NNPDF

Towards NNPDF4.0

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RADCOR-LoopFest

The road to NNPDF4.0

Progresses towards extending data, theory and methodology.

06/2017	NNPDF3.1	[EPJ C77 (2017) 663]
10/2017	NNPDF31.sx: PDFs with small-x resummation	[EPJ C78 (2018) 321]
12/2017	NNPDF3.1luxQED: photon PDF	[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 correlated-replica method	[EPJ C78 (2018) 408]
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 $\overline{MS}$ 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]

1. Dataset and Methodology
2. PDF validation
3. PDFs and Phenomenology

Dataset and Methodology

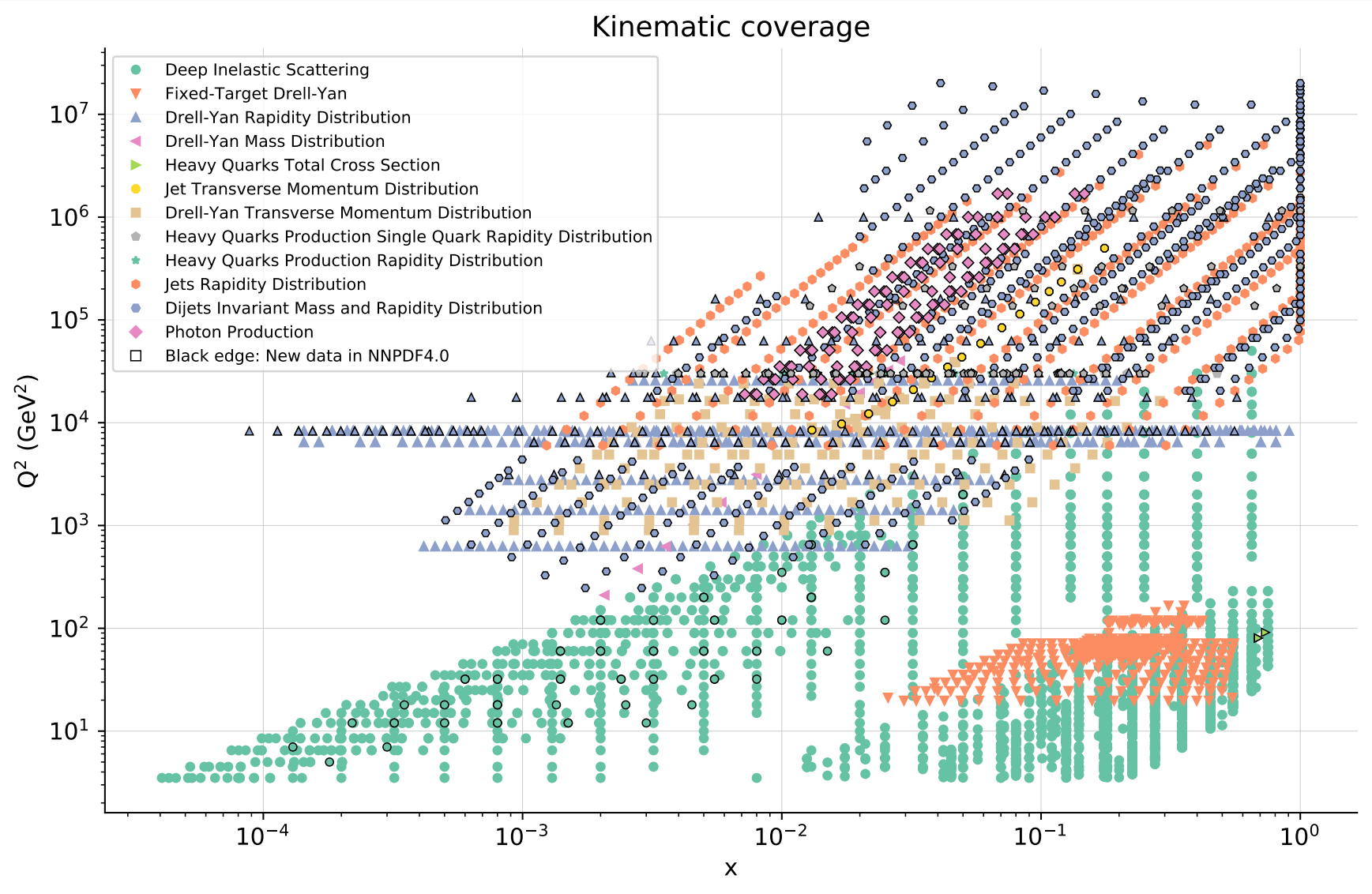
Experimental data in NNPDF4.0

Data set	NNPDF4.0	NNPDF3.1	ABMP16	CT18	MSHT20
ATLAS W, Z 7 TeV (2010)	✓	✓	✓	✓	✓
ATLAS W, Z 7 TeV (2011)	✓	✓	✗	✓	✓
ATLAS low-mass DY 7 TeV	✓	✓	✗	✗	✗
ATLAS high-mass DY 7 TeV	✓	✓	✗	✗	✓
ATLAS W 8 TeV	✓	✗	✗	✗	✓
ATLAS DY 2D 8 TeV	✓	✗	✗	✗	✓
ATLAS high-mass DY 2D 8 TeV	✓	✗	✗	✗	✓
ATLAS $\sigma_{W,Z}$ 13 TeV	✓	✗	✓	✗	✗
ATLAS W^++jet 8 TeV	✓	✗	✗	✗	✓
ATLAS Z p_T 8 TeV	✓	✓	✗	✓	✓
ATLAS $\sigma_{t\bar{t}}^{\rm tot}$ 7, 8 TeV	✓	✓	✓	✗	✗
ATLAS $\sigma_{t\bar{t}}^{\rm tot}$ 13 TeV	✓	✓	✓	✗	✗
ATLAS $t\bar{t}$ lepton+jets 8 TeV	✓	✓	✗	✓	✓
ATLAS $t\bar{t}$ dilepton 8 TeV	✓	✗	✗	✗	✓
ATLAS single-inclusive jets 7 TeV, R=0.6	✗	✓	✗	✓	✓
ATLAS single-inclusive jets 8 TeV, R=0.6	✓	✗	✗	✗	✗
ATLAS dijets 7 TeV, R=0.6	✓	✗	✗	✗	✗
ATLAS direct photon production 13 TeV	✓	✗	✗	✗	✗
ATLAS single top R_t 7, 8, 13 TeV	✓	✗	✓	✗	✗
ATLAS single top diff. 7, 8 TeV	✓	✗	✗	✗	✗
ATLAS single top diff. 8 TeV	✓	✗	✗	✗	✗

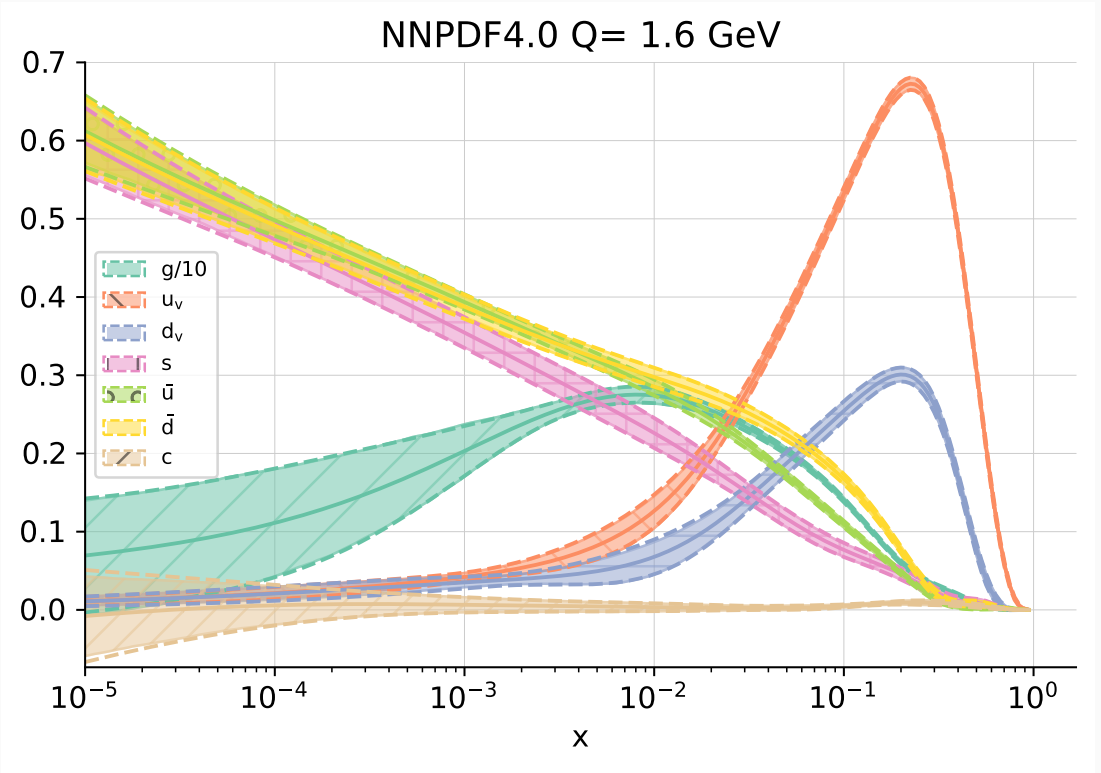
Data set	NNPDF4.0	NNPDF3.1	ABMP16	CT18	MSHT20
LHCb Z 940 pb	✓	✓	✗	✗	✓
LHCb $Z \to ee$ 2 fb	✓	✓	✓	✓	✓
LHCb $W, Z \to \mu$ 7 TeV	✓	✓	✓	✓	✓
LHCb $W, Z \to \mu$ 8 TeV	✓	✓	✓	✓	✓
LHCb $Z \to \mu\mu, ee$ 13 TeV	✓	✗	✗	✗	✗

Data set	NNPDF4.0	NNPDF3.1	ABMP16	CT18	MSHT20
CMS W electron asymmetry 7 TeV	✓	✓	✗	✓	✓
CMS W muon asymmetry 7 TeV	✓	✓	✓	✓	✗
CMS Drell-Yan 2D 7 TeV	✓	✓	✗	✗	✓
CMS W rapidity 8 TeV	✓	✓	✓	✓	✓
CMS Z p_T 8 TeV	✓	✓	✗	✓	✗
CMS $W + c$ 7 TeV	✓	✓	✗	✗	✓
CMS $W + c$ 13 TeV	✓	✗	✗	✗	✗
CMS single-inclusive jets 2.76 TeV	✗	✓	✗	✗	✓
CMS single-inclusive jets 7 TeV	✗	✓	✗	✓	✓
CMS dijets 7 TeV	✓	✗	✗	✗	✗
CMS single-inclusive jets 8 TeV	✗	✗	✗	✓	✓
CMS 3D dijets 8 TeV	✓	✗	✗	✗	✗
CMS $\sigma_{t\bar{t}}^{\rm tot}$ 5 TeV	✓	✗	✓	✗	✗
CMS $\sigma_{t\bar{t}}^{\rm tot}$ 7, 8 TeV	✓	✓	✓	✗	✓
CMS $\sigma_{t\bar{t}}^{\rm tot}$ 13 TeV	✓	✓	✓	✗	✗
CMS $t\bar{t}$ lepton+jets 8 TeV	✓	✓	✗	✗	✓
CMS $t\bar{t}$ 2D dilepton 8 TeV	✓	✗	✗	✓	✓
CMS $t\bar{t}$ lepton+jet 13 TeV	✓	✗	✗	✗	✗
CMS $t\bar{t}$ dilepton 13 TeV	✓	✗	✗	✗	✗
CMS single top $\sigma_t + \sigma_{\bar{t}}$ 7 TeV	✓	✗	✓	✗	✗
CMS single top R_t 8, 13 TeV	✓	✗	✓	✗	✗

- $\mathcal{O}(50)$ datasets investigated
- $\mathcal{O}(400)$ new datapoints wrt NNPDF3.1
- New processes included: **single top, W+jet, isolated photon, di-jets.**


Kinematic coverage
Deep Inelastic Scattering
Fixed-Target Drell-Yan
Drell-Yan Rapidity Distribution
Drell-Yan Mass Distribution
Heavy Quarks Total Cross Section
Jet Transverse Momentum Distribution
Drell-Yan Transverse Momentum Distribution
Heavy Quarks Production Single Quark Rapidity Distribution
Heavy Quarks Production Rapidity Distribution
Jets Rapidity Distribution
Dijets Invariant Mass and Rapidity Distribution
Photon Production
Black edge: New data in NNPDF4.0
Q^2 (GeV^2)
10^7
10^6
10^5
10^4
10^3
10^2
10^1
10^{-4}
10^{-3}
10^{-2}
10^{-1}
10^0
x

Data set	N_{dat}	χ^2/N_{dat}
Fixed target DIS	1881	1.10
Fixed target DY	189	1.00
HERA	1208	1.21
CDF	28	1.31
D0	37	1.00
ATLAS	621	1.18
Drell-Yan, 7, 8, 13 TeV	153	1.32
W+jet, 8 TeV	32	1.15
single top, 7, 8, 13 TeV	14	0.36
di-jets, 7 TeV	90	1.93
jets, 8 TeV	171	0.61
top pair, 7, 8, 13 TeV	16	2.30
ZpT , 8 TeV	92	0.86
direct photon, 13 TeV	53	0.72
CMS	411	1.40
Drell-Yan, 7, 8 TeV	154	1.34
single top, 7, 8, 13 TeV	3	0.43
di-jets, 7 TeV	54	1.67
di-jets, 8 TeV	122	1.50
top pair, 5, 7, 8 TeV	29	0.84
top pair, 13 TeV	21	0.67
ZpT , 8 TeV	28	1.42
LHCb	116	1.53
Total	4991	1.17



- overall good fit quality
- slight tension between ATLAS top-pair and di-jets data

Key differences with respect to the 3.1 methodology

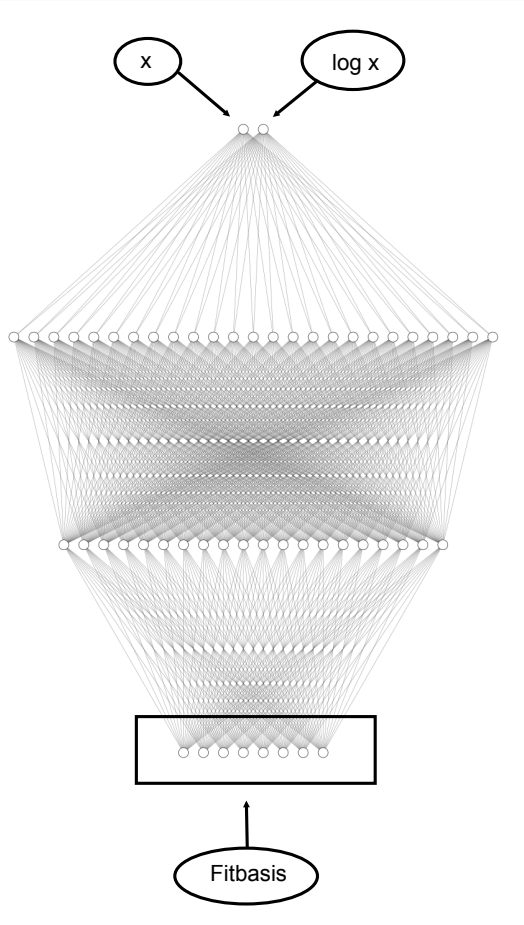
NNPDF 3.1 code

- → C++ monolithic codebase
- → In-house Machine Learning optimization framework
- → One network per flavour
- → Genetic Algorithm optimizer
- → Fitting times of up to various days
- → Fit parameters manually chosen (manual optimization of hyperparameters)

NNPDF 4.0 code

- → Python object oriented codebase
- → Freedom to use external libraries (default: TensorFlow)
- → One network for all flavours
- → Gradient Descent optimization
- → Results available in less than an hour
- → Fit parameters chosen automatically (hyperparameter scan)

NNPDF4.0 methodology



Evolution basis

$$q_k\left(x,Q_0\right) \propto x^{-\alpha_k}\left(1-x\right)^{\beta_k} NN\left(x\right) ,$$
$$q_k = \{V, V_3, V_8, T_3, T_8, T_{15}, \Sigma, g\} .$$

Flavour basis

$$q_k\left(x,Q_0\right) \propto \left(1-x\right)^{\beta_k} NN\left(x\right) ,$$
$$q_k = \{u, \bar{u}, d, \bar{d}, s, \bar{s}, c, g\} .$$

Physical constraints:

- ✓ PDFs positivity [JHEP 11 (2020) 129]
- ✓ Integrability of nonsinglet distributions

We will use the evolution basis, but as an additional check of our methodology we have explicitly checked fitbasis independence.

Beyond the PDF fit: fitting the methodology

The NNPDF methodology is defined by a set of hyperparameters: depth of the network, number of nodes, optimizer, training length, ...

✗ Selecting manually the best set of parameters is a slow process and systematic success is not guaranteed

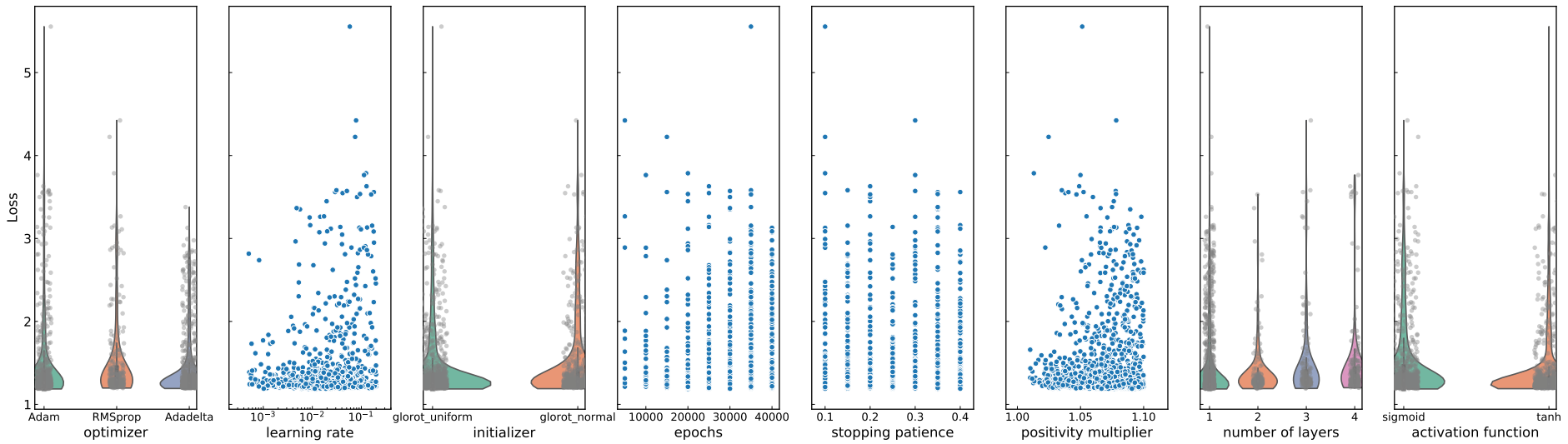
✓ Hyperparameter scan: let the computer decide automatically

- Define a methodology (a specific hyperparameter combination)
- Define a reward function to grade the methodology
- Scan over thousands of hyperparameter combinations and select the best one

In NNPDF4.0 hyperparameter scan is implemented for the first time to select the best methodology.

Hyperparameter scan

Each blue dot corresponds to a fit of a different set of hyperparameters:



Thousands of fits for the hyperoptimization algorithm to choose:

- ✓ Optimizer
- ✓ Initializer
- ✓ Stopping Patience
- ✓ Number of Layers
- ✓ Learning Rate
- ✓ Epochs
- ✓ Positivity Multiplier
- ✓ Activation Function

K-folding algorithm: used to define the reward function and select the best hyperparameters combination (backup slides)

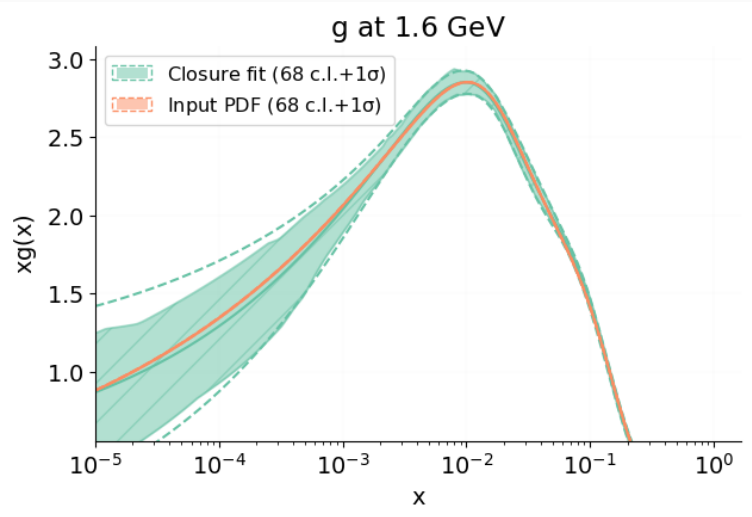
PDF validation

Closure Tests

Fit replicas to pseudodata in usual way

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{f} + \boldsymbol{\eta} + \boldsymbol{\epsilon} \\ &= \boldsymbol{z} + \boldsymbol{\epsilon}, \end{aligned} \tag{1}$$

where $\boldsymbol{\eta} \sim \mathcal{N}(0, C)$ and $\boldsymbol{\epsilon} \sim \mathcal{N}(0, C)$ are sampled independently.
Use predictions from an input PDF as proxy for $\boldsymbol{f}$.



Example closure fit and input PDF.

First presented in NNPDF3.0 arxiv:1410.8849

Allows testing of methodology, if the input assumptions hold.

For example:

Bias: (squared) difference between central prediction and true observable

Variance: variance of model predictions

Bias is a stochastic variable. If PDF uncertainty is faithful then

$$\mathbf{E}_\eta[\text{bias}] = \text{variance} \tag{2}$$

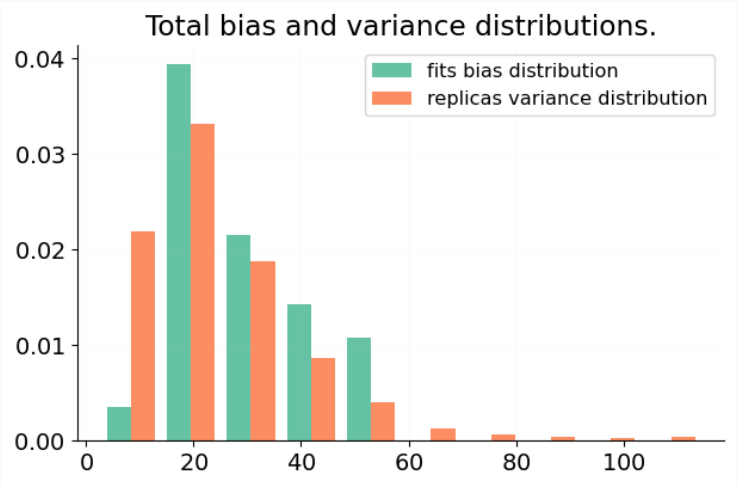
High demand on resources (many fits!) - made feasible with next generation fitting code.

Closure test results

Compare first moments:

	$\sqrt{\mathbf{E}_\eta[\text{bias}]/\mathbf{E}_\eta[\text{variance}]}$
Total	1.03 ± 0.5

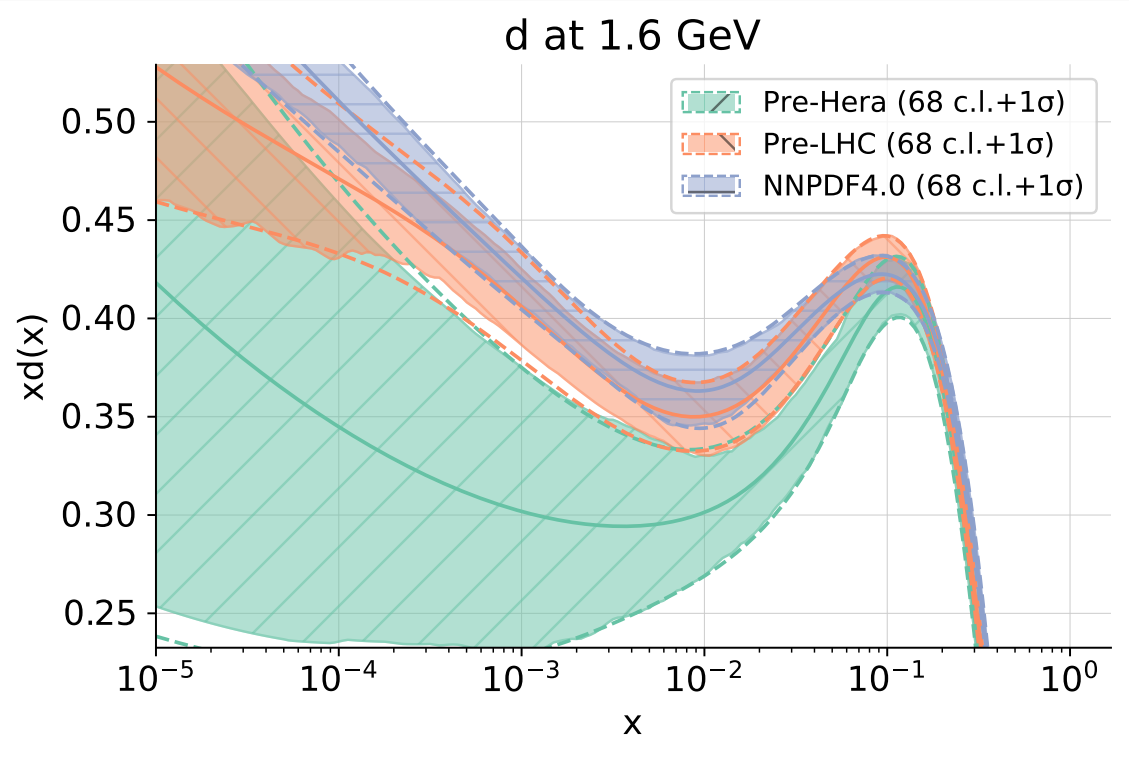
Alternatively look at the respective distributions of differences (averaged across data).



Bias distribution sampled with 25 fits, 40 replicas each.

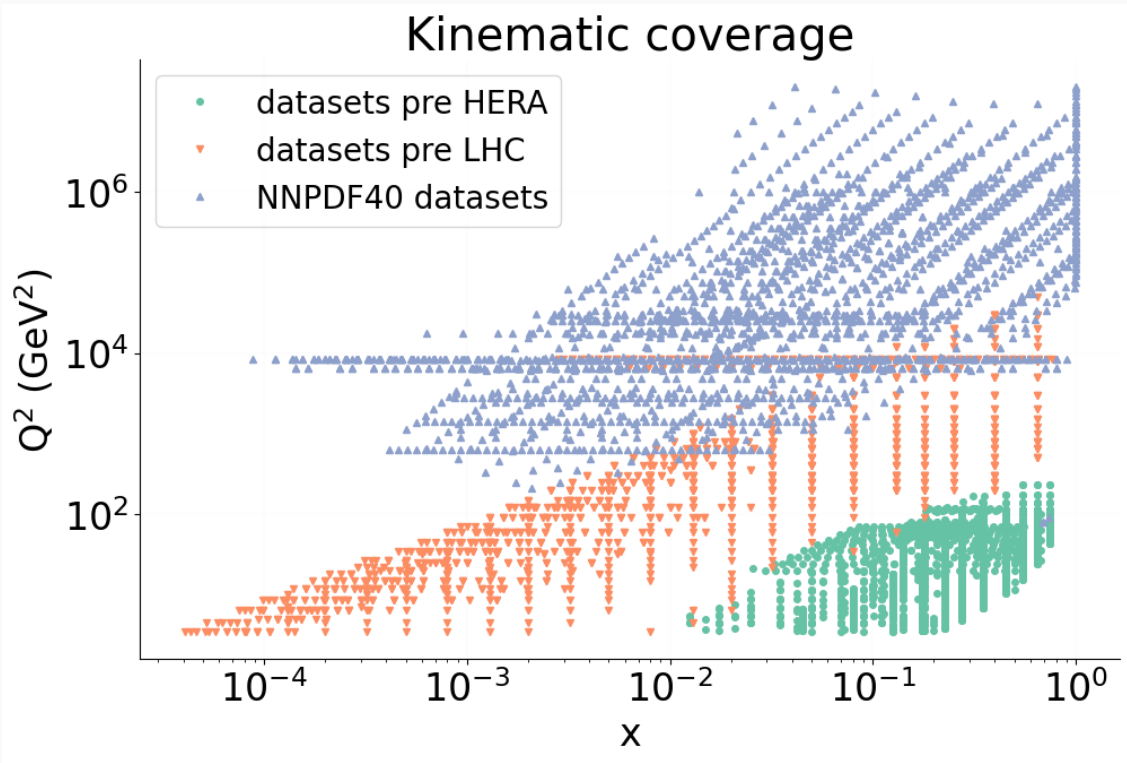
Trusting uncertainties in extrapolation region.

- Smaller PDF uncertainties driven by methodological improvements and increased data.
- uncertainties tested in "data region"
- what about kin. regions not covered by data?



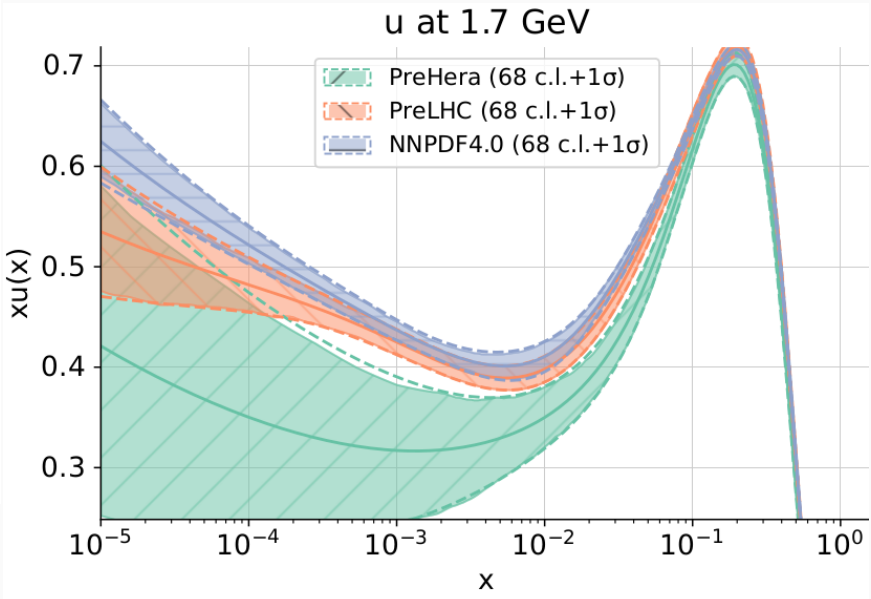
- Ideally, test "extrapolation region" with new experimental data - not an option.
- Retroactively order subsets of data chronologically, named "future tests" - for more information see arxiv:2103.08606

Future tests

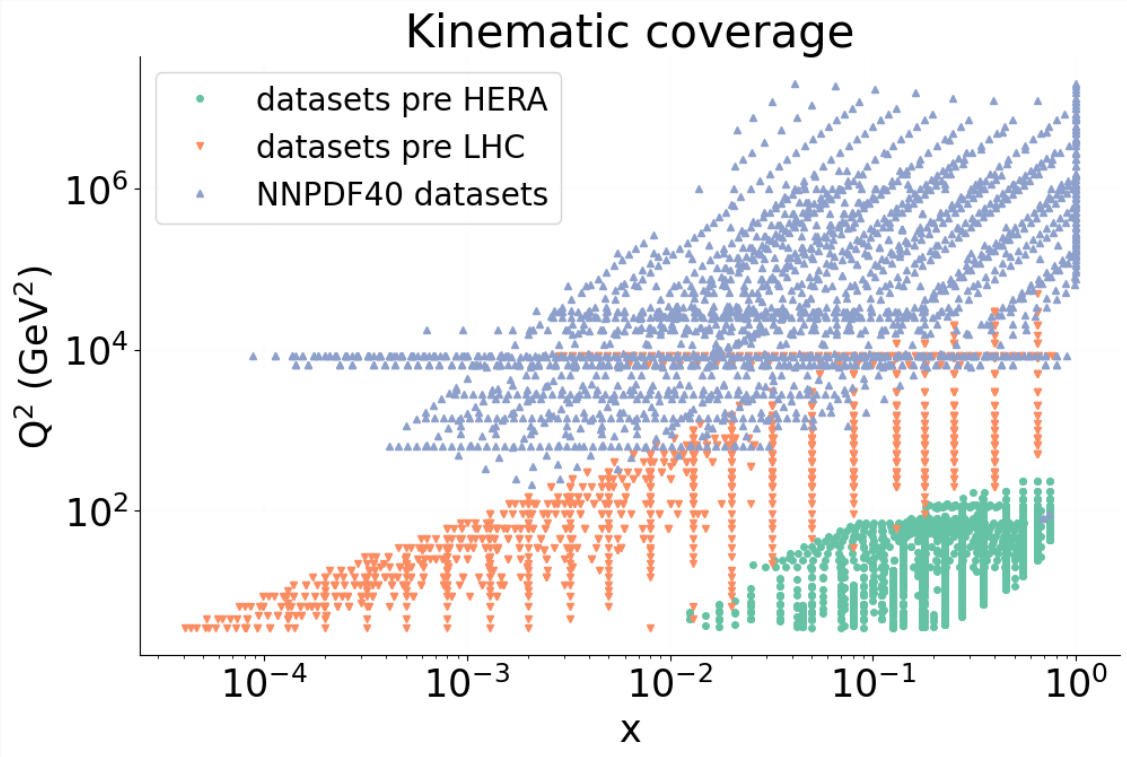


χ^2/N (only exp. covmat)

(dataset)	NNPDF4.0	pre-LHC	pre-Hera
pre-HERA	1.09	1.01	0.90
pre-LHC	1.21	1.20	**23.1**
NNPDF4.0	1.29	**3.30**	**23.1**

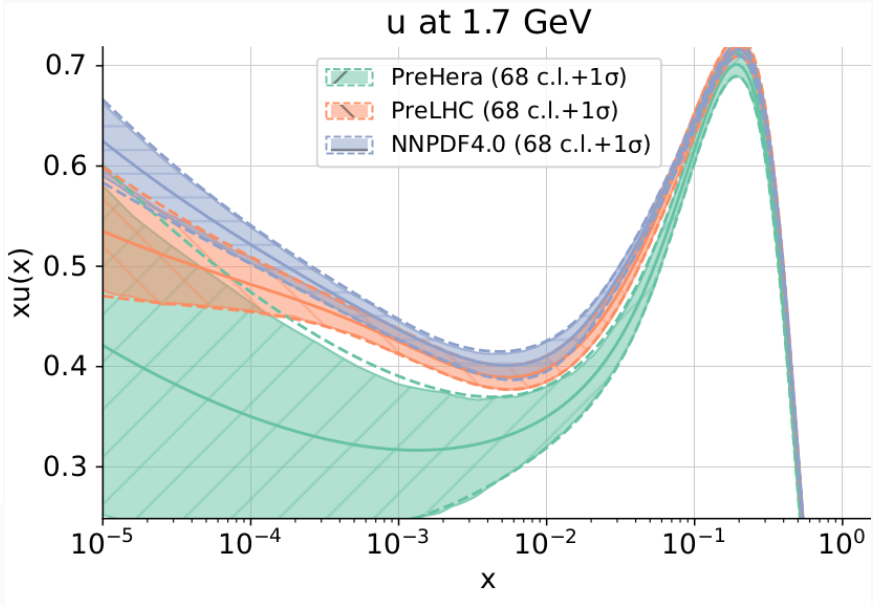


Future tests



χ^2/N (exp. and PDF covmat)

(dataset)	NNPDF4.0	pre-LHC	pre-Hera
pre-HERA			0.86
pre-LHC		1.17	**1.22**
NNPDF4.0	1.12	**1.30**	**1.38**

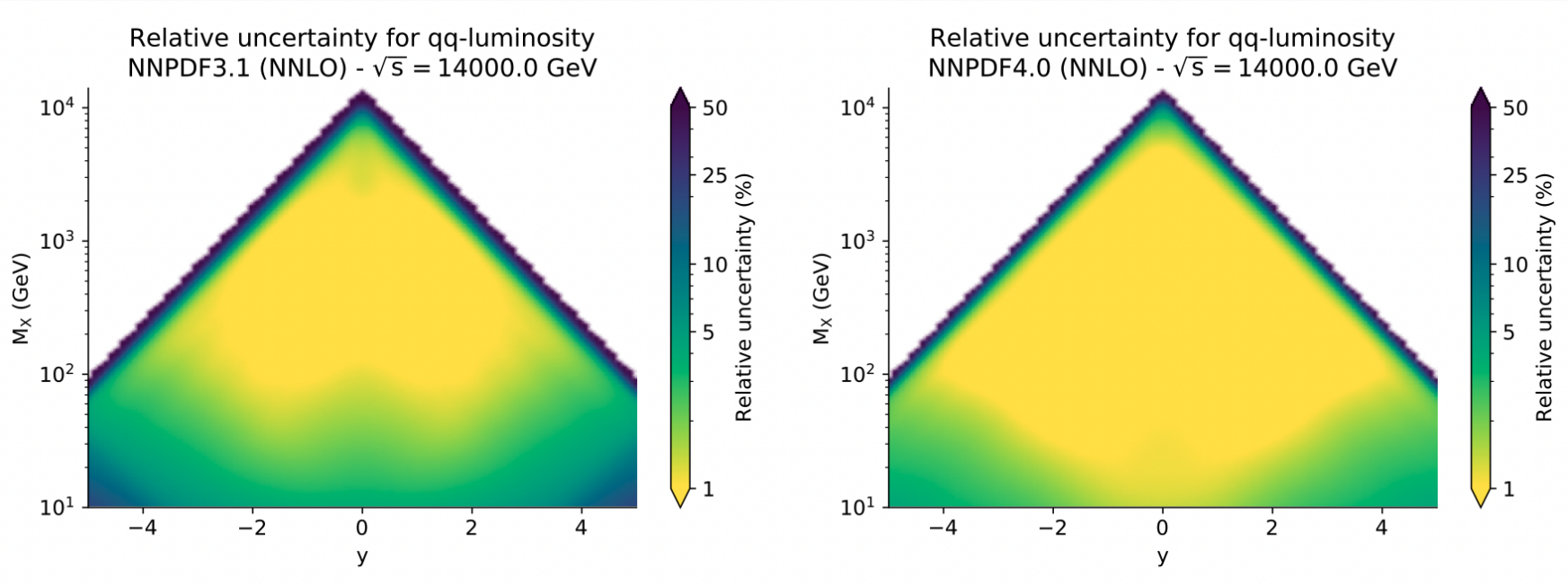


Total uncertainty increases up to a factor ~ 20, and accommodates for difference between predictions and new data.

PDFs and Phenomenology

The road to 1%: the qq channel

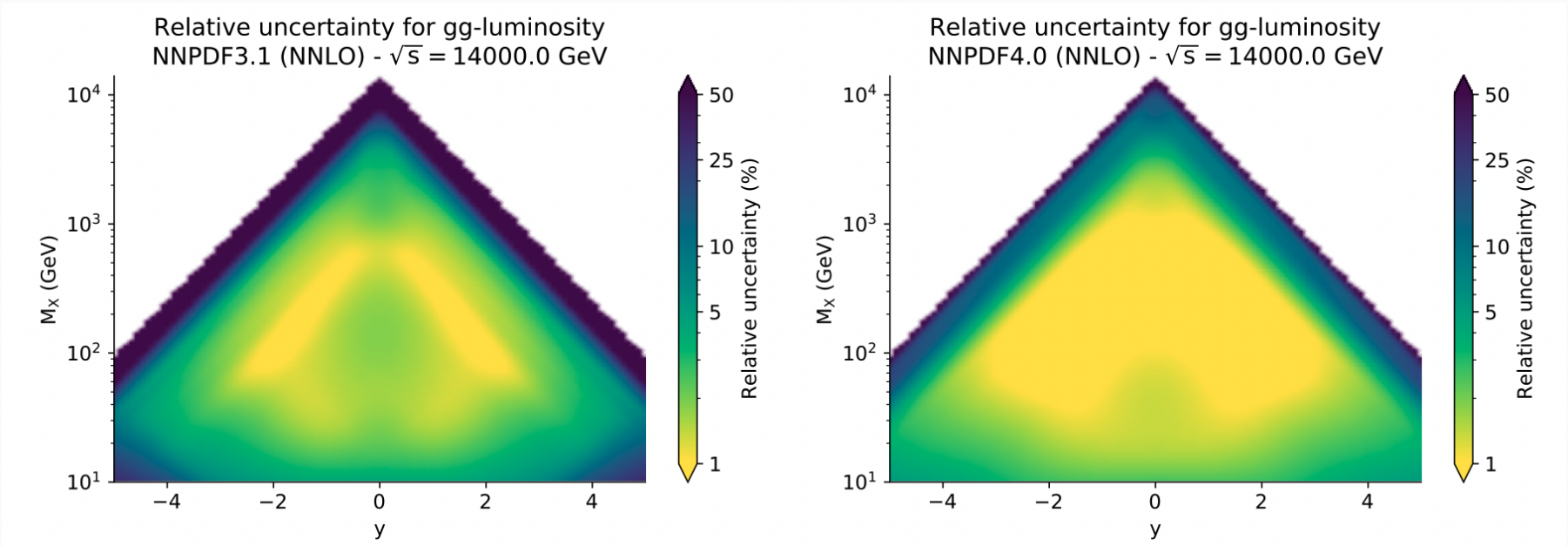
$$\mathcal{L}_{ij}(M_X, y, \sqrt{s}) = \frac{1}{s} \sum_{i,j} f_i \left(\frac{M_X e^y}{\sqrt{s}}, M_X \right) f_j \left(\frac{M_X e^{-y}}{\sqrt{s}}, M_X \right)$$



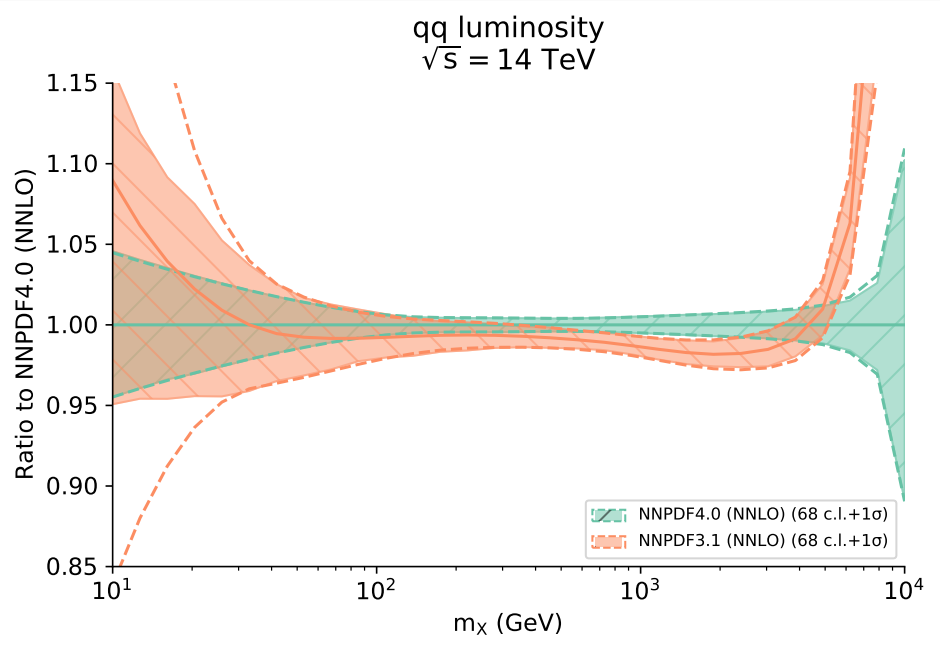
Plan to include MHOU (arXiv:1905.0431) in a future study.

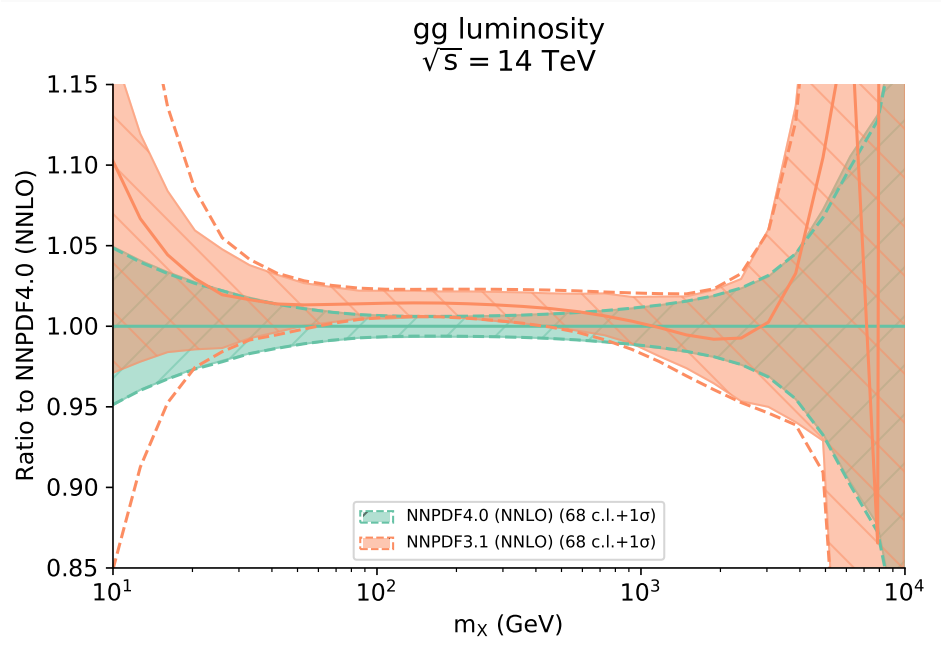
The road to 1%: the gg channel

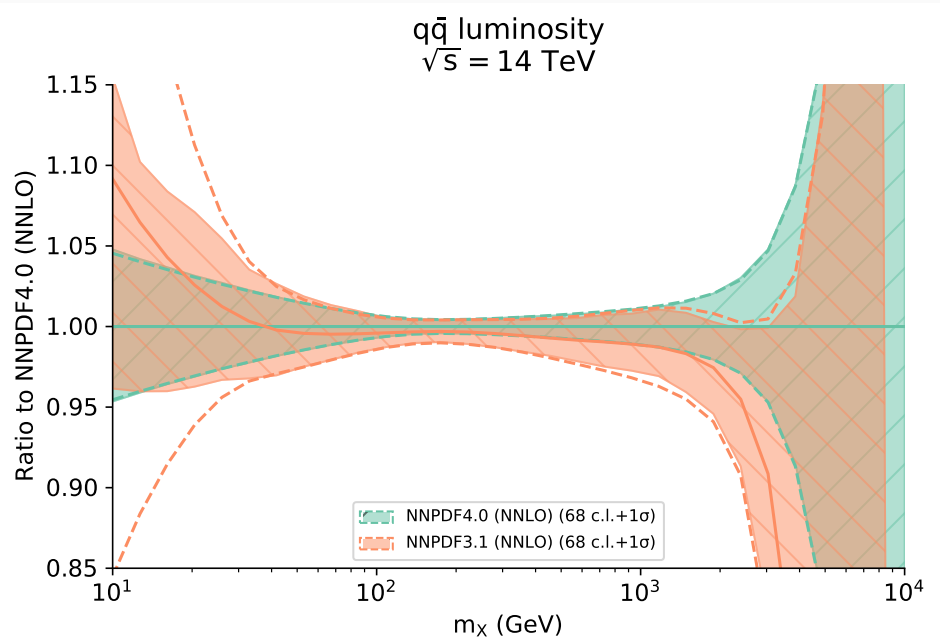
$$\mathcal{L}_{ij}(M_X, y, \sqrt{s}) = \frac{1}{s} \sum_{i,j} f_i \left(\frac{M_X e^y}{\sqrt{s}}, M_X \right) f_j \left(\frac{M_X e^{-y}}{\sqrt{s}}, M_X \right)$$



Precision: NNPDF4.0 vs NNPDF3.1





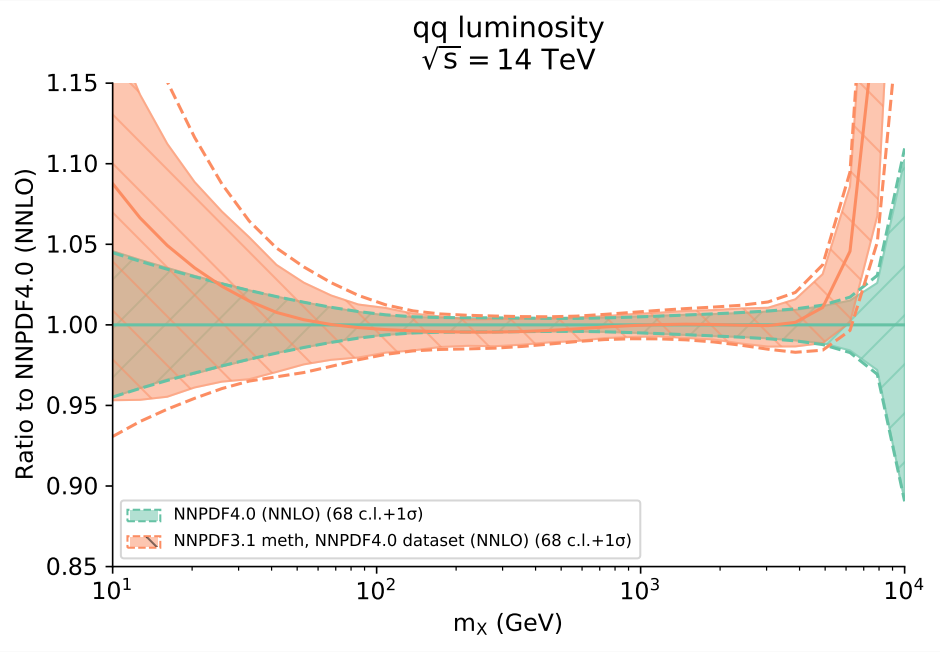


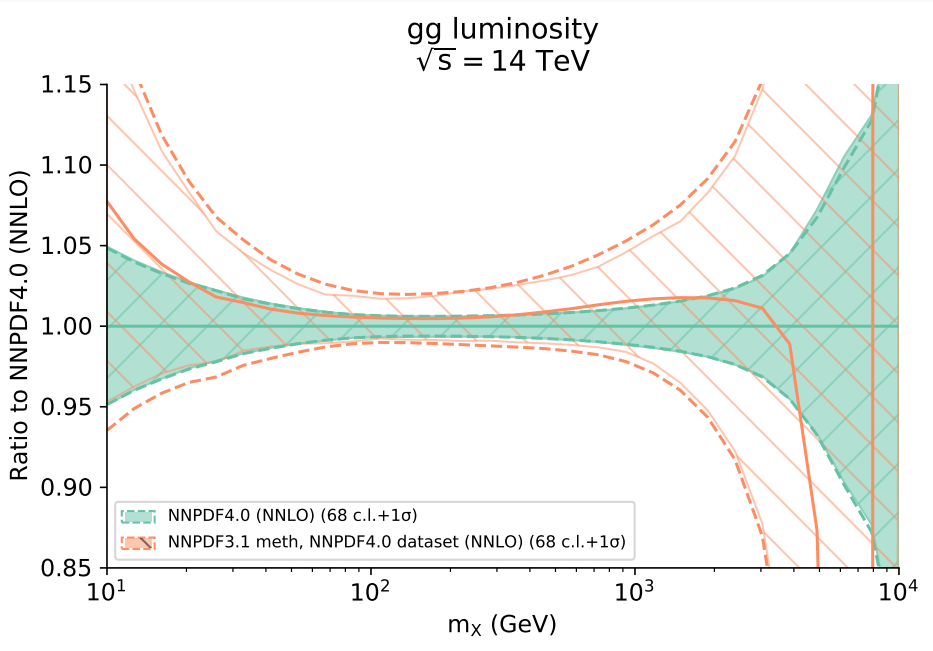
Methodology

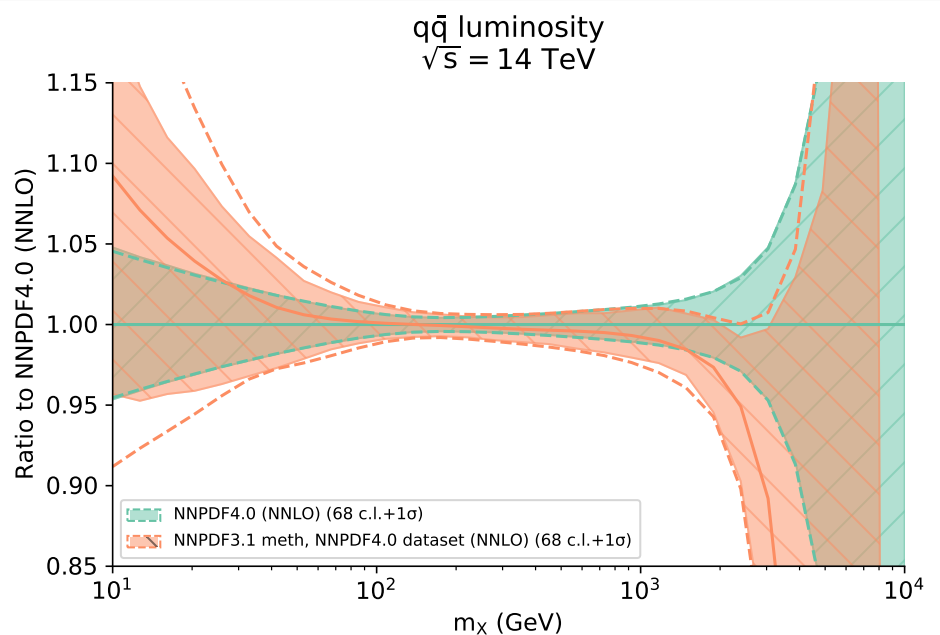
Dataset	NNPDF3.1	NNPDF4.0
NNPDF3.1 (4093)	1.19	1.12
NNPDF4.0 (4491)	1.25	1.17

Shift in PDF luminosity due to addition of ~ 400 new data points. Reduced uncertainties highlighted in smaller error bands: NNPDF4.0 is more precise.

Accuracy: NNPDF4.0 data - NNPDF3.1 vs NNPDF4.0 methodology





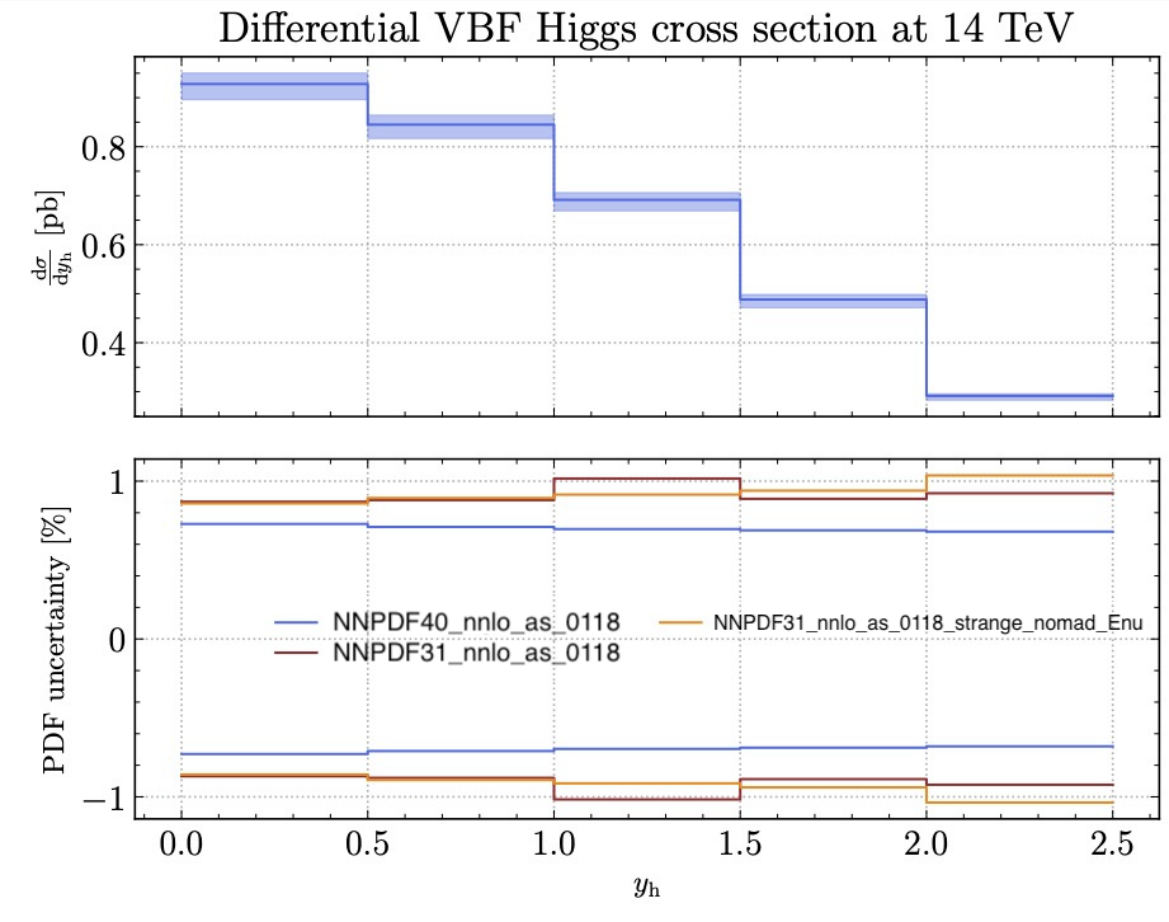


	Methodology	
Dataset	NNPDF3.1	NNPDF4.0
NNPDF3.1 (4093)	1.19	1.12
NNPDF4.0 (4491)	1.25	1.17

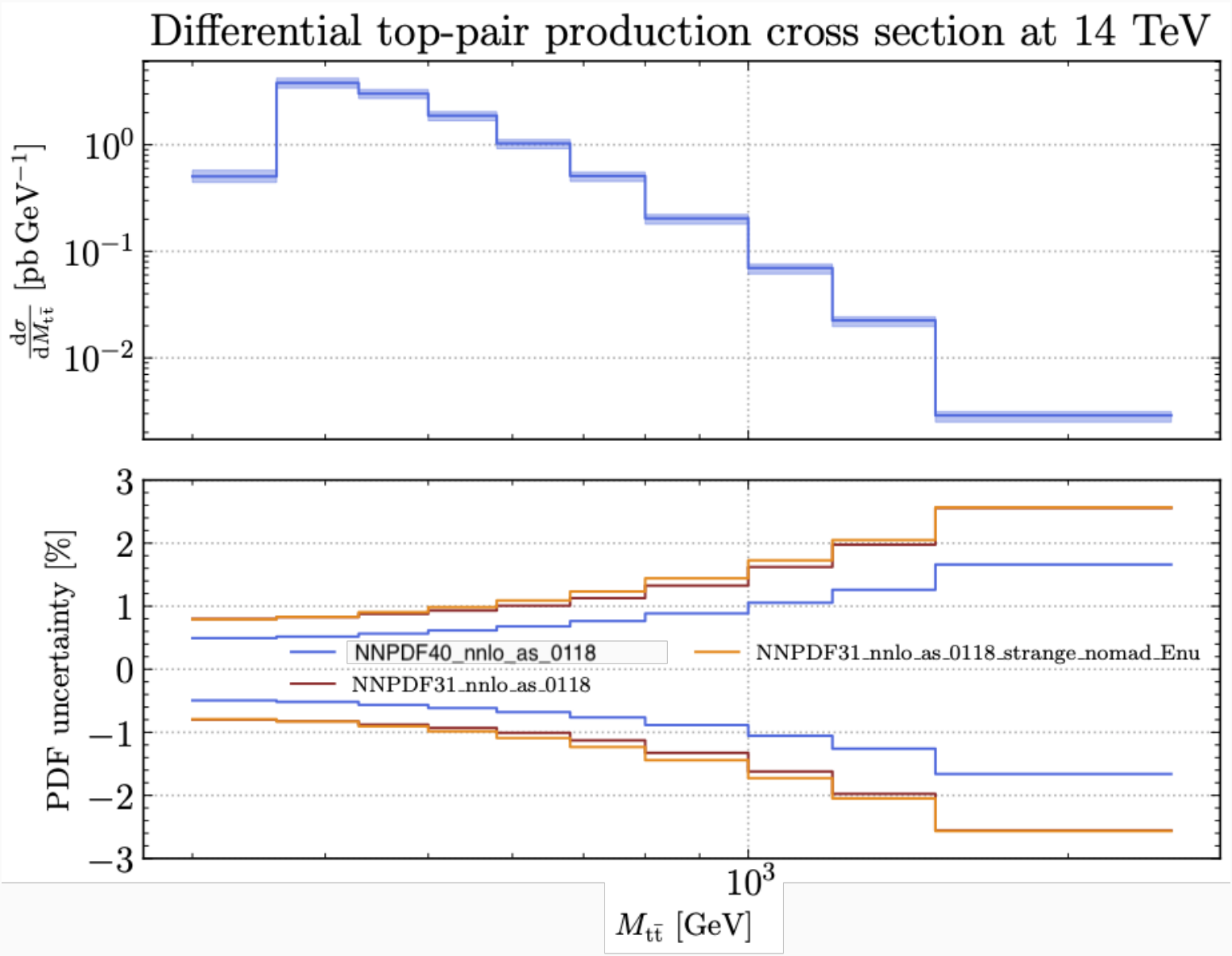
Luminosities fitted to the same dataset are compatible. Achieve a better fit to data: NNPDF4.0 is more accurate.

Accuracy and Precision

Reduced PDF luminosity uncertainties lead to $< 1\%$ uncertainty in various binnings at the observable level.



$t\bar{t}$ at 14TeV



Public code release

Plan to publicly release the code alongside code paper and in depth documentation at `docs.nnpdf.science`:

- Entire `n3fit/nnfit` fitting code: transparent methodology for extensions to other PDF fitting applications
- The `validphys` analysis suite: allowing for fully reproducible plots from various NNPDF papers.
- `Buildmaster` rawdata parsing code: ability for users to their own data to PDF fits.

Science using runcards and reproducibility

User exposed to human readable `YAML` format for analysis and fitting.

Runcards yield *reproducibility*.

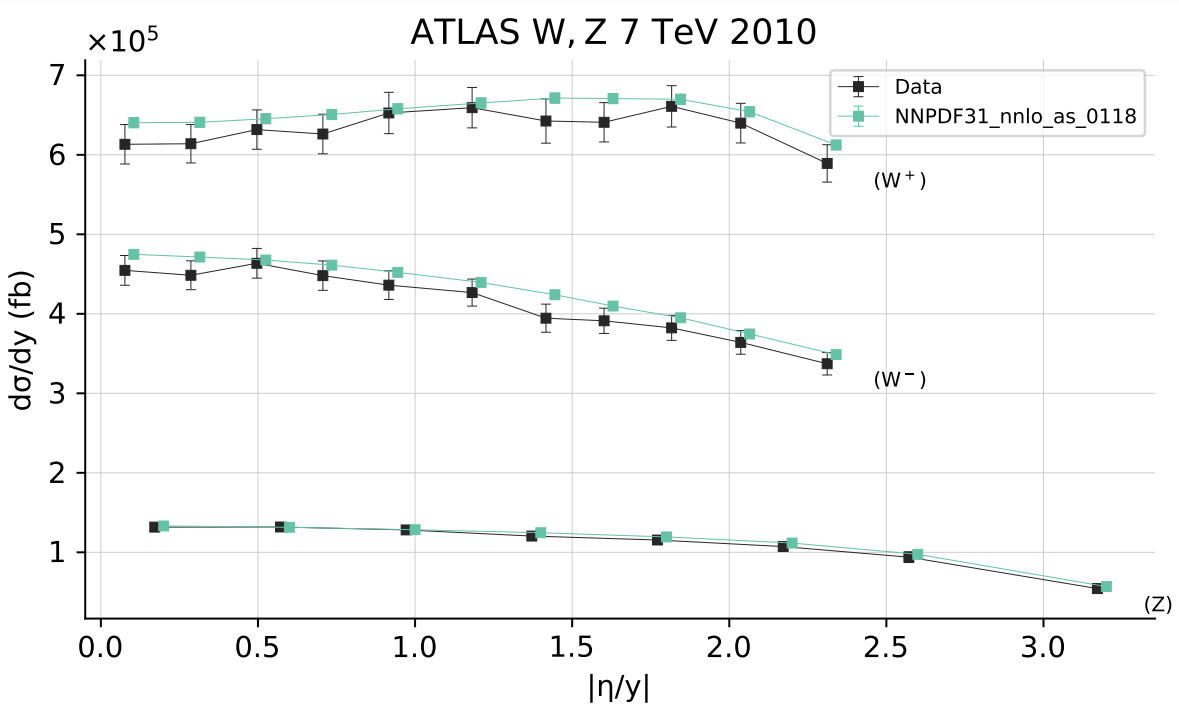
```yaml
# runcard.yaml
# Any valid LHAPDF
pdf: NNPDF31_nnlo_as_0118

# Specify dataset to use
dataset: ATLASWZRAP36PB

# Theory settings
theoryid: nnlo

# Data cuts to use
cuts: internal

# The action we wish the code to perform
actions:
  - data_theory_comparison
```

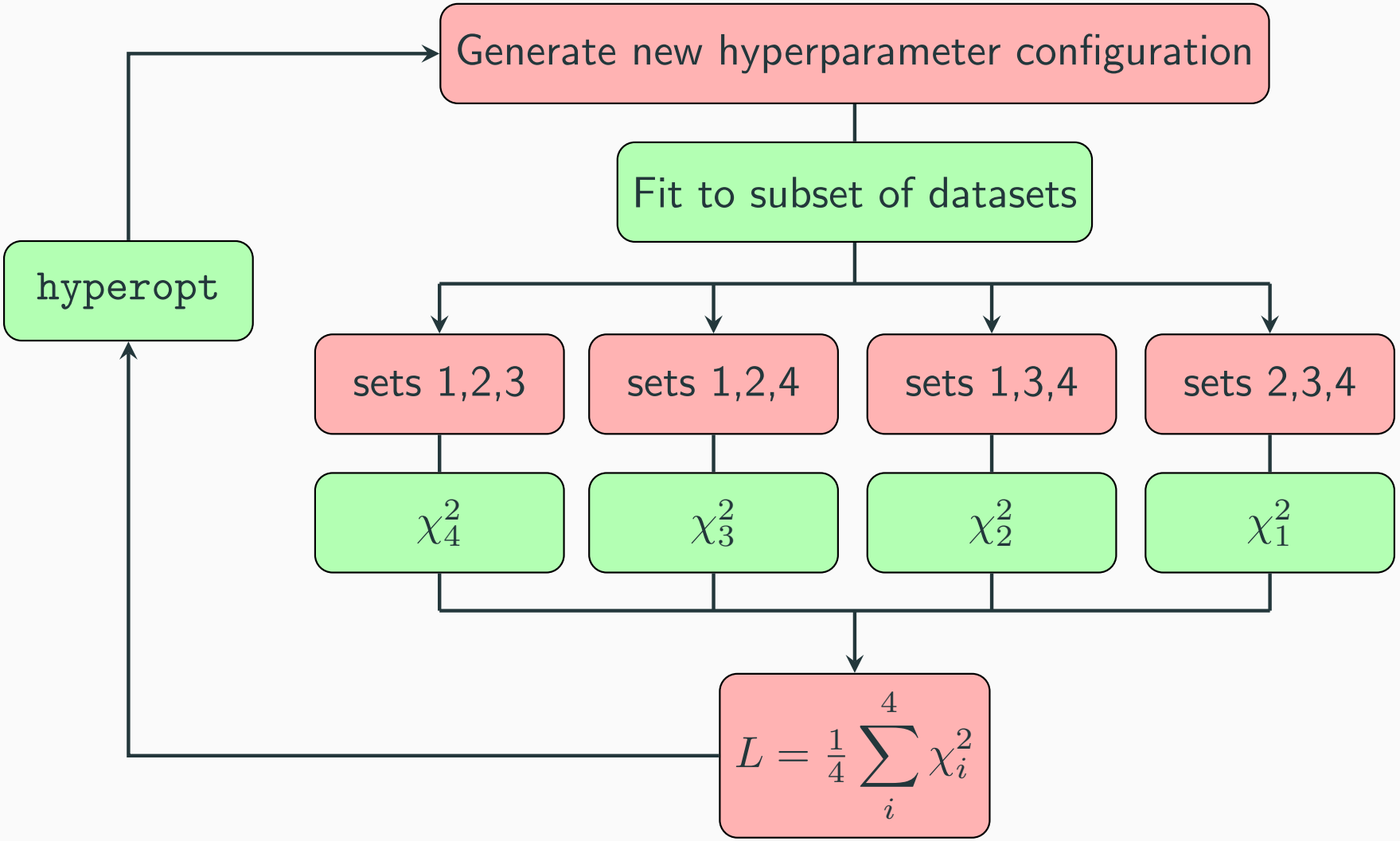


Conclusions

- Added host of new datasets and processes ~ 400 new datapoints
- Improved methodology using TensorFlow and hyperoptimization
- Faithfulness validated through closure and future tests
- Achieving 1% accuracy over impressively broad kinematic range
- Plan to release code publicly
- NNPDF4.0 is our recommended PDF set for LHC phenomenology: superseding previous iterations

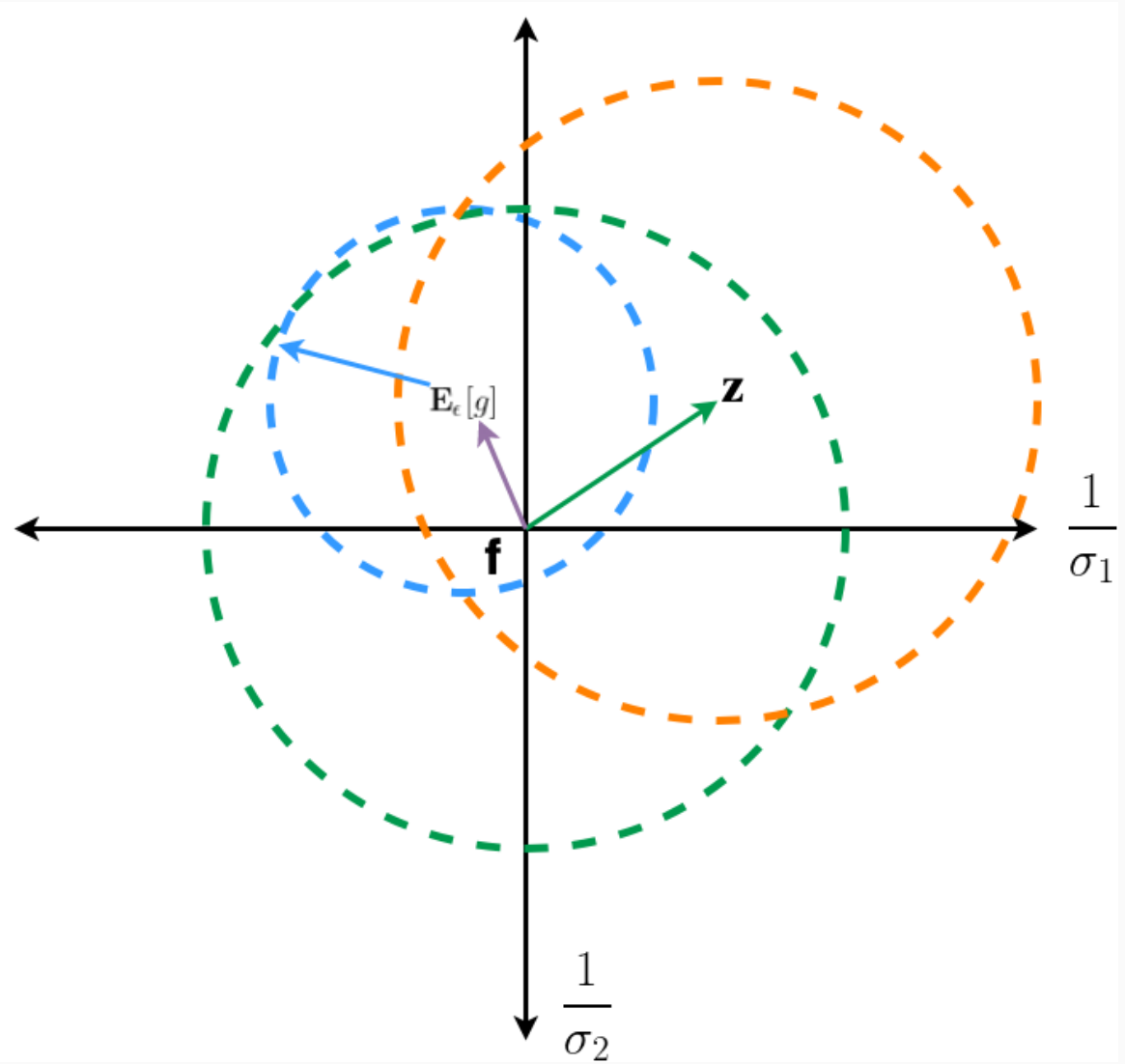
Additional slides

K-folding


Generate new hyperparameter configuration
Fit to subset of datasets
hyperopt
sets 1,2,3
sets 1,2,4
sets 1,3,4
sets 2,3,4
χ^2_4
χ^2_3
χ^2_2
χ^2_1
$L = \frac{1}{4}\sum_i^4 \chi^2_i$

Geometric Interpretation

Consider 2 data points on an axis in the basis which diagonalises C normalised by the square root of the eigenvalues:



Statistical estimators - more detail

Decompose the expectation value of the likelihood function, χ^2, by completing the square. Exposing some statistical indicators

$$\begin{aligned}\mathbf{E}_\epsilon[\chi^2(g;y)] &= \frac{1}{N_{\text{data}}}\mathbf{E}_\epsilon[(\boldsymbol{g}-\boldsymbol{y})^T C^{-1}(\boldsymbol{g}-\boldsymbol{y})] \\ &= \text{bias} + \text{variance} + \text{noise} - \text{crossterm}\end{aligned} \tag{3}$$

focus on the first two terms:

$$\text{bias} = \frac{1}{N_{\text{data}}}(\boldsymbol{f}-\mathbf{E}_\epsilon[\boldsymbol{g}])^T C^{-1}(\boldsymbol{f}-\mathbf{E}_\epsilon[\boldsymbol{g}]) \tag{4}$$

$$\text{variance} = \mathbf{E}_\epsilon\left[\frac{1}{N_{\text{data}}}(\boldsymbol{g}-\mathbf{E}_\epsilon[\boldsymbol{g}])^T C^{-1}(\boldsymbol{g}-\mathbf{E}_\epsilon[\boldsymbol{g}])\right] \tag{5}$$

where $\mathbf{E}_\epsilon[\cdot]$ is the expectation across replicas.

- Faithful uncertainties if $(\boldsymbol{g}-\mathbf{E}_\epsilon[\boldsymbol{g}])$ and $(\boldsymbol{f}-\mathbf{E}_\epsilon[\boldsymbol{g}])$ have same distribution.
- Sample $(\boldsymbol{g}-\mathbf{E}_\epsilon[\boldsymbol{g}])$ through sampling ϵ - usual MC replica procedure
- Sample $(\boldsymbol{f}-\mathbf{E}_\epsilon[\boldsymbol{g}])$ distribution through sampling η - only possible in closure test!

Closure test results

Breakdown of $\mathbf{E}_\eta[\text{bias}]/\mathbf{E}_\eta[\text{variance}]$ for out of sample data by experiment - fitted on NNPDF3.1 dataset and validated on additional datasets to be included in NNDPF4.0

	$\sqrt{\mathbf{E}_\eta[\text{bias}]/\mathbf{E}_\eta[\text{variance}]}$
ATLAS	1.04 ± 0.4
CMS	1.04 ± 0.6
LHCb	0.82 ± 0.6
Total	1.03 ± 0.5

Full Future test subset specification

pre-HERA	Ref.	$N_{\rm dat}$
NMC d/p	[15]	121
NMC p	[16]	204
SLAC p	[17]	33
SLAC d	[17]	34
BCDMS p	[18]	333
BCDMS d	[19]	248
CHORUS σ^{ν}_{CC}	[20]	416
CHORUS $\sigma^{\bar{\nu}}_{CC}$	[20]	416
NuTeV σ^{ν}_{c}	[21]	39
NuTeV $\sigma^{\bar{\nu}}_{c}$	[21]	37
DYE 866 $\sigma^{\bar{p}}_{\rm DY}/\sigma^{p}_{\rm DY}$	[22]	15
DY E886 $\sigma^{\bar{p}}_{\rm DY}$	[23]	89
DY E605 $\sigma^{p}_{\rm DY}$	[24]	85
Total pre-HERA		2070
pre-LHC	Ref.	$N_{\rm dat}$
HERA I+II inclusive NC e^-p	[25]	159
HERA I+II inclusive NC e^+p 460 GeV	[25]	204
HERA I+II inclusive NC e^+p 575 GeV	[25]	254
HERA I+II inclusive NC e^+p 820 GeV	[25]	70
HERA I+II inclusive NC e^+p 920 GeV	[25]	377
HERA I+II inclusive CC e^-p	[25]	42
HERA I+II inclusive CC e^+p	[25]	39
HERA comb. $\sigma^{\rm red}_{c\bar{c}}$	[26]	37
HERA comb. $\sigma^{\rm red}_{b\bar{b}}$	[26]	26
CDF Z rapidity	[27]	28
D0 Z rapidity	[28]	28
D0 $W \to \mu\nu$ asymmetry	[28]	9
Total pre-LHC		1273
NNPDF4.0	Ref.	$N_{\rm dat}$
ATLAS W,Z 7 TeV	[29]	30
ATLAS HM DY 7 TeV	[30]	5
ATLAS low-mass DY 7 TeV	[31]	6
ATLAS W,Z 7 TeV central selection	[32]	46
ATLAS W,Z 7 TeV forward selection	[32]	15
ATLAS DY 2D 8 TeV	[33]	48
ATLAS W,Z inclusive 13 TeV	[34]	3
ATLAS W^++jet 8 TeV	[35]	16

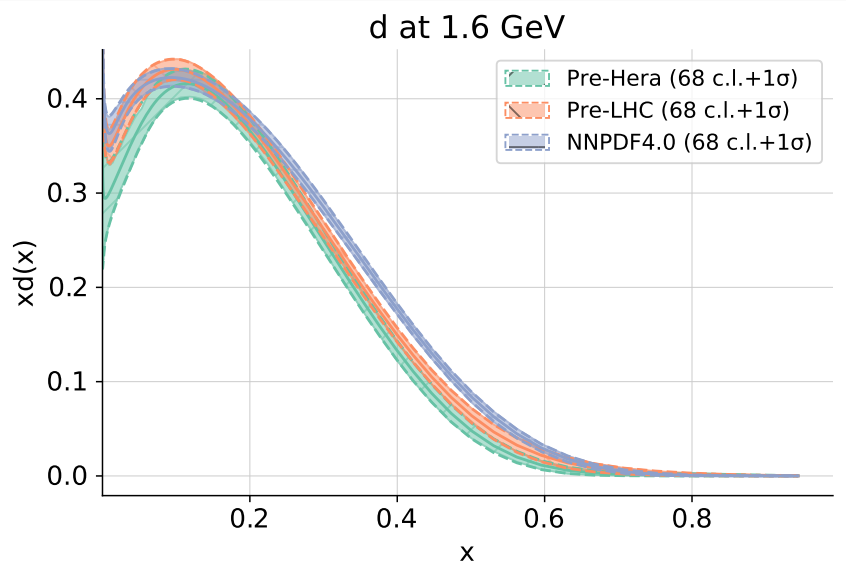
NNPDF4.0 (cont.'d)	Ref.	$N_{\rm dat}$
ATLAS W^-+jet 8 TeV	[35]	16
ATLAS Z p_T 8 TeV (p^{ll}_T, M_{ll})	[36]	44
ATLAS Z p_T 8 TeV (p^{ll}_T, y_{ll})	[36]	48
ATLAS $\sigma^{\rm tot}_{t\bar{t}}$ 7, 8, 13 TeV	[37,38]	3
ATLAS $t\bar{t}$ y_t normalized 8 TeV	[39]	4
ATLAS $t\bar{t}$ $y_{t\bar{t}}$ normalized 8 TeV	[39]	4
ATLAS $t\bar{t}$ normalized $\lvert y_t\rvert$ dilepton 8 TeV	[40]	5
ATLAS jets 8 TeV, R=0.6	[41]	171
ATLAS dijets 7 TeV, R=0.6	[42]	90
ATLAS direct photon production 13 TeV	[43]	53
ATLAS single top R_t 7 TeV	[44]	1
ATLAS single top R_t 13 TeV	[45]	1
ATLAS single top y_t norm. 7, 8 TeV	[44,46]	6
ATLAS single antitop y norm. 7, 8 TeV	[44,46]	6
CMS W electron asymmetry 7 TeV	[47]	11
CMS W muon asymmetry 7 TeV	[48]	11
CMS Drell-Yan 2D 7 TeV	[49]	110
CMS W rapidity 8 TeV	[50]	22
CMS Z p_T (p^{ll}_T, y_{ll}) 8 TeV	[51]	28
CMS dijets 7 TeV	[52]	54
CMS 3D dijets 8 TeV	[53]	122
CMS $\sigma^{\rm tot}_{t\bar{t}}$ 7, 8, 13 TeV	[54,55]	3
CMS $t\bar{t}$ rapidity $y_{t\bar{t}}$ ℓ+jet 8 TeV	[56]	9
CMS $\sigma^{\rm tot}_{t\bar{t}}$ 5 TeV	[57]	1
CMS $t\bar{t}$ 2D 2ℓ $(m_{t\bar{t}}, y_t)$ 8 TeV	[58]	16
CMS $t\bar{t}$ absolute y_t ℓ+jet 13 TeV	[59]	10
CMS $t\bar{t}$ absolute $\lvert y_t\rvert$ 2ℓ 13 TeV	[60]	11
CMS single top $\sigma_t + \sigma_{\bar{t}}$ 7 TeV	[61]	1
CMS single top R_t 8 TeV	[62]	1
CMS single top R_t 13 TeV	[63]	1
LHCb Z 940 pb	[64]	9
LHCb $Z \to ee$ 2 fb	[65]	17
LHCb $W,Z \to \mu$ 7 TeV	[66]	29
LHCb $W,Z \to \mu$ 8 TeV	[67]	30
LHCb $Z \to \mu\mu$ 13 TeV	[68]	16
LHCb $Z \to ee$ 13 TeV	[68]	15
Total NNPDF4.0		1148
Grand total		4491

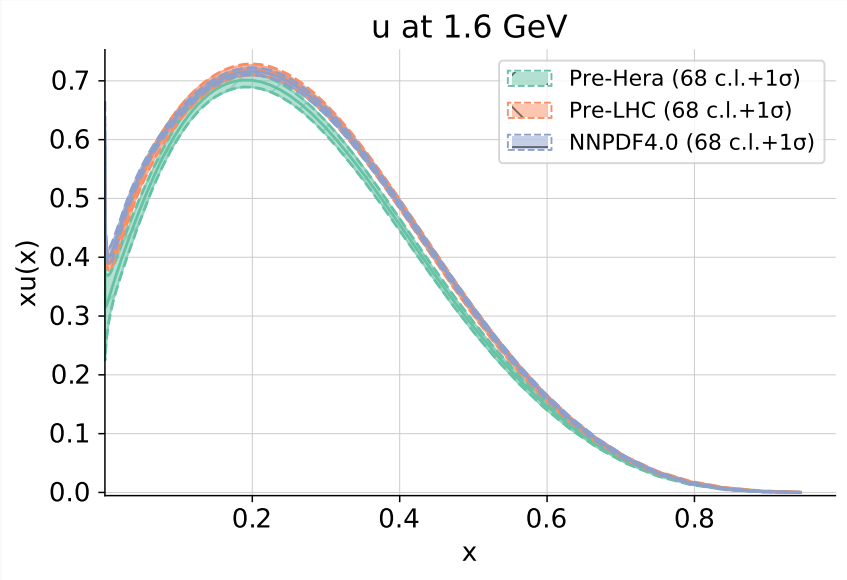
Table 1: The pre-HERA, pre-LHC and NNPDF4.0 datasets: for each experiment the reference to the original publication and the number of datapoints are given. Pre-HERA PDFs are fitted to pre-HERA data, pre-LHC PDFs are fitted to the pre-HERA and pre-LHC data, and NNPDF4.0 PDFs are fitted to the union of the three datasets.

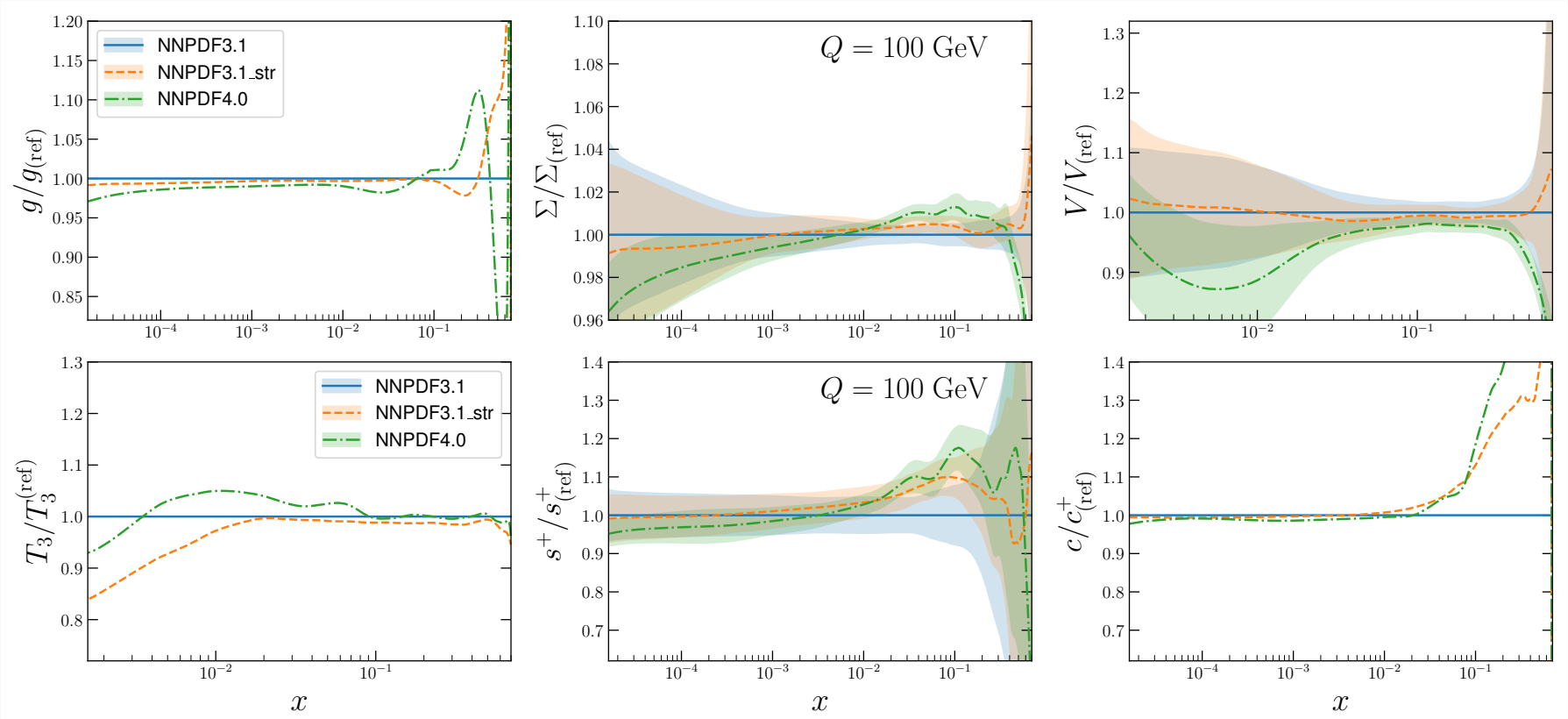
For more information see

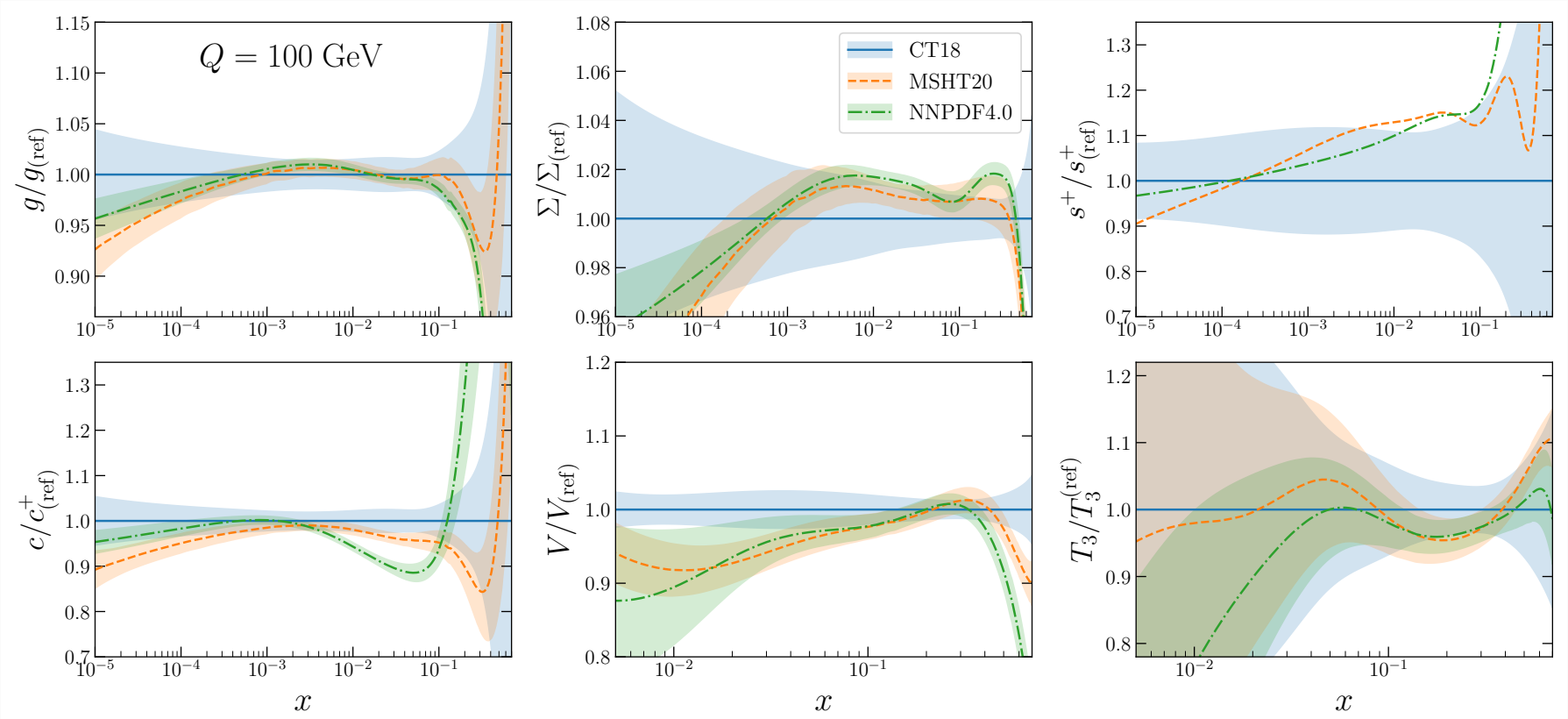
arxiv:2103.08606

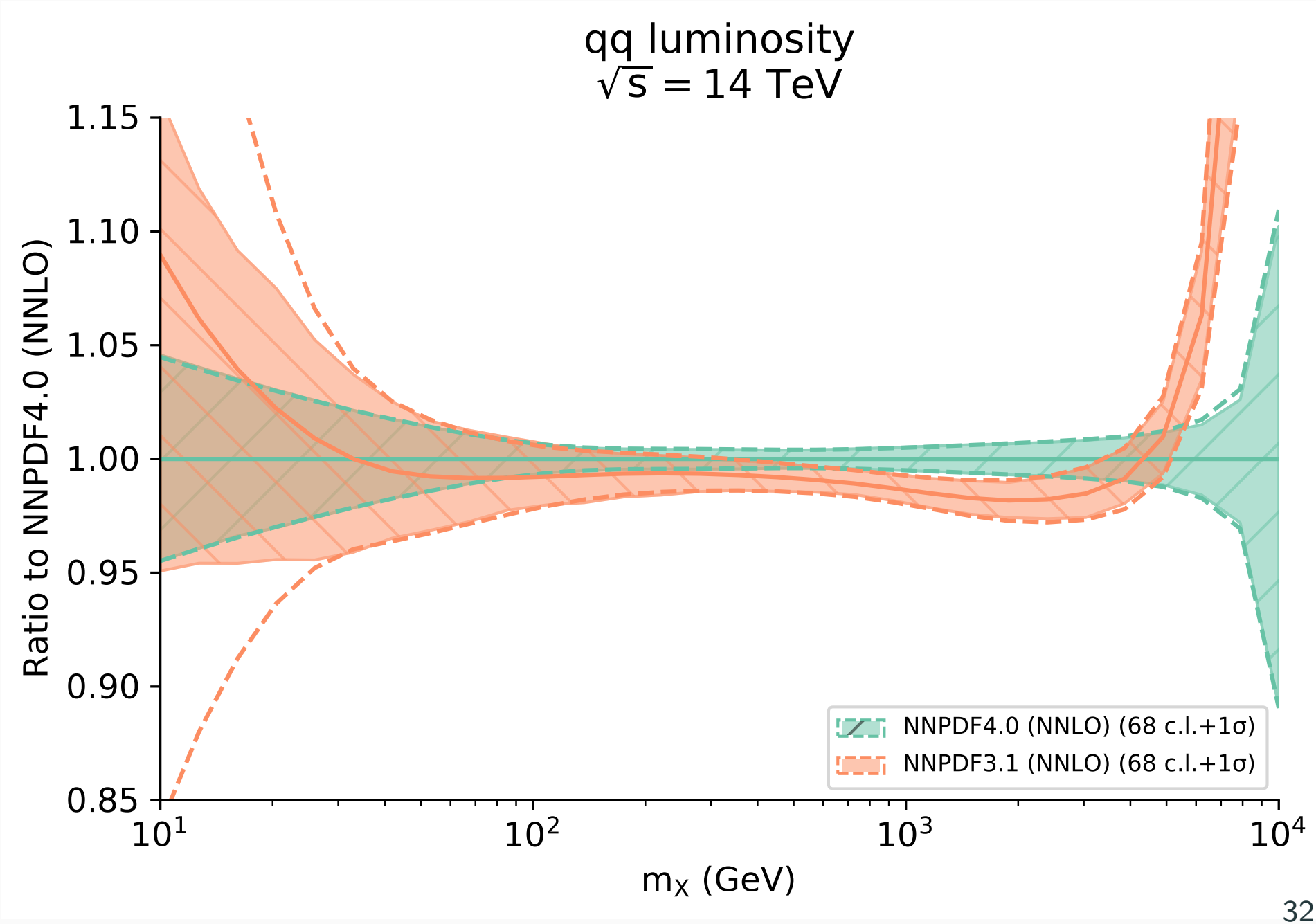
Future Test linear scale quarks

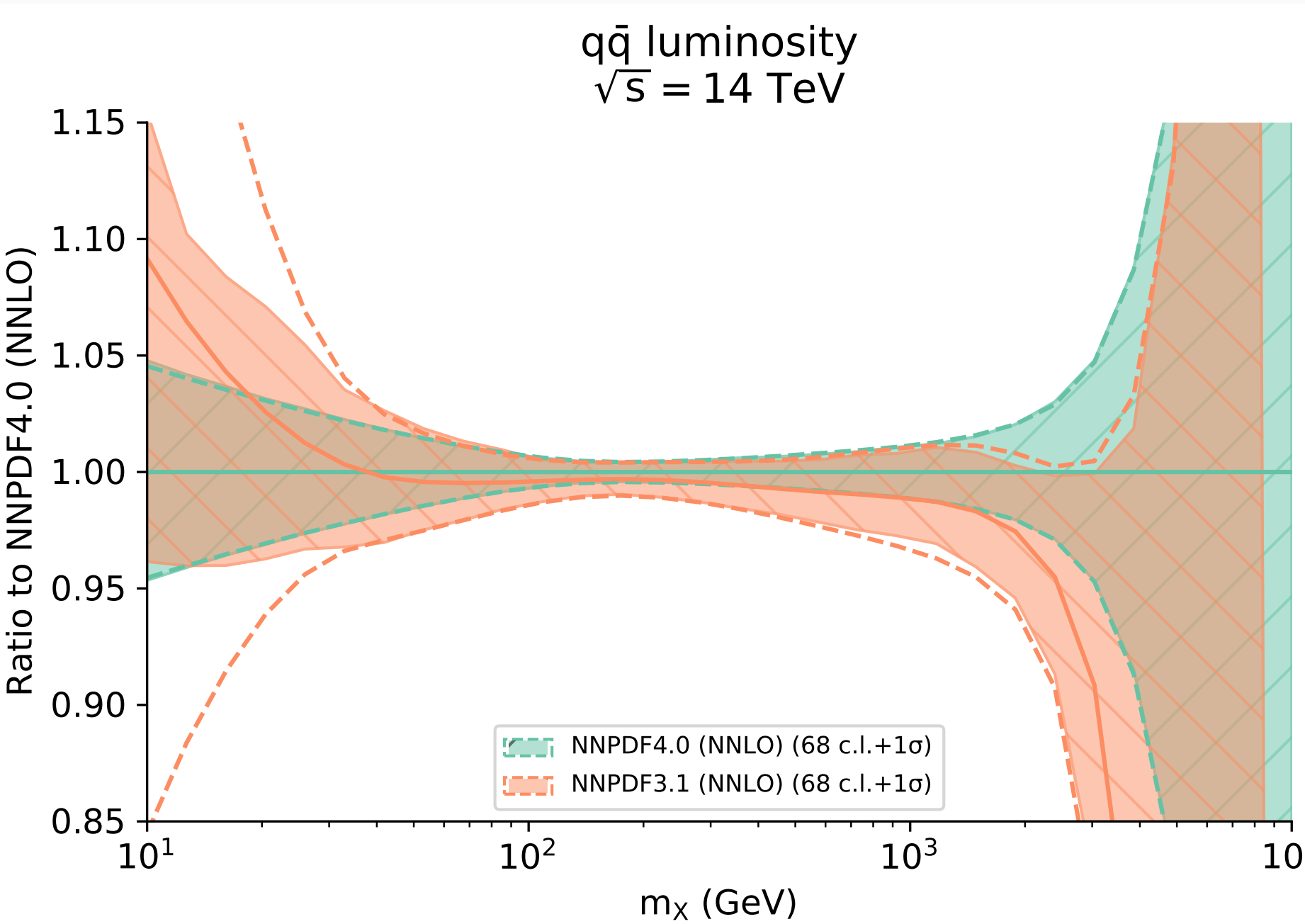


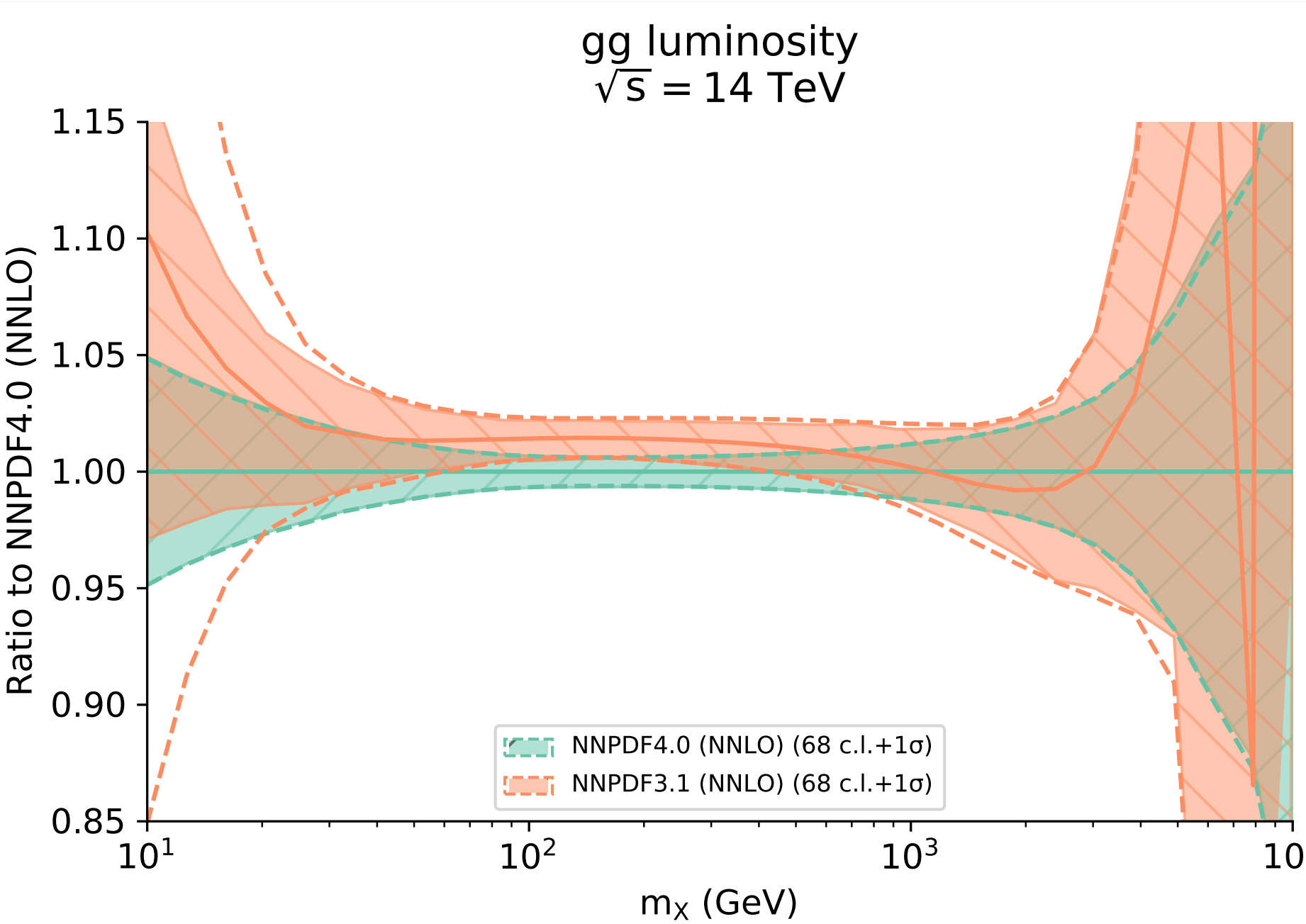



NNPDF3.1
NNPDF3.1_str
NNPDF4.0
$Q = 100$ GeV
$g/g_{(\mathrm{ref})}$
$\Sigma/\Sigma_{(\mathrm{ref})}$
$V/V_{(\mathrm{ref})}$
$T_3/T_3^{(\mathrm{ref})}$
$s^+/s^+_{(\mathrm{ref})}$
$c/c^+_{(\mathrm{ref})}$
x


$Q = 100$ GeV
CT18
MSHT20
NNPDF4.0
$g/g_{(\mathrm{ref})}$
$\Sigma/\Sigma_{(\mathrm{ref})}$
$s^+/s^+_{(\mathrm{ref})}$
$c/c^+_{(\mathrm{ref})}$
$V/V_{(\mathrm{ref})}$
$T_3/T_3^{(\mathrm{ref})}$
x


qq luminosity
$\sqrt{s} = 14$ TeV
Ratio to NNPDF4.0 (NNLO)
1.15
1.10
1.05
1.00
0.95
0.90
0.85
10^1
10^2
10^3
10^4
m_X (GeV)
NNPDF4.0 (NNLO) (68 c.l.+1σ)
NNPDF3.1 (NNLO) (68 c.l.+1σ)


qq̄ luminosity
√s = 14 TeV
Ratio to NNPDF4.0 (NNLO)
1.15
1.10
1.05
1.00
0.95
0.90
0.85
10^1
10^2
10^3
10^4
m_X (GeV)
NNPDF4.0 (NNLO) (68 c.l.+1σ)
NNPDF3.1 (NNLO) (68 c.l.+1σ)


gg luminosity
$\sqrt{s} = 14$ TeV
Ratio to NNPDF4.0 (NNLO)
1.15
1.10
1.05
1.00
0.95
0.90
0.85
10^1
10^2
10^3
10^4
m_X (GeV)
NNPDF4.0 (NNLO) (68 c.l.+1σ)
NNPDF3.1 (NNLO) (68 c.l.+1σ)