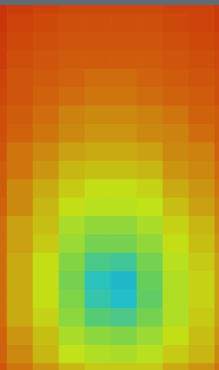


Theory perspective on Data Preservation: Experimental data in Flavio

Peter Stangl CERN





flavio: what can it do for me?

<https://github.com/flav-io/flavio>
D. Straub, arXiv:1810.08132

1. Computing theory predictions

for a large number of observables (flavour physics, electroweak precision observables, Higgs physics, ...)

- ▶ **Standard Model** (SM) predictions
- ▶ Predictions in the presence of **new physics** (NP) (parameterized by Wilson coefficients)
- ▶ Theory **uncertainties** for SM and NP

2. Database of experimental measurements


for all implemented observables that have been measured

- ▶ provided in terms of YAML file
- ▶ easy to update and extend

→ more on this later!

3. Likelihoods

Combining predictions with experimental data allows constructing likelihoods

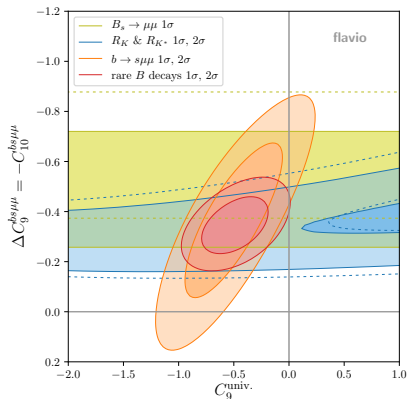
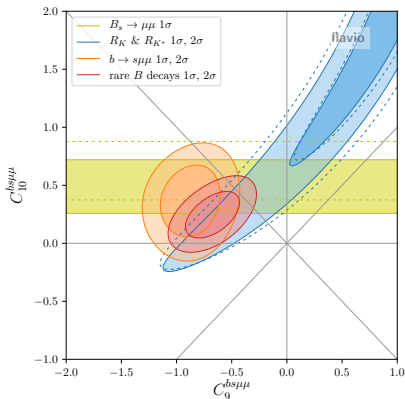
- ▶ Likelihoods in parameters (e.g. CKM parameters) or Wilson coefficients
- ▶ Possibility to use Gaussian approximation for **fast likelihood** estimates
- ▶ Use external fitters to perform Bayesian or frequentist statistics with `flavio` likelihoods
- ▶ Basis for the  **smelli** global **SMEFT LikeLI**hood Python package

<https://github.com/smelli/smelli>
Aebischer, Kumar, PS, Straub, arXiv:1810.07698
PS, arXiv:2012.12211

4. Plots

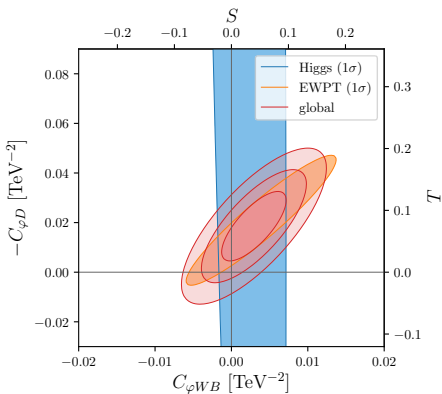
- ▶ Visualize experimental measurements & theory predictions
- ▶ Visualize your likelihoods

New physics in B -decays in Weak effective theory Wilson coefficients @ 4.8 GeV



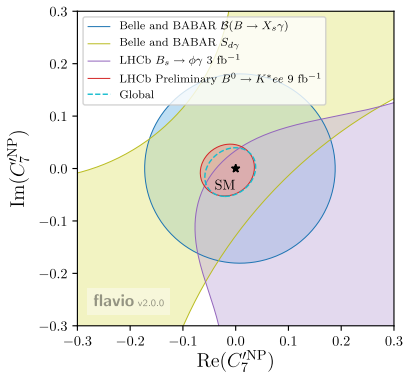
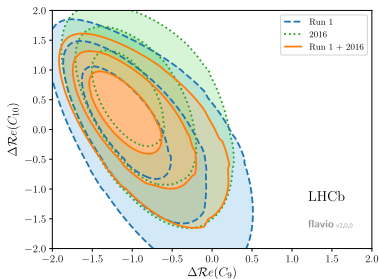
Altmannshofer, PS, arXiv:2103.13370

S-T fit using combined Higgs and electroweak likelihood in SMEFT



Falkowski, Straub, arXiv:1911.07866

Fits to new physics Wilson coefficients from recent LHCb analyses



LHCb-PAPER-2020-002
LHCb-TALK-2020-155

Measurements in flavio

Measurements in flavio

- ▶ A **measurement** in `flavio` corresponds to a **likelihood** associated with one (or more) **observable(s)**
- ▶ The likelihood is provided by experiments and included in `flavio`
- ▶ Predefined measurements contained in file `measurements.yaml`
- ▶ Simple example in `flavio` YAML format:

```
1 Belle Rmue(B->D*lnu) 2017:           # name
2   experiment: Belle                   # experiment
3   inspire: Abdesselam:2017kjf        # INSPIRE tex key
4   values:
5     Rmue(B->D*lnu): 0.96 ± 0.05 ± 0.01 # constraint
```

- ▶ The constraint is interpreted as Gaussian likelihood
- ▶ Different error contributions are summed in quadrature

Measurements in flavio

- ▶ Observables can have **asymmetric uncertainties**

```
1 K+->pinunu NA62 2019:           # name
2   experiment: NA62                # experiment
3   values:
4     BR(K+->pinunu): 0.47 + 0.72 - 0.47 e-10  # constraint
```

- ▶ The constraint is interpreted as combination of two half Gaussians

Measurements in flavio

- ▶ For measurement of **correlated observables**, the correlation can be specified

```
1 Belle RD* sl 2019: # name
2 experiment: Belle # experiment
3 inspire: Abdesselam:2019dgh # INSPIRE tex key
4 values:
5   Rtaul(B->Dlnu): 0.307 ± 0.037 ± 0.016 # constraint observable 1
6   Rtaul(B->D*lnu): 0.283 ± 0.018 ± 0.014 # constraint observable 2
7   correlation: -0.53 # correlation
```

- ▶ The constraints are interpreted as 2D Gaussian likelihood
- ▶ Different error contributions are summed in quadrature

Measurements in flavio

- ▶ For more than two correlated observables, the **correlation matrix** can be specified (in quadratic or triangular form)

```
1 A_1 SLD: # name
2 experiment: SLD # experiment
3 inspire: ALEPH:2005ab # INSPIRE tex key
4 description: Table 3.6 of arXiv:hep-ex/0509008 # description
5 values:
6 A(Z->ee): 0.1516 ± 0.0021 # constraint observable 1
7 A(Z->mumu): 0.142 ± 0.015 # constraint observable 2
8 A(Z->tautau): 0.136 ± 0.015 # constraint observable 2
9 correlation: [[1.0, 0.038, 0.033], [1.0, 0.007], [1.0]]#corr.matrix
```

- ▶ The constraints are interpreted as 3D Gaussian likelihood

Measurements in flavio

- ▶ Simple **upper limits** on positive quantities can be specified

```
1 Belle B->K*emu 2018:           # name
2   experiment: Belle             # experiment
3   inspire: Sandilya:2018pop     # INSPIRE tex key
4   values:
5     BR(B0->K*emu): < 1.2e-7 @ 90% CL # constraint observable 1
6     BR(B0->K*mue): < 1.6e-7 @ 90% CL # constraint observable 2
```

- ▶ The constraints are interpreted as half Gaussians with mode at 0 and cumulative probability below the limit being 0.90 (in this example)

Measurements in flavio

- ▶ More appropriate **upper limit** likelihood for low-statistics counting experiments if **number of events** is available

```
1 DELPHI Z LFV: # name
2   experiment: DELPHI # experiment
3   inspire: Abreu:1996mj # INSPIRE tex key
4   values:
5     BR(Z->mutau): # constraint
6     distribution: gamma_upper_limit # type of distribution
7     limit: 1.2e-5
8     confidence_level: 0.95
9     counts_total: 0
10    counts_background: 0
```

- ▶ The constraint is implemented as a Gamma distribution

Measurements in flavio

- ▶ If number of expected background events is uncertain, **background uncertainty** can be specified

```
1 Belle B->hnunu SL 2017: # name
2 experiment: Belle # experiment
3 inspire: Grygier:2017tzo # INSPIRE tex key
4 values:
5 BR(B0->K*nunu): # constraint
6 distribution: general_gamma_upper_limit # type of distribution
7 limit: 1.8e-5
8 confidence_level: 0.9
9 counts_total: 13
10 counts_signal: -2.0
11 background_uncertainty: 1.8
```

- ▶ The constraint is implemented as a Gamma distribution convoluted with a (folded) Gaussian for the background uncertainty

Measurements in flavio

- ▶ Arbitrary **non-Gaussian** likelihoods can be given in **numerical form**

```
1 LHCb RK 2021:
2   experiment: LHCb
3   url: http://moriond.in2p3.fr/2021/EW/slides/3_flavour_02_moise.pdf
4   values:
5     - name: <Rmue>(B+->Kll)           # constraint for binned observable
6       q2min: 1.1                       # lower bin boundary
7       q2max: 6.0                       # upper bin boundary
8       value:
9         distribution: numerical         # type of distribution
10        x: [0.55, 0.56, 0.57, 0.58, 0.59, 0.60, 0.61, 0.62, ... ]
11        y: [4.592421315031857e-16, 5.5901132147031404e-15, ... ]
```

- ▶ y value of the likelihood with arbitrary normalisation
- ▶ number of points should not be too small as likelihood is interpolated only linearly between them
- ▶ likelihood is assumed to be zero outside of provided range, so range must be large enough, including possible tails

Measurements in flavio

- ▶ **Numerical likelihoods** can be specified in **arbitrary number of dimensions**, e.g.

```
1 LHCb Bs->mumu 2021:
2   experiment: LHCb
3   url: http://moriond.in2p3.fr/2021/EW/slides/3_flavour_01_archilli.
      pdf
4   observables:
5     - BR(Bs->mumu)
6     - BR(B0->mumu)
7   values:
8     distribution: multivariate_numerical
9     xi: [[8.161097450987314e-10, 9.172370129183739e-10, ... ],
10         [-4.806317281473294e-13, 1.2345785573114215e-11, ... ]]
11     y: [[1.3143971288076154e-07, 1.6755574140528865e-07, ... ],
12         [3.878158386282714e-07, 4.923565057071156e-07, ... ],
13         [1.2014436902795998e-06, 1.5185447893919208e-06, ... ],
14         [3.5512584579519983e-06, 4.468647340339764e-06, ... ],
15         ...
16         [1.1380897209303134e-06, 1.1676827880277567e-06, ... ]]
```

- ▶ N dimensional grid given by xi values (here 2D)
- ▶ y provides value of the likelihood on the grid as N-dim array

Approximations used for likelihoods

Gaussian likelihoods

- ▶ Central values and uncertainties
 - ▶ have to be approximated as Gaussian
 - ▶ correlations have to be neglected
- ▶ Central values and uncertainties + correlations
 - ▶ multivariate Gaussian
 - ▶ often good approximation close to central values
 - ▶ deviations from Gaussian have to be neglected

Upper limits

- ▶ Upper limit with confidence level
 - ▶ can be approximated as Half-Gaussian
 - ▶ not necessarily a good approximation
- ▶ Upper limit with confidence level + event counts
 - ▶ can be modelled by Gamma distribution
 - ▶ more appropriate than Half-Gaussian for low-statistics counting experiment
- ▶ Upper limit with confidence level + event counts + background uncertainty
 - ▶ can be modelled by Gamma distribution convoluted with (folded) Gaussian

Generic non-Gaussian likelihoods

- ▶ Likelihoods in parameterized functional form
 - ▶ e.g. (convolutions of) parameterized probability distributions
 - ▶ can be stored in relatively compact way
- ▶ Numerical likelihoods on a grid
 - ▶ precision can be increased by finer grid
 - ▶ might require large amounts of data to be stored
- ▶ Samples from the likelihood distribution
 - ▶ precision can be increased by larger number of samples
 - ▶ might require large amounts of data to be stored
- ▶ New ideas?
 - ▶ Neural Networks trained to represent a likelihood
 - ▶ ...

Example: $\text{BR}(B_{d,s} \rightarrow \mu\mu)$

Example: $\text{BR}(B_{d,s} \rightarrow \mu\mu)$

LHCb, arXiv:1703.05747

- ▶ Most simple result: uncorrelated central values and uncertainties

Example: $\text{BR}(B_{d,s} \rightarrow \mu\mu)$

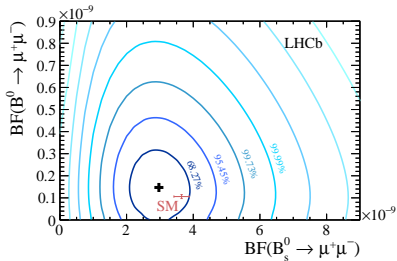
LHCb, arXiv:1703.05747

- ▶ Most simple result: uncorrelated central values and uncertainties
- ▶ More information: correlation between $\text{BR}(B_d \rightarrow \mu\mu)$ and $\text{BR}(B_s \rightarrow \mu\mu)$

Example: $\text{BR}(B_{d,s} \rightarrow \mu\mu)$

LHCb, arXiv:1703.05747

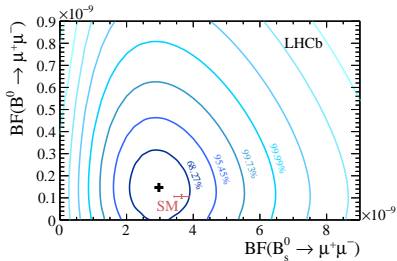
- ▶ Most simple result: uncorrelated central values and uncertainties
- ▶ More information: correlation between $\text{BR}(B_d \rightarrow \mu\mu)$ and $\text{BR}(B_s \rightarrow \mu\mu)$
- ▶ Non-Gaussian likelihood: contour plot



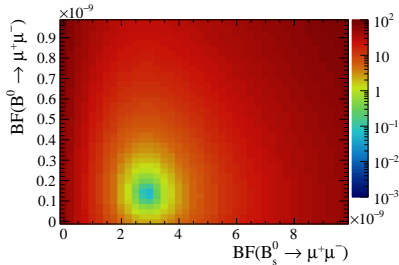
Example: $\text{BR}(B_{d,s} \rightarrow \mu\mu)$

LHCb, arXiv:1703.05747

- ▶ Most simple result: uncorrelated central values and uncertainties
- ▶ More information: correlation between $\text{BR}(B_d \rightarrow \mu\mu)$ and $\text{BR}(B_s \rightarrow \mu\mu)$
- ▶ Non-Gaussian likelihood: contour plot



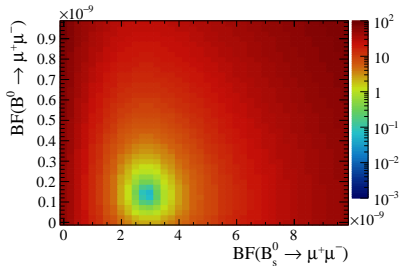
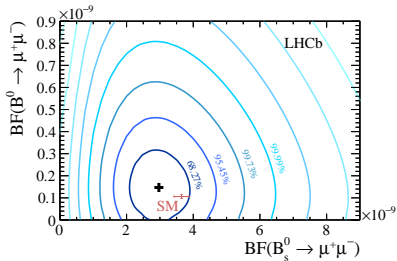
- ▶ Non-Gaussian likelihood: heat map



Example: $BR(B_{d,s} \rightarrow \mu\mu)$

LHCb, arXiv:1703.05747

- ▶ Most simple result: uncorrelated central values and uncertainties
- ▶ More information: correlation between $BR(B_d \rightarrow \mu\mu)$ and $BR(B_s \rightarrow \mu\mu)$
- ▶ Non-Gaussian likelihood: contour plot
- ▶ Non-Gaussian likelihood: heat map



- ▶ Even better: **numerical data** instead of only plots!

Wishlist

Wishlist

- ▶ Correlation matrices for measurements of correlated observables
- ▶ Event counts (and background uncertainties) for upper limits
- ▶ Likelihoods in parameterized functional form (e.g. parameterized Gamma distribution, convolutions of different parameterized distributions, etc.)
- ▶ Full non-Gaussian likelihoods
- ▶ Likelihoods in numerical form instead of only plots!
- ▶ Data files instead of only tables in PDF files!

Wishlist

- ▶ Correlation matrices for measurements of correlated observables
- ▶ Event counts (and background uncertainties) for upper limits
- ▶ Likelihoods in parameterized functional form (e.g. parameterized Gamma distribution, convolutions of different parameterized distributions, etc.)
- ▶ Full non-Gaussian likelihoods
- ▶ Likelihoods in numerical form instead of only plots!
- ▶ Data files instead of only tables in PDF files!

Thank you!

Backup slides