## Towards a global SMEFT likelihood

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# EFT phenomenology: two approaches

## EFT phenomenology: two approaches

► Top-Down approach: start with (renormalizable) UV model

- Integrate out heavy particles with masses  $m \approx \Lambda$
- ▶ Obtain EFT containing non-renormalizable operators suppressed by powers of ∧
- Wilson coefficients are expressed in terms of parameters of UV model
- Observables are predicted in terms of Wilson coefficients
- Parameters of UV model are constrained by experimental measurements
- Bottom-Up approach: start with field content & symmetries at low energy
  - Construct all operators from field content that are allowed by symmetries
  - Non-renormalizable operators are suppressed by powers of cutoff Λ
  - Observables are predicted in terms of Wilson coefficients
  - Wilson coefficients are constrained by experimental measurements

## EFT phenomenology: two approaches - pros and cons

### Top-Down approach:

- (+) Correlations between EFT parameters fixed by UV model
- (+) Small number of model parameters
- (-) Requires UV model
- (-) Parameter fits are specific to the given model

### Bottom-Up approach:

- (+) Parameterization of generic UV completions
- (+) Suitable for model-independent interpretation of experimental data
- (+) Patterns of non-zero Wilson coefficients in EFT fits hint at possible UV models
- (-) Very large number of parameters
- (-) EFT fits require simplifying assumptions (e.g. flavor structure, vanishing coefficients, etc.)
- (-) EFT fits can in general not be used to constrain UV models

## Lessons learned from *B* anomalies

The  $b \rightarrow s\ell\ell$  anomalies



LHCb: arXiv:2003.04831, arXiv:2012.13241, arXiv:1403.8044, arXiv:1506.08777, arXiv:1606.04731, arXiv:2105.14007, arXiv:1705.05802, arXiv:2103.1769, arXiv:2108.09283, arXiv:2108.09283, arXiv:2108.13870 ATLAS: arXiv:1812.03017, CMS: arXiv:1910.12127, Altmanshofer, PS: arXiv:2103.13370

HEFT 2022, Granada, 16 June 2022

## The $b \rightarrow c \ell \nu$ anomalies



HFLAV, hflav.web.cern.ch BaBar, arXiv:1205.5442, arXiv:1303.0571 LHCb, arXiv:1506.08614, arXiv:1708.08856 Belle, arXiv:1607.03233, arXiv:1607.07923, arXiv:1612.00529, arXiv:1904.08794

### EFT fits in weak effective theory (WET/LEFT)



Altmannshofer, PS, arXiv:2103.13370

#### Murgui, Peñuelas, Jung, Pich, arXiv:1904.09311

## Model building - lessons learned

• Model explaining  $R_{D^{(*)}}$  using  $b_L \rightarrow c_L \tau_L \nu_{\tau L}$ 

$$b_L 
ightarrow c_L au_L 
u_{ au L} \xrightarrow{SU(2)_L} b_L 
ightarrow s_L 
u_{\mu L} 
u_{ au L}$$

Constrained by  $B \to K \nu \bar{\nu}$  searches

Buras, Girrbach-Noe, Niehoff, Straub, arXiv:1409.4557



Model explaining R<sub>D</sub>(\*) and R<sub>K</sub>(\*) using mostly 3rd gen. couplings Modifies LFU in *τ* and Z decays, strongly constrained

Feruglio, Paradisi, Pattori, arXiv:1705.00929



► Model explaining  $b \rightarrow s\mu\mu$  using  $tt\mu\mu$  interaction Modifies  $Z \rightarrow \mu\mu$ , constrained by LEP



Camargo-Molina, Celis, Faroughy, arXiv:1805.04917

### What one would have to do

► Compute **all relevant observables**  $\vec{\mathcal{O}}$  (flavour, EWPO, ...) in terms of Lagrangian parameters  $\vec{\xi}$ 

 $\mathcal{L}_{\mathsf{NP}}(\vec{\xi}) \to \vec{\mathcal{O}}(\vec{\xi})$ 

Take into account loop / RGE effects

$$\mathcal{L}_{\mathsf{NP}}(\vec{\xi}) \xrightarrow{\Lambda_{\mathsf{NP}} \to \Lambda_{\mathsf{IR}}} \vec{\mathcal{O}}(\vec{\xi})$$

Compare to experiment

$$\vec{\mathcal{O}}(\vec{\xi}) \rightarrow \underbrace{L_{\exp}(\vec{\mathcal{O}}(\vec{\xi}))}_{\text{Likelihood}}$$

Tedious to do this for each model...

## SMEFT top-down approach

Assuming A<sub>NP</sub> ≫ v, NP effects in flavour, EWPO, Higgs, top,... can be expressed in terms of Standard Model Effective Field Theory (SMEFT) Wilson coefficients

$$\mathcal{L}_{\mathsf{SMEFT}} = \mathcal{L}_{\mathsf{SM}} + \sum_{n>4} \sum_{i} \frac{C_i}{\Lambda_{\mathsf{NP}}^{n-4}} \mathsf{O}_i$$

Buchmuller, Wyler, Nucl. Phys. B 268 (1986) 621 Grzadkowski, Iskrzynski, Misiak, Rosiek, arXiv:1008.4884

- Powerful tool to connect model-building to phenomenology without need to recompute hundreds of observables in each model
  - Model building and matching:

see talks by Pablo Olgoso, Anders Eller Thomsen, and Alejo Nahuel Rossia

$$\mathcal{L}_{\mathsf{NP}}(\vec{\xi}) 
ightarrow \vec{C}(\vec{\xi})$$
 @  $\Lambda_{\mathsf{NP}}$ 

Model-independent pheno:

$$\vec{C} \xrightarrow{\Lambda_{\rm NP} \to \Lambda_{\rm IR}} \vec{\mathcal{O}}(\vec{C}) \to L_{\rm exp}(\vec{\mathcal{O}}(\vec{C}))$$

SMEFT likelihood  $L_{exp}(\vec{C})$  can tremendously simplify analyses of NP models

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## SMEFT: two approaches

**Top-Down approach** 

NP model  $\mathcal{L}_{NP}(\vec{\xi})$ , Parameters  $\vec{\xi}$   $\downarrow$  Matching SMEFT Wilson coefficients  $\vec{C}(\vec{\xi})$   $\downarrow$ Observable predictions  $\vec{\mathcal{O}}(\vec{C})$   $\downarrow$ Likelihood function  $L_{exp}(\vec{\mathcal{O}})$   $\downarrow$ Analysis of NP model **Bottom-Up approach** 

SMEFT Wilson coefficients  $\vec{C}$ (with restricting assumptions)  $\downarrow$ Observable predictions  $\vec{O}(\vec{C})$  $\downarrow$ Likelihood function  $L_{exp}(\vec{O})$  $\Downarrow$ FFT ft

## SMEFT: two approaches

**Top-Down approach** 

NP model  $\mathcal{L}_{NP}(\vec{\xi})$ , Parameters  $\vec{\xi}$   $\downarrow$  Matching SMEFT Wilson coefficients  $\vec{C}(\vec{\xi})$   $\downarrow$ Observable predictions  $\vec{\mathcal{O}}(\vec{C})$   $\downarrow$ Likelihood function  $L_{exp}(\vec{\mathcal{O}})$   $\downarrow$ Analysis of NP model **Bottom-Up approach** 

SMEFT Wilson coefficients  $\vec{C}$ (with restricting assumptions)  $\downarrow$ Observable predictions  $\vec{O}(\vec{C})$  $\downarrow$ Likelihood function  $L_{exp}(\vec{O})$  $\Downarrow$ FFT ft

### SMEFT: two approaches

#### **Top-Down approach**

NP model  $\mathcal{L}_{NP}(\vec{\xi})$ , Parameters  $\vec{\xi}$   $\downarrow$  Matching SMEFT Wilson coefficients  $\vec{C}(\vec{\xi})$  $\downarrow$ 

SMEFT Likelihood  $L_{exp}(\vec{C})$ 

↓ Analysis of NP model **Bottom-Up approach** 

SMEFT Wilson coefficients  $\vec{C}$  (with restricting assumptions)

 $\downarrow$ 

SMEFT Likelihood  $L_{exp}(\vec{C})$ 

↓ EFT fit

## The global SMEFT likelihood

## The global SMEFT likelihood

 Several likelihood functions have been considered in the context of EFT fits in the **bottom-up** approach

But in the top-down approach these likelihood functions should not be considered separately since RG (loop) effects mix different sectors and UV models match to several sectors

We need to consider the global SMEFT likelihood

## Basis for implementation

- Computing hundreds of relevant flavour observables properly accounting for theory uncertainties
  - flavio https://flav-io.github.io

Straub. arXiv:1810.08132

- Already used in O(100) papers since 2016
- Representing and exchanging thousands of Wilson coefficient values, different EFTs, possibly different bases

Wilson coefficient exchange format (WCxf) https://wcxf.github.io/

Aebischer et al., arXiv:1712.05298

RG evolution above and below the EW scale, matching from SMEFT to the weak effective theory (WET)



wilson https://wilson-eft.github.io Aebischer, Kumar, Straub, arXiv:1804.05033

> SMEFT RGE: Alonso, Jenkins, Manohar, Trott, arXiv:1308.2627, arXiv:1310.4838, arXiv:1312.2014 (ported from DsixTools: Celis, Fuentes-Martin, Vicente, Virto, arXiv:1704.04504) SMEFT→ WET matching: Jenkins, Manohar, Stoffer, arXiv:1709.04486 WET RGE: Jenkins, Manohar, Stoffer, arXiv:1711.05270

based on

## Implementing the global SMEFT likelihood

- Based on these tools, we have started building the SMEFT LikeLIhood

smelli https://github.com/smelli/smelli

► 
$$L(\vec{C}) \approx \prod_i L^i_{exp}(\vec{O}_{th}(\vec{C}, \vec{\theta}_0)) \times \tilde{L}_{exp}(\vec{O}_{th}(\vec{C}, \vec{\theta}_0))$$

where

- ► *C* WET or SMEFT Wilson coefficients
- $\vec{\theta_0}$  fixed nuisance parameters
- $\vec{O}_{\text{th}}(\vec{C}, \vec{\theta}_0)$  observable predictions
- ►  $L_{exp}^i(\vec{O})$  experimental likelihood from measurement *i* for observables  $\vec{O}$
- $\tilde{L}_{exp}(\vec{O})$  modified exp. likelihood:  $-2 \ln \tilde{L}_{exp}(\vec{O}) = \vec{D}^T (\Sigma_{exp} + \Sigma_{th})^{-1} \vec{D}$ , with  $\vec{D} = \vec{O} - \vec{O}_{exp}$  and covariance matrices  $\Sigma_{exp,th}$  (Gaussian approx.)

 $\vec{C}_{\text{SMEFT}}(\Lambda_{\text{NP}})$ 



Aebischer, Kumar, PS, Straub, arXiv:1810.07698

### smelli v1.1.1: Flavor + EWPT



Peter Stangl (University of Bern)

smelli v2.0: Higgs and beta decays,  $K \to \pi \ell \nu$ ,  $e^+e^- \to W^+W^-$ 

#### New observables

- Higgs physics: signal strengths for various decay ( $h \rightarrow \gamma \gamma, Z\gamma, ZZ, WW, bb, cc, \tau \tau, \mu \mu$ ) and production (gg, VBF, Zh, Wh, tth) channels Falkowski, Straub, arXiv:1911.07866
- Beta decays: lifetime and correlation coefficients of neutron beta decay, superallowed nuclear beta decays Gonzalez-Alonso, Naviliat-Cuncic, Severijns, arXiv:1803.08732 see talk by Martín González-Alonso
- $K \to \pi \ell \nu$ : total branching ratios of  $K^+ \to \pi^0 \ell^+ \nu$ ,  $K_{L,S} \to \pi^\pm \ell^\mp \nu$  ( $\ell = e, \mu$ ), and  $K^+ \to \pi^0 \mu^+ \nu$  effective scalar form factor In C and tensor coupling  $R_T$
- ▶  $e^+e^- \rightarrow W^+W^-$ : total and differential cross sections for  $e^+e^- \rightarrow W^+W^-$  pair production measured in LEP-2
- Proper treatment of the CKM matrix in SMEFT

based on Descotes-Genon, Falkowski, Fedele, González-Alonso, Virto, arXiv:1812.08163

- CKM input scheme using 4 observables to fix 4 CKM parameters:
  - $R_{K\pi} = \Gamma(K^+ \to \mu^+ \nu) / \Gamma(\pi^+ \to \mu^+ \nu)$  (mostly fixing  $V_{us}$ )
  - $BR(B^+ \rightarrow \tau \nu)$  (fixing  $V_{ub}$ )
  - ▶  $BR(B \rightarrow X_c e\nu)$  (fixing  $V_{cb}$ )
  - $\Delta M_d / \Delta M_s$  (mostly fixing CKM phase  $\delta$ )
- Determine effective CKM matrix in presence of SMEFT operators

## New developments related to smelli

• New numerical methods developed for  $b \rightarrow s\ell^+\ell^-$  analyses

Altmannshofer, PS, arXiv:2103.13370

- numerical efficient implementation of NP dependence of theory covariance matrix
- computational speed increased by orders of magnitude through numerical improvements (O(s) → O(ms) per parameter point)

 $\rightarrow$  makes smelli suitable for parameter scans of NP models and EFT fits with many parameters

- will be implemented for all observables in smelli
- ▶ Neutral and charged current **Drell-Yan tails** ( $pp \rightarrow \ell^+ \ell^-$ ,  $pp \rightarrow \ell \nu$  for  $\ell = e, \mu$ )

Greljo, Šalko, Smolkovič, PS, work in progress see talks by Admir Greljo , Felix Wilsch, and Maeve Madigan

- sensitivity to all semi-leptonic four-fermion operators with all quark flavor combinations of u, d, s, c, b (from parton distributions)
- complimentary to flavor physics constraints
- will be implemented in smelli

# Applications of smelli

## Bottom-Up approach: EFT fits



Altmannshofer, PS, arXiv:2103.13370

Falkowski, Straub, arXiv:1911.07866

## Top-Down approach: Analyses of NP models



 $S_1 + S_3$  scalar leptoquarks

## Z' model from gauged $U(1)_X$ matched to SMEFT at tree level



Greljo, PS, Thomsen, arXiv:2103.13991 (matching: Gherardi, Marzocca, Venturini, arXiv:2003.12525)

Allanach, Camargo-Molina, Davighi, arXiv:2103.12056

# Conclusion

## Conclusions

- Global SMEFT likelihood can be used in
  - Bottom-Up approach: global EFT fits
  - Top-Down approach: analyses of NP models
- Python package smelli currently contains
  - FCNC flavor observables ( $b \rightarrow s, b \rightarrow d, s \rightarrow d$ , and meson mixing)
  - ▶ FCCC flavor observables ( $b \rightarrow c, b \rightarrow u, s \rightarrow u, d \rightarrow u$ )
  - LFV observables (μ, τ, Ζ, B-meson, and Kaon decays)
  - ► EWPT (W and Z pole observables, τ decays, (g 2)<sub>e,µ,τ</sub>)
  - Higgs physics (signal strengths)
  - Beta decays (neutron and superallowed nuclear beta decays)
- smelli will be extended soon
  - New numerical methods to improve accuracy and computational speed
  - Implementation of Drell-Yan tails
- Truly global likelihood is work in progress
  - ▶ To be added: top physics, dijets, vector boson scattering, diboson production, ...
  - smelli is completely open-source
    You are welcome to participate 
    > https://github.com/smelli/smelli

## **Backup slides**

- Prerequisite: working installtion of Python version 3.7 or above
- Installation from the command line:

python3 -m pip install smelli --user

- downloads smelli with all dependencies from Python package archive (PyPI)
- installs it in user's home directory (no need to be root)

#### As any Python package, smelli can be used

- as library imported from other scripts
- directly in the command line interpreter
- in an interactive session
  - $\rightarrow$  we recommend the Jupyter notebook

# **smelli** tutorial in a Jupyter notebook at https://github.com/peterstangl/smelli-talk

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6 * × Ø	K + + H Run E C H Code		
	smelli playground		
	This Jupyter notebook allows you to try out the smell1. Python package. Note that the execution speed is limited. To make full use of the package, install it locally with		
	pip3 installuser smelli		
	Execute the cells of this notebook with shift + enter.		
In [1]:	from playground import *		
	Step 1: EFT and basis		
	Execute this cell and select an EFT and basis		
M = In []:	widgets.HBox([widget_eft, widget_basis])		
	Step 2: likelihood		
	execute this cell to initialize the likelihood. This will only take a moment.		
In [ ]:	<pre>gl = smelli.GlobalLikelihood(eft=select_eft.value, basis=select_basis.value)</pre>		
	Step 3: Wilson coefficients		
	select a point in EFT parameter space by entering in the text field Wiscon coefficient values in the form name: value, one coefficient per line (this format is called YAML). The allowed names in the chosen basis can be found in the PDF file linked below.		
	Example in the SMEFT Warsaw basis:		
	lq1_2223: le-9 lq1_3323: le-8 lq3_3323: le-8		
In [ ]:	widgets.VBox([out_basispdf, widgets.HBox([ta_wc, t_scale])])		
	Step 4: parameter point		
	execute this cell to initialize the GlobalLikeLihoodPoint object		

Step 1:

Import package and initalize GlobalLikelihood class

```
import smelli
gl = smelli.GlobalLikelihood()
```

possible arguments are

- eft='WET' to use Wilson coefficients in weak effective theory (no EWPOs)
   (default: eft='SMEFT')
- basis='...' to select different WCxf basis (default: basis='Warsaw' for SMEFT, basis='flavio' for WET)

Step 2:

Select point in Wilson coefficient space using parameter\_point method

- Three possible input formats:
  - Python dictionary with Wilson coefficient name/value pair and input scale

```
glp = gl.parameter_point({'lq1_2223': 1e-8}, scale=1000)
```

fixes Wilson coefficient  $[C_{lg}^{(1)}]_{2223}$  to  $10^{-8}$  GeV<sup>-2</sup> at scale 1 TeV

WCxf data file in YAML or JSON format (specified by file path)

```
glp = gl.parameter_point('my_wc.yaml')
```

instance of class wilson.Wilson from wilson package

```
glp = gl.parameter_point(wilson_instance)
```

Step 3:

Get results from GlobalLikelihoodPoint instance glp defined in step 2

The most important methods are:

```
glp.log_likelihood_global()
```

returns 
$$\Delta \log L = \log \left( \frac{L_{\text{global}}(\vec{C})}{L_{\text{global}}^{\text{SM}}} \right)$$

1 glp.log\_likelihood\_dict()
2

returns Python dictionary with contributions to  $\Delta \log L$  from different sets of observables (EWPOs, charged current LFU, neutral current LFU,...)

glp.obstable()

returns table listing individual observables with their experimental and theoretical central values and uncertainties

```
1 glp = gl.parameter_point({}, scale=1000)
2 glp.obstable(min_pull='2.35')
3
```

#### returns observables with highest pull in Standard Model (no Wilson coefficient set)

Observable	Prediction	Measurement	Pull
$\left(\frac{d\overline{BR}}{da^2}\right)(B_s \rightarrow \phi \mu^+ \mu^-)^{[1.0,6.0]}$	$(5.37 \pm 0.65) \times 10^{-8} \frac{1}{\text{GeV}^2}$	$(2.57 \pm 0.37)  imes 10^{-8} \frac{1}{\text{GeV}^2}$	3.8 <i>o</i>
a <sub>µ</sub>	$(1.1659182\pm0.0000004)\times10^{-3}$	$(1.1659209\pm0.0000006)\times10^{-3}$	$3.5\sigma$
$\langle P'_5 \rangle (B^0 \to K^{*0} \mu^+ \mu^-)^{[4,6]}$	$-0.756 \pm 0.074$	$-0.21\pm0.15$	$3.3\sigma$
$R_{\tau\ell}(B \to D^* \ell^+ \nu)$	0.248	$0.306\pm0.018$	$3.3\sigma$
$\langle A_{FB}^{\ell h} \rangle (\Lambda_b \rightarrow \Lambda \mu^+ \mu^-)^{[15,20]}$	$0.1400 \pm 0.0075$	$0.250\pm0.041$	<b>2.6</b> $\sigma$
$\langle R_{\mu e} \rangle (B^{\pm} \rightarrow K^{\pm} \ell^+ \ell^-)^{[1.0,6.0]}$	1.000	$0.745\pm0.098$	<b>2.6</b> $\sigma$
$\epsilon'/\epsilon$	$(-0.3\pm 6.0)\times 10^{-4}$	$(1.66\pm 0.23)\times 10^{-3}$	<b>2.6</b> σ
$BR(W^{\pm} \rightarrow \tau^{\pm} \nu)$	0.1084	$0.1138 \pm 0.0021$	<b>2.6</b> $\sigma$
$\langle R_{\mu e} \rangle (B^0 \to K^{*0} \ell^+ \ell^-)^{[1.1, 6.0]}$	1.00	$0.68\pm0.12$	$2.5\sigma$
$R_{ au\ell}(B  o D\ell^+  u)$	0.281	$0.406\pm0.050$	$2.5\sigma$
$\left\langle \frac{dBR}{da^2} \right\rangle (B^{\pm} \rightarrow K^{\pm} \mu^+ \mu^-)^{[15.0,22.0]}$	$(1.56 \pm 0.12) \times 10^{-8} \frac{1}{\text{GeV}^2}$	$(1.210 \pm 0.072) \times 10^{-8} \frac{1}{\text{GeV}^2}$	$2.5\sigma$
A <sup>0,b</sup> <sub>FB</sub>	$10.31 \times 10^{-2}$	$(9.92\pm0.16) imes10^{-2}$	$2.4\sigma$
$\langle \frac{dBR}{dg^2} \rangle (B^0 \to K^0 \mu^+ \mu^-)^{[15.0,22.0]}$	$(1.44 \pm 0.11)  imes 10^{-8} \ rac{1}{ m GeV^2}$	$(9.6 \pm 1.6) \times 10^{-9} \ \frac{1}{\text{GeV}^2}$	$2.4\sigma$
$\langle R_{\mu e} \rangle (B^0 \to K^{*0} \ell^+ \ell^-)^{[0.045, 1.1]}$	0.93	0.65±0.12	$2.4\sigma$