Neural Network Parton Distributions from High Precision Collider Data

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CTEQ Workshop @ JLAB – 8th November 2018

Foreword: theoretical framework

1. Collinear leading twist factorisation of physical observables [Adv.Ser.Direct.HEP 5 (1988) 1]

$$\mathcal{O}_I = \sum_{f=q,\bar{q},g} C_{If}(x,\alpha_s(\mu^2)) \otimes f(x,\mu^2) + \text{p.s. corrections} \qquad f \otimes g = \int_x^1 \frac{dy}{y} f\left(\frac{x}{y}\right) g(y)$$

2. Evolution of PDFs; DGLAP equations [NPB 126 (1977) 298]

$$\frac{\partial}{\partial \ln \mu^2} f_i(x,\mu^2) = \sum_j^{n_f} \int_x^1 \frac{dz}{z} P_{ji}\left(z,\alpha_s(\mu^2)\right) f_j\left(\frac{x}{z},\mu^2\right)$$

3. Perturbative expansion of coefficient and splitting functions

$$C_{If}(y,\alpha_s) = \sum_{k=0} a_s^k C_{If}^{(k)}(y), \qquad P_{ji}(z,\alpha_s) = \sum_{k=0} a_s^{k+1} P_{ji}^{(k)}(z), \qquad a_s = \alpha_s/(4\pi)$$

C_{If} known up to NNLO for an increasing number of processes $\qquad P_{ji}$ known up to NNLO

4. Theoretical constraints
positivity of cross sections, sum rules, symmetries, integrability of some PDF combinations

5. Sophistications in the factorisation paradigm
heavy-quark mass schemes, electroweak corrections, higher-twist terms, ...

Foreword: methodological framework

Determining the probability density (measure) $\mathcal{P}[f]$ in the spaace of PDFs $[f]$
from a finite piece of experimental information

For any observable $\mathcal{O}$ depending on a set of PDFs $[f]$

its expectation value and uncertainty are functional integrals over the space of PDFs

$$\langle \mathcal{O}[f] \rangle = \int \mathcal{D}f \, \mathcal{P}[f] \, \mathcal{O}[f] \qquad \text{expectation value}$$

$$\sigma_{\mathcal{O}}[f] = \left[\int \mathcal{D}f \, \mathcal{P}[f] \, \left(\mathcal{O}[f] - \langle \mathcal{O}[f] \rangle \right)^2 \right]^{1/2} \qquad \text{uncertainty}$$

Ingredients:

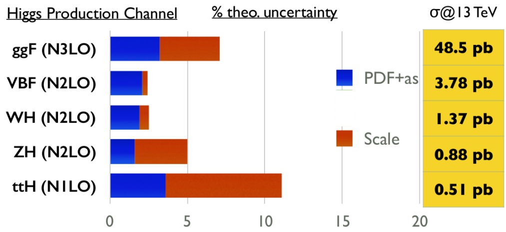
1. Parametrisation: general, smooth, flexible at an initial scale Q_0^2
2. A prescription to determine/compute/represent expectation values and uncertainties
3. A self-validating procedure (closure test, dynamic tolerance, . . .)

Problem reduced to determine an optimal set of parameters
usually by maximising the log-likelihood χ^2

Data, theory and methodology are all a source of uncertainty in the PDF determination
PDFs with faithful uncertainties are crucial for high-energy precision physics

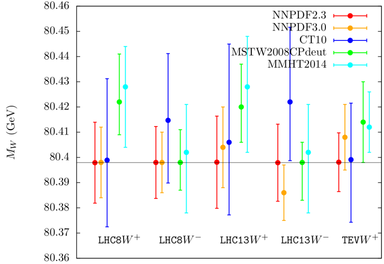
Foreword: the role of PDF uncertainties

[CERN Yellow report, 1610.07922]

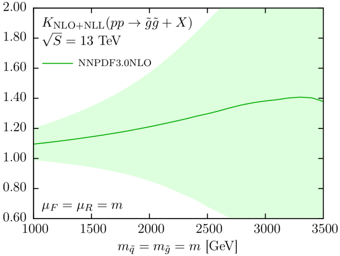


1. **Higgs boson characterisation**
   PDF uncertainty often dominant contribution to theory uncertainty
2. **Determination of SM parameters**
   PDF uncertainty largest theoretical uncertainty in M_W determination
3. **BSM gluino production**
   the larger the mass of the final state the larger the PDF uncertainty

[PRD 91 (2015) 113005]



[EPJ C76 (2016) 53]



1. The NNPDF methodology

Parametrisation: neural networks

1. Neural network (NN), *i.e.* a generator of random functions in the space of PDFs

$$\boxed{xf_i^h(x,Q_0^2) = x^a(1-x)^b\mathscr{F}_i^h(x,\{\mathbf{c}\})}$$

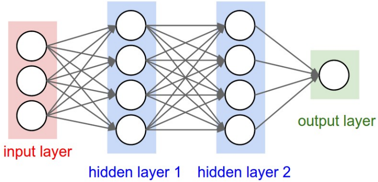
$\mathscr{F}_i^h(x,\{\mathbf{c}\})$ is a feed-forward NN

in terms of a huge set of parameters ($\mathcal{O}(200)$ per PDF set)

$$\{\mathbf{c}\} = \{\omega_{ij}^{(L-1),D_i^h}, \theta_i^{(L),D_i^h}\}$$

a and b are preprocessing exponents

2. What a feed-forward NN exactly is?



$$\xi_i^{(l)} = g\left(\sum_j^{n_l-1} \omega_{ij}^{(l-1)}\xi_j^{(l-1)} - \theta_i^{(l)}\right)$$

$$g(y) = \frac{1}{1+e^{-y}}$$

- made of neurons grouped into layers (define the architecture)
- each neuron receives input from neurons in the preceding layer (feed-forward NN)
- activation $\xi_i^{(l)}$ determined by a set of parameters (weights and thresholds)
- activation determined according to a non-linear function (except the last layer)

$\Rightarrow$ **potentially non-smooth**

$\Rightarrow$ **bias due to the parametrisation reduced as much as possible**

Uncertainty representation: Monte Carlo method

1. Generate (art) replicas of (exp) data according to the distribution

$$\mathcal{O}_i^{(art)(k)} = \mathcal{O}_i^{(exp)} + r_i^{(k)}\sigma_{\mathcal{O}_i}\,, \qquad i = 1, \dots N_{\rm dat}\,, \qquad k = 1, \dots, N_{\rm rep}$$

   where $r_i^{(k)}$ are (Gaussianly distributed) random numbers for each k-th replica ($r_i^{(k)}$ can be generated with any distribution, not neccesarily Gaussian)

2. Validate the Monte Carlo sample size against experimental data
3. Perform a fit for each replica $k = 1, \dots, N_{\rm rep}$
4. Compact computation of observables and their uncertainties (PDF replicas are equally probable members of a statistical ensemble)

$$\langle \mathcal{O}[f(x,Q^2)] \rangle = \frac{1}{N_{\sf rep}} \sum_{k=1}^{N_{\sf rep}} \mathcal{O}[f^{(k)}(x,Q^2)]$$

$$\sigma_{\mathcal{O}}[f(x,Q^2)] = \left[\frac{1}{N_{\sf rep}-1} \sum_{k=1}^{N_{\sf rep}} \Big(\mathcal{O}[f^{(k)}(x,Q^2)] - \langle \mathcal{O}[f(x,Q^2)] \rangle \Big)^2 \right]^{1/2}$$

$\Rightarrow$ **no need to rely on linear approximation**

$\Rightarrow$ **computational expensive: need to perform $N_{\rm rep}$ fits instead of one**

Minimisation: goodness-of-fit

1. Define the fit quality (the χ^2 function)

$$\chi^2 = \sum_{i,j}^{\mathrm{N_{dat}}} (T_i[\{\mathbf{a}\}] - D_i) \left(\mathrm{cov}^{-1}\right)_{ij} (T_j[\{\mathbf{a}\}] - D_j)$$

with the experimental covariance matrix

$$(\mathrm{cov})_{ij} = \delta_{ij} s_i^2 + \sum_{\alpha}^{N_c} \sigma_{i,\alpha}^{(c)} \sigma_{j,\alpha}^{(c)} D_i D_j + \sum_{\alpha}^{N_{\mathcal{L}}} \sigma_{i,\alpha}^{(\mathcal{L})} \sigma_{j,\alpha}^{(\mathcal{L})} T_i^0 T_j^0$$

s_i are N_{dat} uncorrelated uncertainties (statistic + uncorrealted systematic uncertainties)
$\sigma_{i,\alpha}^{(c)}$ are $N_{\mathrm{dat}} \times N_c$ additive correlated uncertainties
$\sigma_{i,\alpha}^{(\mathcal{L})}$ are $N_{\mathrm{dat}} \times N_{\mathcal{L}}$ multiplicative uncertainties

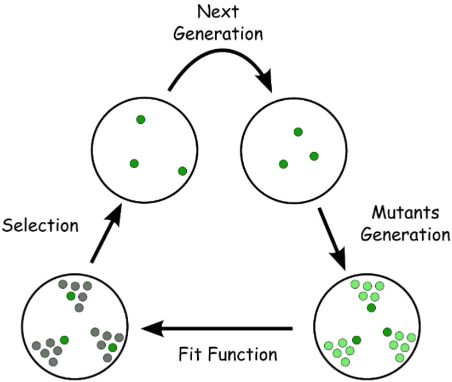
2. Find the best-fit configuration of parameters $\{\mathbf{a_0}\}$ which minimise the χ^2

3. Treat conveniently
   - uncorrelated/correlated uncertainties
     need not to overestimate uncertainties
   - additive/multiplicative uncertainties
     need to avoid the D'Agostini bias [JHEP 1005 (2010) 075]

Minimisation: genetic algorithm

1. Initial population of NNs
   $\longrightarrow$ pars initialised randomly
2. Mutants generation
   $\longrightarrow$ mutations are introduced
3. Fit function
   $\longrightarrow$ the total χ^2 is computed
4. Selection
   $\longrightarrow$ best pars configs selected
5. Next generation
   $\longrightarrow$ iterate the process

until convergence is achieved



Good exploration of the parameter space

No need to compute gradients

Lower computational efficiency than standard gradient descent methods

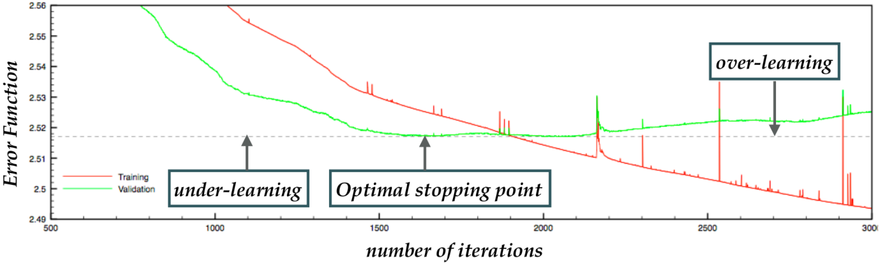
Possible sensitivity to noise in χ^2 driven by noisy data

Minimisation: stopping criterion

If the parametrisation is redundant, statistical noise in the data can be learnt

CROSS-VALIDATION METHOD

- divide the data into two subsets (training & validation)
- train the NN on training subset and compute χ^2 for each subset
- stop when the χ^2 of validation subset no longer decreases (NN are learning noise!)



The best fit does not coincide with the χ^2 absolute minimum

Minimisation: adaptive algorithms [N. Hansen, Springer (2016)]

The Covariance Matrix Adaption - Evolution Strategy (CMA-ES)

1. Initialisation at the (0)-th generation

$$\mathbf{a}^{(0)} \sim \mathcal{N}(0, \mathbf{C}^{(0)})\,, \qquad \mathbf{C}^{(0)} = \mathbf{I}$$

2. Mutation at the (i)-th generation, λ mutants, step-size $\sigma^{(i-1)}$

$$\mathbf{x}_k^{(i)} \sim \mathbf{a}^{(i-1)} + \sigma^{(i-1)}\mathcal{N}(0, \mathbf{C}^{(i-1)})\,, \qquad \text{for } k = 1, \ldots, \lambda$$

   compute the fitness of each mutant and rank them such that $\chi^2(\mathbf{x}_k) < \chi^2(\mathbf{x}_{k+1})$

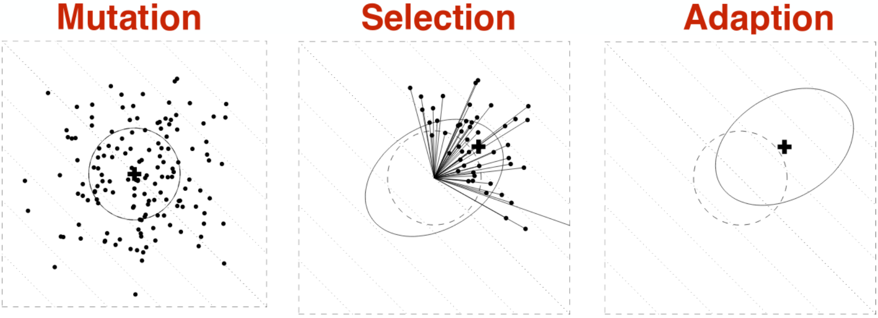
3. (Non-elitist) recombination
   compute the new search centre as a weighted average over the $\mu = \lambda/2$ best mutants

$$\mathbf{a}^{(i)} = \mathbf{a}^{(i-1)} + \sum_{i=1}^{\mu} w_i \left(\mathbf{x}_k^{(i)} - \mathbf{a}^{(i-1)}\right)$$

   update $\mathbf{C}$ using information on the parameter space learnt from the mutants

4. Iterate until convergence is reached

Minimisation: the CMA-ES algorithms [N. Hansen, Springer (2016)]

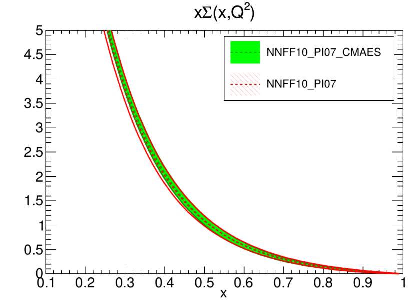


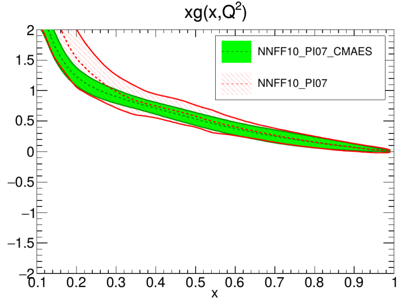
The key features of the CMA-ES family of algorithms are the determination of the search distribution covariance matrix $\mathbf{C}^{(i)}$ (and possibly of the step-size σ^{i})

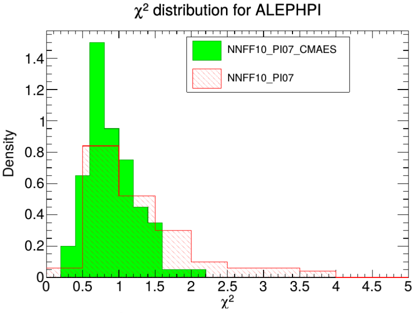
These features are optimised by the fit procedure, making use of the information present in the ensemble of mutants to learn preferred directions in parameter space

Internal parameters ($\sigma^{(0)}$, λ, w_i) tuned by trial and error

Minimisation: dependence on the algorithm







Singlet and Gluon FFs at $Q = 5$ GeV

	NNFF10_PI07_CMAES	NNFF10_PI07
$\chi^2_{\rm tot}/N_{\rm dat}$	0.93	0.92
$\langle E_{\rm tr}\rangle \pm \sigma_{\rm tr}$	1.97±0.28	1.97±0.71
$\langle E_{\rm val}\rangle \pm \sigma_{\rm val}$	2.16±0.37	2.91±1.72
$\langle {\rm TL}\rangle \pm \sigma_{\rm TL}$	3065±1673	5560±9394

Validation: closure tests

1. Level 0: generate pseudodata D_i^0 with zero uncertainty
   (but $(\mathrm{cov})_{ij}$ in the χ^2 is the data covariance matrix)
   $\rightarrow$ fit quality can be arbitrarily good, if the fitting methodology is efficient: $\chi^2/N_{\mathrm{dat}} \sim 0$
   $\rightarrow$ validate fitting methodology (parametrisation, minimisation)
   $\rightarrow$ interpolation and extrapolation uncertainty
2. Level 1: generate pseudodata D_i^1 with stochastic fluctuations (no replicas)

$$D_i^1 = (1 + r_i^{\mathrm{nor}}\sigma_i^{\mathrm{nor}}) \left(D_i^0 + \sum_p^{N_{\mathrm{sys}}} r_{i,p}^{\mathrm{sys}}\sigma_{i,p}^{\mathrm{sys}} + r_i^{\mathrm{stat}}\sigma_i^{\mathrm{stat}} \right)$$

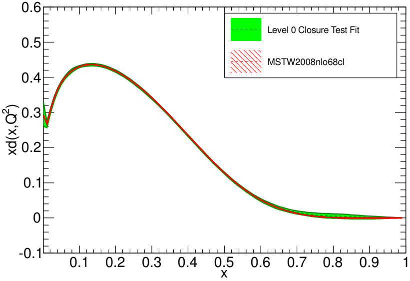
   $\rightarrow$ experimental uncertainties are not propagated into FFs: $\chi^2/N_{\mathrm{dat}} \sim 1$
   $\rightarrow$ functional uncertainty (a large number of functional forms with equally good χ^2)
3. Level 2: generate N_{rep} Monte Carlo pseudodata replicas $D_i^{2,k}$ on top of Level 2

$$D_i^{2,k} = (1 + r_i^{\mathrm{nor},k}\sigma_i^{\mathrm{nor}}) \left(D_i^1 + \sum_p^{N_{\mathrm{sys}}} r_{i,p}^{\mathrm{sys},k}\sigma_{i,p}^{\mathrm{sys}} + r_i^{\mathrm{stat},k}\sigma_i^{\mathrm{stat}} \right)$$

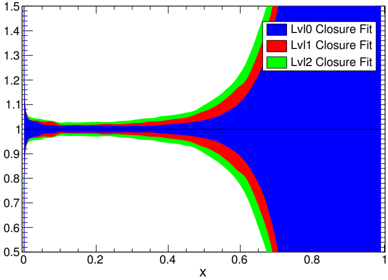
   $\rightarrow$ propagate the fluctuations due to experimental uncertainties into PDFs: $\chi^2/N_{\mathrm{dat}} \sim 1$
   $\rightarrow$ input PDFs within the one-sigma band of the fitted PDFs with a probability of $\sim$ 68%
   $\rightarrow$ data uncertainty

Closure tests: examples

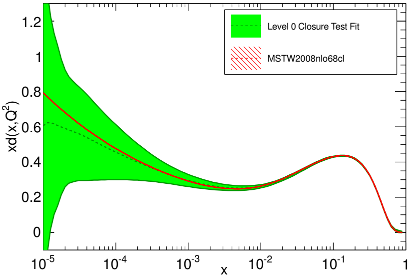
Level 0 closure test vs. MSTW



Ratios of d at different closure test levels



Level 0 closure test vs. MSTW



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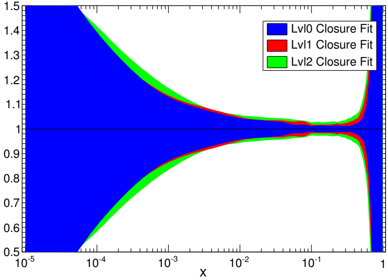


2. NNPDF3.1

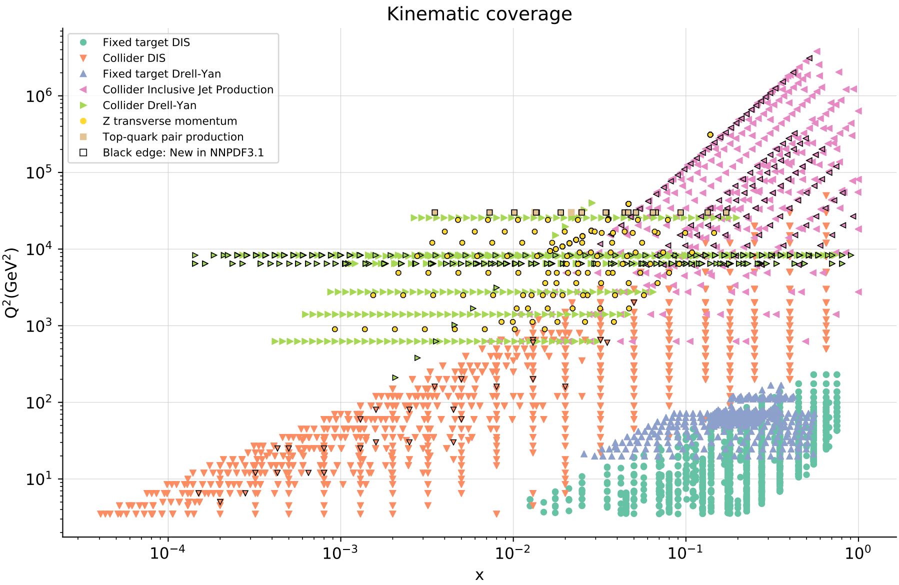
The NNPDF3.1 layout

1. Availability of a wealth of high-precision PDF-sensitive measurements

Combined HERA inclusive data	Run I+II	quark singlet and gluon
D0 legacy W asymmetries	Run II	quark flavour separation
ATLAS inclusive W, Z rapidity 7 TeV	2011	strangeness
ATLAS inclusive jets 7 TeV	2011	large-x gluon
ATLAS low-mass Drell-Yan 7 TeV	2010+2011	small-x quarks
ATLAS Z p_T 8 TeV	2011+2012	medium-x gluons and quarks
ATLAS $t\bar{t}$ differential distributions 8 TeV	2012	large-x gluon
CMS Z (p_T,y) 2D cross sections 8 TeV	2012	medium-x gluon and quarks
CMS Drell-Yan low+high mass 8 TeV	2012	small-x and large-x quarks
CMS W asymmetry 8 TeV	2012	quark flavour separation
CMS 2.76 TeV jets	2012	medium- and large-x gluon
CMS $t\bar{t}$ differential distributions 8 TeV	2012	large-x gluon
LHCb W,Z rapidity distributions 7 TeV	2011	large-x quarks
LHCb W,Z rapidity distributions 8 TeV	2012	large-x quarks

2. Progress in the computation of NNLO QCD corrections for a wealth of processes
3. Realisation that fitting the charm PDF [EPJ C76 (2016) 647]
   $\longrightarrow$ stabilises the dependence on m_c
   $\longrightarrow$ improves the data/theory agreement

The NNPDF3.1 data set



NNPDF3.1: fit quality $\chi^2/N_{\rm dat}$

	$N_{\rm dat}$ (NNLO/NLO)	NNLO (FC)	NNLO (PC)	NLO (FC)	NLO (PC)
HERA	1211/1221	1.16	1.21	1.14	1.15
ATLAS	399/397	1.09	1.17	1.37	1.45
CMS	517/505	1.06	1.09	1.20	1.21
LHCb	85/93	1.47	1.48	1.61	1.77
TOTAL	4285/4295	1.148	1.187	1.168	1.197

NNLO usually better than NLO, FC better than PC

Challenge 1: ATLAS 7 TeV jets [EPJ C78 (2018) 248]

Each rapidity bin can be fitted with $\chi^2/N_{\rm dat} \sim 1$, best-fit PDFs indistinguishable

If all bins are fitted simultaneously, $\chi^2/N_{\rm dat} \sim 3$

$\Longrightarrow$ misestimated correlations?

Challenge 2: The ATLAS 8 TeV Z p_T distribution [EPJ C77 (2017) 663]

uncorrelated statistical uncertainties at permille level

large NNLO corrections $\sim 10\%$, but nominal K-factor uncertainties very small

$\Longrightarrow$ fit only possible with estimate of theory uncertainties

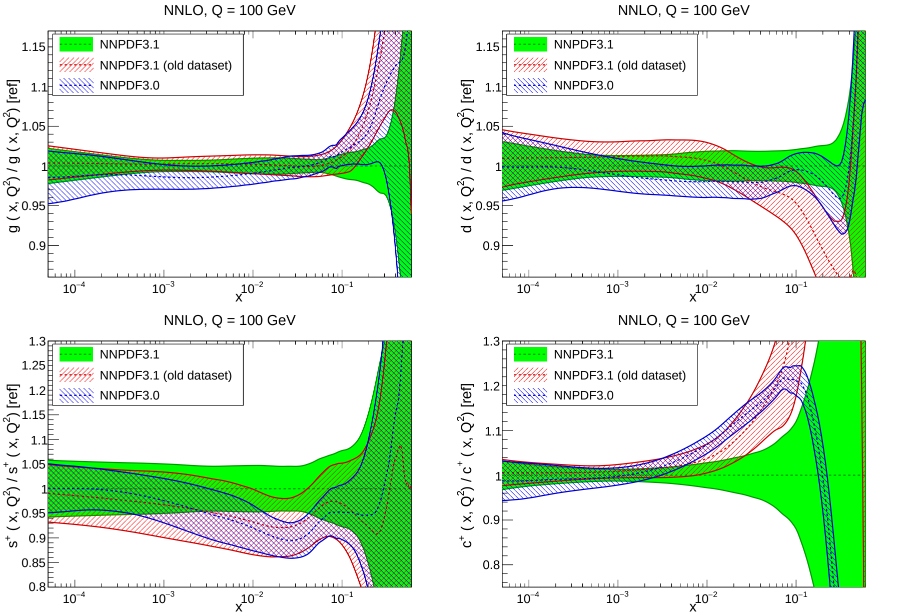
Challenge 3: The CMS double differential DY 2011 [EPJ C77 (2017) 663]

from 2011 to 2012, uncorrelated uncertainties down to sub-permille

2011: $\chi^2/N_{\rm dat} \sim 1$; 2012: impossible to fit better than $\chi^2/N_{\rm dat} \sim 3$

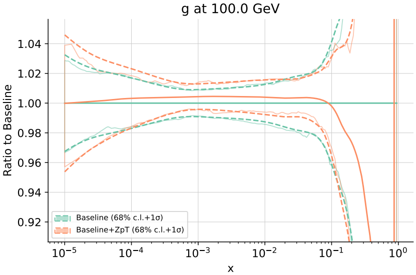
$\Longrightarrow$ pathological behaviour of covariance matrix, what is the uncertainty on it?

Overall impact of the new data and methodology



The gluon PDF [JHEP 1704 044; JHEP 1707 130; PoS DIS2017 (2018) 008; PRL 118 (2017) 072001]

$Z\ p_T$ distributions

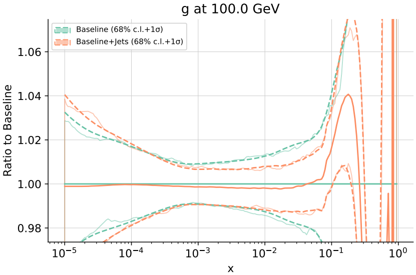


Various processes (included in NNPDF3.1)
$Z\ p_T$, jets, $t\bar{t}$

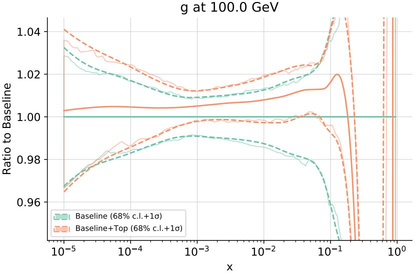
Largest impact of jets and $t\bar{t}$ at large x
comparable uncertainty

Forward charm production (not in NNPDF3.1)
large impact at small x
potentially crucial for UHE neutrino-nucleus cross section measurements

jets

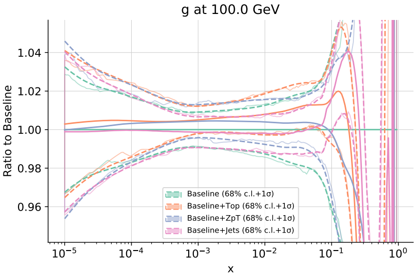


$t\bar{t}$ differential



The gluon PDF [JHEP 1704 044; JHEP 1707 130; PoS DIS2017 (2018) 008; PRL 118 (2017) 072001]

ratio to the baseline fit



Various processes (included in NNPDF3.1)
$Z\ p_T$, jets, $t\bar{t}$

Largest impact of jets and $t\bar{t}$ at large x
comparable uncertainty

Forward charm production (not in NNPDF3.1)
large impact at small x
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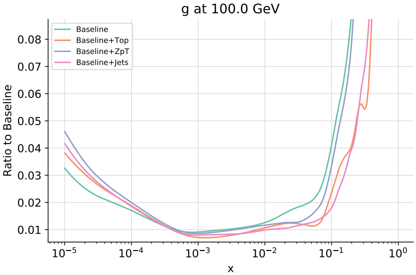
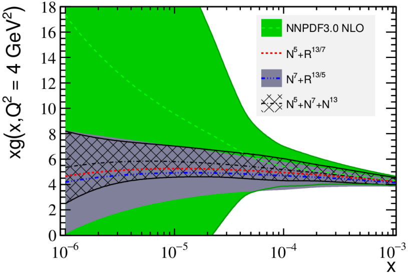
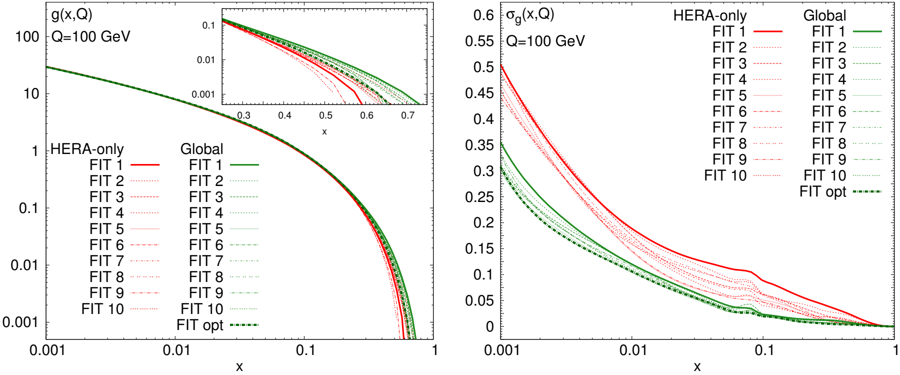
total absolute uncertainty



forward charm production



Impact of $t\bar{t}$ distributions on the gluon PDF at large x



Fair degree of consistency in the impact of various distributions on the gluon PDF

HERA-only fit (red): $t\bar{t}$ data prefers a harder gluon w.r.t. to the baseline (solid red)

Global fit (green): $t\bar{t}$ data prefers a softer gluon w.r.t. to the baseline (solid green)

Nice convergence/consistency check

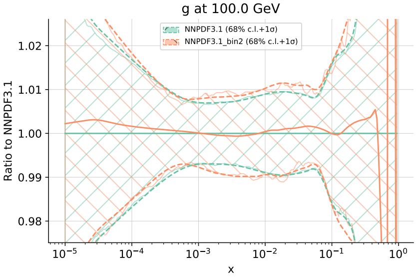
Largest constraining power on the gluon PDF uncertainty in the global fit

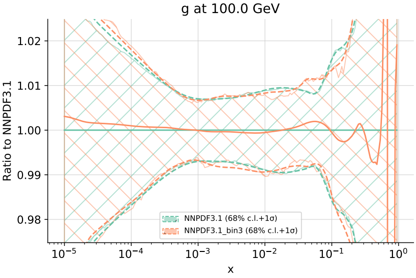
There exists an optimal combination of $t\bar{t}$ data that maximises this effect (bold dashed green)

Dependence upon the choice of the jet bin

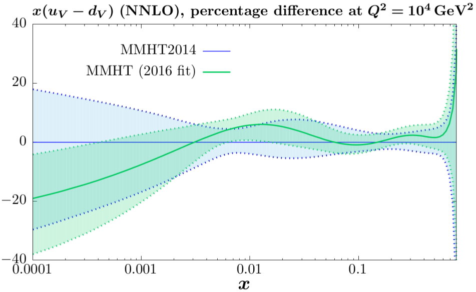
If all bins in the 2011 ATLAS 7 TeV data set are fitted simultaneously, $\chi^2/N_{\rm dat} \sim 3$
Central rapidity bin selected in NNPDF3.1
The gluon PDF is stable upon the choice of any of the other rapidity bins

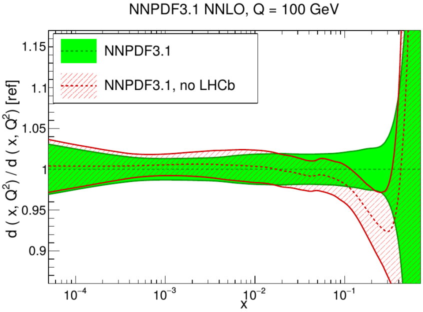
Fit	$\chi^2_{\rm ATLAS}/N_{\rm dat}$ (before fit)	$\chi^2_{\rm ATLAS}/N_{\rm dat}$ (after fit)	$\chi^2_{\rm tot}/N_{\rm dat}$ (after fit)
NNPDF3.1 centralbin	1.07	1.07	1.148
NNPDF3.1 bin2	1.27	1.27	1.150
NNPDF3.1 bin3	0.95	0.93	1.151
NNPDF3.1 bin4	1.06	1.07	1.145
NNPDF3.1 bin5	0.97	0.96	1.146
NNPDF3.1 bin6	0.73	0.67	1.145





Quark flavour separation from LHC data





High-precision W and Z production data from ATLAS, CMS and LHCb

handle on quark/antiquark flavour separation

Largest impact on light quarks at large x provided by LHCb data

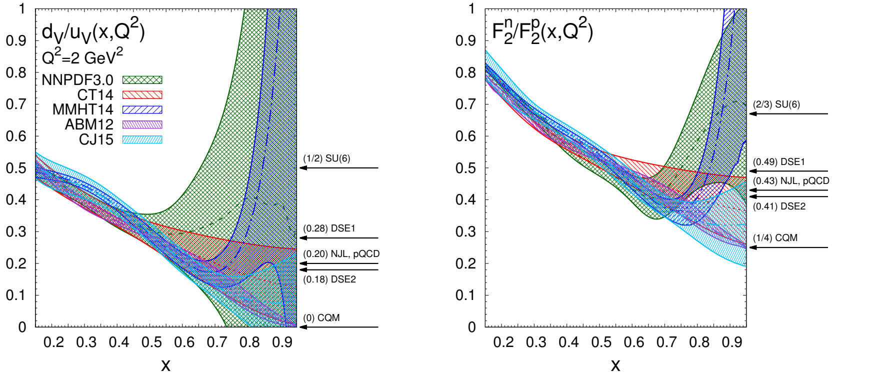
error reduction by a factor 2 in NNPDF3.1 at $x \sim 0.1$

Combined effect of (LHC) CMS, LHCb and (Tevatron) D0 W, Z data

improved determination of $x(u_V - d_V)$

[see R. Thorne's talk at DIS2017 and EPJ C77 (2017) 663 for details]

The PDF ratio d_V/u_V at large x [EPJC 76 (2016) 383]

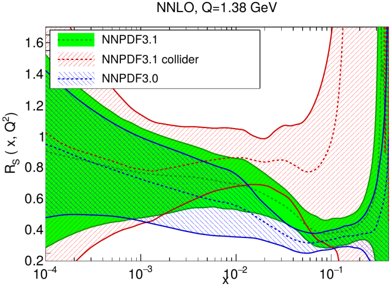


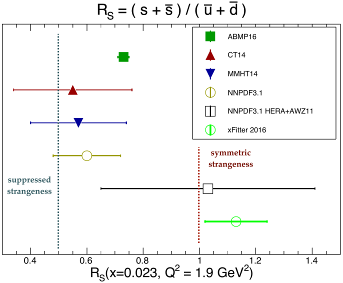
$$\frac{d_V}{u_V} \xrightarrow{x\to 1} (1-x)^{b_{d_V}-b_{u_V}} \xrightarrow[\text{c. r.}]{b_{d_V}=b_{u_V}} k \qquad \frac{F_2^n}{F_2^p} \xrightarrow{x\to 1} \frac{4(1-x)^{b_{u_V}}+(1-x)^{b_{d_V}}}{(1-x)^{b_{u_V}}+4(1-x)^{b_{d_V}}} \xrightarrow[\text{c. r.}]{b_{d_V}=b_{u_V}} 1$$

case $b_{u_V} \gg b_{d_V}$: $\frac{d_V}{u_V} \xrightarrow{x\to 1} \infty$; $\frac{F_2^n}{F_2^p} \xrightarrow{x\to 1} 4$ case $b_{u_V} \ll b_{d_V}$: $\frac{d_V}{u_V} \xrightarrow{x\to 1} 0$; $\frac{F_2^n}{F_2^p} \xrightarrow{x\to 1} \frac{1}{4}$

No predictive power from current PDF determinations, no discrimination among models unless $\frac{d_V}{u_V} \xrightarrow{x\to 1} k$ is built in the parametrisation (CT14, CJ16, ABM12)

The strange PDF from collider data





In most PDF fits the strange PDF is suppressed w.r.t up and down sea quark PDFs

effect mostly driven by neutrino dimuon data

A symmetric strange sea PDF is preferred by collider data

in particular by ATLAS W, Z rapidity distributions (2011) [EPJ C77 (2017) 367]

$$R_s(x, Q^2) = \frac{s(x,Q^2) + \bar{s}(x,Q^2)}{\bar{u}(x,Q^2) + \bar{d}(x,Q^2)} \begin{cases} \sim 0.5 \text{ from neutrino and CMS } W + c \text{ data} \\ \sim 1.0 \text{ from ATLAS } W, Z \end{cases}$$

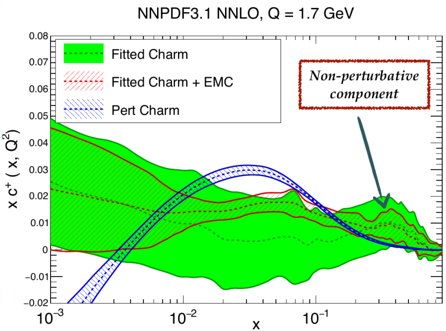
The ATLAS data can be accommodated in the global fit

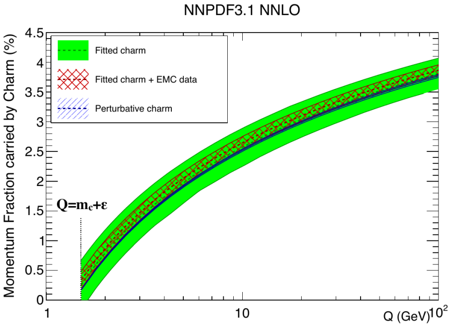
increased strangeness, though not as much as in a collider-only fit

some tension remains between collider and neutrino data

Suppressed strangeness confirmed by recent $W + c$ CMS analysis [CMS PAS SMP-17-014]

The charm PDF: perturbative vs fitted [EPJ C76 (2016) 647]





Parametrise the $c^+(x, Q_0^2)$, quark and gluon PDFs on the same footing

stabilise the dependence of LHC processes upon variations of m_c

quantify the nonperturbative charm component in the proton (BHPS? sea-like?)

take into account massive charm-initiated contribution to the DIS structure functions

Fitted charm found to differ from perturbative charm at scales $Q \sim m_c$ in NNPDF3.1

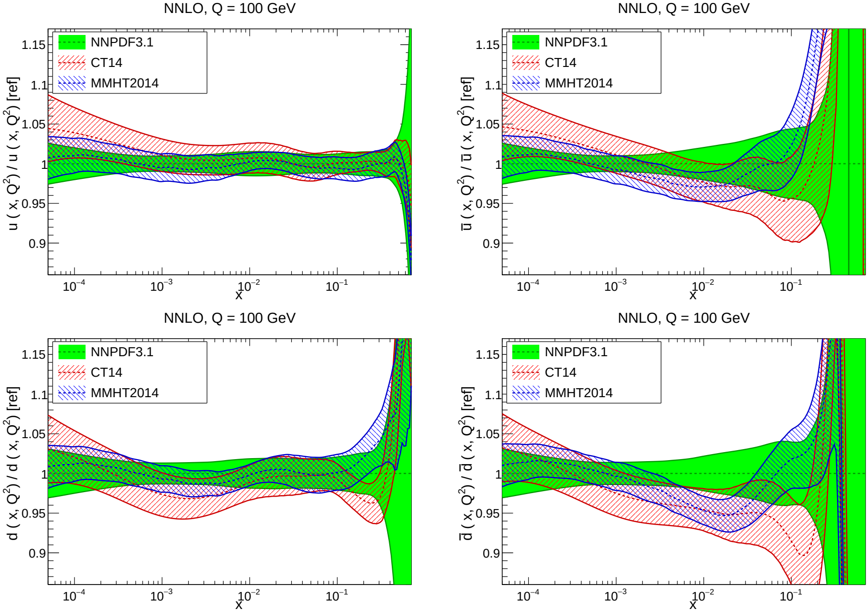
preference for a BHPS-like shape

shape driven by LHCb W, Z data + EMC data

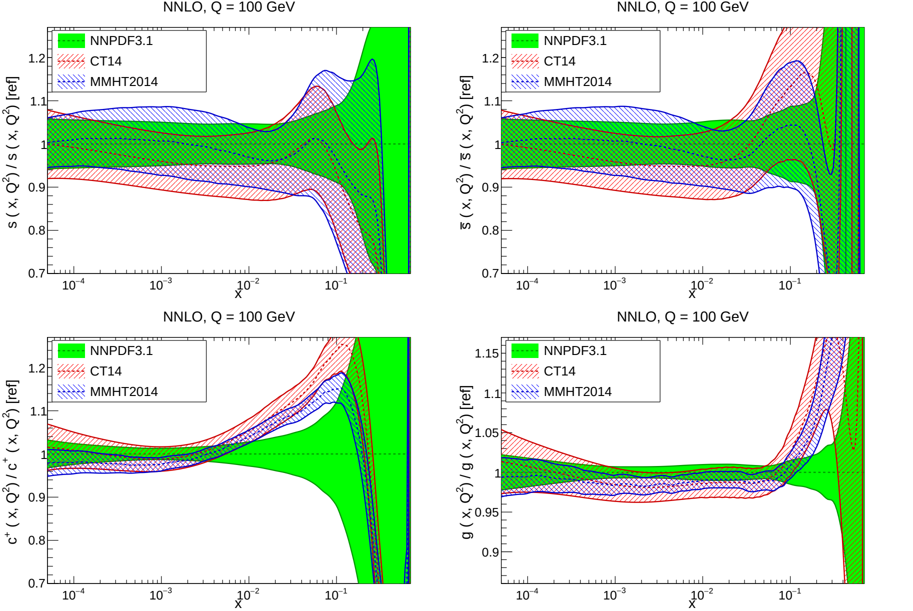
At $Q = 1.65$ GeV charm carry 0.26 ± 0.42 % of the proton momentum

but it is affected by large uncertainties, especially if no EMC data are included

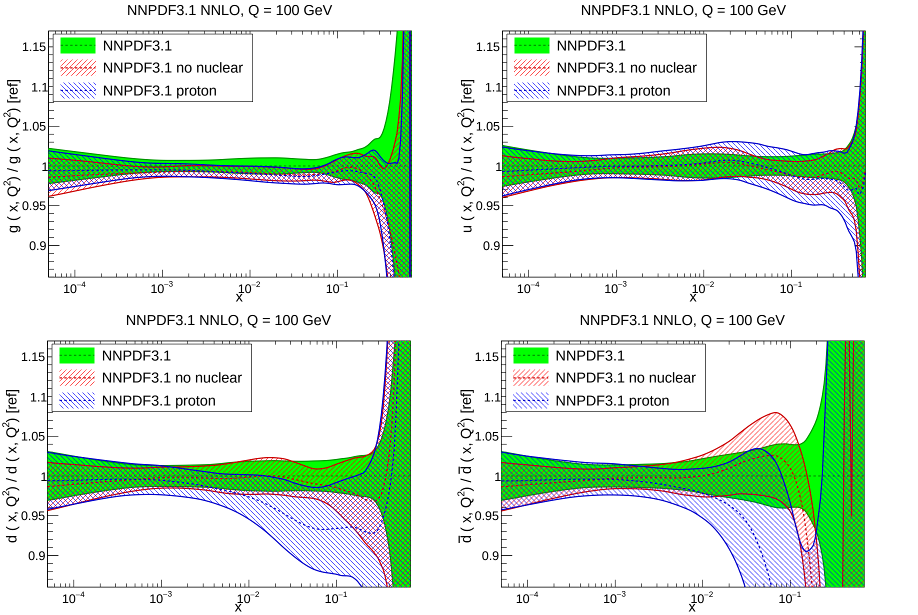
Comparison with other PDF sets



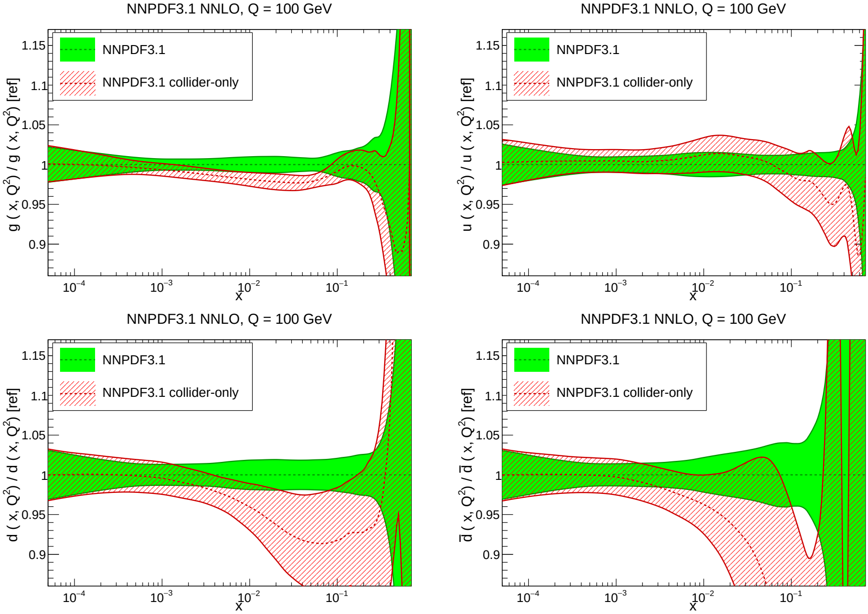
Comparison with other PDF sets



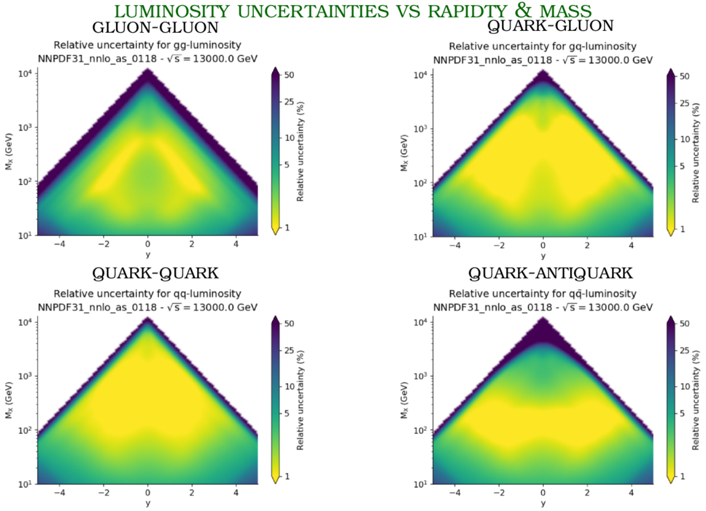
Data set variations: proton only fits



Data set variations: collider only fits



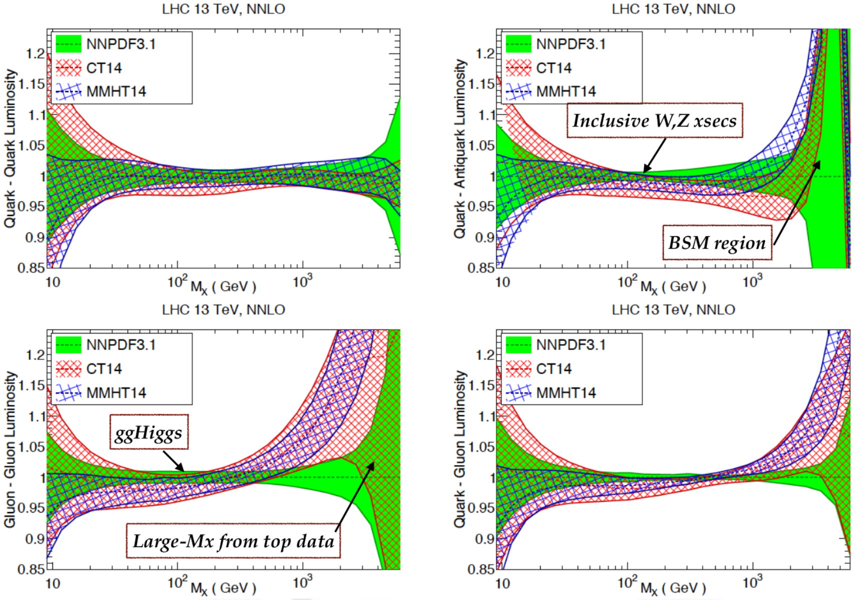
Towards 1% PDF uncertainties



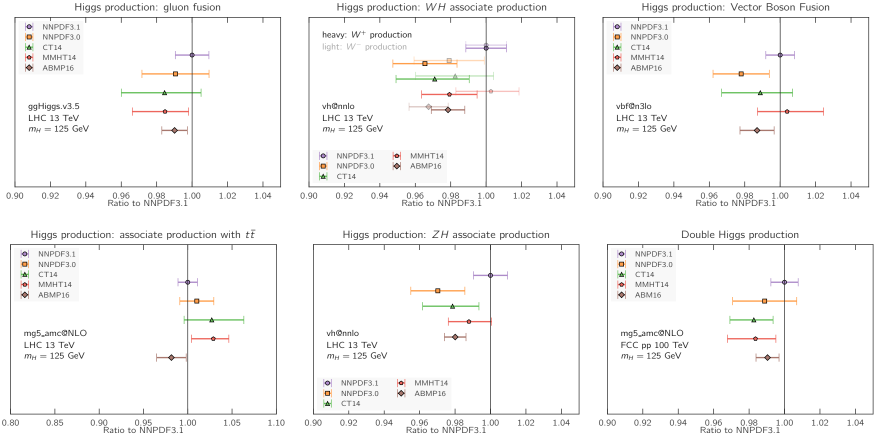
Typical PDF uncertainty in data region of order 1%

Can we believe in 1% PDF uncertainties? What are the consequences?

Parton luminosities



Higgs production cross sections



For gluon-initiated processes, good agreement between NNPDF3.1 and NNPDF3.0 (with reduced PDF uncertainties in the latter case)

For quark-initiated processes, the new collider data pulls towards higher cross sections

The new ABMP16 set is in reasonable agreement with the other sets (provided the PDG value of the strong coupling is used)

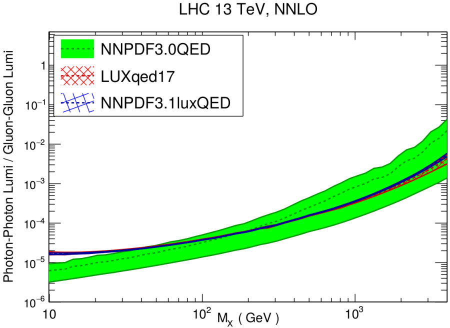
3. Beyond NNPDF3.1

The photon PDF: how bright is the proton?

The photon PDF $\gamma(x,Q)$ in LUXqed

$$xf_{\gamma/p}(x,\mu^2) = \frac{1}{2\pi\alpha(\mu^2)}\int_x^1 \frac{dz}{z}\left\{\int_{\frac{x^2m_p^2}{1-z}}^{\frac{\mu^2}{1-z}} \frac{dQ^2}{Q^2}\alpha^2(Q^2)\right.$$
$$\left[\left(zp_{\gamma q}(z) + \frac{2x^2m_p^2}{Q^2}\right)F_2(x/z,Q^2) - z^2F_L\left(\frac{x}{z},Q^2\right)\right]$$
$$\left. - \alpha^2(\mu^2)z^2F_2\left(\frac{x}{z},\mu^2\right)\right\}$$

Good agreement with NNPDF3.0QED, model-independent fit from LHC DY data



NNPDF3.0QED: model-independent determination of $\gamma(x,Q)$ from LHC W, Z data

affected by large uncertainties, $\mathcal{O}(100\%)$ due to limited experimental information

LUXQED: compute $\gamma(x,Q)$ in terms of inclusive structure functions F_2 and F_L

significant improvement in the PDF uncertainty

implications for high-mass processes for BSM searches, *e.g.* DY production at the TeV scale

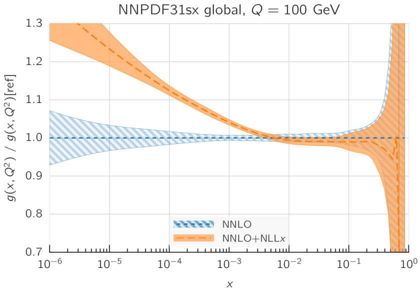
NNPDF3.1LUXQED: consistent NNPDF fit with LUXQED constraint

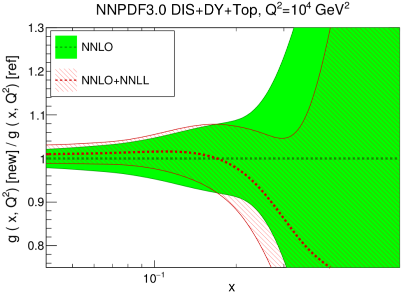
good agreement, but smaller uncertainties

sizable impact on precision physics: *e.g.* associated Higgs production with W

[See NPB 877 (2013) 290; arXiv:1606.07130; PRL 117 (2016) 242002; SciPost Phys. 5 (2018) 008]

Beyond fixed-order accuracy





small x: $\frac{1}{x}\ln^k x$

high-energy gluon emission: single logs

large x: $\left(\frac{\ln^k(1-x)}{(1-x)}\right)_+$

soft gluon emission: double logs

Large logs $\alpha_s \ln \sim 1$ spoil the convergence of the perturbative series

PDFs with threshold resummation [JHEP 1509 (2015) 191] (only DIS, DY Z/γ, total $t\bar{t}$ + evol.)

suppression in PDFs partially or totally compensates enhancements in partonic cross-sections

accuracy of the resummed fit competitive with the fixed-order fit, except for the large-x gluon

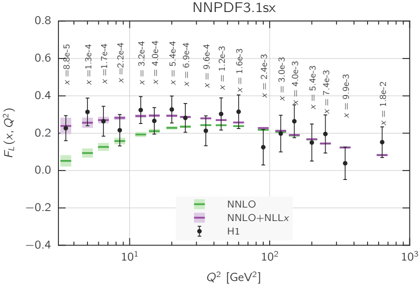
large uncertainties for MSSM particle resummed cross-sections [EPJ C76 (2016) 53]

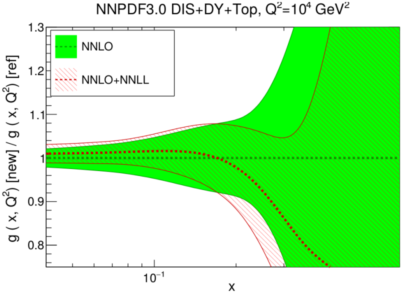
PDFs with high-energy resummation [EPJ C78 (2018) 321] (only DIS + evol.)

Resummed PDFs enhanced at small x, uncertainties reduced, observed onset of BFKL evolution

Large effects for future colliders, or b production at LHC

Beyond fixed-order accuracy





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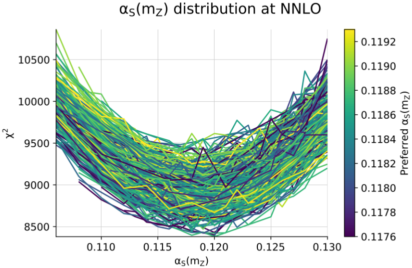
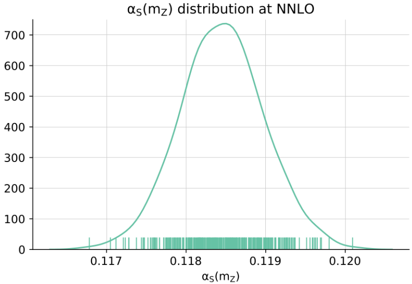
Large effects for future colliders, or b production at LHC

The correlated replica method and α_s [EPJ C78 (2018) 408]



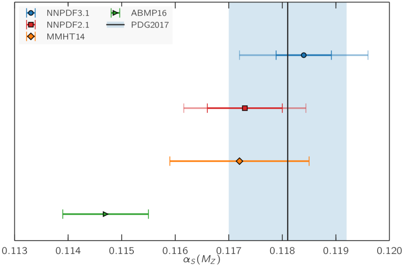


How can we take into account PDF/α_s correlations in a Monte Carlo way?

for each data sample (replica), perform a scan in α_s

each replica has a preferred value of α_s (the minimum of each parabola)

these preferred values form a Monte Carlo distribution

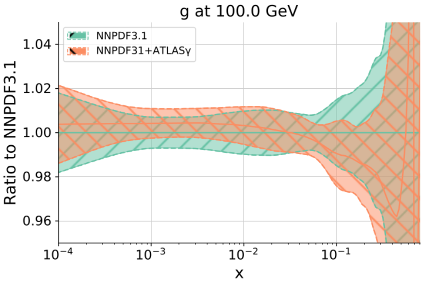


$$\alpha_s^{\mathrm{NNLO}}(M_Z) = 0.1185 \pm 0.0005^{\mathrm{exp}} \pm 0.0001^{\mathrm{meth}} \pm 0.0011^{\mathrm{th}} = 0.1185 \pm 0.0012(1\%)$$

New data

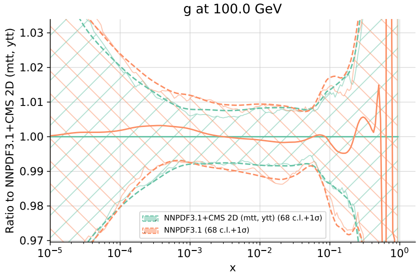
Direct photon production
(ATLAS 8 TeV data) [EPJ C78 (2018) 470]
theory based on NNLO QCD + LL EW

	1st bin	2nd bin	3rd bin	Total
NNPDF3.1	0.81	1.61	0.89	1.12
+ATLASγ	0.66	1.37	0.82	0.96



$t\bar{t}$ double differential distributions
(CMS 8 TeV)
theory based on NLO QCD

	$(p_T^t, y_{t\bar{t}})$	$(m_{t\bar{t}}, y_{t\bar{t}})$	$(m_{t\bar{t}}, y_t)$
NNPDF3.1	2.94	1.80	1.24
+2D $t\bar{t}$ distrs	2.49	1.18	1.18



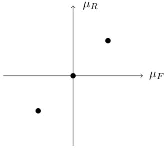
Good description of all data sets (except for 2D $(p_T^t, y_{t\bar{t}})$ distribution at NLO)

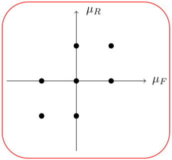
Moderate impact of the data on the gluon PDF

Fits with varied scales [NNPDF, in preparation, see also arXiv:1810.01996]

Standard technique to estimate MHOU:

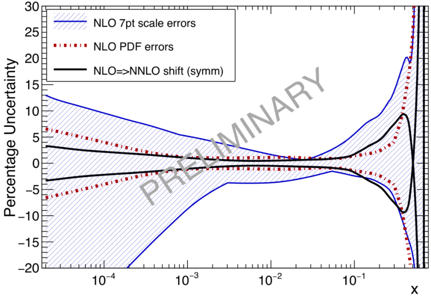
vary scales by 2 and $1/2$, and compute observables for various scale combinations



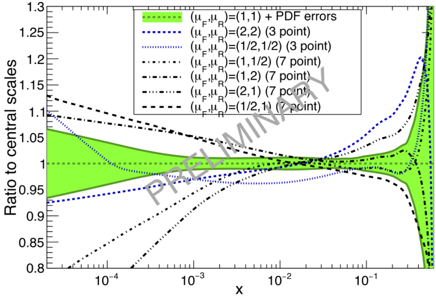


HXSWG recommendation

g(x,Q²=100 GeV²), NNPDF3.1 Global dataset



g(x,Q=100 GeV) [NNPDF3.1 NLO Global]



Useful for estimating MHOUs in PDFs but want to include them in fitting methodology, and in a way that is also applicable to other theoretical uncertainties

Theoretical uncertainties in PDF fits [arXiv:1801.04842]

1. Assuming that theoretical uncertainties are Gaussian, it follows from Bayes' theorem that they can be included in a fit by modifying the log-likelihood as

$$\chi^2(y,t[f],\sigma) \to \chi^{2\prime}(y,t[f],\sigma+s) = (y-t[f])^T(\sigma+s)^{-1}(y-t[f])$$

2. Problem reduced to estimate the theoretical covariance matrix s
$\longrightarrow$ missing higher order perturbative corrections

$$s_{ij}^{\rm mhou} = \Delta_i^+\Delta_j^+ - \Delta_i^-\Delta_j^- \quad \Delta_{i,j}^+ = t_{i,j}[f;\mu_0] - t_{i,j}[f;2\mu] \quad \Delta_{i,j}^- = t_{i,j}[f;\mu_0] - t_{i,j}[f;\frac{1}{2}\mu]$$

$\longrightarrow$ nuclear target uncertainties

$$s_{ij}^{\rm nucl} = \frac{1}{n_{\rm nuis}}\sum_{k=1}^{n_{\rm nuis}}\Delta_i^{(k)}\Delta_j^{(k)} \qquad \Delta_{i,j}^{(k)} = t_{ij}^{(k)}[f^N] - \langle t_{i,j}[f]\rangle$$

$\longrightarrow$ numerical uncertainties from Monte Carlo generators (read off from generators)
$\longrightarrow$ uncertainties from missing higher-twist terms and other non-perturbative effects
$\longrightarrow$ unpolarised PDF/FF uncertainties in the determination of polarised/unpolarised PDFs

$$s_{ij}^{\rm PDFs/FFs} = \frac{1}{N_{\rm rep}}\sum_{k=1}^{N_{\rm rep}}\Delta_i^{(k)}\Delta_j^{(k)} \qquad \Delta_{i,j}^{(k)} = t_{ij}^{(k)}[f^N] - \langle t_{i,j}[f]\rangle$$

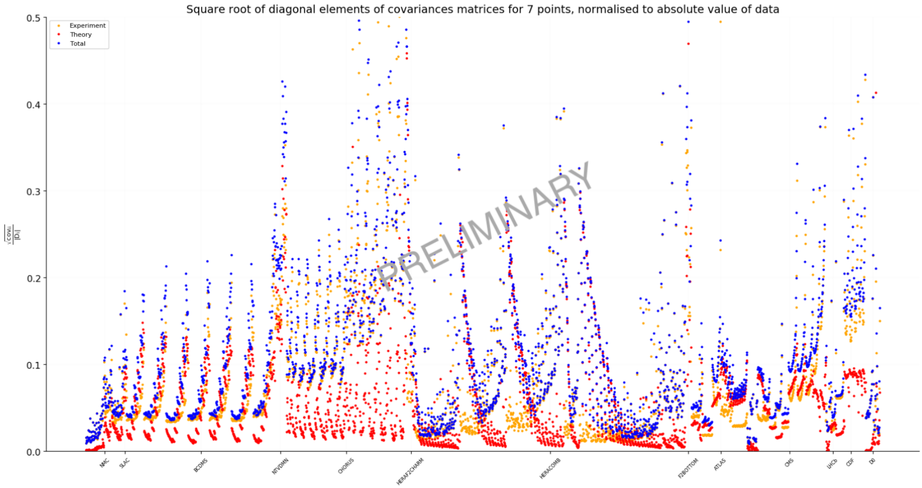
Example: MHO uncertainties in PDF fits [NNPDF, in progress]

μ_F variations are correlated across all processes (PDF evolution)

μ_R variations are correlated by process (hard cross section)

vary scales in $\frac{1}{2} \leq \frac{\mu_F}{\mu_{F,0}}, \frac{\mu_R}{\mu_{R,0}} \leq 2$; consider 3- or 7- point variations

average over flat distribution of points; consider different correlation treatments



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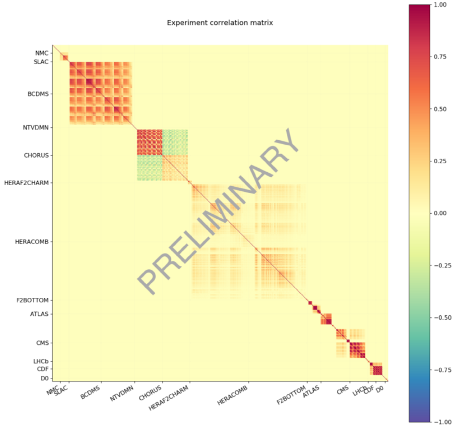
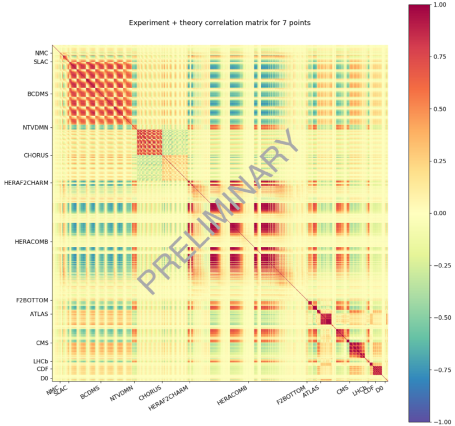
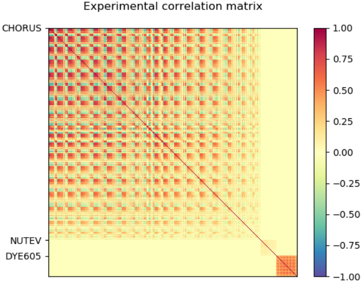
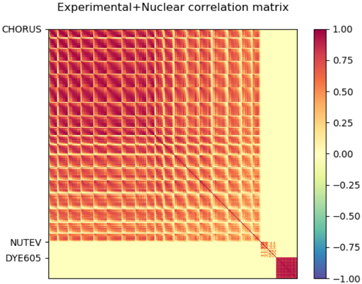




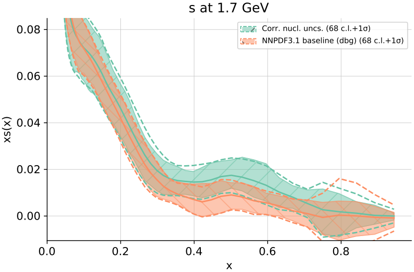
$\chi^2/N_{\rm dat} = 1.123$ (NLO, exp only) $\chi^2/N_{\rm dat} = 1.111$ (NLO, exp + th corr) $\chi^2/N_{\rm dat} = 0.579$ (NLO, exp + th unc)

Example: nuclear uncertainties in PDF fits [NNPDF, in progress]





nuclear uncertainties determined by averaging over Monte Carlo replicas from three nuclear PDF sets: DSSZ12, nCTEQ15 and EPPS16



Experiment	$N_{\rm dat}$	$\chi^2/N_{\rm dat}$ (bas.)	$\chi^2/N_{\rm dat}$ (nucl.)
CHORUS (ν)	416	1.20	0.75
CHORUS ($\bar{\nu}$)	416	1.29	0.95
NUTEV (ν)	37	0.90	0.40
NUTEV ($\bar{\nu}$)	39	0.41	0.29
DYE605	85	1.18	0.64
	4285	1.18	1.06

4. Conclusions

Summary

NNPDF3.1	June 2017	[Eur.Phys.J. C77 (2017) 663]
NNPDF3.1sx	October 2017	[Eur.Phys.J. C78 (2018) 321]
NNPDF3.1luxQED	December 2017	[SciPost Phys. 5 (2018) 008]
NNPDF α_s	January 2018	[Eur.Phys.J. C78 (2018) 408]

For more information, visit the NNPDF and LHAPDF web sites
`http://nnpdf.mi.infn.it/`   `https://lhapdf.hepforge.org/`

Outlook: the path towards NNPDF4.0

New data

Almost 40 new data sets due to be investigated

Theory uncertainties

How can we best represent PDF uncertainties due to MHO corrections?
What about nuclear corrections?

Electroweak corrections

Can electroweak effects be included systematically in the analysis of the observables?

Methodology

How can our fitting procedure keep pace with the data set?
Can modern optimisation tools help (evolutionary strategies, analytical gradients, . . .)?

Thank you