Factorizing Theory Uncertainties

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based on
A novel approach to Higgs Coupling Measurements
[arXiv:1401.0080]
with Tilman Plehn, Sven Kreiss, & David Lopez-Val
Introduction

Shortly after “On the Presentation of LHC Higgs Results” [arXiv:1307.5865] was initially released, ATLAS published profile likelihood scans in the ggF vs VBF signal strength plane.

These data are directly linked to the paper in INSPIRE and have been cited:

Data from Figure 7 from: Measurements of Higgs boson production and couplings in diboson final states with the ATLAS detector at the LHC

ATLAS Collaboration (Aad, Georges (Freiburg U.) [...]) Show all 2923 authors

Introduction

While this is a major step forward in communicating LHC Higgs results, there are some issues that still need to be addressed.

1. Some systematics are shared between these different channels, so simply multiplying them together will lead to **double-counting** those constraint terms (priors)

2. In addition, the **profiling** of the common systematics is **not consistent**, different channels can pull nuisance parameters in different directions

3. **Theory uncertainties** use the standard prescription from the LHC XSWG. That prescription and the magnitude of the uncertainties is **likely to change** in the future as progress is made on the theoretical side.

**Goal:** We want to **decouple** shared uncertainties from the reported likelihood scan
### Disentangling multiple production modes

![Graph showing signal composition and signal strength](image)

**ATLAS Preliminary**

- **Data 2012, \( \sqrt{s} = 8 \text{ TeV} \)**
- \( \int \text{Ldt} = 20.7 \text{ fb}^{-1} \)
- \( m_H = 126.8 \text{ GeV} \)

\[
L_{\text{full}}(\mu, \alpha) = \prod_{c \in \text{category}} \left[ \text{yield} \ Pois(n_c|\nu_c(\mu, \alpha)) \prod_{e=1}^{n_c} f_c(x_e|\mu, \alpha) \right] \prod_{i \in \text{syst}} f_i(a_i|\alpha_i)
\]

≡ \( L_{\text{main}}(\mu, \alpha) \)

≡ \( L_{\text{constr}}(\alpha) \)

**Subscripts**
- \( c \ldots \) category
- \( p \ldots \) production
- \( d \ldots \) decay
- \( e \ldots \) event
- \( i \ldots \) systematic

**Expected number of events:**

\[
\nu_c(\mu, \alpha) = \sum_{p,d} \mu_{pd} s_{cpd}(\alpha) + b_c(\alpha)
\]
**Basic idea (1/2 )**

**Left:** contours with / without theory uncertainties

**Center:** contours w/o theory uncertainty shifted by changing ggF inclusive x-sec up by 1σ

**Right:** collection of vectors indicating how best fit point moves due to each source of uncertainty

All plots are based on counting models that mimic ATLAS results.

Points move in this plane when varying common nuisance parameters.

\[
\frac{\partial \hat{\mu}_{p}^{\text{fix}}}{\partial \alpha_i} \hat{\mu}, \hat{\alpha} = -\hat{\mu}_{p} \eta_{ip}
\]
Basic idea (2/2)

Basic idea: Instead of folding the theoretical uncertainties into the experimental result, experiments would publish an effective likelihood $L_{\text{eff}}(\mu_{\text{eff}})$ with respect to some fixed theoretical reference and a reparametrization template $\mu_{\text{eff}}(\mu, \alpha)$ that documents the affect of individual sources of uncertainty.

theoretical uncertainties are **decoupled** from experimental result!

Then the full likelihood (left) can be **recoupled** by composition and one is free to modify the constraint term (prior)

$$L_{\text{full}}(\mu, \alpha) \approx L_{\text{recouple}}(\mu, \alpha) \equiv L_{\text{eff}}(\mu_{\text{eff}}(\mu, \alpha)) \cdot L_{\text{constr}}(\alpha)$$
Effective Likelihoods

Start with the full likelihood function

\[ L_{\text{full}}(\mu, \alpha) = \prod_{c \in \text{category}} \left[ \text{Pois}(n_c|\nu_c(\mu, \alpha)) \prod_{e=1}^{n_c} f_e(x_e|\mu, \alpha) \right] \prod_{i \in \text{syst}} f_i(a_i|\alpha_i) \]

≡ \( L_{\text{main}}(\mu, \alpha) \)

≡ \( L_{\text{constr}}(\alpha) \)

Expected number of events \( \nu \) has signal strength \( \mu \) that scales a signal yield \( s \) which depends on \( \alpha \)

\[ \nu_c(\mu, \alpha) = \sum_{p,d} \mu_{pd}s_{cpd}(\alpha) + b_c(\alpha) \]

Introduce \( \mu^{\text{eff}} \) that scales with respect to some fixed theoretical reference at \( \alpha_0 \).

Absorb \( \alpha \)-dependence into \( \mu^{\text{eff}}(\mu, \alpha) \)

\[ \nu_c(\mu, \alpha) \rightarrow \sum_{p,d} \mu_{cpd}^{\text{eff}}(\mu, \alpha) s_{cpd}(\alpha_0) + b_c(\alpha_0) \]

Here \( \mu^{\text{eff}}(\mu, \alpha) \) is a function that absorbs the dependence on \( \alpha \), but we can also think of \( \mu^{\text{eff}} \) as a parameter on its own and measure \( L_{\text{eff}}(\mu^{\text{eff}}) \)

\[ L_{\text{full}}(\mu, \alpha) \approx L_{\text{recouple}}(\mu, \alpha) \equiv L_{\text{eff}}(\mu^{\text{eff}}(\mu, \alpha)) \cdot L_{\text{constr}}(\alpha) \]

Need a reparametrization template \( \mu^{\text{eff}}(\mu, \alpha) \) with parameters \( \eta \) and a method to determine the \( \eta \)s such that \( L_{\text{recouple}} \) approximates \( L_{\text{full}} \):
Reparametrization Templates

For uncertainties that affect the signal yield inclusively

\[ s_{cpd}(\alpha) = s_{cpd}(\alpha_0) \left[ 1 + \sum_i \eta_{pi}(\alpha_i - \alpha_{0,i}) \right] \rightarrow \mu_{pd}^{\text{eff}}(\mu, \alpha) = \mu_{pd} \left[ 1 + \sum_i \eta_{pi}(\alpha_i - \alpha_{0,i}) \right] \]

as in the full likelihood, bi-linear in (\mu, \alpha)

Similarly, for nuisance parameters that affect background rates:

\[ b_c(\alpha) = b_c(\alpha_0) \left[ 1 + \sum_i \phi_{ci}(\alpha_i - \alpha_{0,i}) \right] \rightarrow \mu_{pd}^{\text{eff}}(\mu, \alpha) = \mu_{pd} + \frac{b_c(\alpha_0)}{s_{cpd}(\alpha_0)} \left[ \sum_i \phi_{ci}(\alpha_i - \alpha_{0,i}) \right] \]

as in the full likelihood, linear in \mu and \alpha

For “cross-talk” nuisance parameters:

Example: a ggF+2j uncertainty affecting VBF signal yield through ggF contamination in a VBF–optimized category: p=VBF, p’=ggF

\[ \mu_{pd}^{\text{eff}}(\mu, \alpha) = \mu_{pd} + \sum_{i,p'} \mu_{p'd}^{\alpha} \eta_{pi}^{p'} (\alpha_i - \alpha_{0,i}) \]

A flexible reparametrization template including above effects

\[ \mu_{pd}^{\text{eff}}(\mu, \alpha) = \mu_{pd} + \sum_{i,p'} \mu_{pd}^{p'} \eta_{pi}^{p'} (\alpha_i - \alpha_{0,i}) + \sum_i \phi_i (\alpha_i - \alpha_{0,i}) \]

Paper outlines method needed to determine and coefficients of template
An extreme example

Three examples for a simple 2 channel case with large uncertainties.
The recoupled likelihood excellent approximation to full likelihood

Figure 7. Comparison of full likelihood (solid) and recoupled (dashed) likelihood for Scenarios A, B, and C. Scenario C illustrates the impact of using three templates ‘aligned’ (red), ‘by hand’ (green), and ‘learning’ (blue) as described in the text. The top row is based on the nominal Gaussian constraint and the bottom row shows the result of replacing it with an alternative $R_{\text{FIT}}$ constraint term. The effective likelihood with $\alpha = 0$ is shown as a dotted line.
Combination of Effective Likelihoods

Demo at https://github.com/svenkreiss/decoupledDemo (works on lxplus).  
_Leff_ is an efficient lookup table that replaces most of the complexity of the full model. What is normally a job for a cluster runs in 16min on my laptop.

Decoupled Demo

Demo of recoupling a decoupled project. Effective likelihoods and template parametrizations are hosted on the web.

View the Project on GitHub svenkreiss/decoupledDemo

Download ZIP File  Download TAR Ball  View On GitHub

Decoupled Models

Effective likelihoods and template parameters are hosted here:

- \( H \rightarrow γγ \) effective likelihood (root), template (pickle .py)
- \( H \rightarrow ZZ^* \rightarrow 4t \) effective likelihood (root), template (pickle .py)
- \( H \rightarrow WW^* \rightarrow llv \) effective likelihood (root), template (pickle .py)

These links are just for your information. The makefile will automatically download these files to the right location.

Effective likelihoods and template to common nuisance parameters can be published on the web.

Recoupling with two prescriptions for theory uncertainties.

Full model contours are added to the plots for comparison.
Conclusions

The ability to decouple theoretical uncertainties from experimental results would be a big step forward

- theory uncertainties are somewhat **ill-defined** and will evolve with time.
- this technique gives a lot of **flexibility** in how they are handled.

We have outlined a technique that achieves this

- In addition, the technique solves a problem associated to double counting constraint terms and inconsistent profiling that is present if we publish profile likelihood scans for the individual channels.

This approach still requires that the experiments understand the effect of individual sources of uncertainty on the various channels in the way that we are doing it now coordinated via the LHC HXSWG.

Thank you!
Determining Template Parameters

The covariance matrix can be used to determine up to $n_p \cdot n_\alpha$ of the template parameters $\eta$. For example, for templates without “cross-talk” and only category universal, symmetric uncertainties, the template parameters $\eta$ are determined by:

$$\frac{\partial \hat{\mu}_{\text{fix}}}{\partial \alpha_i} \bigg|_{\hat{\mu}, \hat{\alpha}} = -\hat{\mu}_p \eta_{ip}$$

Similar equations can be derived for other scenarios, but usually knowledge has to be added “by-hand” to keep the number of parameters $\leq n_p \cdot n_\alpha$.

For more general templates, the local information contained in the likelihood and its first and second derivative is not enough, and information from various points of the likelihood needs to be used. This can be done by minimizing a loss function with the full and recoupled likelihoods:

$$\text{Loss}(\eta) = \int d\mu d\alpha \, \pi(\mu, \alpha) \left| L_{\text{full}}(\mu, \alpha) - L_{\text{recouple}}(\mu, \alpha; \eta) \right|^2$$

where $\pi(\mu, \alpha)$ is a weight function. One possibility is to treat $\pi(\mu, \alpha)$ as a posterior obtained using a baseline constraint term: $\pi(\mu, \alpha) \propto L_{\text{main}}(\mu, \alpha)L_{\text{constr}}(\alpha)$

In practical terms, this means that the integral in the loss function can be obtained using MCMC [note, does not make the method Bayesian].
BSM Models in Prod Mode Plan

So far, we publish a SM point in the 2-d plane. However, it is also possible to come up with a 1-parameter description of various BSM models and show them as a line in the same plane.

**Figure 5.** Decay–diagonal correlations of signal strengths $\mu_{GF,d}$ vs $\mu_{VBF,d}$ for $d = \gamma\gamma, VV, \tau\tau$ in different models. The coupling variation is limited to $\xi < 0.4$ and the value $\xi = 0.2$ is singled out. The slight deviations from a complete decoupling are discussed in the text.
Robustness of New Models to Theory

Robustness R in the three channels of various BSM models to changes in the QCD scale for the inclusive and ≥2 jets bins.

\[ R_i(\mu) = \frac{|\mu - 1|^2 \left| \partial_{\alpha_i} \mu_{\text{fix}} \right|}{(\mu - 1) \cdot (\partial_{\alpha_i} \mu_{\text{fix}})} \]

**Figure 6.** The sensitivity heuristic \( R_i(\xi) \) evaluated for various new physics models and the theoretical uncertainties \( i \) associated to the gluon fusion cross section for \( \geq 0 \)-jets and \( \geq 2 \)-jets.