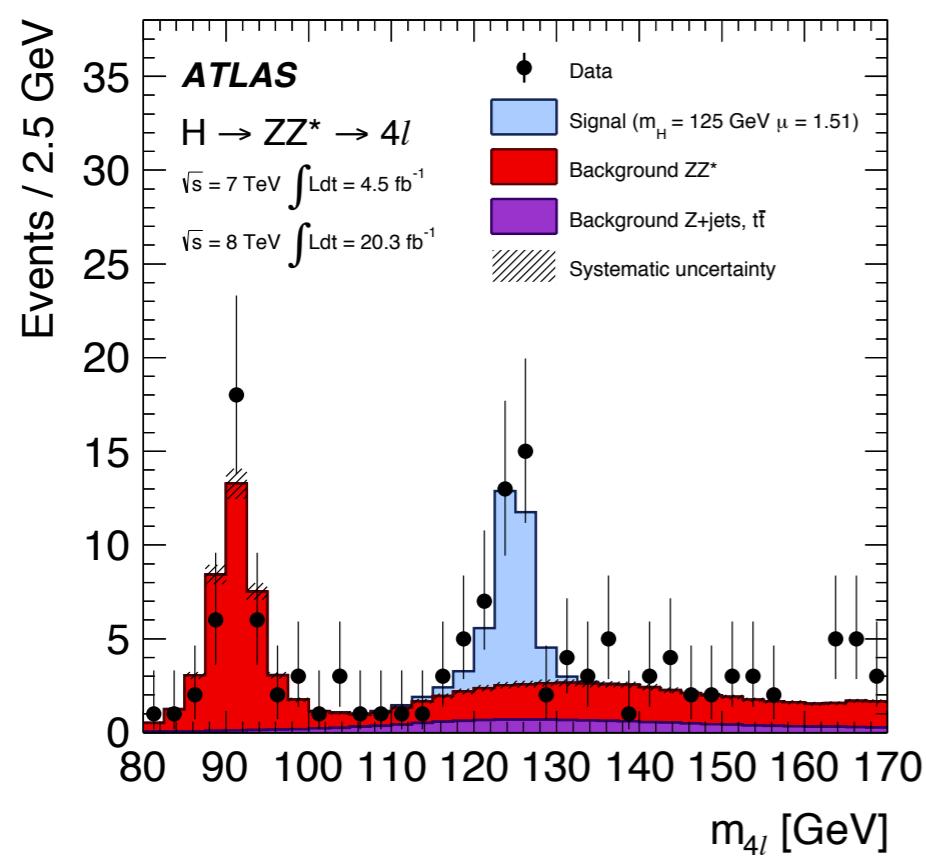


# The likelihood for an analysis with different selections



# In practice: formulating the PDF using RooFit

- Model building based on the **RooFit** package
  - **Key concept:** represent mathematical model by C++ objects from which the likelihood function is build
  - Support for normalisation relies on numeric techniques when analytical integrals not available
  - Support for conditional probability models, convolutions, etc.
- Commonly adopted by the **LHC experiments**



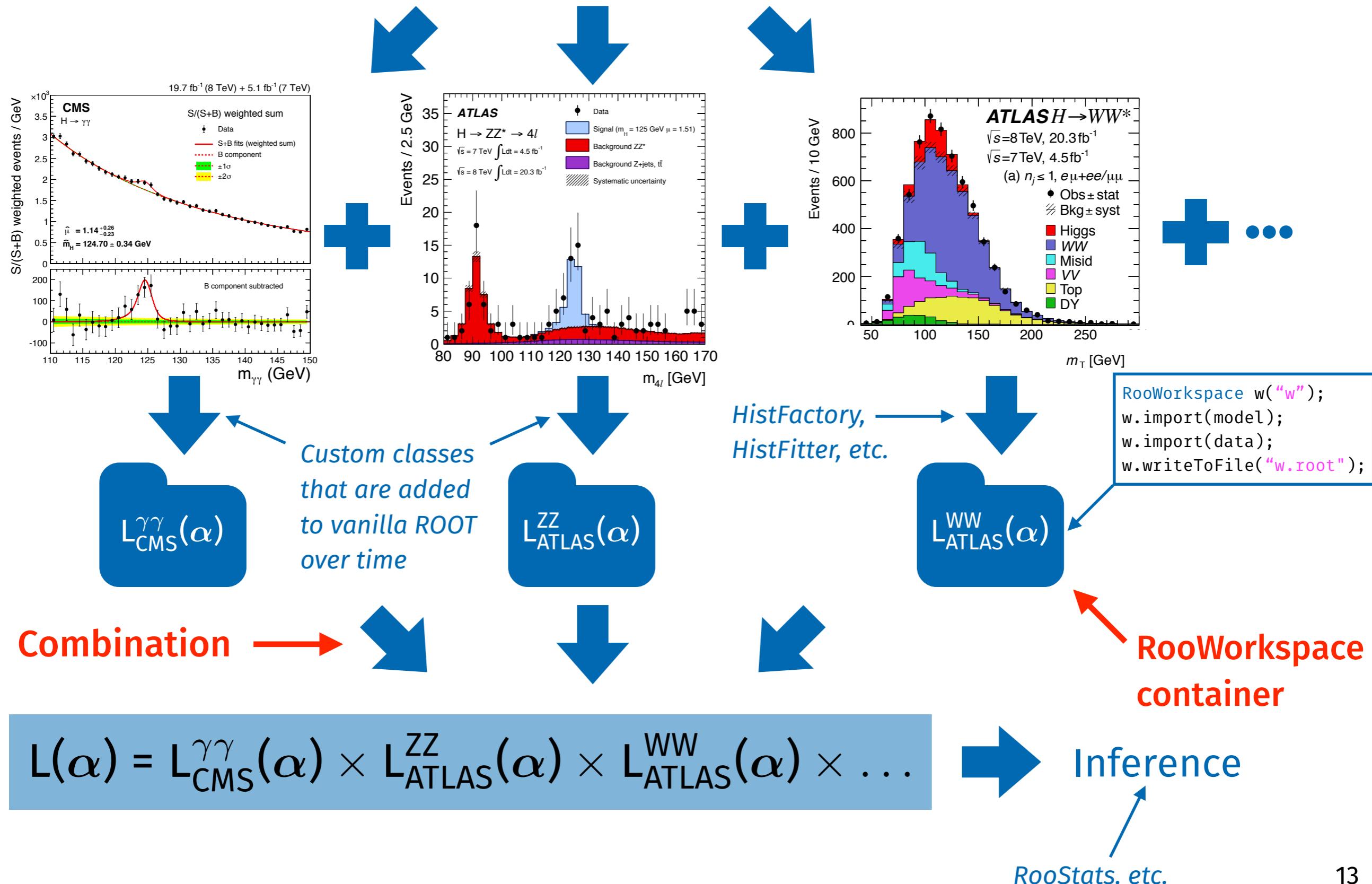
```
RooRealVar s("s", "s", 5);  
RooRealVar b("b", "b", 50);  
RooRealVar n("n", "n", 0, 100);  
RooRealVar mu("mu", "mu", 0, 10);  
RooFormulaVar nexp("nexp", "nexp", "mu*s+b",  
    RooArgList(mu, s, b));  
RooPoisson model("model", "model", n, nexp);
```

```
RooDataSet data("data", "data", n);  
n=55;  
data.add(n);
```



# The analysis workflow

Analysers specialised in simulation, specific measurements, etc.



# The combination step

- Combining involves more than building a **simultaneous PDF** and implementing parameterisations

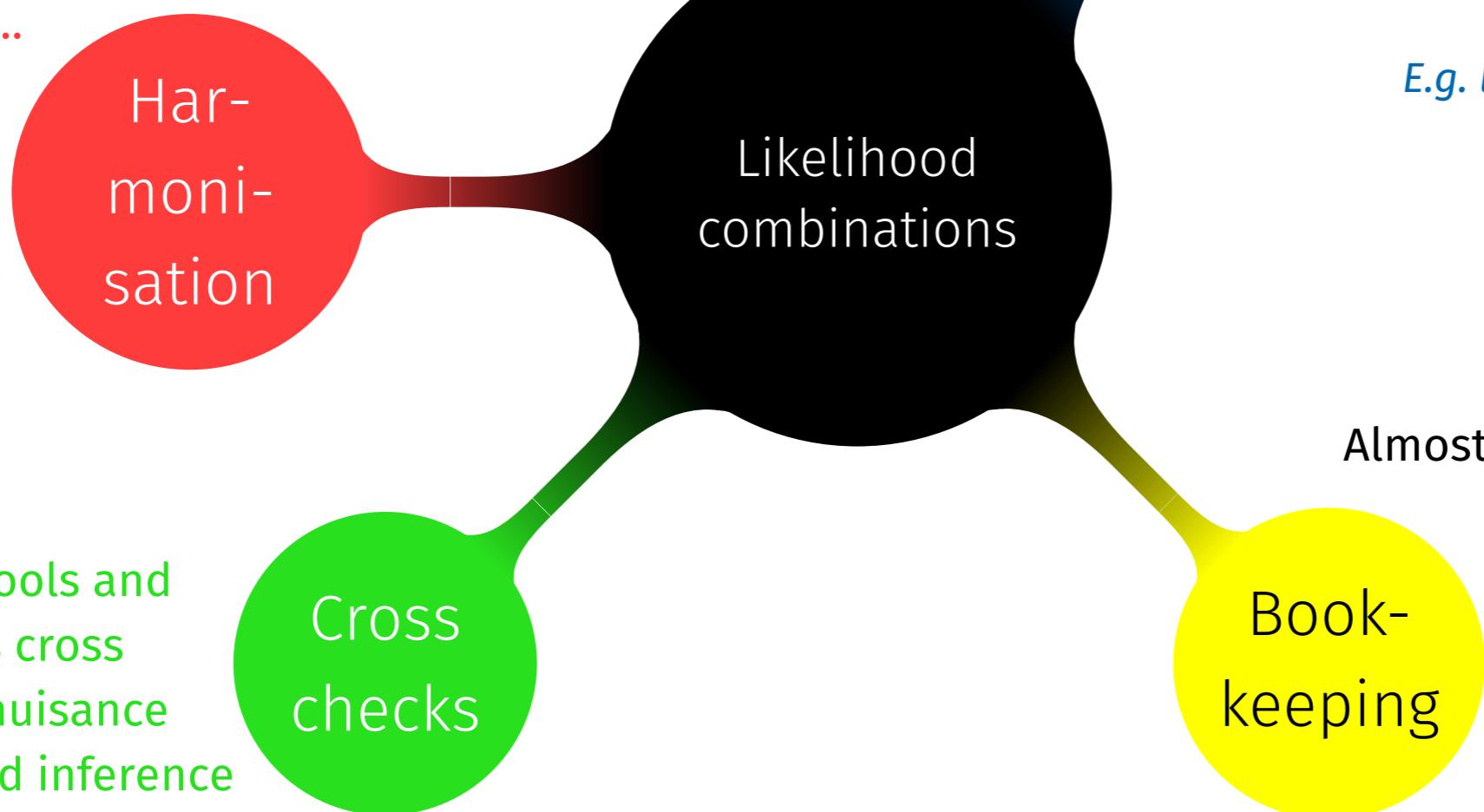
Detector uncertainties follow strategy of individual experiments  
 Theoretical uncertainties on inclusive cross sections are generally correlated between experiments, but correlation between processes is often not clear and depends on phase space  
 Acceptance and efficiency related uncertainties not correlated  
 Monte Carlo statistics related nuisances affect a single bin only

*Eigenbasis, multivariate subsidiary measurements, template morphing, ...*

Corre-  
lations

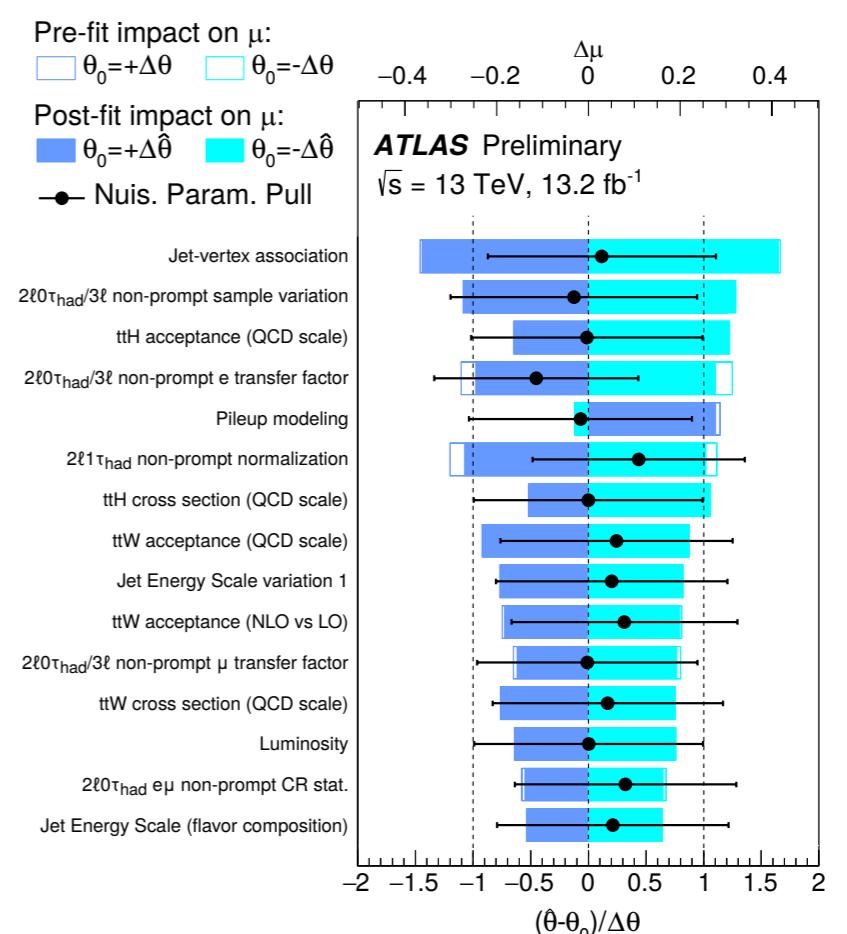
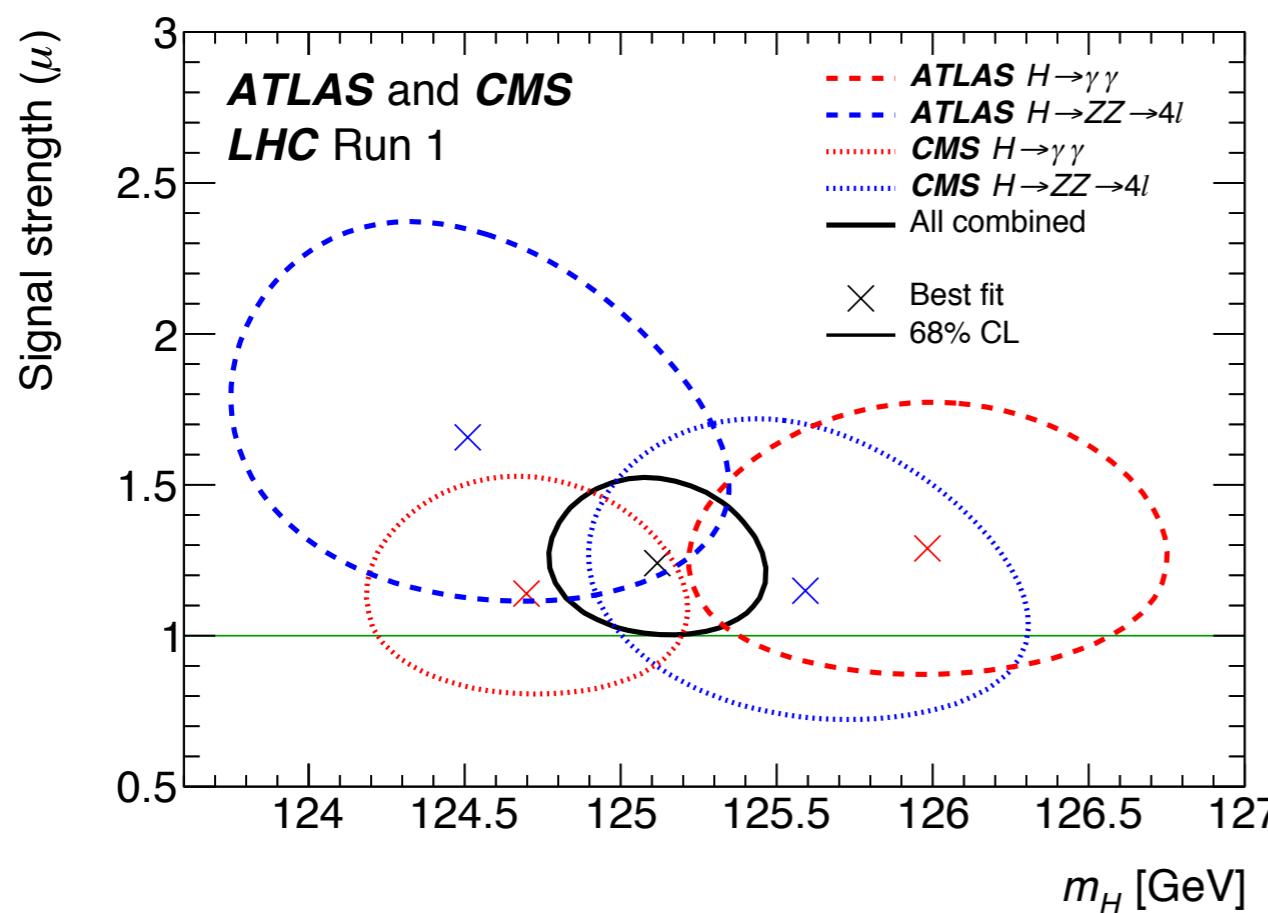
Fully or partially correlated parameters, correlated and uncorrelated parts, ...

*E.g. luminosity, jet energy scale*



# Statistical inference using RooStats

- Follow standard **frequentist methods** for constructing confidence intervals, hypothesis testing and evaluating the tensions
  - Often the **asymptotic approximation** is used  E. Gross
- RooStats provides a series of tools for this tasks
  - General concepts are completely **decoupled** from model building and work on any probability model and dataset provided
- Internally developed tools for **additional cross checks**
  - E.g. pulls, constraints, correlations and impact of nuisance parameters



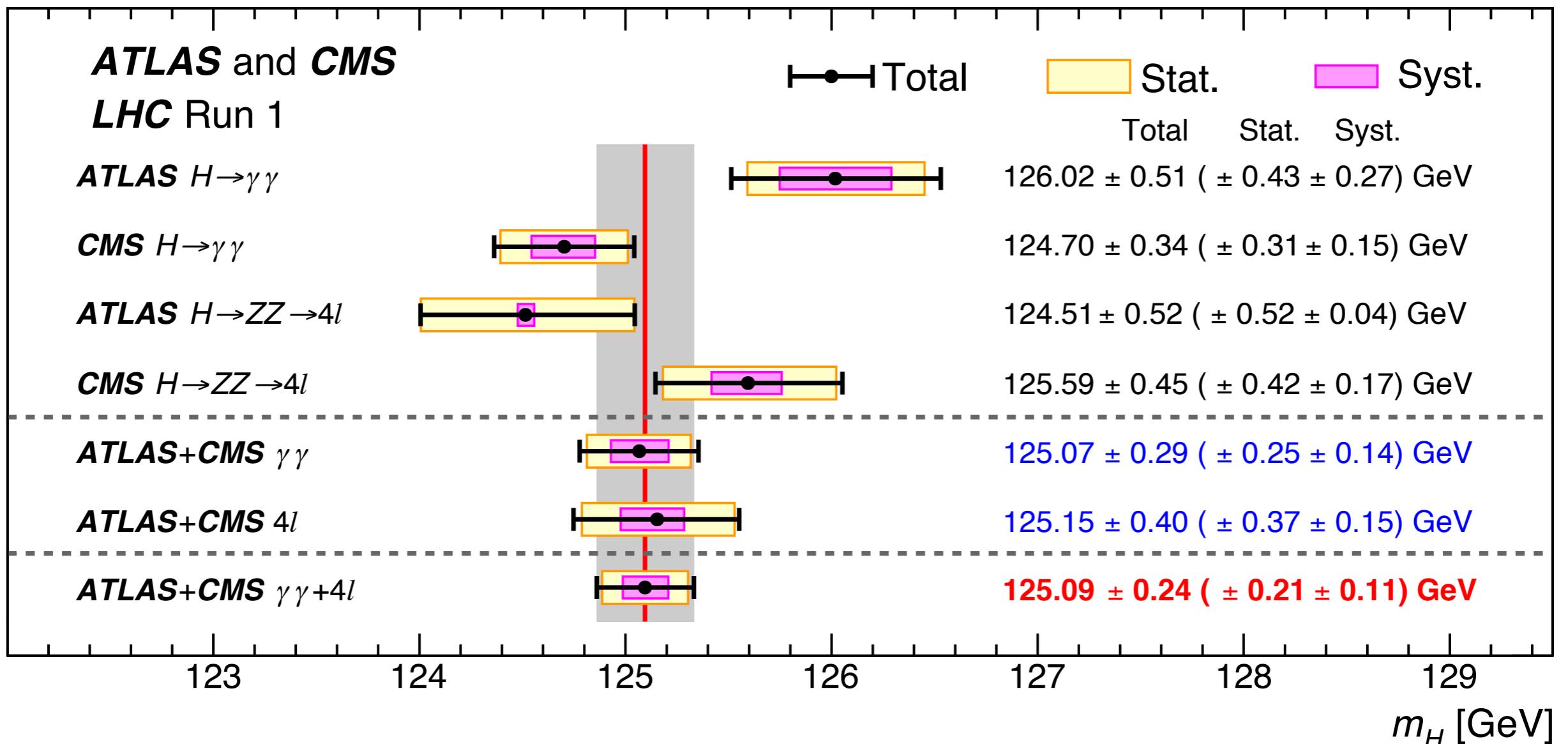
# Improving the performance for complex models



- Complex likelihood function may lead to **instabilities** and **performance issues**, even though many aspects are simplified
  - Minimisation of the likelihood function takes several hours (with Hesse days) and requires large (> 7G) memory nodes
  - Largest fraction of time spend in **interpolation**
- Several strategies to **reduce number of interpolations**
  - Disentangle “real” effect of systematic variations from **statistical noise**, e.g. using **bootstrap replicas**
  - Performance groups provide **reduced set of variations**
  - Depending on the measurement performed, non-significant uncertainties can be **pruned** on analysis level
    - **Examples:** evaluate the variation of the counts and templates or the correlation with measurements
- Complementary **technical developments**
  - Constant term optimisation, caching, vectorisation, binned evaluation

D. Börner

# Naive combinations vs. full model (I)

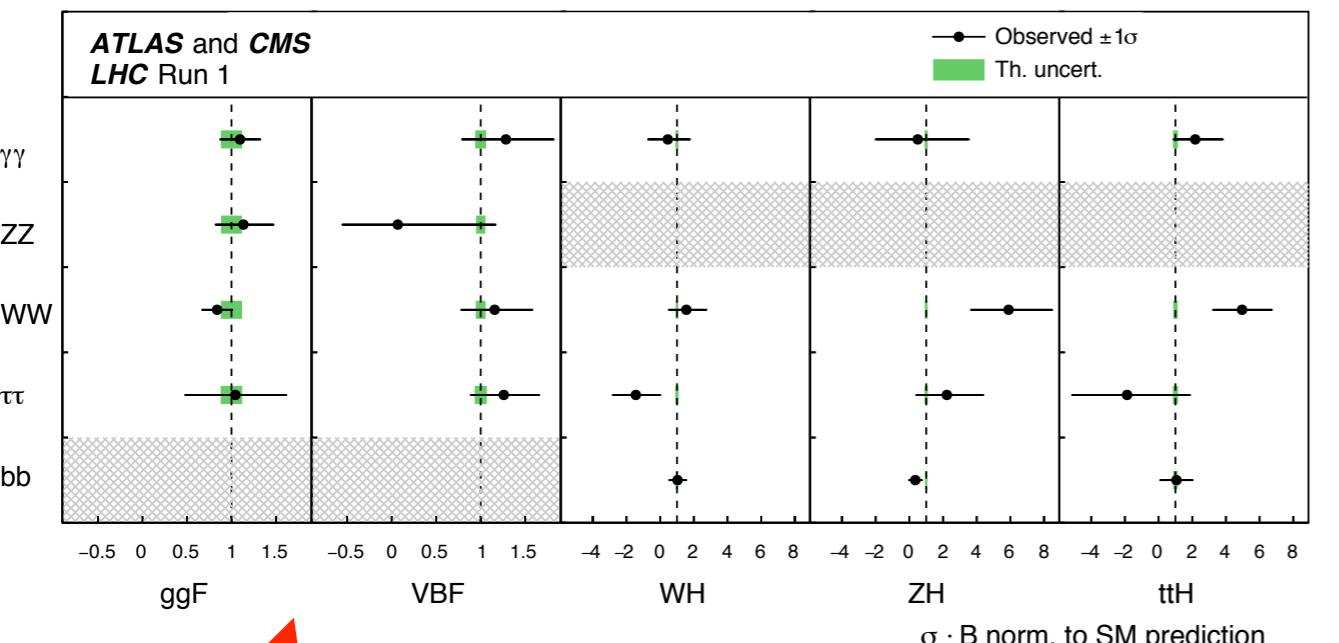


In a gaussian regime, e.g. statistically limited analyses with no complex correlations, weighted average is a good approximation:

$$m_H^{\gamma\gamma+4l} = 125.11 \pm 0.22 \text{ GeV}$$

# Naive combinations vs. full model (II)

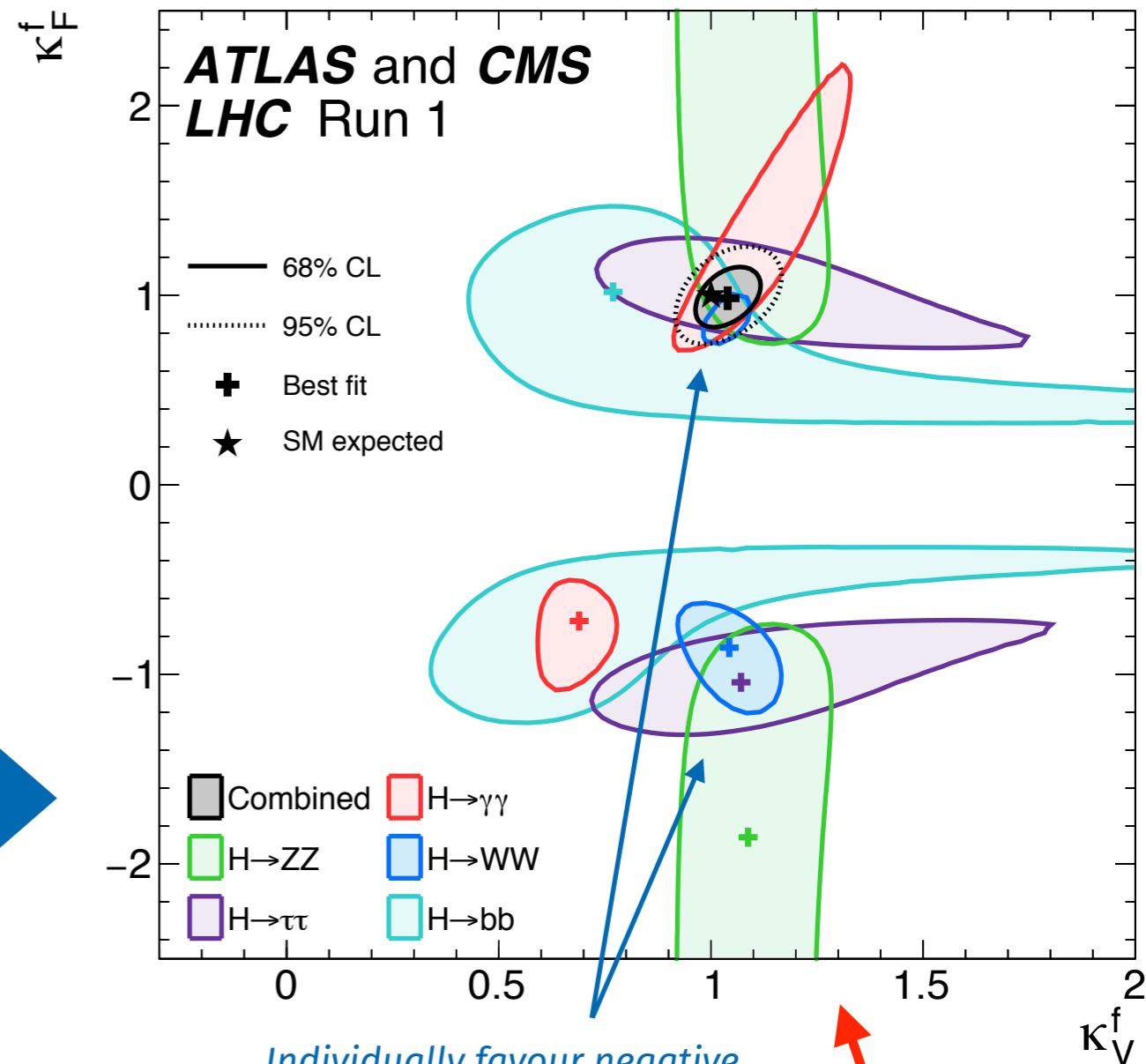
For more complex models, naive combinations are not feasible and may not reproduce results accurately



Measurements

Hides all intrinsic measurements,  
e.g. background rates, phase  
space regions, etc.

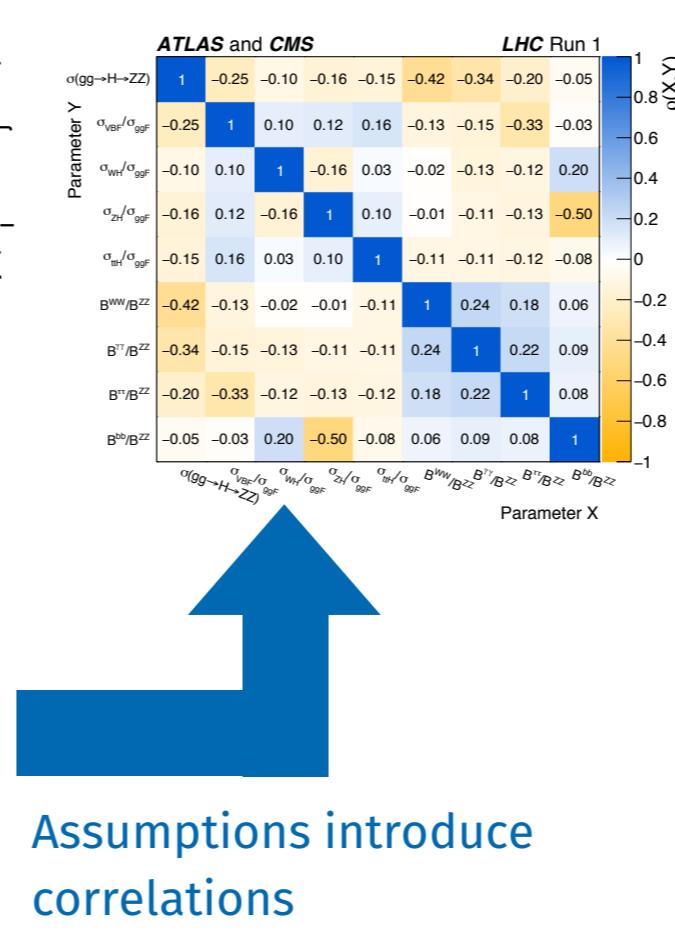
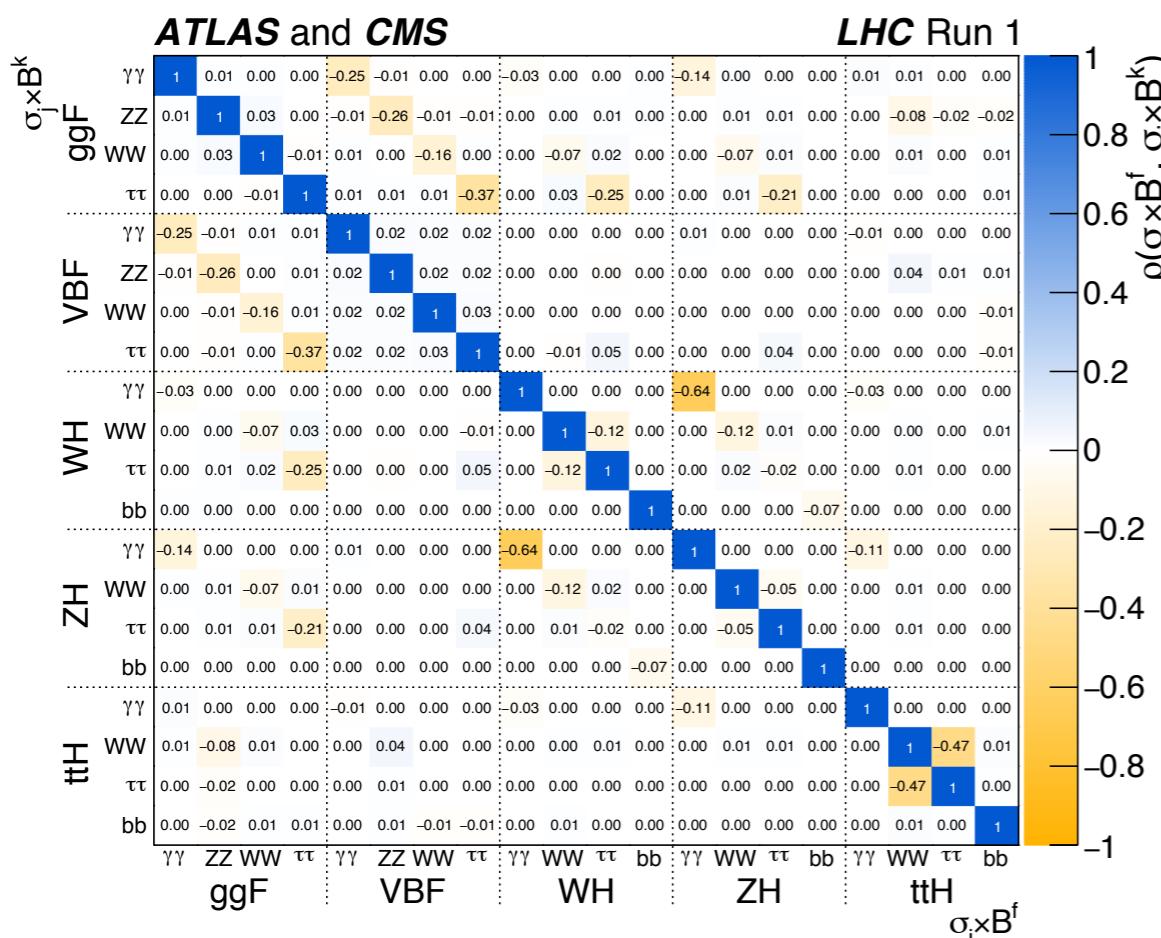
Requires knowledge of  
parametrisation, correlations, etc.



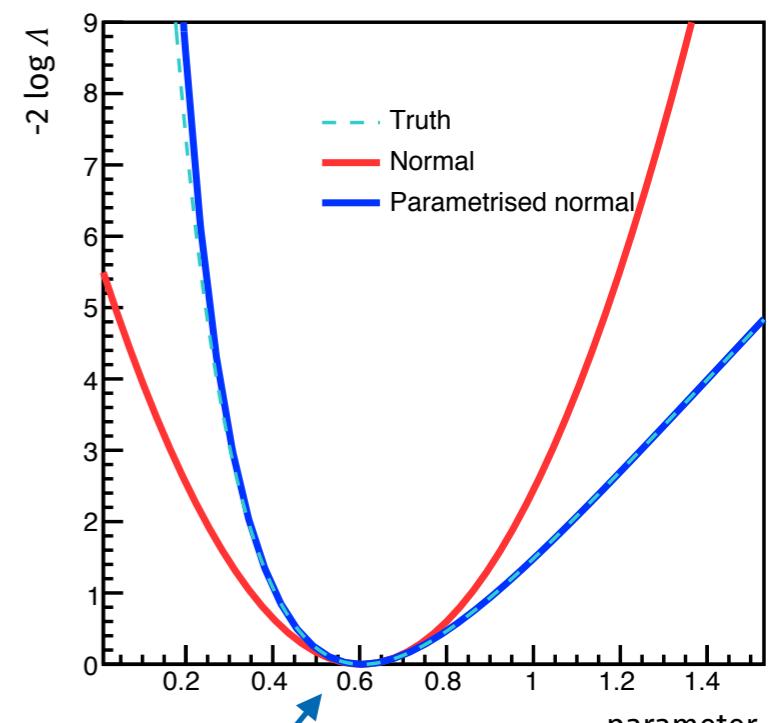
# Making the results available (I)

## Ongoing efforts to make results from generic models available for re-interpretations

- Typically quote  $1\sigma$  and  $2\sigma$  confidence intervals
  - Sufficient to perform **naive combination** of results, but may differ significantly from full model when neglecting correlations, etc.
  - **Correlation matrix** at the minimum provides additional information
  - Can build **(parametrised) normal distributions** that reproduce likelihood scans if model sufficiently Gaussian



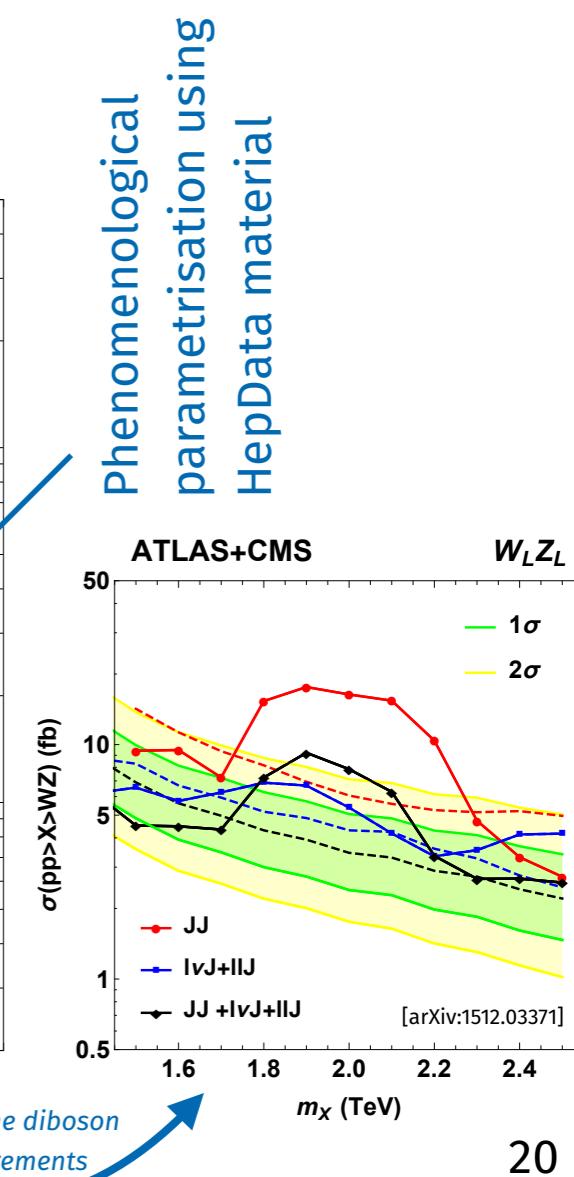
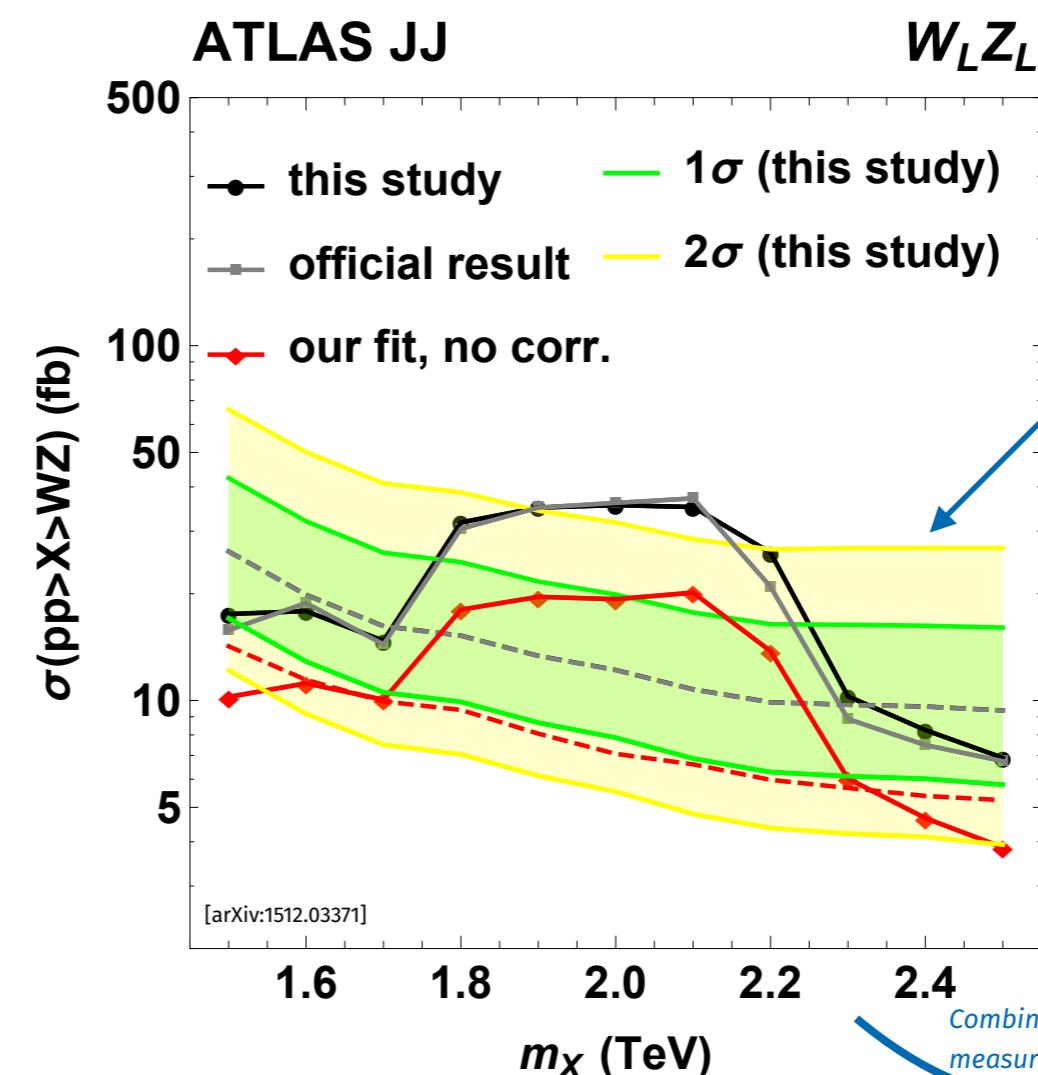
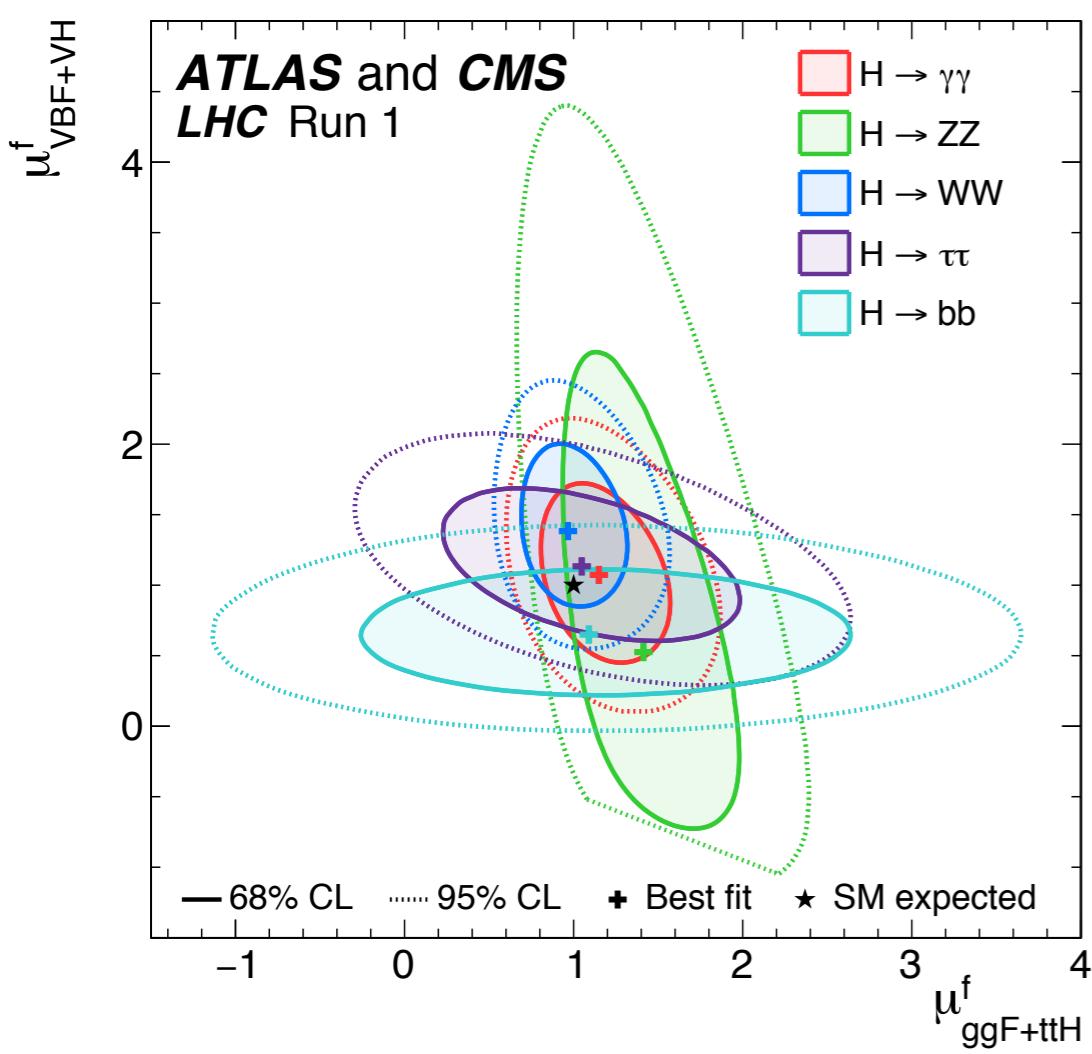
Assumptions introduce correlations



Uses just knowledge of confidence interval

# Making the results available (II)

- Often provide (multi-dimensional) profile likelihood scans to compare predictions, e.g. from simulating custom model
- Improving habit to make templates available, e.g. on HepData
  - Build simplified likelihood that can be combined
- Within the collaboration, share the persisted pdf, e.g. for BSM interpretations



# What's next?



- With increasing data statistics, more sophisticated **theoretical models** can be tested, but also **systematic uncertainties** and **statistical modelling** gain in importance
  - Experimental systematics will shrink with more data being available for calibration measurements
  - Theoretical uncertainties will shrink when calculations improve
- This poses many **questions** and requires **technical developments**:
  - *What distributions of subsidiary measurements are correct?*
  - *Does the parametrisation of an systematic uncertainty capture the “real” effect, or introduces it too much detail?*
  - *Is the interpolation between sampling points for response mapping accurate, e.g. hadronisation/fragmentation model and non-factorisable uncertainties?*

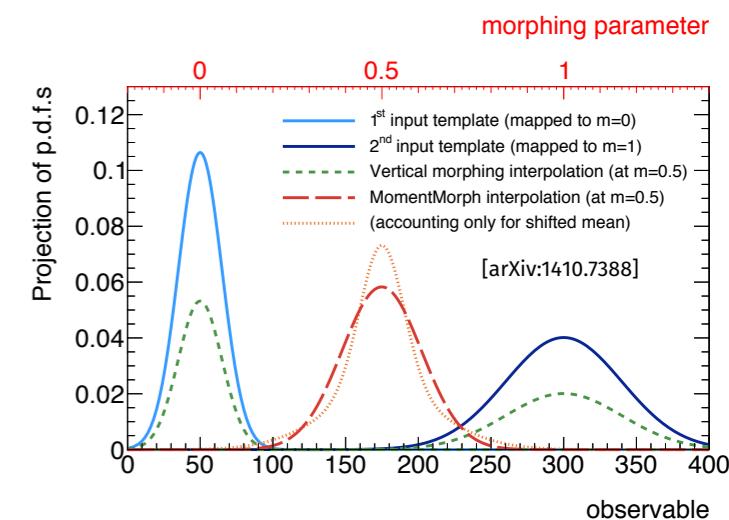
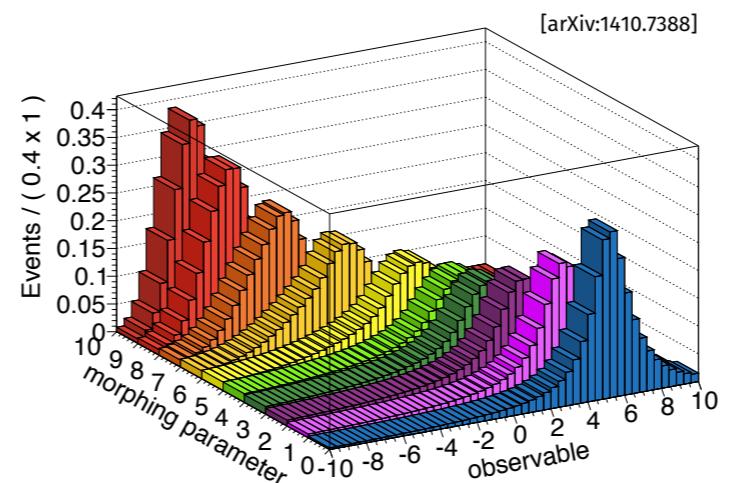
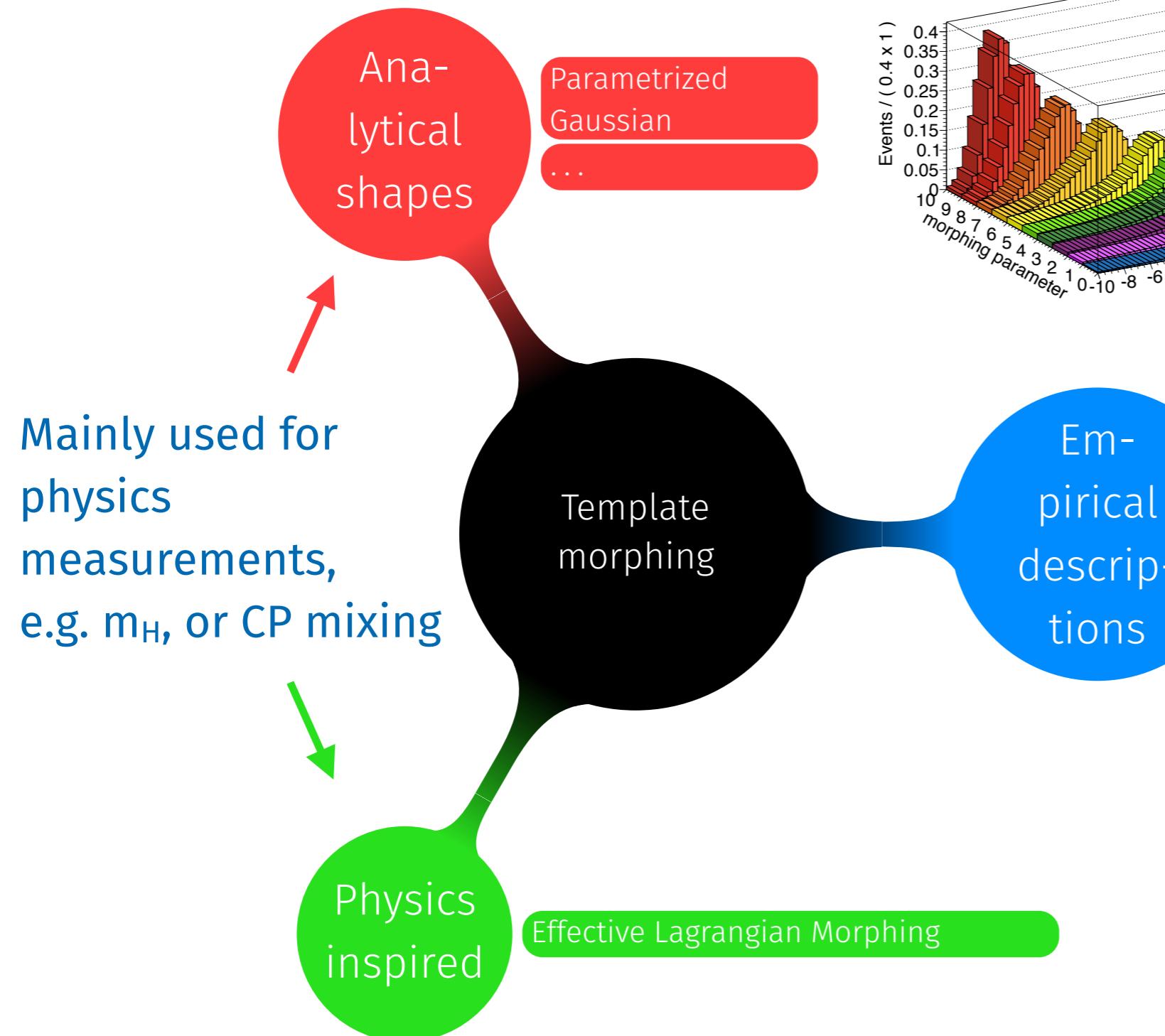
	Best fit $\mu$	Uncertainty				
		Total	Stat	Expt	Thbgd	Thsig
ATLAS + CMS (measured)	1.09	+0.11 -0.10	+0.07 -0.07	+0.04 -0.04	+0.03 -0.03	+0.07 -0.06
ATLAS + CMS (expected)		+0.11 -0.10	+0.07 -0.07	+0.04 -0.04	+0.03 -0.03	+0.07 -0.06
ATLAS (measured)	1.20	+0.15 -0.14	+0.10 -0.10	+0.06 -0.06	+0.04 -0.04	+0.08 -0.07
ATLAS (expected)		+0.14 -0.13	+0.10 -0.10	+0.06 -0.05	+0.04 -0.04	+0.07 -0.06
CMS (measured)	0.97	+0.14 -0.13	+0.09 -0.09	+0.05 -0.05	+0.04 -0.03	+0.07 -0.06
CMS (expected)		+0.14 -0.13	+0.09 -0.09	+0.05 -0.05	+0.04 -0.03	+0.08 -0.06

# Summary

- Combinations are gaining in importance in HEP
- Combining **full likelihood preserves all available information**, i.e. correlations, composition of selections, subsidiary measurements, etc.
- Build the likelihood function using **RooFit**, persist it in a sharable **RooWorkspace** container, and perform inference using **RooStats** tools
- Combination requires **harmonisation**, poses **technical challenges** and drives **developments**
- Naive combinations can be done quickly, but do often not reproduce full results
- Ongoing efforts to make results available to community

# Backup

# Template morphing

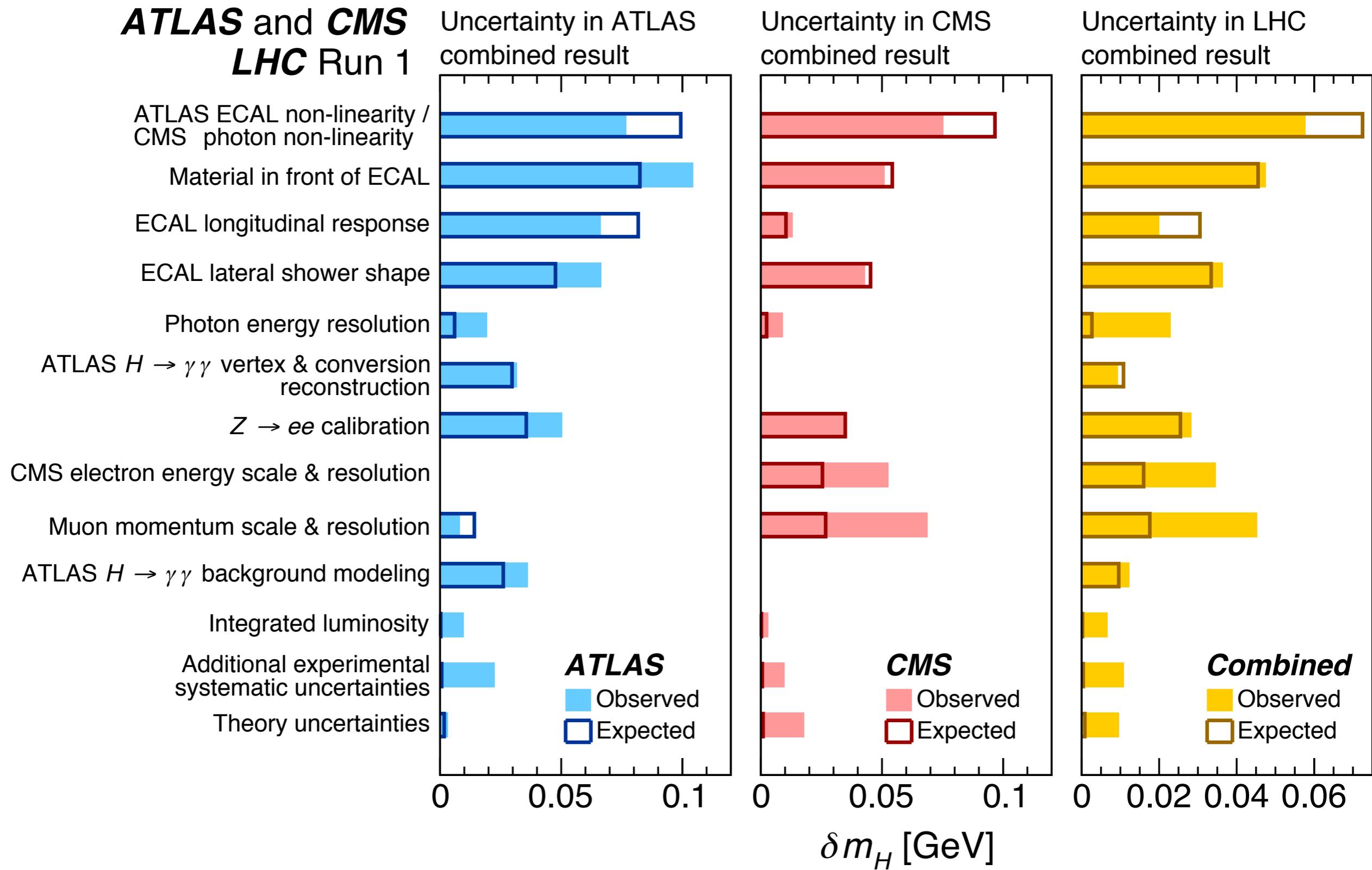


Handles multidimensional morphing for systematics, but no simple interface

- Piecewise linear interpolation
- Integral morphing
- Moment morphing
- ...

Typically used for modelling effect of systematic uncertainties on templates

# Uncertainties on the Higgs boson mass



# Uncertainties in the Higgs combination



Parameter	SM prediction	Best fit					Uncertainty					Best fit					Uncertainty					Best fit					
		value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	
ATLAS+CMS																											
$\sigma(gg \rightarrow H \rightarrow ZZ) [\text{pb}]$	$0.51 \pm 0.06$	$0.59^{+0.11}_{-0.10}$	$+0.11$	$+0.02$	$+0.01$	$+0.01$	$0.77^{+0.19}_{-0.17}$	$+0.19$	$+0.04$	$+0.02$	$+0.01$	$0.44^{+0.14}_{-0.12}$	$+0.13$	$+0.04$	$+0.01$	$+0.02$	$0.44^{+0.14}_{-0.13}$	$+0.15$	$+0.03$	$-0.01$	$-0.01$	$0.44^{+0.14}_{-0.13}$	$+0.15$	$+0.03$	$+0.01$	$+0.02$	
$\sigma_{\text{VBF}}/\sigma_{ggF}$	$0.082 \pm 0.009$	$0.109^{+0.034}_{-0.027}$	$+0.029$	$+0.013$	$+0.006$	$+0.010$	$0.079^{+0.035}_{-0.026}$	$+0.030$	$+0.014$	$+0.008$	$+0.009$	$0.138^{+0.073}_{-0.051}$	$+0.061$	$+0.033$	$+0.014$	$+0.015$	$0.138^{+0.073}_{-0.051}$	$+0.07$	$-0.046$	$-0.019$	$-0.006$	$-0.010$	$0.138^{+0.073}_{-0.051}$	$+0.06$	$+0.006$	$+0.010$	$+0.008$
$\sigma_{WH}/\sigma_{ggF}$	$0.037 \pm 0.004$	$0.031^{+0.028}_{-0.026}$	$+0.024$	$+0.012$	$+0.008$	$+0.003$	$0.054^{+0.036}_{-0.026}$	$+0.031$	$+0.012$	$+0.014$	$+0.007$	$0.005^{+0.044}_{-0.037}$	$+0.037$	$+0.021$	$+0.010$	$+0.003$	$0.005^{+0.044}_{-0.032}$	$+0.027$	$+0.014$	$+0.009$	$+0.003$	$0.005^{+0.044}_{-0.032}$	$+0.020$	$-0.008$	$-0.006$	$-0.001$	
$\sigma_{ZH}/\sigma_{ggF}$	$0.0216 \pm 0.0024$	$0.066^{+0.039}_{-0.031}$	$+0.032$	$+0.018$	$+0.014$	$+0.005$	$0.013^{+0.028}_{-0.014}$	$+0.021$	$+0.013$	$+0.013$	$+0.003$	$0.123^{+0.076}_{-0.053}$	$+0.063$	$+0.038$	$+0.019$	$+0.009$	$0.123^{+0.076}_{-0.053}$	$+0.020$	$-0.012$	$+0.010$	$-0.008$	$0.123^{+0.076}_{-0.053}$	$+0.019$	$-0.013$	$-0.005$	$-0.001$	
$\sigma_{t\bar{t}H}/\sigma_{ggF}$	$0.0067 \pm 0.0010$	$0.0220^{+0.0068}_{-0.0057}$	$+0.0055$	$+0.0031$	$+0.0023$	$+0.0014$	$0.0126^{+0.0066}_{-0.0053}$	$+0.0052$	$+0.0031$	$+0.0024$	$+0.0013$	$0.0340^{+0.0158}_{-0.0116}$	$+0.0121$	$+0.0085$	$+0.0048$	$+0.0026$	$0.0340^{+0.0158}_{-0.0116}$	$+0.0097$	$-0.0051$	$-0.0036$	$-0.0015$	$0.0340^{+0.0158}_{-0.0116}$	$+0.0027$	$+0.0032$	$+0.0006$	$+0.0002$	
$B^{WW}/B^{ZZ}$	$8.09 \pm < 0.01$	$6.7^{+1.6}_{-1.3}$	$+1.5$	$+0.4$	$+0.4$	$+0.3$	$6.5^{+2.1}_{-1.6}$	$+2.0$	$+0.6$	$+0.5$	$+0.3$	$7.1^{+2.9}_{-2.1}$	$+2.6$	$+1.0$	$+0.7$	$+0.4$	$7.1^{+2.9}_{-2.1}$	$+1.8$	$-0.7$	$-0.5$	$-0.3$	$7.1^{+2.9}_{-2.1}$	$+1.1$	$+0.7$	$+0.5$	$+0.4$	
$B^{\gamma\gamma}/B^{ZZ}$	$0.0854 \pm 0.0010$	$0.069^{+0.018}_{-0.014}$	$+0.018$	$+0.003$	$+0.002$	$+0.002$	$0.062^{+0.024}_{-0.018}$	$+0.023$	$+0.007$	$+0.002$	$+0.003$	$0.079^{+0.034}_{-0.023}$	$+0.032$	$+0.009$	$+0.003$	$+0.004$	$0.079^{+0.034}_{-0.023}$	$+0.023$	$-0.005$	$-0.002$	$-0.003$	$0.079^{+0.034}_{-0.023}$	$+0.007$	$+0.002$	$+0.004$	$+0.004$	
$B^{\tau\tau}/B^{ZZ}$	$2.36 \pm 0.05$	$1.77^{+0.59}_{-0.46}$	$+0.52$	$+0.27$	$+0.05$	$+0.06$	$2.17^{+1.07}_{-0.74}$	$+0.89$	$+0.53$	$+0.16$	$+0.17$	$1.56^{+0.90}_{-0.61}$	$+0.78$	$+0.45$	$+0.07$	$+0.07$	$1.56^{+0.90}_{-0.61}$	$+0.54$	$-0.26$	$-0.05$	$-0.04$	$1.56^{+0.90}_{-0.61}$	$+0.66$	$+0.04$	$+0.12$	$+0.07$	
$B^{bb}/B^{ZZ}$	$21.5 \pm 1.0$	$4.2^{+4.4}_{-2.6}$	$+2.8$	$+2.3$	$+2.5$	$+0.4$	$9.6^{+10.1}_{-5.7}$	$+7.4$	$+4.5$	$+5.1$	$+1.3$	$3.7^{+4.1}_{-2.4}$	$+3.1$	$+1.8$	$+1.9$	$+0.4$	$3.7^{+4.1}_{-2.4}$	$+2.0$	$-0.9$	$-1.1$	$-0.2$	$3.7^{+4.1}_{-2.4}$	$+23.4$	$+12.7$	$+12.2$	$+2.5$	

Parameter	Best fit					Uncertainty					Best fit					Uncertainty					Best fit					
	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	value	Stat	Expt	Thbgd	Thsig	
ATLAS+CMS																										
$\kappa_{gZ}$	$1.09^{+0.11}_{-0.11}$	$+0.09$	$+0.02$	$+0.00$	$+0.06$	$1.20^{+0.16}_{-0.15}$	$+0.14$	$+0.03$	$+0.02$	$+0.07$	$0.99^{+0.14}_{-0.13}$	$+0.12$	$+0.03$	$+0.01$	$+0.06$	$0.99^{+0.14}_{-0.14}$	$+0.13$	$-0.12$	$-0.04$	$-0.01$	$0.99^{+0.14}_{-0.14}$	$+0.13$	$-0.12$	$-0.04$	$-0.05$	
$\lambda_{Zg}$	$1.27^{+0.23}_{-0.20}$	$+0.18$	$+0.10$	$+0.06$	$+0.10$	$1.07^{+0.26}_{-0.22}$	$+0.21$	$+0.10$	$+0.07$	$+0.09$	$1.47^{+0.45}_{-0.34}$	$+0.35$	$+0.22$	$+0.11$	$+0.13$	$1.47^{+0.45}_{-0.34}$	$+0.28$	$-0.28$	$-0.14$	$-0.10$	$1.47^{+0.45}_{-0.34}$	$+0.19$	$-0.09$	$-0.05$	$-0.07$	
$\lambda_{tg}$	$1.78^{+0.30}_{-0.27}$	$+0.21$	$+0.13$	$+0.09$	$+0.14$	$1.40^{+0.34}_{-0.33}$	$+0.25$	$+0.14$	$+0.12$	$+0.14$	$-2.26^{+0.50}_{-0.53}$	$+0.43$	$+0.22$	$+0.04$	$+0.14$	$-2.26^{+0.50}_{-0.53}$	$+0.39$	$-0.23$	$-0.23$	$-0.18$	$-2.26^{+0.50}_{-0.53}$	$+0.31$	$-0.22$	$-0.21$	$-0.11$	
$\lambda_{WZ}$	$0.88^{+0.10}_{-0.09}$	$+0.09$	$+0.03$	$+0.03$	$+0.02$	$0.92^{+0.14}_{-0.12}$	$+0.13$	$+0.04$	$+0.03$	$+0.02$	$-0.85^{+0.13}_{-0.15}$	$+0.11$	$-0.13$	$-0.06$	$-0.04$	$-0.85^{+0.13}_{-0.15}$	$+0.13$	$-0.13$	$-0.06$	$-0.04$	$-0.85^{+0.13}_{-0.15}$	$+0.15$	$-0.05$	$-0.03$	$-0.02$	
$ \lambda_{\gamma Z} $	$0.89^{+0.11}_{-0.10}$	$+0.10$	$+0.03$	$+0.01$	$+0.02$	$0.87^{+0.15}_{-0.13}$	$+0.15$	$+0.04$	$+0.02$	$+0.02$	$0.91^{+0.17}_{-0.14}$	$+0.16$	$+0.04$	$+0.02$	$+0.02$	$0.91^{+0.17}_{-0.14}$	$+0.14$	$-0.14$	$-0.03$	$-0.02$	$0.91^{+0.17}_{-0.14}$	$+0.18$	$+0.04$	$+0.01$	$+0.02$	
$ \lambda_{\tau Z} $	$0.85^{+0.13}_{-0.12}$	$+0.12$	$+0.06$	$-0.02$	$-0.01$	$0.96^{+0.21}_{-0.18}$	$+0.18$	<math																		