Global View on SMEFT interpretations and UV connection

Maeve Madigan

Heidelberg University

UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

LHC Reinterpretation Forum 31.08.23

Global SMEFT interpretations

The SMEFT: a powerful framework for capturing deviations from the SM:

$$\mathcal{L}_{\mathrm{SMEFT}} = \mathcal{L}_{\mathrm{SM}} + \frac{C^{(5)}}{\Lambda}\mathcal{O}^{(5)} + \sum_i \frac{C_i^{(6)}}{\Lambda^2}\mathcal{O}_i^{(6)} + \ldots$$

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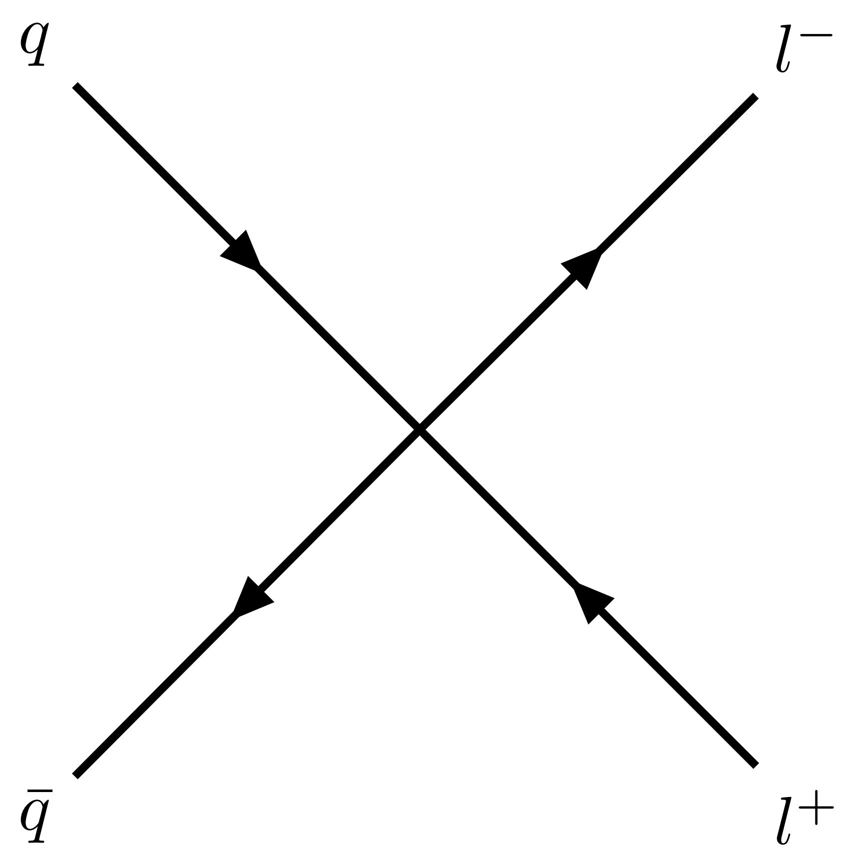

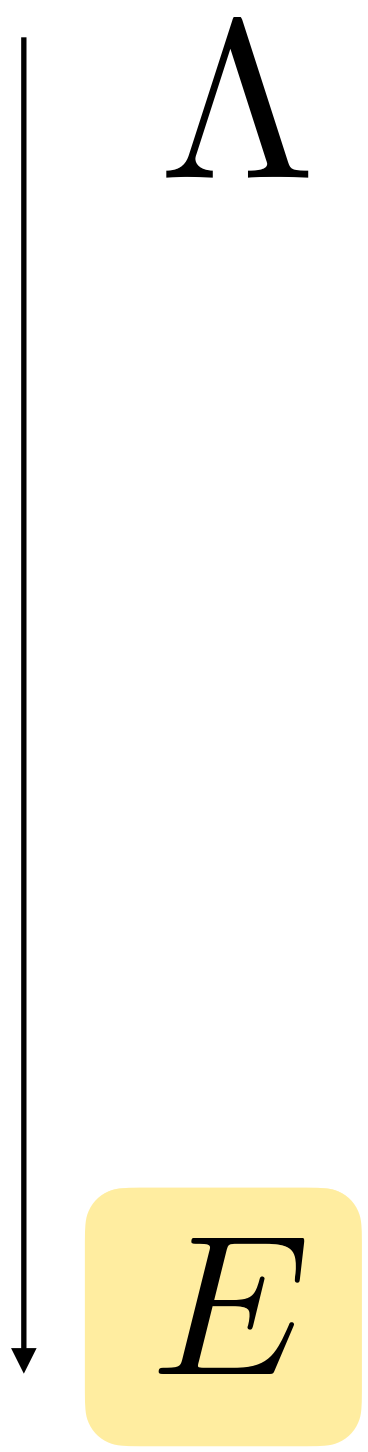

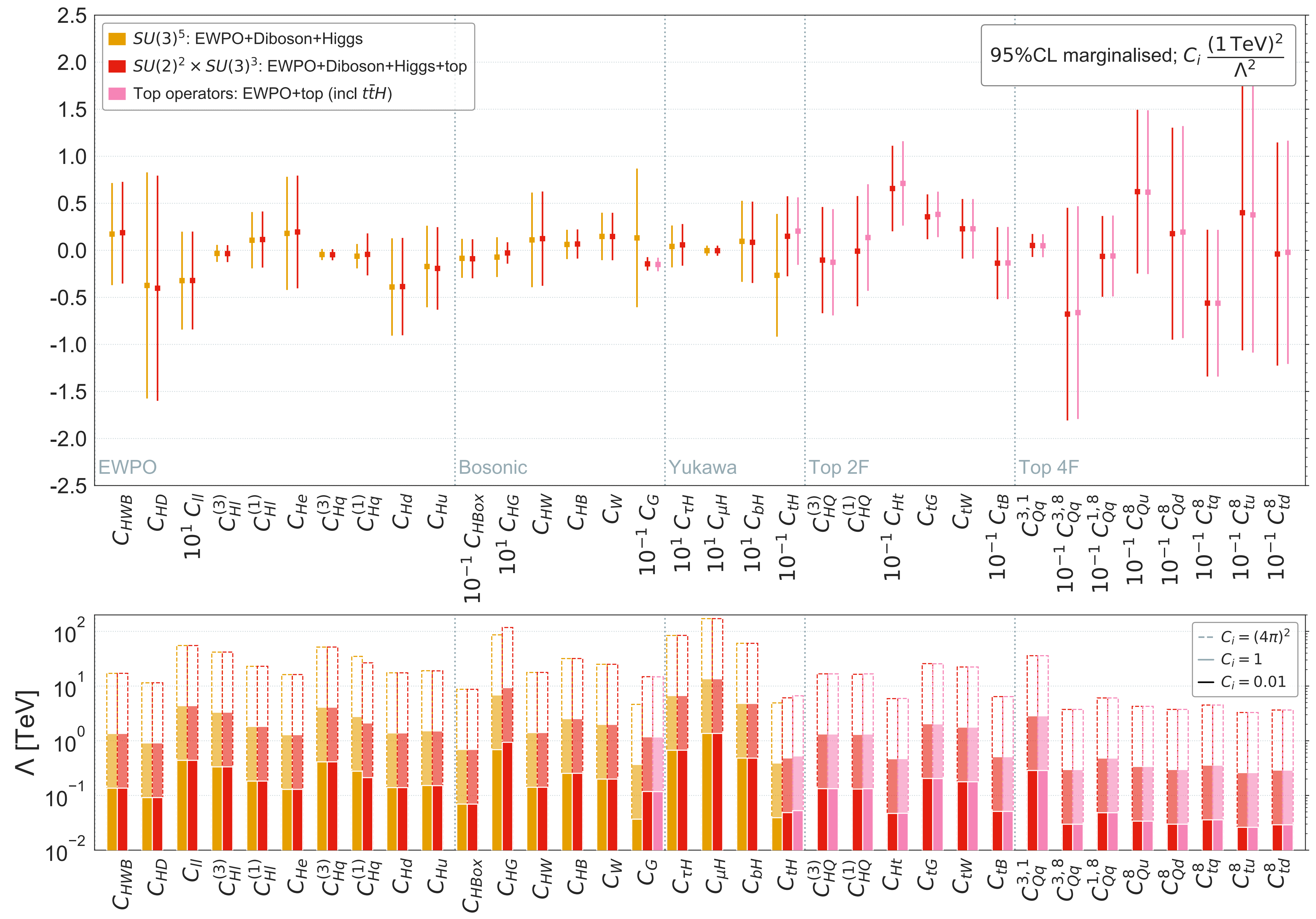

Talks by Jaco ter Hoeve, Danny van Dyk, Kirill Skovpen, Rahul Balasubramanian,…

2012.02779, J. Ellis, MM, K. Mimasu, V. Sanz, T. You

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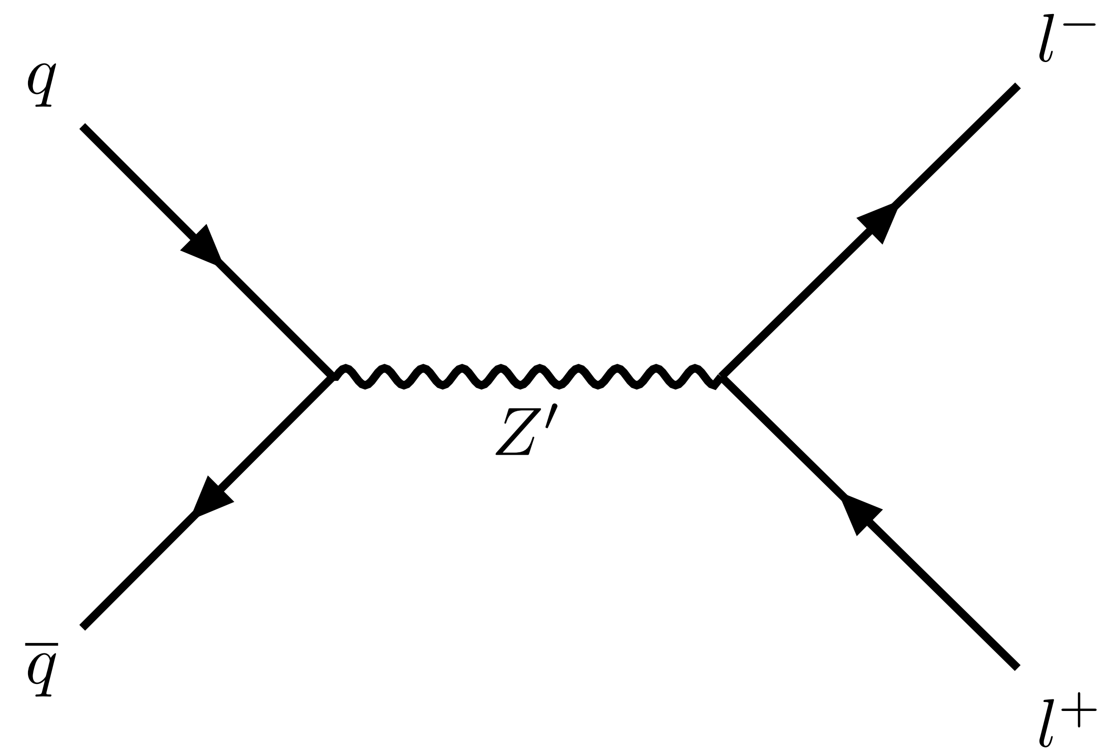

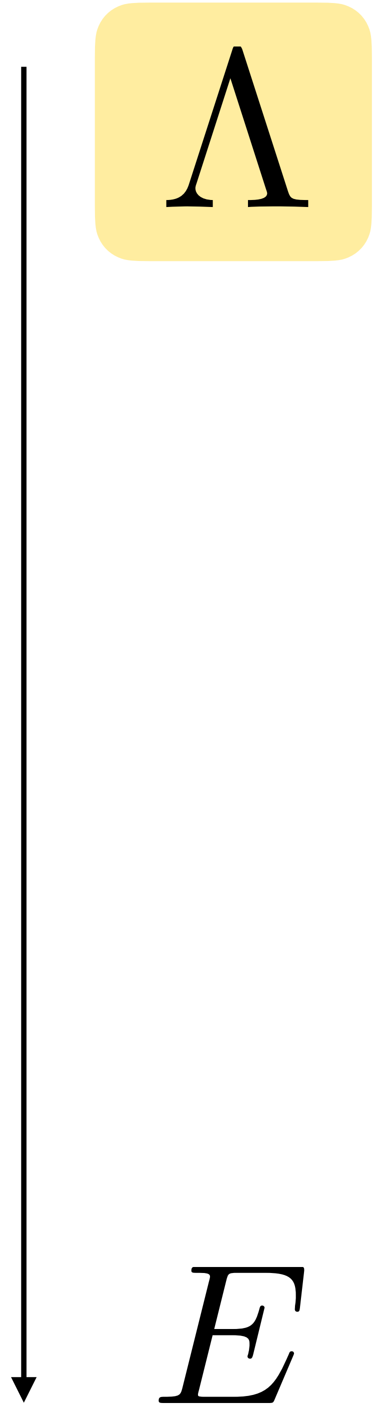

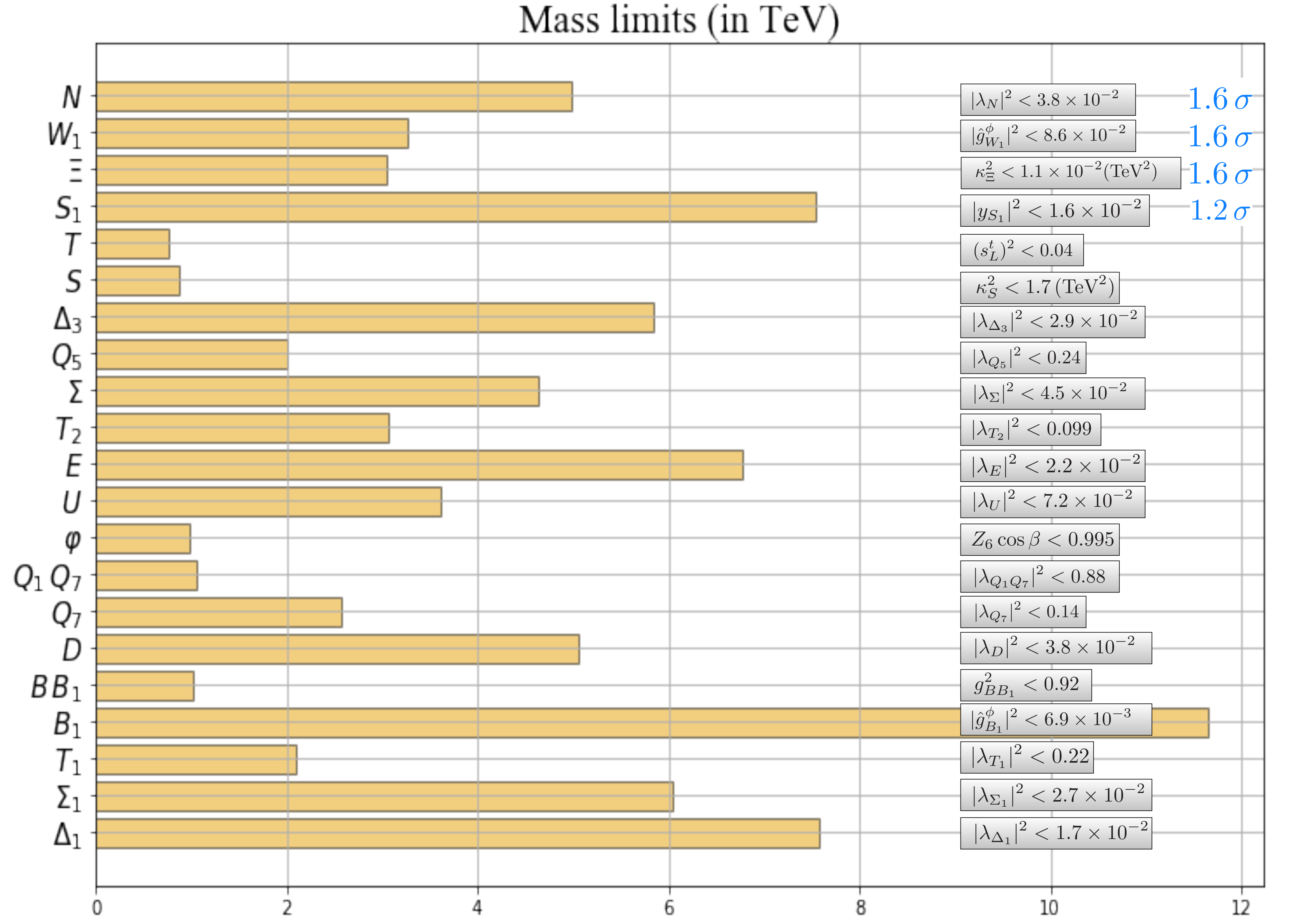

Talk by Shankha Banerjee, Jaco ter Hoeve, …

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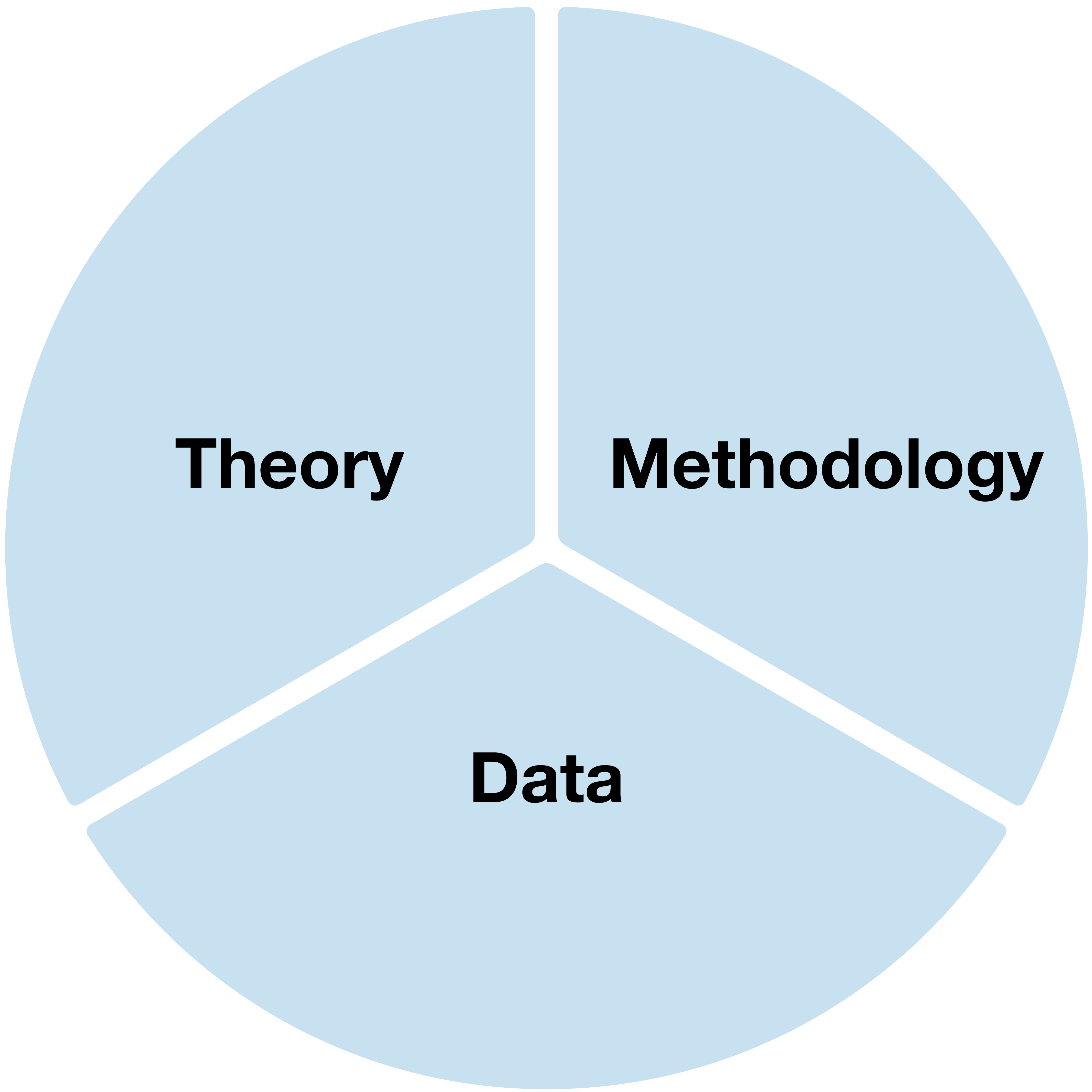
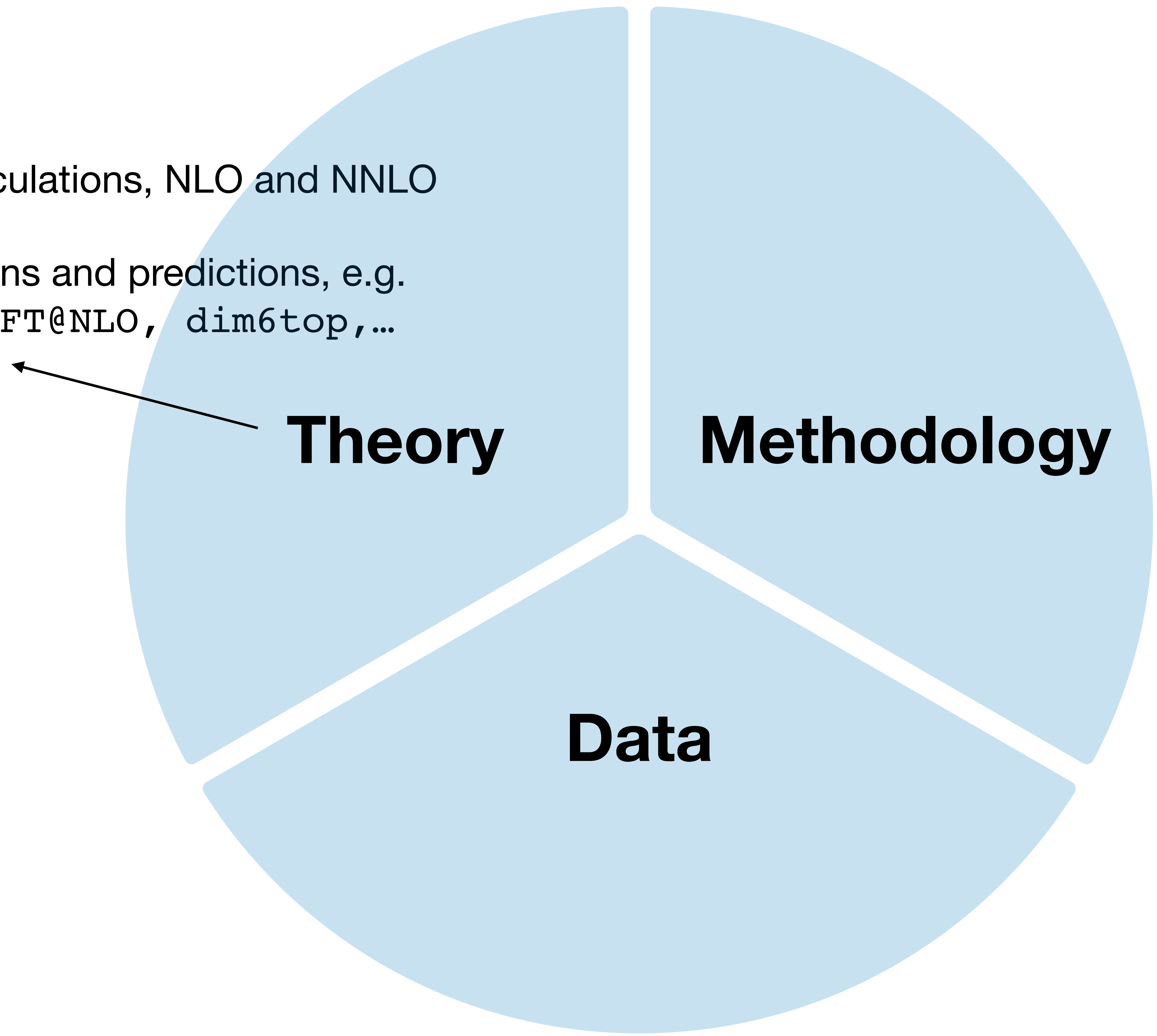
Global SMEFT interpretations



Global SMEFT interpretations

- Precision SM calculations, NLO and NNLO
- PDFs
- SMEFT calculations and predictions, e.g. `SMEFTsim, SMEFT@NLO, dim6top,…`



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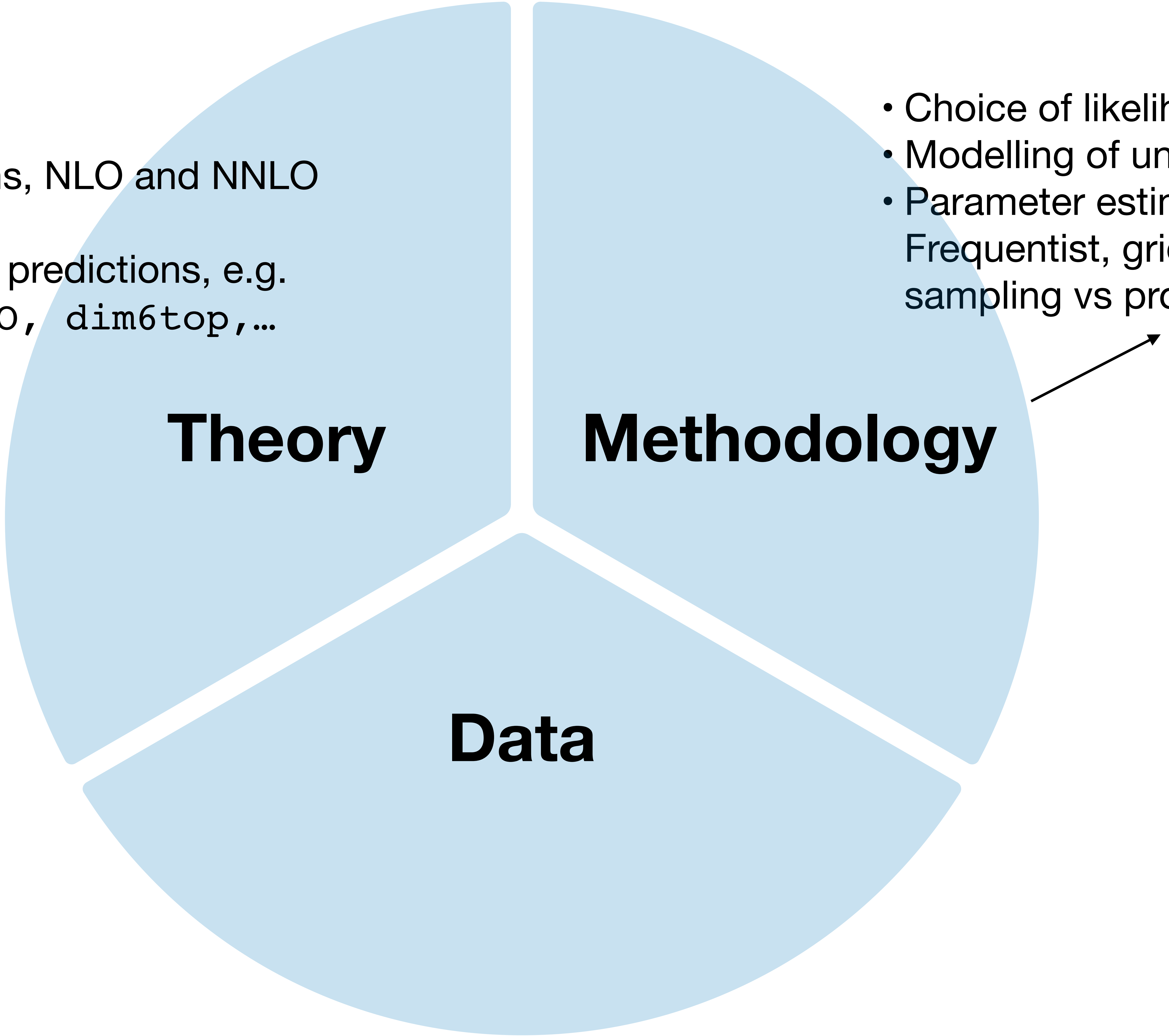
- Choice of likelihood
- Modelling of uncertainties
- Parameter estimation: Bayesian vs Frequentist, grid scan vs MCMC vs Nested sampling vs profiling vs …



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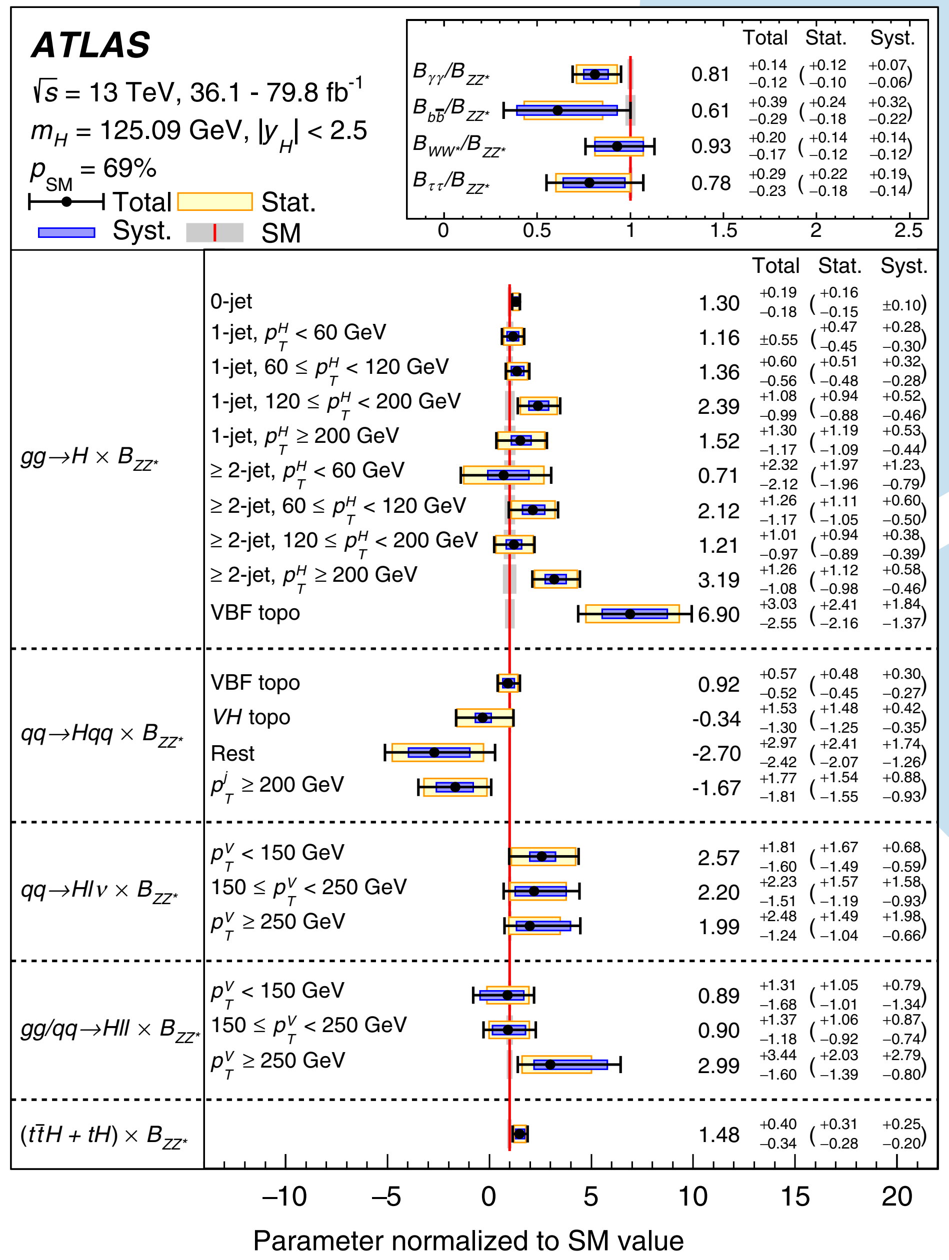
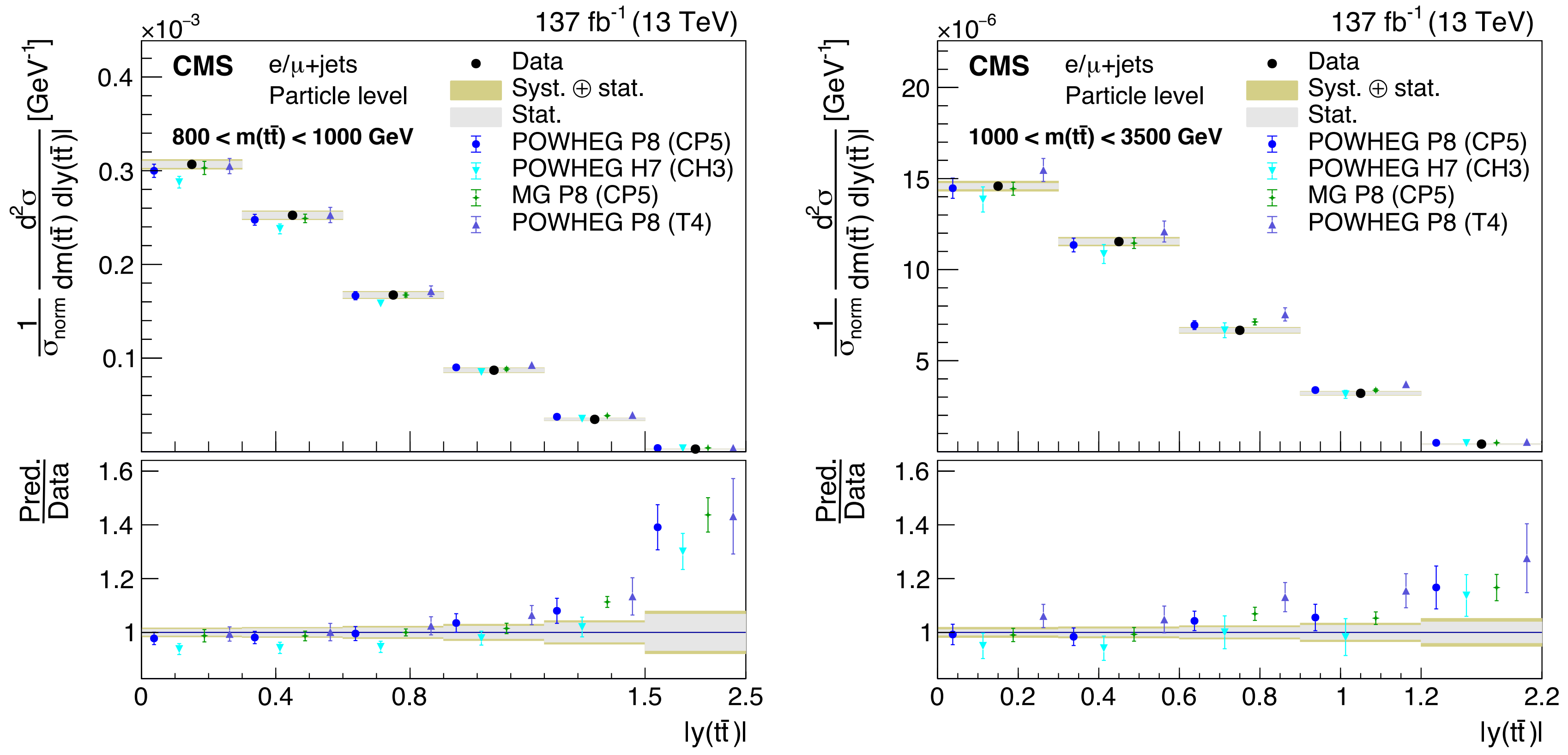
Theory

Methodology

Data



[ATLAS, Phys. Rev. D 101 (2020) 012002]

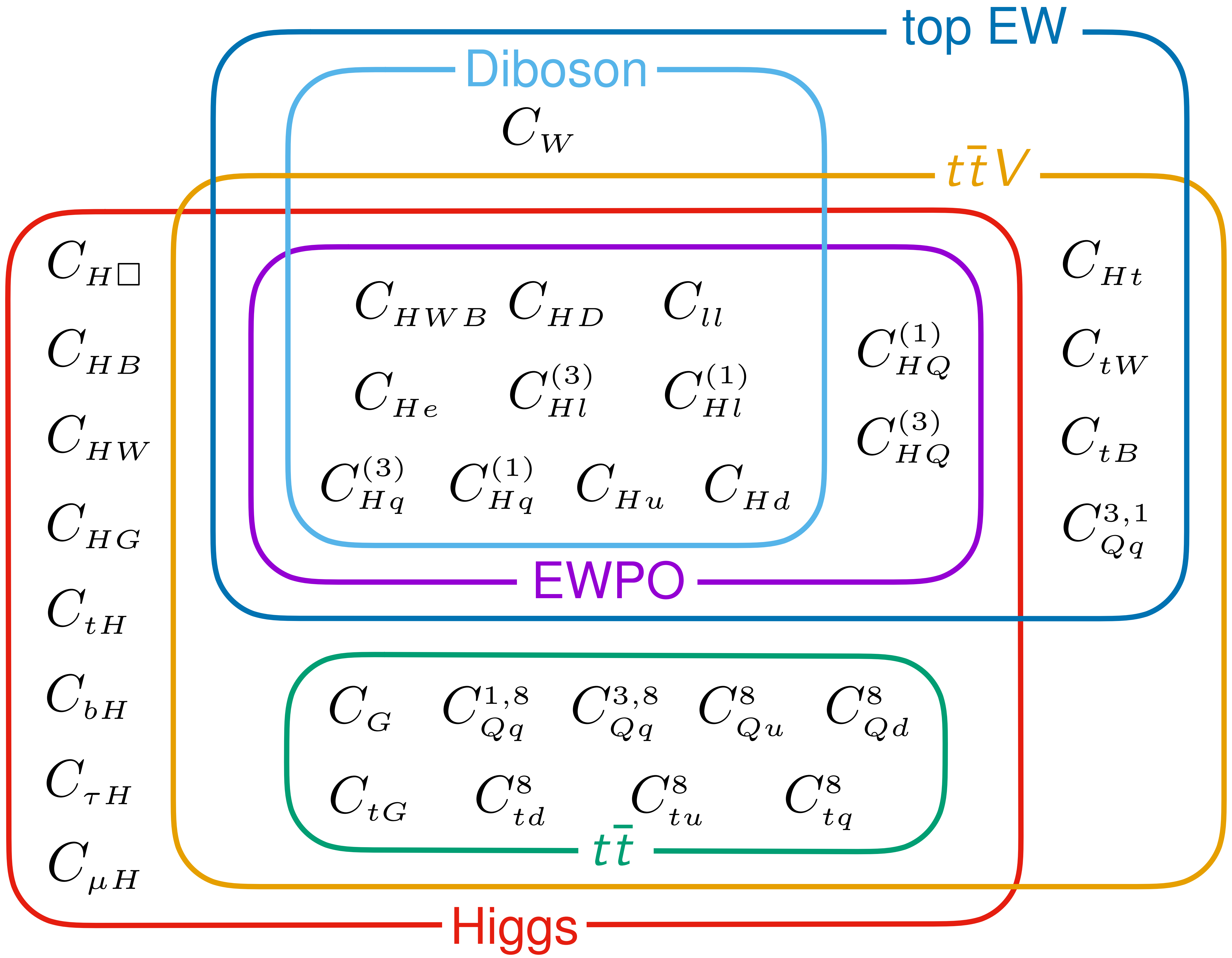


[CMS, Phys. Phys. Rev. D 104 (2021) 092013]

Global SMEFT interpretations: Data

Global: as much data constraining as many processes as possible

Data: the use of data in SMEFT fits depends on *how the data is presented*



2012.02779, J. Ellis, MM, K. Mimasu, V. Sanz, T. You

Datapoints & covariance matrices

Likelihoods

Unbinned measurements

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Covariance matrices

Access to **datapoints** and their **correlated uncertainties (statistical and systematic)** allows us to calculate the Gaussian likelihood:

$$\mathcal{L}(c) \propto \exp\Big(-\frac{1}{2}(D - T(c))^T V^{-1}(D - T(c))\Big)$$

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Datapoints*:*

$p_T(t_h)$ [GeV]	$\frac{1}{\sigma_{\text{norm}}}\frac{d\sigma}{dp_T(t_h)}$ [GeV^{-1}]
0.0 - 40.0	0.002762 ±1.883e-05 stat ±4.883e-05 sys
40.0 - 80.0	0.006028 ±2.874e-05 stat ±5.586e-05 sys
80.0 - 120.0	0.005937 ±2.685e-05 stat ±3.092e-05 sys
120.0 - 160.0	0.004291 ±2.126e-05 stat ±3.18e-05 sys
160.0 - 200.0	0.002639 ±1.502e-05 stat ±2.198e-05 sys
200.0 - 250.0	0.001376 ±7.9e-06 stat ±1.562e-05 sys
250.0 - 300.0	0.0006568 ±5.249e-06 stat ±9.987e-06 sys
300.0 - 350.0	0.000311 ±3.904e-06 stat ±6.535e-06 sys
350.0 - 400.0	0.0001562 ±3.109e-06 stat ±3.774e-06 sys
400.0 - 450.0	7.761e-05 ±2.569e-06 stat ±2.633e-06 sys
450.0 - 500.0	4.085e-05 ±2.015e-06 stat ±1.772e-06 sys
500.0 - 600.0	1.791e-05 ±6.153e-07 stat ±7.734e-07 sys

CMS Phys.Rev.D 104 (2021) 092013, 2021.

https://www.hepdata.net/record/ins1901295

Availability of data on HEPData is growing

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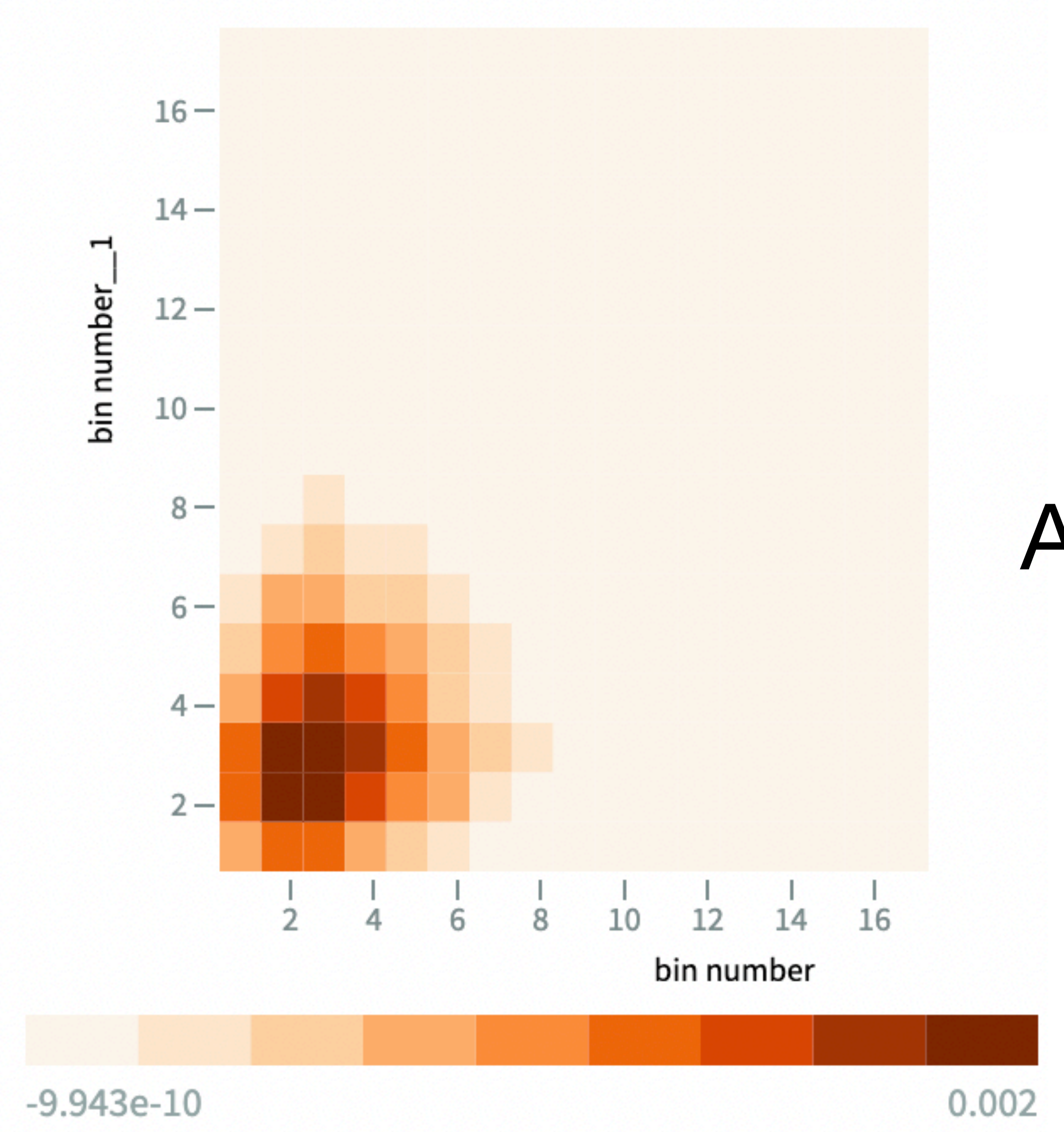
Covariance matrix:



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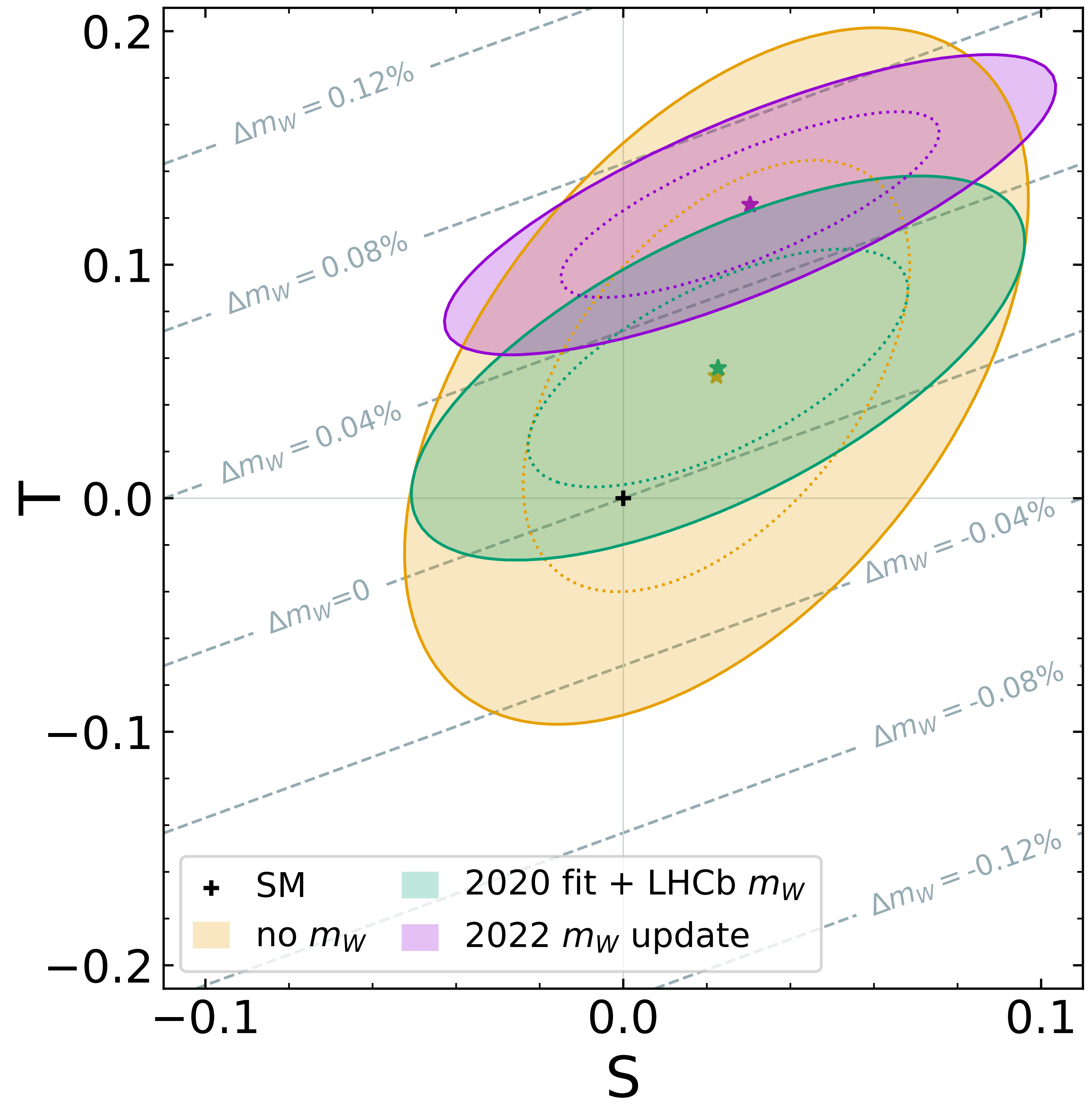
$$\mathcal{L}(c) \propto \exp\Big(-\frac{1}{2}(D - T(c))^T V^{-1} (D - T(c)) \Big)$$

Used in many fits, e.g.

- `Fitmaker`
- SMEFIT - *see Jaco's talk this morning*
- PDF fits - *e.g. NNPDF, see also Zahari's talk*
- + *many others not mentioned here*



2204.05260, E. Bagnaschi, J. Ellis, MM, K. Mimasu, V. Sanz, T. You

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Be aware of assumptions, including:

- Relies on the assumption of symmetric uncertainties, see e.g. *Lilith, 1908.03952 Kraml et. al*
- Covariance matrices do not capture correlations **between different measurements** (more on this later)

Covariance matrices for double-differential distributions

Global SMEFT fits can benefit from **double differential distributions**

- more information → better constraints

Correlations between distributions are necessary

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Ideal for simultaneous **PDF & SMEFT** determinations;

- optimal choice of distribution may be different for PDFs and SMEFT

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In arxiv 2303.06159, PDF & EFT fit in the top sector

see also Zahari's talk today

- *ATLAS 2006.09274 13 TeV* top pair production in the all-hadronic channel
- *CMS 1703.01630 8 TeV* top pair production in the dilepton channel

$$\frac{d^2\sigma}{dy_{t\bar{t}}dm_{t\bar{t}}}$$

Availability of covariance matrix made it possible to include both rapidity and top pair invariant mass

Covariance matrices and unfolded distributions

- Unfolding detector effects
- Measurements unfolded to the full phase space
- Measurements unfolded to e.g. stable top quarks

Efficient calculation of SMEFT and SM predictions for global SMEFT interpretations of O(100) datapoints

Covariance matrices and unfolded distributions

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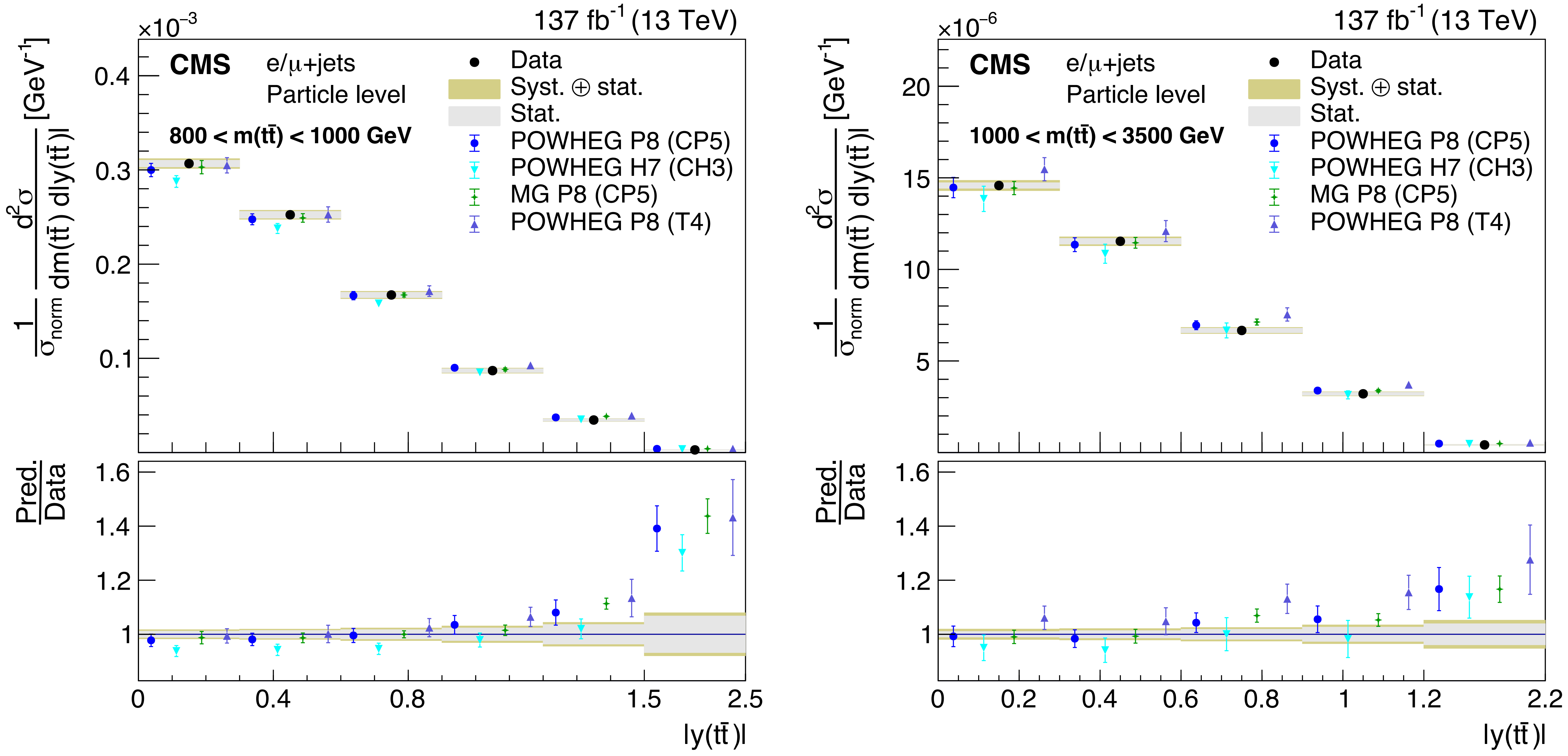
} Efficient calculation of SMEFT and SM predictions for global SMEFT interpretations of O(100) datapoints

Many examples already exist, e.g. **in the top sector:** *[CMS, Phys. Phys. Rev. D 104 (2021) 092013]*



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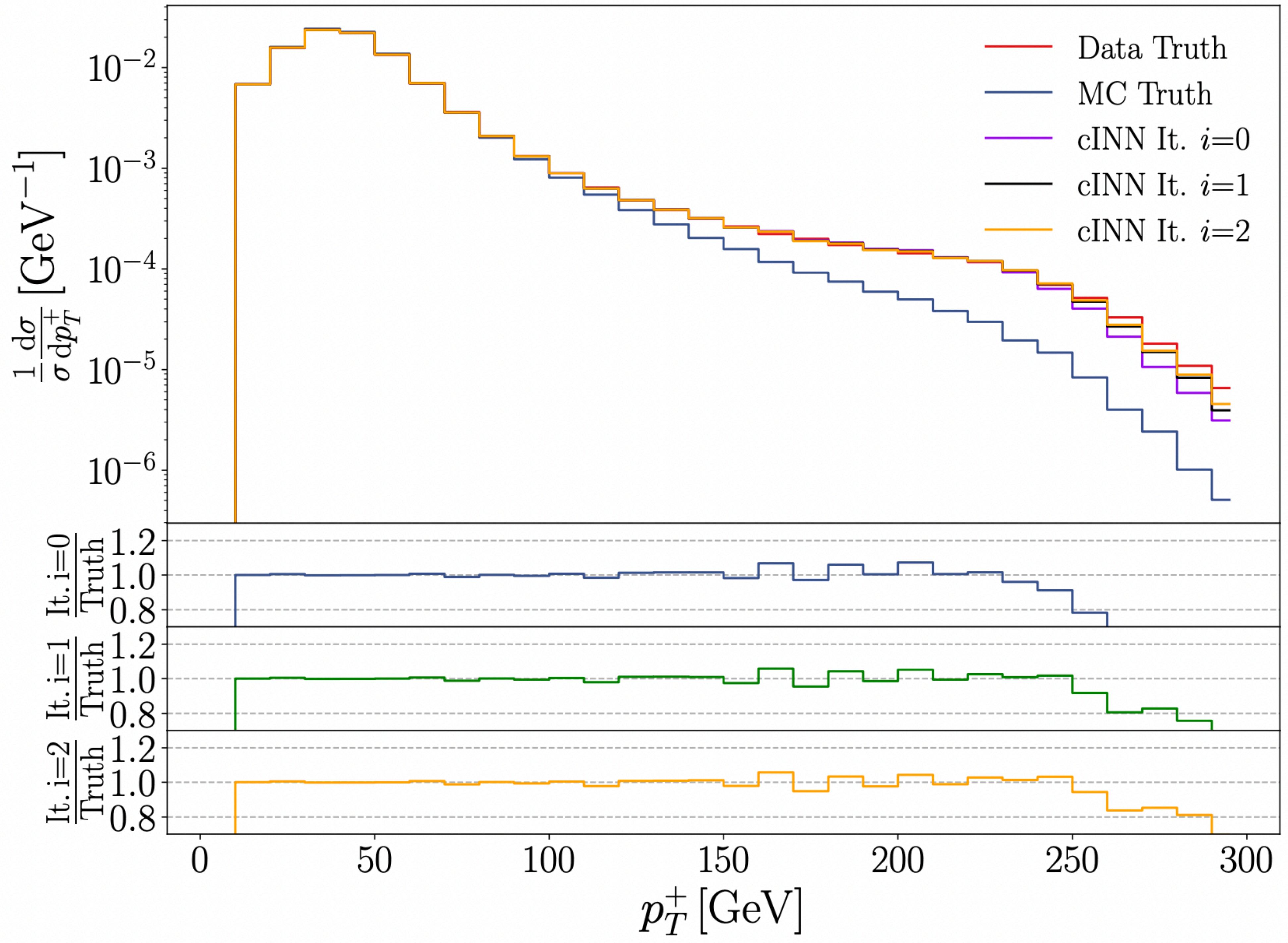
e.g. *Butter et. al, 2212.08674*

Unfolding using conditional invertible neural networks
- iteratively **remove model bias**
- dimension-8 SMEFT in $pp \to Z\gamma\gamma$

$$\mathcal{L} = \mathcal{L}_{\rm SM} + \frac{C_{T,8}}{\Lambda^4} B_{\mu\nu} B^{\mu\nu} B_{\alpha\beta} B^{\alpha\beta}$$



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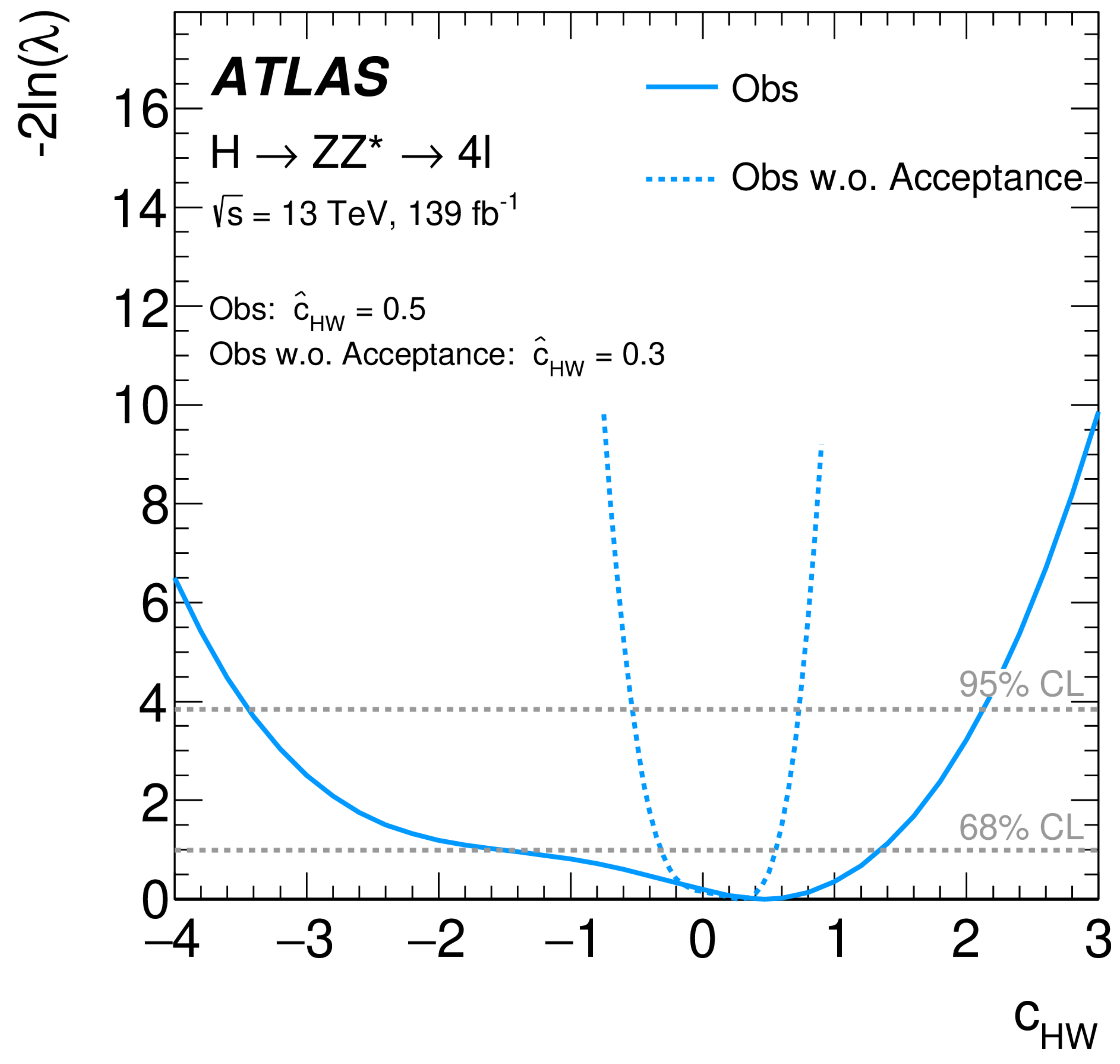
Efficient calculation of SMEFT and SM predictions for global SMEFT interpretations of O(100) datapoints

However: unfolding relies on SM assumptions

e.g. *ATLAS 2004.03447:*
SM signal acceptance may not be a valid assumption for some SMEFT operators

- impact of including SMEFT dependence in signal acceptance is large
- effect reduced in a global fit, *2012.02779*

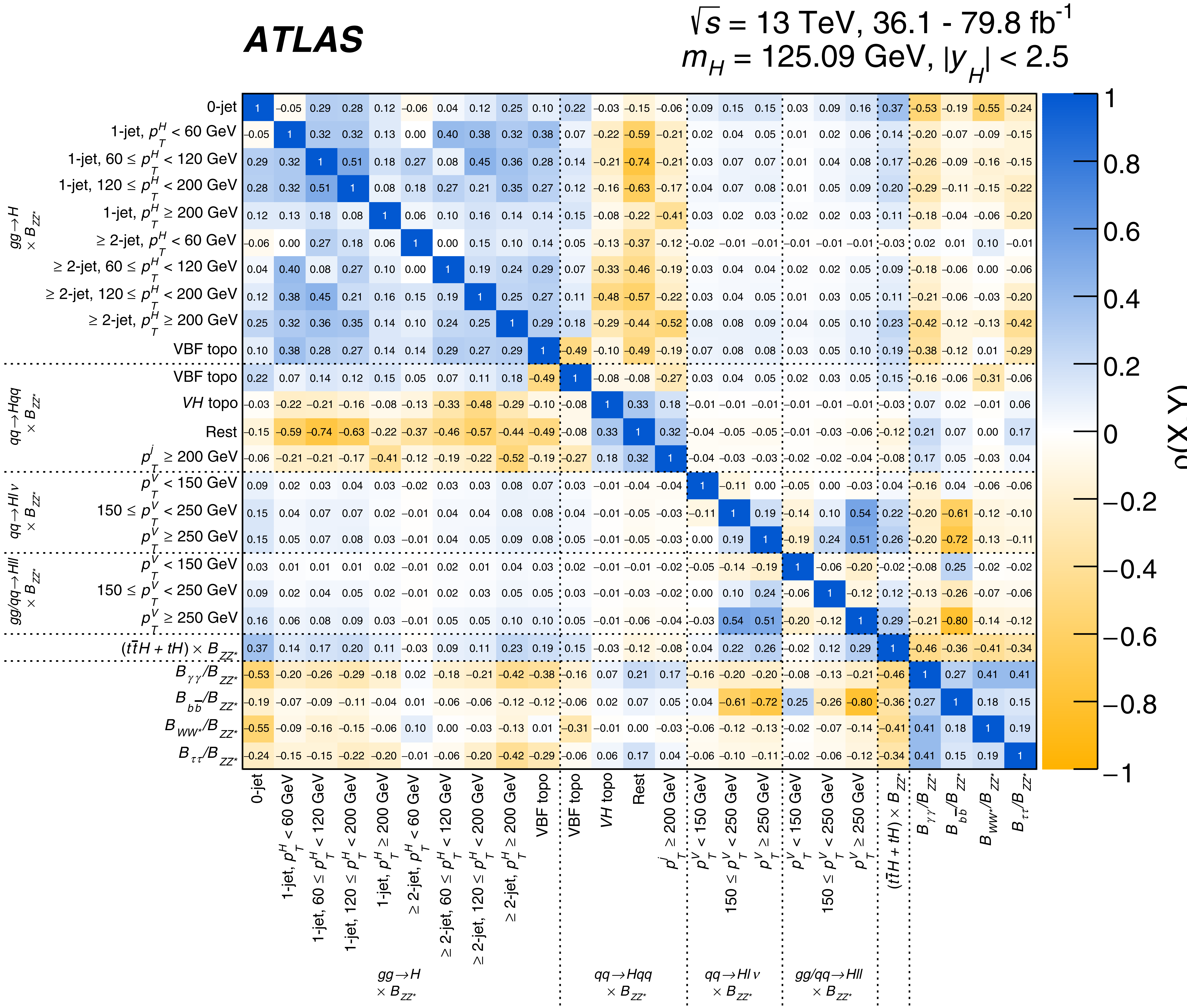
see also talk by Rahul



Combined fits

Combined Higgs fits of STXS/signal strengths

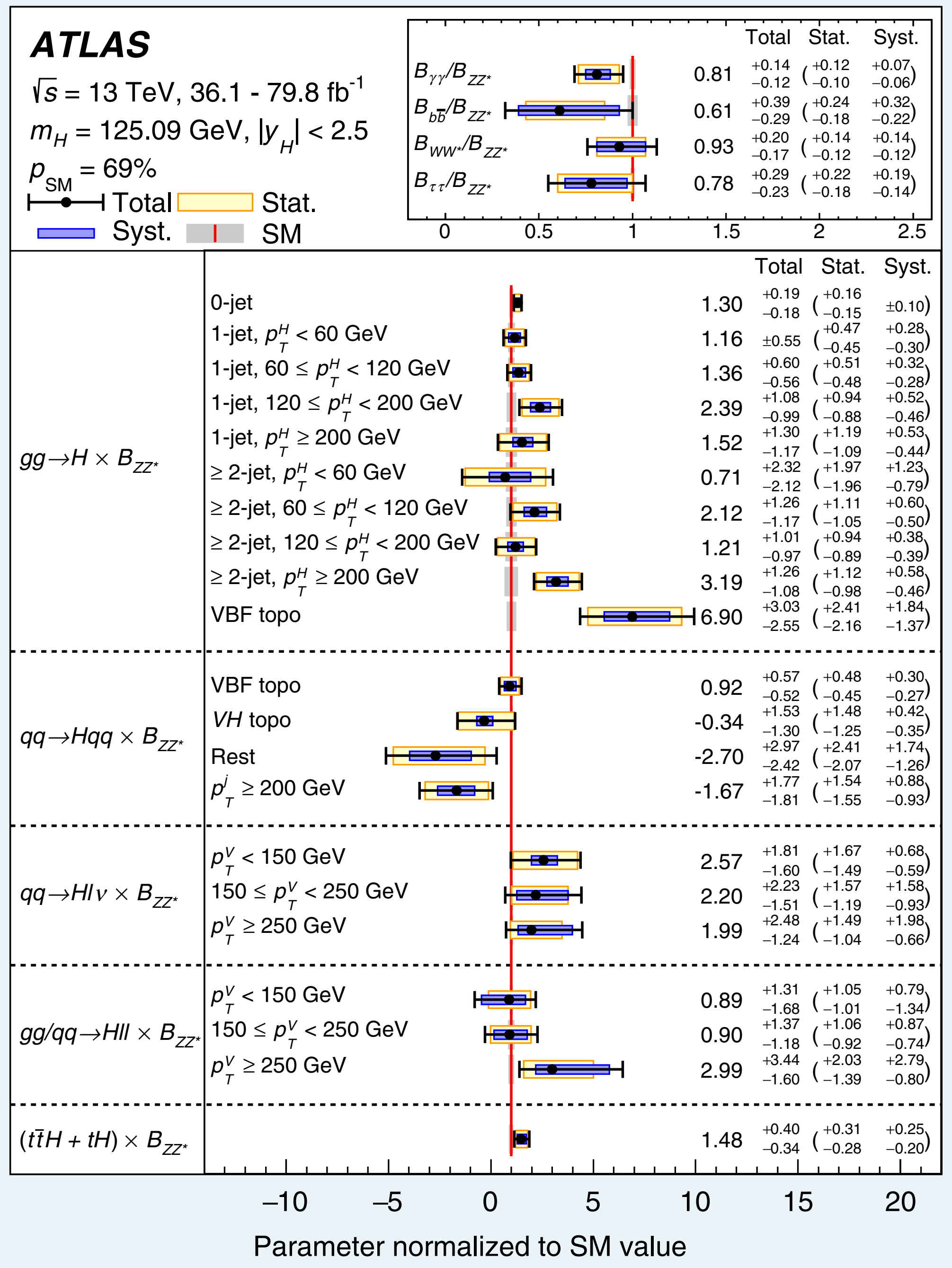
→ a single HEPData entry provides information on many different channels, *including correlations between channels*

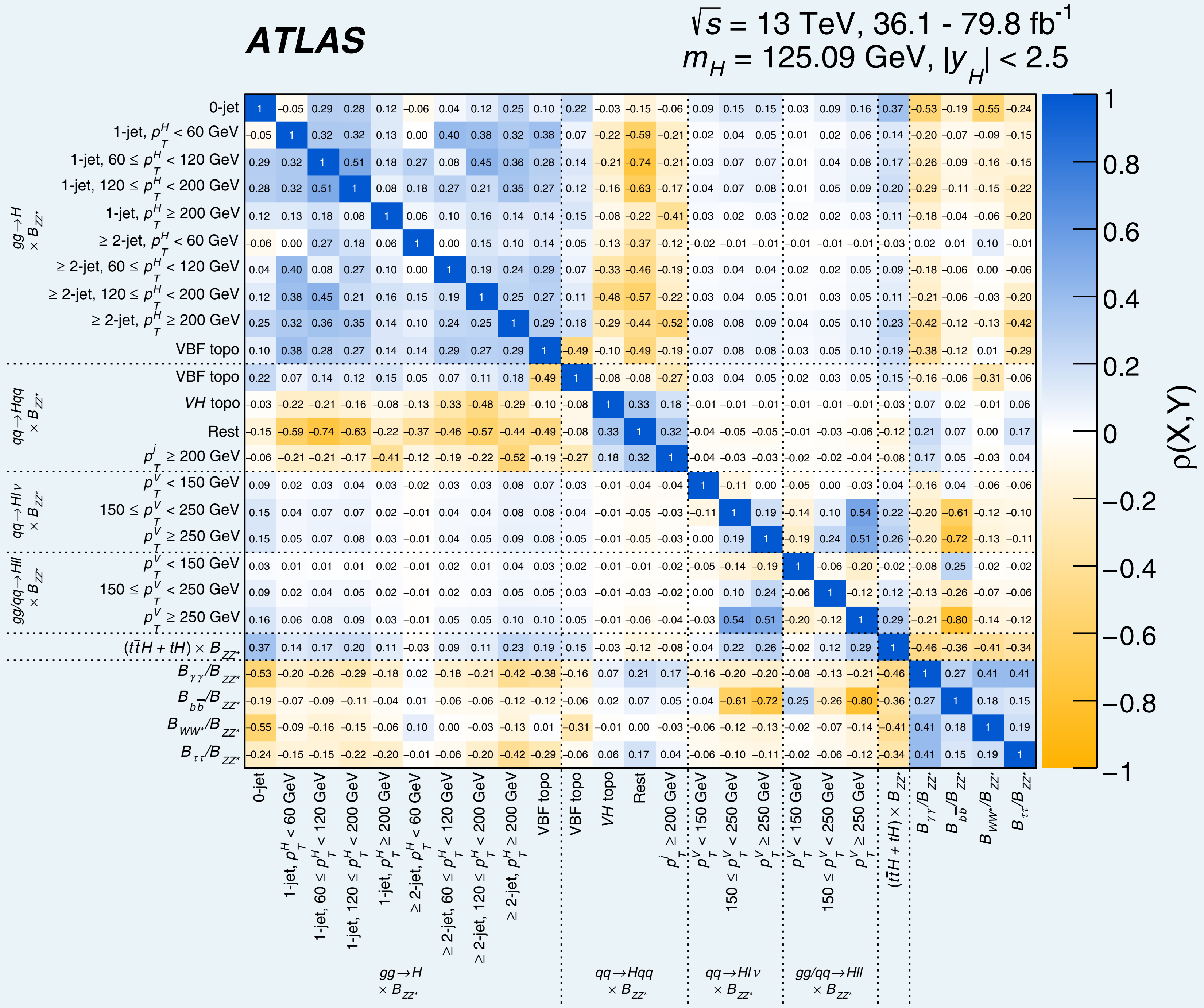


Combined fits

ATLAS Run II STXS combination:

[Phys. Rev. D 101 (2020) 012002]





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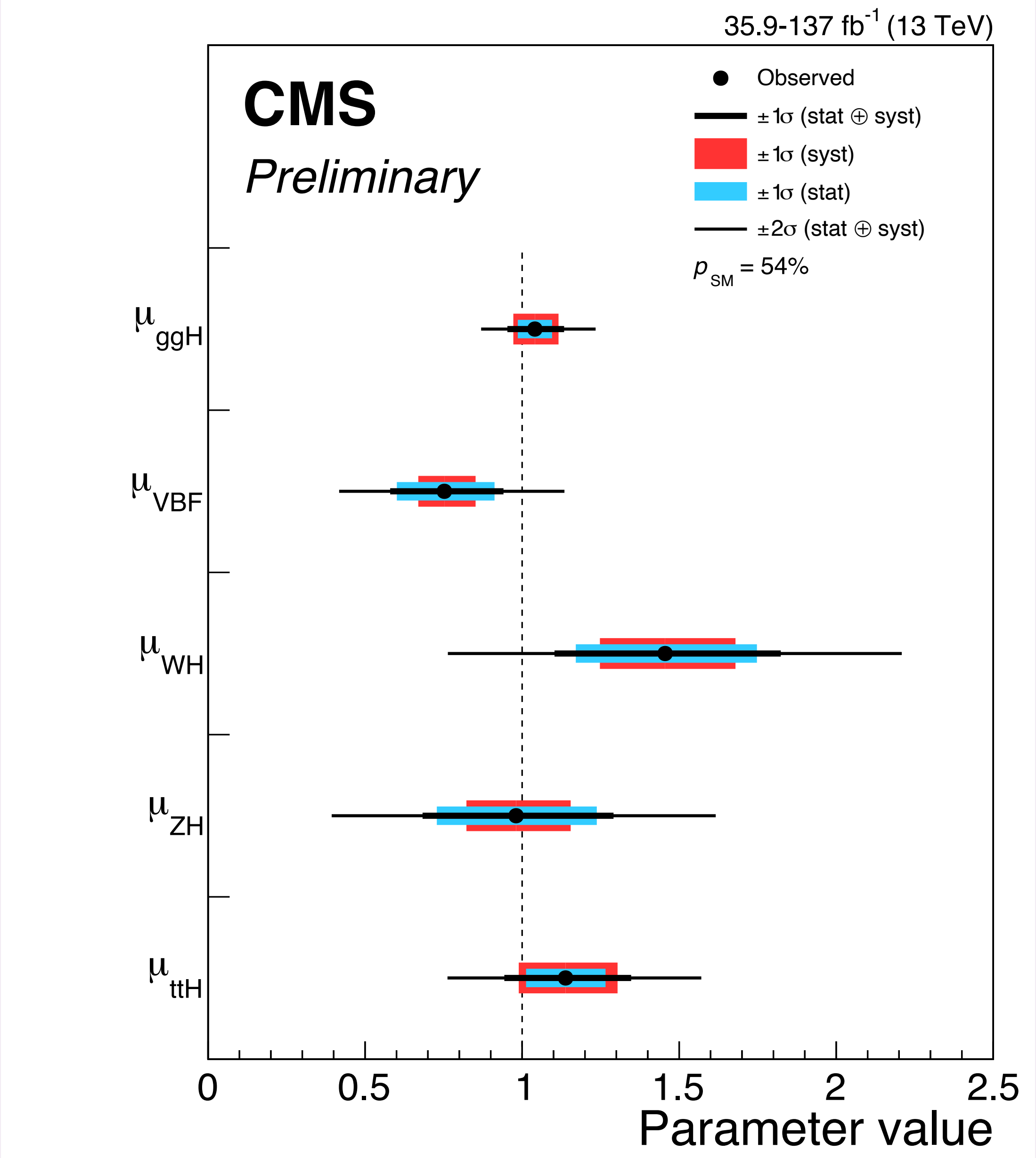
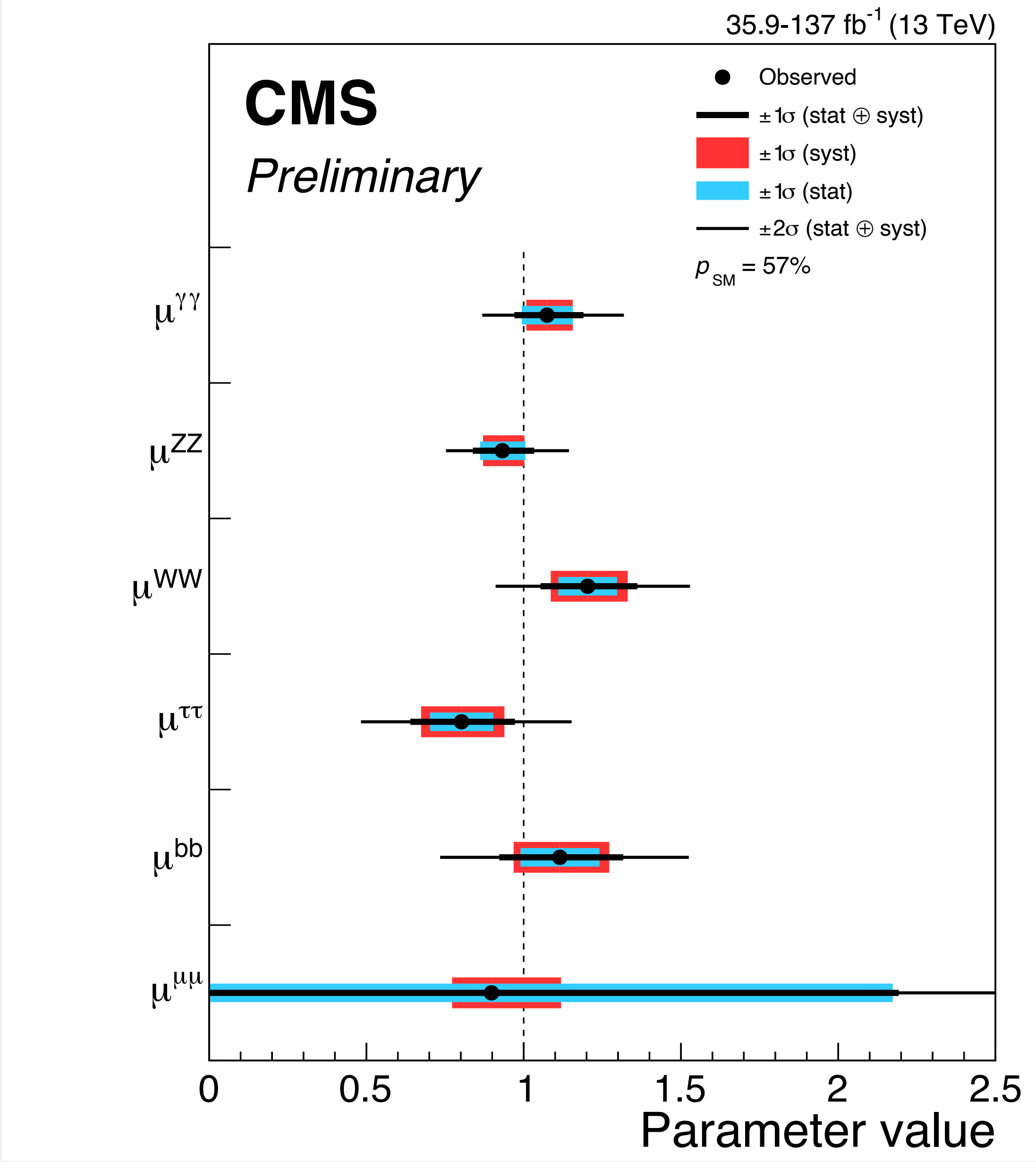
CMS Run II SS combination:

[CMS-PAS-HIG-19-005]





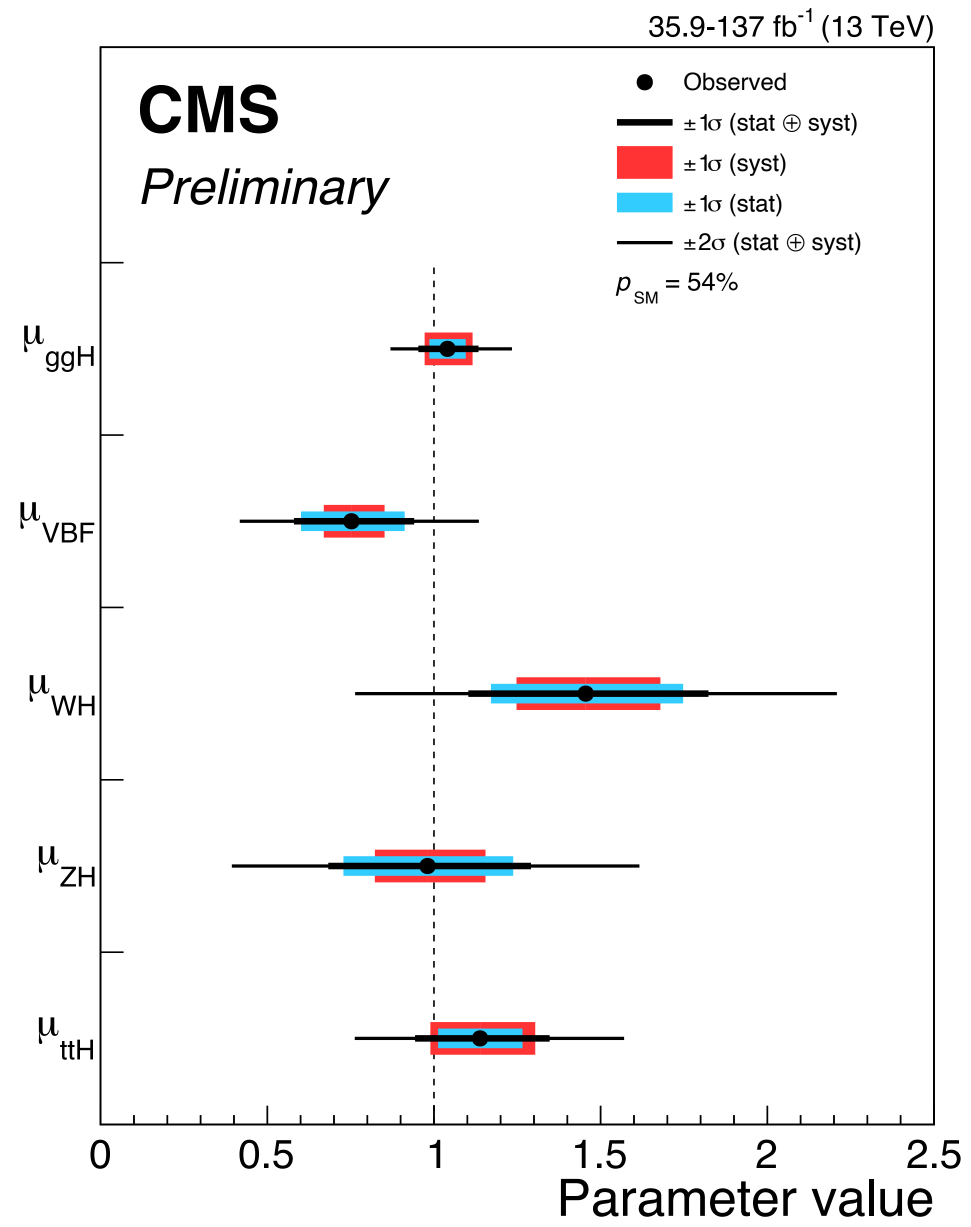
Combined fits

However: when new measurements become available, they cannot be easily swapped for measurements already in the combination

for example:

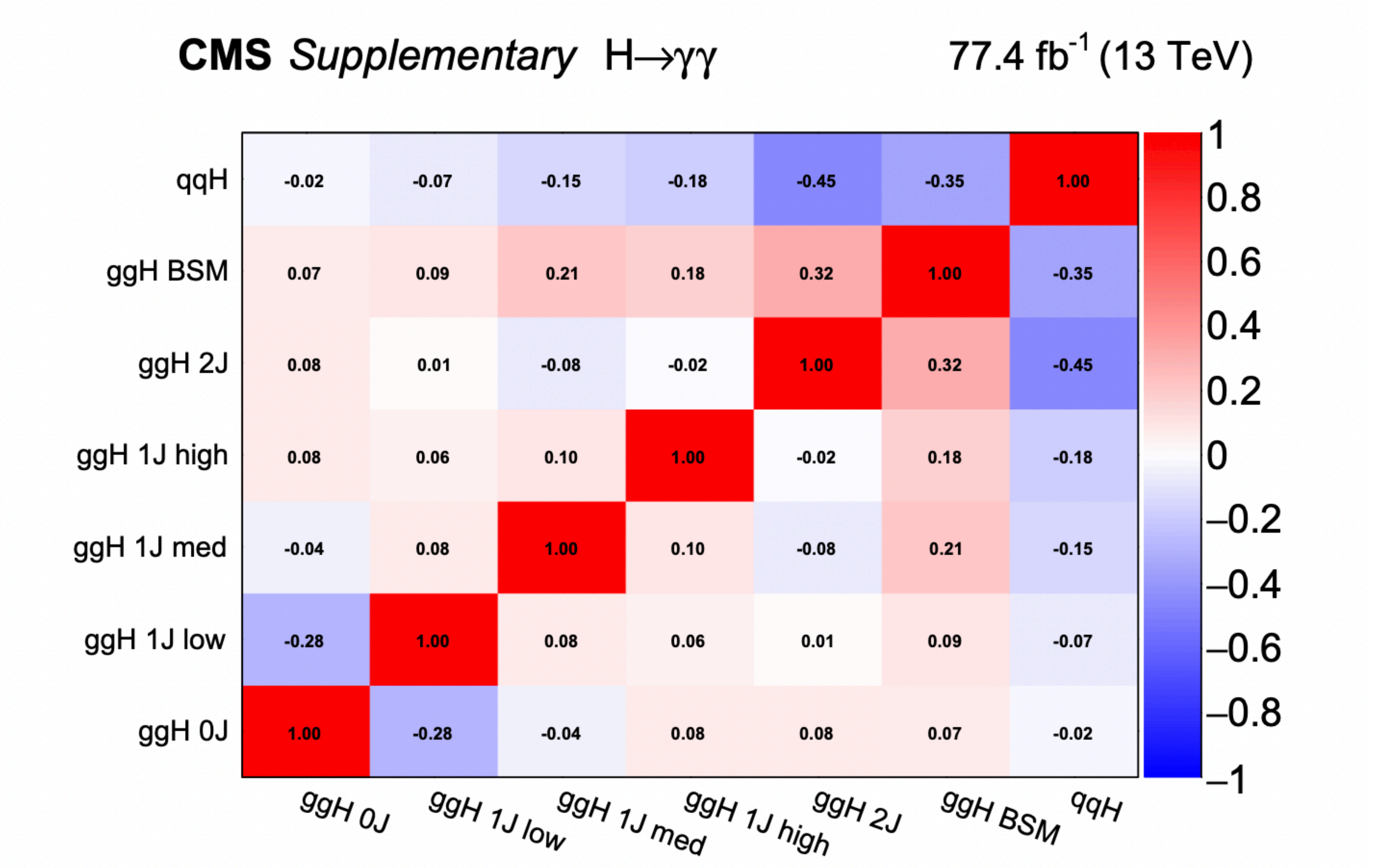
CMS Run II SS combination:
[CMS-PAS-HIG-19-005]

CMS Run II measurements of Higgs boson production via gluon fusion and vector boson fusion in the diphoton decay channel: [CMS-HIG-18-029-pas]



More channels - broader set of SMEFT coefficients constrained

Finer binning - better constraints on some energy-growing SMEFT coefficients



Datapoints & covariance matrices

Likelihoods

Unbinned measurements

Statistical Models

'Publishing statistical models: Getting the most out of particle physics experiments', 2109.04981, Cranmer et. al

$$p(n, x, y|\mu, \theta) = \prod_{i=1}^{N_c} \left[\mathrm{Pois}(n_i|\nu_i(\mu, \theta)) \prod_{j=1}^{n_i} p_i(x_{ij}|\mu, \theta) \right] p(y, \theta)$$

$$\rightarrow \mathcal{L}(\mu, \theta)$$ likelihoods

Statistical Models

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Measured #events, features and auxiliary measurements

Predicted #events

Constraints on nuisance parameters from auxiliary measurements

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Predictions for individual distributions

Parameter of interest & nuisance parameters

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Parameter of interest & nuisance parameters

Predictions for individual distributions

Nuisance parameters are profiled/ marginalised away

Access to full statistical model allows to e.g. reparametrise in terms of new parameters of interest

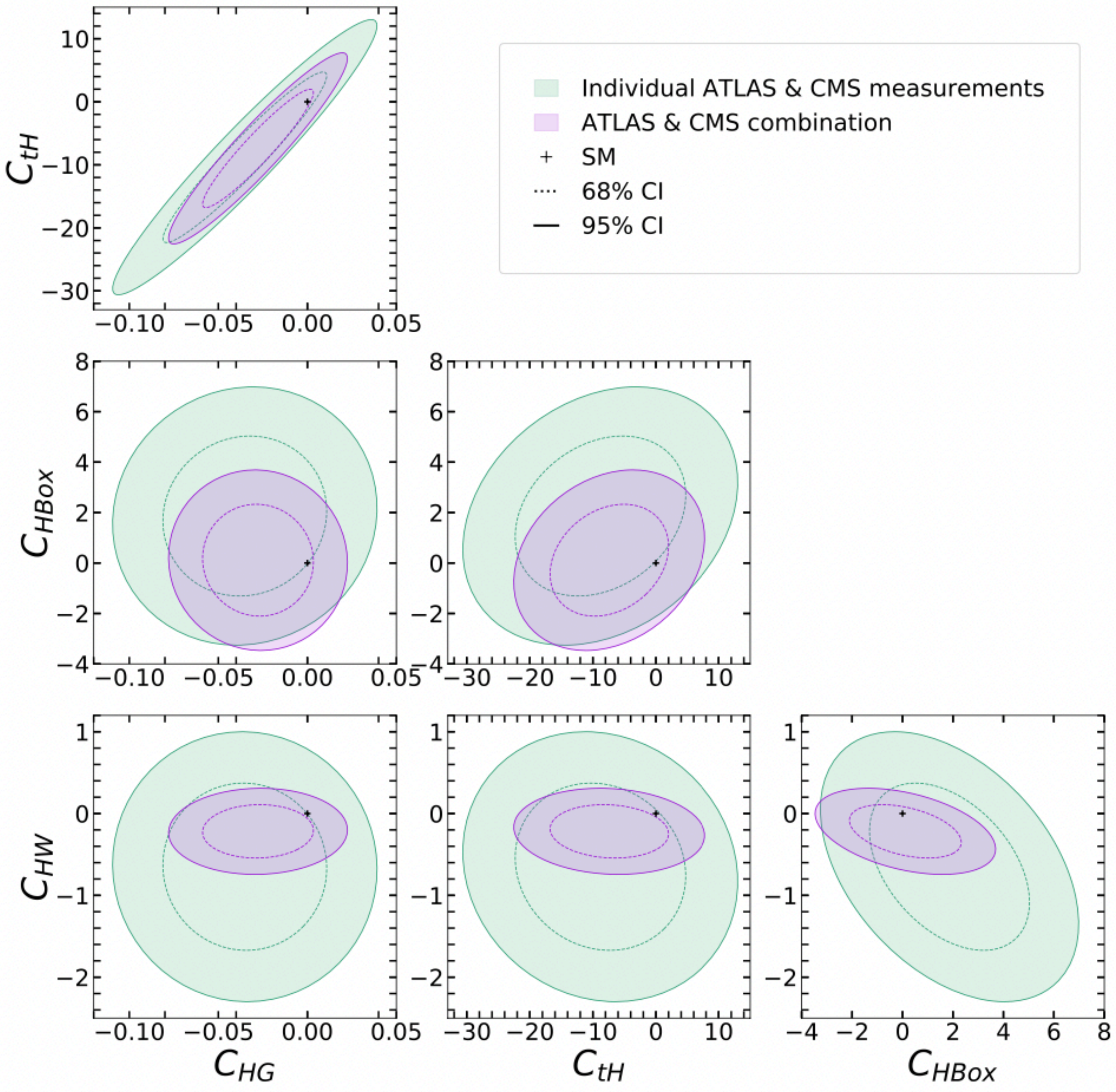
$$\mu \to \mu(\mu')$$

Example: statistical models allow for better combinations

Marginalised fit of

$$C_{tH}, C_{H\Box}, C_{HW}, C_{HB}, C_{HG}$$

to Higgs Run I signal strengths.



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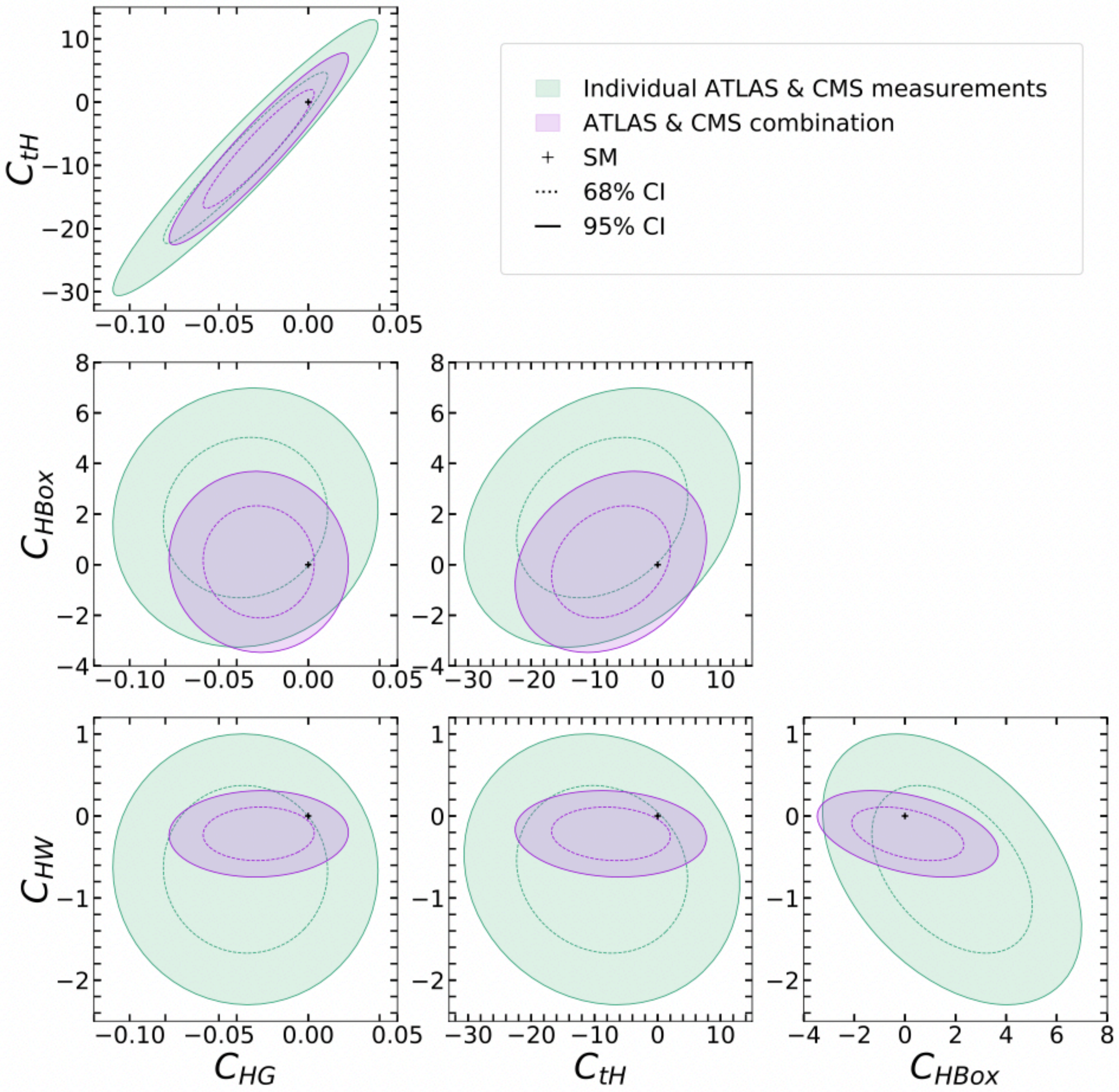
Green:

ATLAS 1507.04548 *(including published covariance matrix)*
CMS 1412.8662 *(no published covariance matrix)*

Combined in Fitmaker code, neglecting correlations between measurements



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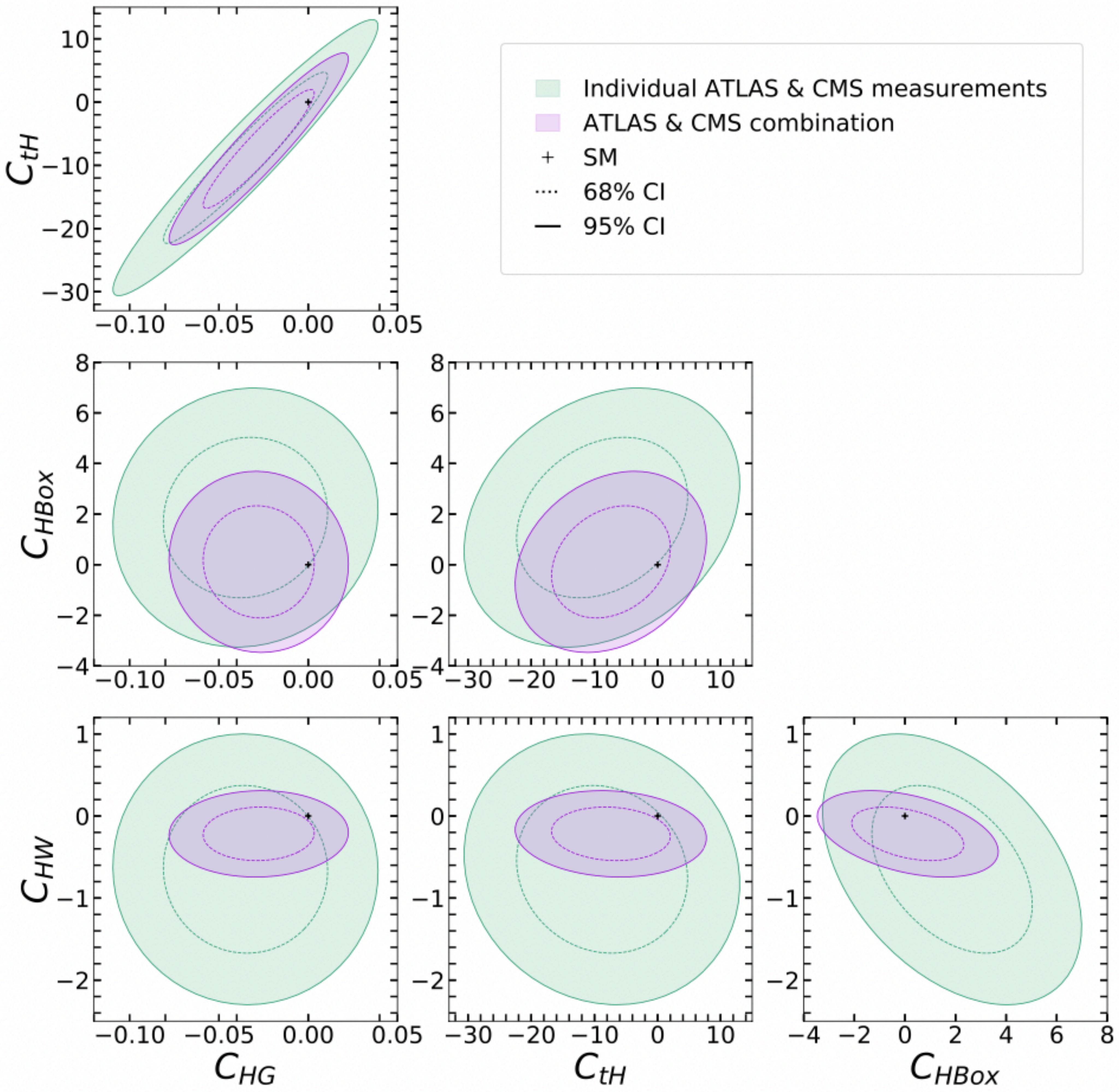
Purple:

Combination by ATLAS & CMS 1606.02266

Combined datasets are presented with finer binning



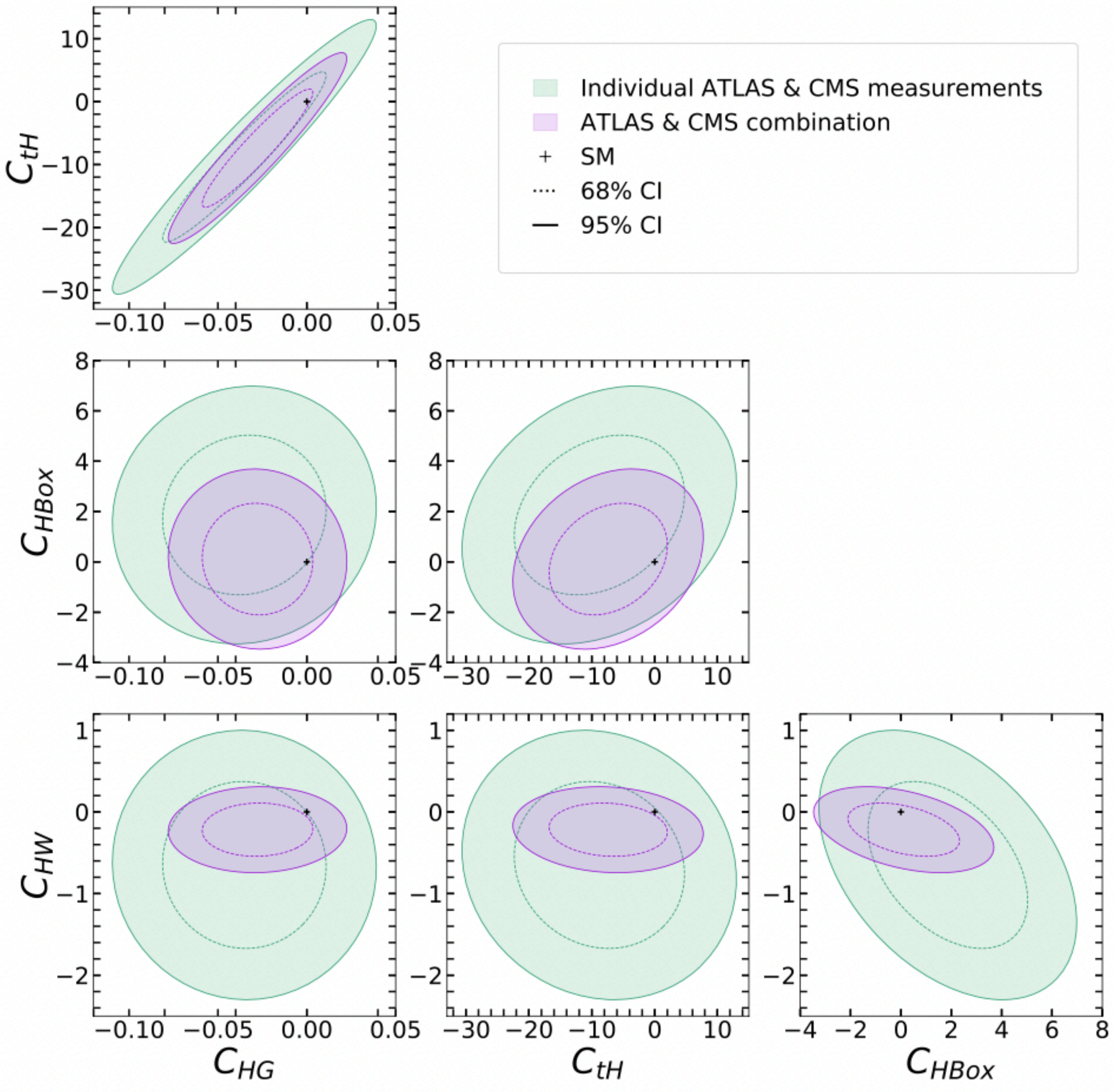
2109.04981, Cranmer et. al

Example: statistical models allow for better combinations

Access to the statistical model allows for proper combinations of data

- correlations can be taken into account
- better stats ⟶ finer binning can be used

➡ Improved sensitivity to the SMEFT

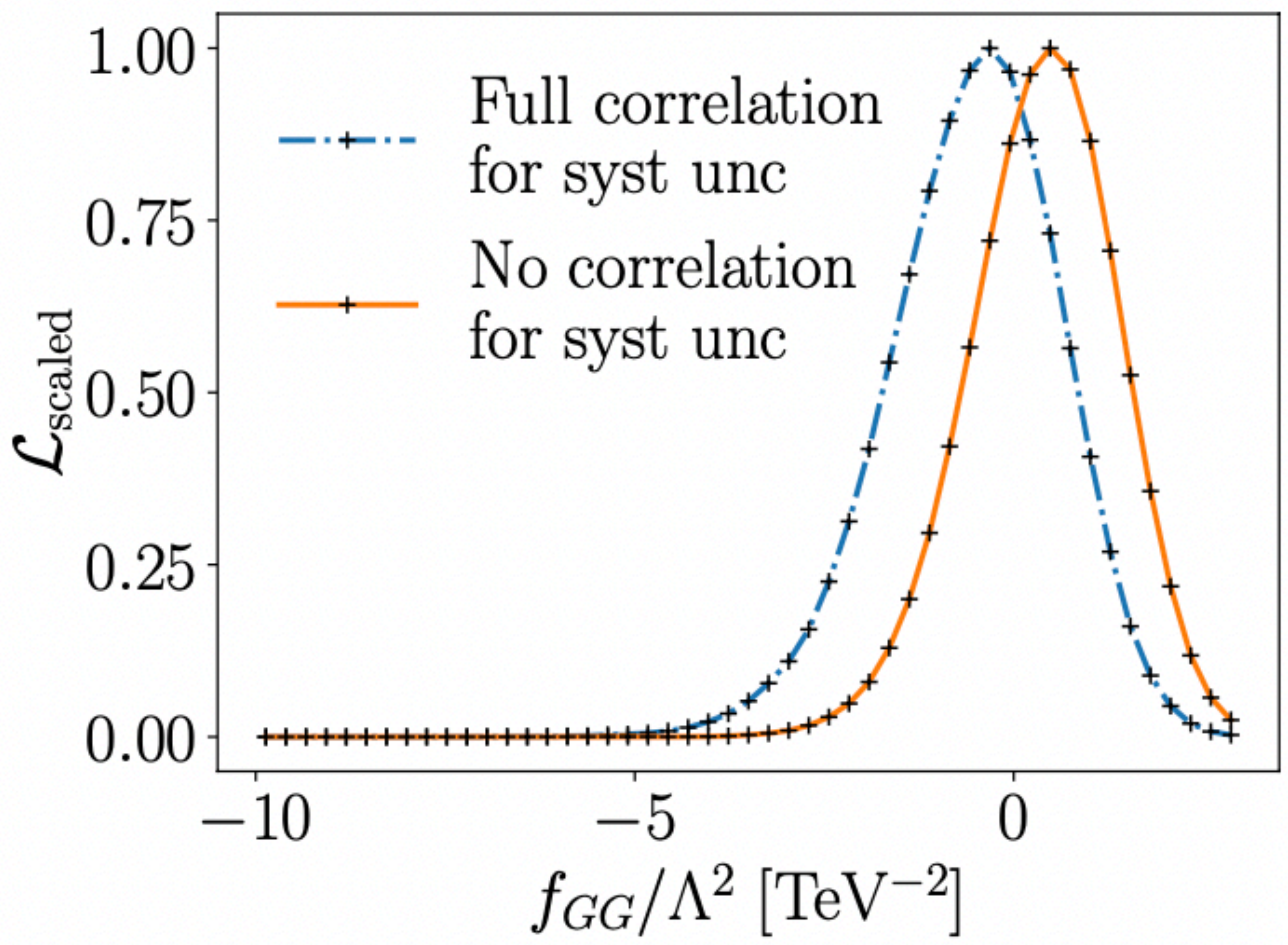


2109.04981, Cranmer et. al

Example: correlations between measurements

Published statistical models allow for a better understanding of correlated systematic uncertainties between measurements

Taking these into account has an impact on global SMEFT fits



I. Brivio et. al, 2208.08454

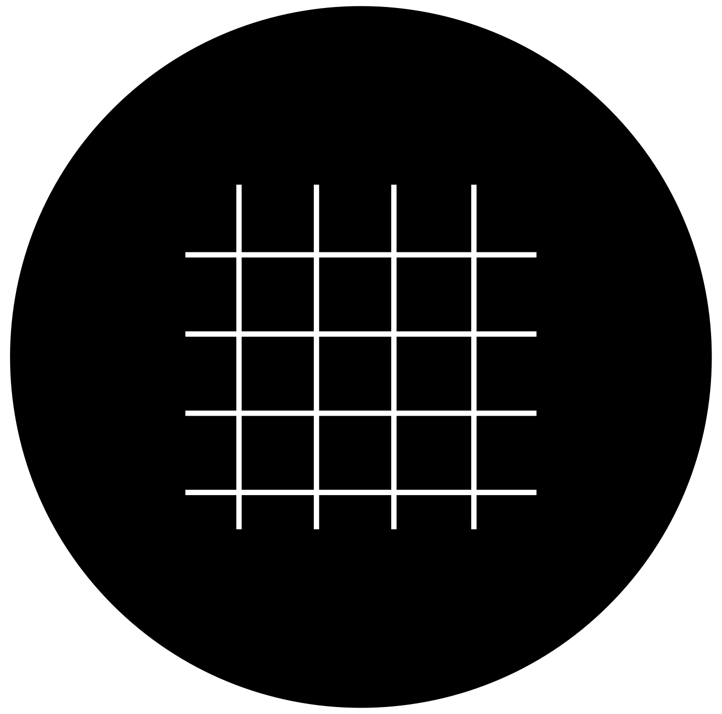
Published likelihoods

from https://twiki.cern.ch/twiki/bin/view/AtlasPublic

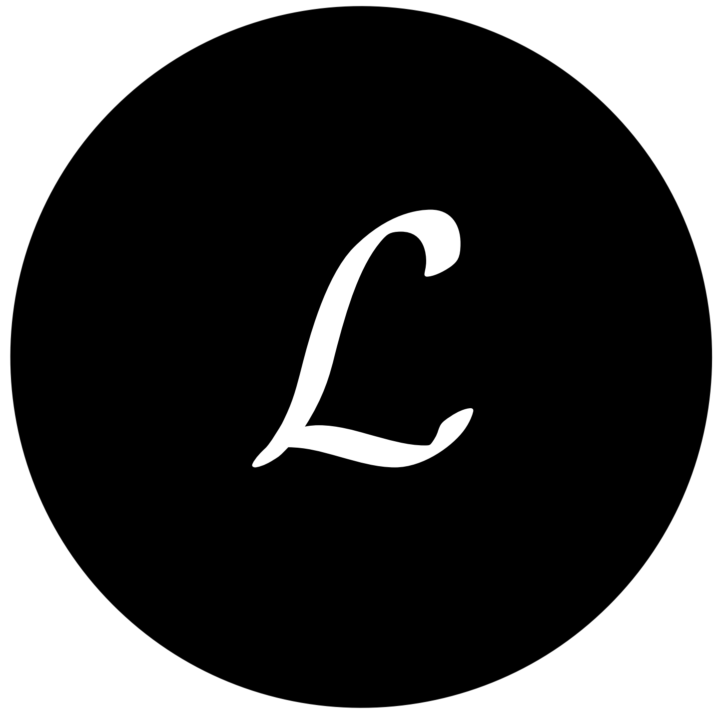
Observation of the tgamma production	TOPQ	Accepted by PRL	2023-02-02	13	140 fb^{-1}	Documents | 2302.01283 Inspire | HepData Internal
Search for gluinos in multi-b final states	SUSY	Eur. Phys. J. C 83 (2023) 561	2022-11-15	13	139 fb^{-1}	Documents | 2211.08028 Inspire | HepData Internal
Measurement of the s-channel single top cross-section at 13 TeV	TOPQ	JHEP 06 (2023) 191	2022-09-19	13	139 fb^{-1}	Documents | 2209.08990 Inspire | HepData Internal
Search for flavor-changing neutral-current couplings between the top-quark and the photon at 13 TeV	TOPQ	Phys. Lett. B 842 (2023) 137379	2022-05-05	13	139 fb^{-1}	Documents | 2205.02537 Inspire | HepData Internal
Search for SUSY in events with 2 leptons, jets and MET	SUSY	Eur. Phys. J. C 83 (2023) 515	2022-04-27	13	139 fb^{-1}	Documents | 2204.13072 Inspire | HepData Internal
Search BSM H→hh→bb gamma gamma and hh→bb gamma gamma	HDBS	Phys. Rev. D 106 (2022) 052001	2021-12-22	13	139 fb^{-1}	Documents | 2112.11876 Inspire | HepData Internal
Search for charginos and neutralinos in all-hadronic final states	SUSY	Phys. Rev. D 104 (2021) 112010	2021-08-17	13	139 fb^{-1}	Documents | 2108.07586 Inspire | HepData Briefing | Internal
4-top xsec measurement	TOPQ	JHEP 11 (2021) 118	2021-06-22	13	139 fb^{-1}	Documents | 2106.11683 Inspire | HepData Internal
Search for gluinos, stops and electroweakinos in RPV models in final states with 1L and many jets	SUSY	Eur. Phys. J. C 81 (2021) 1023	2021-06-17	13	139 fb^{-1}	Documents | 2106.09609 Inspire | HepData Briefing | Internal

Many more likelihoods being published alongside measurements 🥳

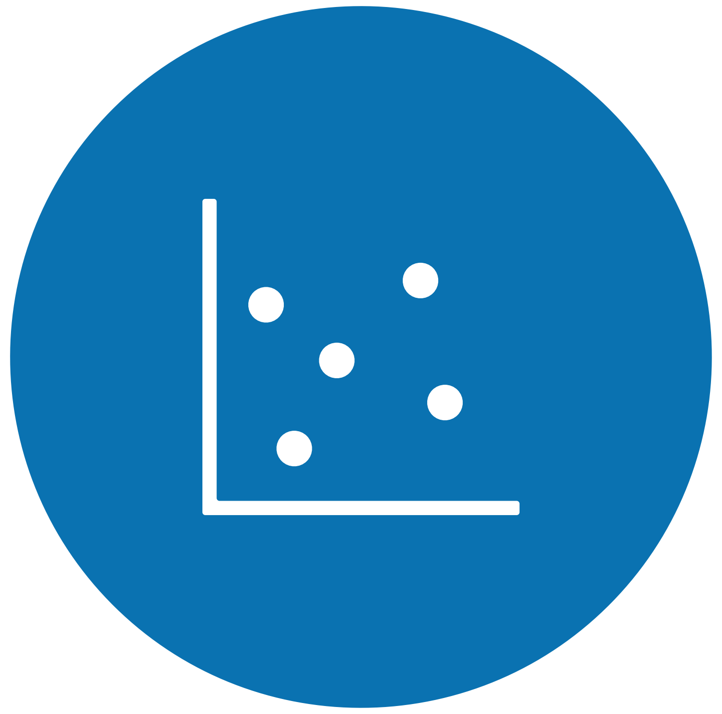
Work in progress will assess their impact on global SMEFT fits, *N. Elmer, MM, T. Plehn, N. Schmal*



Datapoints & covariance matrices



Likelihoods



Unbinned measurements

Unbinned Measurements

'Presenting Unbinned Differential Cross Section Results', Arratia et al, 2109.13243

1. **Inference-aware binning:**
    - optimal choice of binning can be made at the time of *each* statistical analysis or global fit

Unbinned Measurements

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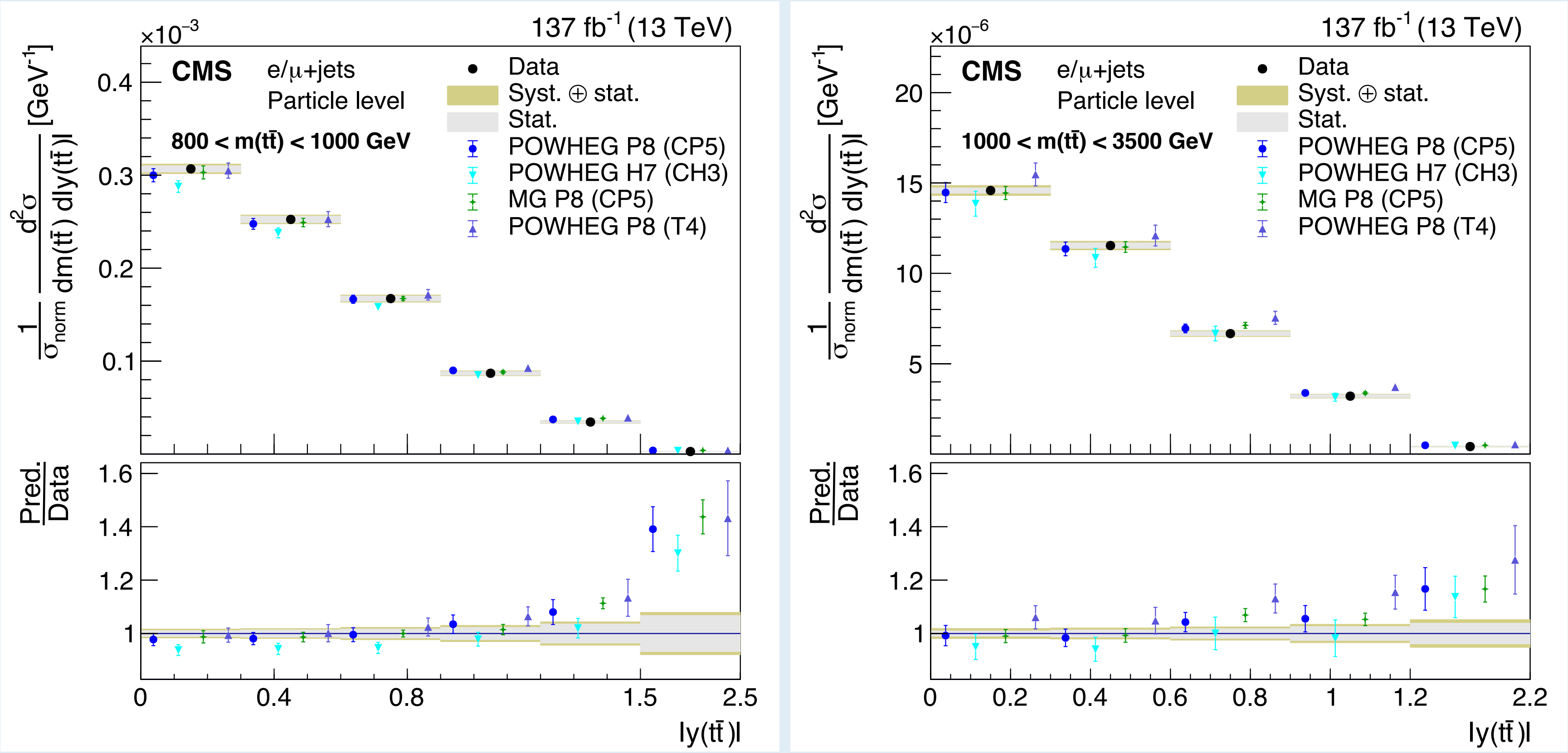
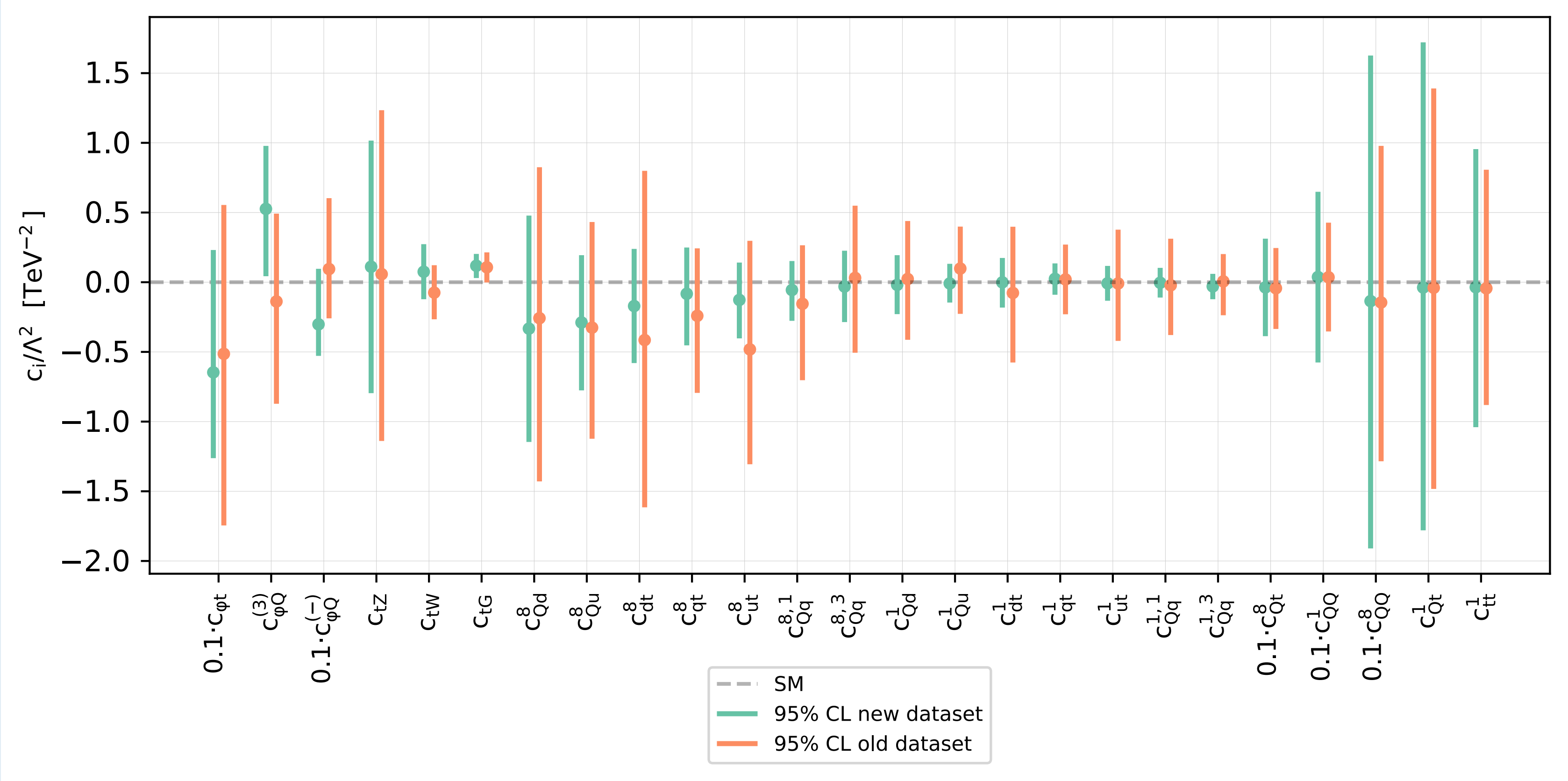
Typically we **reinterpret** measurements optimised for SM measurements or NP resonance searches





e.g. CMS measurement of top pair production in the l+jets channel 2108.02803

Unbinned Measurements

'Presenting Unbinned Differential Cross Section Results', Arratia et al, 2109.13243

1. **Inference-aware binning:**
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2. **Derivative measurements:**
   - given measurements of features $x_1, ..., x_n$, 'post-hoc measurement' of $f(x_1, ..., x_n)$ possible

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3. **Extension to higher dimensions:**
   - ML-based unbinned unfolding techniques better suited to multiple features

ML4EFT

https://lhcfitnikhef.github.io/ML4EFT/

2211.02058 Raquel Gomez Ambrosio, Jaco ter Hoeve, MM, Juan Rojo, Veronica Sanz

Open-source NN-based python framework for the integration of unbinned multivariate observables into global SMEFT interpretations.

Goal: to provide optimal constraints on the SMEFT:

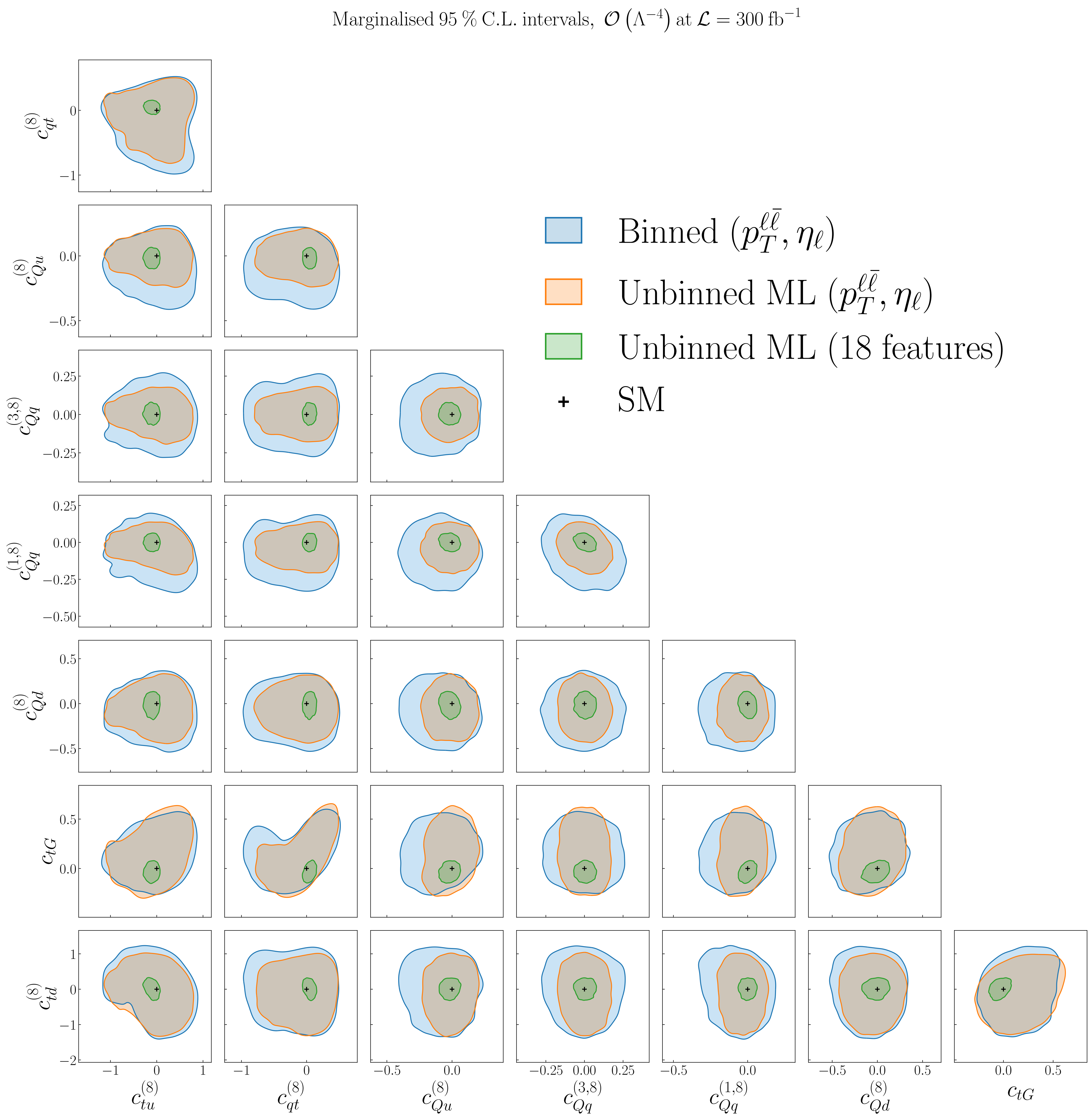
Diagnostic tool:

What is the information loss given a particular choice of bins?

Projections:

If unbinned data are made available, how will SMEFT constraints improve?

Unbinned observables in the top sector



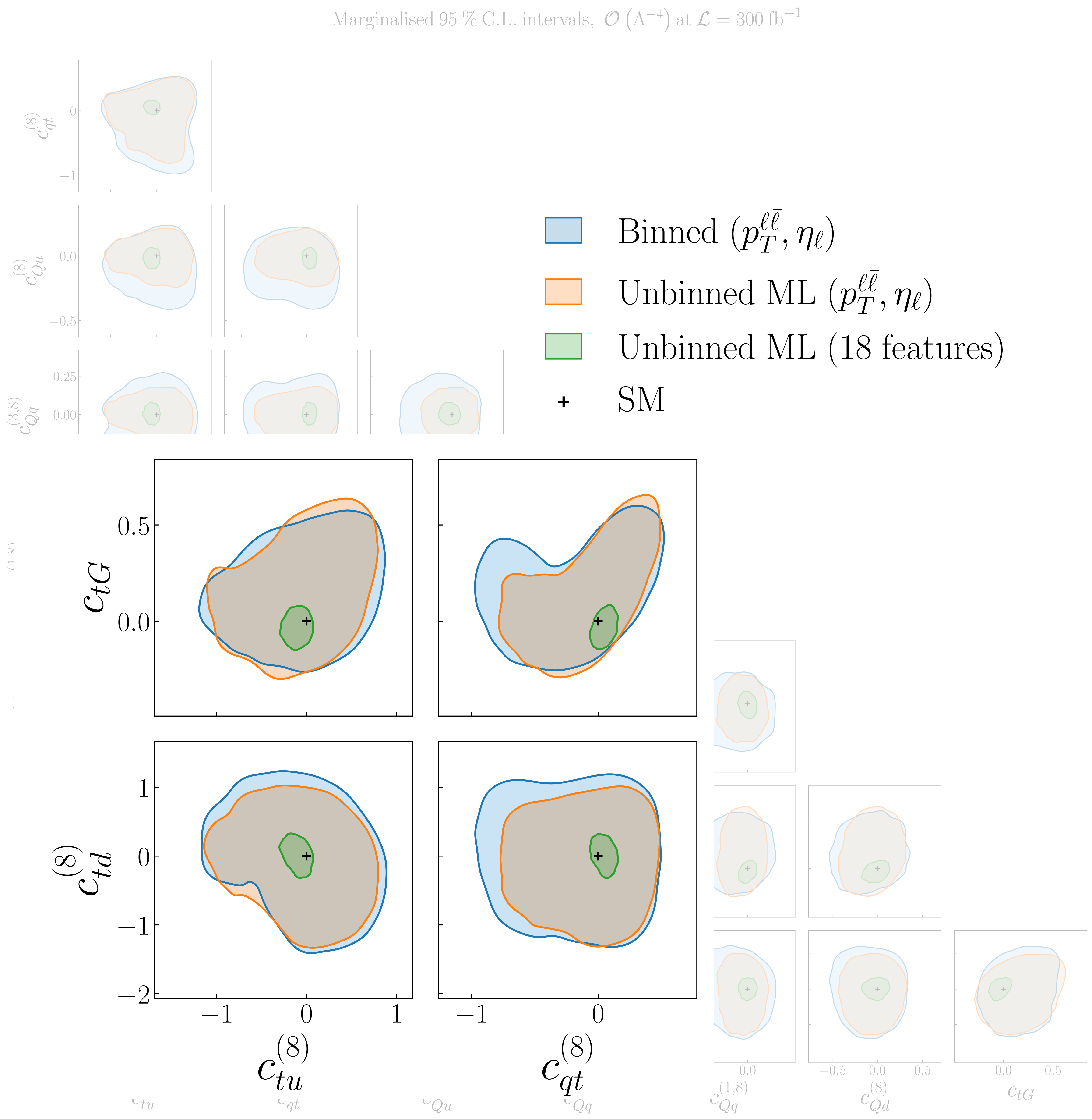
Particle-level top quark pair production in the dileptonic channel:

$$pp \to t\bar{t} \to \ell^+\ell^- b\bar{b}\nu_\ell\bar{\nu}_\ell$$

Constraints on 8 SMEFT operators:

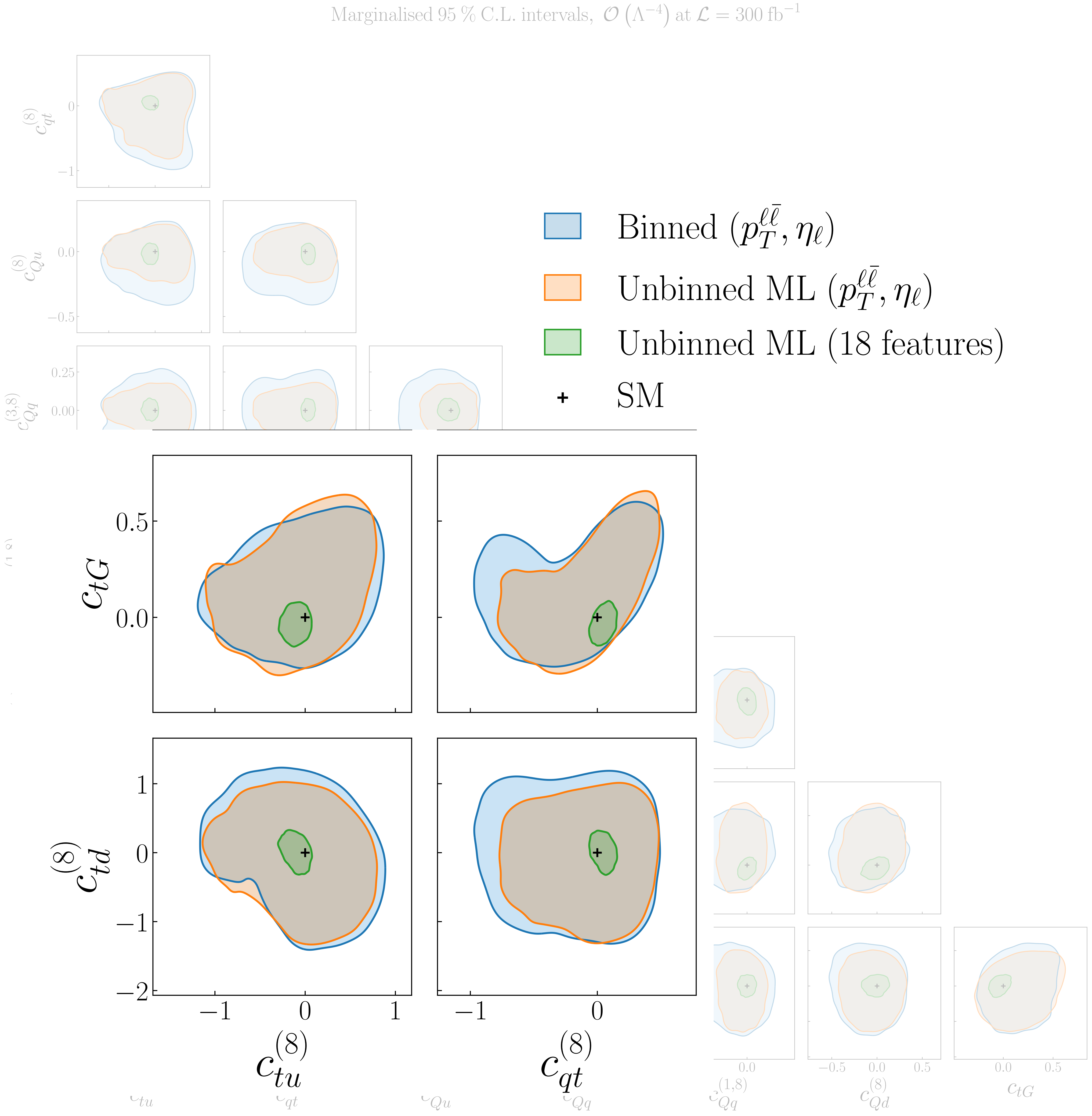
$$O_{tG} + \text{4-fermion operators}$$

Unbinned observables in the top sector



Binned vs unbinned in $(p_T^{\ell\bar{\ell}}, \eta_\ell)$: small improvement from unbinned measurements, relative to nominal choice of bins

Unbinned observables in the top sector



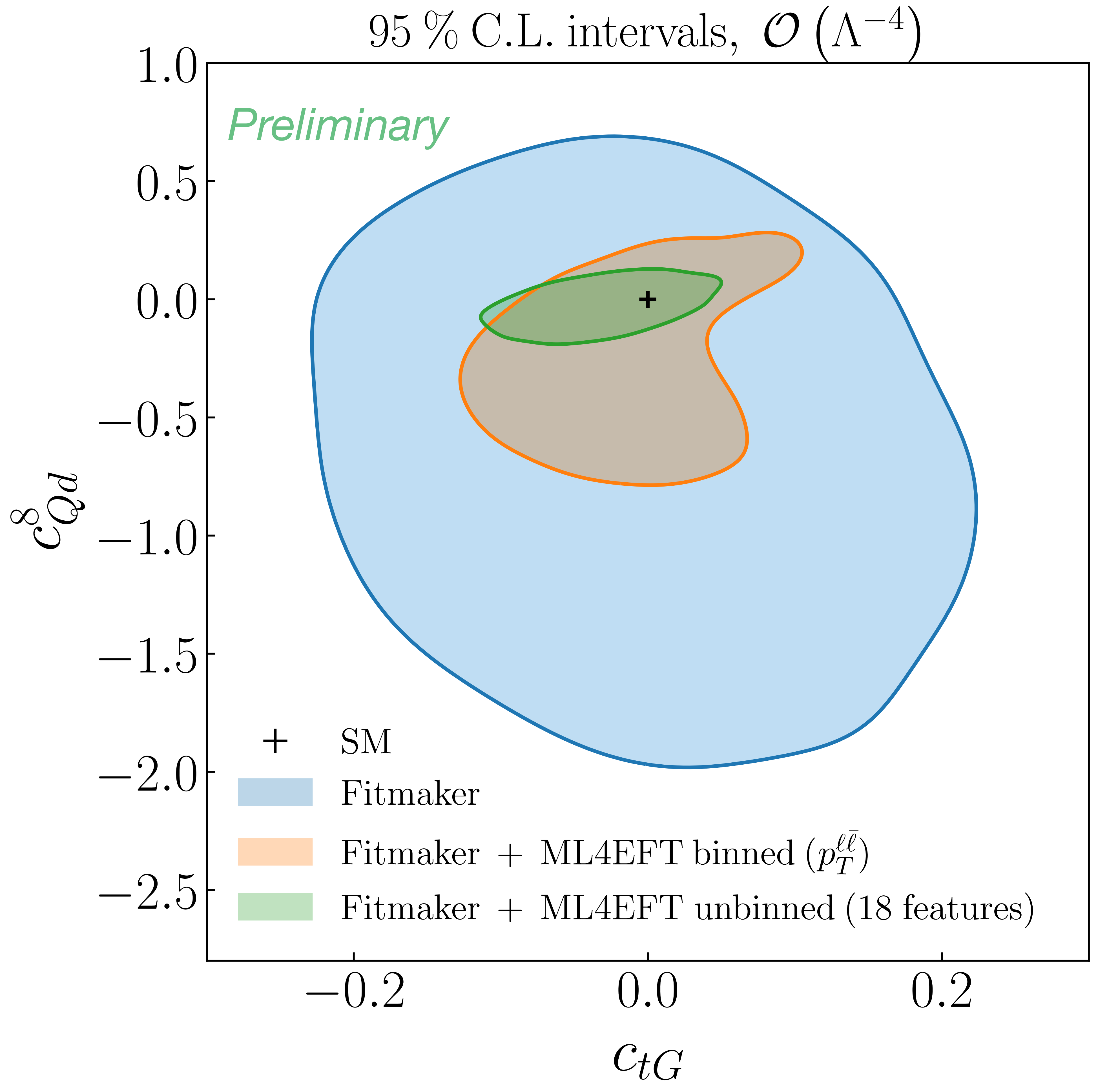
Binned vs unbinned in $(p_T^{\ell\bar{\ell}}, \eta_\ell)$: small improvement from unbinned measurements, relative to nominal choice of bins

2 features vs 18 features: vast improvement in constraining power

Integration into global SMEFT fits

New unbinned measurements can be combined alongside existing binned measurements:

$$\log\mathcal{L}(c) = \sum_{k=1}^{N_D^{(\mathrm{unbinned})}} \log\mathcal{L}_k^{\mathrm{unbinned}}(c) + \sum_{k=1}^{N_D^{(\mathrm{binned})}} \log\mathcal{L}_k^{\mathrm{binned}}(c)$$



Work in progress, Jaco ter Hoeve, MM

Conclusions

Reinterpretation of LHC data for global SMEFT fits

more information → **better SMEFT fits**

- HEPData 😍
- Likelihoods 🥳
- Unbinned measurements 🤩

Discussion points:

- Double and triple differential distributions with covariance matrices
- Unfolded data - careful of the unfolding assumptions and model dependence
- Preservation of combinations of measurements e.g. the Higgs sector
- Publication of likelihoods
- Unbinned measurements have the potential to better constrain the SMEFT

Conclusions

Thank you for listening!

Reinterpretation of LHC data for global SMEFT fits

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Backup

ML4EFT

For parameter estimation, we would like to be able to calculate the **likelihood:** $\mathcal{L}(D|\mathbf{c}) \propto \prod_{i=1}^{N_{ev}} f_\sigma(\mathbf{x}_i, \mathbf{c})$

where $f_\sigma(\mathbf{x}, \mathbf{c}) = \frac{1}{\sigma(\mathbf{x}, \mathbf{c})} \frac{d\sigma(\mathbf{x}, \mathbf{c})}{d\mathbf{x}}$

$D = \{\mathbf{x}_i\}$ $\mathbf{x}_i = \{m_{t\bar{t}}, p_T^{\ell_1}, p_T^{\ell_2}, \Delta\eta_{\ell_1,\ell_2}, \Delta\phi_{\ell_1,\ell_2}, ...\}$

→ multi-differential cross section in **all features**

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However: analytical calculation of $\mathcal{L}$ is intractable in most realistic cases.

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→ multi-differential cross section in **all features**

However: analytical calculation of $\mathcal{L}$ is intractable in most realistic cases.

Instead: approximate $\mathcal{L}$ using neural networks

ML4EFT

Train a classifier ***g*** to distinguish the SM from the SMEFT:

$$L[g(\mathbf{x},\mathbf{c})] = -\sum_{i=1}^{N_{\rm ev}^{\rm SMEFT}} \frac{d\sigma(\mathbf{x}_i,\mathbf{c})}{dx}\log(1-g(\mathbf{x}_i,\mathbf{c})) - \sum_{i=1}^{N_{\rm ev}^{\rm SM}} \frac{d\sigma(\mathbf{x}_i,\mathbf{0})}{dx}\log(g(\mathbf{x}_i,\mathbf{0}))$$

SMEFT training pseudodata sample

SM training pseudo data sample

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SMEFT training pseudodata sample

SM training pseudo data sample

$$\frac{\delta L}{\delta g} = 0 \Rightarrow g(\mathbf{x},\mathbf{c}) = \left(1 + \frac{d\sigma(\mathbf{x},\mathbf{c})}{dx}\Big/\frac{d\sigma(\mathbf{x},\mathbf{0})}{dx}\right)^{-1} \equiv \frac{1}{1+r_\sigma(\mathbf{x},\mathbf{c})}$$

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In the limit of infinite training samples, the decision boundary is 1:1 with the likelihood

ML4EFT

$$\hat{g} = \frac{1}{1 + \hat{r}_\sigma(x, c)}$$

$$r_\sigma(\mathbf{x}, \mathbf{c}) = \frac{d\sigma(\mathbf{x}, \mathbf{c})}{dx} \Big/ \frac{d\sigma(\mathbf{x}, 0)}{dx}$$

Exploit the polynomial structure of the SMEFT when defining the classifier ***g***:

$$\hat{r}_\sigma(\mathbf{x}, \mathbf{c}) = 1 + \sum_{j=1}^{n_{\text{eft}}} \text{NN}^{(j)}(\mathbf{x}) c_j + \sum_{j=1}^{n_{\text{eft}}} \sum_{k \geq j}^{n_{\text{eft}}} \text{NN}_\sigma^{(j,k)}(\mathbf{x}) c_j c_k$$

Parallelisable: generate a training sample with only c_i and learn only $\text{NN}^i(\mathbf{x})$

well-suited to global fits of many SMEFT coefficients