What to do with the two-point systematics?

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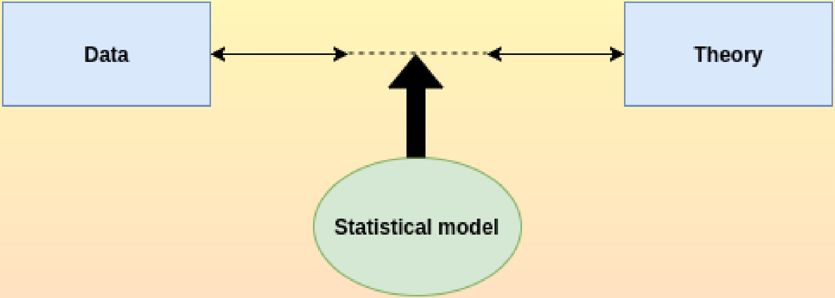
Benasque — Higgs Toppings 2018



- We model our problem using profile likelihoods (See Michele's talk)

$$\mathcal{L}(\boldsymbol{n}, \boldsymbol{\alpha}^{\mathbf{0}} | \mu, \boldsymbol{\alpha}) = \prod_{i \in bins} \mathcal{P}(n_i | \mu S_i(\boldsymbol{\alpha}) + B_i(\boldsymbol{\alpha})) \times \prod_{j \in syst} \mathcal{G}(\alpha_j^0 | \alpha_j, \delta\alpha_j)$$

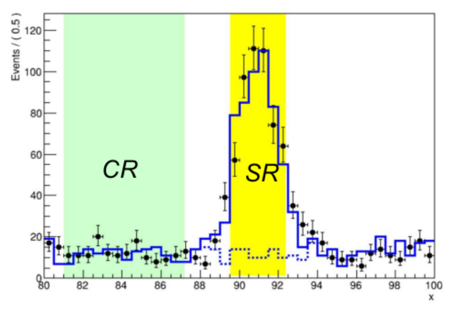
$$\lambda(\mu) = \frac{\mathcal{L}(\mu, \hat{\hat{\boldsymbol{\alpha}}}_\mu)}{\mathcal{L}(\hat{\mu}, \hat{\boldsymbol{\alpha}})}$$

From sidebands to systematic uncertainties

- Sideband measurement:

$$L_{SR}(s,b) = Poisson(N_{SR} \mid s+b)$$
$$L_{CR}(b) = Poisson(N_{CR} \mid \tilde{\tau} \cdot b)$$

$$\mathcal{L}_{full}(s,b) = \mathcal{P}(N_{SR}|s+b) \times \mathcal{P}(N_{CR}|\tilde{\tau} \cdot b)$$



- Subsidiary measurement of the background rate:
  - *8% systematic uncertainty on the MC rates*
  - $\tilde{b}$: *measured background rate by MC simulation*
  - $\mathcal{G}(\tilde{b}|b, 0.08)$: our

$$\mathcal{L}_{full}(s,b) = \mathcal{P}(N_{SR}|s+b) \times \mathcal{G}(\tilde{b}|b, 0.08)$$

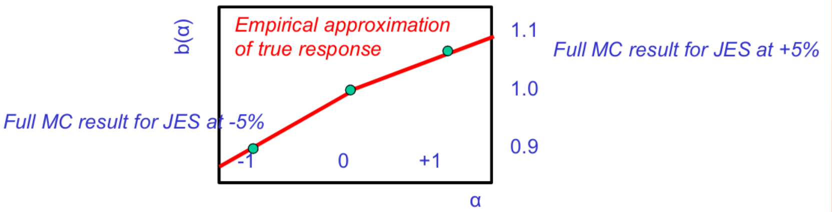
Renormalization of the subsidiary measurement

$$\mathcal{L}(\boldsymbol{n}, \boldsymbol{\alpha}^{\mathbf{0}} | \mu, \boldsymbol{\alpha}) = \prod_{i \in bins} \mathcal{P}(n_i | \mu S_i(\boldsymbol{\alpha}) + B_i(\boldsymbol{\alpha})) \times \prod_{j \in syst} \mathcal{G}(\alpha_j^0 | \alpha_j, \delta\alpha_j)$$

$$\downarrow$$

$$\mathcal{L}(\boldsymbol{n}, 0 | \mu, \boldsymbol{\alpha}) = \prod_{i \in bins} \mathcal{P}(n_i | \mu S_i(\boldsymbol{\alpha}) + B_i(\boldsymbol{\alpha})) \times \prod_{j \in syst} \mathcal{G}(0 | \alpha_j, 1)$$

- Subsidiary measurement often labelled *constraint term*
- It is not a PDF in α: $\mathcal{G}(\alpha_j | 0, 1) \neq \mathcal{G}(0 | \alpha_j, 1)$
- Response function: $\tilde{B}_i(1 + 0.1\alpha)$ (a unit change in α –e.g. 5% JES– changes the acceptance by 10%)



Graphics from W. Verkerke

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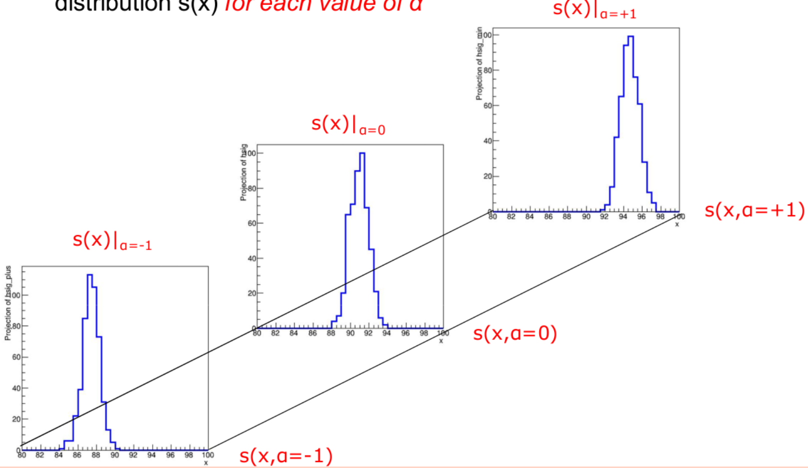
- Need to define 'morphing' algorithm to define distribution s(x) *for each value of α*



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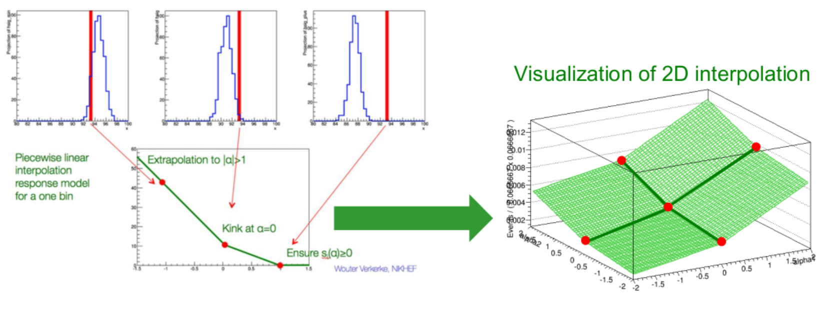
Interpolation needed between template models — 2

- Can fail dramatically if the change in shape is comparable with or smaller than MC statistical fluctuations
- Sometimes we may want to avoid adding this new degree of freedom in the model
- Decoupling rate and shape effects is always possible, even when not neglecting the shape ones)



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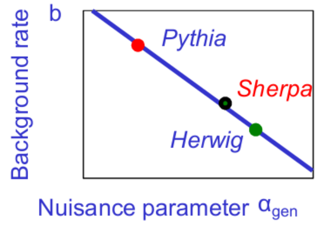
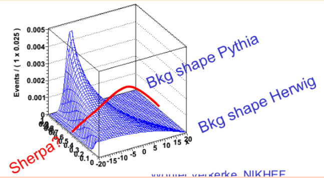
- Cross section uncertainty: easy, assuming a gaussian for the constraint term
  $\mathcal{L}_{full}(s,b) = \mathcal{P}(N_{SR}|s+b) \times \mathcal{G}(\tilde{b}|b, 0.08)$
- Factorization scale: what distribution $\mathcal{F}$ is meant to model the constraint???
  $\mathcal{L}_{full}(s,b) = \mathcal{P}(N_{SR}|s+b(\alpha_{FS}) \times \mathcal{F}(\tilde{\alpha_{FS}}|\alpha_{FS})$
  - “Easy” case, there is a single parameter α_{FS}, clearly connected to the underlying physics model
- Hadronization/fragmentation model: run different generators, observing different results
  - Difficult! Not just one parameter, how do you model it in the likelihood?
  - 2-point systematics: you can evaluate two (three, four...) configurations, but underlying reason for difference unclear

Define an empirical response function

- Counting experiment: easy extend to other generators
- There must exist a value of α corresponding to SHERPA



- Shape experiment: ouch!
- SHERPA is in general not obtainable as an interpolation of PYTHIA and HERWIG



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Define a constraint term

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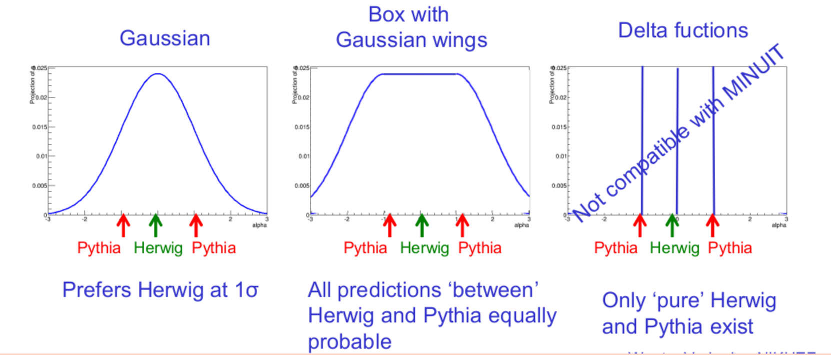
- Attempting to quantify our knowledge of the models
- There is no single parameter, difficult to model the differences within a single underlying model
- Which of these is the “correct” one?



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Solving the delta functions issue: discrete profiling

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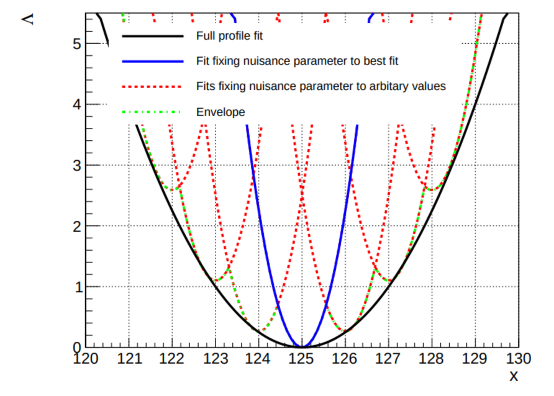
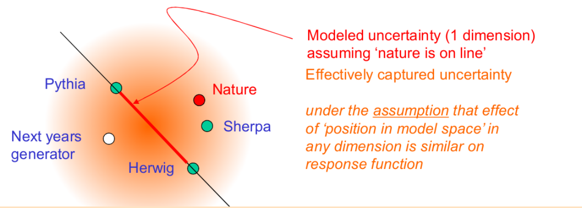
- Label each shape with an integer, and use the integer as nuisance parameter
- Can obtain the original log-likelihood as an envelope of different fixed discrete nuisance parameter values
- How do you define the various shapes?
  - Need many additional generators!
  - Interpolation unlikely to work (*SHERPA is not midway between PYTHIA and POWHEG*)

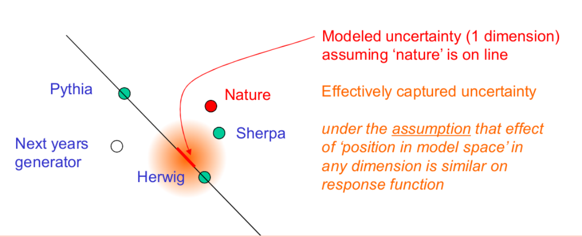


From arXiv:1408.6865

The issue of over-constraining

- How to interpret constraints?
- **Not as measurements**
- Correlations in the fit make interpretation complicated
- Avoid statements when profiling as a nuisance parameter





For discussion

- Are the shape variations big w.r.t. MC statistical uncertainties?
  - If so, decoupling rate and shape is probably fine
- How to model response and constraint?
  - Interpolation between generators works badly in the shape case
  - Discrete profiling likely affected by the same issue, but can help if there is a sufficient number of additional generators
- What to do in case of over-constraints of the parameter?
  - If you don't even cover the two generators you have, how can you cover others/Nature?
- **Statistical problem looks to be well defined. The issue lies in the physics modelling!**
  - Is it feasible to go towards a global description of the physics model, with common parameters and easily interpretable transformations between generators?

Best solution: solve the modelling issue!

THANKS FOR THE ATTENTION!