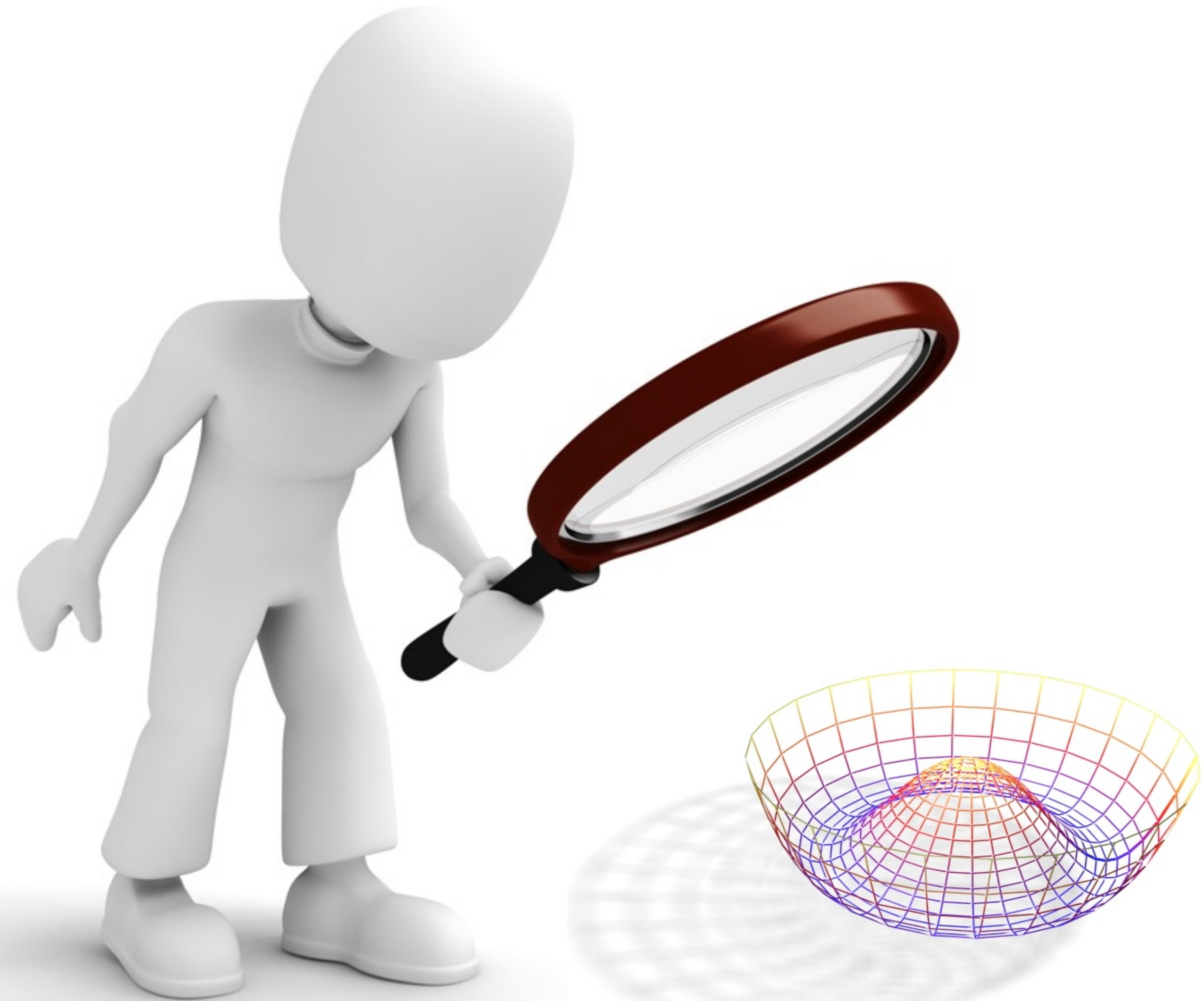
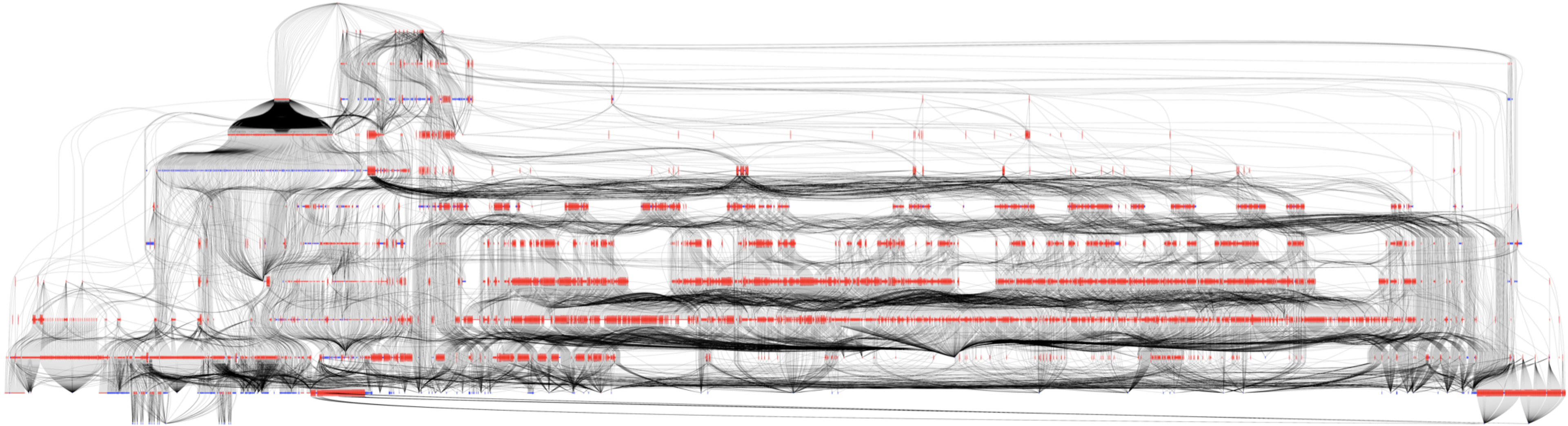
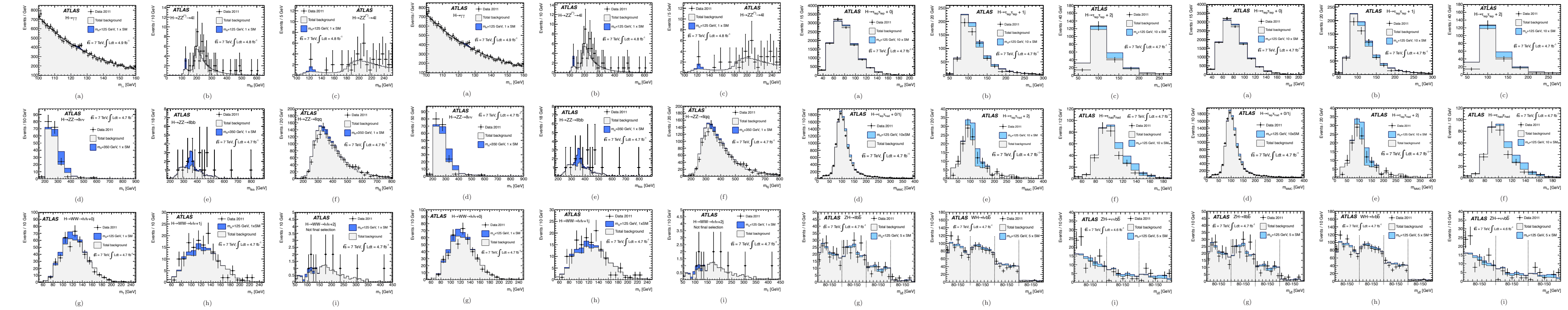


# GRAND COMBINATIONS @ HL-LHC & FAIROS-HEP



**@KyleCranmer**  
University of Wisconsin-Madison  
Data Science Institute  
Physics, Computer Science, Statistics

# Combined fits for the Higgs discovery



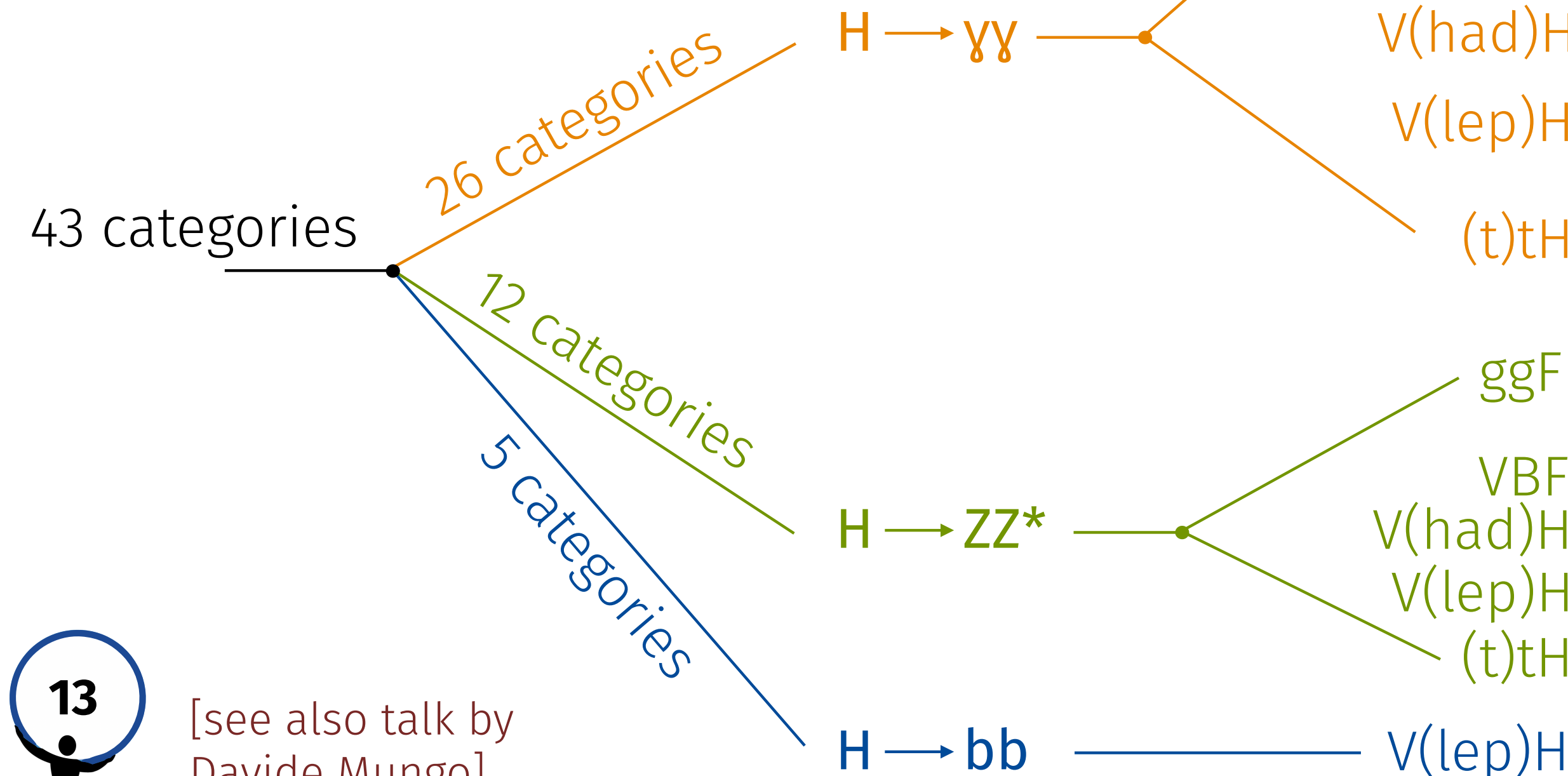
$$\mathbf{f}_{\text{tot}}(\mathcal{D}_{\text{sim}}, \mathcal{G} | \boldsymbol{\alpha}) = \prod_{c \in \text{channels}} \left[ \text{Pois}(n_c | \nu_c(\boldsymbol{\alpha})) \prod_{e=1}^{n_c} f_c(x_{ce} | \boldsymbol{\alpha}) \right] \cdot \prod_{p \in \mathcal{S}} f_p(a_p | \alpha_p)$$

# Combined fits for EFTs

## The STXS combination measurement

**Aim:** EFT interpretation of the 139 fb<sup>-1</sup> combination of H → ZZ\* → 4ℓ, H → γγ and H → bb merged stage-1.2 STXS measurement

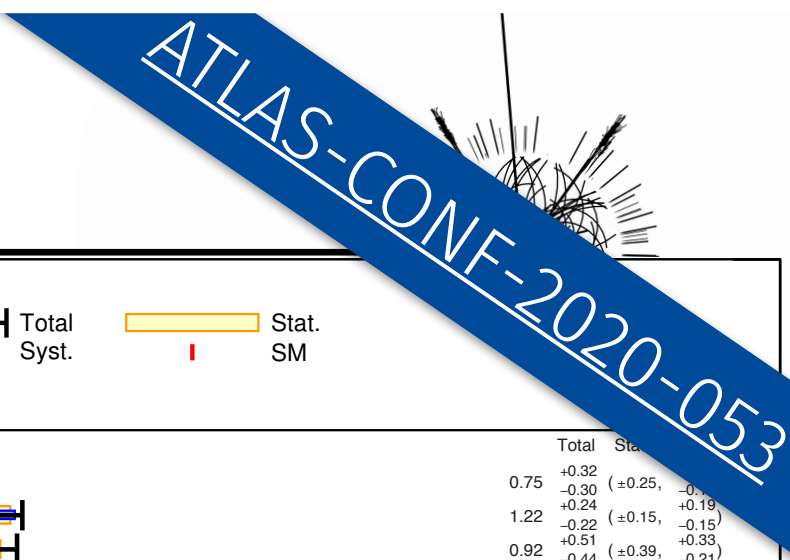
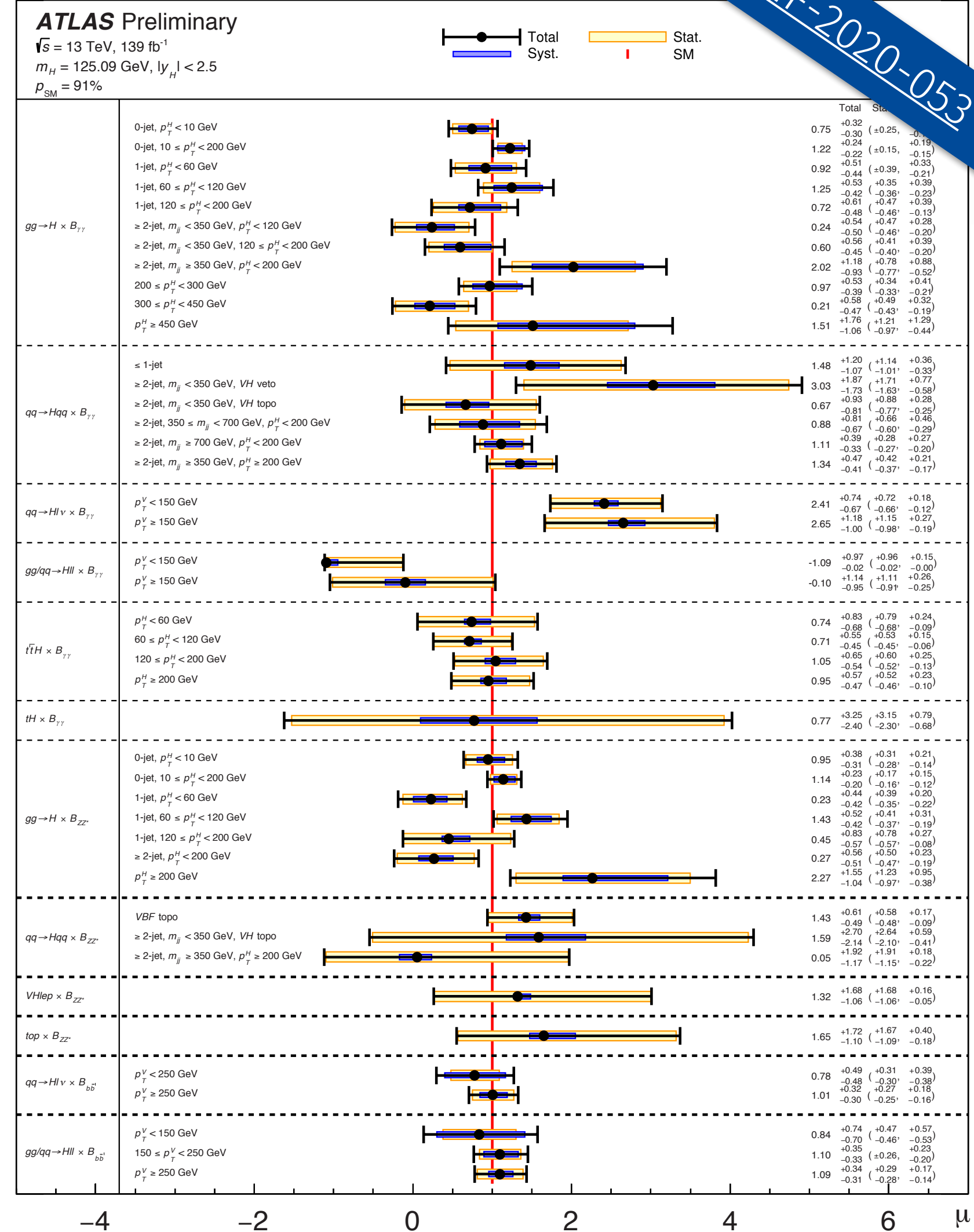
Mostly split into p<sub>T</sub><sup>H</sup> categories (and n<sub>jet</sub>)



[see also talk by [Davide Mungo](#)]

Brian Moser

SMEFT Higgs Measurements with ATLAS



# Comments on Unfolding

- Fiducial and differential cross section measurements
  - minimise model dependence
  - relatively restricted sensitivity (hard to combine different channels)
  - re-interpretable outside experiment

Saskia Falke, Higgs2020

▶ Desirable to have results at particle level, and distributions (STXS or fiducial distr.)

## Unfolding is deceptively attractive

- It seems very convenient and to address what we want to know, but
- unfolding is a can of worms statistically and pushes many problems down stream
  - Combinations, correlated systematics, artifacts and bias introduced by the unfolding procedure. These will all turn into systematics in the final results.
- It is good for fast approximate answers, but
- I do not recommend it as a platform for the final “gold standard” results.

# Likelihood scans vs. full statistical models

## Combining detector-level analyses

- EFT analyses cannot always be summarised in a covariance matrix
  - Most likely possible if only linear terms are taken into account
- Combinations **must be done by at the likelihood level**

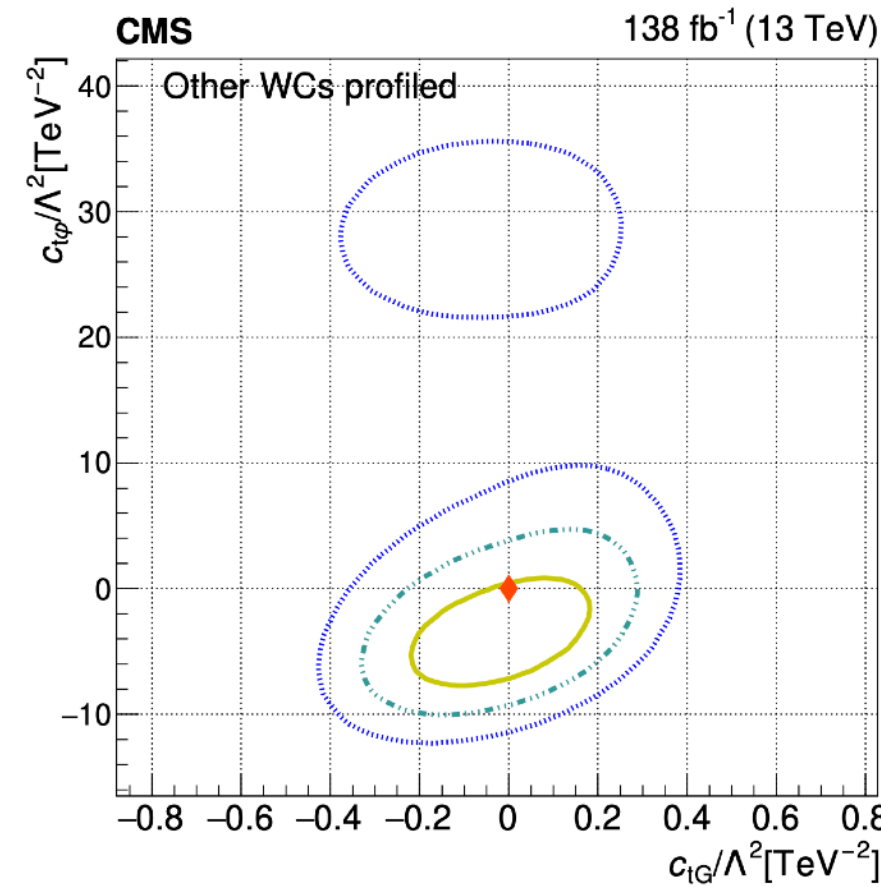
$$\mathcal{L} = \prod \mathcal{P}(x_i | n_{\text{bkg}}(\theta) + n_{\text{Signal}}(C_i, \theta)) P(\theta)$$

- All necessary **changes must be implemented at detector level**
- In the near future, detector-level analyses will be available for combination also outside the collaborations
  - **CMS is planning to release the analysis likelihoods** along with instructions to evaluate them
  - Ideas to provide profiled likelihood ratio parametrised by a neural network (see [CHEP 2023 contribution](#))



Sergio Sánchez Cruz

5



**Warning:** the term “likelihood” is used to describe both full statistical model and the likelihood function for observed data.

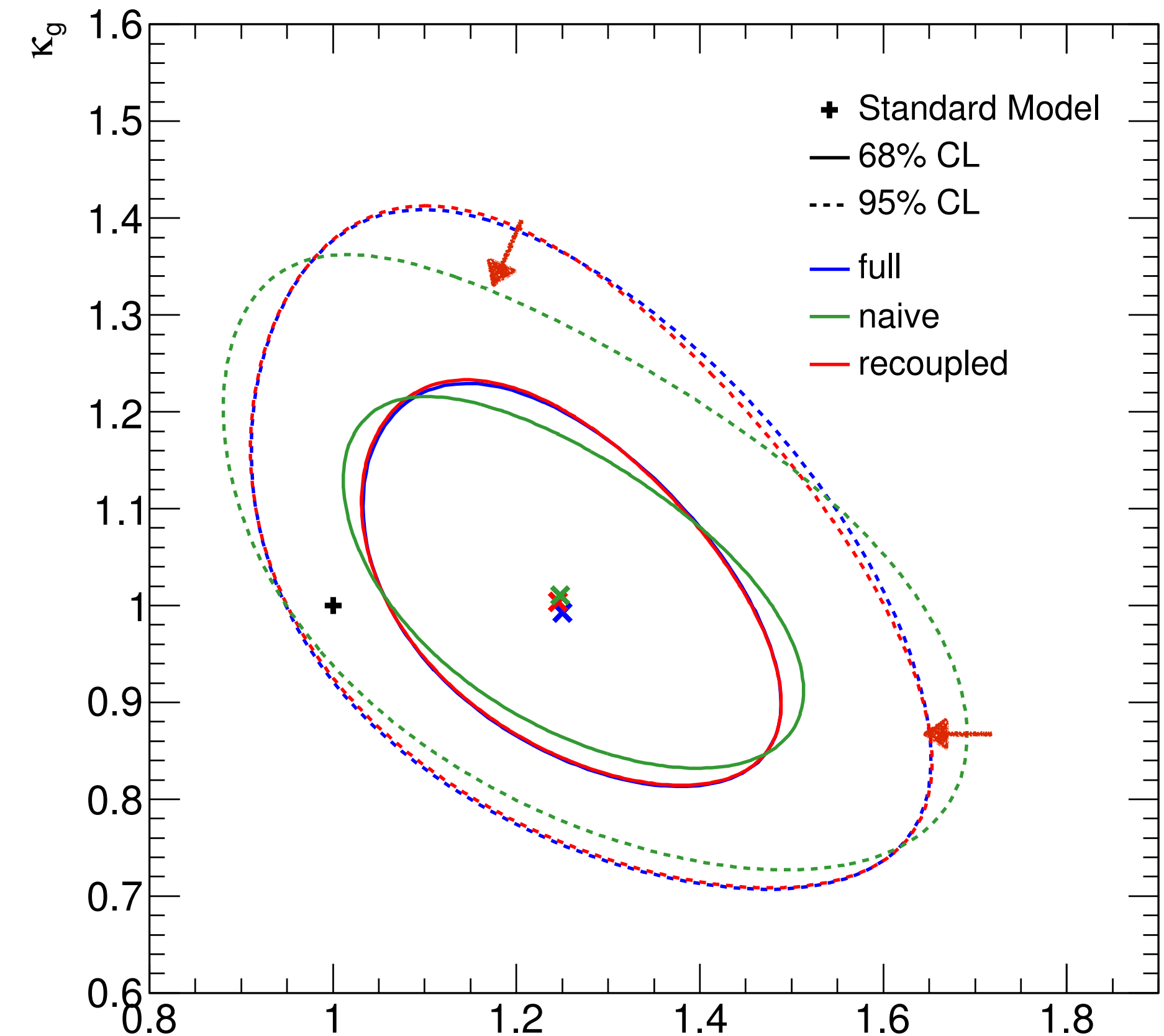


Sharing profile likelihood isn't a good approach to combinations, you **double count** constraint terms and have **inconsistent profiling**.

- Studied extensively in

<https://inspirehep.net/literature/1275827>

See also section 4.2.3 in [arxiv:2109.04981](#)



K<sub>γ</sub>

# My message

**Top Level Message:** We should publish the full statistical model (aka “likelihood”) for measurements that constrain EFT coefficients

- Lots of progress in publishing statistical models recently in BSM searches

**Second Level Message:** There are a few ways to describe the dependence on EFT parameters. We can and should separate the specification and implementation.

- First define a **specification** for one or more of these choices that removes all ambiguity. This allows multiple groups to **implement** the specification.

**Third Level Message:** In addition to publishing statistical models, RECAST-like infrastructure would allow us to consider new EFT operators and update / improve background modeling after publishing

- This infrastructure is being used in BSM searches already

*Likelihood Publishing + RECAST*

=



Message 1:  
Publishing Statistical Models



# The first PhyStat

It was 24 years ago!

## Massimo Corradi

It seems to me that there is a general consensus that what is really meaningful for an experiment is *likelihood*, and almost everybody would agree on the prescription that experiments should give their likelihood function for these kinds of results. Does everybody agree on this statement, to publish likelihoods?

## Louis Lyons

Any disagreement ? Carried unanimously. That's actually quite an achievement for this Workshop.

<https://cds.cern.ch/record/411537?ln=en>

CERN 2000-005  
30 May 2000

see 2000 26

ORGANISATION EUROPÉENNE POUR LA RECHERCHE NUCLÉAIRE  
**CERN** EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH

## WORKSHOP ON CONFIDENCE LIMITS

CERN, Geneva, Switzerland  
17-18 January 2000

CERN LIBRARIES, GENEVA



P00037096

## PROCEEDINGS

Editors: F. James, L. Lyons, Y. Perrin

GENEVA  
2000

# Publishing statistical models: Getting the most out of particle physics experiments

Kyle Cranmer <sup>1\*</sup>, Sabine Kraml <sup>2‡</sup>, Harrison B. Prosper <sup>3§</sup> (editors), Philip Bechtle <sup>4</sup>, Florian U. Bernlochner <sup>4</sup>, Itay M. Bloch <sup>5</sup>, Enzo Canonero <sup>6</sup>, Marcin Chrzaszcz <sup>7</sup>, Andrea Coccaro <sup>8</sup>, Jan Conrad <sup>9</sup>, Glen Cowan<sup>10</sup>, Matthew Feickert <sup>11</sup>, Nahuel Ferreiro Iachellini <sup>12,13</sup> Andrew Fowlie <sup>14</sup>, Lukas Heinrich <sup>15</sup>, Alexander Held <sup>1</sup>, Thomas Kuhr <sup>13,16</sup>, Anders Kvellestad <sup>17</sup>, Maeve Madigan <sup>18</sup>, Farvah Mahmoudi<sup>15,19</sup>, Knut Dundas Morå <sup>20</sup>, Mark S. Neubauer <sup>11</sup>, Maurizio Pierini <sup>15</sup>, Juan Rojo <sup>8</sup>, Sezen Sekmen <sup>22</sup>, Luca Silvestrini <sup>23</sup>, Veronica Sanz <sup>24,25</sup>, Giordon Stark <sup>26</sup>, Riccardo Torre <sup>8</sup>, Robert Thorne <sup>27</sup>, Wolfgang Waltenberger <sup>28</sup>, Nicholas Wardle <sup>29</sup>, Jonas Wittbrodt <sup>30</sup>

# Concepts

While it may seem overly technical, these subtle distinctions are very important.

We overcame decades of stagnation when we focused on **declarative specification** for **closed-world** models and moved to standard approaches to **serialization** (e.g. ROOT binary to JSON/yaml)

- breakthrough with pyhf

## Glossary of terms

- **Statistical model:** This is a synonym for the probability model  $p(x, y|\mu, \theta)$  as in Eq. (7) that includes dependence on the data  $x$  and  $y$ , the parameters of interest  $\mu$  and nuisance parameters  $\theta$ , access to the individual terms and the ability to generate pseudo- (or synthetic-) data (i.e., “toy Monte Carlo”).
- **Likelihood:** The value of the statistical model for a given *fixed* dataset as a function of the parameters, e.g.,  $L(\mu, \theta)$  in Eq. (7).
- **Constraint term:** A term in the full statistical model that relates auxiliary data  $y$  to a particular nuisance parameter  $\theta$ .
- **Observed data** the  $n$ ,  $x$ , and  $y$  of Eq. (7) needed to construct the likelihood.
- **Open-world:** An approach to statistical modelling that allows users to define and implement custom components in the statistical model.
- **Closed-world:** An approach to statistical modelling that requires users to work with a finite set of modelling components.
- **Declarative specification:** An unambiguous specification (e.g., of a statistical model) that is independent of implementation. Often there exists a reference implementation of a specification, but in the declarative approach there may be multiple implementations that are conceptually and mathematically equivalent.
- **Serialization:** The process of writing a data structure (e.g., a statistical model) in memory to a file in a way that can be read back into memory. Loading the serialized object typically requires access to compatible software libraries present at the time of serialization.

# It's a reality

The screenshot shows the ATLAS Public Results Page with the following sections and filters:

- Global Selections:** Show All, Deselect All, Show Latest 10
- CM Energy:** 14 TeV, 13.6 TeV, 13 TeV, 8 TeV, 7 TeV, 5 TeV, 2.36 TeV, 2.76 GeV, 900 GeV, 8.16 TeV/NN, 5.44 TeV/N, 5.02 TeV/N, 2.76 TeV/NN
- Physics theme:** B-physics and light states, Standard Model, Top, Higgs, BSM Searches, Heavy Ion, Upgrade Studies, Outreach, Statistical methods, Tracking, Egamma, Muon, Tau, Jet/Etmiss, Flavour tagging, Physics Modelling
- Signature:** W, Z, Photon, H, WW, WZ, ZZ, Di-photon, Vphoton, HH, VVV, Single top, Top pair,  $\geq 3$  tops, Charged tracks, 0 lepton, 1 lepton, 2 leptons, 2 leptons (same charge),  $\geq 3$  leptons, Taus, Photons, 0 jets, 1 jet, 2 jets,  $\geq 3$  jets, All hadronic, c-jets, b-jets, Boosted, MET, Long-lived massive particle, Forward Proton
- Analysis characteristics:** Cross-section measurement, Mass measurement, Statistical combination, ISR, Gluon fusion, VBF, VBS, PDF fits, Double parton scattering, BSM search, BSM reinterpretation, LFV, FCNC, Particle flow, MVA / machine learning, EFT interpretation, Differential measurement, Displaced vertex, Lepton-jets, Trigger-level analysis, High luminosity upgrade studies, Photon-induced, Likelihood available
- Min luminosity:** 0 fb<sup>-1</sup>, Filter by minimum integrated luminosity
- Date:** Min: 11/14/2023, Max: 11/14/2023, ArXiv release, Publication

# It's a reality

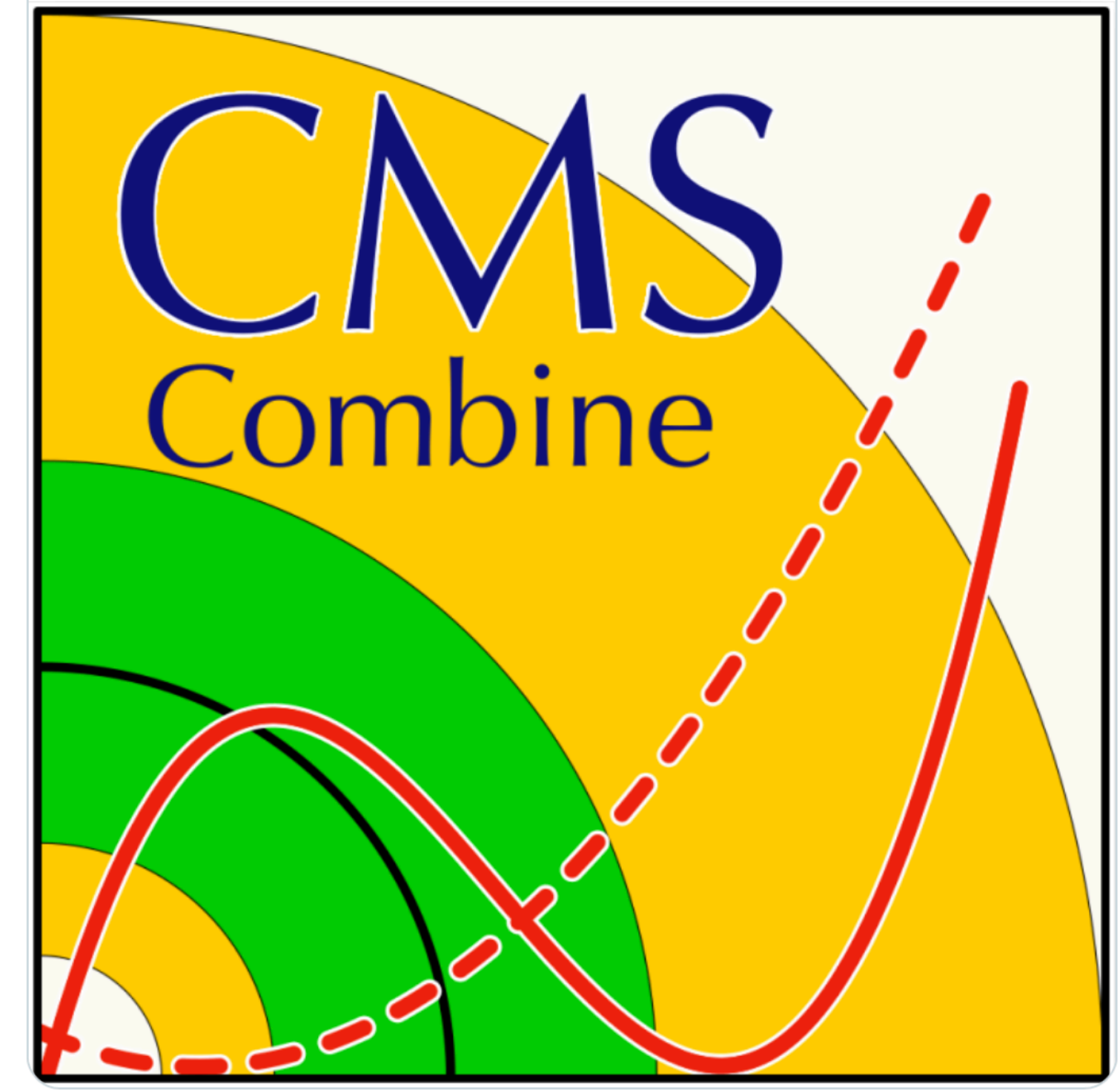
Find all papers which include specific types of **analysis**.

- analysis:rivet** (Rivet analysis)
- analysis:MadAnalysis** (MadAnalysis 5 analysis)
- analysis:HistFactory** (likelihoods in HistFactory format)

**Clemens Lange** @clelange · Apr 16  
 Finally out: the first full statistical model of a **CMS** physics analysis (the 2012 #HiggsBoson discovery), together with one of the most important pieces of software used and developed in the collaboration, the "**Combine**" tool. Correct link to the briefing: [cms.cern/news/cms-commi...](https://cms.cern/news/cms-commi...)

**CMS Experiment CERN** @CMSExperiment · Apr 16  
 More than #OpenData, CMS continues to move towards #OpenScience 🙌  
 The statistical analysis tool used to find the #Higgs boson, along with the full statistical model and the data used to make the ...  
[Show more](#)

The screenshot shows the HEPData search results page for the query 'analysis:HistFactory'. The interface includes a search bar with the query, navigation options like 'About', 'Submission Help', 'File Formats', and 'Sign in'. On the left, there are filters for 'Date' (with a bar chart showing results from 2019 to 2023), 'Collaboration' (listing ATLAS), 'Subject\_areas' (listing hep-ex), 'Phrases' (listing Proton-Proton Scattering, Cross Section, SUSY, Supersymmetry, Top), and 'Reactions' (listing P P --> CHARGINO+ CHARGINO-, P P --> CHARGINO+ NEUTRALINO, P P --> CHARGINO+ NEUTRALINO). The main content area displays three search results, each with a 'HistFactory' badge, the title, authors, journal reference, and a brief description. The first result is 'Search for flavour-changing neutral-current couplings between the top quark and the photon with the ATLAS detector at  $\sqrt{s} = 13$  TeV'. The second is 'Measurement of the  $t\bar{t}\bar{t}\bar{t}$  production cross section in  $\mu\mu$  collisions at  $\sqrt{s}=13$  TeV with the ATLAS detector'. The third is 'Observation of single-top-quark production in association with a photon using the ATLAS detector'.



# Using published likelihoods

Just a few lines of code to download the statistical model, re-run fit, make diagnostic plots

```
1 import json
2 import cabinetry
3 import pyhf
4 from cabinetry.model_utils import prediction
5 from pyhf.contrib.utils import download
6
7 # download the ATLAS bottom-squarks analysis probability models from HEPData
8 download("https://www.hepdata.net/record/resource/1935437?view=true", "bottom-squarks")
9
10 # construct a workspace from a background-only model and a signal hypothesis
11 bkg_only_workspace = pyhf.Workspace(json.load(open("bottom-squarks/RegionC/BkgOnly.json")))
12 patchset = pyhf.PatchSet(json.load(open("bottom-squarks/RegionC/patchset.json")))
13 workspace = patchset.apply(bkg_only_workspace, "sbottom_600_280_150")
14
15 # construct the probability model and observations
16 model, data = cabinetry.model_utils.model_and_data(workspace)
17
18 # produce visualizations of the pre-fit model and observed data
19 prefit_model = prediction(model)
20 cabinetry.visualize.data_mc(prefit_model, data)
21
22 # fit the model to the observed data
23 fit_results = cabinetry.fit.fit(model, data)
24
25 # produce visualizations of the post-fit model and observed data
26 postfit_model = prediction(model, fit_results=fit_results)
27 cabinetry.visualize.data_mc(postfit_model, data)
```

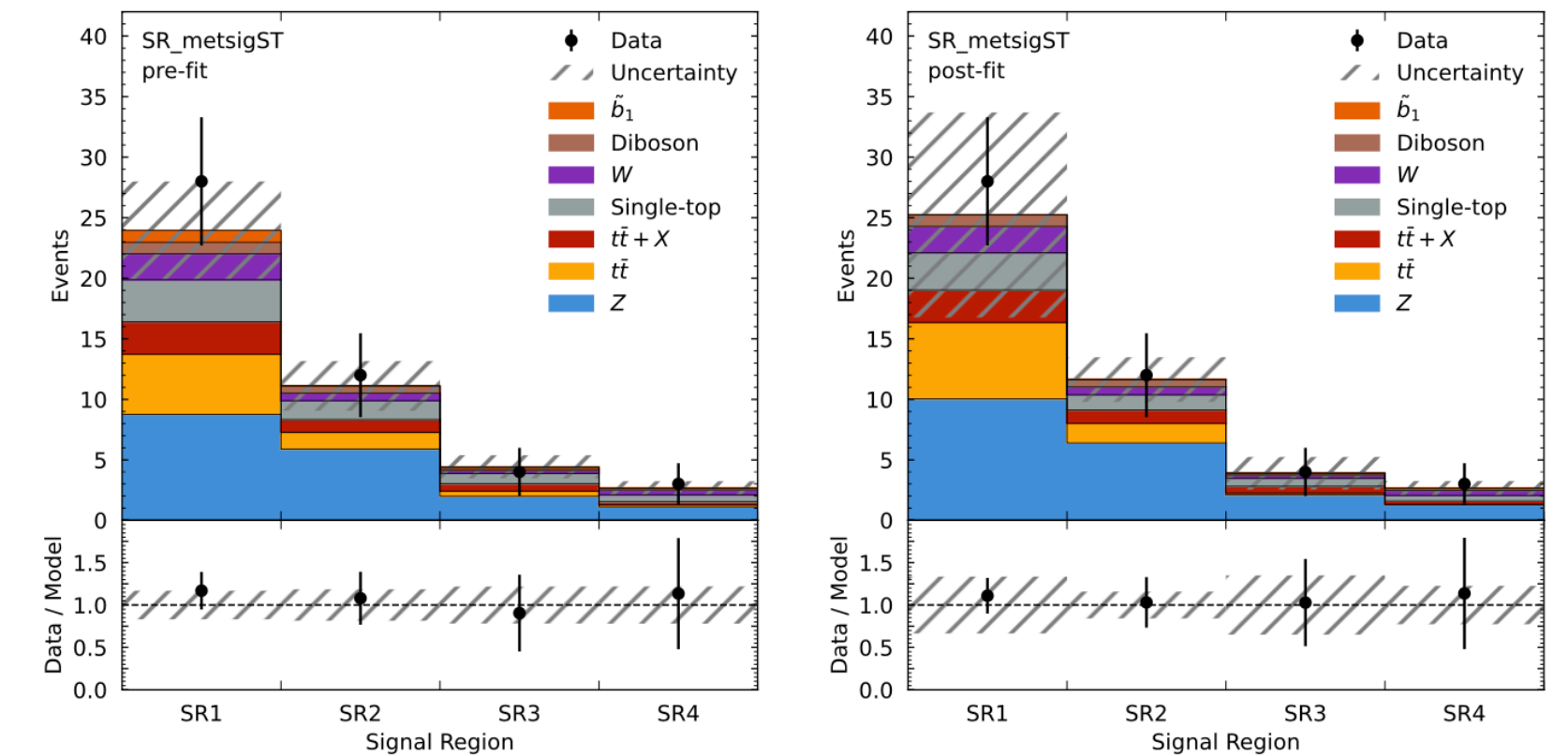
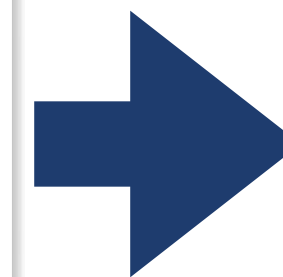
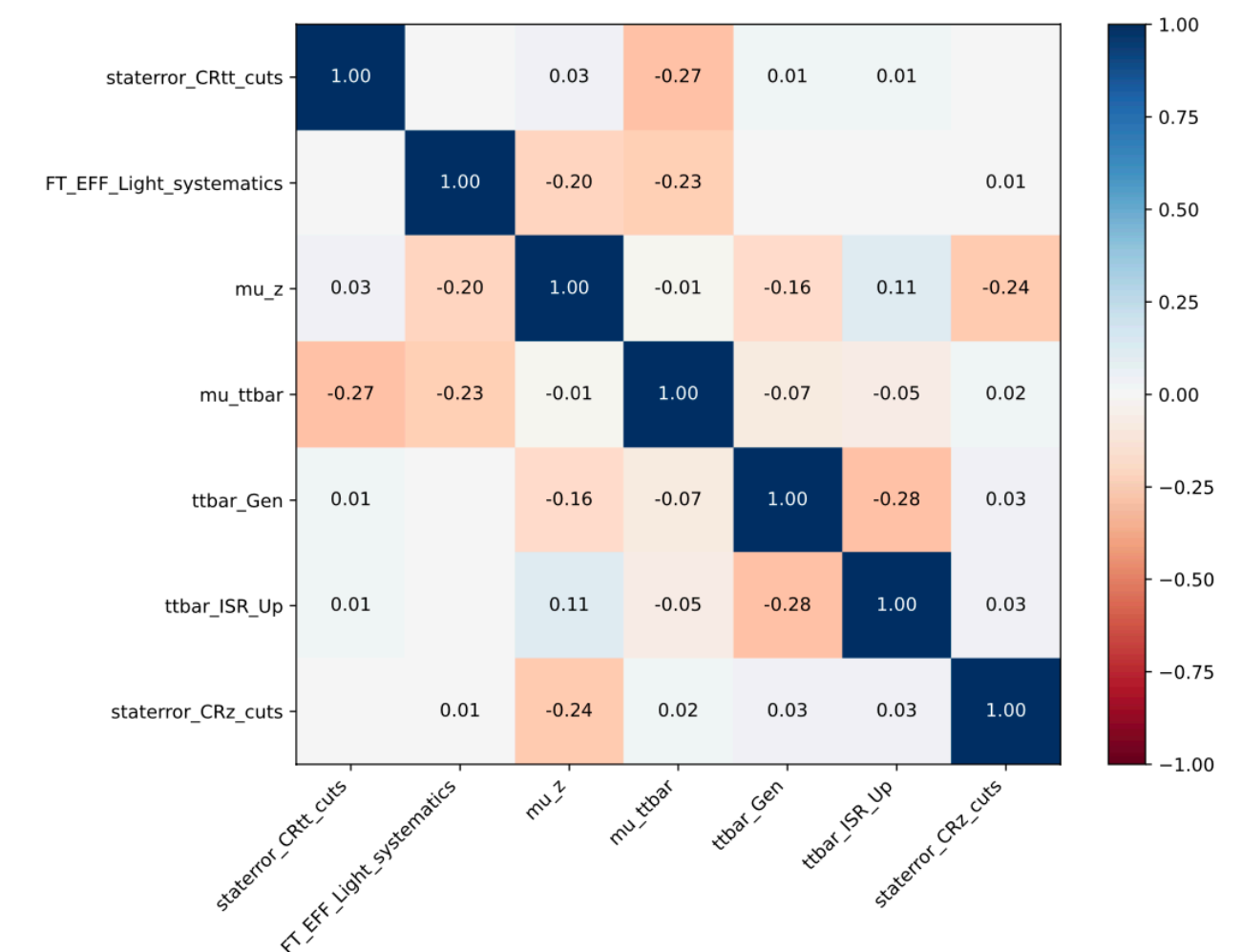


Figure 3: Pre-fit (left) and post-fit (right) visualizations of a selected signal hypothesis for four signal regions of the ATLAS search [41] of a bottom-squark of mass 600 GeV with a second-lightest neutralino of mass 280 GeV and lightest supersymmetric particle of mass 150 GeV generated from the full statistical models published in Ref. [20] using code from Ref. [40].



# Browse and interact with published statistical models

<http://hepexplorer.net>. Built by FAIROS-HEP

The screenshot displays the HEP Explorer web interface. On the left is a control panel with the following sections:

- Plots:** Radio buttons for **Histogram** (selected) and **Pull Plot**.
- Channels:** A list of channels with checkboxes: **WyCR (custom parameters)**, **SR 1fj (custom parameters)**, **ttyCR (custom parameters)**, and **SR 0fj (custom parameters)**. All are checked.
- Parameters:** A section with a sort dropdown set to **Impact**. It contains four parameter sliders, each with a value of 0 and a range from -5 to 5:
  - tW ME generator**
  - ttbar XS**
  - Lumi**
  - hfakeweight unconv 20 TOT**

On the right, four stacked histograms are shown, each with a corresponding pull plot below it. The histograms show event counts per bin, with data points (black diamonds) and various background components (stacked areas) and uncertainty bands (hatched areas). The pull plots show the ratio of data to model, with a horizontal line at 1.0 and a hatched uncertainty band.

The histograms are titled as follows:

- Top-left: **WyCR custom\_parameters** (bin range 0.0 to 1.0)
- Top-right: **SR\_1fj custom\_parameters** (bin range 0.0 to 20.0)
- Bottom-left: **ttyCR custom\_parameters** (bin range 0 to 12)
- Bottom-right: **SR\_0fj custom\_parameters** (bin range 0 to 16)

Each histogram includes a legend with the following items: **tty\_prod** (pink), **tty\_dec** (orange), **tqy\_dec** (green), **tqy** (blue), **prompt** (cyan), **hfake** (yellow), **efake** (light pink), **Zy** (red), **Wy** (teal), **FakeLeptons** (dark blue), **Uncertainty** (hatched), and **Data** (black diamonds).

# The HS3 Effort

There is now an effort to create a common serialization standard for pyhf, RooFit, BAT, zfit, etc. models

- Key idea: separate **specification** from **implementation**

## RooWorkspace $\rightleftharpoons$ JSON/YAML

**Carsten Burgard**  
huge thanks to *Nicolas Morange* and *Jonas Rembser* for their help with getting this together!  
special thanks also to the whole *pyhf* team as well as *Jonas Eschle* for valuable input

for the ROOT Users Workshop 2022

Disclaimer: This talk has an ATLAS bias!  
Disclaimer: This talk draws some inspiration from pyhf!



# HS<sup>3</sup>

## High Energy Physics

### Statistics Serialization Standard

Carsten Burgard

Tomas Dado, Jonas Eschle, Matthew Feickert, Cornelius Grunwald,  
Alexander Held, Robin Pelkner, Jonas Rembser, Oliver Schulz

 technische universität dortmund

Aug 30, 2023

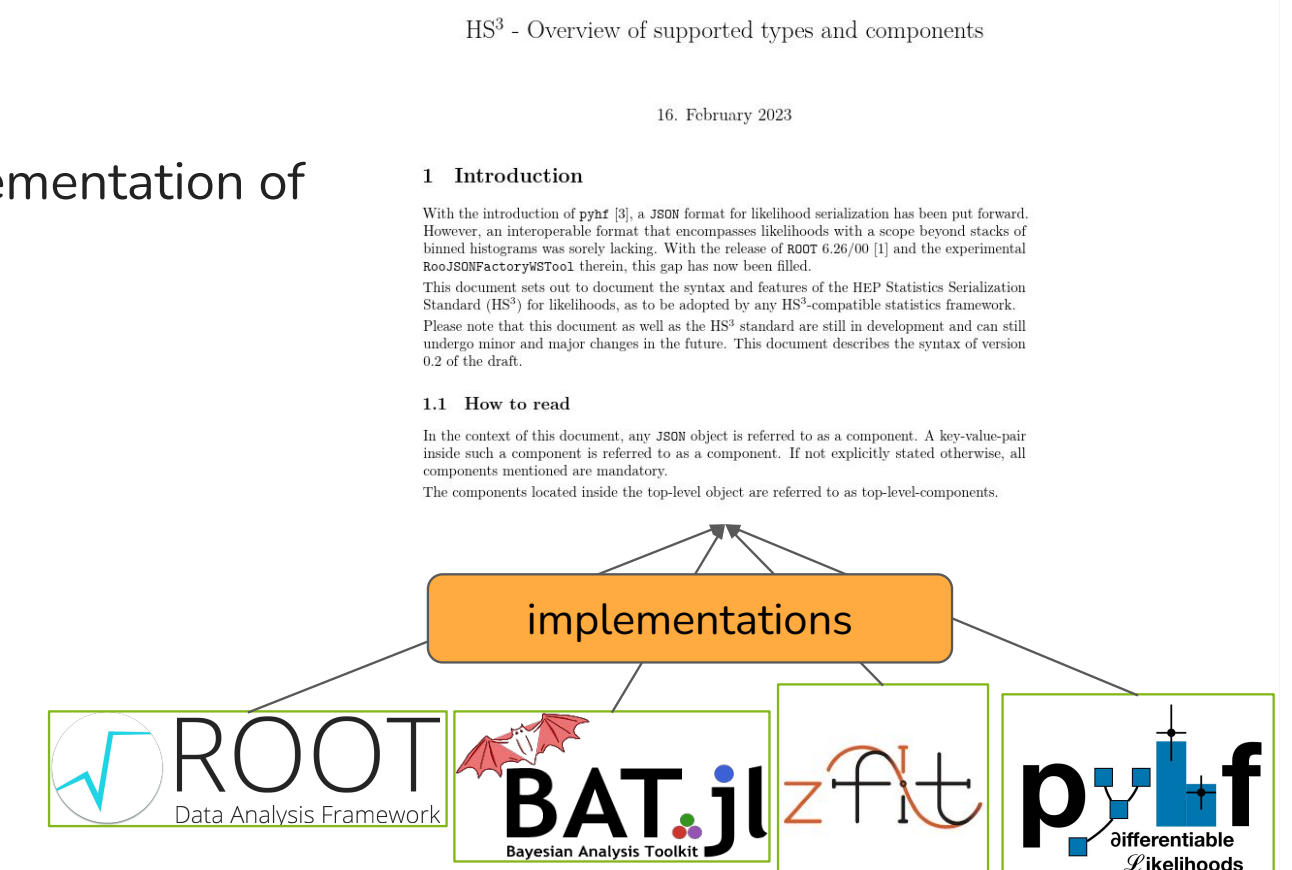
1

## HS<sup>3</sup> - HEP Statistics Serialization Standard technische universität dortmund

idea: provide standardized format for statistical models:

- human-readable, in JSON format
- machine-readable for direct implementation of statistical models
- software-independent
- generic, mathematical definitions
- full compatibility with respect to RooWorkspace and pyhf

<https://github.com/hep-statistics-serialization-standard>



Robin Pelkner (TU Dortmund)

HS<sup>3</sup> - HEP Statistics Serialization Standard

4

Talk at Reinterpretation Forum [link]

<https://indico.cern.ch/event/1264371/contributions/5338176/>

<https://videos.cern.ch/record/2296062>

<https://github.com/hep-statistics-serialization-standard>



Message 2:  
EFT-Specific Model Specification

The HistFactory **specification** is pure math with two main implementations (original C++ version in ROOT/RooFit and newer python version pyhf)

- Widely used and has *almost everything* needed for EFT

## HistFactory Template: at a glance

$$f(\text{data}|\text{parameters}) = f(\vec{n}, \vec{a}|\vec{\eta}, \vec{\chi}) = \prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb}|\nu_{cb}(\vec{\eta}, \vec{\chi})) \prod_{\chi \in \vec{\chi}} c_{\chi}(a_{\chi}|\chi)$$

$\vec{n}$ : events,  $\vec{a}$ : auxiliary data,  $\vec{\eta}$ : unconstrained pars,  $\vec{\chi}$ : constrained pars

$$\nu_{cb}(\vec{\eta}, \vec{\chi}) = \sum_{s \in \text{samples}} \underbrace{\left( \sum_{\kappa \in \vec{\kappa}} \kappa_{scb}(\vec{\eta}, \vec{\chi}) \right)}_{\text{multiplicative}} \left( \nu_{scb}^0(\vec{\eta}, \vec{\chi}) + \underbrace{\sum_{\Delta \in \vec{\Delta}} \Delta_{scb}(\vec{\eta}, \vec{\chi})}_{\text{additive}} \right)$$

**Use:** Multiple disjoint channels (or regions) of binned distributions with multiple samples contributing to each with additional (possibly shared) systematics between sample estimates

### Main pieces:

- Main Poisson p.d.f. for simultaneous measurement of multiple channels
- Event rates  $\nu_{cb}(\vec{\eta}, \vec{\chi})$  (nominal rate  $\nu_{scb}^0$  with rate modifiers)
  - encode systematic uncertainties (e.g. normalization, shape)
- Constraint p.d.f. (+ data) for "auxiliary measurements"

... but the HistFactory **specification** is not natural for describing interference effects encountered in EFTs.

- We can create / **extend the specification** to handle EFT parameter dependence

## HistFactory Template: at a glance

$$f(\text{data}|\text{parameters}) = f(\vec{n}, \vec{a}|\vec{\eta}, \vec{\chi}) = \prod_{c \in \text{channels}} \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb}|\nu_{cb}(\vec{\eta}, \vec{\chi})) \prod_{\chi \in \vec{\chi}} c_{\chi}(a_{\chi}|\chi)$$

$\vec{n}$ : events,  $\vec{a}$ : auxiliary data,  $\vec{\eta}$ : unconstrained pars,  $\vec{\chi}$ : constrained pars

$$\nu_{cb}(\vec{\eta}, \vec{\chi}) = \sum_{s \in \text{samples}} \underbrace{\left( \sum_{\kappa \in \vec{\kappa}} \kappa_{scb}(\vec{\eta}, \vec{\chi}) \right)}_{\text{multiplicative}} \left( \nu_{scb}^0(\vec{\eta}, \vec{\chi}) + \underbrace{\sum_{\Delta \in \vec{\Delta}} \Delta_{scb}(\vec{\eta}, \vec{\chi})}_{\text{additive}} \right)$$

**Use:** Multiple disjoint channels (or regions) of binned distributions with multiple samples contributing to each with additional (possibly shared) systematics between sample estimates

### Main pieces:

- Main Poisson p.d.f. for simultaneous measurement of multiple channels
- Event rates  $\nu_{cb}(\vec{\eta}, \vec{\chi})$  (nominal rate  $\nu_{scb}^0$  with rate modifiers)
  - encode systematic uncertainties (e.g. normalization, shape)
- Constraint p.d.f. (+ data) for "auxiliary measurements"

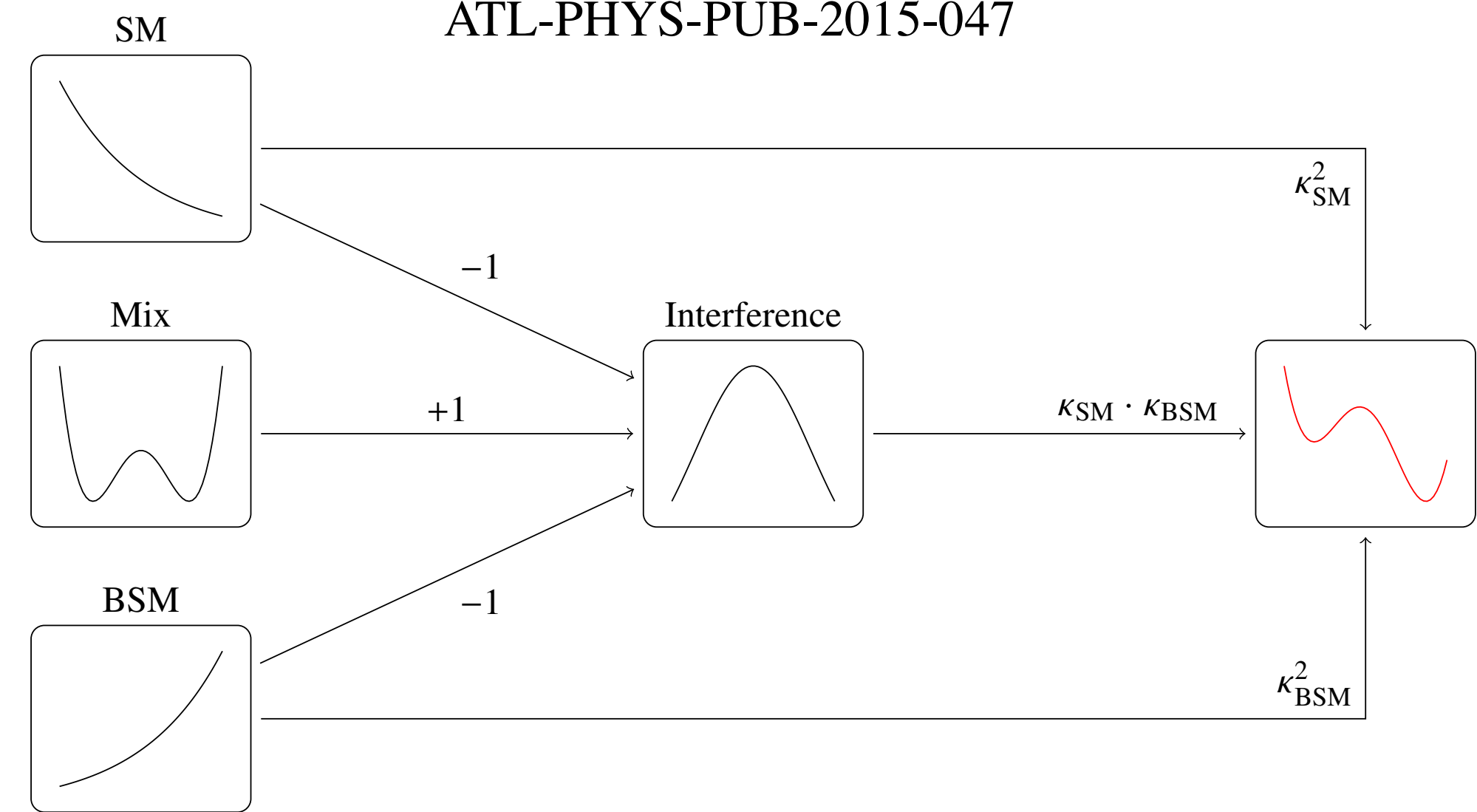
# EFT "morphing" trick

As one changes the parameters of the EFT, the distributions  $p(x|\alpha)$  change due to interference.

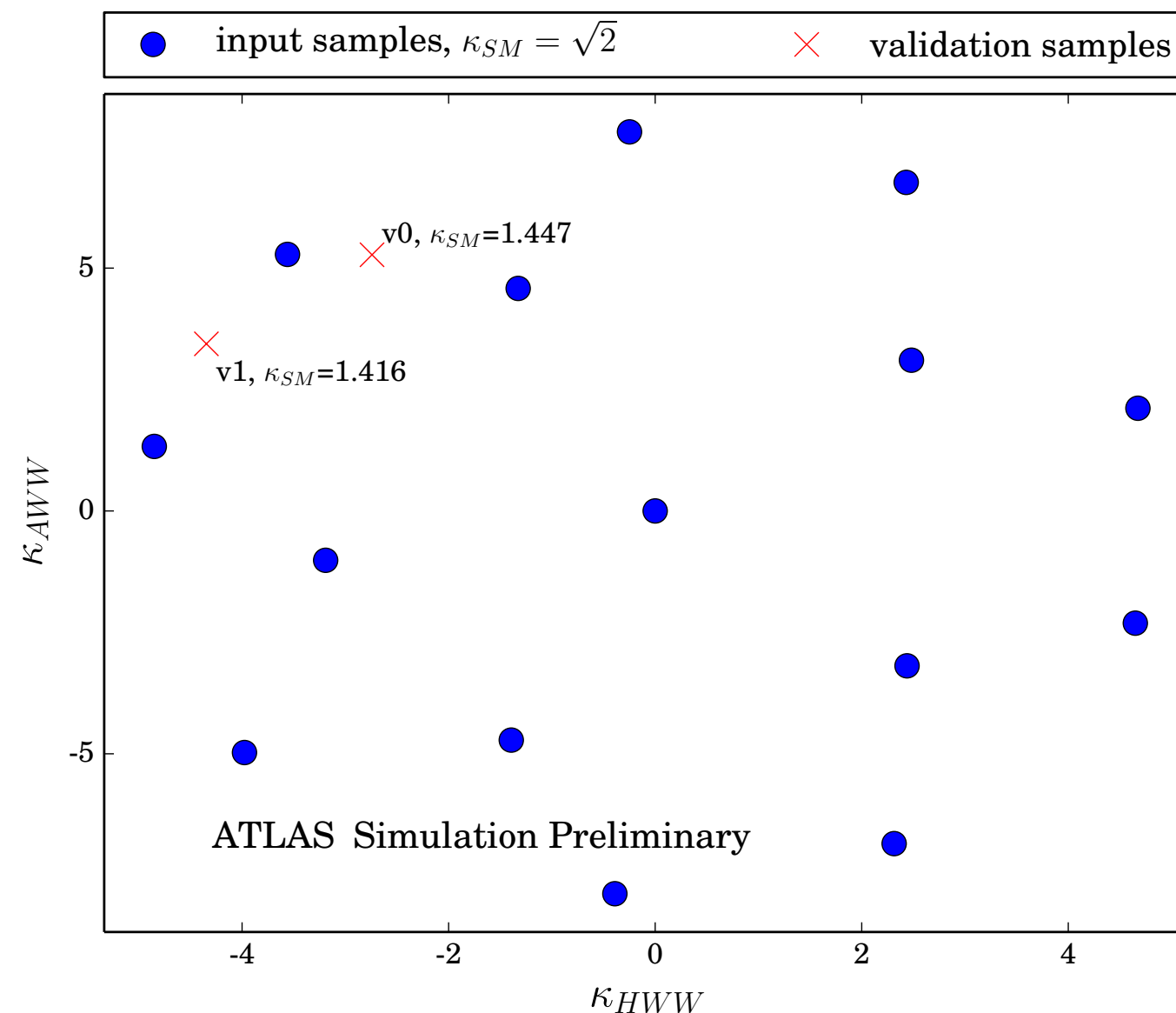
**But there is a trick:**

Simple example:

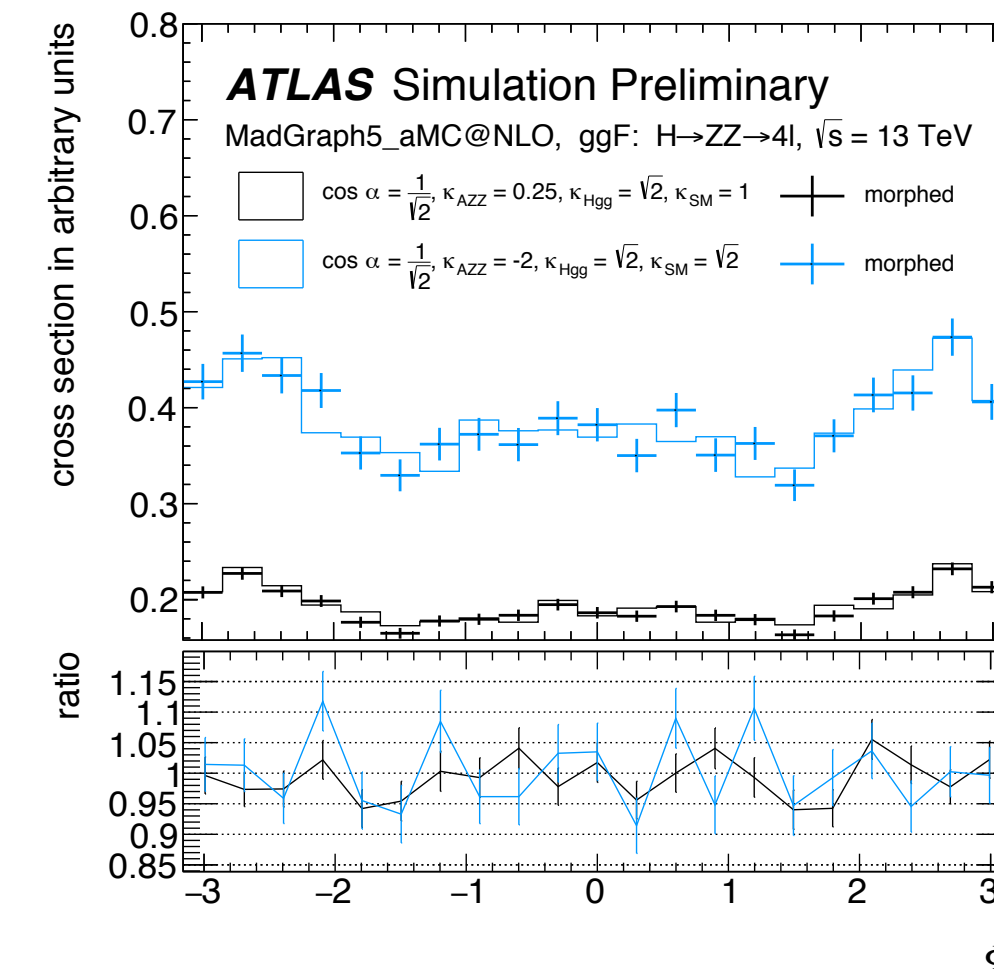
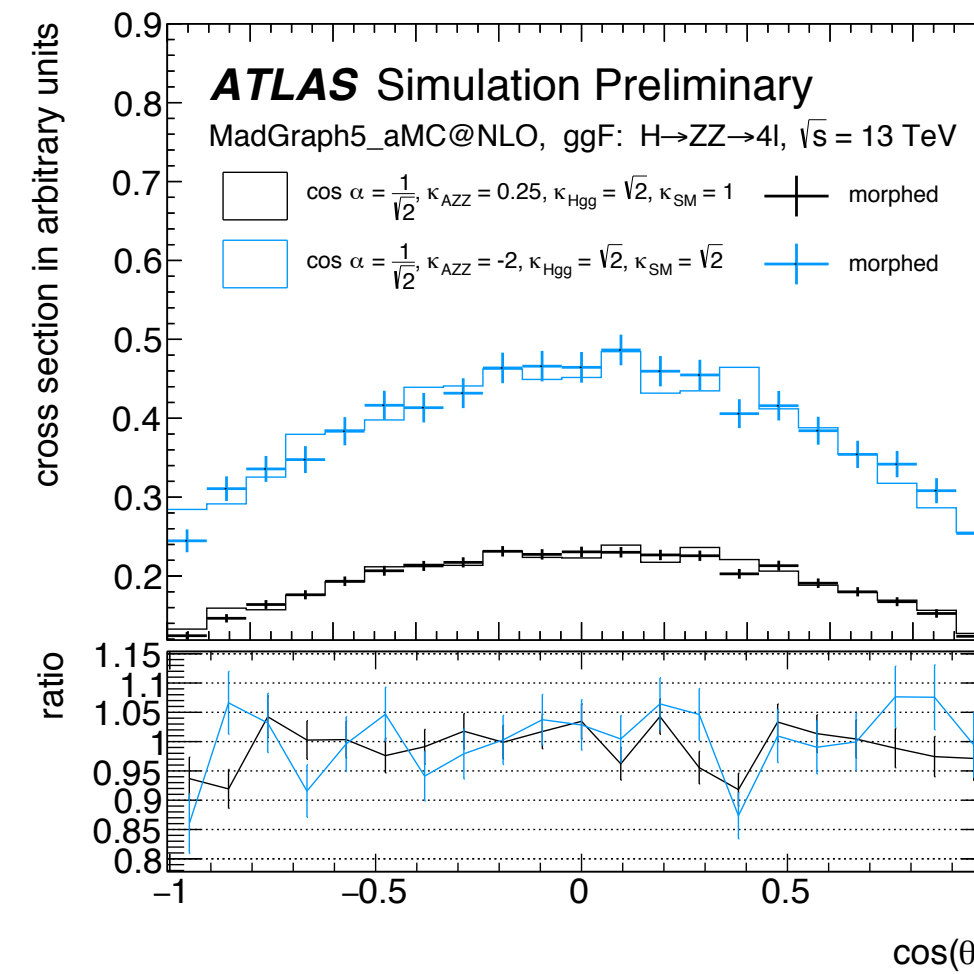
$$|g_1 M_{SM} + g_2 M_{BSM}|^2 = g_1^2 |M_{SM}|^2 + 2g_1 g_2 \text{Re}[M_{SM}^* M_{BSM}] + g_2^2 |M_{BSM}|^2$$



3-d vector space, distribution for any point in this space is linear mixture of distribution for 3 basis samples!



(real examples need more basis samples)



↑  
Physical  
Positive  
Probabilities

# EFT "morphing" trick

$$d\sigma \propto \left| \left( \mathcal{M}_{\text{SM}}^p + \sum_i \frac{f_i}{\Lambda^2} \mathcal{M}_i^p \right) \left( \mathcal{M}_{\text{SM}}^d + \sum_j \frac{f_j}{\Lambda^2} \mathcal{M}_j^d \right) \right|^2$$

Express EFT as a mixture:

$$p(x | \alpha) = \sum_c w_c(\alpha) p_c(x)$$

$w_c(\alpha)$  are polynomials,  $p_c(x)$  are physical distributions!

Can truncate to  $\mathcal{O}(\Lambda^{-n})$  if desired

Fully differential cross-section

| Process                  | Number of components for $n$ operators |                             |                             |                             |                             | $\Sigma$               |
|--------------------------|--|-----------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------|
|                          | $\mathcal{O}(\Lambda^0)$               | $\mathcal{O}(\Lambda^{-2})$ | $\mathcal{O}(\Lambda^{-4})$ | $\mathcal{O}(\Lambda^{-6})$ | $\mathcal{O}(\Lambda^{-8})$ |                        |
| $hV$ / WBF production    | 1                                      | $n$                         | $\frac{n(n+1)}{2}$          |                             |                             | $\frac{(n+1)(n+2)}{2}$ |
| $h \rightarrow VV$ decay | 1                                      | $n$                         | $\frac{n(n+1)}{2}$          |                             |                             | $\frac{(n+1)(n+2)}{2}$ |
| Production + decay       | 1                                      | $n$                         | $\frac{n(n+1)}{2}$          | $\binom{n+2}{3}$            | $\binom{n+3}{4}$            | $\binom{n+4}{4}$       |

Table 1: Number of components  $c$  as given in Eq. (6) for different processes, sorted by their suppression by the EFT cutoff scale  $\Lambda$ .

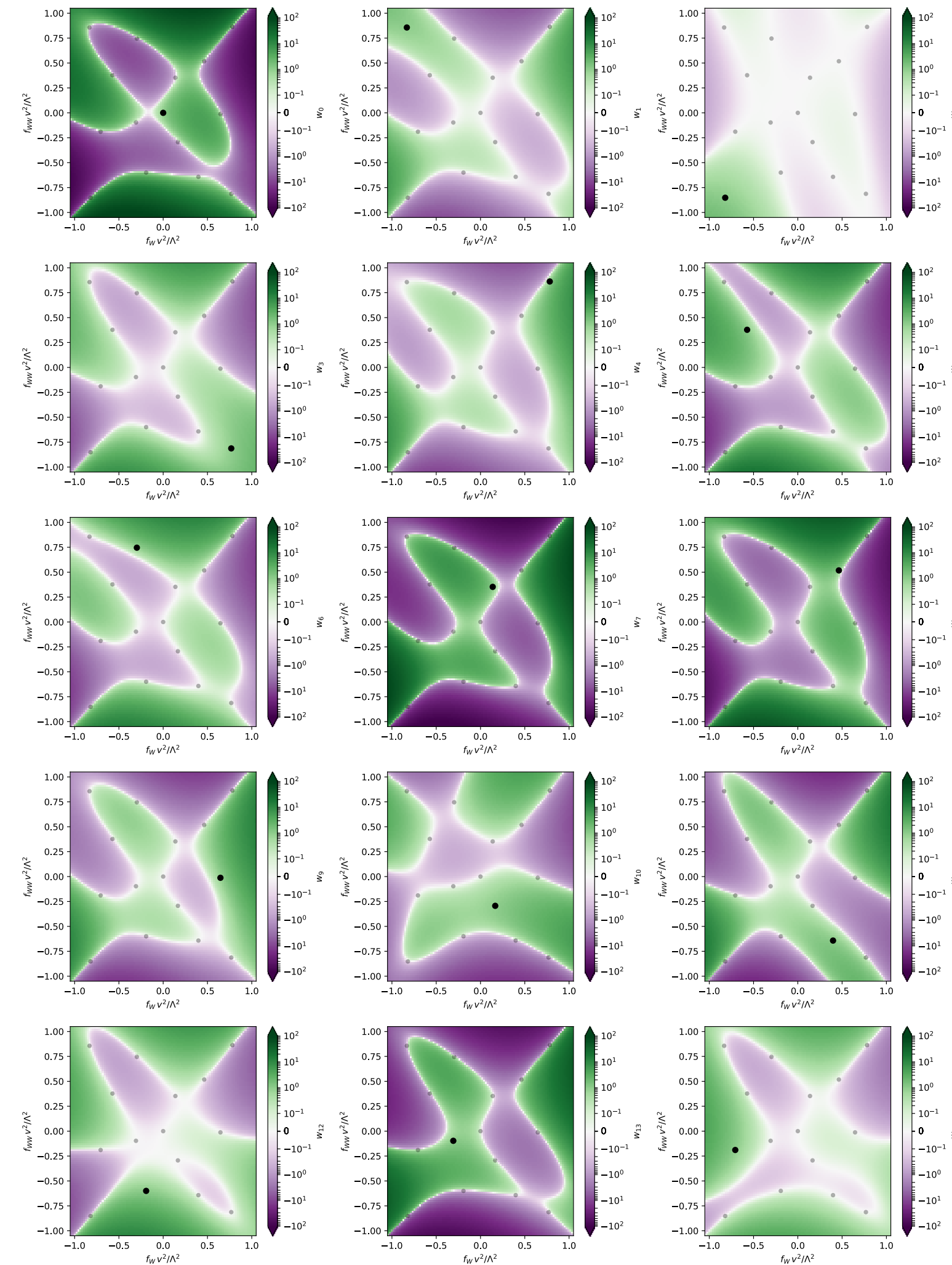


Figure 13: Morphing weights  $w_i(\theta)$  for basis points distributed over the full relevant parameter space.

For 2 BSM operators affecting VBF Higgs production and decay, we need a 15-D vector space

For 5 BSM operators we need 126-D vector space

This is implemented in MadMiner

# Other descriptions

Same idea, different in details

Here are two concrete examples for describing how the (truth-level) fiducial cross section in phase space region  $k'$  depends on the EFT coefficients  $\alpha = \{c_j\}$

- Can extend to fully differential cross-section  $\left. \frac{d\sigma(\alpha)}{dz} \right|_{z_i}$  where  $z_i$  is the truth-level kinematics
- Used in MadMiner for Simulation-based inference

### 3.1.3 Cross-section calculation with linear and quadratic terms

The SMEFT prediction including the available terms proportional to  $\Lambda^{-4}$  is:

$$(\sigma \times B)_{\text{SMEFT}}^{i,k',H \rightarrow X} = (\sigma \times B)_{\text{SM},((N)N)\text{NLO}}^{i,k',H \rightarrow X} \left( 1 + \sum_j A_j^{\sigma_{i,k'}} c_j + \sum_j B_j^{\sigma_{i,k'}} c_j^2 + \dots \right) \quad (13)$$

### 3.1.2 Cross-section

In a scenario where the partial width and Wilson coefficients are given by Eqs. (8)–(10), the

$$(\sigma \times B)_{\text{SM}}^{i,k',H \rightarrow X}$$

**When EFT for new physics is not linear**

Speaker: Duarte Fontes

Presentation.pdf

**Which orders**

Speaker: Adam Orion Martin (University of Notre Dame (US))

Martin\_ND\_EFT.pdf

**Truncation and validity**

Speaker: William Shepherd

LPC\_EFT\_0423.pdf

LPC\_EFT\_0423.pptx

$$= (\sigma \times B)_{\text{SM},((N)N)\text{NLO}}^{i,k',H \rightarrow X} \times \left( 1 + \sum_j A_j^{\sigma_{i,k'}} c_j \right) \times \left( \frac{1 + \sum_j A_j^{\Gamma_{H \rightarrow X}} c_j}{1 + \sum_j A_j^{\Gamma_H} c_j} \right), \quad (12)$$

$$= (\sigma \times B)_{\text{SM},((N)N)\text{NLO}}^{i,k',H \rightarrow X} \times \left( \frac{1 + \sum_j (A_j^{\sigma_{i,k'}} + A_j^{\Gamma_{H \rightarrow X}}) c_j + O(\Lambda^{-4})}{1 + \sum_j A_j^{\Gamma_H} c_j + O(\Lambda^{-4})} \right), \quad (12)$$

# Extending template specifications for EFT fits

This was done by Belle II

- Subject of my talk at LHC EFT WG, with some more details about “on-the-fly” reweighting

Focus of LHC EFT effort should be to converge on the specification(s).

A model-independent likelihood function for the Belle II  $B^+ \rightarrow K^+ \nu \bar{\nu}$  analysis

Lorenz Gärtner<sup>1,2</sup> on behalf of Belle II,  
in collaboration with  
Danny van Dyk<sup>3</sup>, Lukas Heinrich<sup>2,4</sup>, Mériel Reboud<sup>3</sup>

<sup>1</sup>LMU Munich, <sup>2</sup>Excellence Cluster ORIGINS,  
<sup>3</sup>IPPP Durham, <sup>4</sup>TU Munich

30.08.2023

Implementation

**EOS**  
eos.github.io

- Calculate theoretical predictions
- Theory parameters: Wilson coefficients & hadronic parameters

**pyhf**  
differentiable Likelihoods  
pyhf.readthedocs.io

- Built a "custom modifier" that generates new signal template from theory parameters.
- Theory parameters become fitting parameters.

L. Gärtner (LMU) RIF 2023 30.08.2023 14 / 18

## Summary

- **Challenge:** Neutrino-induced experimental complexities in  $B^+ \rightarrow K^+ \nu \bar{\nu}$  lead to model-dependent results due to kinematic assumptions and hadronic matrix element description.
- **Solution:** A model-independent likelihood function enables maximum likelihood fits for any given (B)SM signal prediction, using the supplied information about the  $q^2$  distribution.
- **Tool integration:**
  - Extend **pyhf** and interface it with **EOS** for run-time template updating.
  - Method fully applicable to other decay channels and results.
- **Benefits:**
  - **Exploration of exclusions in BSM parameter space.**
  - Individual model studies with provided decay rate predictions.
  - ...
- **Significance:** Publishing such likelihoods is crucial for a full exploitation of experimental results.

lorenz.gaertner@physik.uni-muenchen.de

L. Gärtner (LMU) RIF 2023 30.08.2023 18 / 18

## A PRACTICAL FRAMEWORK OF EFT FITS WITH PUBLISHED LIKELIHOODS

**@KyleCranmer**  
University of Wisconsin-Madison  
Data Science Institute  
Physics, Computer Science, Statistics

Message 3:  
Extensible EFT reinterpretation with  
RECAST infrastructure



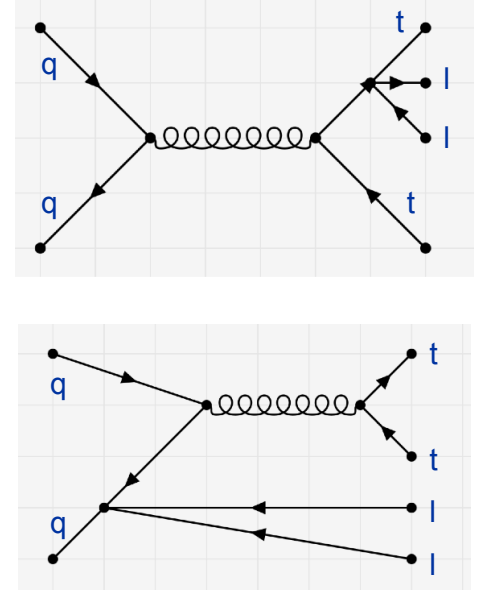
# Extending the EFT reinterpretation

This morning, Sergio covered motivations and strategies for incorporating changes at a lower level (new EFT operators, changes to sig/bkg models, etc.) keeping the analysis strategy (event selection, observables, etc.) fixed

- Update signal / background components & export a new statistical model

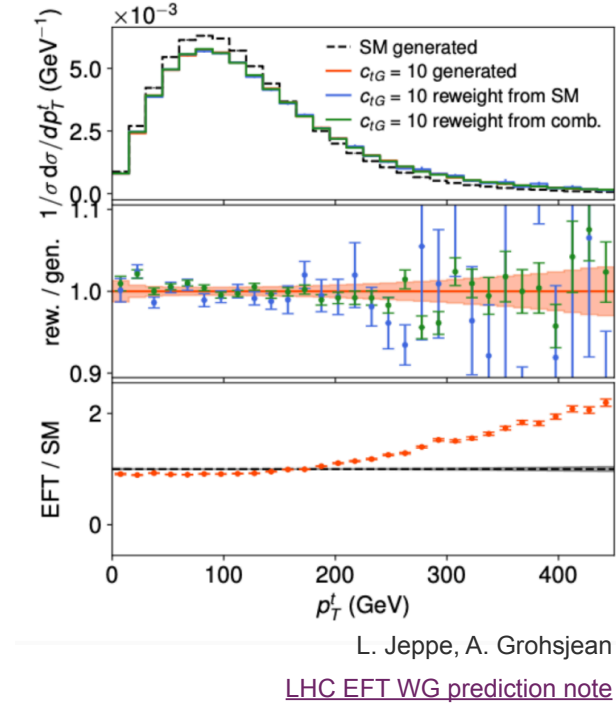
### Why would we want to incorporate changes?

- **Expand the interpretation**
  - Analyses are performed for a fixed set of WCs (typically one sector, say, "top physics")
  - (Global) combinations may be interested in a superset of those
- **"Promote" backgrounds to signals**
  - Consider EFT effects on the background
- **Updated signal/background models**
  - More precise calculations will necessarily appear
- **Inside the collaborations it is often possible to assess these problems**
- **Predictions can only be updated by running the analysis code**
  - Communication among theorists and experimentalists is of utmost importance!!



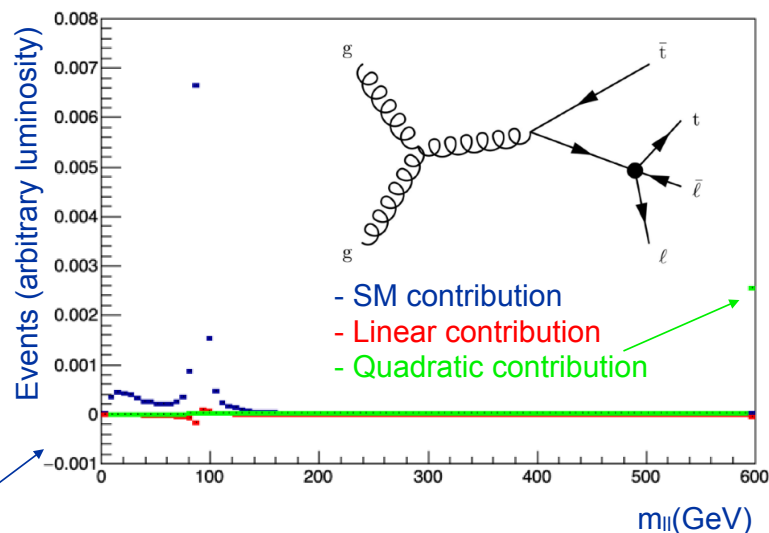
### Post-generation reweighting

- Samples can be reweighted after the generation
  - Conceptually the same to what reco-level analyses typically do already
  - Reweighting needs to be carefully validated
    - Phase space is not guaranteed to be fully covered
    - These validations are "standard" when designing the analysis → generation point can be tuned
    - Not guaranteed when adding new operators
    - In practice, helicity-ignorant reweighting works better for many use-cases (see next slide)
- Procedure straightforward for EFT effects → those are evaluated at parton level



### If everything else fails: full simulation

- Full simulation is expensive may be the last resort in some cases
- Simulating SM + EFT contribution requires significant resources
  - O(1B) ttbar events are used for Run 2 measurements
- In Madgraph is possible to produce samples with including only (some of) the EFT contributions
- Example of SM, linear and quadratic terms simulated with three independent samples
  - May be even useful beyond reinterpretations



In BSM context, this is often referred to as "recasting" and we have built infrastructure to do this

# Preservation & Reinterpretation

First results using the RECAST reinterpretation framework and publishing full statistical likelihoods (using pyhf) in 2019

- Recent pMSSM effort uses 10 searches, 19 parameter pMSSM, and 20,000 parameter points



ATLAS PUB Note  
ATL-PHYS-PUB-2019-029  
5th August 2019



## Reproducing searches for new physics with the ATLAS experiment through publication of full statistical likelihoods

The ATLAS Collaboration

The ATLAS Collaboration is starting to publicly provide likelihoods associated with statistical fits used in searches for new physics on HEPData. These likelihoods adhere to a specification first defined by the HistFactory p.d.f. template. This note introduces a JSON schema that fully describes the HistFactory statistical model and is sufficient to reproduce key results from published ATLAS analyses. This is per-se independent of its implementation in ROOT and it can be used to run statistical analysis outside of the ROOT and RooStats/RooFit framework. The first of these likelihoods published on HEPData is from a search for bottom-squark pair production. Using two independent implementations of the model, one in ROOT and one in pure Python, the limits on the bottom-squark mass are reproduced, underscoring the implementation independence and long-term viability of the archived data.

ATL-PHYS-PUB-2019-029  
05 August 2019



ATLAS PUB Note  
ATL-PHYS-PUB-2019-032  
11th August 2019



## RECAST framework reinterpretation of an ATLAS Dark Matter Search constraining a model of a dark Higgs boson decaying to two $b$ -quarks

The ATLAS Collaboration

The reinterpretation of a search for dark matter produced in association with a Higgs boson decaying to  $b$ -quarks performed with RECAST, a software framework designed to facilitate the reinterpretation of existing searches for new physics, is presented. Reinterpretation using RECAST is enabled through the sustainable preservation of the original data analysis as re-executable declarative workflows using modern cloud technologies and integrated with the wider CERN Analysis Preservation efforts. The reinterpretation targets a model predicting dark matter production in association with a hypothetical dark Higgs boson decaying into  $b$ -quarks where the mass of the dark Higgs boson  $m_\chi$  is a free parameter, necessitating a faithful reinterpretation of the analysis. The dataset has an integrated luminosity of  $79.8 \text{ fb}^{-1}$  and was recorded with the ATLAS detector at the Large Hadron Collider at a centre-of-mass energy of  $\sqrt{s} = 13 \text{ TeV}$ . Constraints on the parameter space of the dark Higgs model for a fixed choice of dark matter mass  $m_\chi = 200 \text{ GeV}$  exclude model configurations with a mediator mass up to  $3.2 \text{ TeV}$ .

ATL-PHYS-PUB-2019-032  
12 August 2019

# ENERGY FRONTIERS

Reports from the Large Hadron Collider experiments

ATLAS

## Electroweak SUSY after LHC Run 2

Supersymmetry (SUSY) provides elegant solutions to many of the problems of the Standard Model (SM) by introducing new boson/fermion partners for each SM fermion/boson, and by extending the Higgs sector. If SUSY is realised in nature at the TeV scale, it would accommodate a light Higgs boson without excessive fine-tuning. It could furthermore provide a viable dark-matter candidate, and be a key ingredient to the unification of the electroweak and strong forces at high energy. The SUSY partners of the SM bosons can mix to form what are called charginos and neutralinos, collectively referred to as electroweakinos.

Electroweakinos would be produced only through the electroweak interaction, where their production cross sections in proton-proton collisions are orders of magnitude smaller than strongly produced squarks and gluinos (the supersymmetric partners of quarks and gluons). Therefore, while extensive searches using the Run 1 (7–8 TeV) and Run 2 (13 TeV) LHC datasets have turned up null results, the corresponding chargino/neutralino exclusion limits remain substantially weaker than those for strongly interacting SUSY particles.

The ATLAS collaboration has recently released a comprehensive analysis of the electroweak SUSY landscape based on its Run 2 searches. Each individual search targeted specific chargino/neutralino production mechanisms and subsequent decay modes. The analyses were originally interpreted in so-called “simplified models”, where only one production mechanism is considered, and only one possible decay. However, if SUSY is realised in nature, its particles will have many possible production and decay modes, with rates depending on the SUSY parameters. The new ATLAS analysis brings these pieces together by reinterpreting 10 searches in the phenomenological Minimal Supersymmetric Standard Model (pMSSM), which includes a range of SUSY particles, production mechanisms and decay modes governed by 19 SUSY parameters. The results provide a global picture of ATLAS’s sensitivity to electroweak SUSY and, importantly, reveals the gaps that

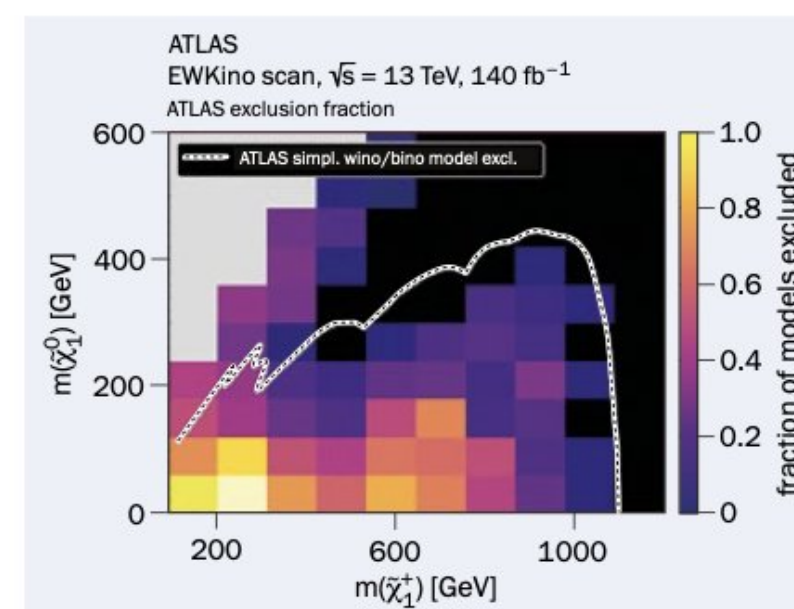


Fig. 1. The fraction of pMSSM models excluded by ATLAS in the plane of the lightest chargino mass (x-axis) versus the lightest neutralino mass (y-axis). The dashed line shows the exclusion of simplified SUSY models reported by individual searches in this mass plane.

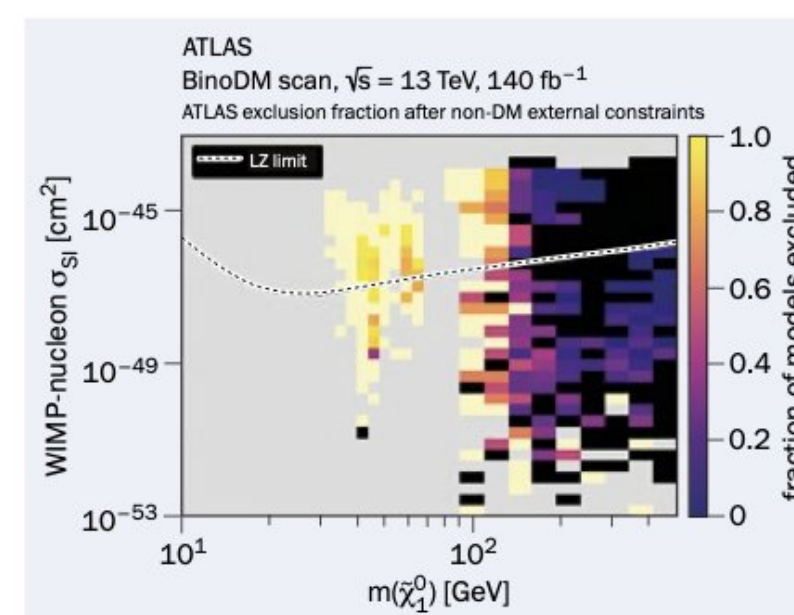


Fig. 2. The fraction of pMSSM models excluded by ATLAS in the plane of the lightest neutralino (i.e. the dark-matter candidate) mass (x-axis) versus the spin-independent WIMP-nucleon scattering cross-section (y-axis). The dashed line shows the upper limits from the LZ experiment.

remain to be explored.

The 19-dimensional pMSSM parameter space was randomly sampled to produce a set of 20,000 SUSY model points. The 10 selected ATLAS searches were then performed on each model point to determine whether it is excluded with at least 95% confidence level. This involved simulating datasets for each

SUSY model, and re-running the corresponding analyses and statistical fits. An extensive suite of reinterpretation tools was employed to achieve this, including preserved likelihoods and RECAST – a framework for preserving analysis workflows and re-applying them to new signal models.

The results show that, while electroweakino masses have been excluded up to 1 TeV in simplified models, the coverage with regard to the pMSSM is not exhaustive. Numerous scenarios remain viable, including mass regions nominally covered by previous searches (inside the dashed line in figure 1). The pMSSM models may evade detection due to smaller production cross-sections and decay probabilities compared to simplified models. Scenarios with small mass splittings between the lightest and next-to-lightest neutralino can reproduce the dark-matter relic density, but are particularly elusive at the LHC. The decays in these models produce challenging event features with low-momentum particles that are difficult to reconstruct and separate from SM events.

Beyond ATLAS, experiments such as LZ aim at detecting relic dark-matter particles through their scattering by target nuclei. This provides a complementary probe to ATLAS searches for dark matter produced in the LHC collisions. Figure 2 shows the LZ sensitivity to the pMSSM models considered by ATLAS, compared to the sensitivity of its SUSY searches. ATLAS is particularly sensitive to the region where the dark-matter candidate is around half the Z/Higgs-boson mass, causing enhanced dark-matter annihilation that could have reduced the otherwise overabundant dark-matter relic density to the observed value.

The new ATLAS results demonstrate the breadth and depth of its search programme for supersymmetry, while uncovering its gaps. Supersymmetry may still be hiding in the data, and several scenarios have been identified that will be targeted, benefiting from the incoming Run 3 data.

Further reading

ATLAS Collab. 2024, arXiv:2402.01392.

# A RECAST-like service for EFTs

Consider the case where ATLAS and CMS publish statistical models parametrized for some subset of operators in a specified EFT basis.

- **Sometime later** one wants to reinterpret the analysis for **a different set of operators** keeping the same event selection, breakdown of signal and control regions, observables, binning, etc.

RECAST is a framework for reinterpretations like this for BSM searches

- In general, this requires running new signal through the full MC simulation + reco + analysis chain. ATLAS is actually doing this with preserved analysis workflows!

In most cases for EFTs we can simply **reweight the existing fully simulated SM events** (doesn't require running more simulation, reconstruction, etc.)

- The service could calculate the coefficients for the mini-database based on truth-level kinematics and export a new statistical model that implements the specification as describe above.

FAIROS-HEP

# What is FAIROS-HEP?



Recently, the US National Science Foundation funded a new Research Coordination Network project titled "FAIROS-HEP".

**FAIROS** = **F**indable. **A**ccessible. **I**nteroperable. **R**eusable. **O**pen **S**cience.

The FAIROS-HEP project aims to connect groups of researchers thinking about FAIR data in HEP and other experts in this field to envision a more **cohesive infrastructure** around **data and publications** in HEP.

- By focusing on FAIR data practices and how data and software can be linked to physics results, we hope to build a network of researchers thinking about how we can create a "living publication" to preserve and extend physics results.
- The project includes **some funding for building infrastructure** as well as future **workshops connecting groups**.

# FAIROS-HEP Continues a Legacy of Contributions

## DASPOS (2012-2016)

- <https://daspos.crc.nd.edu/>
- Contributions to **RECAST** led to **REANA** as a spinoff project now led by CERN
- Supported REANA Common Workflow Language

## DIANA-HEP (2015-2021)

- <https://diana-hep.org/>
- Contributions to **REANA**, **RECAST**, launched **pyhf likelihood publishing**, early work in **simulation-based inference**, Active Learning for reinterpretation
- Supported GitHub -> Zenodo DOI minting

## IRIS-HEP (2018-?)

- <https://iris-hep.org/>
- Major contributions to likelihood publishing, **HEPData** integration,

## SCAILFIN (2018-2021)

- <https://scailfin.github.io/>
- Contributions to REANA (Slurm and HPC backends, applications built on top of REANA), Active Learning for reinterpretation

## FAIROS-HEP (2022-2025)

- <https://fairos-hep.org/>
- **Continue the legacy of contributions, help coordinate the ecosystem**

# Conclusion

**Top Level Message:** We should publish the full statistical model (aka “likelihood”) for measurements that constrain EFT coefficients

- Lots of progress in publishing statistical models recently in BSM searches

**Second Level Message:** There are a few ways to describe the dependence on EFT parameters. We can and should separate the specification and implementation.

- First define a **specification** for one or more of these choices that removes all ambiguity. This allows multiple groups to **implement** the specification.

**Third Level Message:** In addition to publishing statistical models, RECAST-like infrastructure would allow us to consider new EFT operators and update / improve background modeling after publishing

- This infrastructure is being used in BSM searches already

**Bonus:** The FAIROS-HEP project has funds to support (travel to) workshops to coordinate the design of this infrastructure.

## PHYSTAT-SBI 2024 - Simulation Based Inference in Fundamental Physics

15–17 May 2024  
Max Planck Institute for Physics  
Europe/Zurich timezone

- Overview
- Call for Abstracts
- Timetable
- My Conference
- My Contributions
- Registration
- Participant List
- Videoconference
- Practical Information

Fueled by the recent advances of Machine Learning in the last decade, a new breed of techniques have been developed to tackle statistical inference problems for "likelihood-free" cases, where it is possible to sample from the data-generating process (i.e. via stochastic simulators) but a closed form evaluation of the density is intractable.

This group of methods is known as "simulation-based inference" (SBI) or "likelihood-free inference" (LFI) and will be the dedicated topic of this PHYSTAT Workshop taking place from May 15th - May 17th 2024 at the Max-Planck Institute for Physics (MPP) in Garching near Munich.

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- Noemi Montel (U of Amsterdam)
- Jakub Tomczak (Eindhoven)
- Christoph Weniger (GRAPPA)
- Alexander Held (U Wisconsin-Madison)



# Backup & Referees

# Related talks

## Talk at Higgs 2020

- <https://indico.cern.ch/event/900384/contributions/3796227/>
- Unfolding vs. simplified likelihoods vs. full statistical models
- STXS vs. Fully differential
- Simulation-based inference

## Talk at LHC EFT WG in 2023

- <https://indico.cern.ch/event/1296757/>
- Full statistical models and on-the-fly reweighting

## Recasting through reweighting

By [Kyle Cranmer](#), [Lukas Heinrich](#)

physics reinterpretation lhc

*Recasting* refers to reinterpreting the results of searches for new particles or standard model measurements in the context of different theoretical models [1]. The fundamental task is to replace the original hypothesis  $p_0(x)$  with a new hypothesis  $p_1(x)$ , where  $x$  is some observed quantity. The effect of the detector response and analysis cuts can be encoded in a *folding* operator  $\int W(x|z)dz$  acting on the truth-level distribution  $p(z)$ . By keeping the analysis fixed,  $W(x|z)$  does not change, thus recasting amounts to:

$$p_0(x) = \int p_0(z)W(x|z)dz \implies p_1(x) = \int p_1(z)W(x|z)dz$$

There are two primary approaches:

- **folding:** Samples from  $p_1(z)$  are run through a detector simulation and analysis chain to estimate  $p_1(x)$  [2]. This is common when  $z$  is high-dimensional,  $p_0(z)$  and  $p_1(z)$  are very different, or  $W(x|z)$  is sensitive to experimental details.
- **unfolding:** An alternate theory  $p_1(z)$  is compared directly to an unfolded distribution  $\hat{p}(z)$  obtained from applying an approximate inverse operation to the observed data. Typically, unfolding is restricted to low-dimensional  $x, z$  and Gaussian uncertainties.

We point out a third option

- **reweighting:** Reweight pre-folded events  $(x_i, z_i) \sim p_0(x, z)$  by the factor  $r(z_i) = p_1(z_i)/p_0(z_i)$ , as in

$$p_1(x) = \int p_1(z)W(x|z)dz = \int p_0(z) \underbrace{\frac{p_1(z)}{p_0(z)}}_{\text{reweighting}} W(x|z)dz$$

This approach does not require simulating new events or the approximations used in unfolding. Note, sample variance becomes a problem if  $r(z_i) \gg 1$ .

 Sign in with ORCID

### Authors

[Kyle Cranmer](#), [Lukas Heinrich](#)

### Metadata

DOI <https://doi.org/10.5281/zenodo.1013926>

Published: 14 Oct, 2017



Exceprts from  
Simulation-Based Inference

# Conclusion

Likelihood fits in the data space are the gold standard for statistical inference

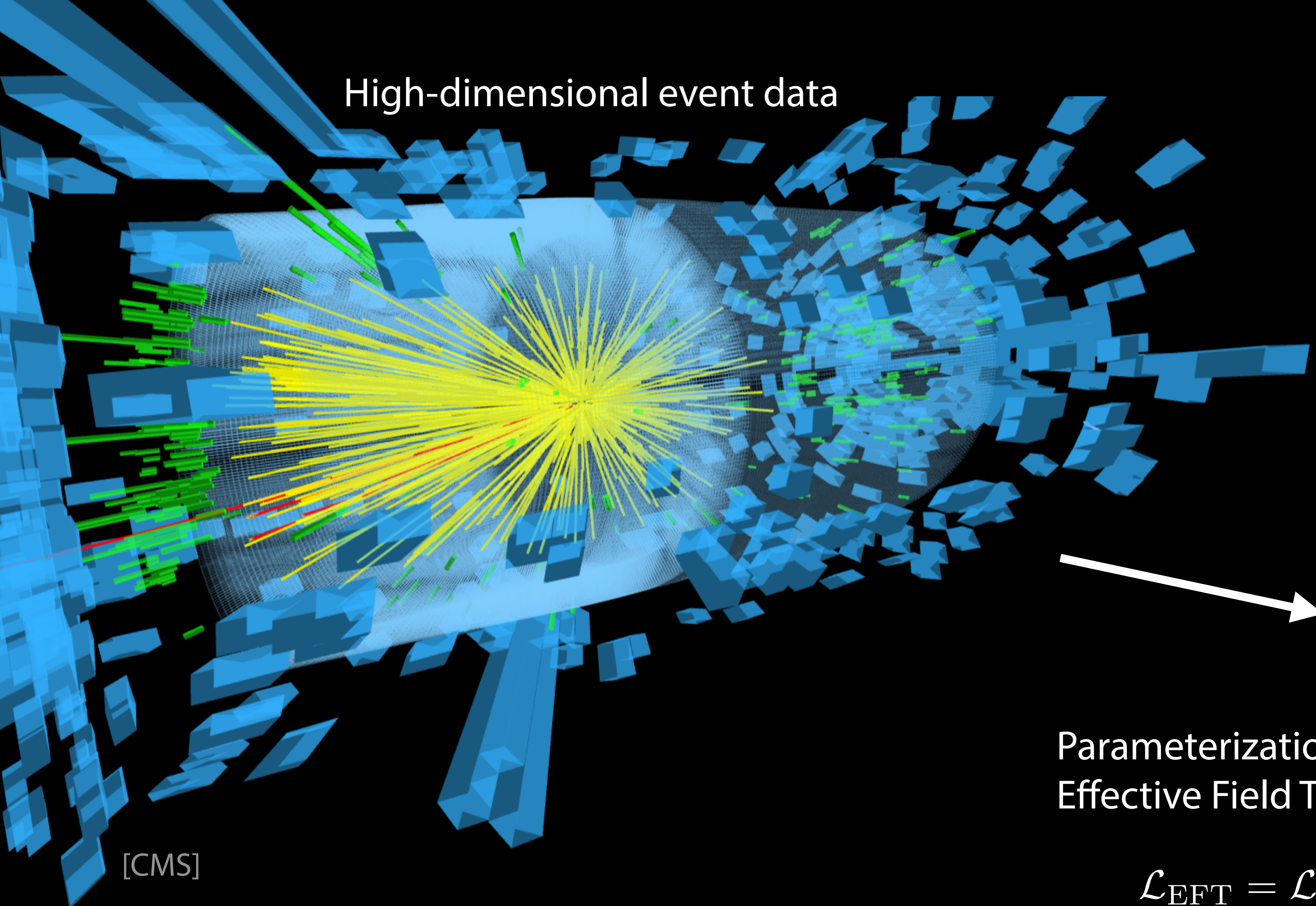
- RECAST and likelihood publishing are technical solutions that address model dependence and the theory-experiment interface
- STXS a good step, but more differential information can lead to large gain in sensitivity

Properties we want

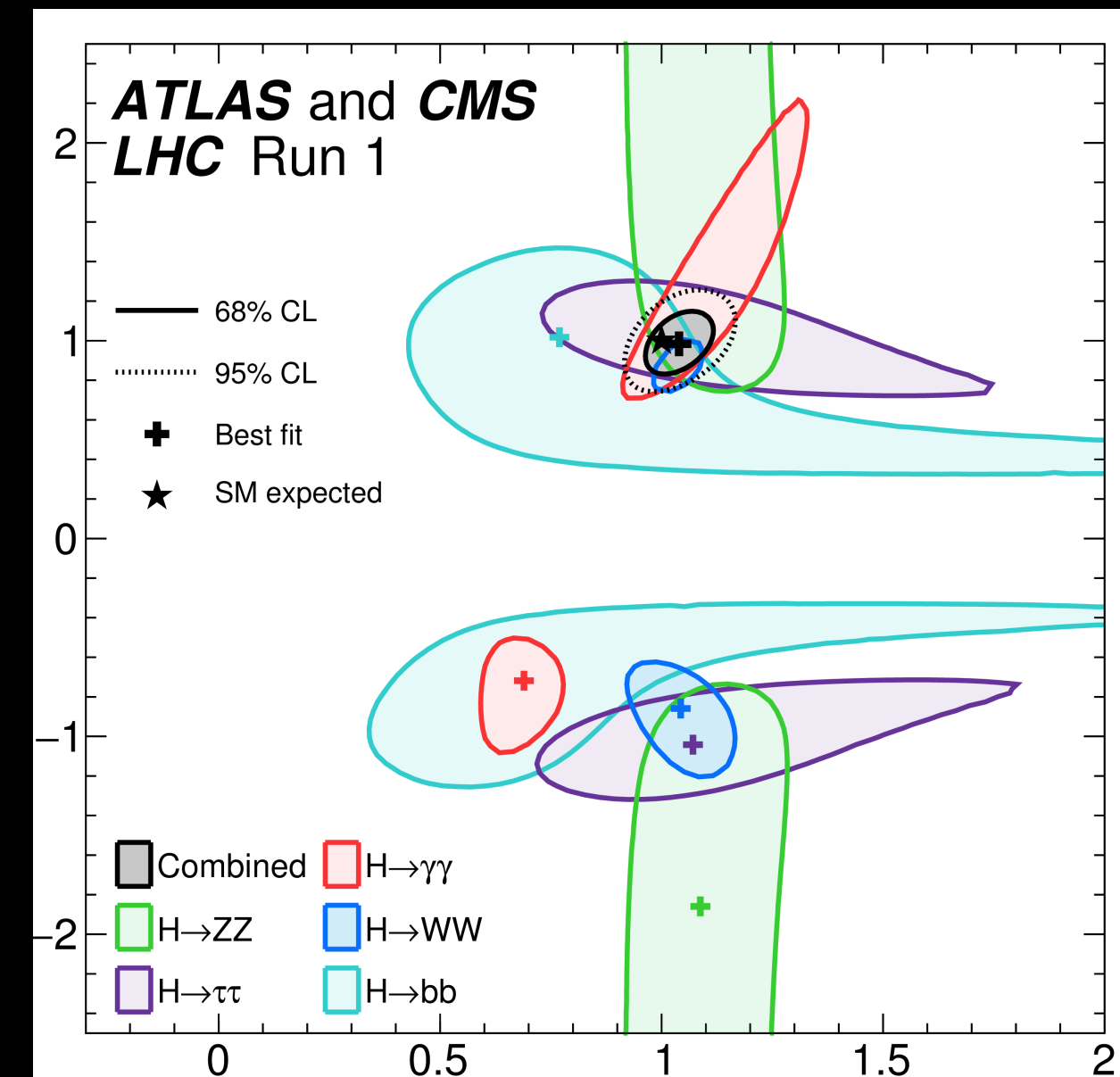
- Ability to be fully differential
- Exploit highest fidelity simulation (QCD, detector simulation) without approximations that introduce additional systematic errors
- Clear statistical motivation and compatibility with traditional combined analyses
- Scalability in terms of channels and parameters

The approach I presented (implemented in MadMiner) achieves these goals

High-dimensional event data



[CMS]



[ATLAS, CMS 1606.02266]

Precision constraints on new physics

Parameterization e.g. in Effective Field Theory:

systematic expansion of new physics around Standard Model

$$\mathcal{L}_{\text{EFT}} = \mathcal{L}_{\text{SM}} + \sum_i \frac{f_i}{\Lambda^2} \mathcal{O}_i + \dots$$

10s to 100s "universal" parameters to measure

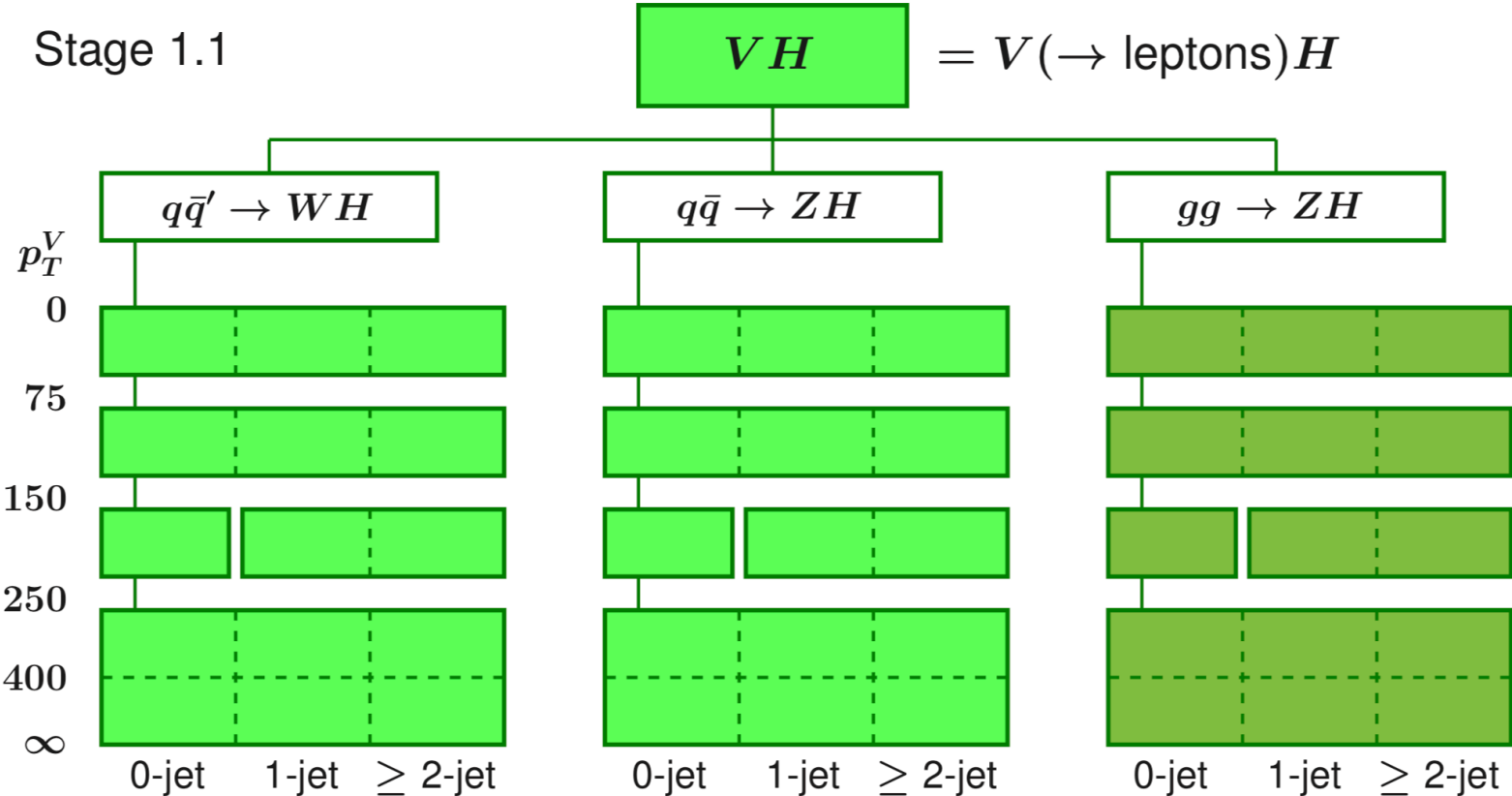
# Benchmarking STXS in WH

[JB, S. Dawson, S. Homiller, F. Kling, T. Plehn 1908.06980]

- Simplified Template Cross-Sections (STXS) define observable bins that are supposed to capture as much information on NP as possible

- Results: **STXS** are indeed sensitive to operators, adding a few more bins improve them, but a **multivariate analysis** is still stronger

[N. Berger et al. 1906.02754; HXSWG YR4]



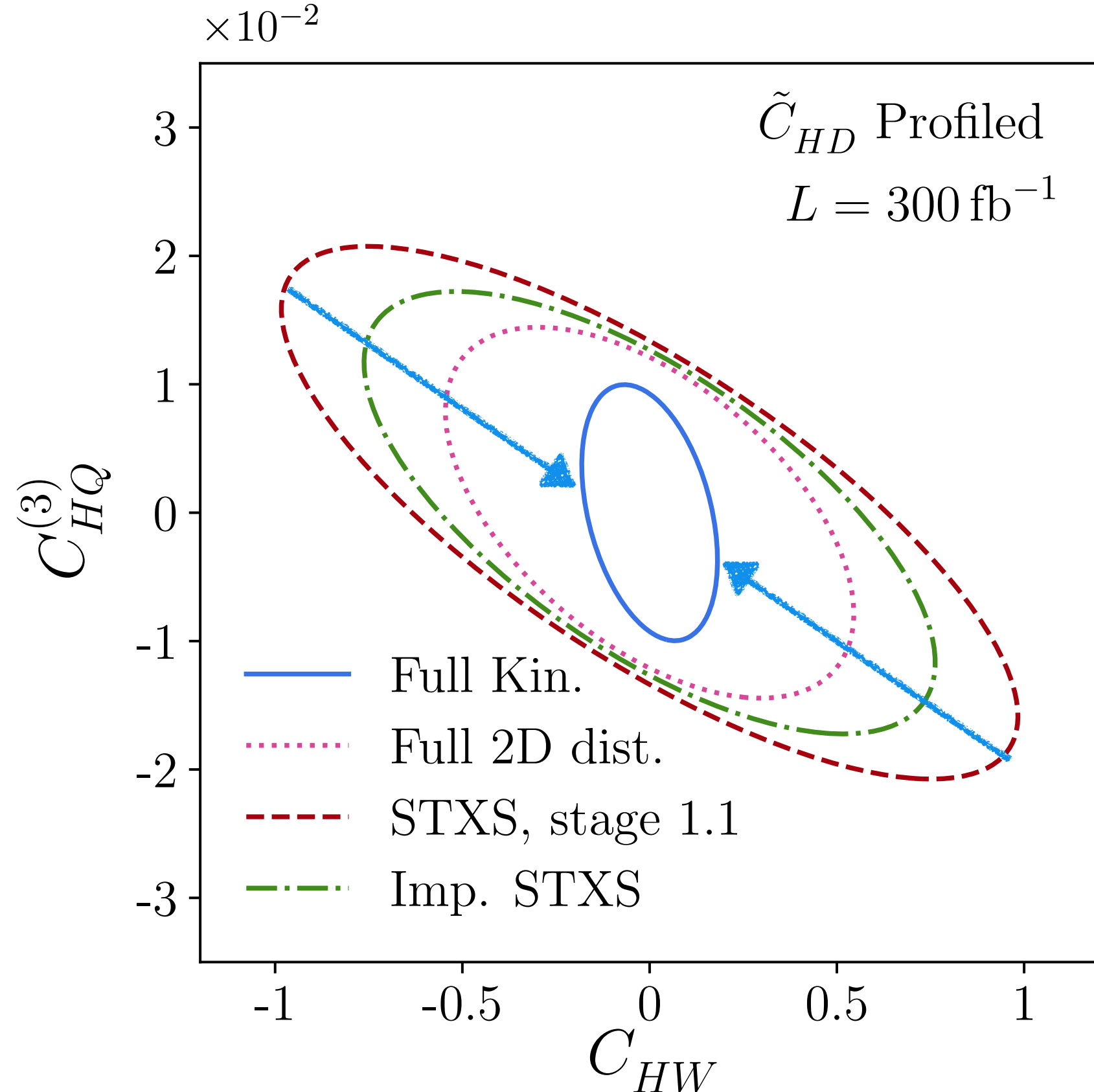
- Let's check! How much information on

$$\tilde{\mathcal{O}}_{HD} = \mathcal{O}_{H\Box} - \frac{\mathcal{O}_{HD}}{4} = (\phi^\dagger \phi) \Box (\phi^\dagger \phi) - \frac{1}{4} (\phi^\dagger D^\mu \phi)^* (\phi^\dagger D_\mu \phi)$$

$$\mathcal{O}_{HW} = \phi^\dagger \phi W_{\mu\nu}^a W^{\mu\nu a}$$

$$\mathcal{O}_{Hq}^{(3)} = (\phi^\dagger i \overleftrightarrow{D}_\mu^a \phi) (\bar{Q}_L \sigma^a \gamma^\mu Q_L),$$

can we extract from  $pp \rightarrow WH \rightarrow \ell\nu b\bar{b}$  ?



# An incomplete wrap-up of simulation-based inference methods

| Method   | Approximations                     | Upfront cost       | Eval    |
|--|------------------------------------|--------------------|---------|
| Summary statistics:                                  |                                    |                    |         |
| Likelihood for summary stats (standard histograms)   | Reduction to summary stats         | Fast               | Fast    |
| Approximate Bayesian Computation                     | Reduction to summary stats         | Depends            | Depends |
| Matrix elements:                                     |                                    |                    |         |
| Matrix Element Method                                | Transfer fns                       | Fast               | Slow    |
| Optimal Observables                                  | Transfer fns, optimal only locally | Fast               | Slow    |
| Neural networks:                                     |                                    |                    |         |
| Neural likelihood                                    | NN                                 | Needs many samples | Fast    |
| Neural posterior                                     | NN                                 | Needs many samples | Fast    |
| Neural likelihood ratio                              | NN                                 | Needs many samples | Fast    |
| Neural networks + matrix elements:                   |                                    |                    |         |
| Neural likelihood (ratio) + gold mining (RASCAL etc) | NN                                 | Needs less samples | Fast    |
| Neural optimal observables (SALLY)                   | NN, optimal only locally           | Needs less samples | Fast    |



# Simulation-based inference references

## Opinionated review

K. Cranmer, JB, G. Louppe:  
“The frontier of simulation-based inference”  
[1911.01429]

## Do It Yourself (for LHC physics)

JB, F. Kling, I. Espejo, K. Cranmer:  
“MadMiner: Machine learning—based inference for particle physics”  
[CSBS, 1907.10621, <https://github.com/diana-hep/madminer>]

## LHC HXSWG YR4 STXS

JB, S. Dawson, S. Homiller, F. Kling, T. Plehn:  
“Benchmarking simplified template cross sections in WH production”  
[JHEP, 1908.06980]

## Use in Astro: Strong lensing

JB, S. Mishra-Sharma, J. Hermans, G. Louppe, K. Cranmer  
“Mining for Dark Matter Substructure: Inferring subhalo population properties from strong lenses with machine learning”  
[ApJ, 1909.02005]

## Original works

JB, K. Cranmer, G. Louppe, J. Pavez:  
“A guide to constraining Effective Field Theories with machine learning”  
[PRD, 1805.00020]

JB, G. Louppe, J. Pavez, K. Cranmer:  
“Mining gold from implicit models to improve likelihood-free inference”  
[PNAS, 1805.12244]

## Follow-up with incremental improvements

M. Stoye, JB, K. Cranmer, G. Louppe, J. Pavez:  
“Likelihood-free inference with an improved cross-entropy estimator”  
[NeurIPS workshop, 1808.00973]

# PhyStat workshop on SBI in Munich

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- Alexander Held (U Wisconsin-Madison)

<https://indico.cern.ch/event/1355601/overview>

On-the-fly Event-by-Event Reweighting

Excerpts from

<https://indico.cern.ch/event/1296757/>

# Abstract

Recently there has been rapid increase in the number of full statistical models (or "likelihoods") published by the experiments.

- Most are based on the HistFactory (pyhf) format and published in HEPData.
- This allows theorists and others to reproduce and combine measurements with the same gold standard as the internal experimental results.
- However, these are mainly from SUSY and exotics searches and
- working with EFTs is more complicated because quantum interference effects lead to changes in the signal template (via the dependence of the differential cross-sections and phase-space dependent selection efficiency on the EFT parameters).

In this talk I will propose a simple, lightweight framework that would extend current likelihood publishing to overcome these challenges and enable 'exact' EFT fits (i.e. with the same level of detail as the internal experimental fits and combinations).

# Scope of this talk

The focus of this talk is about a practical statistical framework for doing EFT fits

- Emphasis is on statistical correctness, not optimality of observables, etc.
- Fit distributions in the data space (no unfolding)
  - Focusing on binned template fits with full systematic uncertainty treatment
- With some user-defined observables  $x$  (probably 1-D or 2-D)
  - This talk is **not** about what is a good observable
- Independent of which EFT operators, which basis, how many parameters, etc.

The framework lends itself well to publishing the full statistical model so that groups outside experiments can re-do fits, perform combinations, etc.

- So it addresses many of the motivations for unfolding, but its cleaner statistically

# Morphing histograms vs. event-by-event reweighting

Morphing histograms (or fiducial cross-sections estimated with MC) has some subtle issues:

- Statistical fluctuations for bin probability (or fiducial cross-section) can lead to unphysical negative probabilities when morphing to a new value of  $\alpha$
- Efficiency and acceptance aren't constant for all events in a given bin of the observable  $x$ , so there is some (mild) approximation

The acceptance factors  $\epsilon_{\text{STXS}}$  and  $\epsilon_{\text{diff.}}$ , as well as the signal shape factors  $f_s$ , are derived under the assumption of SM Higgs boson kinematics. For interpretations of the measurements in physics models that significantly alter kinematic distributions, additional correction factors may be needed to account for changes in the acceptance and signal shape as a function of BSM model parameters. These are discussed when applicable in Sections 3 and 4.

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# Morphing histograms vs. event-by-event reweighting

Morphing histograms (or fiducial cross-sections estimated with MC) has some subtle issues:

- Statistical fluctuations for bin probability (or fiducial cross-section) can lead to unphysical negative probabilities when morphing to a new value of  $\alpha$
- Efficiency and acceptance aren't constant for all events in a given bin of the observable  $x$ , so there is some (mild) approximation

However, event-by-event reweighting based on morphing avoids these issues

- The event weights are always positive
- The weights are for a specific event (that either passes or fails selection criteria), so there is no approximation due to averaging efficiencies / acceptances for different types of events.

# Idea 1: a model that builds histograms on-the-fly

For any fully simulated event with observable  $x_i$  and MC truth record  $z_i$  that was generated from EFT with parameters  $\alpha_0$  (e.g. the SM), we can reweight to a new EFT parameter point  $\alpha$  with

$$w_i(\alpha) = \frac{d\sigma(\alpha)/dz}{d\sigma(\alpha_0)/dz} \Big|_{z_i}$$

- Similar to what we do with PDF reweighing.
- Kinematics don't change! Efficiency and acceptance are already included by selection on reconstructed quantities on event-by-event basis.
- The  $\alpha$ -dependence of differential cross-sections can be computed using "morphing" equations or closely related approaches

**Idea:** For each value of  $\alpha$  fill a signal histogram with set of weighted events  $\{x_i, w_i(\alpha)\}$

- Can do this on-the-fly while doing the fit.
- It captures the  $\alpha$ -dependence of efficiency and acceptance



# Details: how to build histograms on-the-fly

**Idea:** For each value of  $\alpha$  fill a signal histogram with set of weighted events  $\{x_i, w_i(\alpha)\}$

- Can do this on-the-fly while doing the fit
- It captures the  $\alpha$ -dependence of efficiency and acceptance

**Details:** To do this, the statistical model would need to maintain a **tiny database** that includes information for a set of simulated events:

- Store  $x_i$  (observed value of observable) and the coefficients needed to reweight event to a new point  $\alpha$ . For example:
  - The differential cross-section (at truth-level) for set of basis points as implemented in **MadMiner**
  - The fully differential versions of the coefficients  $A_j^{i,k'}$  in ATLAS-CONF-2023-052

It may be a bit slow, but its very flexible and avoids the problems mentioned above.

## Idea 2: RECAST-like service for EFTs

Consider the case where ATLAS and CMS publish statistical models parametrized for some subset of operators in a specified EFT basis.

- **Sometime later** one wants to reinterpret the analysis for **a different set of operators** keeping the same event selection, breakdown of signal and control regions, observables, binning, etc.

RECAST is a framework for reinterpretations like this for BSM searches

- In general, this requires running new signal through the full MC simulation + reco + analysis chain. ATLAS is actually doing this with preserved analysis workflows!

But for EFTs we can simply to **reweight the existing fully simulated SM events** (doesn't require running more simulation, reconstruction, etc.)

- The service could calculate the coefficients for the mini-database based on truth-level kinematics and export a new statistical model that implements the statistical model for those operators as describe above.

# Conclusion

Recently there has been rapid increase in the number of full statistical models (or "likelihoods") published by the experiments — mainly for BSM searches and their reinterpretation.

- **Ironically, it's not being used much for EFTs. This should change!**
- It would allow theorists and others to reproduce and combine measurements with the same gold standard as the internal experimental results.

We will need to define new **specifications** for components of statistical models that describe the details for how distributions of observables depend on EFT parameters including interference effects

- This is already very mature, but we should make the specifications concrete and then **implement** them in public tools
- Approaches based on **event-by-event reweighting** and **on-the-fly creation of histograms** have some nice properties and should be explored

Finally, we have all the ingredients needed to create a **RECAST-like service for EFTs** that would allow us to reweight fully simulated samples of events to **new EFT scenarios at some point in the future**