

NNPDF in the LHC Era

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- Issues in Standard PDF Determination
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Part I

Introduction

- Extraction of a set of functions with errors from a set of data points.
- We need an error band, i.e. a **probability density** $\mathcal{P}[f(x)]$ in the space of PDFs :

$$\langle \mathcal{O} \rangle = \int \mathcal{D}f \mathcal{P}[f] \mathcal{O}[f]$$

$$\sigma_{\mathcal{O}}^2 = \int \mathcal{D}f \mathcal{P}[f] (\mathcal{O}[f] - \langle \mathcal{O} \rangle)^2$$

Standard approach:

- 1 Choose a specific functional form:
 $q_i(x, Q_0^2) = A_i x^{b_i} (1-x)^{c_i} (1+\dots)$.
- 2 Errors determined by means of linear error propagation.

But:

- 1 Is the **parametrization** flexible enough?
- 2 What is the **error** associated to any particular choice?
- 3 Need to rely on **linear propagation** of errors.

- Generate **Monte Carlo replicas** of the experimental data:
 - **Generation** through Monte Carlo sampling of data,
 - **Validation** against experimental data.

⇒ No need to rely on **linear propagation** of errors,
⇒ possibility to test for **non-gaussian behaviour** in fitted PDFs.
- Fit PDFs with a set of **Neural Networks** on each replica:
 - **Redundant Parametrization**: 7 independent PDFs ⇒ 259 free parameters.
 - **Dynamical Stopping Criterion**: Cross-Validation method.

⇒ Neural Networks provide an **unbiased** parametrization.
- **Expectation values** for observables are **Monte Carlo integrals**:

$$\langle \mathcal{O}[f] \rangle = \frac{1}{N} \sum_{k=1}^N \mathcal{O}[f_k]$$

... and the same is true for errors, correlations, etc.

Part II

NNPDF2.1 LO, NLO and NNLO sets

NNPDF2.1 is an ensemble of PDF sets presently available at **LO**, **NLO** and **NNLO**.

The NNPDF Collaboration, R.D. Ball et al., [arXiv:1107.2652]

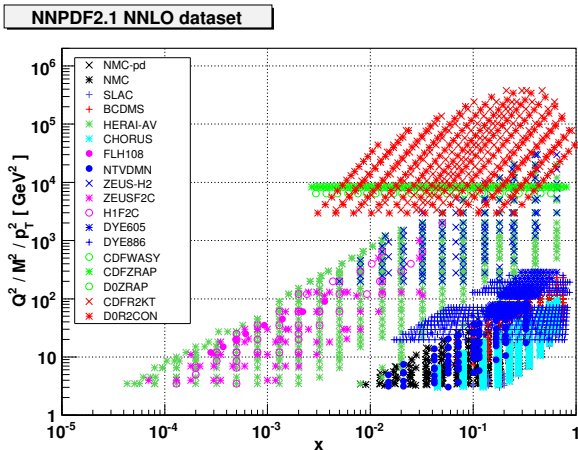
Features:

- **Global Fit**: DIS + DY + JET data.
- **Heavy quark** mass effects included using the **FONLL** method up to NNLO, S. Forte et al., Nucl. Phys. B834 (2010) 116, [arXiv:1001.2312]
- **FastKernel** method for the inclusion of the higher order corrections:
 - **DIS** up to **NNLO**,
 - **DY and JET** up to **NLO**.

The NNPDF Collaboration, R.D. Ball et al., Nucl. Phys. B838 (2010) 136, [arXiv:1002.4407]

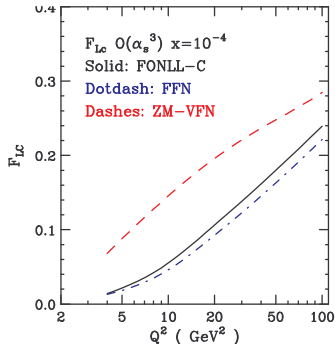
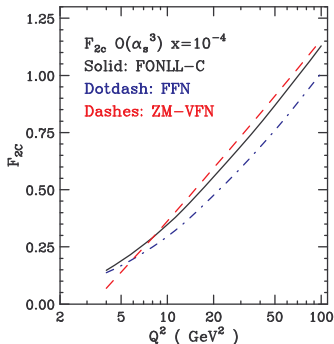
- **NNLO** corrections to **DY** included by means of **K-factors**,
- **NNLO** corrections to inclusive **JET** implemented using **FastNLO**:
 - approximated NNLO corrections based on threshold resummation.

T. Kluge, K. Rabbertz and M. Wobisch, (2006), [hep-ph/0609285]



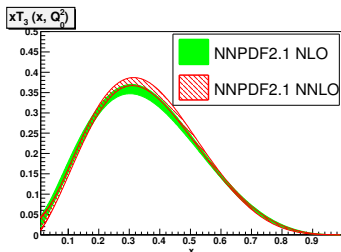
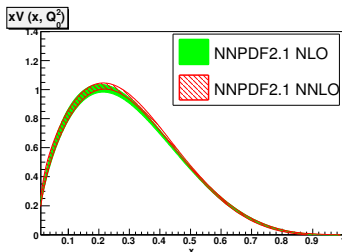
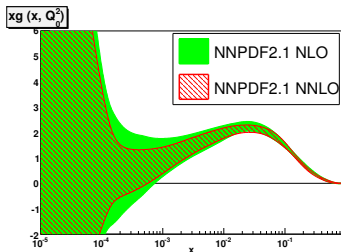
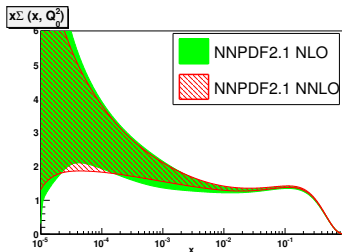
- Inclusion of the HERA F_2^c data.
- Inclusion of **systematics**.

- NNPDF2.1 implements the **FONLL method**: prescription for combining **massive quarks** in the decoupling scheme $N_F = 3$ and **massless quarks** in the \overline{MS} scheme $N_F = 4$, at any given order, **avoiding double counting**.
S.Forte, E.Laenen, P.Nason, J. Rojo [ArXiv:1001.2312]



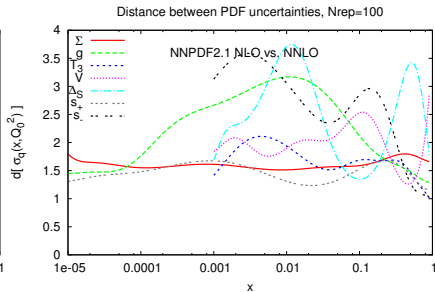
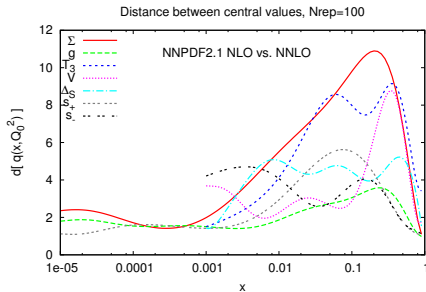
FONLL interpolates smoothly between massive (low Q^2) and massless (high Q^2) scheme.

Stability going from NLO to NNLO



In order to quantify the impact on the NNLO corrections, one defines the **distance**:

$$d^2 = \sum_{i=1}^{N_{rep}} \frac{(\mathcal{O}_{NLO}^{(i)} - \mathcal{O}_{NNLO}^{(i)})^2}{\sigma_{NLO}^2 + \sigma_{NNLO}^2} \quad \Rightarrow \quad \text{for } N_{rep}=100, d \sim \begin{cases} 1 & \text{Statistical equivalence} \\ \sqrt{50} \simeq 7 & 1\text{-}\sigma \text{ shift} \end{cases}$$

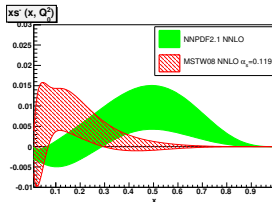
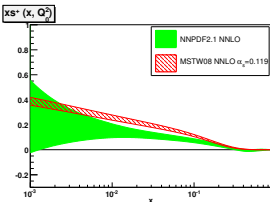
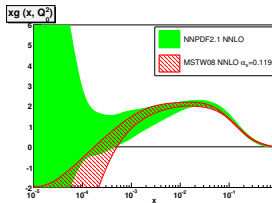
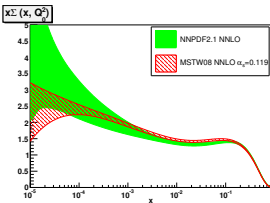


- NLO and NNLO PDFs **very similar at small-x**,
- Largest distances for **quarks at $x \sim 0.1 - 0.2$** ,
- very **small distances for PDF uncertainties**:
 - same (and only) **experimental uncertainties** for both NLO and NNLO fit.

NNPDF2.1

NNLO Parton Distributions: NNPDF2.1 vs. MSTW08

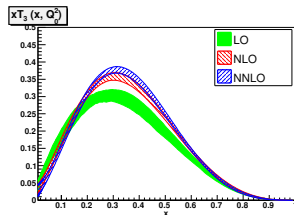
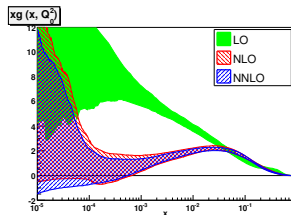
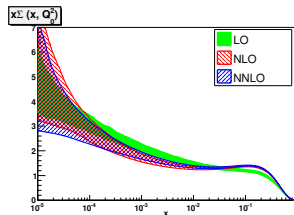
- Apart from NNPDF2.1, MSTW08 is presently the only NNLO PDF set available for different values of α_s .
- Comparison performed with a **common value of $\alpha_s(M_Z) = 0.119$** (NNPDF2.1 default value).



- **Reasonable agreement** between central values,
- MSTW08 uncertainties **unusually small**,
- MSTW08 gluon unstable at small x :
 - it becomes markedly negative.
- Sizable differences in the **Strange distributions**,
- restrictive MSTW parametrization for s^+ and s^- (only 4 parameters).

NNPDF2.1 now available at **LO, NLO and NNLO** \Rightarrow

study of **Perturbative Stability**



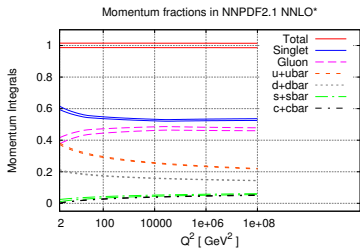
- **Excellent convergence** of the perturbative expansion,
- NLO and NNLO always agree within uncertainties.

Total momentum carried by partons:

$$[q](Q^2) \equiv \int_0^1 dx xq(x, Q^2) \Rightarrow [M] = [\Sigma] + [g] \stackrel{!}{=} 1$$

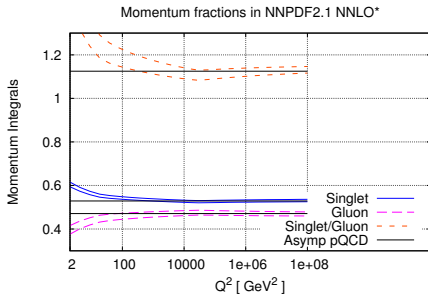
strong **consistency check** of global analysis framework.

- Default NNPDF2.1 sets produced imposing the momentum sum rule (MSR).
- Sets NNPDF2.1 LO*, NLO* and NNLO* produced relaxing MSR:
 - the fit quality doesn't change significantly.

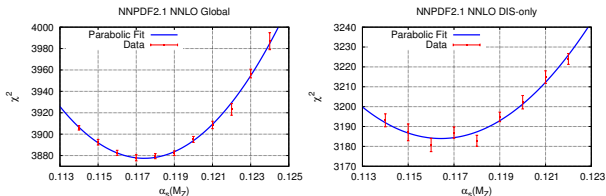


$$\begin{aligned}
 [M]_{\text{LO}^*} &= 1.161 \pm 0.032^{\text{exp}} \\
 [M]_{\text{NLO}^*} &= 1.011 \pm 0.018^{\text{exp}} \\
 [M]_{\text{NNLO}^*} &= 1.002 \pm 0.014^{\text{exp}}
 \end{aligned}$$

$$[\Sigma](Q^2)/[g](Q^2)$$

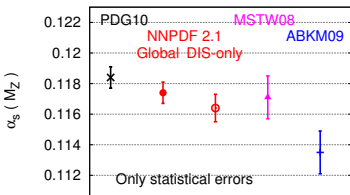


Parabolic fit of the **global** χ^2 as a function of the **input parameter** $\alpha_s(M_Z)$:



	$\alpha_s(M_Z)$	$\chi^2_{\text{par}}/N_{\text{dof}}$
NNPDF2.1 NNLO	$0.1174 \pm 0.0006^{\text{exp}}$	0.6
NNPDF2.1 NNLO DIS-only	$0.1164 \pm 0.0008^{\text{exp}}$	1.1

NNLO $\alpha_s(M_Z)$ from PDF Analyses

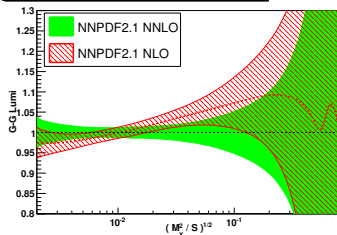


- **NNPDF2.1 global** determination consistent with the **PDG** determination at **1- σ** level,
- NNPDF2.1 global and DIS-only determinations agree within uncertainties,
- MSTW08 and ABKM09 values of α_s extracted as a **fitting parameter**,
- NNPDF2.1 and MSTW08 determinations in **good agreement**.

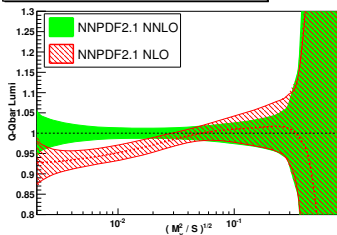
At LHC observables depend on PDFs through **Parton Luminosities**:

$$\Phi_{ij}(\tau) = \frac{1}{s} \int_{\tau}^1 \frac{dx}{x} f_i(x, M_X^2) f_j(\tau/x, M_X^2) \quad \text{with} \quad \tau = \frac{M_X^2}{s}$$

PDF Uncertainty parton lumis - LHC 7 TeV - Ratio to NNPDF2.1 NNLO



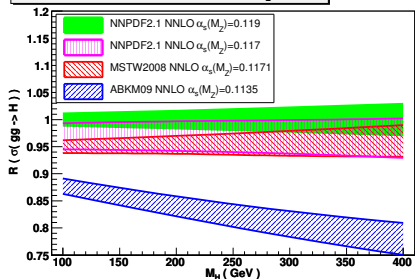
PDF Uncertainty parton lumis - LHC 7 TeV - Ratio to NNPDF2.1 NNLO



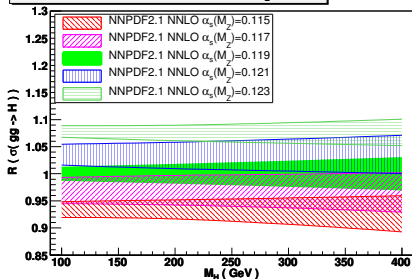
- All luminosities **reasonably compatible**.
- Gluon-gluon luminosity relevant for the **Higgs production**:
 - particularly stable in the “standard Higgs” region ($\sqrt{\tau} \simeq 2 \times 10^{-2}$).
- Quark-antiquark luminosity relevant for the **W/Z production**:
 - NNLO significantly larger than NLO in the W/Z mass region ($\sqrt{\tau} \simeq 10^{-2}$).

Higgs production from gluon-gluon fusion: Higgs exclusion bounds.

LHC 7 TeV, Ratio to NNPDF2.1 NNLO $\alpha_s(M_Z)=0.119$

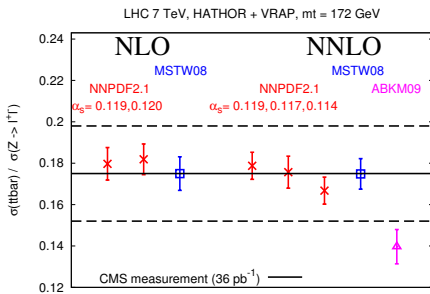
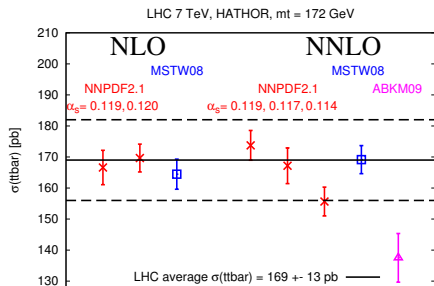


LHC 7 TeV, Ratio to NNPDF2.1 NNLO $\alpha_s(M_Z)=0.119$



- Strong dependence on α_s .
- NNPDF2.1 and MSTW08 in **excellent agreement**, provided the same value of α_s .
- Sizable differences between NNPDF2.1 and ABKM09:
 - partially accounted by the **different value of α_s** (right plot).

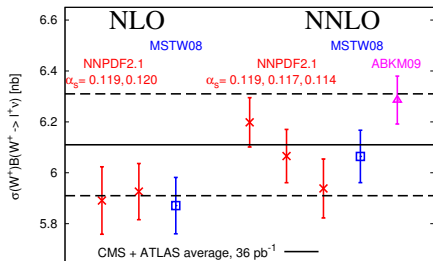
$t\bar{t}$ cross-section: sensitive probe of the gluon distribution.



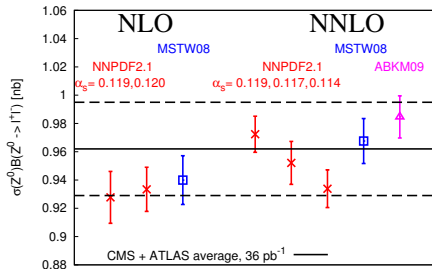
- Comparison with **CMS** and **ATLAS** measurements:
 - **Discrimination** between PDF sets,
 - NNPDF2.1 and MSTW08 in good agreement with LHC data,
 - ABKM09 does not agree with the present LHC measurements.
- NNPDF2.1 and MSTW08 in **good agreement** with each other:
 - consistently, using the **same value of α_s improves the agreement.**

W and Z production: light flavour decomposition.

LHC 7 TeV, VRAP



LHC 7 TeV, VRAP



- **Weaker dependence on α_s** for these processes:
 - but higher order correction not negligible.
- **Less significant differences** between PDF sets.

Part III

The first PDF set including LHC data: NNPDF2.2

The NNPDF Collaboration, R.D. Ball et al., [arXiv:1108.1758]

NNPDF2.2 NLO:



PDF set including D0 and LHC data

Reweighting NNPDF2.1 NLO using **D0**, **ATLAS** and **CMS** W asymmetry data:

$$A'_W = \frac{d\sigma_{I^+}/d\eta_I - d\sigma_{I^-}/d\eta_I}{d\sigma_{I^+}/d\eta_I + d\sigma_{I^-}/d\eta_I}$$

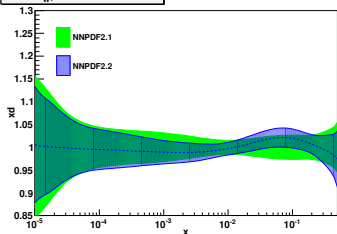
Experiment	N_{dat}	$\chi^2(\text{NNPDF2.1})$	$\chi^2(\text{NNPDF2.2})$
ATLASmuASY	11	[0.77]	1.07
CMSseASY	6	[1.83]	1.08
CMSmuASY	6	[1.24]	0.56
D0eASY	12	[4.39]	1.38
D0muASY	10	[1.48]	0.35
Total		1.165	1.157

*In NNPDF2.2 no deterioration in the χ^2 of the other experiments.

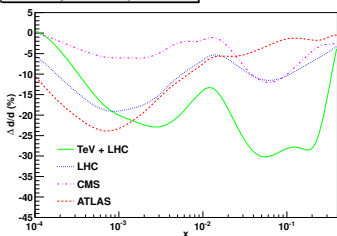
Light flavour PDFs more affected by the W asymmetry data:

- d distribution and light sea asymmetry $\Delta_s = (\bar{d} - \bar{u})$ most affected.

$Q^2 = M_W^2$, Ratio to NNPDF2.1



Percentage uncertainty reduction



Most noticeable effect in **two separate regions**:

- $x \sim 10^{-3}$, mostly affected by the **ATLAS** data.
- $x \sim 10^{-2} - 10^{-1}$, mostly affected by the **CMS** and **D0** data.
- Deviation **up to 1- σ** in the high x region:
 - mostly due to D0 data.

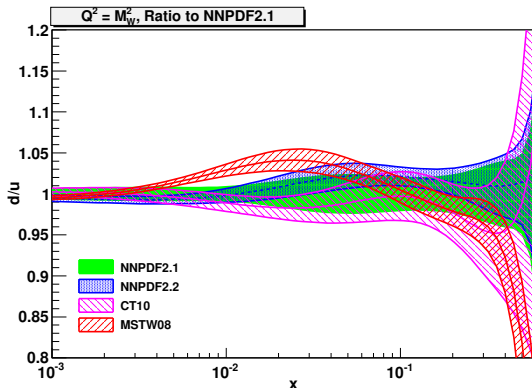
Sizable **uncertainties reduction**:

- $\sim 20\%$ in the low- x region,
- up to 30%** at the higher x .

NNPDF2.2

Results: NNPDF vs. CT10 and MSTW08

- NNPDF2.1 and MSTW08 do not include **any W asymmetry** data,
- CT10 includes **only D0 data**,
- NNPDF2.2 includes **D0, ATLAS and CMS data** (\Rightarrow **most reliable**).



Rather good agreement among NLO global PDFs, but:

- MSTW08 prediction too high at medium x and too low at large x .

Part IV

Conclusions

NNPDF Methodology:

- **Monte Carlo** sampling of data \Rightarrow No need for linear propagation of errors,
- **Neural Networks** as interpolating functions \Rightarrow Unbiased parametrization.

NNPDF2.1:

- **global fit** including **heavy quark** mass effects,
- available at **LO**, **NLO** and **NNLO**,

NNPDF2.2:

- Presently, the only PDF set including **ATLAS and CMS data**.

All the NNPDF PDF sets are available either on the web site:

<http://sophia.ecm.ub.es/nnpdf>

or through the LHAPDF interface.

Part V

Backup Slides

OBS	Data sets
DIS	
F_2^p	NMC,SLAC,BDCMS
F_2^d	SLAC,BCDMS
F_2^d/F_2^p	NMC-pd
σ_{NC}	HERA-I AV, ZEUS-H2
σ_{CC}	HERA-I AV, ZEUS-H2
F_L	H1
$\sigma_\nu, \sigma_{\bar{\nu}}$	CHORUS
dimuon prod.	NuTeV
F_2^c	ZEUS (99,03,08,09)
F_2^c	H1 (01,09,10)
DY	
$d\sigma^{\text{DY}}/dM^2 dy$	E605
$d\sigma^{\text{DY}}/dM^2 dx_F$	E886
W asymmetry	CDF
Z rap. distr.	CDF,D0
JET	
incl. $\sigma^{(\text{jet})}$	D0(cone) Run II
incl. $\sigma^{(\text{jet})}$	CDF(k_T) Run II

NLO cuts:

- $W^2 = Q^2(1-x)/x > 12.5 \text{ GeV}^2$,
- $Q^2 > 3 \text{ GeV}^2$ + further cuts on F_2^c :
 - no data below m_c ($m_c^2 = 2, 2.25, 2.56, 2.89 \text{ GeV}^2$),
- no cuts on hadronic data.

LO cuts:

- NLO cuts,
- F_L data removed (null at LO).

NNLO cuts:

- NLO cuts,
- further cuts on F_2^c removed,
- conversion of the E866 data from x_F to y distributions,
- NMC proton data included as reduced cross-sections, rather than structure functions.

- NNPDF2.1 implements the **FONLL method**: prescription for combining **massive quarks** in the decoupling scheme $N_F = 3$ and **massless quarks** in the \overline{MS} scheme $N_F = 4$, at any given order, **avoiding double counting**.

Reference: S.Forte, E.Laenen, P.Nason, J. Rojo [ArXiv:1001.2312]

- Definition of FONLL structure function:

$$F^{\text{FONLL}}(x, Q^2) = F^{(n_f+1)}(x, Q^2) + F^{(n_f)}(x, Q^2) - F^{(n_f,0)}(x, Q^2)$$

$F^{(n_f+1)}(x, Q^2)$: massless-scheme structure function

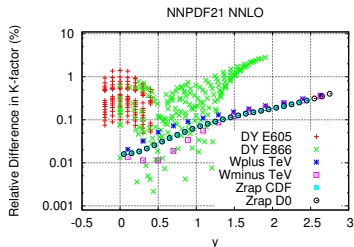
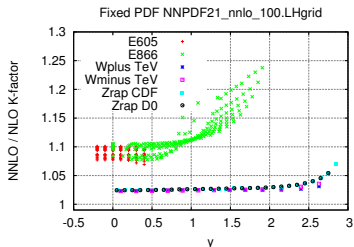
$F^{(n_f)}(x, Q^2)$: massive-scheme structure function \Rightarrow inclusion of the mass suppressed terms

$F^{(n_f,0)}(x, Q^2)$: massless limit of $F^{(n_f)}(x, Q^2) \Rightarrow$ subtraction of the double counting terms

- At the moment, three possibilities:
 - FONLL-A: $\mathcal{O}(\alpha_s)$ PDFs + $\mathcal{O}(\alpha_s)$ coefficient functions (NNPDF2.1 NLO set),
 - FONLL-B: $\mathcal{O}(\alpha_s)$ PDFs + $\mathcal{O}(\alpha_s^2)$ coefficient functions,
 - FONLL-C: $\mathcal{O}(\alpha_s^2)$ PDFs + $\mathcal{O}(\alpha_s^2)$ coefficient functions (NNPDF2.1 NNLO set).
- $\mathcal{O}(\alpha_s^2)$ coefficient functions available only in the NC and not the CC sector.
- **NNPDF2.1** is presently available in **all** the above schemes.

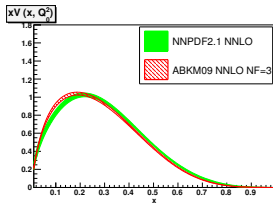
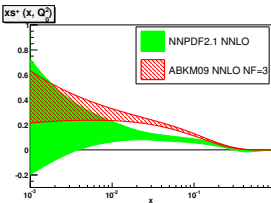
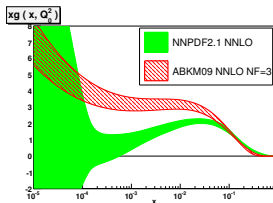
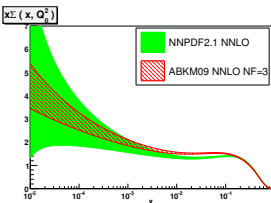
- **Hadronic data** treated **consistently in pQCD up to NNLO**.
- **DY NNLO** effects included by means of **K-factors**:

$$K = \frac{(d^2\sigma/dy dM^2)_{\text{NNLO}}}{(d^2\sigma/dy dM^2)_{\text{NLO}}}$$



- **Collider data**: a few percent level,
- **fixed-target data**: up to 25% \Rightarrow but experimental errors $\mathcal{O}(20\%)$.
- **K-factor recomputed with NNPFD2.1 NNLO set**:
 - accuracy $< 2\%$ \Rightarrow cross-section uncertainty $< 0.5\%$
- Inclusive **JET** data, exact NNLO corrections not known yet, but:
 - **approximated NNLO corrections** based on threshold resummation,
 - exact NNLO PDF evolution.

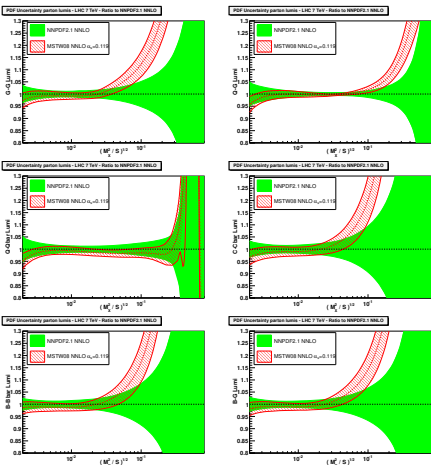
- Interesting comparison with the ABKM09 ($N_f = 3$) NNLO set, but some caveat:
 - only one value of α_s available for the ABKM set: $\alpha_s(M_Z) = 0.1135 \pm 0.0014$,
 - the ABKM distributions account for the combined PDF+ α_s error.



- Comparison performed with the smallest value of α_s provided by NNPDF2.1: $\alpha_s = 0.114$,
- worse agreement with respect of MSTW08.
- Reasonable agreement for Total Strangeness and Valence.

At LHC observables depend on PDFs through **Parton Luminosities**:

$$\Phi_{ij}(\tau) = \frac{1}{s} \int_{\tau}^1 \frac{dx}{x} f_i(x, M_X^2) f_j(\tau/x, M_X^2) \quad \text{with} \quad \tau = \frac{M_X^2}{s}$$



- Same value of $\alpha_s = 0.119$.
- General good agreement in the region of τ of the typical electroweak final states at LHC ($M_X \sim 100$ GeV).
- Huge disagreement at high M_X :
 - MSTW08 NNLO gluon instability at small- x

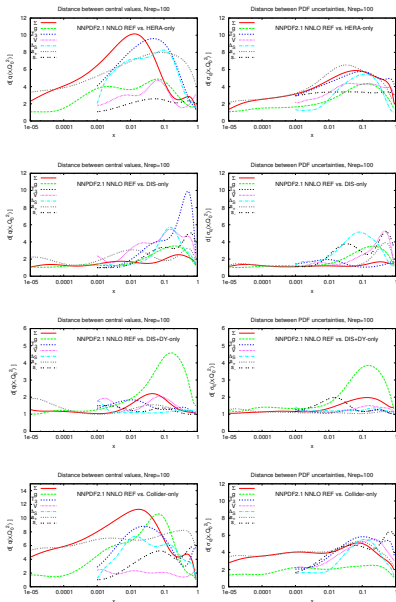
The **NNPDF approach** allows to obtain reliable PDFs from datasets of widely varying size without having to modify any aspect of the methodology.



Study of the dependence of PDFs on the underlying dataset.

NNPDF provides **four new NNLO PDF set**, based on subsets of the full dataset:

- 1 **NNPDF2.1 NNLO HERA-only**: **only HERA data**
 - the HERAPDF group provides PDFs based on the same dataset.
- 2 **NNPDF2.1 NNLO DIS-only**: **no hadron-hadron data**
 - DIS data theoretically and experimentally more clean.
- 3 **NNPDF2.1 NNLO DIS+DY**: **no JET data**
 - approximated NNLO JET.
- 4 **NNPDF2.1 NNLO Colliders-only**: **no fixed-target data**
 - fixed-target data less clean: low energy and nuclear targets.



HERA-only: **general poor description of data,**

- s^+ very uncertain $\Rightarrow \chi^2$ NuTeV data very poor.
- bad Singlet-Triplet (Σ and T_3) decomposition,
- bad light sea (Δ_s) decomposition.

DIS-only: **reasonably accurate flavour decomposition,**

- Σ and g in perfect agreement with the global fit,
- also V , s^+ and Δ_s in good agreement,
- substantial deviation of T_3 . (???)

DIS+DY: **quite close to the global fit,**

- almost all PDFs statistically equivalent,
- reduction of the uncertainties.

Colliders-only: **fixed-target data description very poor,**

- almost all PDFs disagree with the global fit,
- colliders-only dataset more consistent (global $\chi^2 = 1.02$),
- improvement expected with the upcoming HERA-II and LHC data.

Experiment	Global	HERA-only	DIS-only	DIS+DY	Collider-only
N_{dat}	3507	976	2933	3321	1232
Total	1.16	1.07	1.15	1.18	1.02
NMC-pd	0.93	[13.15]	0.88	0.94	[3.43]
NMC	1.63	[1.91]	1.69	1.69	[2.06]
SLAC	1.01	[3.17]	0.97	1.03	[1.23]
BCDMS	1.32	[2.15]	1.28	1.30	[2.22]
HERAI-AV	1.10	1.05	1.09	1.09	1.06
CHORUS	1.12	[2.63]	1.08	1.13	[1.74]
FLH108	1.26	1.32	1.27	1.26	1.26
NTVDMN	0.49	[60.51]	0.45	0.54	[23.02]
ZEUS-H2	1.31	1.21	1.26	1.28	1.30
ZEUSF2C	0.88	0.77	0.86	0.88	0.75
H1F2C	1.46	1.30	1.47	1.50	1.24
DYE605	0.81	[9.06]	[6.86]	0.82	[1.34]
DYE866	1.32	[12.41]	[2.70]	1.32	[5.76]
CDFWASY	1.65	[7.71]	[13.94]	1.64	1.07
CDFZRAP	2.12	[3.74]	[2.15]	1.91	1.22
D0ZRAP	0.67	[1.11]	[0.67]	0.65	0.61
CDFR2KT	0.74	[1.15]	[0.99]	[1.25]	0.64
D0R2CON	0.82	[1.28]	[0.88]	[1.03]	0.83

* [...] not fitted sets.

Reweighting allows to incorporate a new dataset into an PDF set **without refitting**.

For users:

- 1 Take an NNPDF parton distribution set $\{f_k\}$, with $k = 1, \dots, N_{rep}$ (NNPDF2.1 for instance),
- 2 take the new dataset $y = \{y_1, \dots, y_n\}$ and its eventual covariance matrix σ_{ij} ,
- 3 compute the χ^2 of each replica on the new set y according to usual formula:

$$\chi_k^2 = \sum_{i,j=1}^n (y_i - y_i[f_k]) \sigma_{ij}^{-1} (y_j - y_j[f_k])$$

where $y_i[f_k]$ is the prediction for the experimental point y_i using the k -th replica,

- 4 evaluate the weights according to the formula:

$$w_k \propto (\chi_k^2)^{\frac{1}{2}(n-1)} e^{-\frac{1}{2}\chi_k^2} \quad \text{with} \quad \sum_{k=1}^{N_{rep}} w_k = N_{rep},$$

- 5 compute the new expectation value of your favourite observable as:

$$\langle \mathcal{O} \rangle_{new} = \frac{1}{N_{rep}} \sum_{k=1}^{N_{rep}} w_k \mathcal{O}[f_k].$$

Unweighting allows to construct a standard PDF set (without weights) **statistically equivalent** to a given reweighted set.

Idea:

Given a weighted set of N_{rep} replicas,
select (eventually more than once) replicas carrying relatively high weight
and discard replicas carrying relatively small weight.

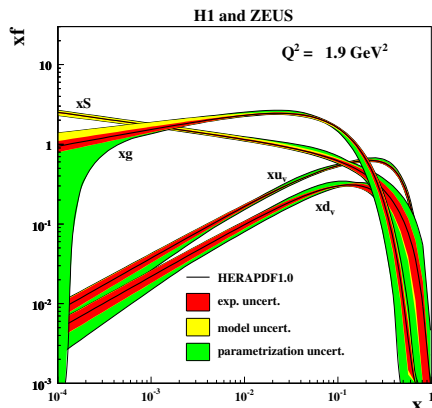
Construction of the unweighted set:

- Decide the number of replicas N'_{rep} of the unweighted set:
 - pointless to choose $N'_{rep} > N_{rep}$: no gain of information.
- calculate for the k -th replica of the reweighted set the **integer non negative** number:

$$w'_k = \sum_{j=1}^{N'_{rep}} \theta \left(\frac{j}{N'_{rep}} - w_{k-1} \right) \theta \left(w_k - \frac{j}{N'_{rep}} \right) \quad \left(\Rightarrow \sum_{k=1}^{N_{rep}} w'_k = N'_{rep} \right),$$

- construct the unweighted set taking w'_k copies of the k -th replica, for $k = 1, \dots, N_{rep}$.

Reference: [arXiv:0911.0884]



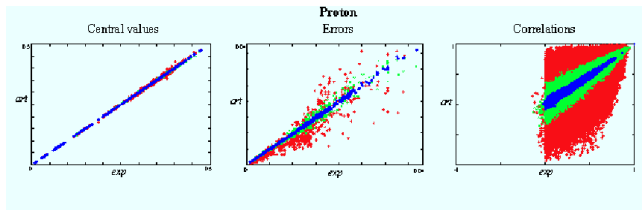
- HERAPDF analysis: computation of parametrization uncertainty on top of the model (initial scale and heavy quark mass effects) and experimental uncertainty.
- In many regions the **parametrization uncertainty** is **dominating**.

- **Generation** of artificial Monte Carlo data according to the distribution:

$$\mathcal{O}_i^{(art)(k)} = (1 + r_{norm}^{(k)}\sigma_{norm}) \left[\mathcal{O}_i^{(exp)} + r_{stat}^{(k)}\sigma_{stat} + \sum_{p=1}^{N_{sys}} r_{sys,p}^{(k)}\sigma_{sys,p} \right]$$

where $r_i^{(k)}$ are univariate (gaussianly distributed) random numbers.

- **Validation** of the Monte Carlo replicas against experimental data .



Red points: 10 replicas
 Green points: 100 replicas
 Blue points: 1000 replicas

- $\mathcal{O}(1000)$ replicas needed to reproduce correlations to the percent accuracy.

- **Unbiased basis** of functions parameterized by a very large and **redundant set of parameters** \Rightarrow **Neural Networks**.
- Each one of the **7 independent PDFs**:

Gluon	$g(x)$
Singlet	$\Sigma(x) = \sum_q (q(x) + \bar{q}(x))$
Valence	$V(x) = \sum_q (q(x) - \bar{q}(x))$
Triplet	$T_3(x) = (u(x) + \bar{u}(x)) - (d(x) + \bar{d}(x))$
Sea asymmetry	$\Delta_S(x) = \bar{d}(x) - \bar{u}(x)$
Total Strangeness	$s^+(x) = s(x) + \bar{s}(x)$
Strange Valence	$s^-(x) = s(x) - \bar{s}(x)$

is parametrized at the initial scale $Q_0^2 = 2 \text{ GeV}^2$ by an individual Neural Network having architecture 2-5-3-1 \Rightarrow **37 parameters**.

259 parameters

Standard fits have ~ 25 parameters in total

$$\xi_i = g \left(\sum_j w_{ij} \xi_j + \theta_i \right),$$

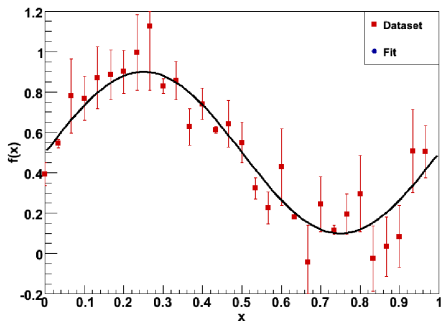
$g(x) = \frac{1}{1 + \exp(-x)}$ **Neural Networks are just functions, which adapt well to any functional behaviour.**

For instance, a **(1-2-1)** NN is:

Drawback:

A redundant parametrization might fit not only to physical behavior but also to random statistical fluctuations of data.

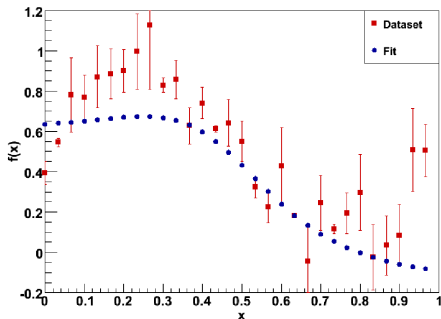
UNDERLYING PHYSICAL LAW



Drawback:

A redundant parametrization might fit not only to physical behavior but also to random statistical fluctuations of data.

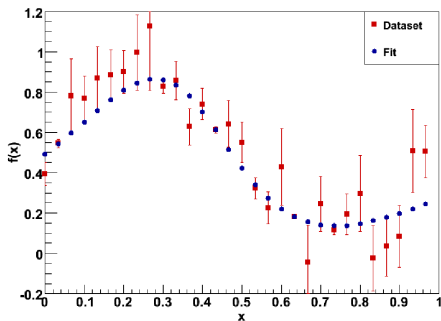
UNDERLEARNING



Drawback:

A redundant parametrization might fit not only to physical behavior but also to random statistical fluctuations of data.

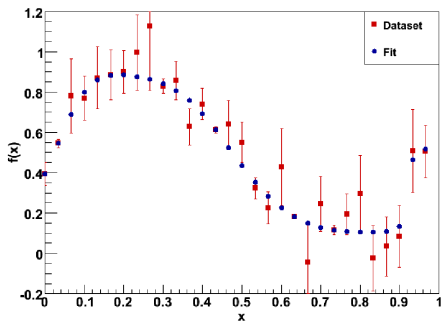
PROPER LEARNING



Drawback:

A redundant parametrization might fit not only to physical behavior but also to random statistical fluctuations of data.

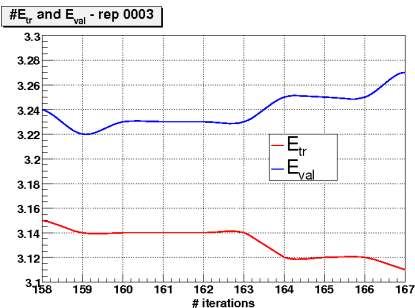
OVERLEARNING

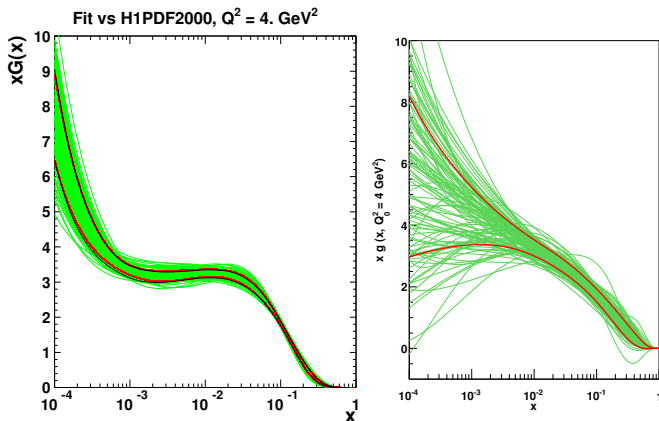


Need for a suitable stopping criterion!

Cross-validation method:

- * Divide data in two sets: training and validation (for each experiment).
- * Random division for each replica (typically $f_t = f_v = 0.5$).
- * Minimisation performed only on the training set. Meantime, the validation χ^2 is monitored.
- * When the training χ^2 still decreases while the validation χ^2 stops decreasing \rightarrow **STOP**.





- Simple functional forms $q(x) = Ax^b(1-x)^cP(x)$ (CT, MSTW, ABKM, HERAPDF)
→ **systematic underestimation of uncertainties**
- Artificial Neural Networks as universal interpolants (NNPDF)
→ avoid **theoretical bias** from choice of **PDF functional form**

- We use **Neural Networks** as functions to represent PDFs at the starting scale.
- We employ Multilayer Feed-Forward Neural Networks trained using a **Genetic Algorithm**
- Activation determined by weights and thresholds:

$$\xi_i = g \left(\sum_j \omega_{ij} \xi_j - \theta_i \right), \quad g(x) = \frac{1}{1 + e^{-x}}$$

For instance, a (1-2-1) NN is:

$$\xi_1^{(3)} = \frac{1}{1 + e^{\theta_1^{(3)} - \frac{\omega_{11}^{(2)}}{1 + e^{\theta_1^{(2)} - \xi_1^{(1)} \omega_{11}^{(1)}}} - \frac{\omega_{12}^{(2)}}{1 + e^{\theta_2^{(2)} - \xi_1^{(1)} \omega_{21}^{(1)}}}}$$

- They provide a parametrization which is redundant and robust against variations.