



AI goes MAD

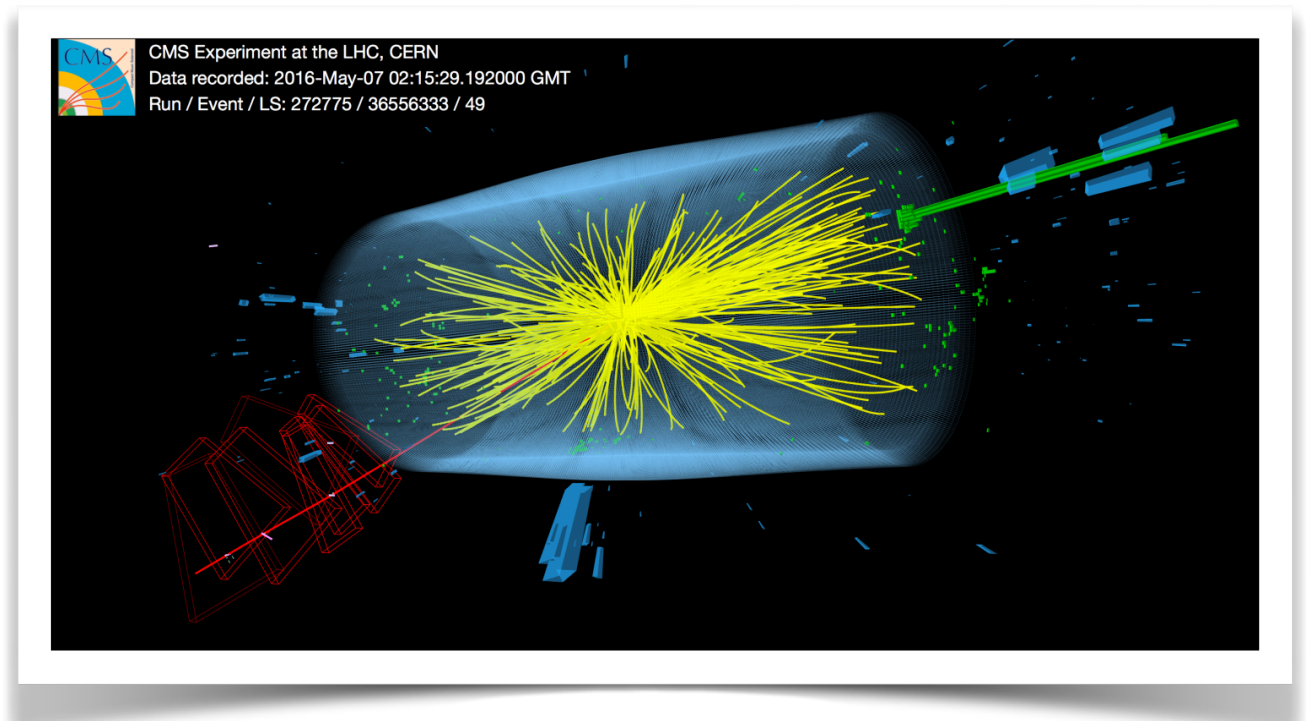
Symbolic regression for precision LHC physics

Manuel Morales-Alvarado

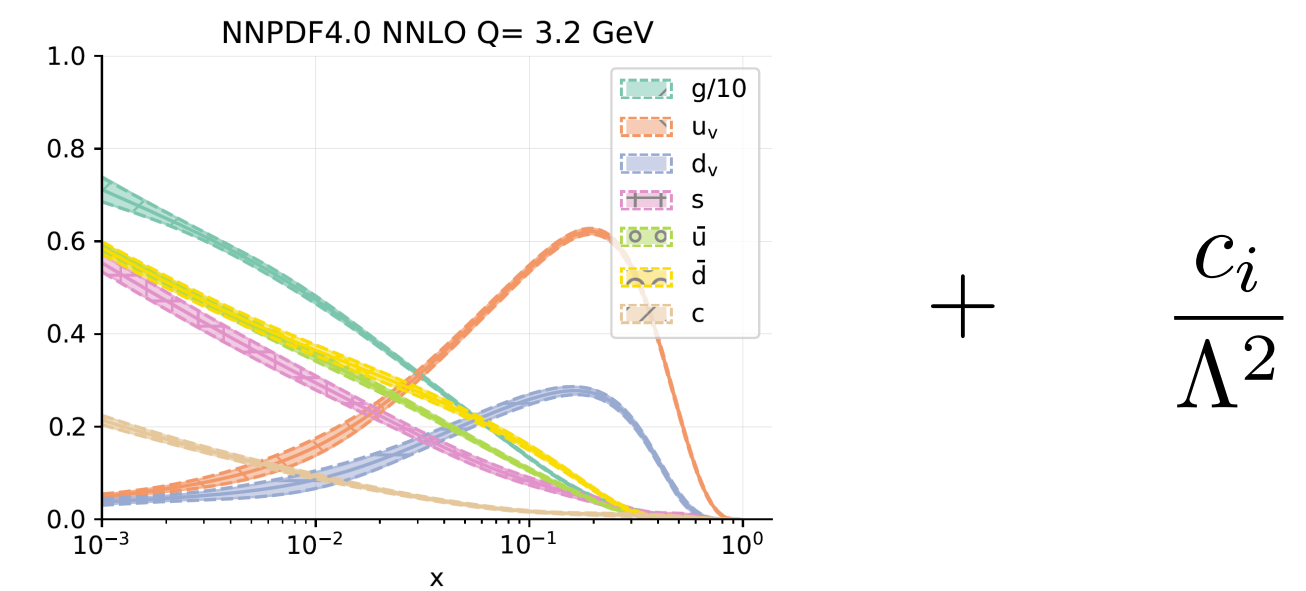
INFN, Sezione di Trieste, SISSA



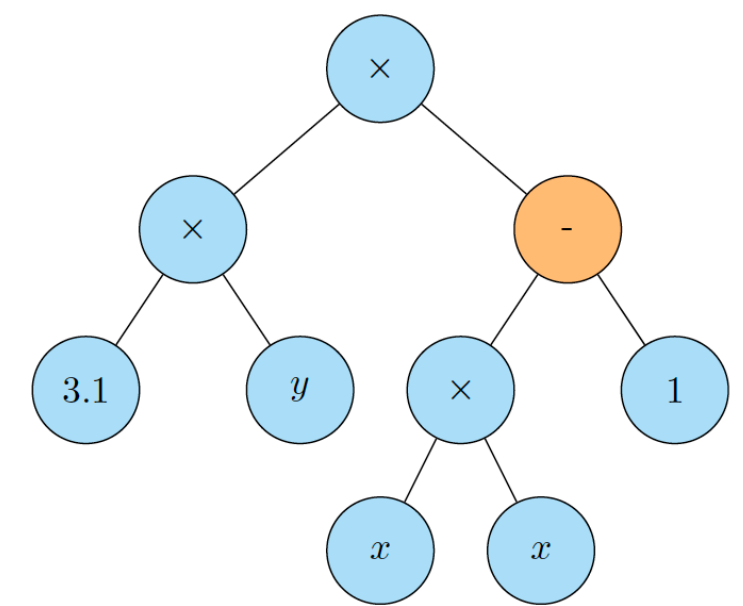
Outline



Some high energy physics

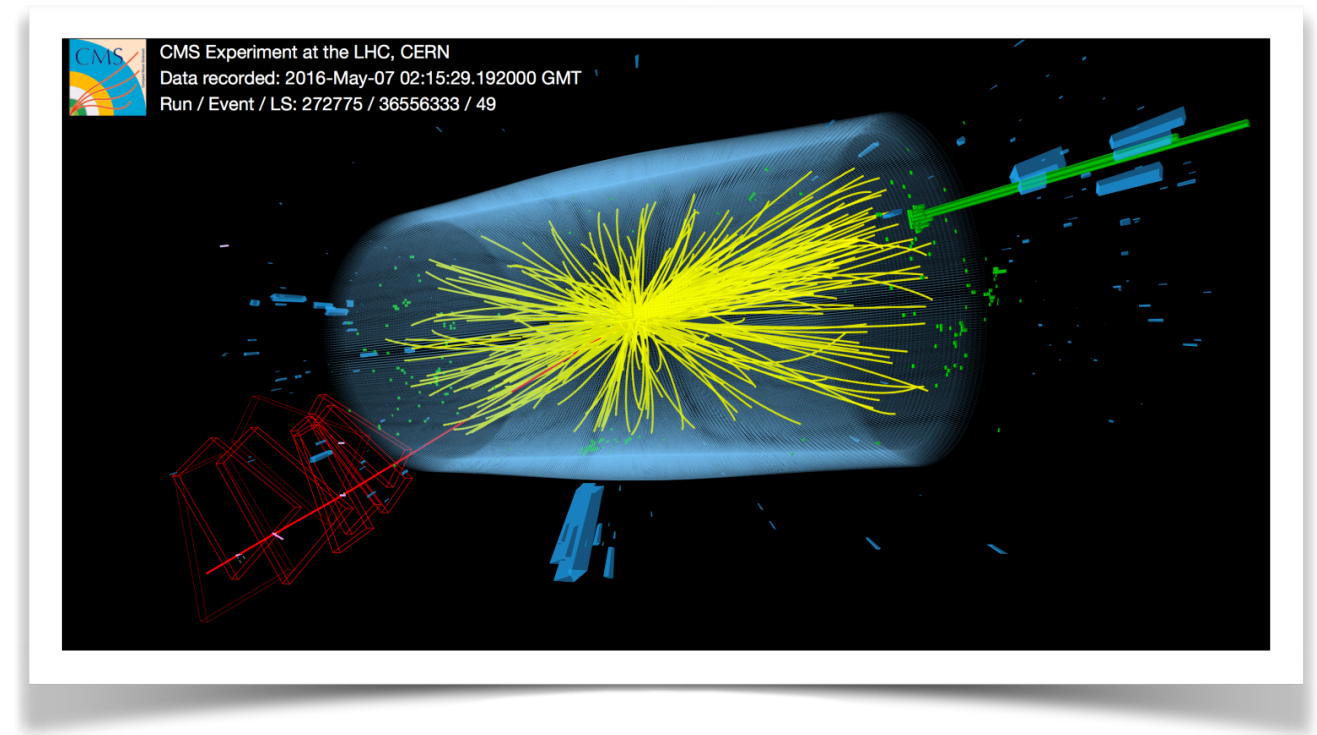


Precision: deep learning the structure of hadrons and new physics

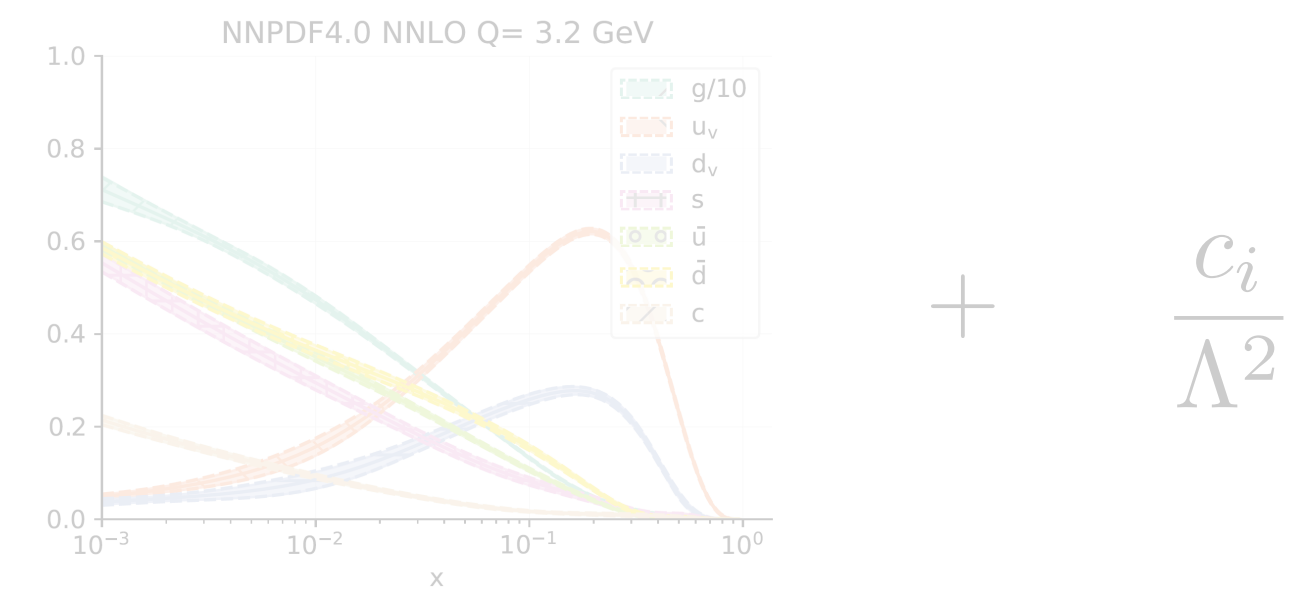


Symbolic regression

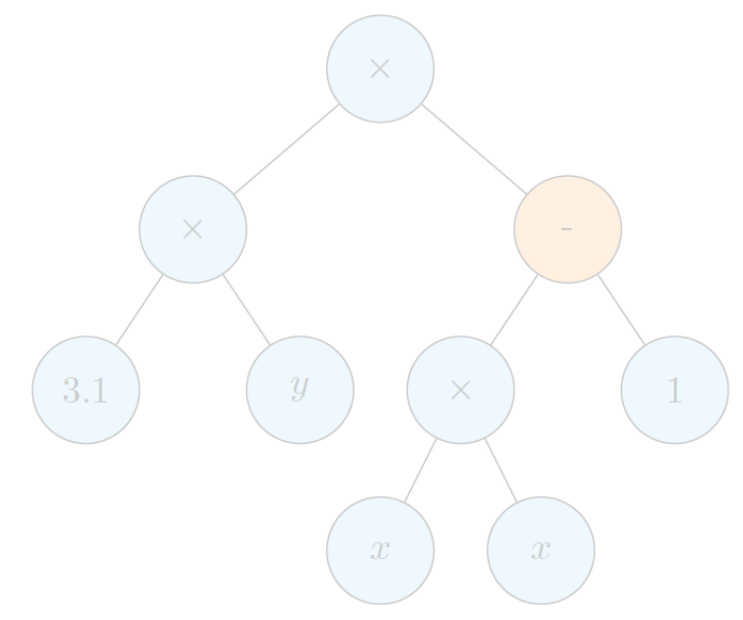
Outline



Some high energy physics



Precision: deep learning the structure of hadrons and new physics

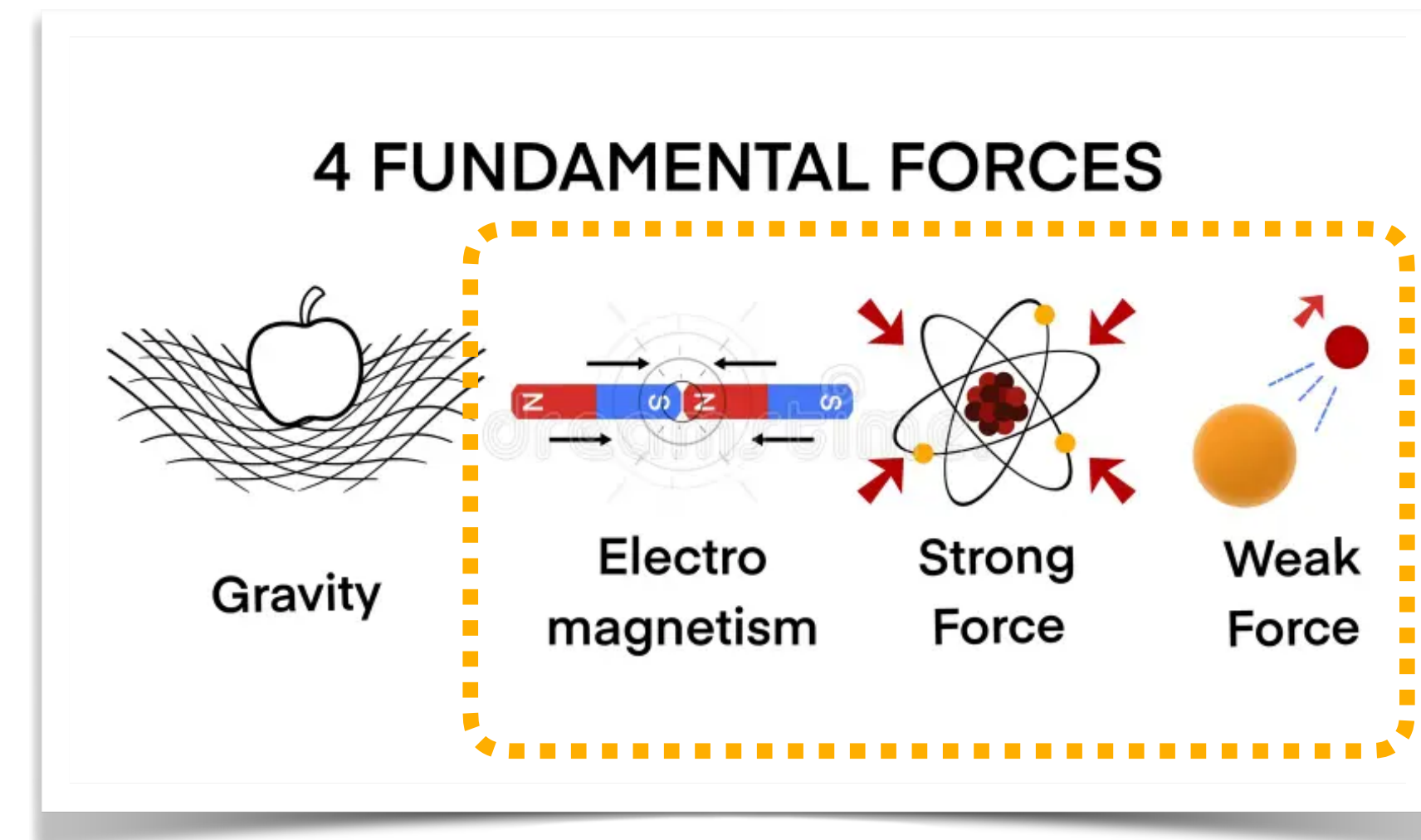


Symbolic regression

Fundamental interactions and particles

High energy physics: the description of fundamental particles and their interactions. It is (very) well described by the Standard Model (SM).

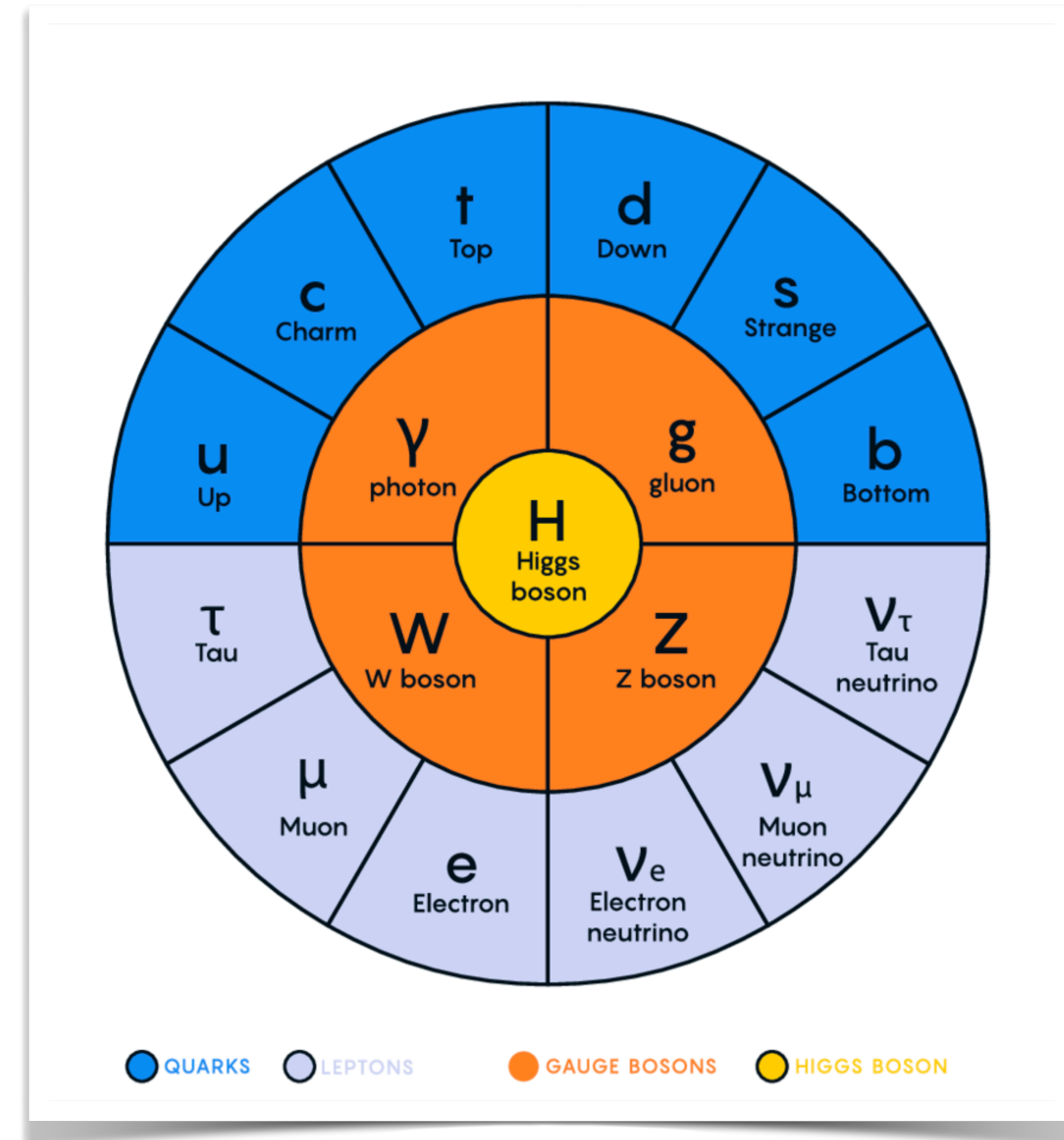
- The SM is a gauge theory that describes elementary particles and their interactions in terms of relativistic quantum fields.
- The SM describes 3 of the 4 fundamental forces through gauge bosons, spin = 1 particles.
 - Electromagnetism (**photon**)
 - The strong force (**gluons**)
 - The weak force (**W** and **Z bosons**)



$$\begin{aligned} \mathcal{L} = & -\frac{1}{4} F_{\mu\nu} F^{\mu\nu} \\ & + i\bar{\psi} \not{D} \psi + h.c. \\ & + \chi_i y_{ij} \chi_j \phi + h.c. \\ & + |D_\mu \phi|^2 - V(\phi) \end{aligned}$$

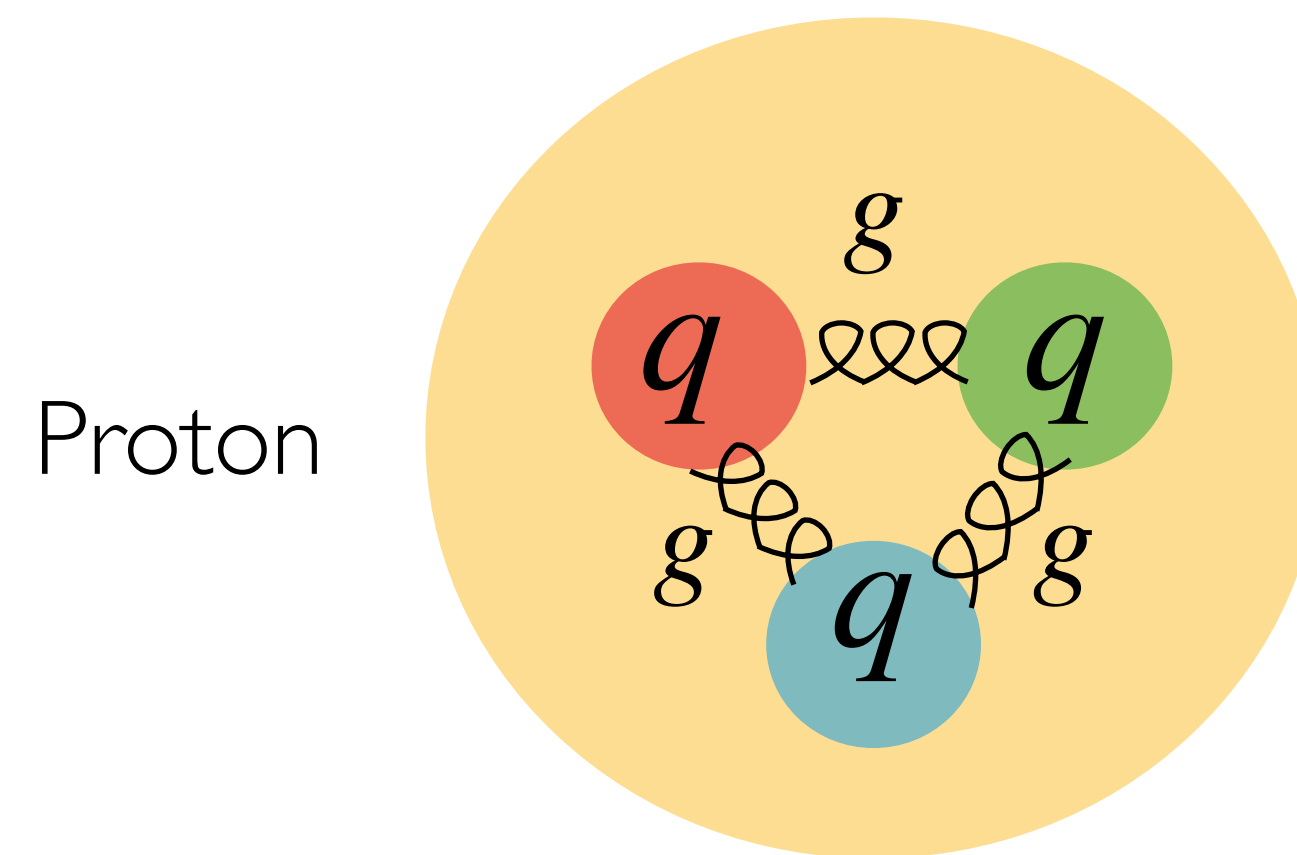
Fundamental interactions and particles

- In the SM there are also **quarks** and **leptons**, spin = 1/2 fermions.
- Quarks carry colour charge and interact via the strong force, whereas leptons do not.
- In the SM we also have the **Higgs** boson, a spin = 0 particle, responsible for giving mass to the elementary particles.



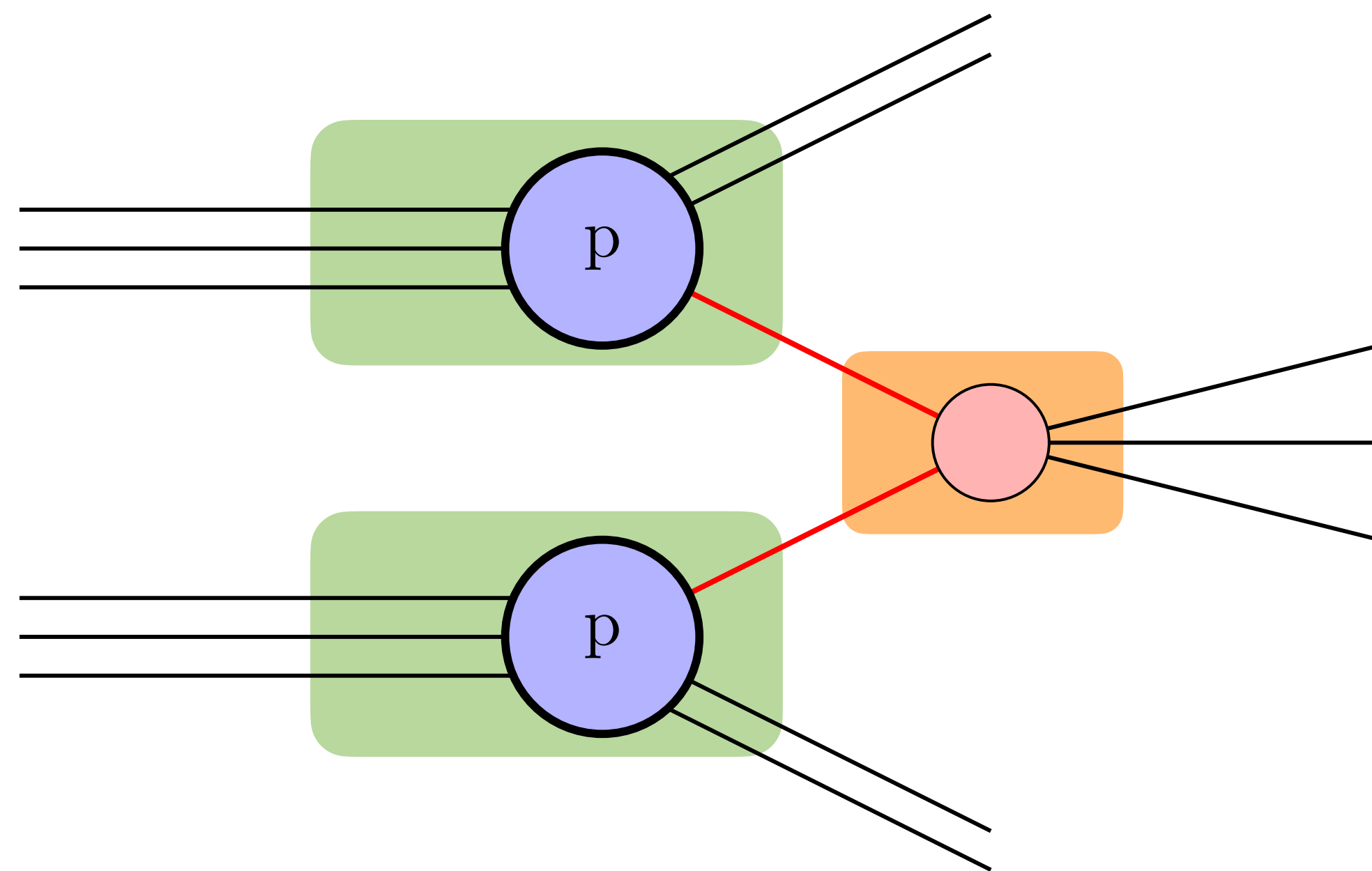
Protons and partons

- At the LHC we collide *protons*.
- Protons are not elementary particles. They are QCD bound states of elementary particles called *partons* (quarks, gluons, ...).
- The parton model postulates that interactions between hadrons (protons, in particular) are interactions of point-like partons convolved with functions that parametrise the structure of the hadron: *parton distribution functions* (PDFs).



Factorisation and hadronic observables

Consider a proton-proton collision:



$$\sigma = \sum_{i,j} \int_0^1 dx_1 \int_0^1 dx_2 f_i(x_1) f_j(x_2) \hat{\sigma}_{ij}(x_1, x_2)$$

$x_{1,2}$: fraction of the hadron's momentum that is carried by the hadron

$\hat{\sigma}_{ij}$: partonic cross section

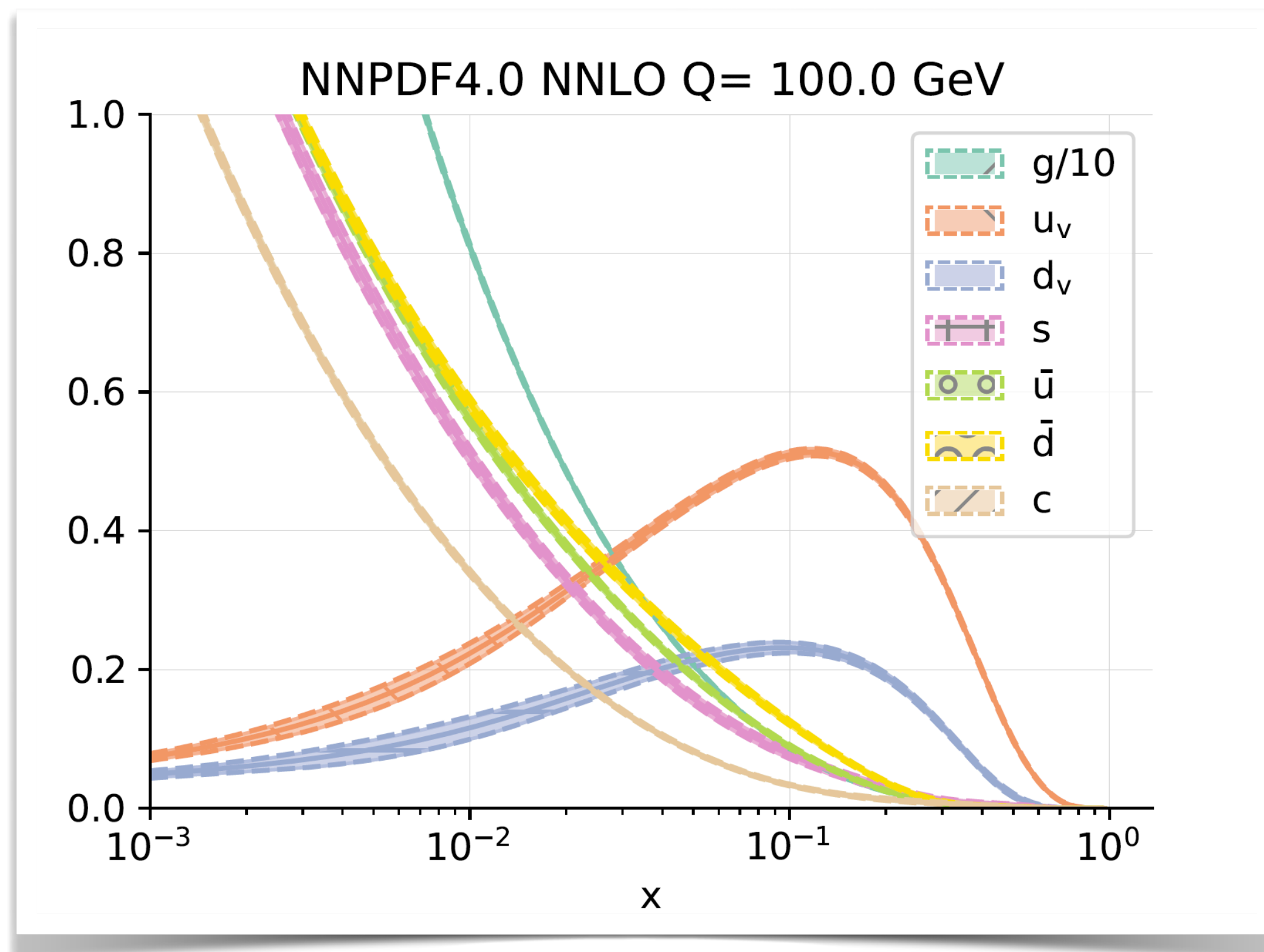
$f_i(x)$: PDF of parton of type i

- Radiative corrections introduce IR singularities that have to be factorised: $f(x) \rightarrow f(x, Q^2)$

PDF determination

PDFs **cannot** be calculated from first principles in perturbation theory, they have to be extracted from *data*.

$$f(x, Q^2)$$



Some recent PDF fits include:

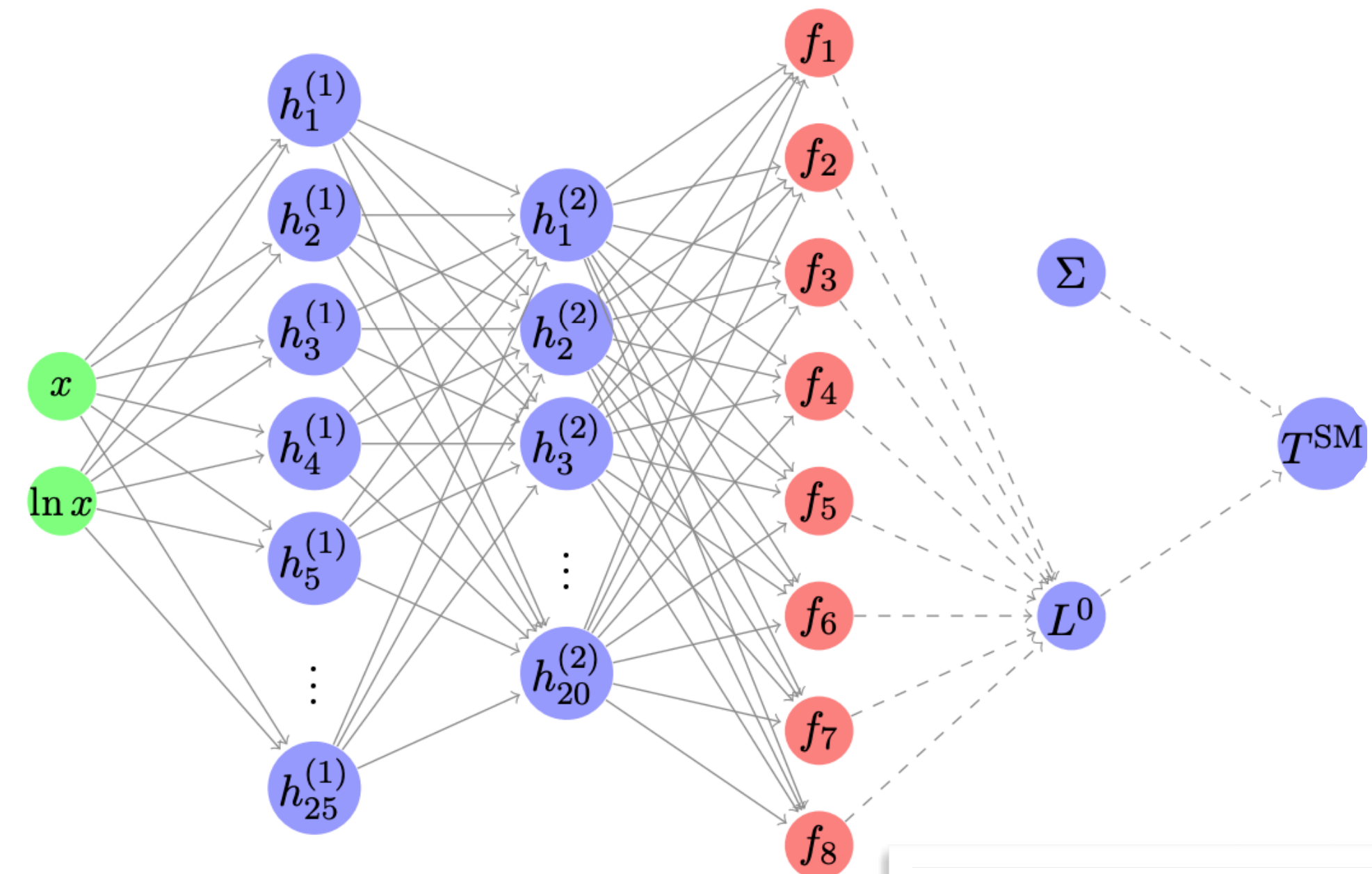
- NNPDF4.0, Ball et al., 2109.02653
- MSHT20, McGowan et al., 2012.04684
- CT18, Hou et al., 1912.10053

NNPDF4.0

Input layer Hidden layer 1 Hidden layer 2 PDF flavours Convolution step SM Observable

- PDFs are parametrised by neural networks (NNs):

$$f(x, Q_0^2) = \text{NN}(x) \quad \rightarrow$$

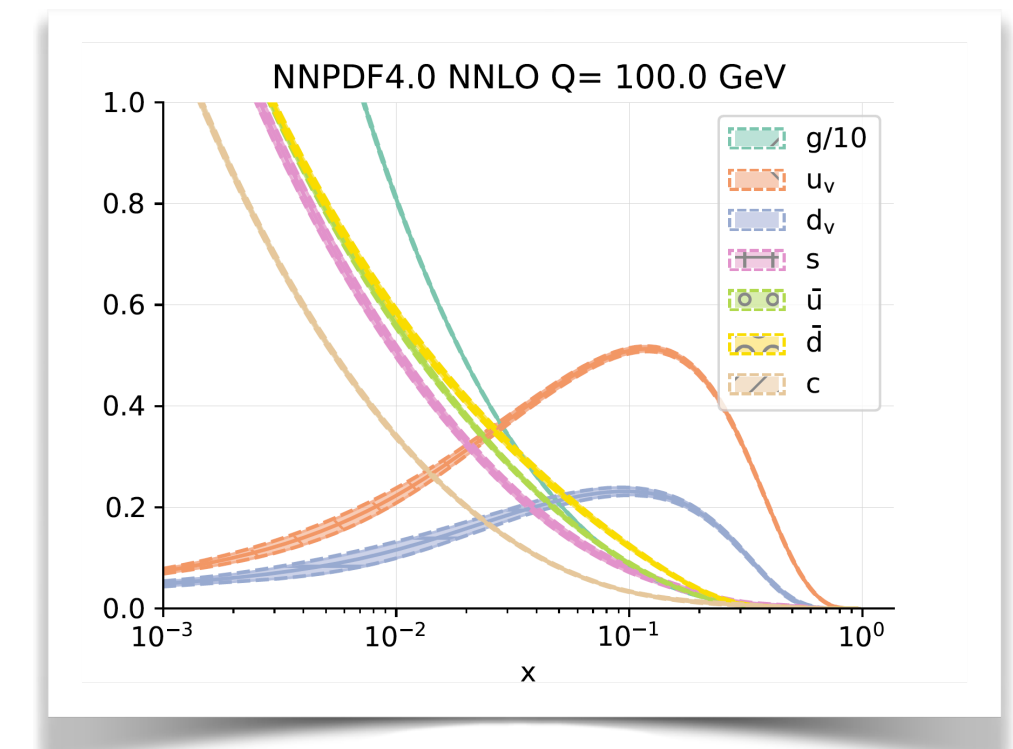


- The optimal weights of the NN are found by minimising a loss function:

$$\chi^2(\theta) = \frac{1}{N_{\text{dat}}} (\mathbf{D} - \mathbf{T}(\theta))^T (\mathbf{cov})^{-1} (\mathbf{D} - \mathbf{T}(\theta)) \quad \rightarrow \quad \theta = \theta_{\text{opt}} \quad \rightarrow$$

- Uncertainty is propagated via de Monte Carlo replica method.

[2109.02653](#), [2404.10056](#)



NNPDF4.0

Input layer	Hidden layer 1	Hidden layer 2	PDF flavours	Convolution step	SM Observable
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- PDFs are parametrised with neural networks (NN)

$f(x, Q^2)$

Other parametrisations are possible. For example, in the case of MSHT20, PDFs are parametrised with *fixed functional forms* of the type:

$$xf(x, Q_0^2) = A(1-x)^\eta x^\delta \left(1 + \sum_{i=1}^n a_i T_i^{\text{Ch}}(y(x)) \right)$$

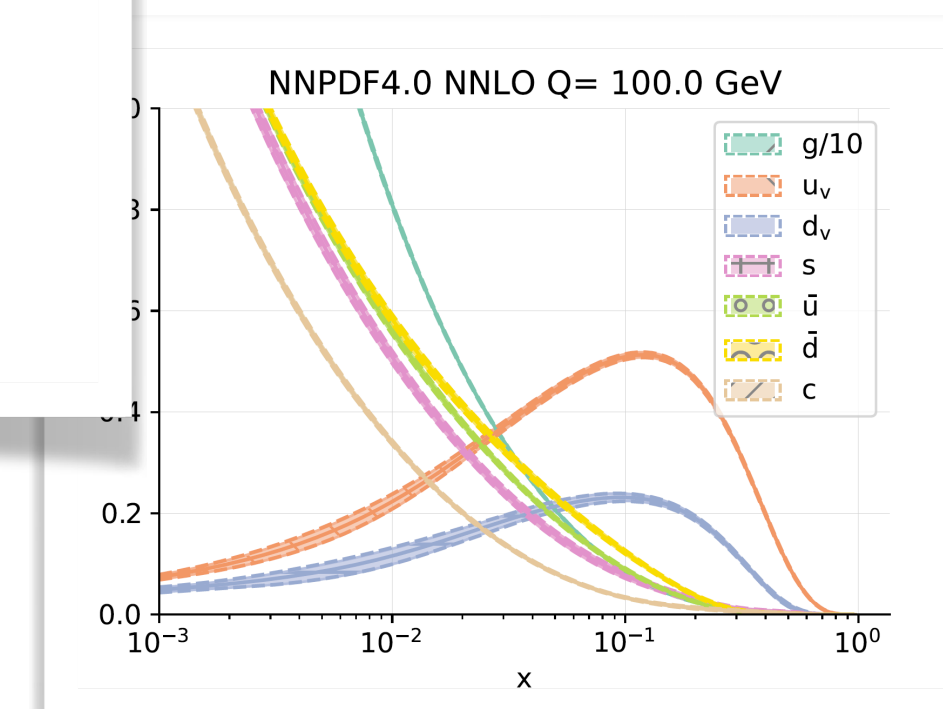
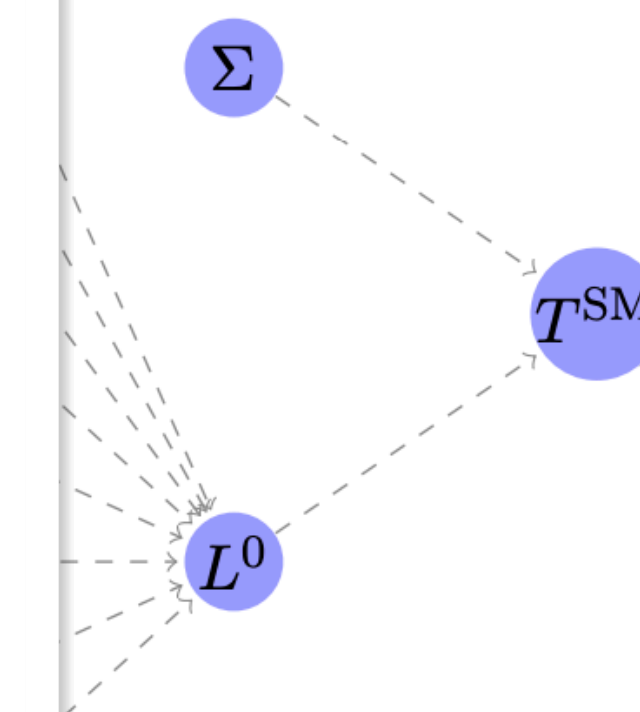
T_i^{Ch} : Chebyshev polynomials

where

$$\chi^2(\theta) = \frac{1}{N_{\text{data}}}$$

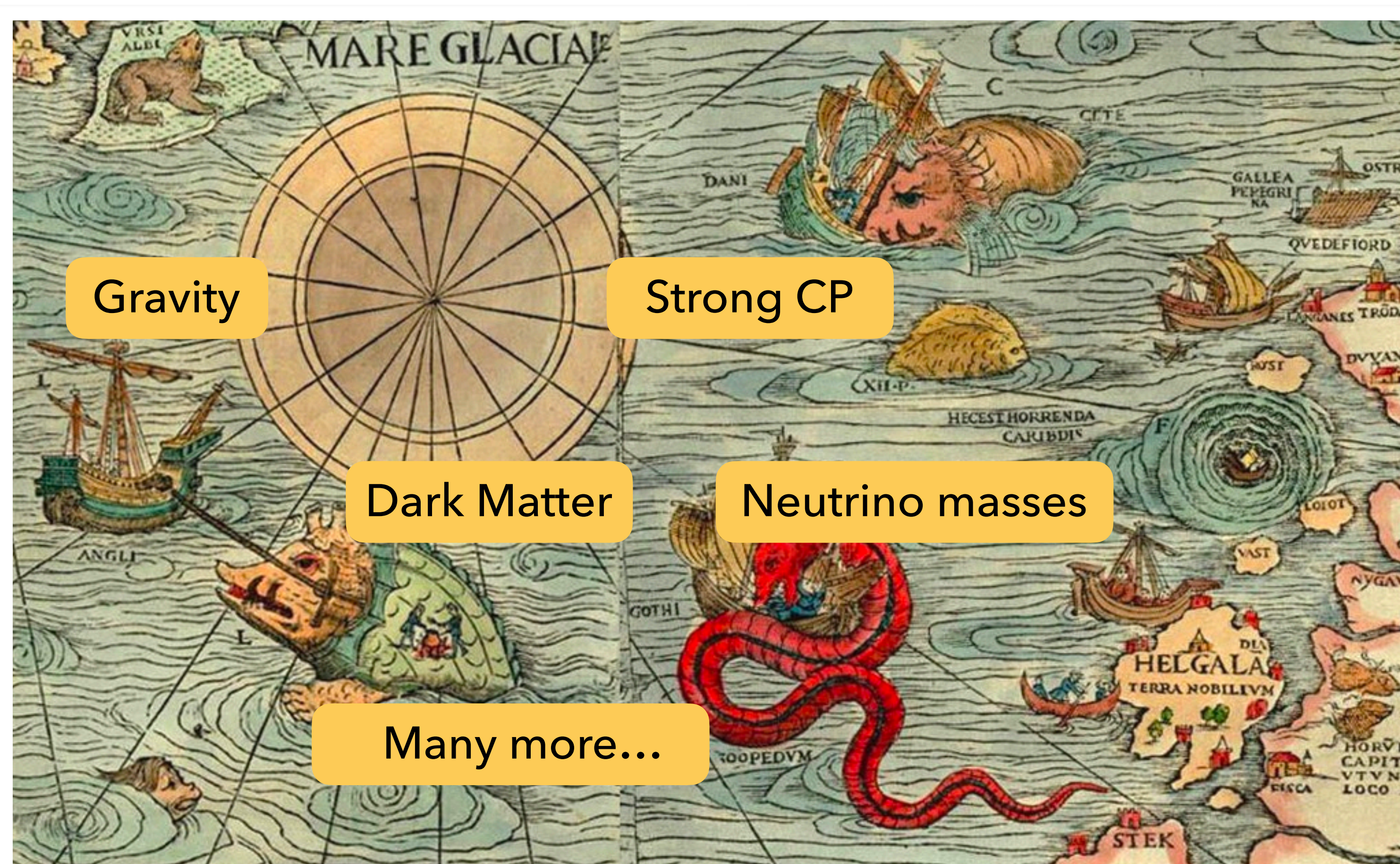
- The optimal parameters are found by minimising $\chi^2(\theta)$
- Uncertainty is propagated via de Monte Carlo replica method.

[2109.02653](#), [2404.10056](#)



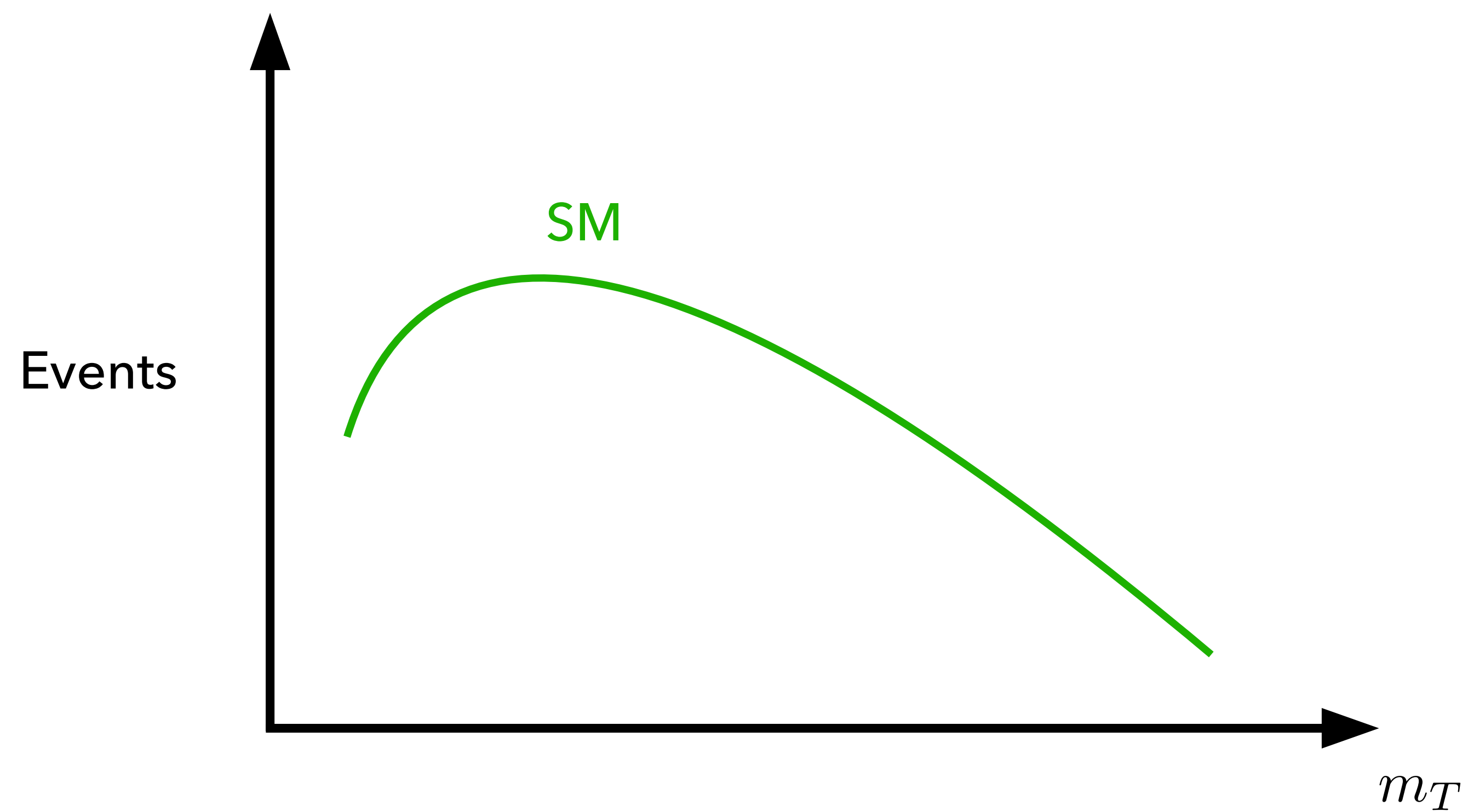
Is that it?

All that we have discussed so far is in the context of the SM, but we know that it cannot be the whole story ...



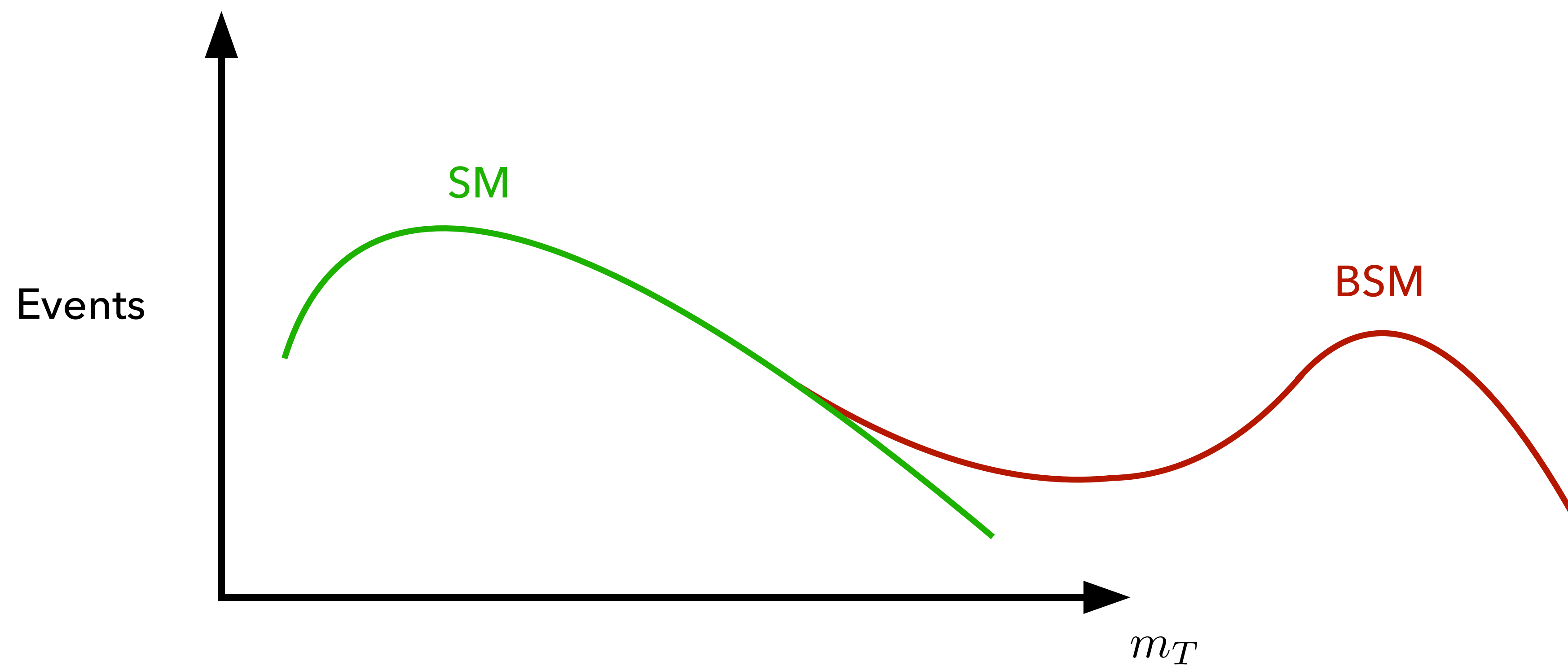
Beyond the SM

We can look for physics beyond the SM (BSM)!



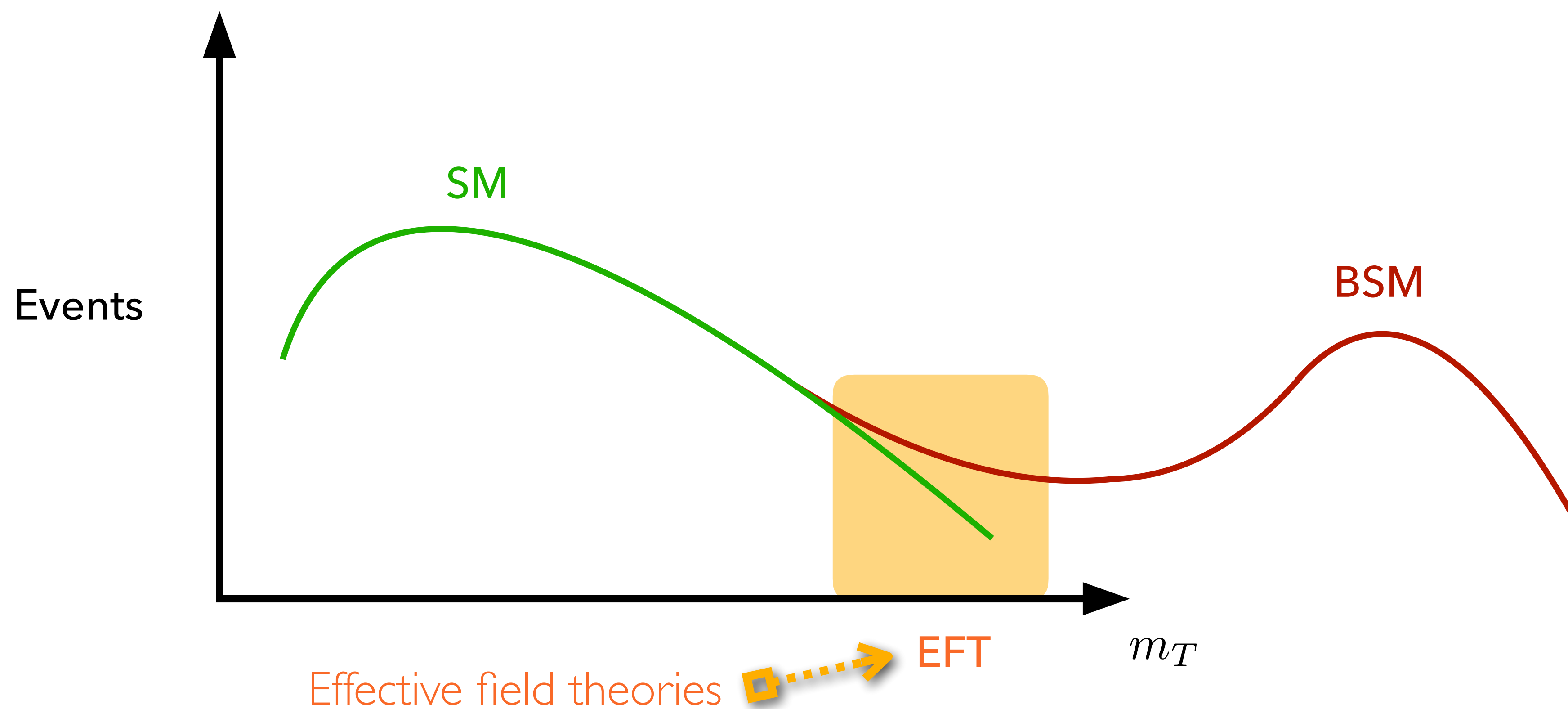
Beyond the SM

We can look for physics beyond the SM (BSM)!



Beyond the SM

We can look for physics beyond the SM (BSM)!



SM effective field theory

- The deviations from the SM predictions can be parametrised in terms of the SM effective field theory (SMEFT).
- The SMEFT supplements the SM Lagrangian with higher dimensional operators whose action is suppressed by a new physics scale:

$$\mathcal{L}_{\text{SMEFT}} = \mathcal{L}_{\text{SM}} + \sum_i \frac{c_i}{\Lambda^2} Q_i^{(6)} + \dots$$

$\{c_i\}$: Wilson coefficients
$\{Q_i^{(6)}\}$: Dimension-6 operators
Λ	: New physics scale

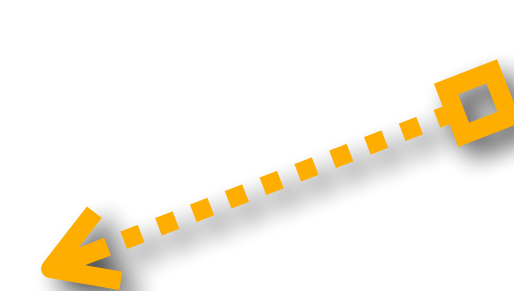
SMEFT fits

Precision is essential!

- The mismatch between the SM and the experiment is:

$$\Delta O = O^{\text{exp}} - O^{\text{SM}} = \sum_i \frac{c_i A_i}{\Lambda^2} + \mathcal{O}\left(\frac{1}{\Lambda^3}\right)$$

Linear in the c_i coefficients!



- For BSM searches we are interested in measuring the c_i coefficients as best as we can:
 - We need a global dataset.
 - We need precise and accurate experimental measurements and theory predictions.

But here is the problem ...

PDF-BSM interplay

The problem is that PDF and BSM worlds do not usually talk to each other.

θ : PDF parameters

c : BSM parameters

PDF fits

BSM coefficient are kept fixed

$$c = \bar{c}$$

$$\sigma(\theta, \bar{c}) = \text{PDF}(\theta) \otimes \hat{\sigma}(\bar{c})$$

EFT fits

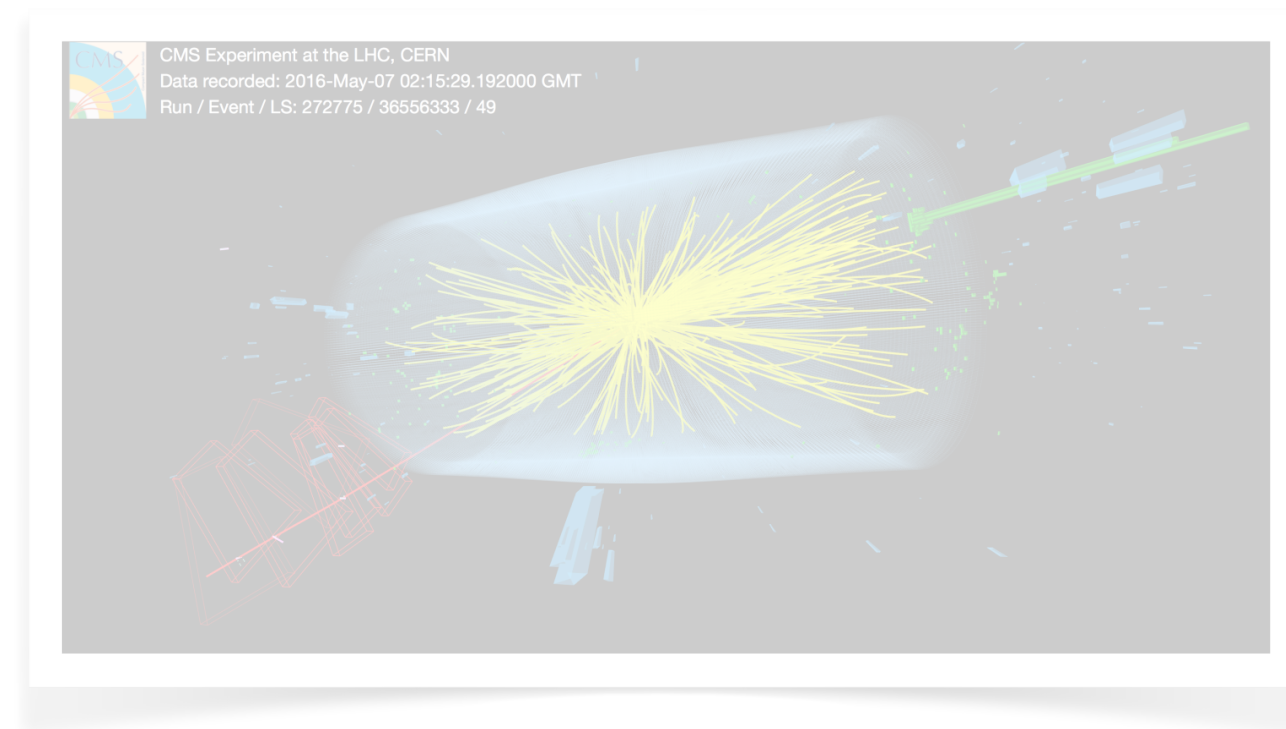
PDF coefficients are kept fixed

$$\theta = \bar{\theta}$$

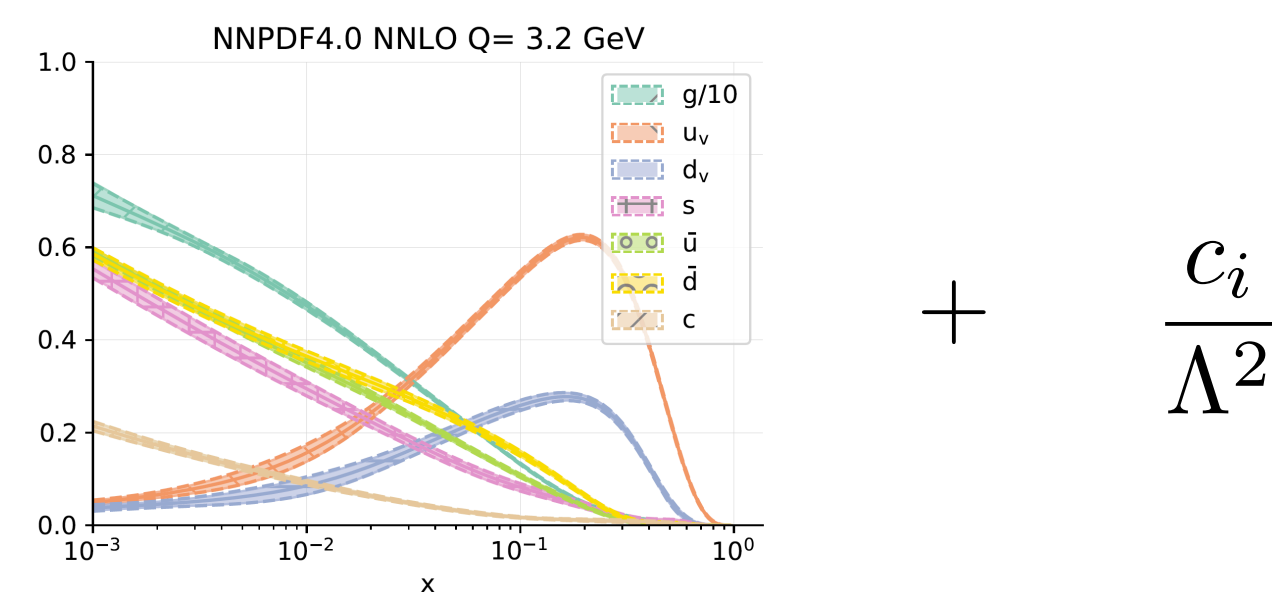
$$\sigma(\bar{\theta}, c) = \text{PDF}(\bar{\theta}) \otimes \hat{\sigma}(c)$$

Need a **simultaneous** determination!

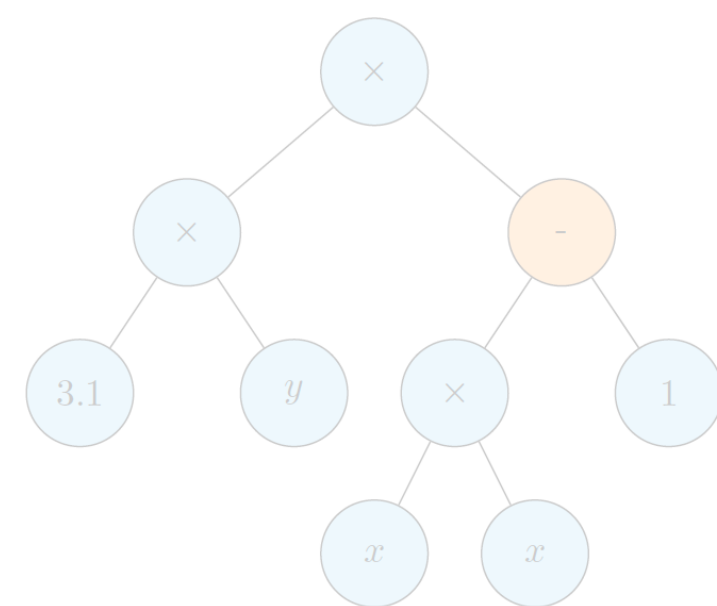
Outline



Some high
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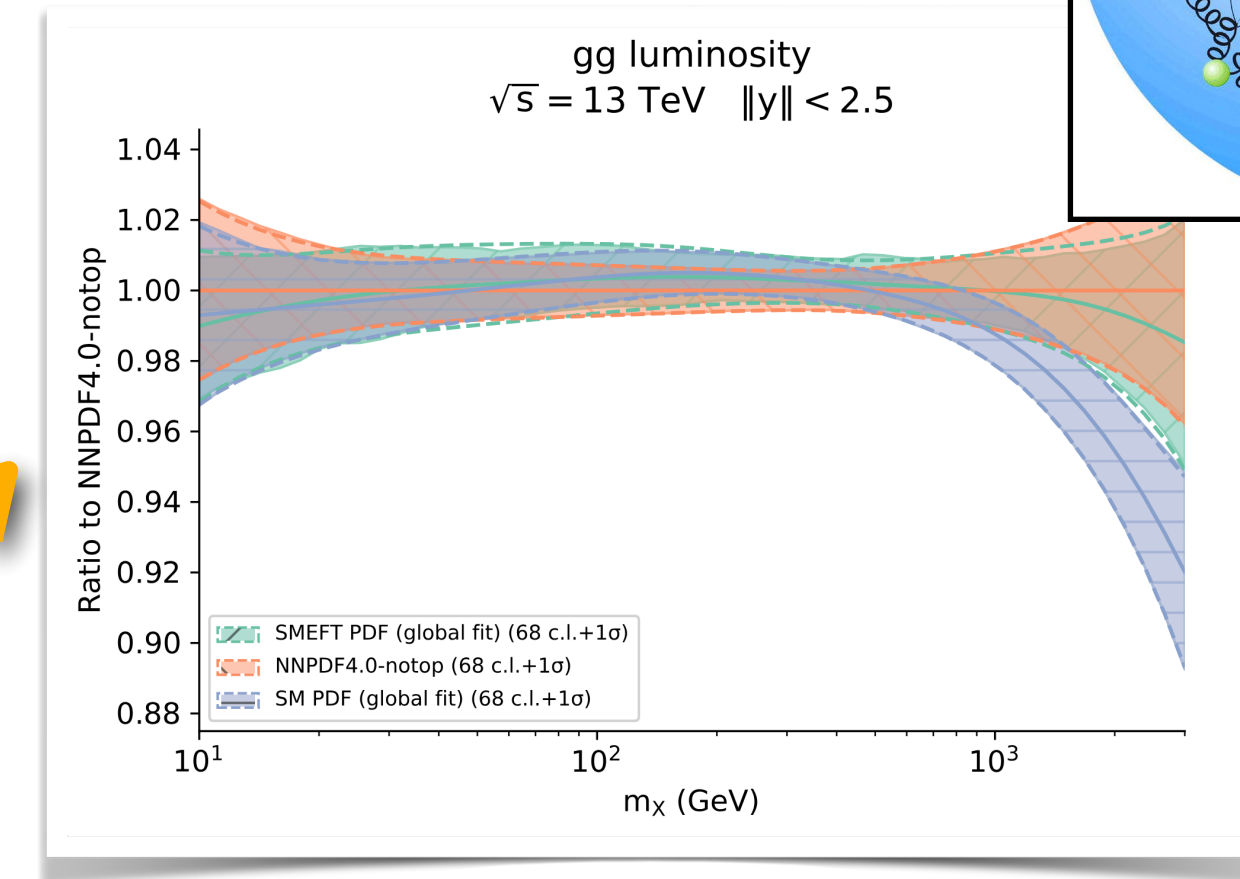
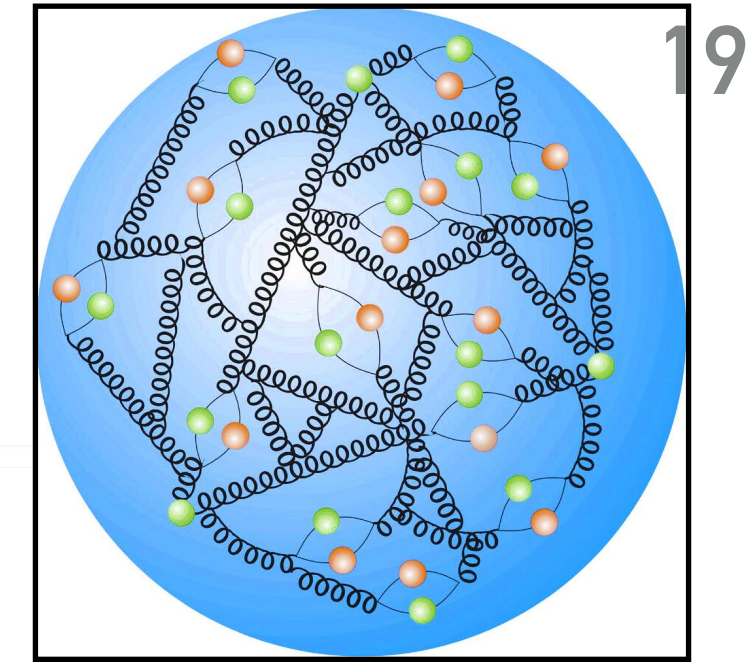
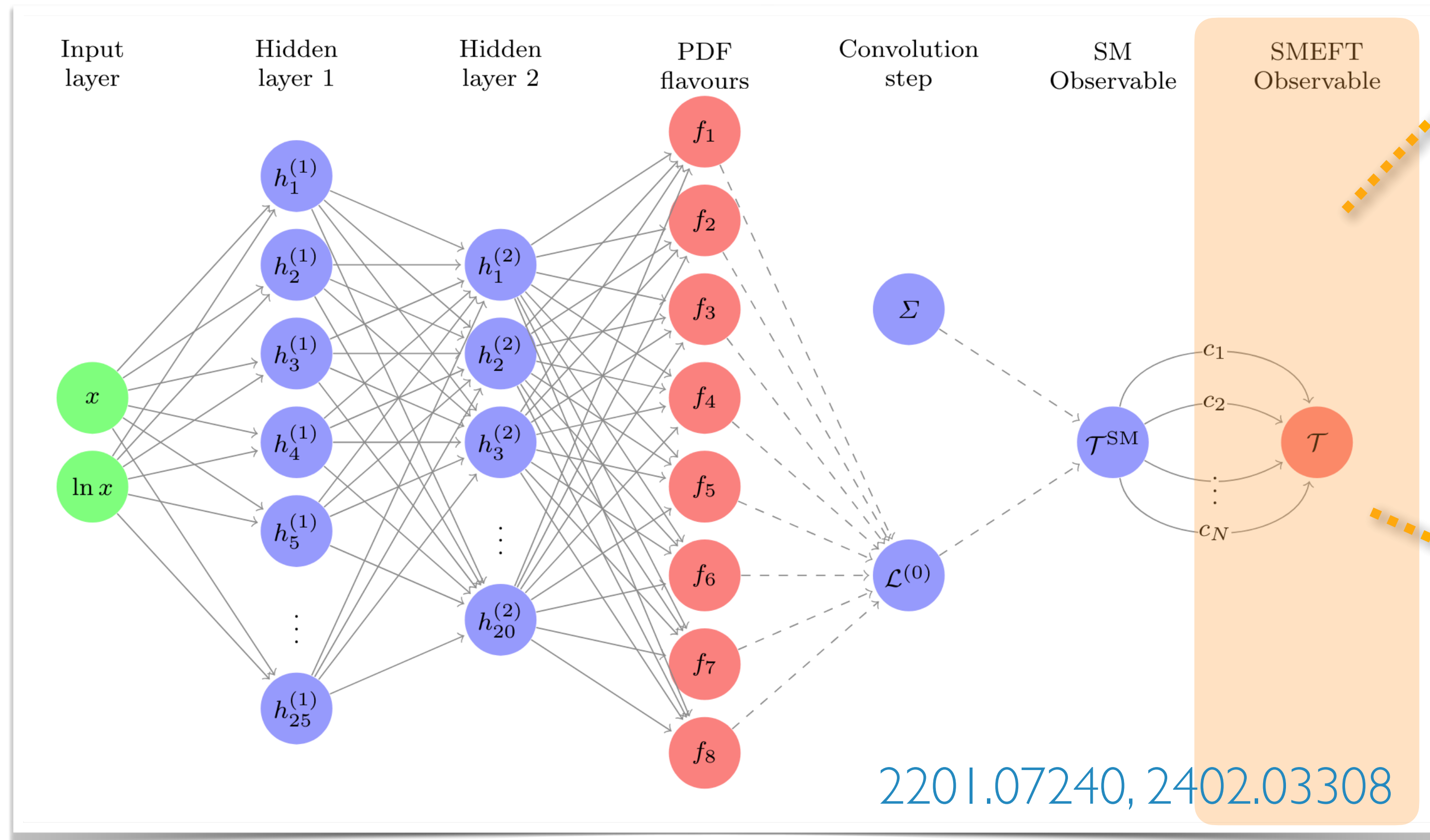
Precision: deep learning the
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physics



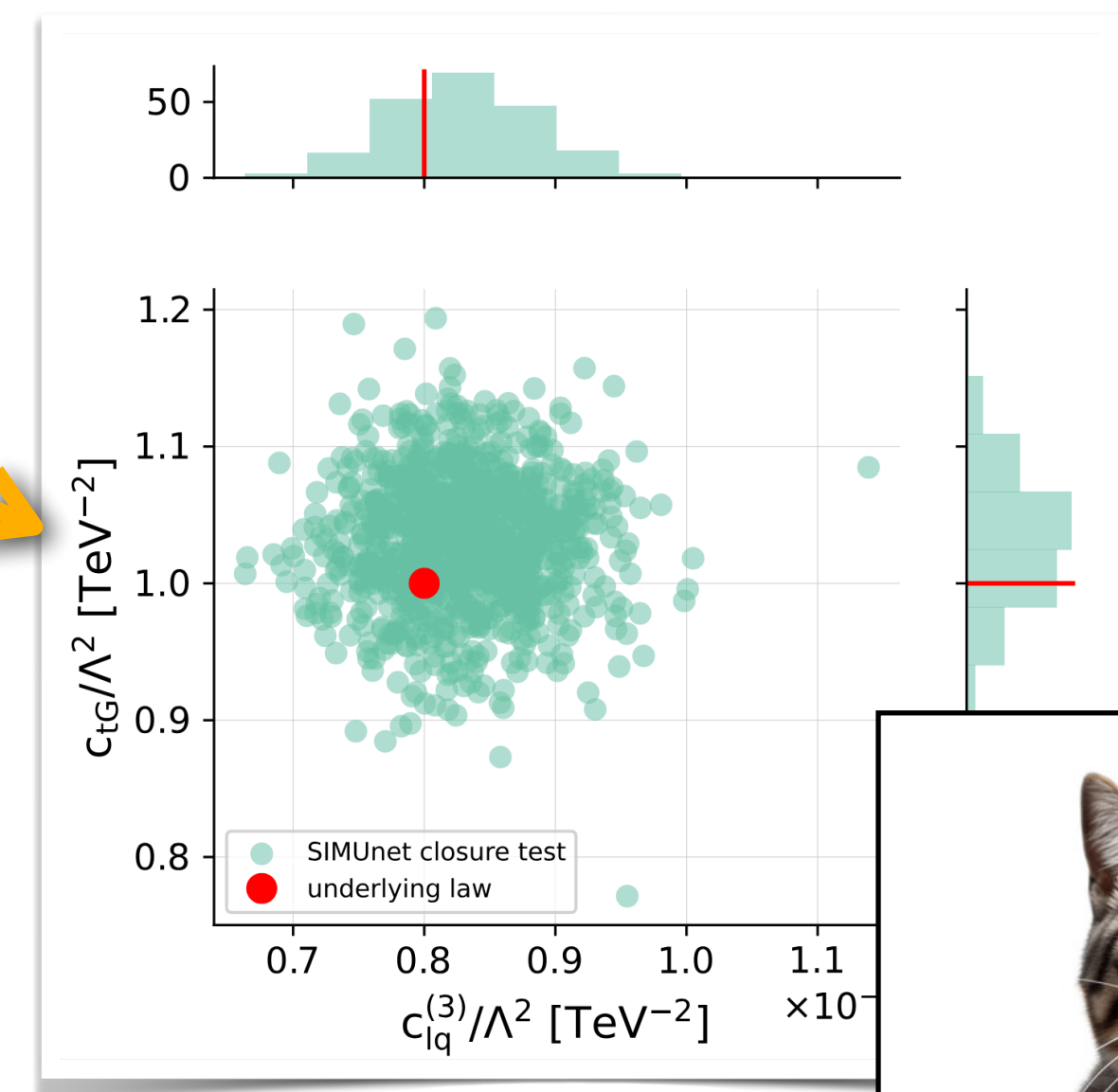
Symbolic regression

SIMUnet

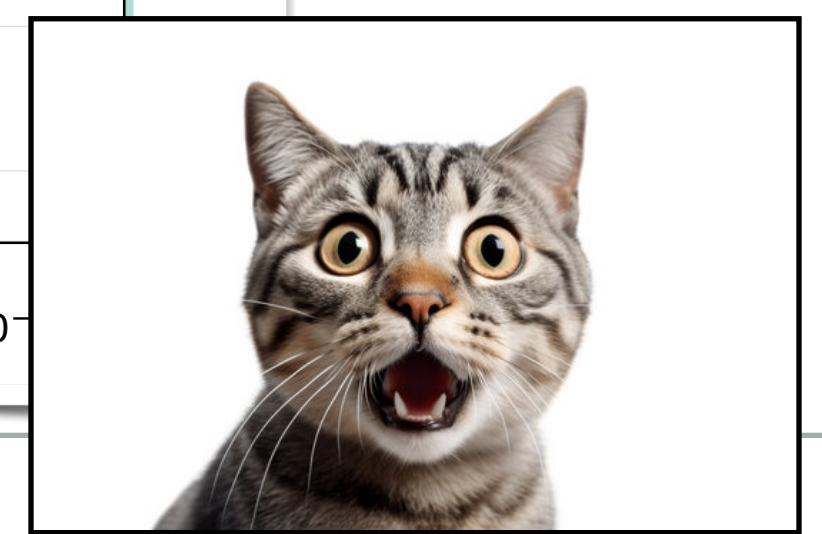
We can explore the structure of the proton and potential signals of BSM physics *simultaneously* with deep learning



proton structure



new physics



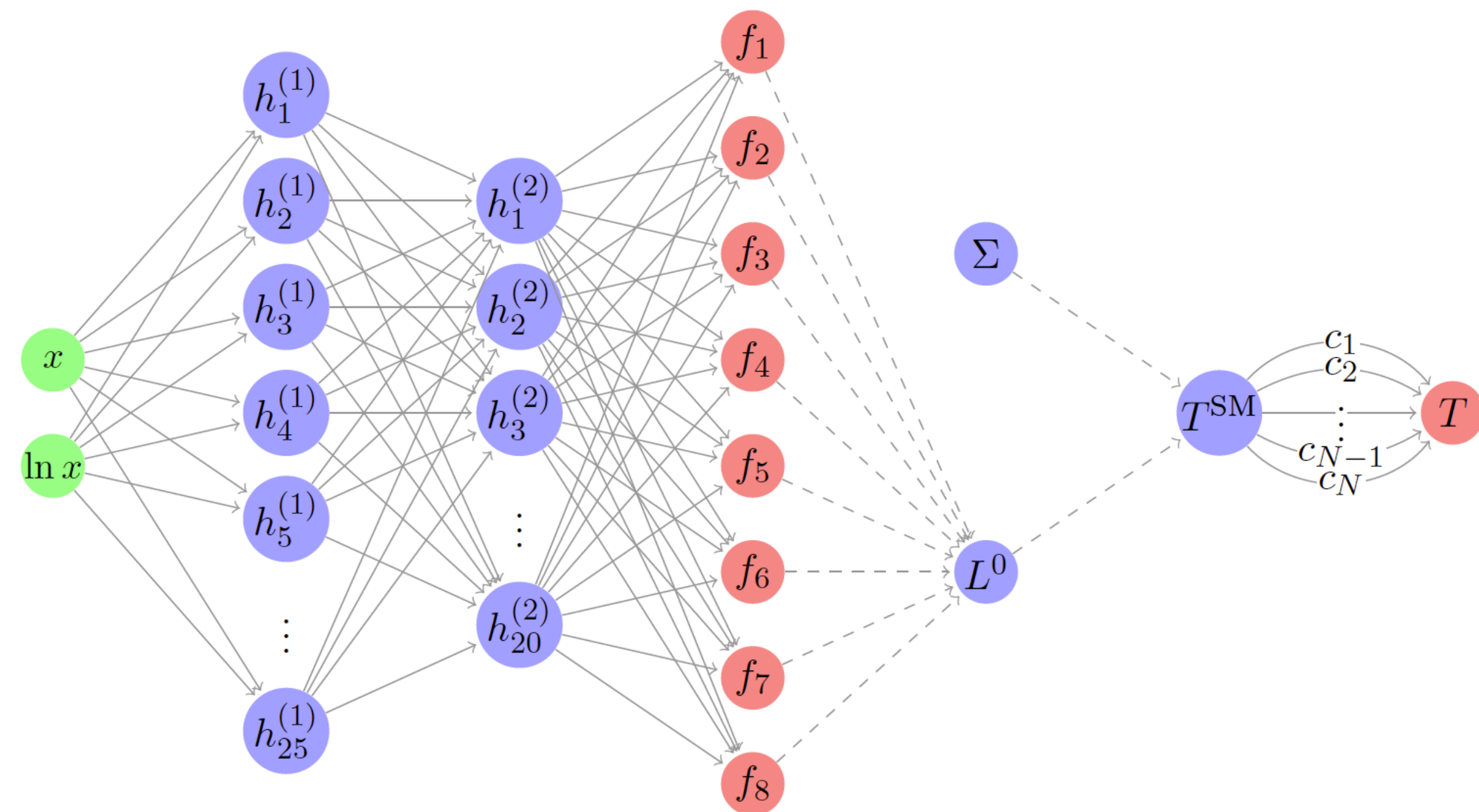
SIMUnet

Input layer	Hidden layer 1	Hidden layer 2	PDF flavours	Convolution step	SM Observable	SMEFT Observable
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- SIMUnet: NNPDF architecture supplemented with a SMEFT layer.
- PDF and BSM parameters are optimised simultaneously.

$$\chi^2(\hat{\theta}) = \frac{1}{N_{\text{dat}}} (\mathbf{D} - \mathbf{T}(\hat{\theta}))^T (\mathbf{cov})^{-1} (\mathbf{D} - \mathbf{T}(\hat{\theta}))$$

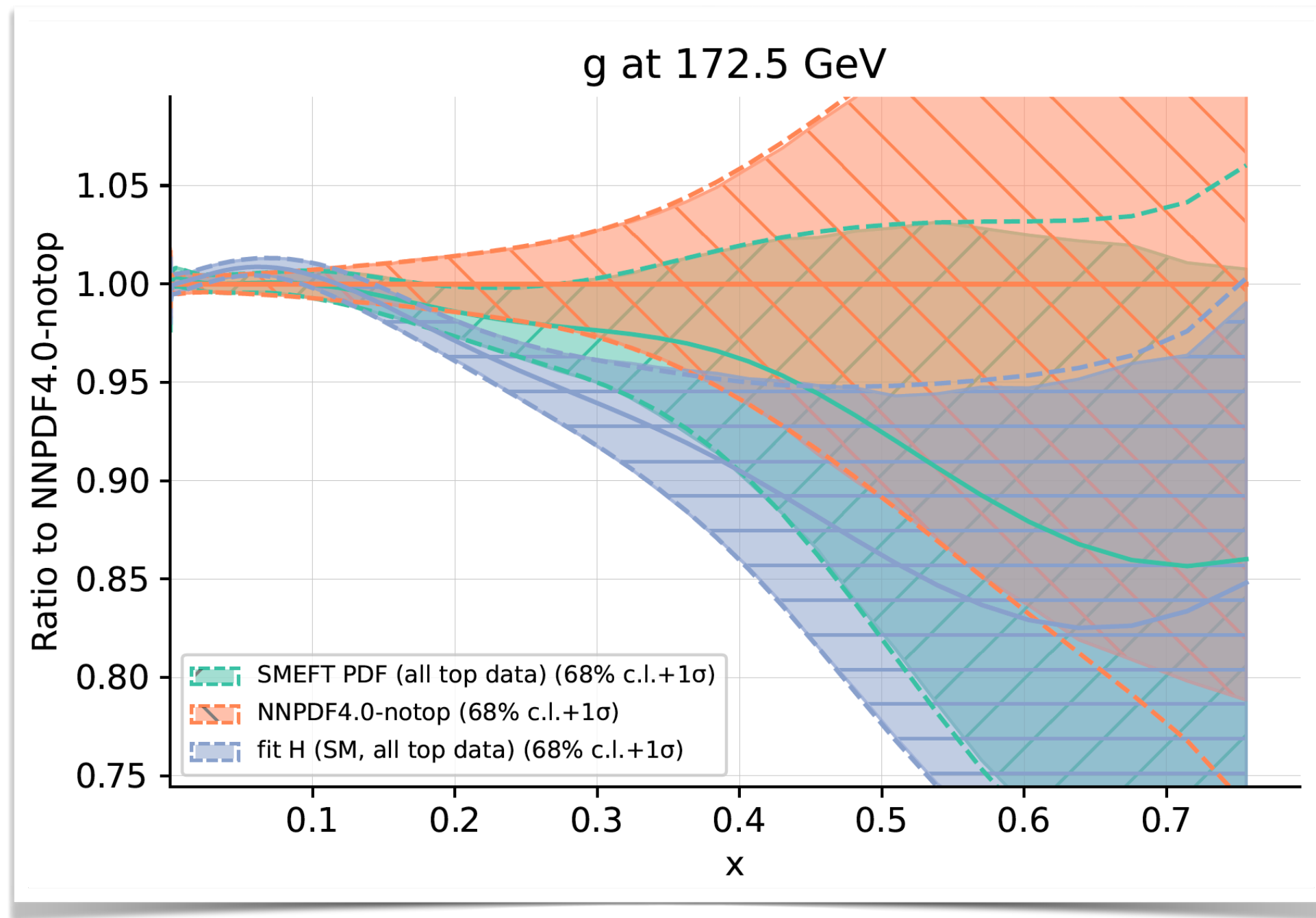
$$\hat{\theta} = \theta \cup \{c_i\}$$



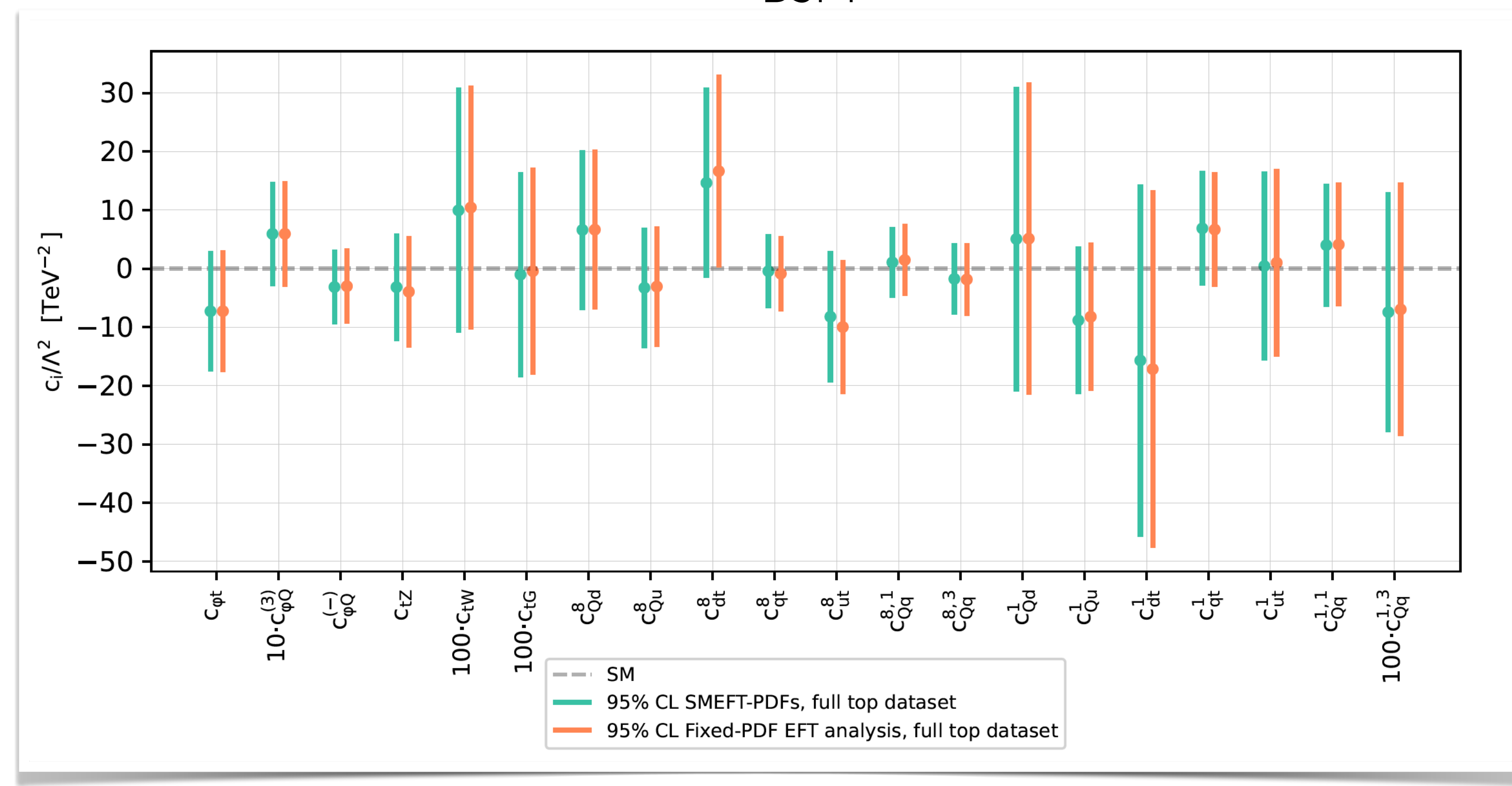
SIMUnet: simultaneous PDF + BSM coefficients

Here we perform a fit in the top-quark sector.

PDFs



BSM

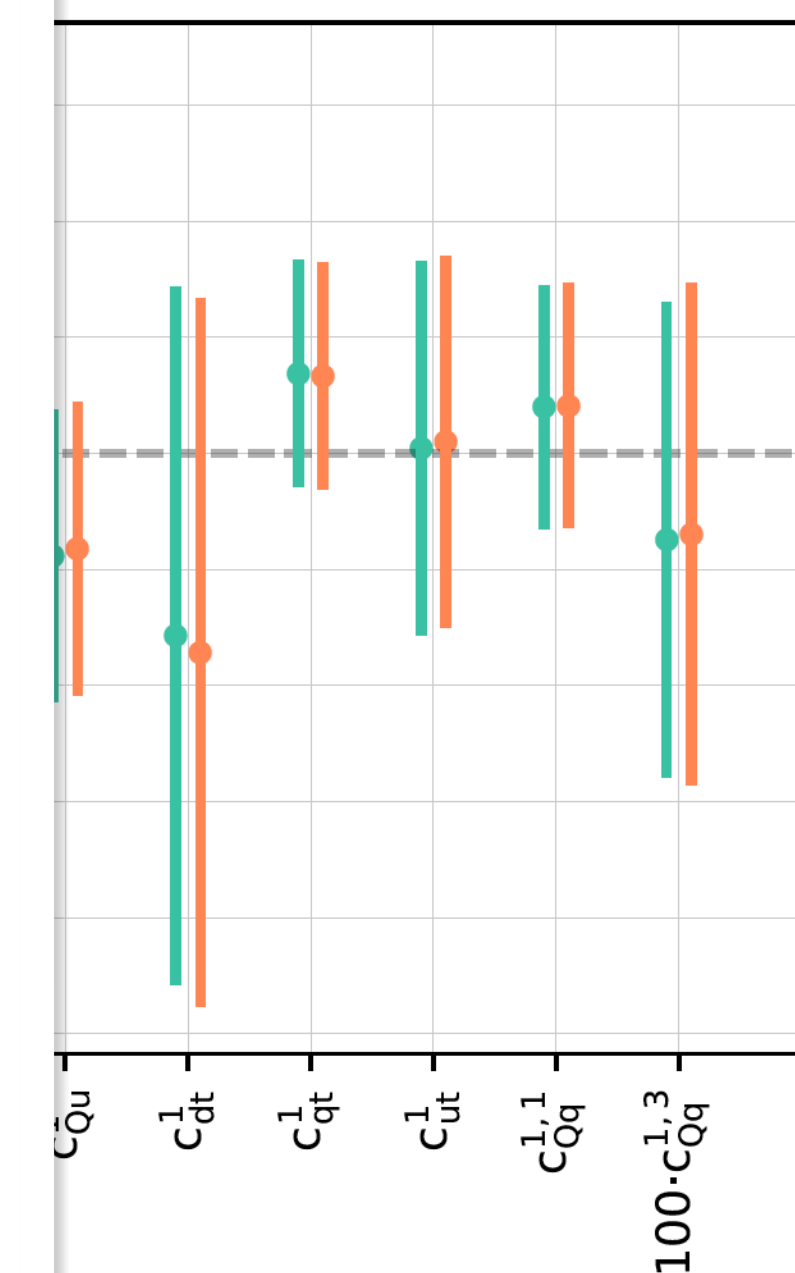
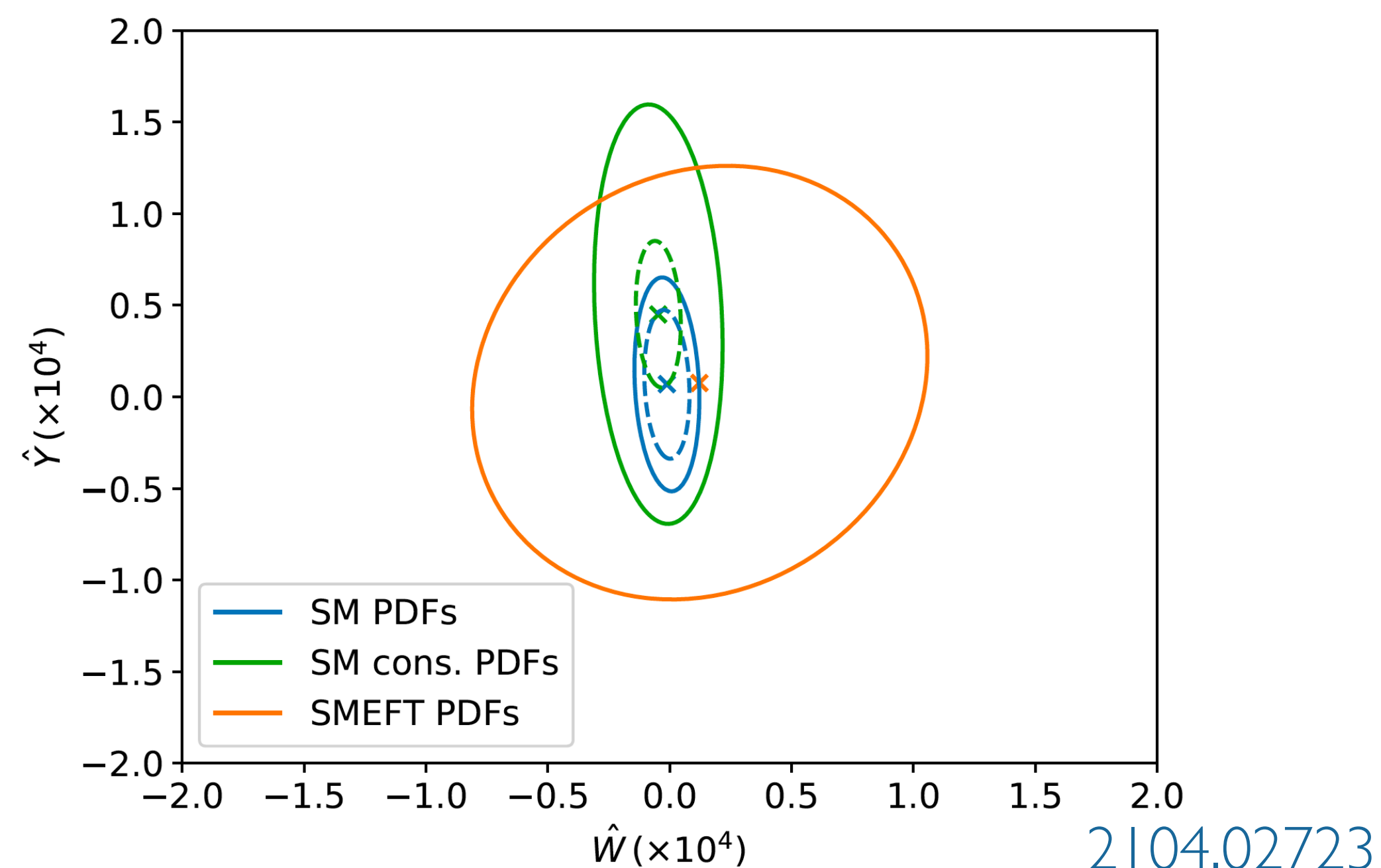
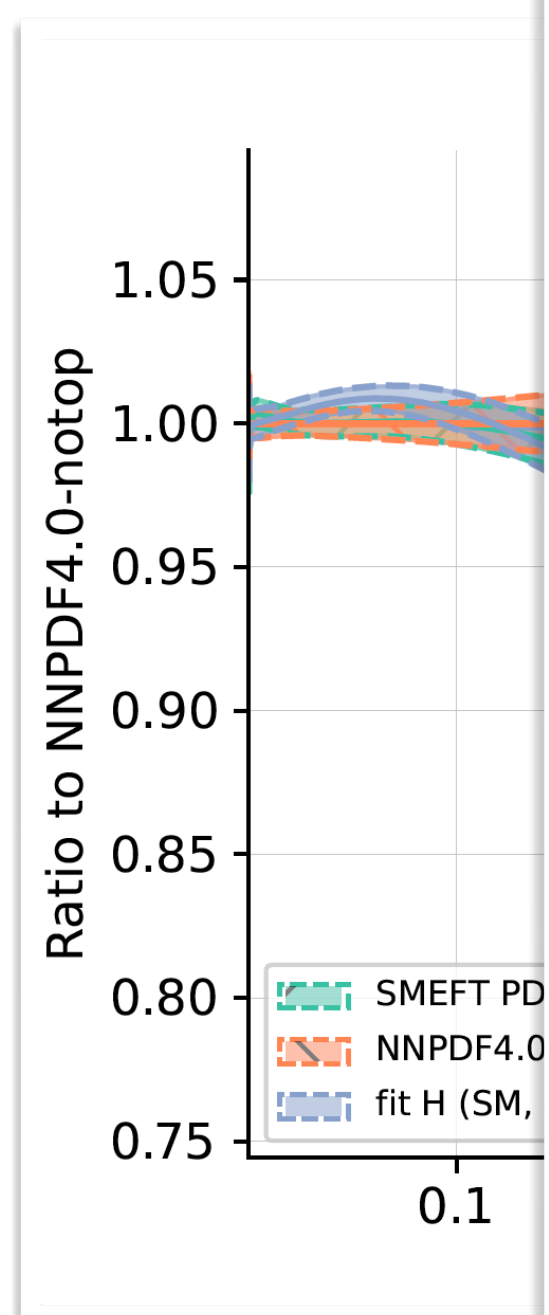


2303.06159

SIMUnet: simultaneous PDF + BSM coefficients

Here we

Neglecting the PDF-BSM interplay can lead to an overestimate of the constraints on BSM physics in other sectors.



SIMUnet: BSM physics absorption

Now, we move on to a different potential problem.

- Both PDFs and potential BSM physics are extracted from fits to data.
- Can PDFs **absorb** potential BSM physics?
 - We will work in a setting where we know the law of Nature: we will generate pseudodata according to our model, perform a fit, and see what comes out.

Let us suppose that the law of Nature is given by the SM plus some new physics (NP) contributions

$$T \equiv T(\theta_{\text{SM}}, \theta_{\text{NP}})$$

We have

True value of the observable

$$T^* \equiv T(\theta_{\text{SM}}^*, \theta_{\text{NP}}^*)$$

The observed data

$$D_0 = T^* + \eta \quad \eta \sim \mathcal{N}(0, \Sigma)$$

Pseudodata generation

- We perform two kinds of fits:

Fit name	Nature	Fitted parameters
Baseline	Standard Model: $\theta_{\text{NP}}^* \equiv 0$	Standard Model only: θ_{SM}
Contaminated	SM + new physics: $\theta_{\text{NP}}^* \neq 0$	Standard Model only: θ_{SM}

- NP is injected into the pseudodata via K-factor

$$T \equiv (1 + cK_{\text{lin}} + c^2 K_{\text{quad}}) \hat{\sigma}^{\text{SM}} \otimes \mathcal{L}$$

* NB: now we are not focusing on simultaneous fits: our goal is to assess the absorption of the NP effects in a purely SM fit

NP absorption

- How can we assess if PDFs have been contaminated by NP?
- If there is a considerable number of data that enter the fit that are not affected NP, and some that data that are affected by NP, they could appear inconsistent and poorly described in the global fit.
- PDFs have **absorbed** NP if the fit quality is good i.e., for each dataset,

$$n_\sigma = \frac{\chi^2 - 1}{\sigma_{\chi^2}} < 2$$

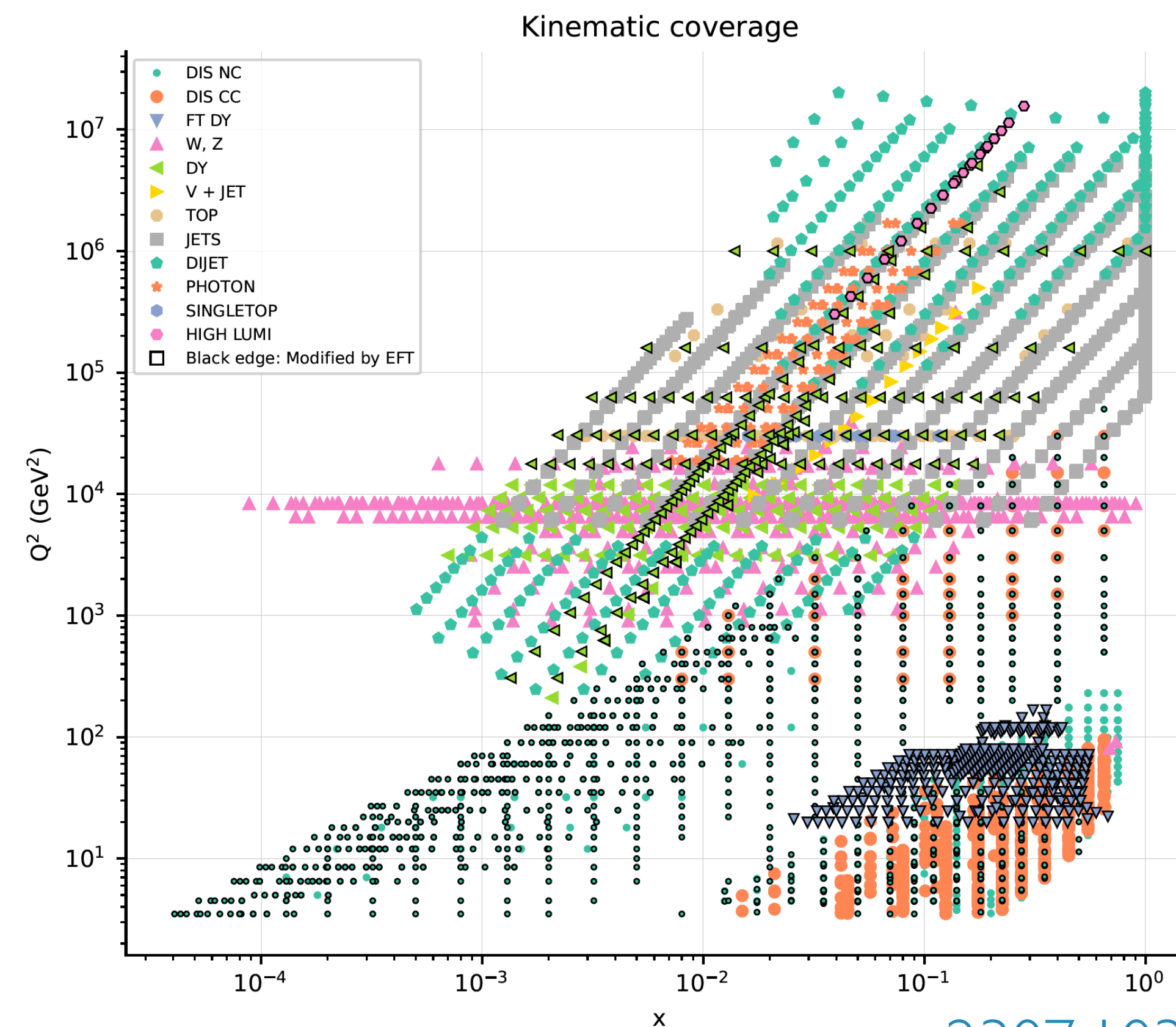
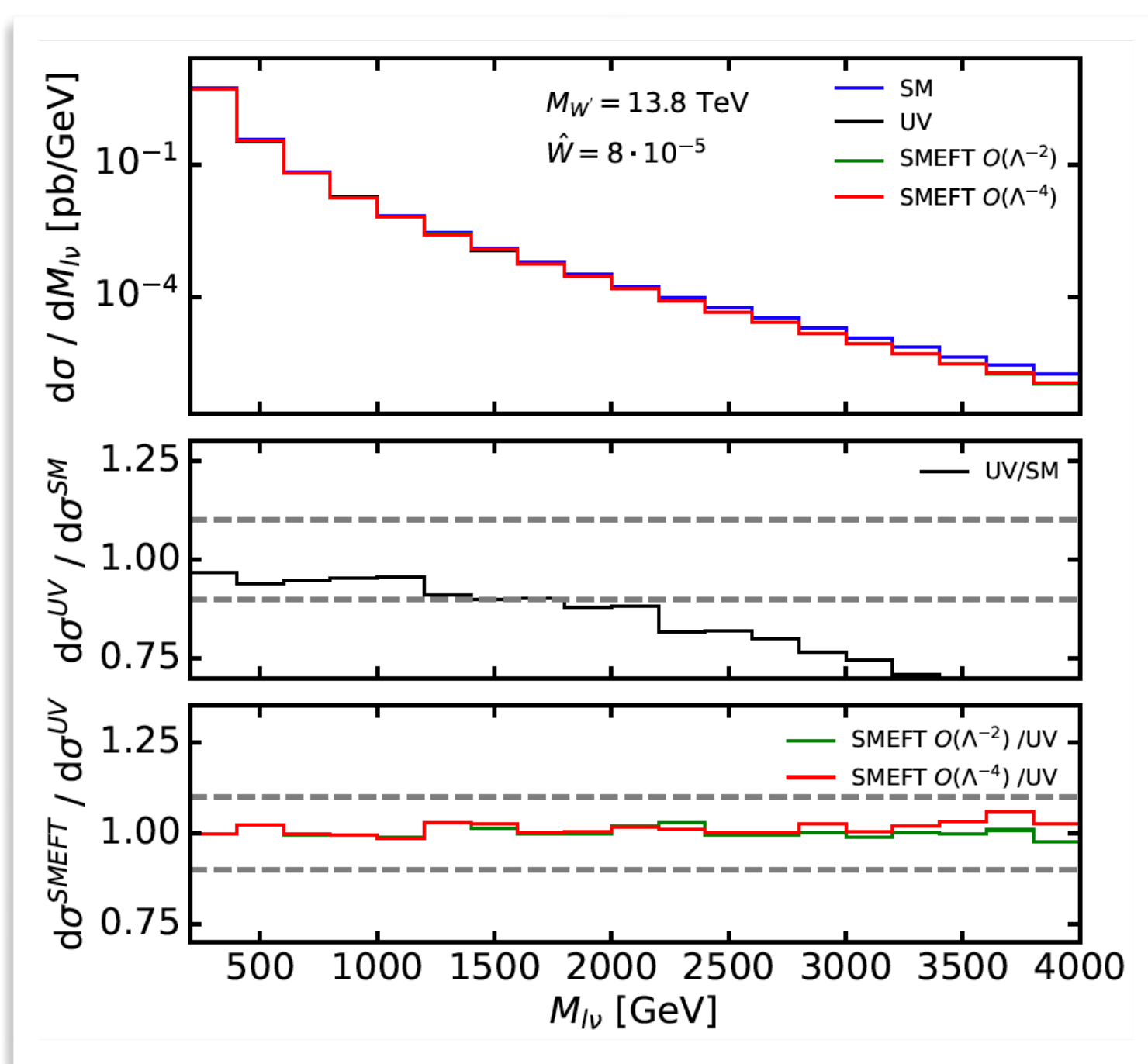
[2109.02653]

- Alternatively, we say that the PDFs would be “**contaminated**”.

New physics model

- We work with a W' NP model and see its effects in LHC processes with respect to the SM.
- This NP model affects Drell-Yan and deep inelastic scattering datasets.

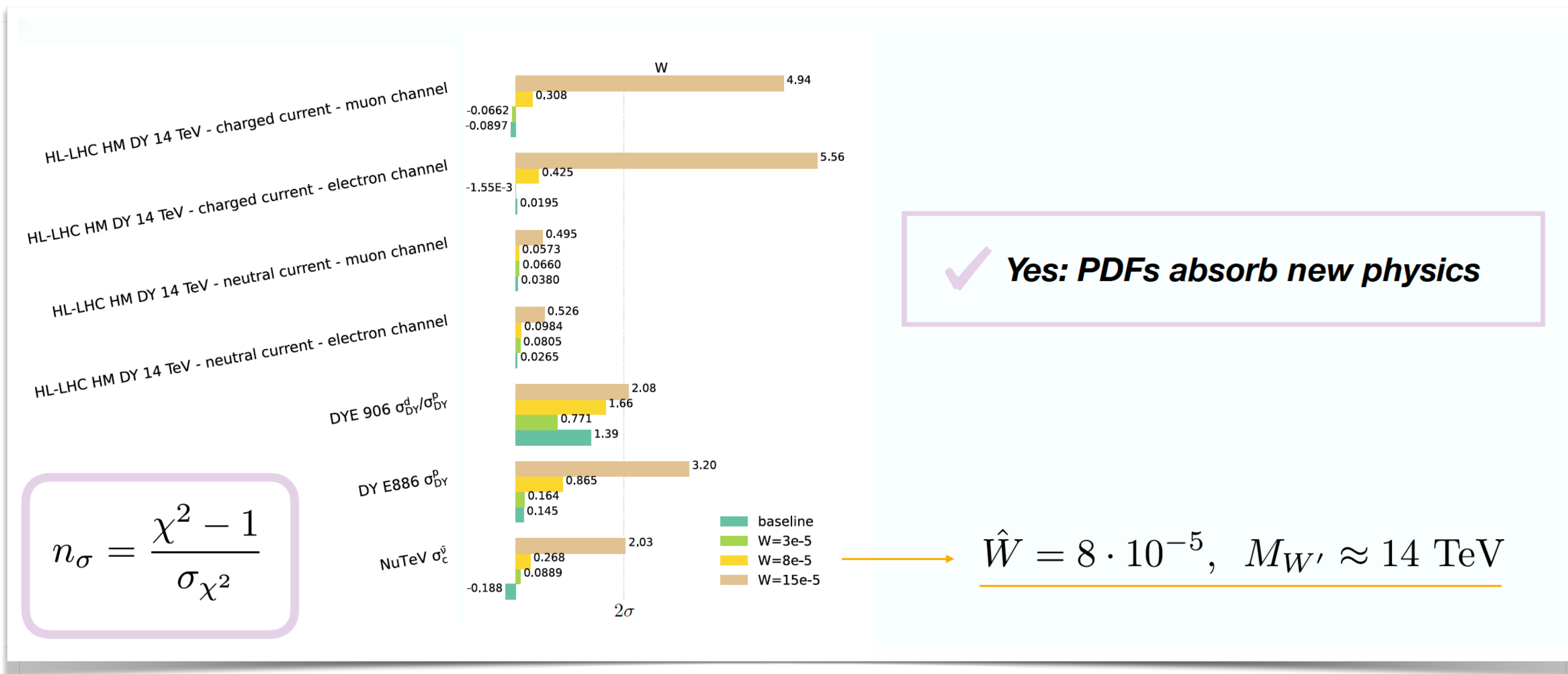
$$\mathcal{L}_{\text{SMEFT}}^{W'} = \mathcal{L}_{\text{SM}} - \frac{g^2 \hat{W}}{2m_{W'}^2} J_L^{a,\mu} J_{L,\mu}^a$$



2307.10370

PDF fit quality summary

* Slide by M. Madigan!



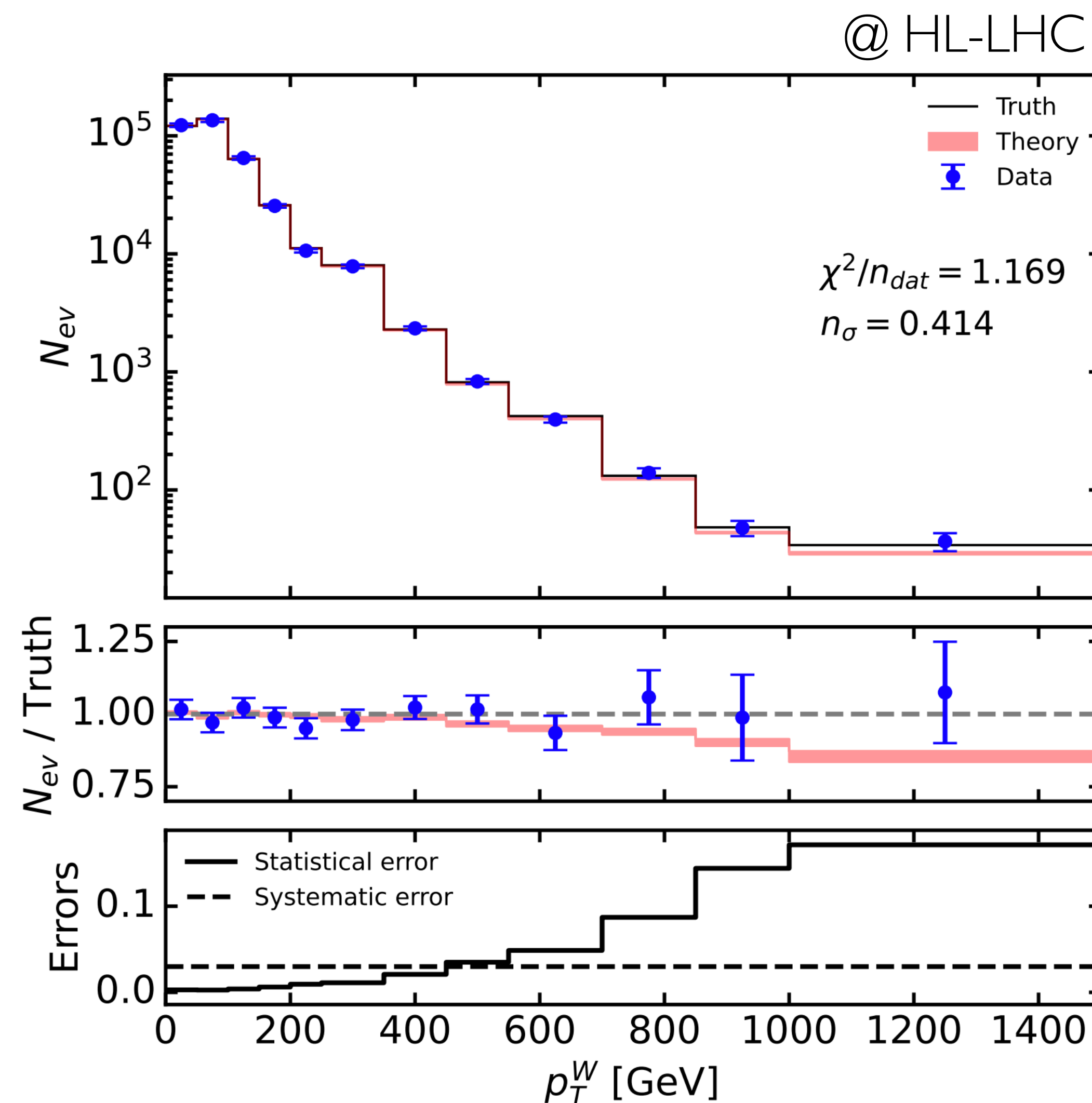
Effects of using a contaminated PDF set

What happens if we unknowingly use contaminated PDFs?

- Consider the results of $W+H$ production (not affected by NP).
- There is an apparent but spurious tension with the SM.

Data: "True" PDF \times SM

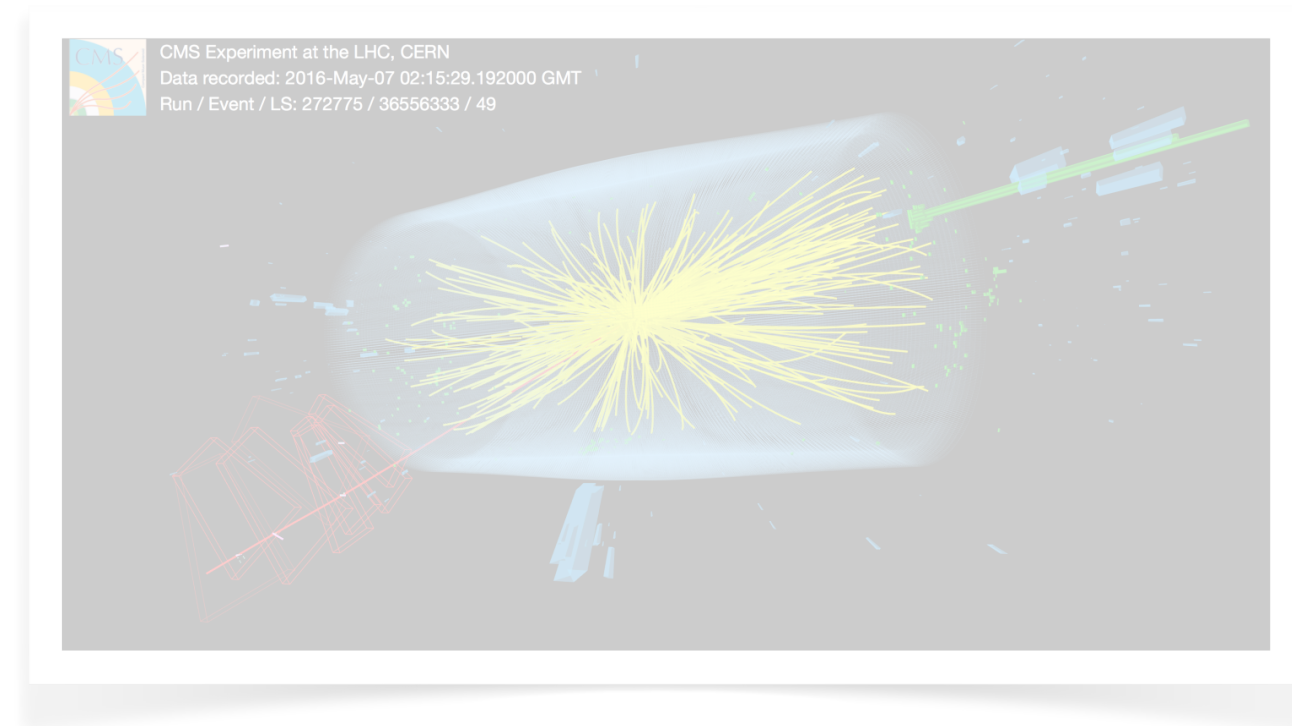
Theory: "Cont" PDF \times SM



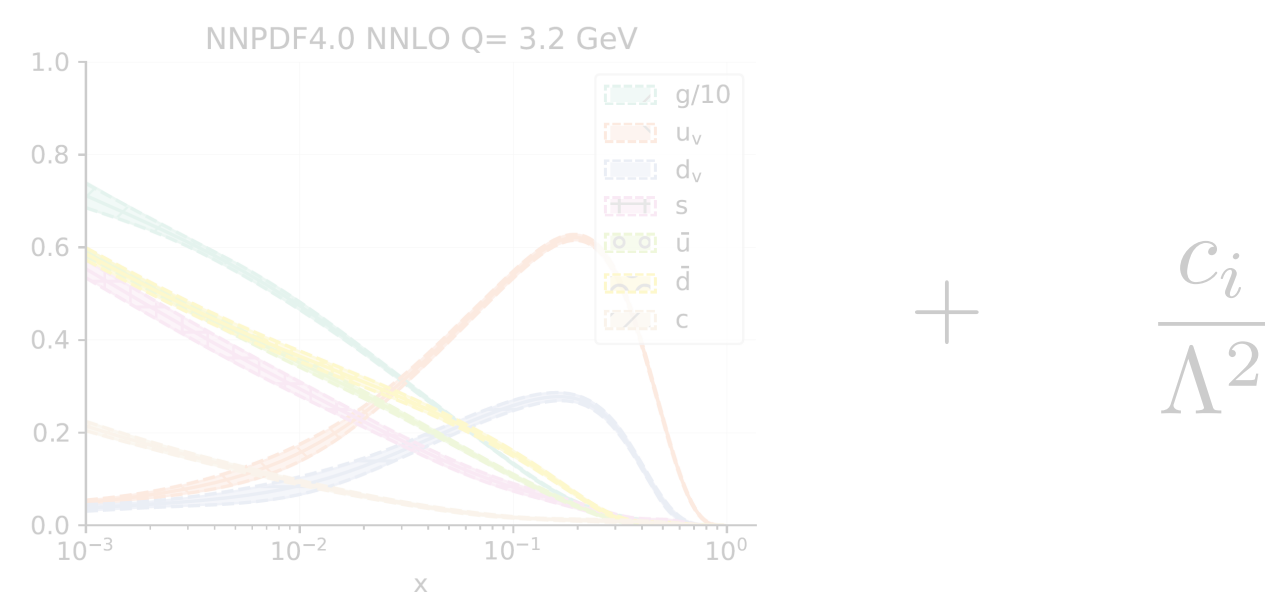
SIMUnet: *summary* and comments

- A open-source deep learning methodology to study precision in the PDF-BSM interplay.
- It allows the simultaneous determination of PDFs and BSM coefficients.
- It allows for the assessment of NP absorption by the PDFs (which can also lead to apparent but spurious tensions).
- There are several directions in which to extend the analysis (quad. SMEFT, running effects, inclusion of new data in the analysis, etc).
- Recently, there has been increasing interest in comparing and stress testing different PDF fitting methodologies, comparing directly NN v/s fixed-form parametrisations, etc.
[Costantini et al., 2404.10056, MSHT, 2407.07944](#)
- **Could ML techniques help in these cases?**

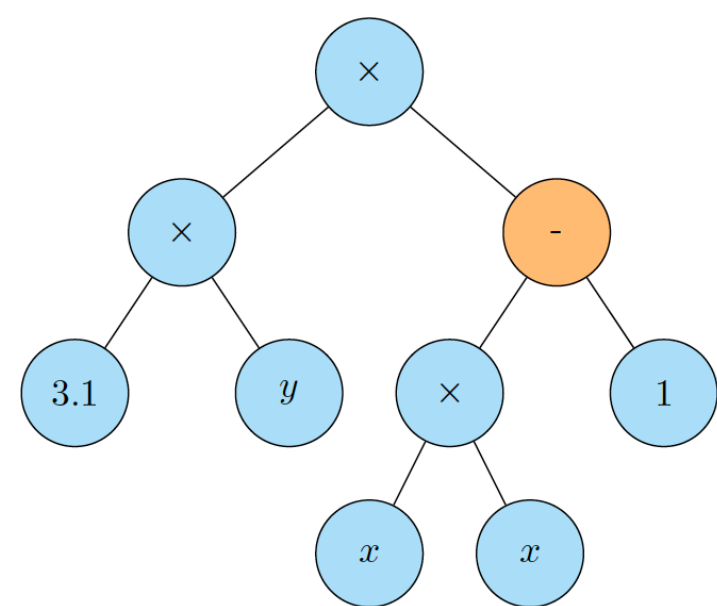
Outline



Some high energy physics



Precision: deep learning the structure of hadrons and new physics



Symbolic regression

Symbolic regression

- Symbolic regression (SR) is a supervised learning technique.
- It seeks to find closed-form analytical expressions (equations) to map inputs to output without completely predefining the functional form of the mapping.
- It has been used in high energy physics in multiple contexts (e.g. 2109.10414, 2206.08901, 2211.08420).
- It can provide interpretable and simpler results (a domain scientist can find connections between a SR result and existing knowledge)

Je n'ai fait celle-ci plus longue que parce que je n'ai pas eu le loisir de la faire plus courte.

If I had more time, I would have written a shorter letter.

*from Lettres Provinciales,
by B. Pascal.*

Symbolic regression

- We make use of the PySR library (2305.01582).
- Our aim is to find analytic formulas for quantities that do not have them yet. However, in precision physics it is *essential* that SR is able to recover what we know from first principles so:
 - We will study if well-known QED cross sections can be recovered.
 - We will study how the binning of an observable and different levels of noise affect the result.
 - We will discuss how SR can help with current and future challenges (angular coefficients).

Symbolic regression

- Formulas are described by expression trees (Fig. 1). They have a *complexity* c associated to their number of nodes.
- The fitness of a set (or many sets) of trees is evaluated.
- Mutations and crossover between trees happen through an evolutionary algorithm (Fig. 2).
- The cycle above is iterated.

$$3.1y (x^2 + 1) \leftrightarrow$$

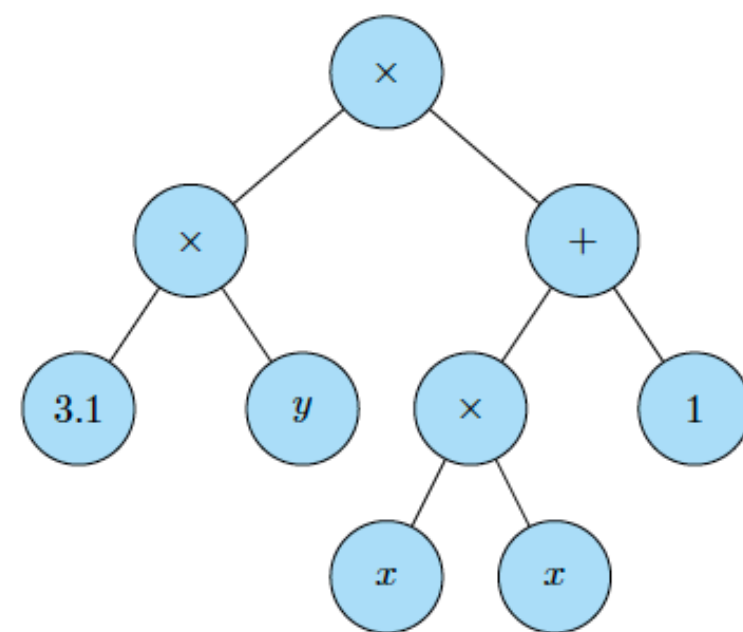


Fig. 1: Expression tree

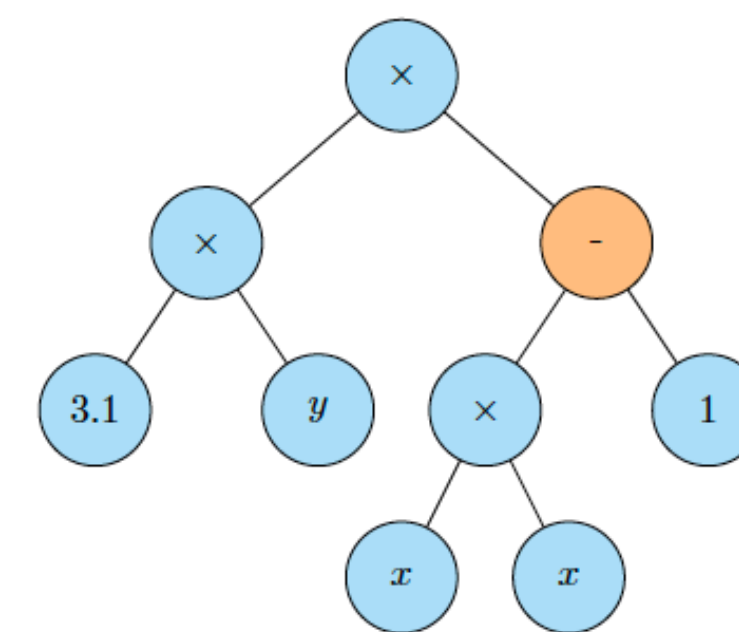


Fig. 2: Mutation

Selection criteria

- Trees can optimise different selection criteria. In PySR these are

Accuracy:

Minimise

$$L = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Score:

Maximise

$$-\frac{\partial \log(L)}{\partial c}$$

Best:

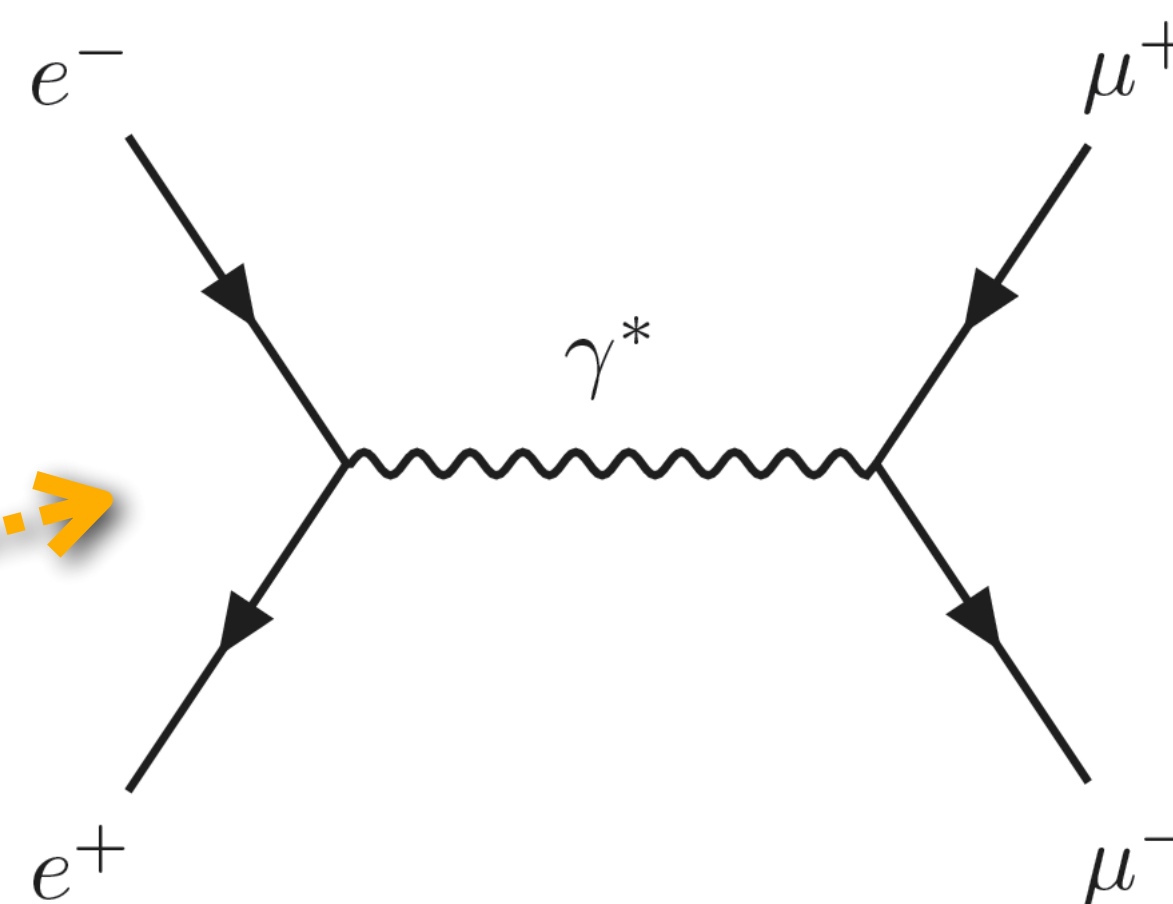
Highest score with

$$L \leq 1.5 \times L_{\min}$$

QED through SR

Can SR rediscover QED cross sections?

We simulate $e^-e^+ \rightarrow \mu^-\mu^+$



$$\frac{d\sigma}{d\cos\theta} = \frac{\pi\alpha^2}{2s} (1 + \cos^2\theta)$$

Differential cross section

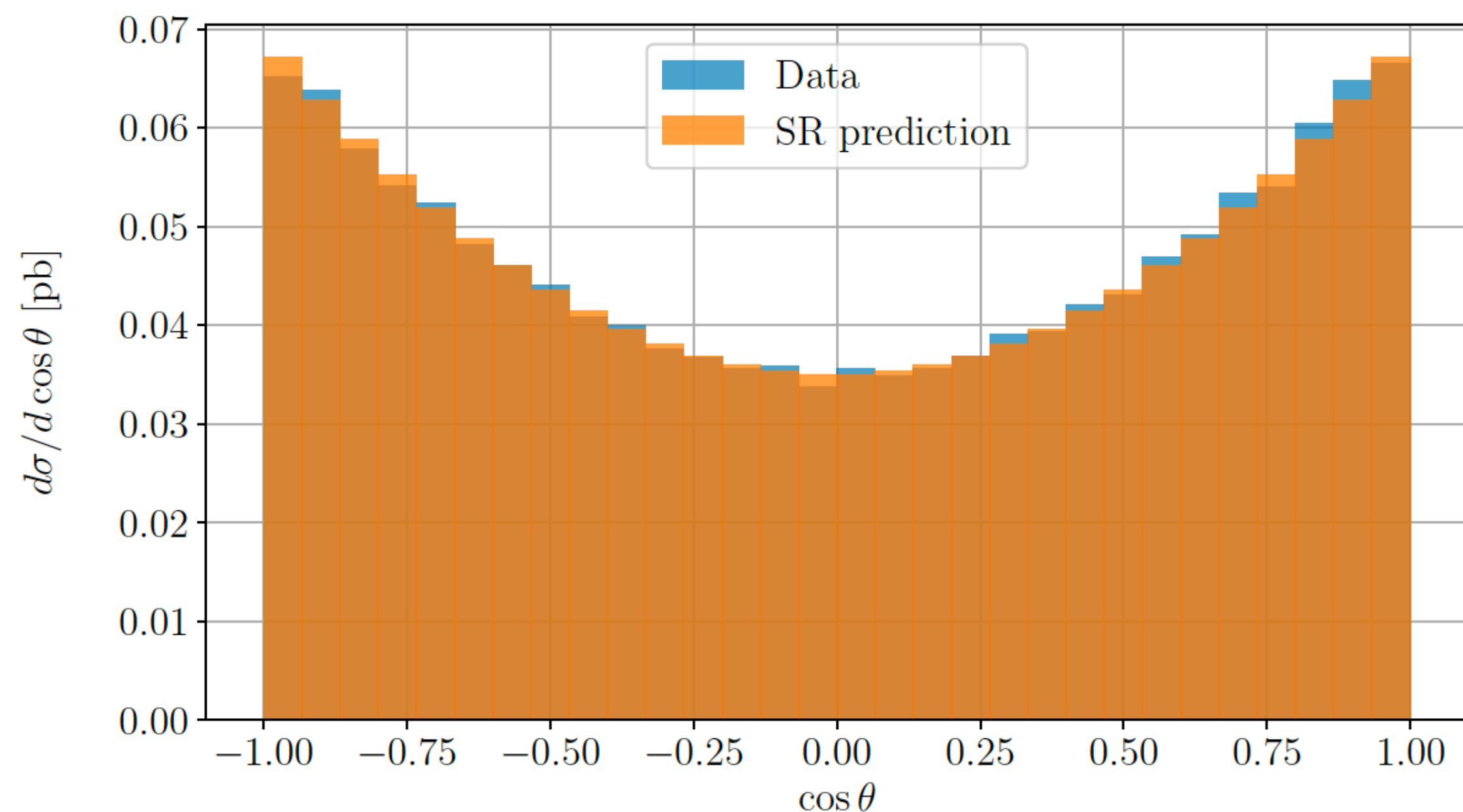


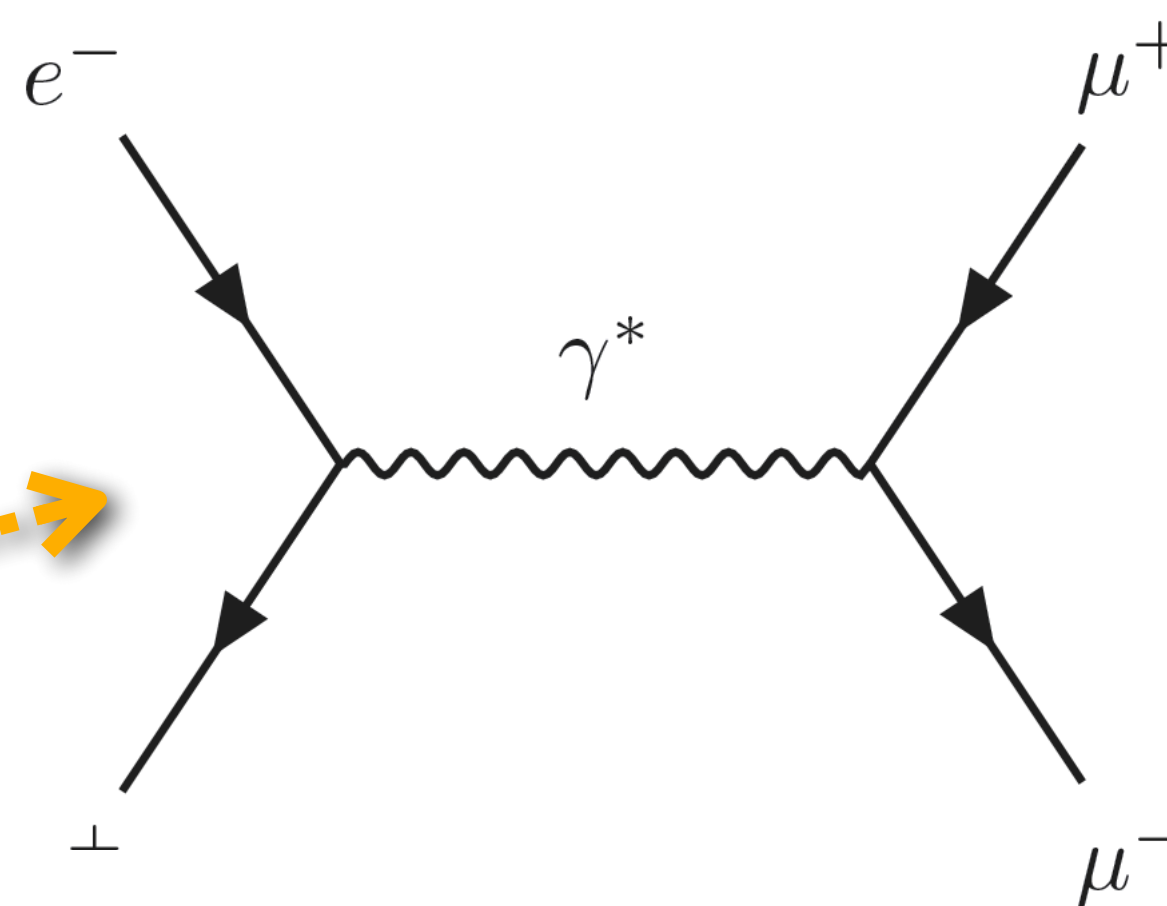
Table 1: Equations according to the three selection criteria for different bin sizes with $x_0 \equiv \cos\theta$. The numbers that appear in these expressions have been approximated to the 5th decimal place.

Bins	Accuracy	Best	Score
10	$x_0(x_0 + 0.00798)(0.00111 \cdot x_0^3 + 0.03459) + 0.03503$	$x_0^2(0.00111 \cdot x_0 + 0.03459) + 0.03503$	$0.03459 \cdot x_0^2 + 0.03503$
20	$x_0(x_0 + 0.01825)(-0.00155 \cdot x_0(x_0 - 0.05138) + 0.03579) + 0.03485$	$x_0(0.03447 \cdot x_0 + 0.00064) + 0.03498$	$0.03447 \cdot x_0^2 + 0.03498$
200	$x_0^2(-0.64647 \cdot x_0(0.00119 \cdot x_0 - 0.00151) + 0.03495) + 0.03495$	$0.03447 \cdot x_0^2 + 0.03495$	$0.03447 \cdot x_0^2 + 0.03495$
1000	$0.03447 \cdot x_0(0.01821 \cdot x_0^2 + x_0 + 0.00723) + 0.03495$	$0.03447 \cdot x_0^2 + 0.03495$	$0.03447 \cdot x_0^2 + 0.03495$

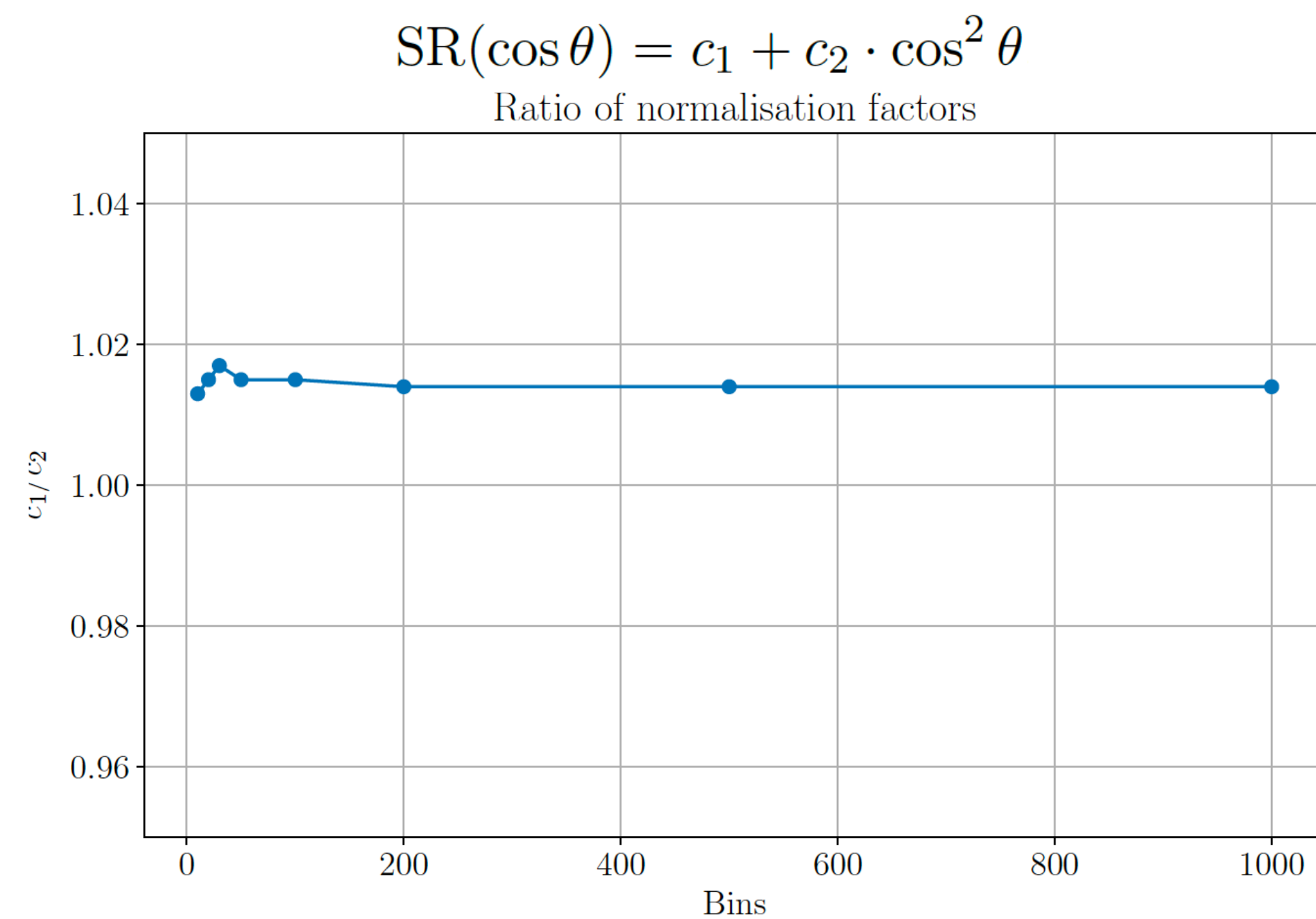
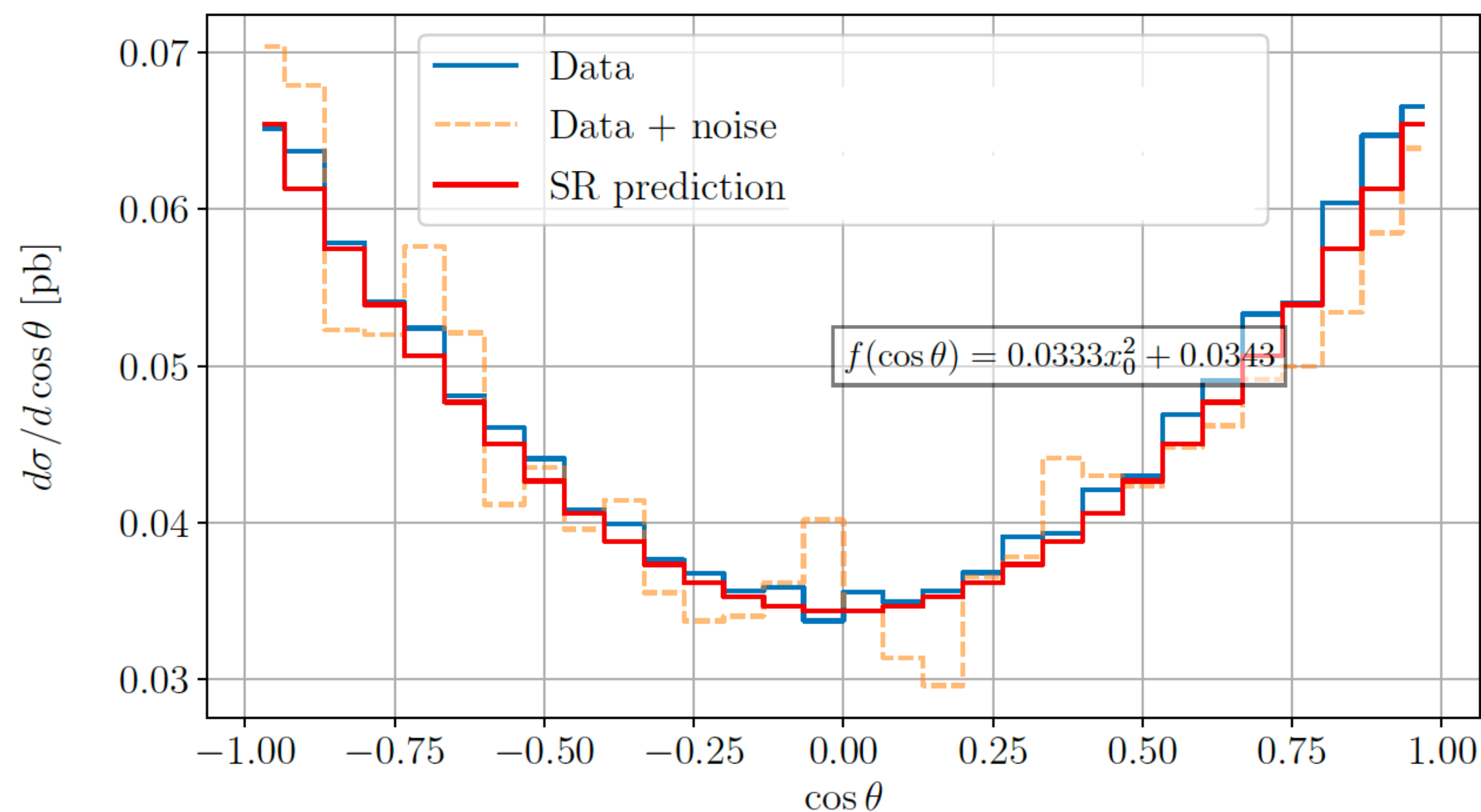
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We simulate $e^-e^+ \rightarrow \mu^-\mu^+$



$$\frac{d\sigma}{d\cos\theta} = \frac{\pi\alpha^2}{2s} (1 + \cos^2\theta)$$



Angular coefficients through SR

SR can also be applied to more complex process (W/Z production at NLO/NNLO):

$$\frac{d^5 \sigma}{dp_T dy_{ll} dm_{ll} d \cos \theta d\phi} = \frac{3}{16\pi} \frac{d^3 \sigma^{U+L}}{dp_T dy_{ll} dm_{ll}} \left[(1 + \cos^2 \theta) + \sum_{i=0}^7 P_i(\theta, \phi) A_i \right],$$

- P_i are spherical harmonics (they encode the angular dependence).
- A_i are *angular coefficients* (they encode the dependence on the other kinematics) for which there is no analytical formula.
- Finding a formula for these coefficients would be useful for experiment and theory.

Angular coefficients through SR

On our way to the full set of angular coefficients, there are intermediate scenarios that have to be studied.

$$\frac{d^5\sigma}{dp_T dy_U dm_U d\cos\theta d\phi} = \frac{3}{16\pi} \frac{d^3\sigma^{U+L}}{dp_T dy_U dm_U} \left[(1 + \cos^2\theta) + \sum_{i=0}^7 P_i(\theta, \phi) A_i \right],$$

E.g. leading order Drell-Yan via Z boson (only the A_4 coefficient is non-zero).

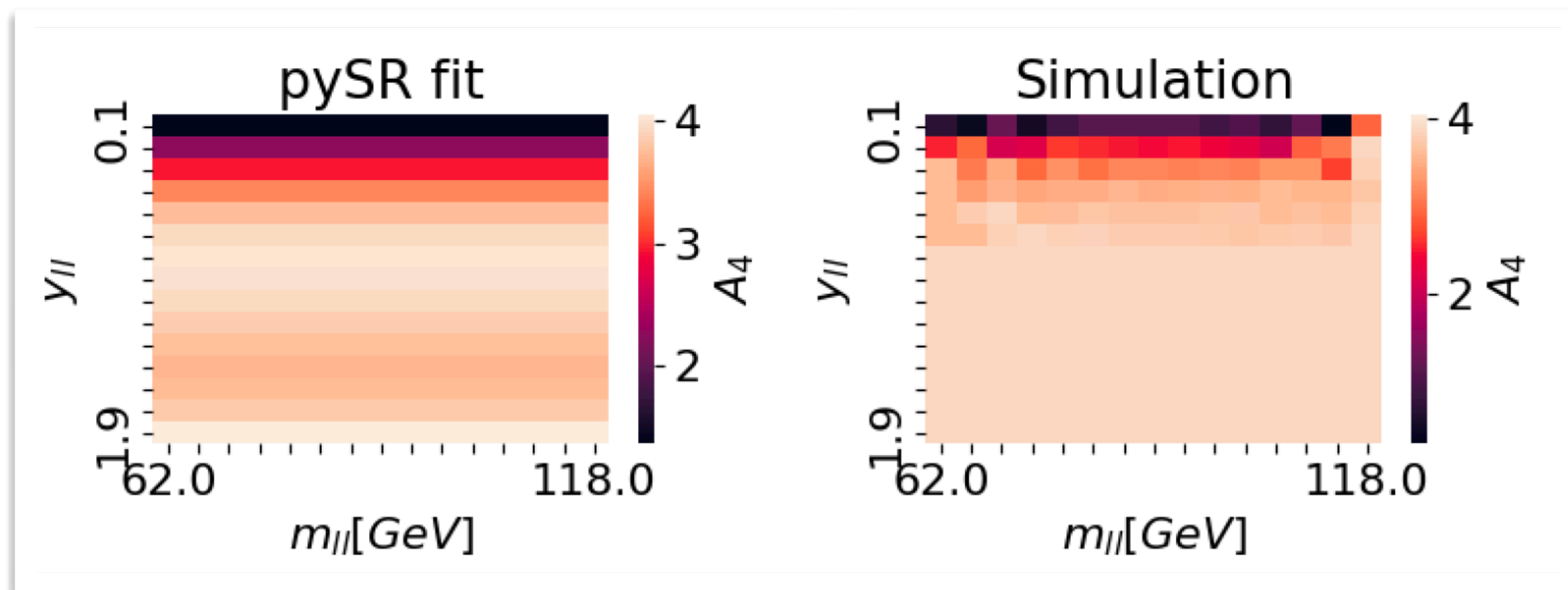


Table 2: Complexity and equations for the A_4 coefficient.

Loss	Complexity	Expression
0.154545	9	$-1.5356994 y_U ^2 + 3.9449594 y_U + 1.613458$
0.092542	11	$ y_U ^3 - 4.4877133 y_U ^2 + 6.2672553 y_U + 1.2202095$
0.073751	15	$2 y_U ^3 - 7.4880592 y_U ^2 + 8.6747910371 y_U + 0.8127258$

PDFs through SR

The scaling in x of the PDFs is dictated by *Regge theory*:

$$\lim_{x \rightarrow 1} f(x, Q^2) = 0$$

$$\lim_{x \rightarrow 0} f(x, Q^2) \propto x^\alpha$$

We can integrate these requirements in the parametrisations we discussed:

$$f(x, Q^2) = x^\alpha (1-x)^\beta \text{NN}(x, Q^2)$$

$$f(x, Q^2) = x^\alpha (1-x)^\beta f_{\text{red}}(x, Q^2)$$

Could SR be of help?

$$f(x, Q^2) = x^\alpha (1-x)^\beta \text{SR}(x, Q^2)$$

Corrections from Regge theory?

NN/analytical comparison?

Simpler functional forms with flexibility?

What about *uncertainty*?

Conclusion

- Precision interpretations and calculations are playing an important role in the search for BSM physics.
- Deep learning is allowing us to explore the interplay between the PDFs (that parametrise the structure of the proton) and BSM physics.
- SR can bring new insights to our studies. We find pure *accuracy* not be a good selection criterion, model complexity is also relevant.
- A careful assessment of the robustness and stability of the SR results is necessary in the era of precision physics.

Thank you for your attention!

Backup slides

Warsaw basis

In the SMEFT, we supplement the SM Lagrangian with towers of higher dimensional operators

$$\mathcal{L}_{\text{SMEFT}} = \mathcal{L}_{\text{SM}} + \sum_i \frac{C_i}{\Lambda^2} Q_i^{(6)} + \dots$$

Up to dimension 6, these operators can be parametrised in the Warsaw basis

X^3		φ^6 and $\varphi^4 D^2$		$\psi^2 \varphi^3$	
Q_G	$f^{ABC} G_\mu^{A\nu} G_\nu^{B\rho} G_\rho^{C\mu}$	Q_φ	$(\varphi^\dagger \varphi)^3$	$Q_{e\varphi}$	$(\varphi^\dagger \varphi)(\bar{l}_p e_r \varphi)$
$Q_{\tilde{G}}$	$f^{ABC} \tilde{G}_\mu^{A\nu} G_\nu^{B\rho} G_\rho^{C\mu}$	$Q_{\varphi\Box}$	$(\varphi^\dagger \varphi)\Box(\varphi^\dagger \varphi)$	$Q_{u\varphi}$	$(\varphi^\dagger \varphi)(\bar{q}_p u_r \tilde{\varphi})$
Q_W	$\varepsilon^{IJK} W_\mu^{I\nu} W_\nu^{J\rho} W_\rho^{K\mu}$	$Q_{\varphi D}$	$(\varphi^\dagger D^\mu \varphi)^* (\varphi^\dagger D_\mu \varphi)$	$Q_{d\varphi}$	$(\varphi^\dagger \varphi)(\bar{q}_p d_r \varphi)$
$Q_{\tilde{W}}$	$\varepsilon^{IJK} \tilde{W}_\mu^{I\nu} W_\nu^{J\rho} W_\rho^{K\mu}$				
$X^2 \varphi^2$		$\psi^2 X \varphi$		$\psi^2 \varphi^2 D$	
$Q_{\varphi G}$	$\varphi^\dagger \varphi G_{\mu\nu}^A G^{A\mu\nu}$	Q_{eW}	$(\bar{l}_p \sigma^{\mu\nu} e_r) \tau^I \varphi W_{\mu\nu}^I$	$Q_{\varphi l}^{(1)}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu \varphi)(\bar{l}_p \gamma^\mu l_r)$
$Q_{\varphi \tilde{G}}$	$\varphi^\dagger \varphi \tilde{G}_{\mu\nu}^A G^{A\mu\nu}$	Q_{eB}	$(\bar{l}_p \sigma^{\mu\nu} e_r) \varphi B_{\mu\nu}$	$Q_{\varphi l}^{(3)}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu^I \varphi)(\bar{l}_p \tau^I \gamma^\mu l_r)$
$Q_{\varphi W}$	$\varphi^\dagger \varphi W_{\mu\nu}^I W^{I\mu\nu}$	Q_{uG}	$(\bar{q}_p \sigma^{\mu\nu} T^A u_r) \tilde{\varphi} G_{\mu\nu}^A$	$Q_{\varphi e}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu \varphi)(\bar{e}_p \gamma^\mu e_r)$
$Q_{\varphi \tilde{W}}$	$\varphi^\dagger \varphi \tilde{W}_{\mu\nu}^I W^{I\mu\nu}$	Q_{uW}	$(\bar{q}_p \sigma^{\mu\nu} u_r) \tau^I \tilde{\varphi} W_{\mu\nu}^I$	$Q_{\varphi q}^{(1)}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu \varphi)(\bar{q}_p \gamma^\mu q_r)$
$Q_{\varphi B}$	$\varphi^\dagger \varphi B_{\mu\nu} B^{\mu\nu}$	Q_{uB}	$(\bar{q}_p \sigma^{\mu\nu} u_r) \tilde{\varphi} B_{\mu\nu}$	$Q_{\varphi q}^{(3)}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu^I \varphi)(\bar{q}_p \tau^I \gamma^\mu q_r)$
$Q_{\varphi \tilde{B}}$	$\varphi^\dagger \varphi \tilde{B}_{\mu\nu} B^{\mu\nu}$	Q_{dG}	$(\bar{q}_p \sigma^{\mu\nu} T^A d_r) \varphi G_{\mu\nu}^A$	$Q_{\varphi u}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu \varphi)(\bar{u}_p \gamma^\mu u_r)$
$Q_{\varphi WB}$	$\varphi^\dagger \tau^I \varphi W_{\mu\nu}^I B^{\mu\nu}$	Q_{dW}	$(\bar{q}_p \sigma^{\mu\nu} d_r) \tau^I \varphi W_{\mu\nu}^I$	$Q_{\varphi d}$	$(\varphi^\dagger i \overleftrightarrow{D}_\mu \varphi)(\bar{d}_p \gamma^\mu d_r)$
$Q_{\varphi \tilde{W}B}$	$\varphi^\dagger \tau^I \varphi \tilde{W}_{\mu\nu}^I B^{\mu\nu}$	Q_{dB}	$(\bar{q}_p \sigma^{\mu\nu} d_r) \varphi B_{\mu\nu}$	$Q_{\varphi ud}$	$i(\tilde{\varphi}^\dagger D_\mu \varphi)(\bar{u}_p \gamma^\mu d_r)$

$(\bar{L}L)(\bar{L}L)$		$(\bar{R}R)(\bar{R}R)$		$(\bar{L}L)(\bar{R}R)$	
Q_{ll}	$(\bar{l}_p \gamma_\mu l_r)(\bar{l}_s \gamma^\mu l_t)$	Q_{ee}	$(\bar{e}_p \gamma_\mu e_r)(\bar{e}_s \gamma^\mu e_t)$	Q_{le}	$(\bar{l}_p \gamma_\mu l_r)(\bar{e}_s \gamma^\mu e_t)$
$Q_{qq}^{(1)}$	$(\bar{q}_p \gamma_\mu q_r)(\bar{q}_s \gamma^\mu q_t)$	Q_{uu}	$(\bar{u}_p \gamma_\mu u_r)(\bar{u}_s \gamma^\mu u_t)$	Q_{lu}	$(\bar{l}_p \gamma_\mu l_r)(\bar{u}_s \gamma^\mu u_t)$
$Q_{qq}^{(3)}$	$(\bar{q}_p \gamma_\mu \tau^I q_r)(\bar{q}_s \gamma^\mu \tau^I q_t)$	Q_{dd}	$(\bar{d}_p \gamma_\mu d_r)(\bar{d}_s \gamma^\mu d_t)$	Q_{ld}	$(\bar{l}_p \gamma_\mu l_r)(\bar{d}_s \gamma^\mu d_t)$
$Q_{lq}^{(1)}$	$(\bar{l}_p \gamma_\mu l_r)(\bar{q}_s \gamma^\mu q_t)$	Q_{eu}	$(\bar{e}_p \gamma_\mu e_r)(\bar{u}_s \gamma^\mu u_t)$	Q_{qe}	$(\bar{q}_p \gamma_\mu q_r)(\bar{e}_s \gamma^\mu e_t)$
$Q_{lq}^{(3)}$	$(\bar{l}_p \gamma_\mu \tau^I l_r)(\bar{q}_s \gamma^\mu \tau^I q_t)$	Q_{ed}	$(\bar{e}_p \gamma_\mu e_r)(\bar{d}_s \gamma^\mu d_t)$	$Q_{qu}^{(1)}$	$(\bar{q}_p \gamma_\mu q_r)(\bar{u}_s \gamma^\mu u_t)$
		$Q_{ud}^{(1)}$	$(\bar{u}_p \gamma_\mu u_r)(\bar{d}_s \gamma^\mu d_t)$	$Q_{qu}^{(8)}$	$(\bar{q}_p \gamma_\mu T^A q_r)(\bar{u}_s \gamma^\mu T^A u_t)$
		$Q_{ud}^{(8)}$	$(\bar{u}_p \gamma_\mu T^A u_r)(\bar{d}_s \gamma^\mu T^A d_t)$	$Q_{qd}^{(1)}$	$(\bar{q}_p \gamma_\mu q_r)(\bar{d}_s \gamma^\mu d_t)$
				$Q_{qd}^{(8)}$	$(\bar{q}_p \gamma_\mu T^A q_r)(\bar{d}_s \gamma^\mu T^A d_t)$
$(\bar{L}R)(\bar{R}L)$ and $(\bar{L}R)(\bar{L}R)$		B -violating			
Q_{ledq}	$(\bar{l}_p^j e_r)(\bar{d}_s^k q_t^j)$	Q_{duq}	$\varepsilon^{\alpha\beta\gamma} \varepsilon_{jk} [(d_p^\alpha)^T C u_r^\beta] [(q_s^{\gamma j})^T C l_t^k]$		
$Q_{quqd}^{(1)}$	$(\bar{q}_p^j u_r) \varepsilon_{jk} (\bar{q}_s^k d_t)$	Q_{ququ}	$\varepsilon^{\alpha\beta\gamma} \varepsilon_{jk} [(q_p^{\alpha j})^T C q_r^{\beta k}] [(u_s^\gamma)^T C e_t]$		
$Q_{quqd}^{(8)}$	$(\bar{q}_p^j T^A u_r) \varepsilon_{jk} (\bar{q}_s^k T^A d_t)$	Q_{qqqq}	$\varepsilon^{\alpha\beta\gamma} \varepsilon_{jnm} [(q_p^{\alpha j})^T C q_r^{\beta k}] [(q_s^{\gamma m})^T C l_t^n]$		
$Q_{lequ}^{(1)}$	$(\bar{l}_p^j e_r) \varepsilon_{jk} (\bar{q}_s^k u_t)$	Q_{duu}	$\varepsilon^{\alpha\beta\gamma} [(d_p^\alpha)^T C u_r^\beta] [(u_s^\gamma)^T C e_t]$		
$Q_{lequ}^{(3)}$	$(\bar{l}_p^j \sigma_{\mu\nu} e_r) \varepsilon_{jk} (\bar{q}_s^k \sigma^{\mu\nu} u_t)$				

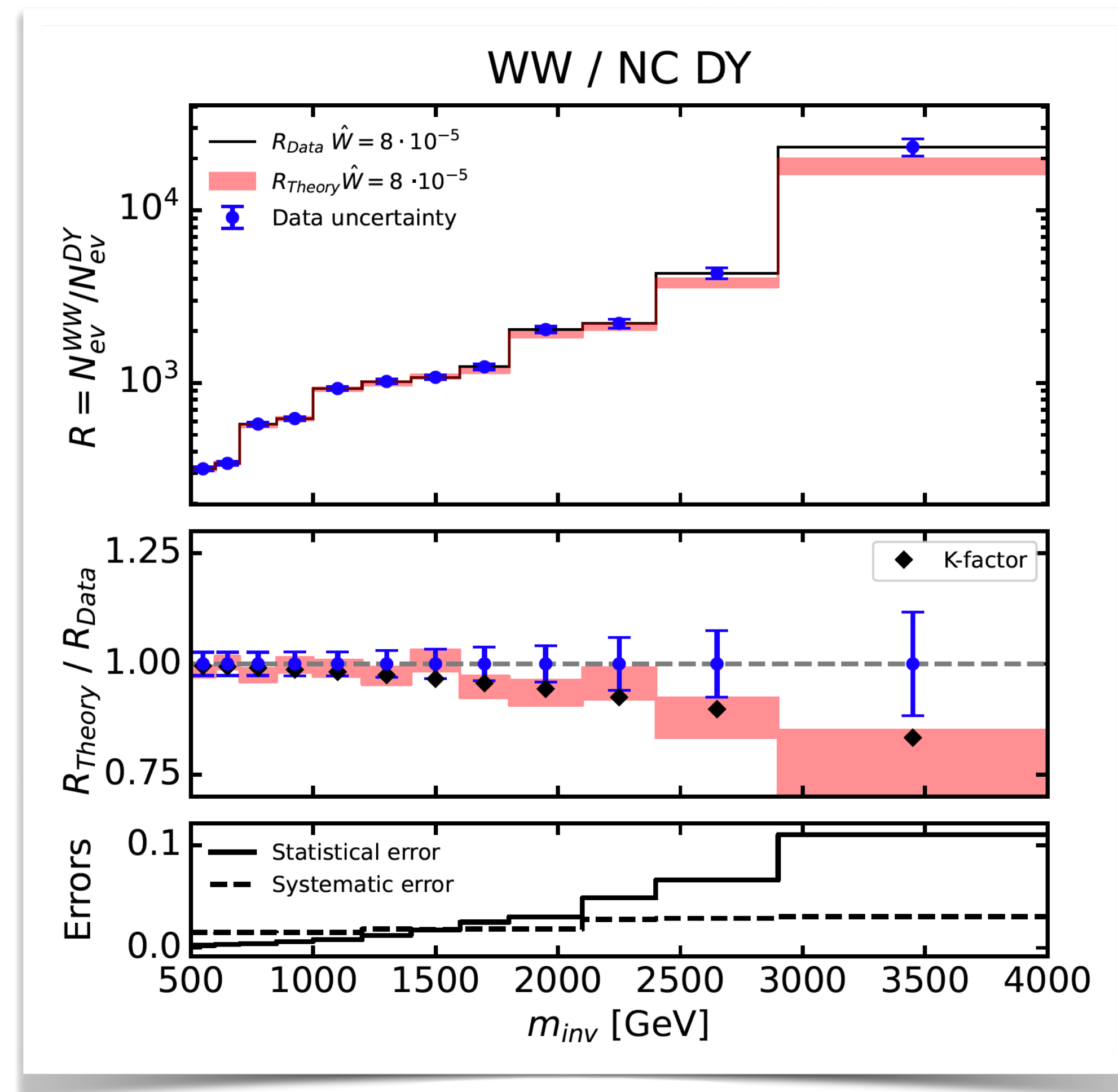
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How to disentangle the contamination

Large- x antiquark PDFs were mostly responsible for accommodating NP. More low energy measurements could help to flag inconsistencies.

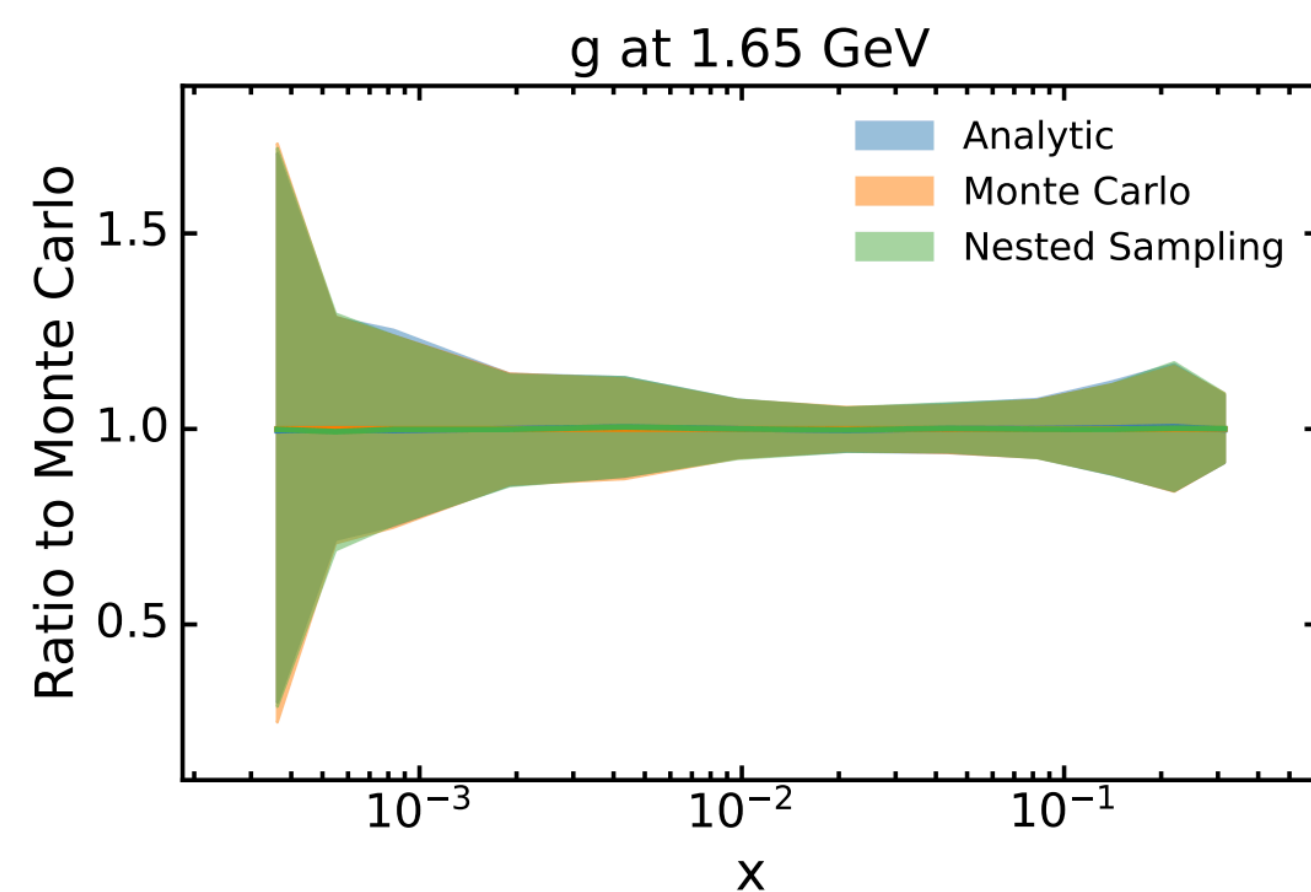
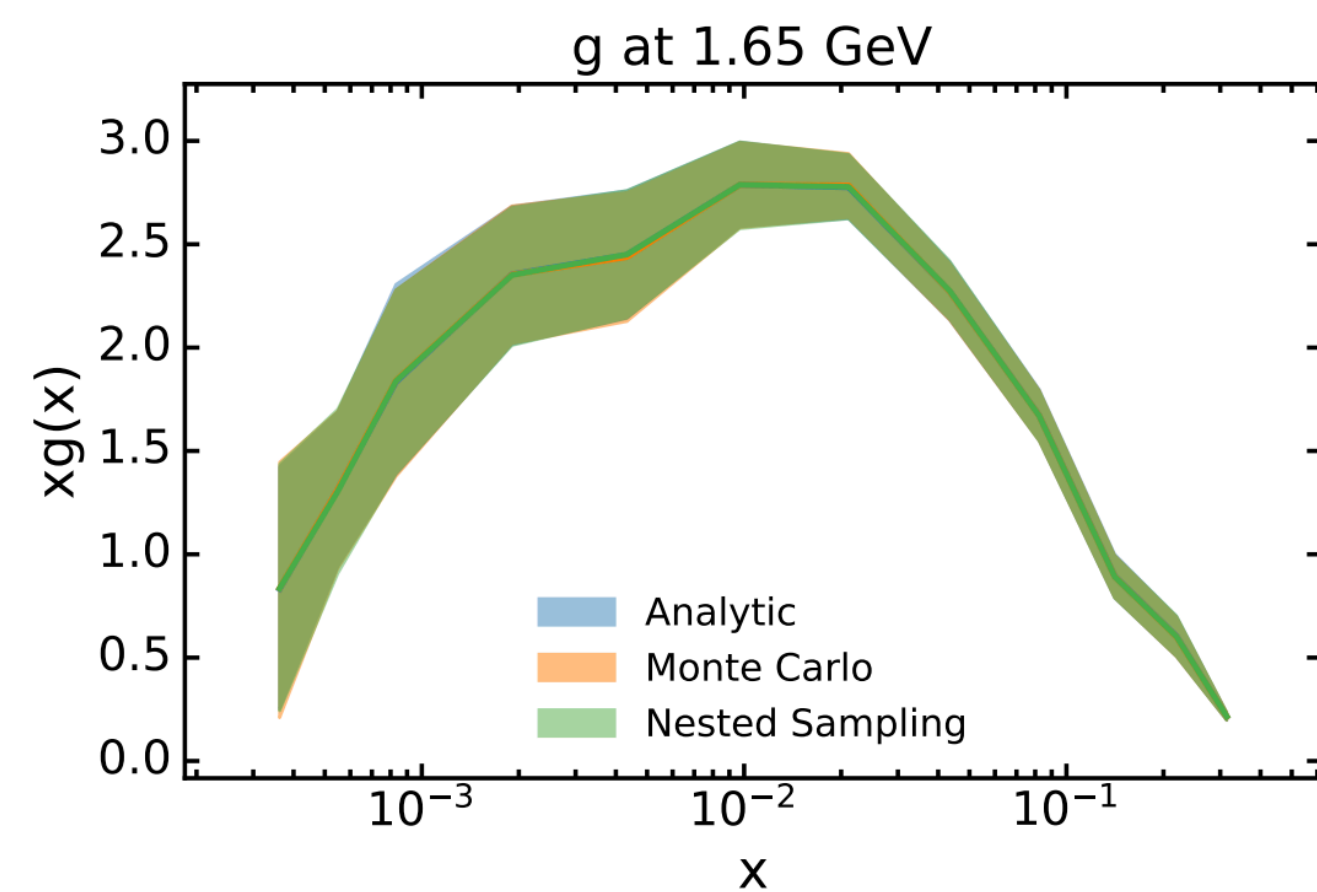
We can disentangle NP effects with ratio observables that probe the same lumi channels.

However, one cannot determine if NP is present in DY or diboson datasets.

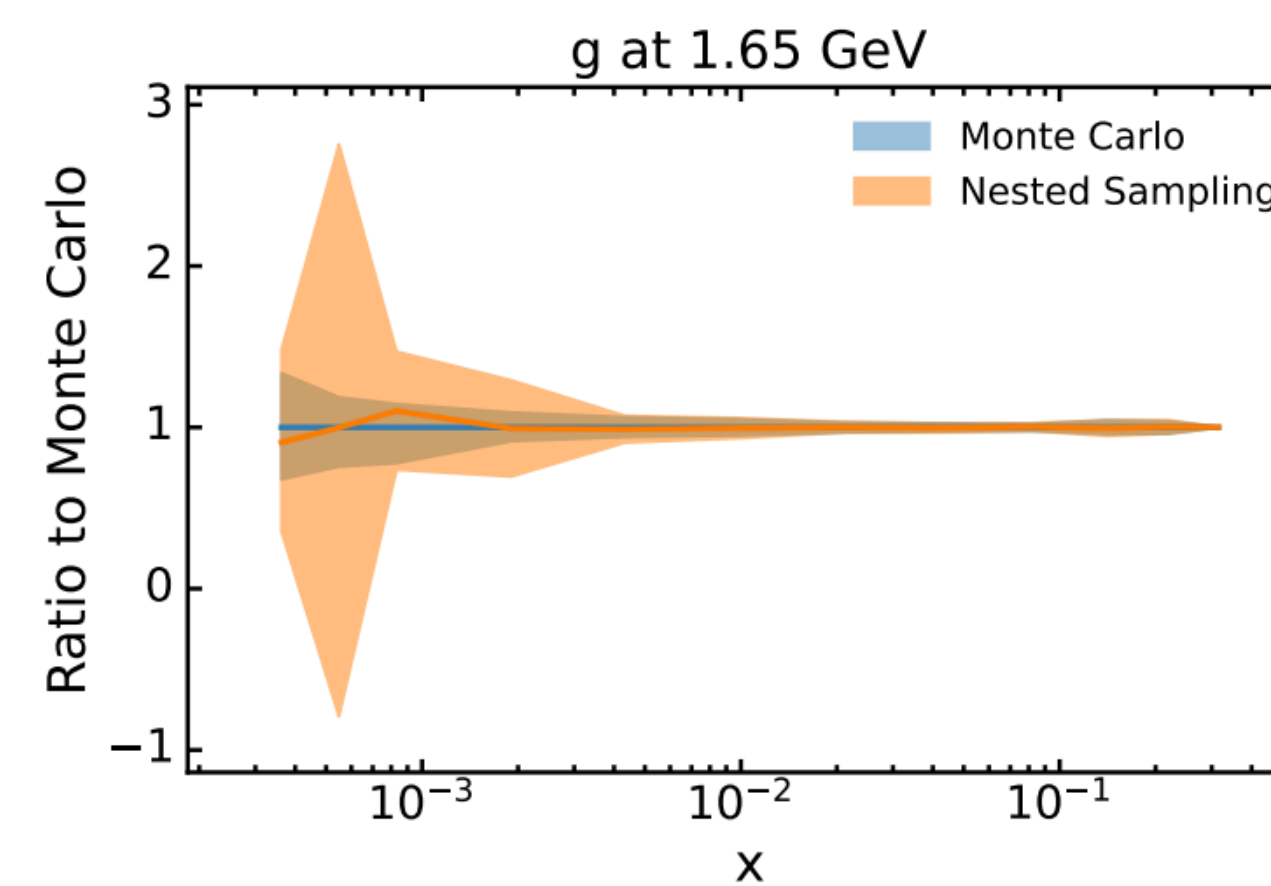
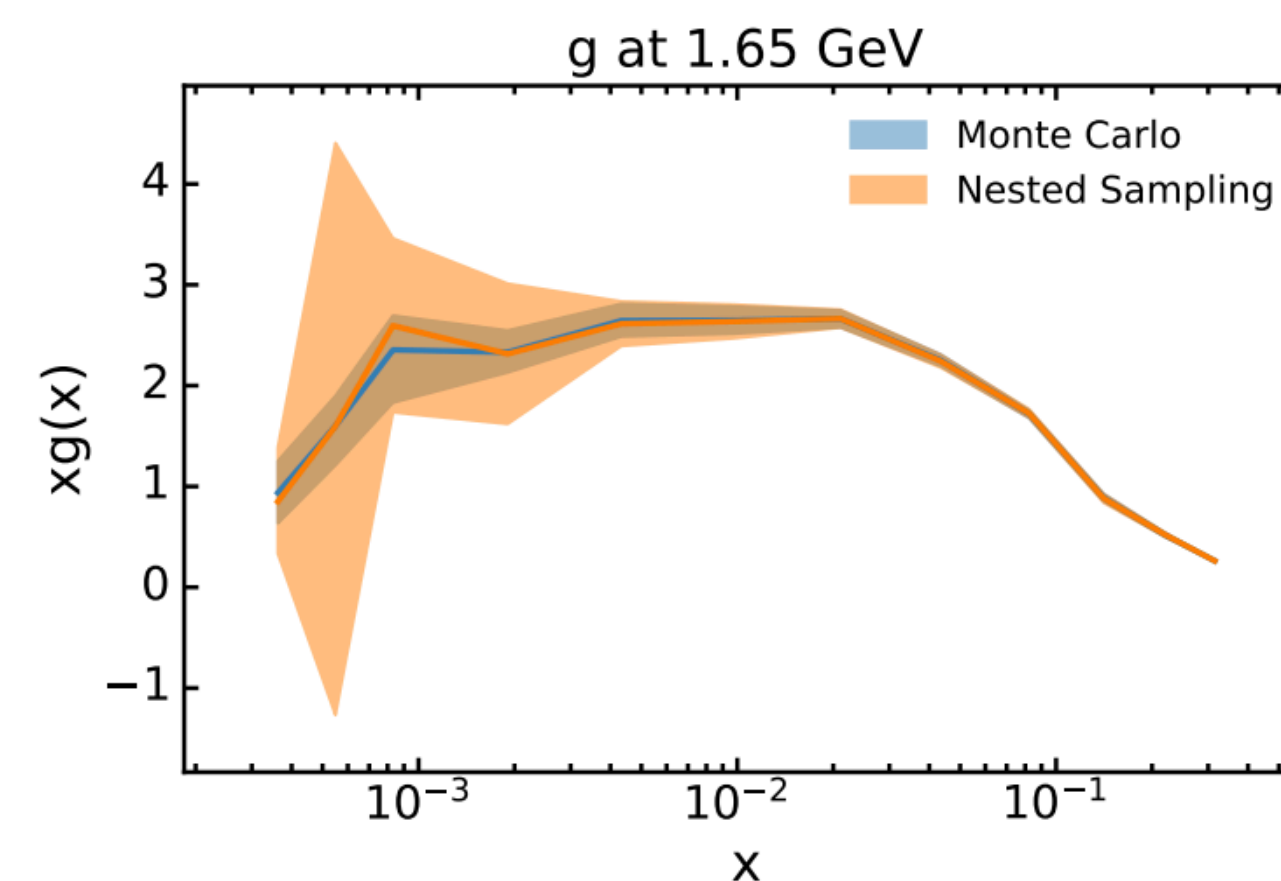


MC Replica vs Bayesian analysis [2404.10056]

PDF: DIS case



PDF: Hadronic case



MC Replica vs Bayesian analysis

Wilson coefficients

