NNPDF4.0: Towards a high-precision Determination of the Proton Structure

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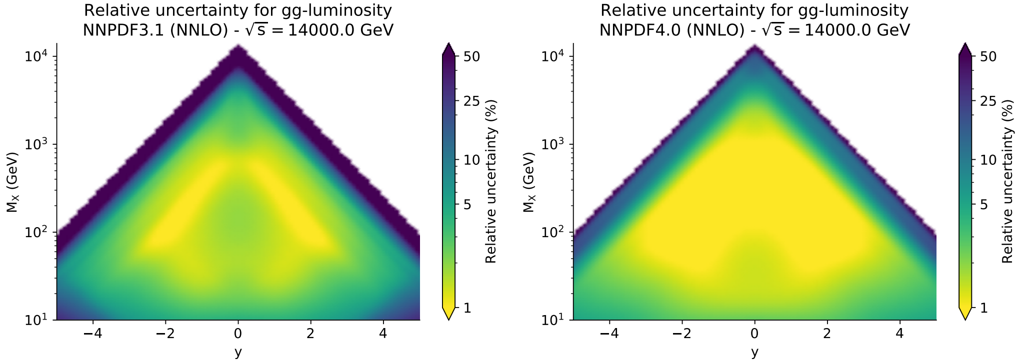
High-precision: gluon

$$\mathcal{L}_{ij}\left(M_X, y, \sqrt{s}\right) = \frac{1}{s}\sum_{i,j} f_i\left(\frac{M_X e^{y}}{\sqrt{s}}, M_X\right) f_j\left(\frac{M_X e^{-y}}{\sqrt{s}}, M_X\right)$$



How did we get here?

High-precision: singlet

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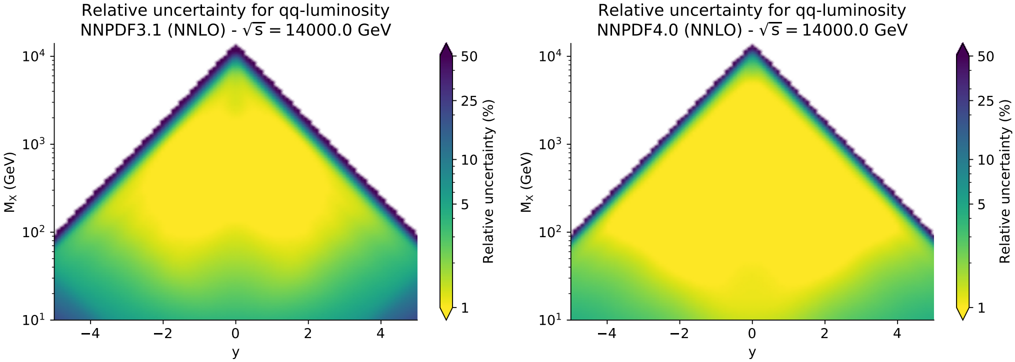


How did we get here?

The path to NNPDF4.0

Progress towards extending data, theory and methodology

06/2017	**NNPDF3.1**	[EPJ C77 (2017) 663]
10/2017	NNPDF3.1sx: PDFs with small-x resummation	[EPJ C78 (2018) 321]
12/2017	NNPDF3.1luxQED: consistent photon PDF à la luxQED	[SciPost Phys. 5 (2018) 008]
02/2018	NNPDF3.1+ATLASphoton: inclusion of direct photon data	[EPJ C78 (2018) 470]
12/2018	NNPDF3.1alphas: α_s from a correlated-replica method	[EPJ C78 (2018) 408]
12/2018	NNPDF3.1nuc: heavy ion nuclear uncertainties in a fit	[EPJ C79 (2019) 282]
05/2019	NNPDF3.1th: missing higher-order uncertainties in a fit	[EPJ C79 (2019) 838; ibid. 931]
07/2019	Gradient descent and hyperoptimisation in PDF fits	[EPJ C79 (2019) 676]
12/2019	NNPDF3.1singletop: inclusion of single top t-channel data	[JHEP 05 (2020) 067]
05/2020	NNPDF3.1dijets: comparative study of single- and di-jets	[EPJ C80 (2020) 797]
06/2020	Positivity of $\overline{\mathrm{MS}}$ PDFs	[JHEP 11 (2020) 129]
08/2020	PineAPPL: fast evaluation of EW$\times$QCD corrections	[JHEP 12 (2020) 108]
08/2020	NNPDF3.1strangeness: assessment of strange-sensitive data	[EPJ C80 (2020) 1168]
11/2020	NNPDF3.1deu: deuteron uncertainties in a fit	[EPJ C81 (2021) 37]
03/2021	Future tests	[arXiv:2103.08606]
2021	**NNPDF4.0**	[to appear]

Experimental data in NNPDF4.0

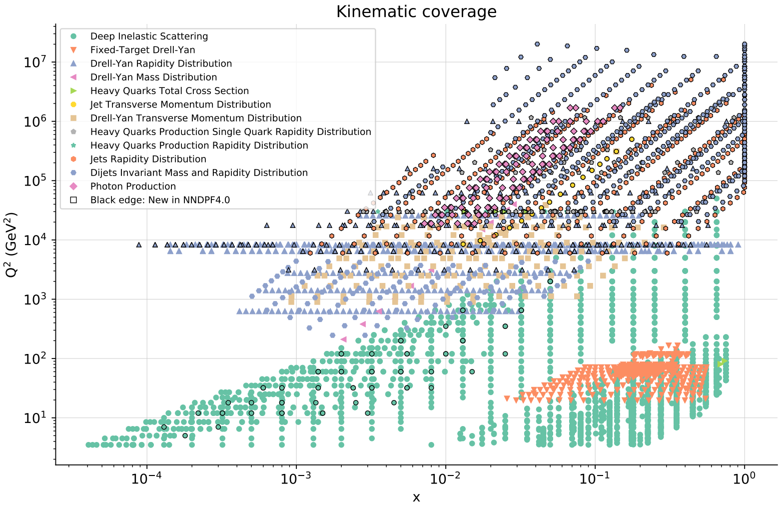
- $\mathcal{O}(35)$ datasets investigated
- $\mathcal{O}(400)$ more data points in NNPDF4.0 than in NNPDF3.1
- New data is mostly from the LHC RUN II

Data set	Ref.	NNPDF3.1	NNPDF4.0	ABMP16	CT18	MSHT20
ATLAS W, Z 7 TeV ($\mathcal{L} = 35$ pb^{-1})	[50]	✓	✓	✓	✓	✓
ATLAS W, Z 7 TeV ($\mathcal{L} = 4.6$ fb^{-1})	[51]	✓	✓	✗	✗	✓
ATLAS low-mass DY 7 TeV	[52]	✓	✓	✗	✗	✗
ATLAS high-mass DY 7 TeV	[53]	✓	✓	✗	✗	✓
ATLAS W 8 TeV	[84]	✗	✓	✗	✗	✓
ATLAS DY 2D 8 TeV	[83]	✗	✓	✗	✗	✓
ATLAS high-mass DY 2D 8 TeV	[82]	✗	✓	✗	✗	✓
ATLAS $\sigma_{W,Z}$ 13 TeV	[86]	✗	✓	✓	✗	✗
ATLAS W^++jet 8 TeV	[98]	✗	✓	✗	✗	✓
ATLAS Z p_T 8 TeV	[62]	✓	✓	✗	✓	✓
ATLAS $\sigma_{tt}^{\rm tot}$ 7, 8 TeV	[64]	✓	✓	✓	✗	✗
ATLAS $\sigma_{tt}^{\rm tot}$ 7, 8 TeV	[213–218]	✗	✗	✓	✗	✗
ATLAS $\sigma_{tt}^{\rm tot}$ 13 TeV ($\mathcal{L} = 3.2\,{\rm fb}^{-1}$)	[65]	✓	✗	✓	✗	✗
ATLAS $\sigma_{tt}^{\rm tot}$ 13 TeV ($\mathcal{L} = 139\,{\rm fb}^{-1}$)	[70]	✗	✓	✗	✗	✗
ATLAS $t\bar{t}$ lepton+jets 8 TeV	[66]	✓	✓	✗	✓	✓
ATLAS $t\bar{t}$ dilepton 8 TeV	[94]	✗	✓	✗	✗	✓
ATLAS single-inclusive jets 7 TeV, R=0.6	[73]	✓	✗	✗	✓	✓
ATLAS single-inclusive jets 8 TeV, R=0.6	[91]	✗	✓	✗	✗	✗
ATLAS dijets 7 TeV, R=0.6	[146]	✗	✓	✗	✗	✗
ATLAS direct photon production 13 TeV	[106]	✗	✓	✗	✗	✗
ATLAS single top R_t 7, 8, 13 TeV	[99, 101, 103]	✗	✓	✓	✗	✗
ATLAS single top diff. 7 TeV	[99]	✗	✓	✗	✗	✗
ATLAS single top diff. 8 TeV	[103]	✗	✓	✗	✗	✗

Data set	Ref.	NNPDF3.1	NNPDF4.0	ABMP16	CT18	MSHT20
CMS W asym. 7 TeV ($\mathcal{L} = 36\,{\rm pb}^{-1}$)	[219]	✗	✗	✗	✗	✓
CMS Z 7 TeV ($\mathcal{L} = 36\,{\rm pb}^{-1}$)	[220]	✗	✗	✗	✗	✓
CMS W electron asymmetry 7 TeV	[54]	✓	✓	✗	✓	✓
CMS W muon asymmetry 7 TeV	[55]	✓	✓	✓	✓	✗
CMS Drell-Yan 2D 7 TeV	[56]	✓	✓	✗	✗	✓
CMS W rapidity 8 TeV	[57]	✓	✓	✓	✓	✓
CMS Z p_T 8 TeV	[63]	✓	✓	✗	✗	✗
CMS $W + c$ 7 TeV	[80]	✓	✓	✗	✗	✓
CMS $W + c$ 13 TeV	[143]	✗	✓	✗	✗	✗
CMS single-inclusive jets 2.76 TeV	[75]	✓	✗	✗	✗	✓
CMS single-inclusive jets 7 TeV	[145]	✓	✗	✗	✓	✓
CMS dijets 7 TeV	[74]	✗	✗	✗	✗	✗
CMS single-inclusive jets 8 TeV	[92]	✗	✓	✗	✓	✓
CMS 3D dijets 8 TeV	[147]	✗	✓	✗	✗	✗
CMS $\sigma_{tt}^{\rm tot}$ 5 TeV	[93]	✗	✓	✗	✗	✗
CMS $\sigma_{tt}^{\rm tot}$ 7, 8 TeV	[144]	✓	✓	✗	✗	✗
CMS $\sigma_{tt}^{\rm tot}$ 8 TeV	[221]	✗	✗	✗	✗	✓
CMS $\sigma_{tt}^{\rm tot}$ 5, 7, 8, 13 TeV	[67, 222–230]	✗	✗	✓	✗	✗
CMS $\sigma_{tt}^{\rm tot}$ 13 TeV	[68]	✓	✓	✓	✗	✗
CMS $t\bar{t}$ lepton+jets 8 TeV	[69]	✓	✓	✗	✗	✓
CMS $t\bar{t}$ 2D dilepton 8 TeV	[95]	✗	✓	✗	✓	✓
CMS $t\bar{t}$ lepton+jet 13 TeV	[96]	✗	✓	✗	✗	✗
CMS $t\bar{t}$ dilepton 13 TeV	[97]	✗	✓	✗	✗	✗
CMS single top $\sigma_t + \sigma_{\bar{t}}$ 7 TeV	[100]	✗	✓	✓	✗	✗
CMS single top R_t 8, 13 TeV	[102, 104]	✗	✓	✓	✗	✗

Data set	Ref.	NNPDF3.1	NNPDF4.0	ABMP16	CT18	MSHT20
LHCb Z 7 TeV ($\mathcal{L} = 940\,{\rm pb}^{-1}$)	[58]	✓	✓	✗	✗	✓
LHCb $Z \to ee$ 8 TeV ($\mathcal{L} = 2\,{\rm fb}^{-1}$)	[60]	✓	✓	✓	✓	✓
LHCb W 7 TeV ($\mathcal{L} = 37\,{\rm pb}^{-1}$)	[231]	✗	✗	✗	✗	✓
LHCb $W, Z \to \mu$ 7 TeV	[81]	✓	✓	✓	✓	✓
LHCb $W, Z \to \mu$ 8 TeV	[61]	✓	✓	✓	✓	✓
LHCb $Z \to \mu\mu, ee$ 13 TeV	[87]	✗	✓	✗	✗	✗

Experimental data in NNPDF4.0



New processes:

- direct photon
- single top
- dijets
- W+jet
- DIS jet

Theoretical improvement

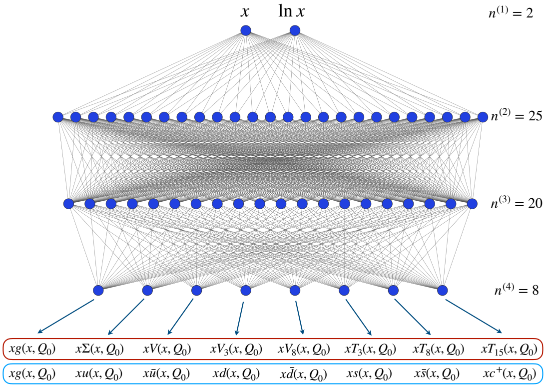
Nuclear uncertainties are included

Improved fitting methodology

- **Stochastic Gradient Descent** for NN training using TensorFlow
- Automated optimization of **model hyperparameters**
- Methodology is validated using **closure tests** (data region), **future tests** (extrapolation region), and **parametrization basis independence**

Physical constraints:

- PDF positivity [JHEP 11 (2020) 129]
- Integrability of nonsinglet distributions (Gottfried sum rules)



$$f_i\,(x,Q_0) = x^{-\alpha_i}(1-x)^{\beta_i}\mathrm{NN}_i(x)$$

Different strategies to parametrize the quark PDF flavour combinations lead to **identical results**

Automated model selection

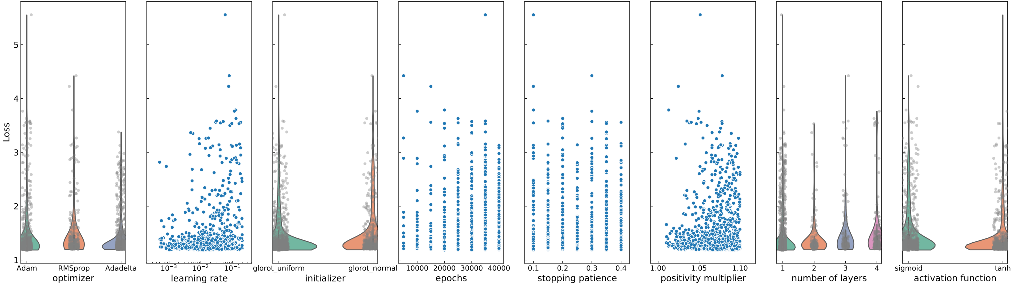
NNPDF aims to minimize sources of bias in the PDF:

- Functional form $\rightarrow$ Neural Network
- Model parameters $\rightarrow$?

Automated model selection

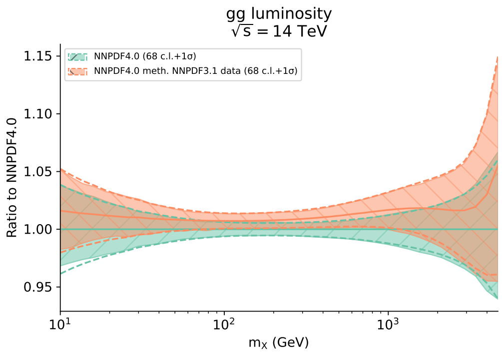
NNPDF aims to minimize sources of bias in the PDF:

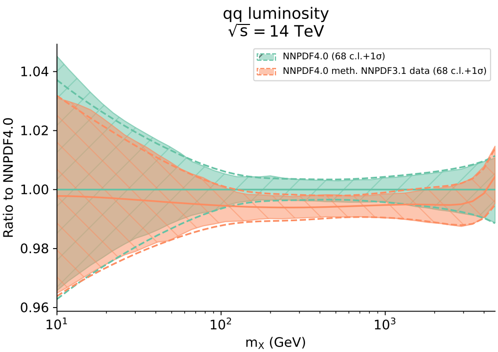
- Functional form → Neural Network
- Model parameters → **Hyperoptimization**



Scan over thousands of hyperparameter combinations and select the best one
k-fold cross-validation: used to define the reward function based on a **test dataset**

Impact of the new data

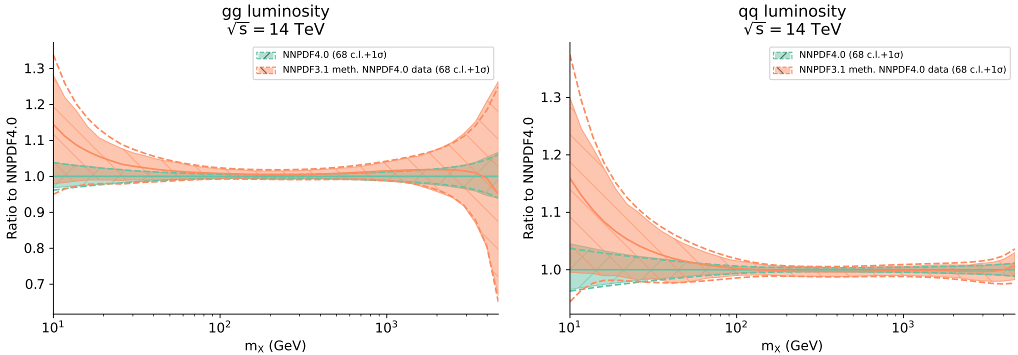




Individual datasets have a limited impact, but collectively they result in:

- Moderate reduction of PDF uncertainties
- Shifts in central value at the one-sigma level

Impact of the new fitting methodology

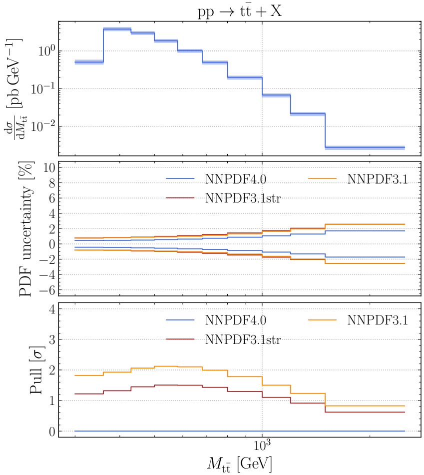


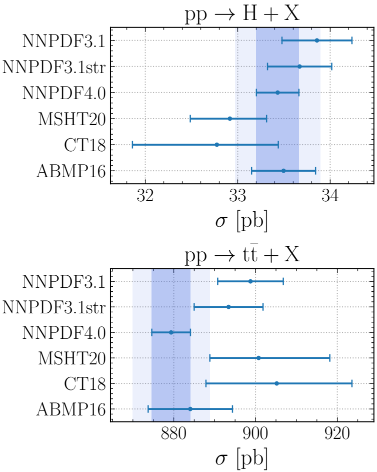
- Significant reduction of PDF uncertainties
- Good agreement between the central values

PDF uncertainties are validated using closure tests and future tests
Validation tests successful for both NNPDF4.0 and NNPDF3.1

Implications for phenomenology

Reduced luminosity uncertainties → Reduced uncertainty at the level of observables





Summary

- Added $\mathcal{O}(400)$ new data points from many new processes
- Improved methodology with Stochastic Gradient Descent and hyperoptimization
- Validation of PDF uncertainties using closure test, future test and parametrization basis independence

$\Rightarrow$ NNPDF4.0 achieves a high precision over a broad kinematic range

The **NNPDF code** will be made **publicly available** along with user-friendly documentation

Summary

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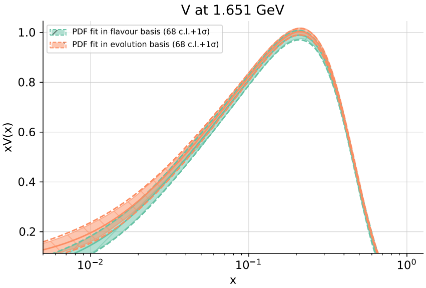
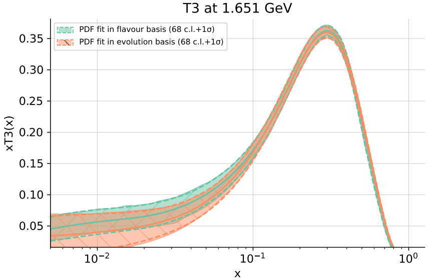
Thank you!

Backup

Parametrization basis independence





Evolution Basis:

$$xV\,(x,Q_0) \propto \mathrm{NN}_V(x)$$
$$xT_3\,(x,Q_0) \propto \mathrm{NN}_{T_3}(x)$$

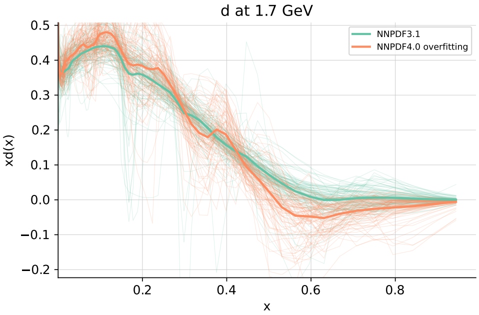
Different strategies to parametrize the quark PDF flavour combinations lead to **identical results**

Flavour Basis:

$$xV\,(x,Q_0) \propto (\mathrm{NN}_u(x) - \mathrm{NN}_{\bar{u}}(x) + \mathrm{NN}_d(x) - \mathrm{NN}_{\bar{d}}(x) + \mathrm{NN}_s(x) - \mathrm{NN}_{\bar{s}}(x))$$
$$xT_3\,(x,Q_0) \propto (\mathrm{NN}_u(x) + \mathrm{NN}_{\bar{u}}(x) - \mathrm{NN}_d(x) - \mathrm{NN}_{\bar{d}}(x))$$

Hyperoptimization: the reward function

Choosing as the hyperoptimization target the χ^2 of fitted data results in overfitting.



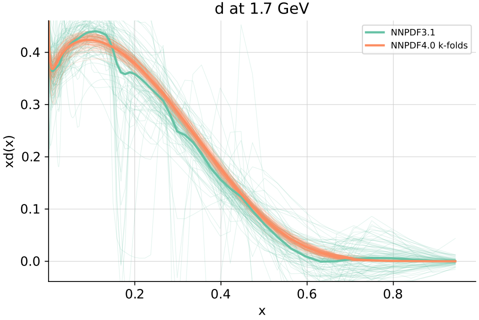
Hyperoptimization: the reward function

Choosing as the hyperoptimization target the χ^2 of fitted data results in overfitting.

We solve this using **k-fold cross-validation**:

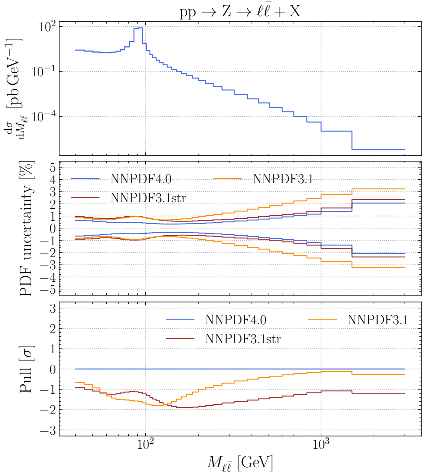
1. Divide the data into k representative subsets
2. Fit $k-1$ sets and use k-th as test set
   $\Rightarrow$ k values of χ^2_{test}
3. Optimize the average χ^2_{test} of the k test sets

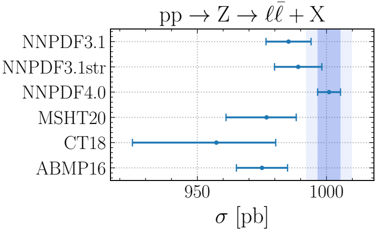
$\Rightarrow$ The hyperoptimization target is not based on data that entered the fit.



- No overfitting
- Compared to NNPDF3.1:
  - Increased stability
  - Reduced uncertainties

More implications for phenomenology





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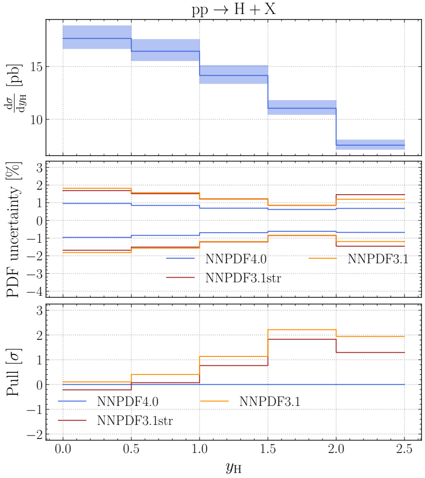

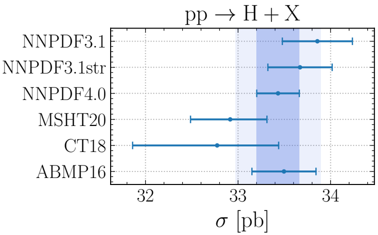

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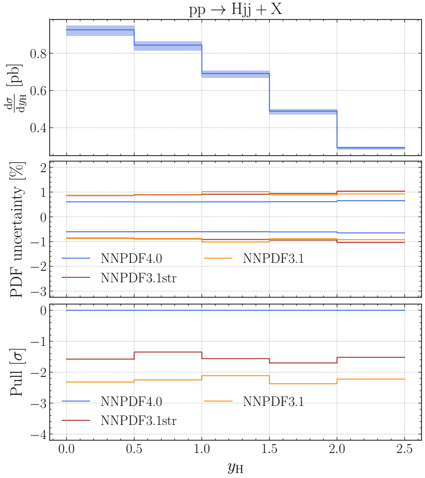

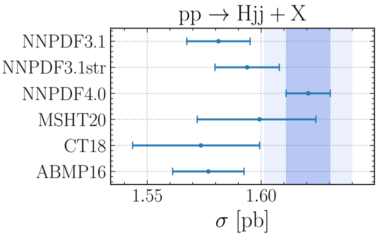

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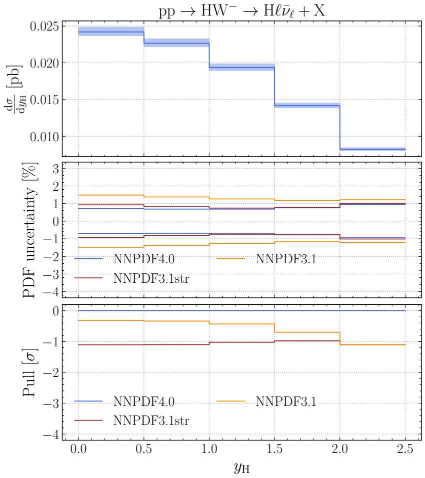

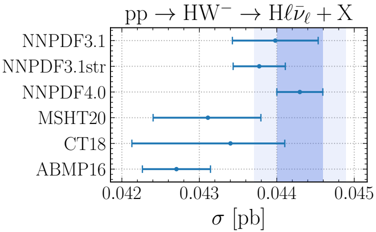

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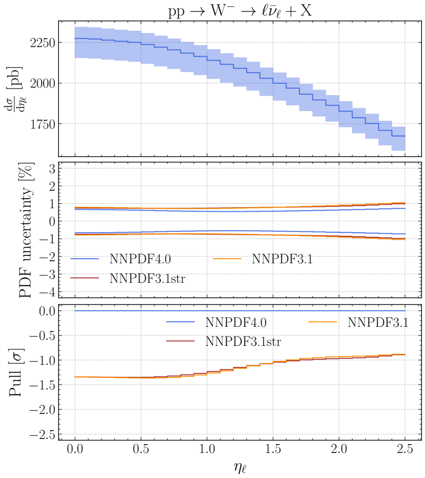

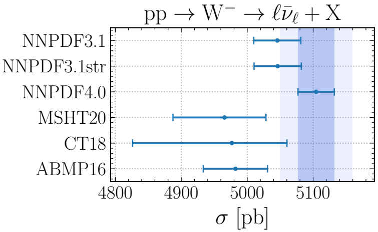

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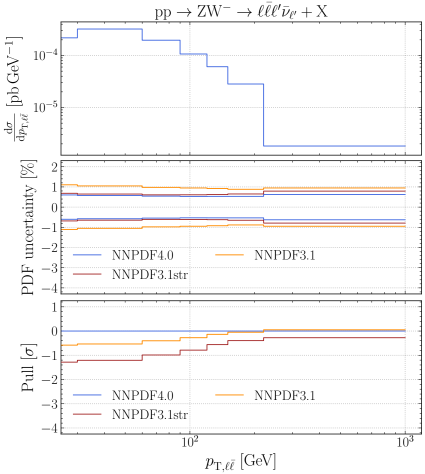

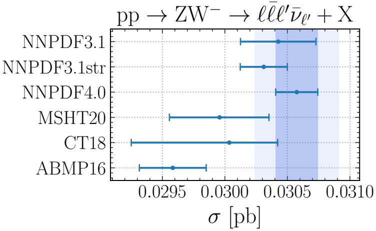

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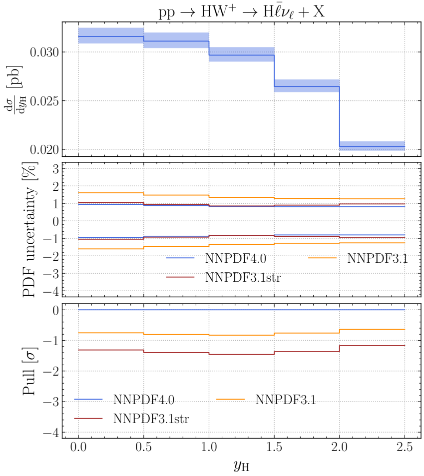

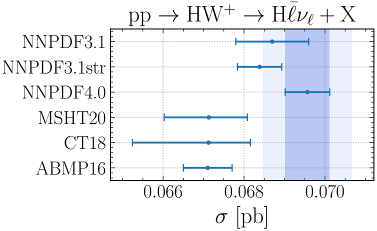

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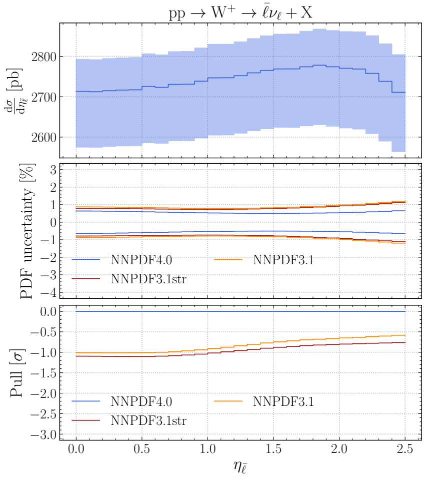

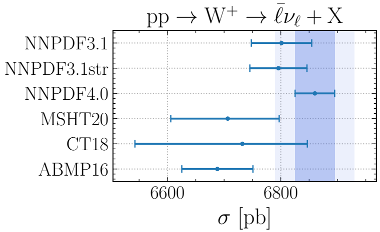

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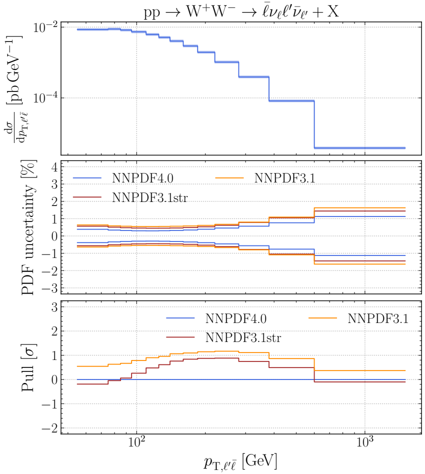

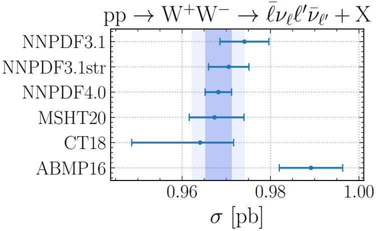

More implications for phenomenology