Colibri

A NEW TOOL FOR FAST-FLYING PDF FITS

10.1140/epjc/s10052-025-15185-8

PBSP

UNIVERSITY OF CAMBRIDGE

erc
European Research Council

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DIS2026

Modelling Parton Distribution Functions

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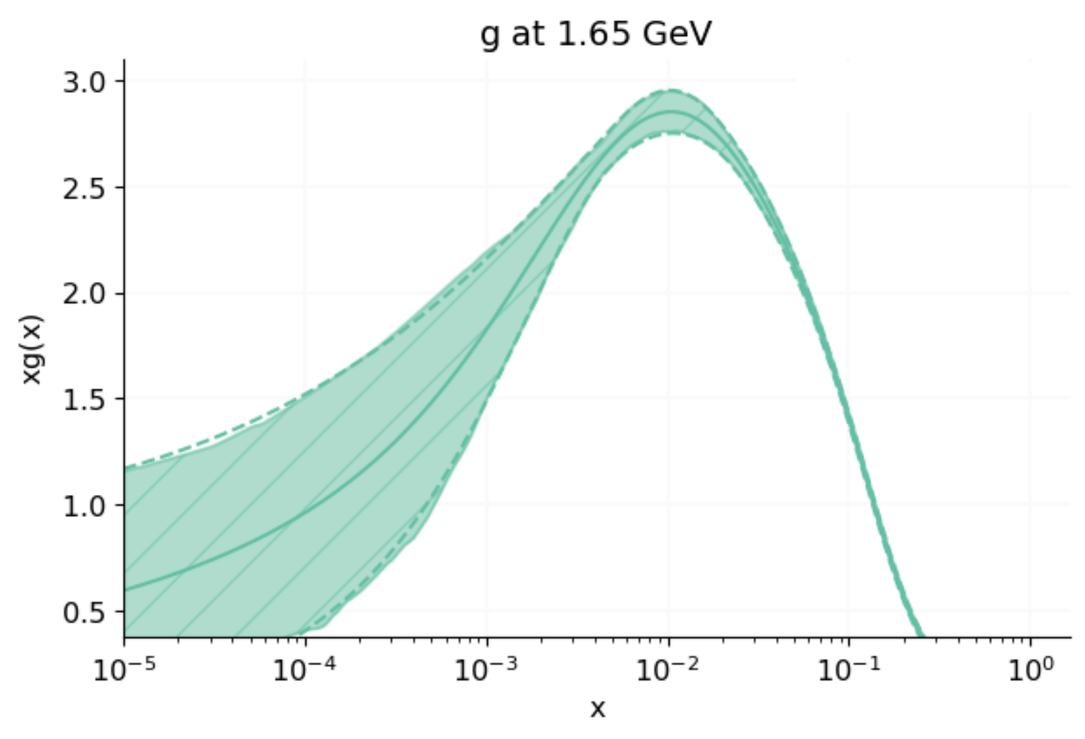
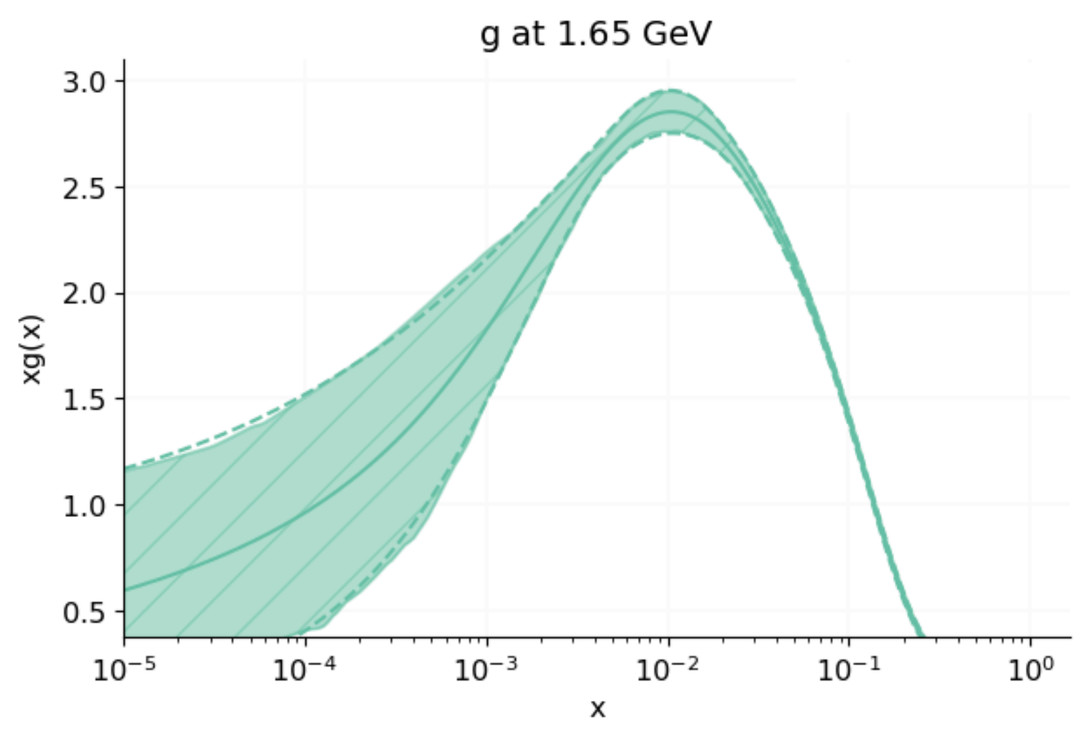
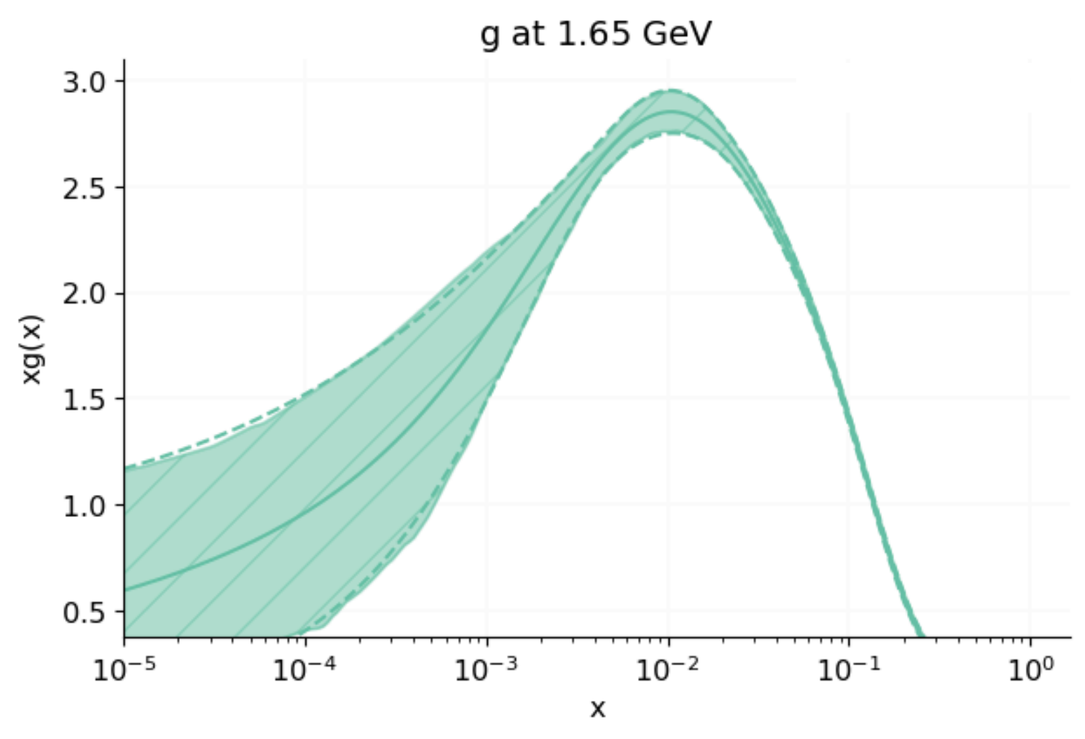


Modelling Parton Distribution Functions



$$f\left(x, Q_0; \theta_i\right) = A x^{-\alpha}(1-x)^{\beta} \widetilde{f}\left(x, Q_0; \theta_i\right)$$

Modelling Parton Distribution Functions



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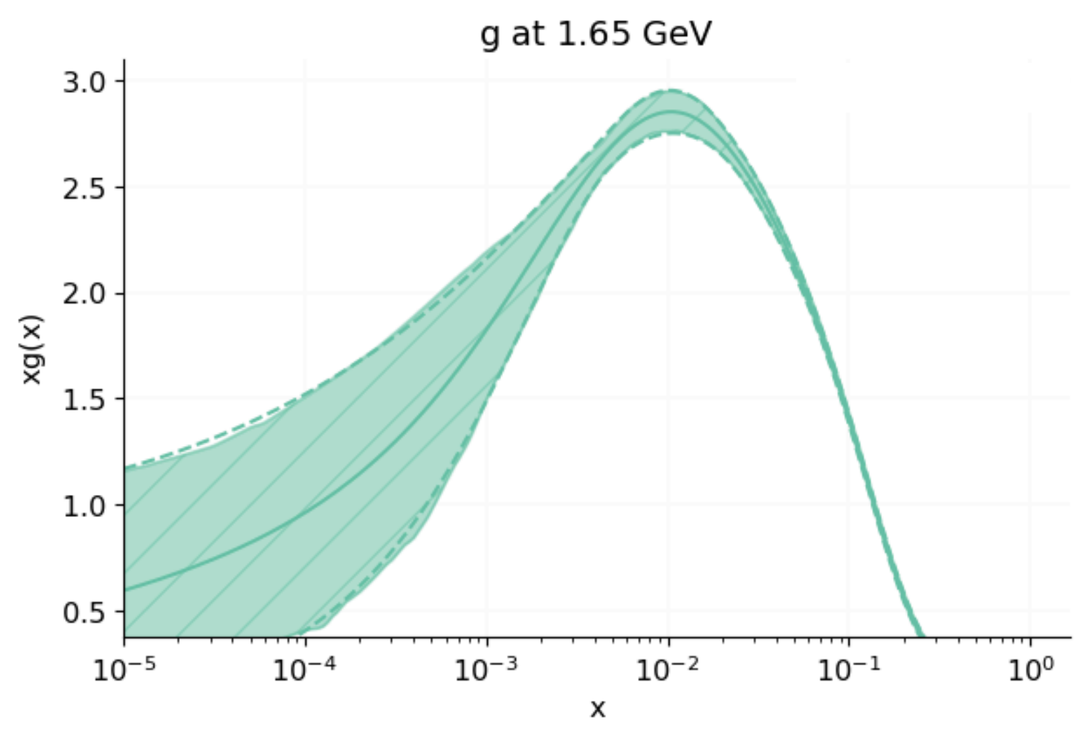
Polynomial parametrisations

$$f\left(x, Q_0\right) = A x^{-\alpha}(1-x)^{\beta}\left(1+\varepsilon\sqrt{x}+\gamma x+\ldots\right)$$

Modelling Parton Distribution Functions



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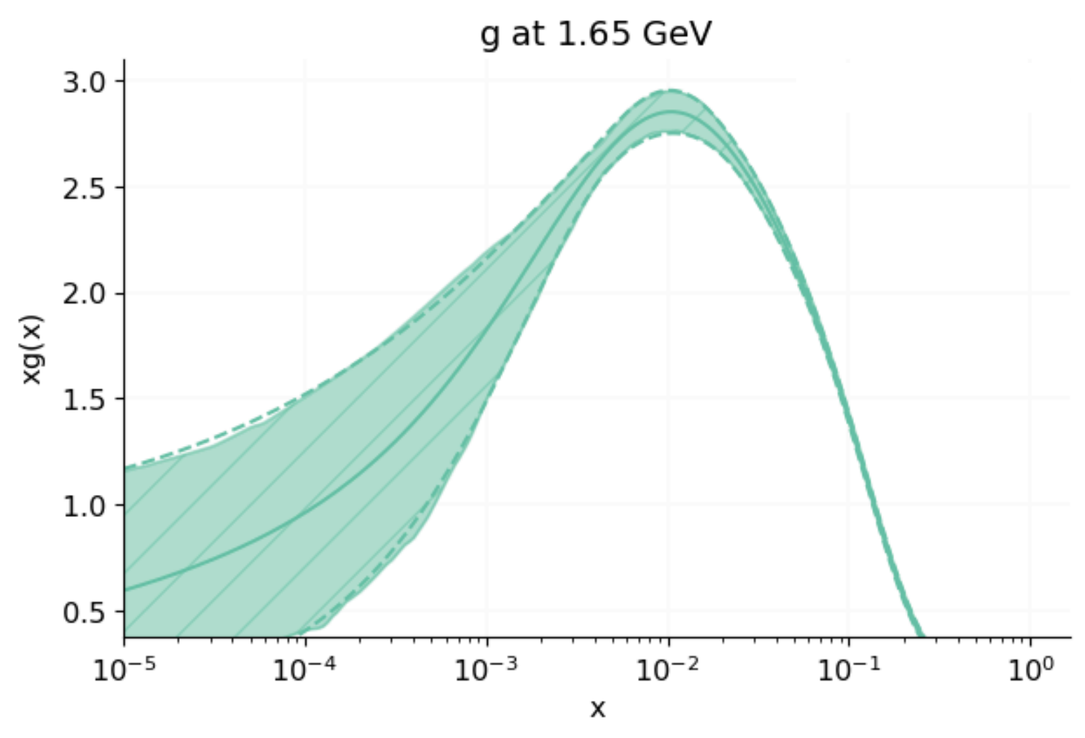

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... and more!

Uncertainty treatment

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Monte Carlo replica method

Uncertainty treatment

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- Monte Carlo replica method
- Hessian

How can we systematically compare different PDF models and benchmark inference methods within the same code framework?

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Monte Carlo replica method → Posterior disagrees with Bayesian statistics with quadratic dependence on parameters

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Bayesian

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- **Monte Carlo replica method** → Posterior disagrees with Bayesian statistics with quadratic dependence on parameters
- **Hessian** → Ad hoc tolerance, Gaussian approximation
- **Bayesian** → Robust uncertainty treatment **BUT**

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Monte Carlo replica method → Posterior disagrees with Bayesian statistics with quadratic dependence on parameters

Hessian → Ad hoc tolerance, Gaussian approximation

Bayesian → Robust uncertainty treatment **BUT**

Computationally expensive...

Motivation

Develop a Bayesian PDF fitting tool that allows for benchmarking fitting methodologies and systematic model comparison

Colibri is an open-source PDF fitting tool where the user controls **what model** to fit and with **which inference method**.

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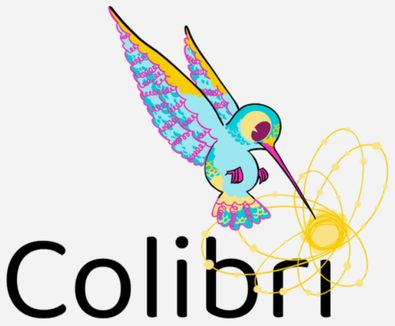
PDF model

Implemented by the user



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PDF model

Implemented by the user

JAX

High-performance computing

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NNPDF

Data and theory predictions

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Monte Carlo fit

Hessian fit

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Monte Carlo fit

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PDF model
Implemented by the user

JAX
High-performance computing

NNPDF
Data and theory predictions

Colibri

Monte Carlo fit

Hessian fit

Bayesian fit

Analytic fit

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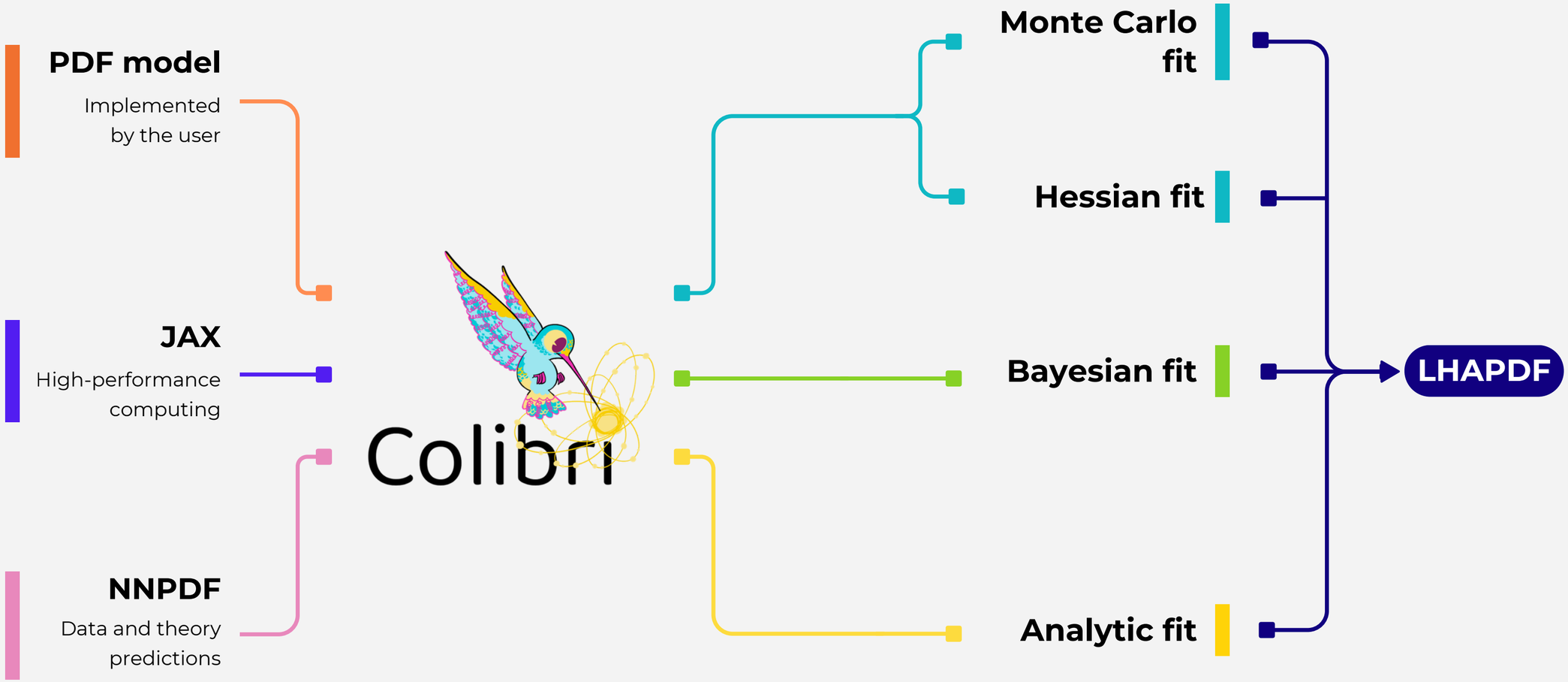
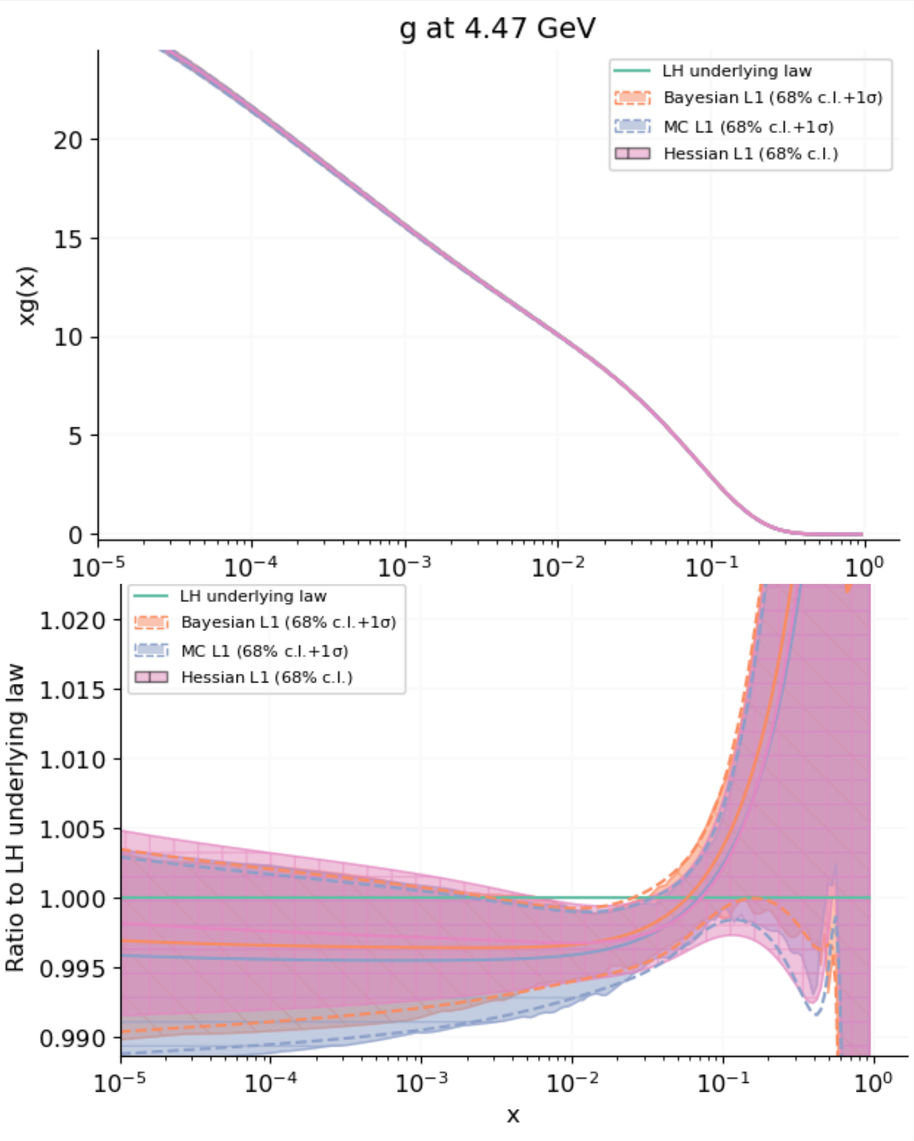
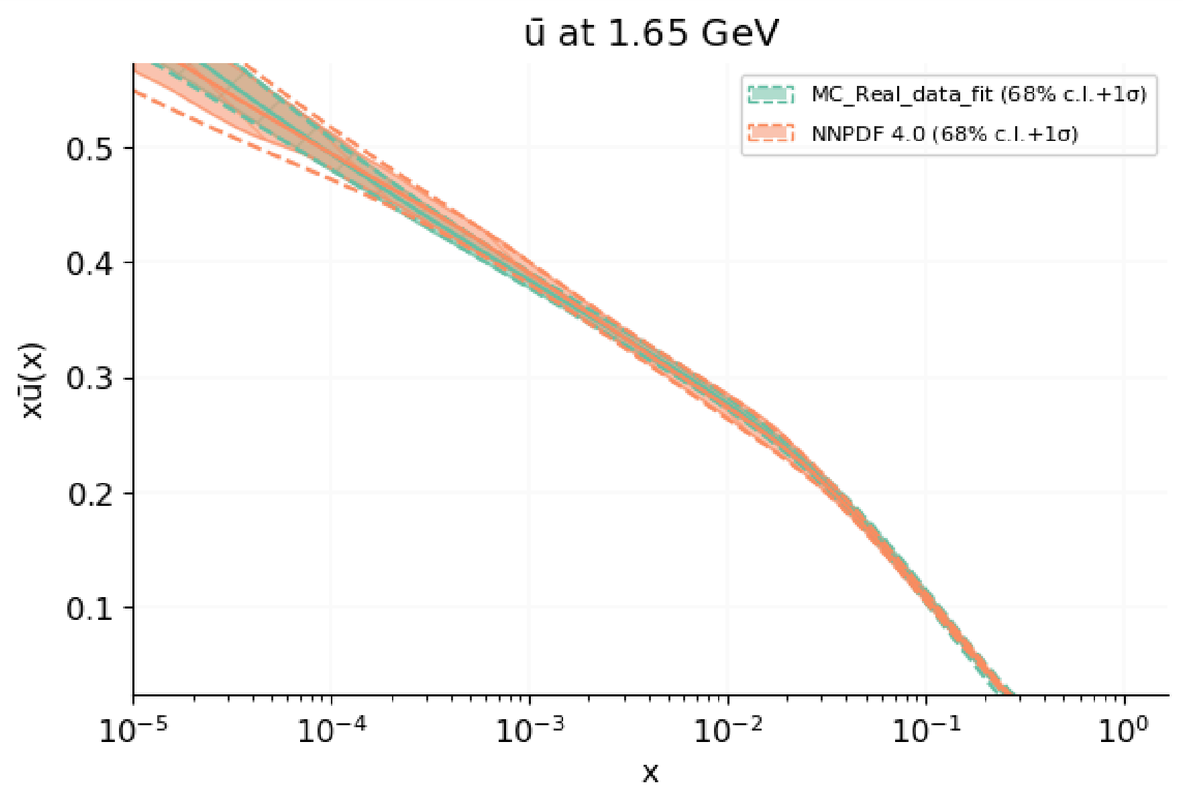




Example:
Les Houches parametrisation

- Polynomial parametrisation
- 13 free parameters

n3fit

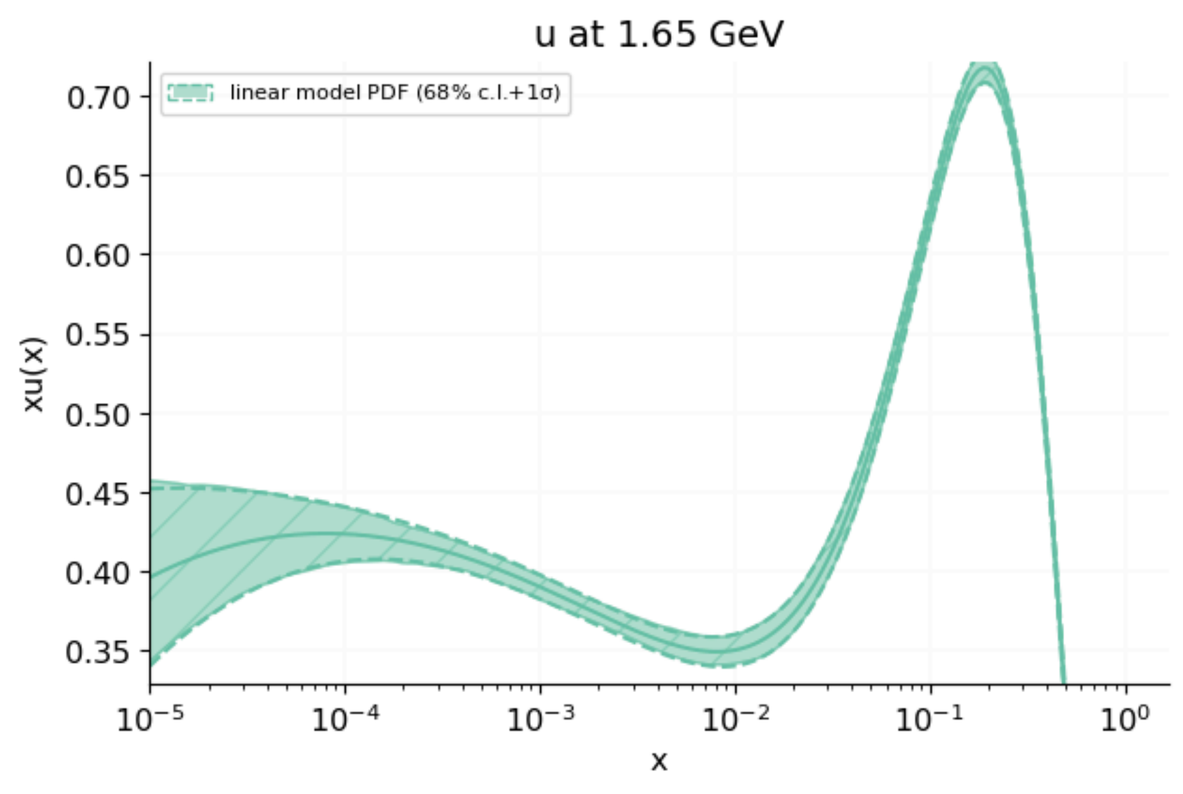


(credits: Ella Cole)

10.1140/epjc/s10052-022-10328-7, NNPDF 4.0

... any Neural Network model could be implemented!

Linear Model



$$f_w(x) = \phi_0(x) + \sum_{k=1}^{N} w_k \phi_k(x)$$

weights

basis functions

First fully Bayesian PDF fit!

arXiv:2507.16913, *Mark N. Costantini et al.*

application: arXiv:2604.13157

Bayesian Model Comparison

Bayesian Model Comparison

Comparing two models, M_1 and M_2, we can compute the *Bayes Factor:*

$$B_{12} = \frac{Z_1}{Z_2} = \frac{p\left(D \,|M_1\right)}{p\left(D \,|M_2\right)}$$

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BAYESIAN PDF MODEL COMBINATION

Applications

Applications

1 **Bayesian PDF fitting**

Applications

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2 **Benchmarking** different models/fitting methods

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3 Perform weighted **PDF combinations**

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Further development

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Further development

1. Implement more realistic polynomial models

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Further development

1. Implement more realistic polynomial models
2. Implement a Bayesian Neural Network model

Applications

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Further development

1. Implement more realistic polynomial models
2. Implement a Bayesian Neural Network model
3. Simultaneous fit with SM/BSM parameters

Useful links

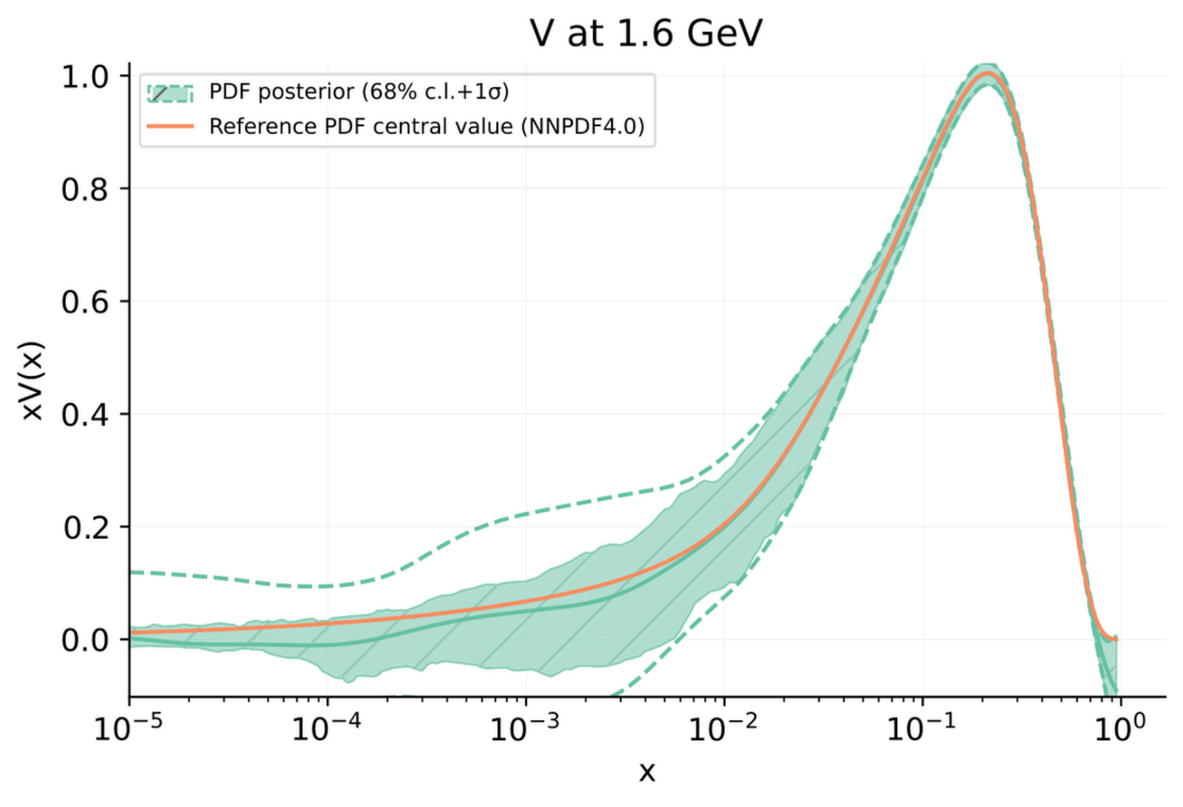
Repository: https://github.com/HEP-PBSP/colibri

Documentation: https://hep-pbsp.github.io/colibri/

Available models: https://hep-pbsp.github.io/colibri/available-models/index.html

Extra slides

Gaussian Processes



PDF described by an N-dimensional Gaussian distribution:

$$\mathbf{f} \sim N(\mathbf{m}, k)$$

arXiv:2404.07573v2, *Tommaso Giani et al.*

Les Houches Parametrisation

$$
\begin{aligned}
x f_g(x, Q_0) &= A_g\, x^{\alpha_g} (1-x)^{\beta_g} \\
x f_{u_v}(x, Q_0) &= A_{u_v}\, x^{\alpha_{u_v}} (1-x)^{\beta_{u_v}} (1 + \epsilon_{u_v} \sqrt{x} + \gamma_{u_v} x) \\
x f_{d_v}(x, Q_0) &= A_{d_v}\, x^{\alpha_{d_v}} (1-x)^{\beta_{d_v}} (1 + \epsilon_{d_v} \sqrt{x} + \gamma_{d_v} x) \\
x f_\Sigma(x, Q_0) &= A_\Sigma\, x^{\alpha_\Sigma} (1-x)^{\beta_\Sigma}.
\end{aligned}
$$

Sum rules:

$$
A_g \int_0^1 x^{\alpha_g} (1-x)^{\beta_g} dx + A_\Sigma \int_0^1 x^{\alpha_\Sigma} (1-x)^{\beta_\Sigma} dx = 1
$$

$$
\begin{aligned}
A_{u_v} \int x^{\alpha_{u_v}-1} (1-x)^{\beta_{u_v}} (1 + \epsilon_{u_v} \sqrt{x} + \gamma_{u_v} x) dx &= 2 \\
A_{d_v} \int x^{\alpha_{d_v}-1} (1-x)^{\beta_{d_v}} (1 + \epsilon_{d_v} \sqrt{x} + \gamma_{d_v} x) dx &= 1
\end{aligned}
$$

Assumptions:

- $\Sigma = \underbrace{u + \bar{u}}_{=0.4\Sigma} + \underbrace{d + \bar{d}}_{=0.4\Sigma} + \underbrace{s + \bar{s}}_{=0.2\Sigma}$
- $\bar{d} = \bar{u}$
- $\varepsilon_g, \gamma_g, \varepsilon_\Sigma, \gamma_\Sigma = 0$

13 free parameters