NNPDF analyses

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QCD at LHC, Trento

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The NNPDF Collaboration
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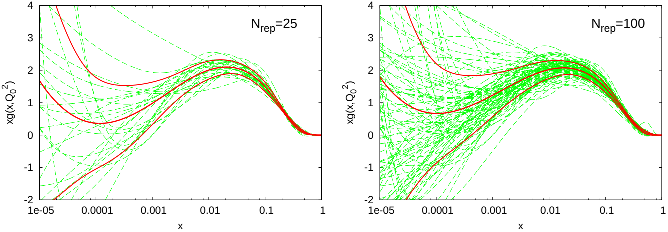
Outline

- Ensemble of replicas: probability distribution in the space of PDFs.
- Any feature of distribution can be determined using statistical tools.



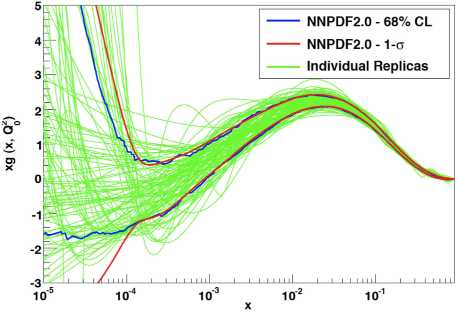
$$\langle \mathcal{F}[\{f\}] \rangle = \frac{1}{N_{\rm rep}} \sum_{k=1}^{N_{\rm rep}} F[f_k]$$

$$\sigma_{\mathcal{F}} = \left(\frac{N_{\rm rep}}{N_{\rm rep}-1} \left(\langle \mathcal{F}[\{f\}]^2 \rangle - \langle \mathcal{F}[\{f\}] \rangle^2 \right) \right)^{1/2}$$

NNPDF: What we do deliver?

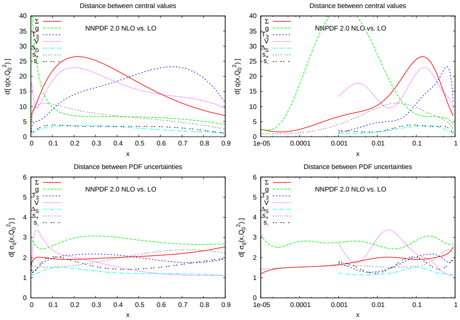
A Monte Carlo set of replicas

- Ensemble of replicas: probability distribution in the space of PDFs.
- Any feature of distribution can be determined using statistical tools.



* Not only the standard deviation but also the 68% CL.
* Uncertainties are Gaussian in the data region, less in the extrapolation.

- Ensemble of replicas: probability distribution in the space of PDFs.
- Any feature of distribution can be determined using statistical tools.



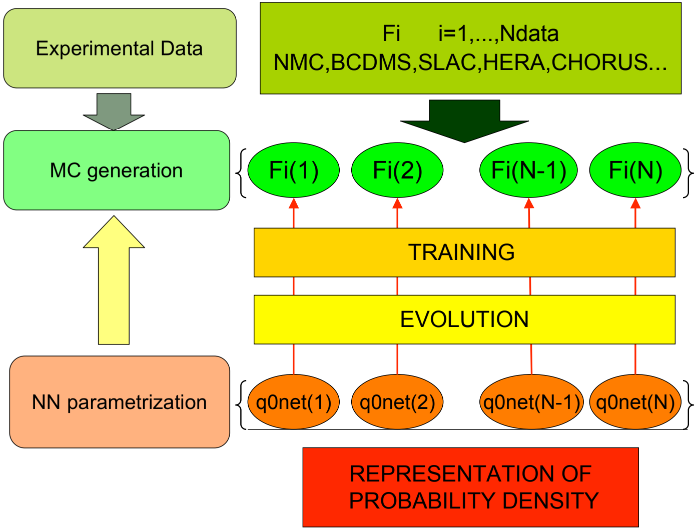
$$d(q_j) = \sqrt{\left\langle \frac{\left(\langle q_j\rangle_{(1)} - \langle q_j\rangle_{(2)}\right)^2}{\sigma_1^2[q_j] + \sigma_2^2[q_j]} \right\rangle_{N_{\rm part}}}$$

$$d(\sigma_j) = \sqrt{\left\langle \frac{\left(\langle \sigma_j\rangle_{(1)} - \langle \sigma_j\rangle_{(2)}\right)^2}{\sigma_1^2[\sigma_j] + \sigma_2^2[\sigma_j]} \right\rangle_{N_{\rm part}}}$$

* Mean PDFs extracted from a Monte Carlo set of N_{rep} replicas fluctuates with standard deviation σ/N_{rep}
* If two Monte Carlo sets are extracted from the same underlying distribution then $d \sim 1$
* We can quantify the stability and the differences between fits.

NNPDF approach

General scheme



- Generate a N_{rep} Monte Carlo sets of artificial data, or "pseudo-data" of the original N_{data} data points.

$$F_i^{(art)(k)}(x_p, Q_p^2) \equiv F_{i,p}^{(art)(k)} \qquad \begin{array}{rcl} i &=& 1,\ldots,N_{\mathrm{data}} \\ k &=& 1,\ldots,N_{\mathrm{rep}} \end{array}$$

- Multi-gaussian distribution centered on each data point:

$$F_{i,p}^{(art)(k)} = S_{p,N}^{(k)}\, F_{i,p}^{\mathrm{exp}} \left(1 + r_p^{(k)} \sigma_p^{\mathrm{stat}} + \sum_{j=1}^{N_{\mathrm{sys}}} r_{p,j}^{(k)} \sigma_{p,j}^{\mathrm{sys}}\right)$$

- If two points have correlated systematic uncertainties,

$$r_{p,j}^{(k)} = r_{p',j}^{(k)}$$

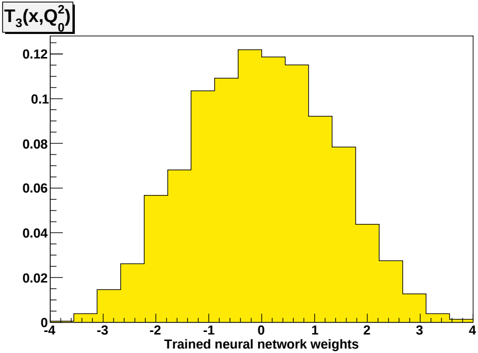
- Correlations are properly taken into account using the full covariance matrix.

- Each independent PDF is described by a large neural network: 259 parameters.
- Normalization is fixed by momentum and valence sum rules.

$$
\begin{aligned}
\Sigma(x,Q_0^2) &= (1-x)^{m_\Sigma} x^{-n_\Sigma} \mathrm{NN}_\Sigma(x)\,, & \mathrm{NN}_\Sigma &\to 37\ \mathrm{pars}\\
V(x,Q_0^2) &= A_V (1-x)^{m_V} x^{-n_V} \mathrm{NN}_V(x)\,, & \mathrm{NN}_V &\to 37\ \mathrm{pars}\\
T_3(x,Q_0^2) &= (1-x)^{m_{T_3}} x^{-n_{T_3}} \mathrm{NN}_{T_3}(x)\,, & \mathrm{NN}_{T_3} &\to 37\ \mathrm{pars}\\
\Delta_S(x,Q_0^2) &= A_{\Delta_S} (1-x)^{m_{\Delta_S}} x^{-n_{\Delta_S}} \mathrm{NN}_{\Delta_S}(x)\,, & \mathrm{NN}_{\Delta_S} &\to 37\ \mathrm{pars}\\
g(x,Q_0^2) &= A_g (1-x)^{m_g} x^{-n_g} \mathrm{NN}_g(x)\,, & \mathrm{NN}_g &\to 37\ \mathrm{pars}\\
s^+(x,Q_0^2) &= (1-x)^{m_s^+} x^{-n_s^+} NN_{s^+}(x)\,, & \mathrm{NN}_{s^+} &\to 37\ \mathrm{pars}\\
s^-(x,Q_0^2) &= (1-x)^{m_s^-} x^{-n_s^-} NN_{s^-}(x) - A_{s^-}[x^{r_{s^-}}(1-x)^{m_{t^-}}], & \mathrm{NN}_{s^-} &\to 37\ \mathrm{pars}
\end{aligned}
$$

- The preprocessing helps in speeding up the learning process.
- The preprocessing exponents are randomly set for each replica within a reasonable range.
- Very weak correlation is found: independence of the preprocessing.

$$
r\left[\chi^2, m_\Sigma\right] \equiv \frac{\langle \chi^2 m_\Sigma \rangle_{\mathrm{rep}} - \langle \chi^2 \rangle_{\mathrm{rep}} \langle m_\Sigma \rangle_{\mathrm{rep}}}{\sigma^2_{m_\Sigma}} \sim 0\,.
$$



* Set of neural networks at stopping provides our best-fit.
* No physical interpretation for parameters: most unconstrained or zero.

NNPDF approach

Fitting procedure

- The figure of merit used in the minimization is the fully correlated χ^2.
- Normalization is treated according to the t_0-prescription.

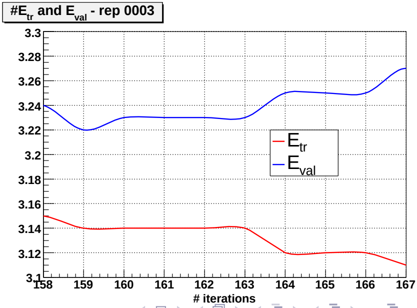
$$E^{(k)}[\omega] \quad = \quad \frac{1}{N_{\rm dat}} \sum_{i,j=1}^{N_{\rm dat}} \left(F_i^{({\rm art})(k)} - F_i^{({\rm net})(k)} \right) \left({\rm cov}_{t_0}^{(k)} \right)^{-1}_{ij} \left(F_j^{({\rm art})(k)} - F_j^{({\rm net})(k)} \right) \, ,$$

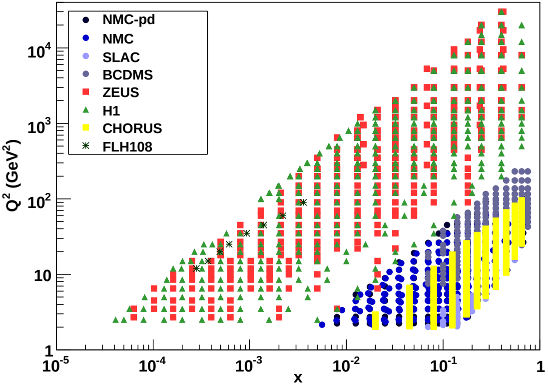
$$\left({\rm cov}_{\rm t_0}^{\rm (k)} \right)_{ij} \quad = \quad \left(\sum_{l=1}^{N_c} \sigma_{i,l}\sigma_{j,l} + \delta_{ij}\sigma_{i,s}^2 \right) F_i^{({\rm art})(k)} F_j^{({\rm art})(k)} + \left(\sum_{n=1}^{N_a} \sigma_{i,n}\sigma_{j,n} + \sum_{n=1}^{N_r} \sigma_{i,n}\sigma_{j,n} \right) F_i^{(0)} F_j^{(0)} \, ,$$

- In a redundant parameter space the minimum is not give by the absolute minimum

Cross-validation method

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





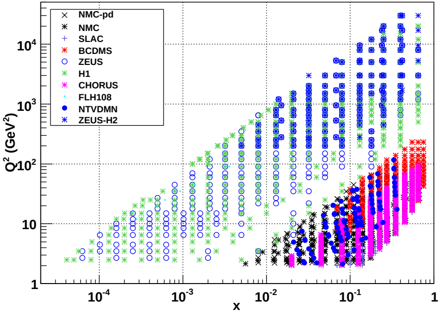
OBS	Data set	OBS	Data set
F_2^p	NMC	σ^{-}_{NC}	ZEUS
	SLAC		H1
	BCDMS	σ^{+}_{CC}	ZEUS
F_2^d	SLAC		H1
	BCDMS	σ^{-}_{CC}	ZEUS
σ^{+}_{NC}	ZEUS		H1
	H1	σ_{ν} , $\sigma_{\bar{\nu}}$	CHORUS
F_2^d / F_2^p	NMC-pd	F_L	H1

- Kinematical cuts:
  $Q^2 > 2$ GeV^2
  $W^2 = Q^2(1-x)/x > 12.5$ GeV^2
- Target mass corrections included.
- No nuclear corrections.

3161 data points

NNPDF features

Data sets: NNPDF1.2

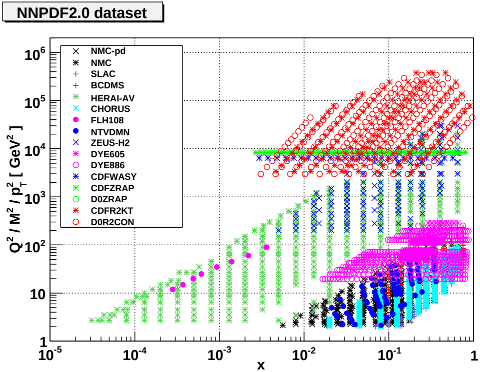


3372 data points

- Tested the impact of nuclear corrections (NuTeV, A=49.6; CHORUS, A=206). Effect within statistical fluctuation.
- I-ZMVFN scheme for F_i^c structure functions (ZMVFN scheme for all other data). $\chi_c = x(1 + m_c^2/Q^2)$

$$
\begin{aligned}
\tilde{\sigma}^{\nu(\bar{\nu}),c} &\propto (F_2^{\nu(\bar{\nu}),c}, F_3^{\nu(\bar{\nu}),c}, F_L^{\nu(\bar{\nu}),c}) \\
F_2^{\nu,c} &= x\left[C_{2,q} \otimes 2|V_{cs}|^2 s + \frac{1}{n_f} C_{2,g} \otimes g\right] \\
F_2^{\bar{\nu},c} &= x\left[C_{2,q} \otimes 2|V_{cs}|^2 \bar{s} + \frac{1}{n_f} C_{2,g} \otimes g\right]
\end{aligned}
$$

* Neutrino and anti-neutrino dimuon production from NuTeV.
* HERA-II ZEUS data on NC and CC reduced xsec at large-Q^2.
* HERA-II ZEUS data on $xF_3^{\gamma Z}$.
* CCFR $\sigma^{\nu,c}$ not included since less accurate.
* CHORUS $\sigma^{\nu,c}$ since only LO QCD analysis available.



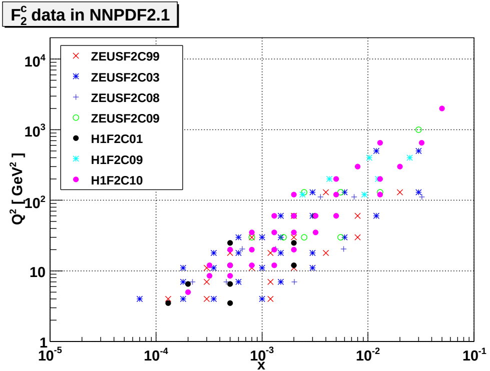
OBS	Data sets
F_2^p	NMC,SLAC,BDCMS
F_2^d	SLAC,BCDMS
F_2^d / F_2^p	NMC-pd
σ_{NC}	HERA-I AV, ZEUS-H2
σ_{CC}	HERA-I AV, ZEUS-H2
F_L	H1
σ_ν , $\sigma_{\bar{\nu}}$	CHORUS
dimuon prod.	NuTeV
$d\sigma^{\mathrm{DY}} / dM^2 dy$	E605
$d\sigma^{\mathrm{DY}} / dM^2 dx_F$	E886
W asymmetry	CDF
Z rap. distr.	CDF,D0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

3477 data points

- No cuts on hadronic data.
- ZM-VFN scheme for treatment of heavy quark masses.

* Included combined HERA data.
* Included Tevatron Run II and DY fixed target data.

* E772 and E886d not included since they do not add information.
* W lepton asymmetries not included (see re-weighting studies)
* Tevatron Run I jet data not included due to increased statistics in run II.



OBS	Data sets
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
σ_ν , $\sigma_{\bar{\nu}}$	CHORUS
dimuon prod.	NuTeV
$d\sigma^{\rm DY} / dM^2 dy$	E605
$d\sigma^{\rm DY} / dM^2 dx_F$	E886
W asymmetry	CDF
Z rap. distr.	CDF,D0
incl. $\sigma^{\rm (jet)}$	D0(cone) Run II
incl. $\sigma^{\rm (jet)}$	CDF(k_T) Run II
F_2^c	**ZEUS (99,03,08,09)**
F_2^c	**H1 (01,09,10)**

3554 data points

- HQ mass effects implemented according to the FastKernel method. Exact NLO analysis.
- * Included F_2^c data from H1 and ZEUS.

* Does not include F_2^b due to large uncertainties.

NNPDF features

Theoretical side: perturbative order and heavy quark treatment

- A truly NLO analysis (no K-factors).
  * NNPDF2.0 includes full NLO calculation of hadronic observables.
  * Use available fastNLO interface for jet inclusive cross-sections.[hep-ph/0609285]
  * Built up our own FastKernel computation of Drell-Yan observables.

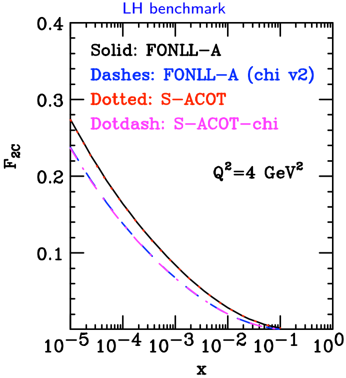
- Both PDFs evolution and double convolution are sped up by:
  * Use of high-orders polynomial interpolation
  * Pre–computing all Green Functions

$$\int_{x_{0,1}}^{1} dx_1 \int_{x_{0,2}}^{1} dx_2\, f_a(x_1) f_b(x_2) C^{ab}(x_1, x_2) \to \sum_{\alpha,\beta=1}^{N_x} f_a(x_{1,\alpha}) f_b(x_{2,\beta}) \int_{x_{0,1}}^{1} dx_1 \int_{x_{0,2}}^{1} dx_2\, \mathcal{I}^{(\alpha,\beta)}(x_1, x_2) C^{ab}(x_1, x_2)$$

- Up to NNPDF2.0, the ZM-VFNS is implemented for inclusion of HQ mass effects.

- NNPDF2.1 implements a GM-VFNS based on the FONLL scheme.

$$F^{\mathrm{FONLL}}(x, Q^2) = F^{(n_l)}(x, Q^2) + \theta(Q^2 - m^2)\left(1 - \frac{m^2}{Q^2}\right)^2 \left[F^{(n_l+1)}(x, Q^2) - F^{(n_l,0)}(x, Q^2)\right]$$



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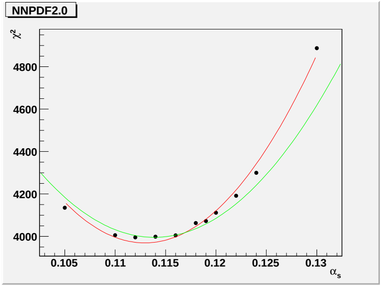
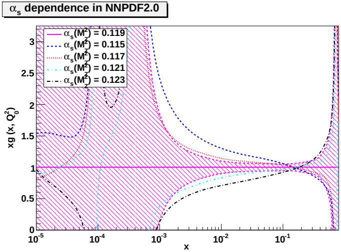
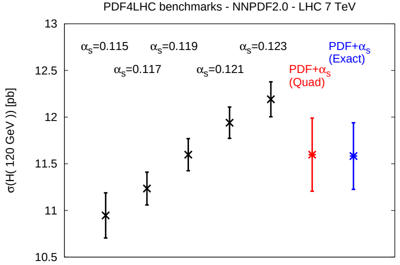
- α_s is not fitted, it is fixed beforehand to $\alpha_s = 0.119$.
- In principle we could also fit α_s

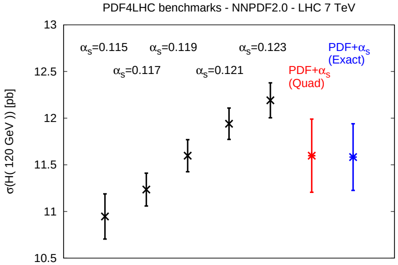
$$\alpha_s = \text{NNPDF2.0}$$
$$\alpha_s = \text{NNPDF1.2}$$





- Study dependency on α_s: stronger than in NNPDF1.2.
- Study dependency on α_s: still within uncertainty.





- With Monte Carlo ensemble one can evaluate combined $PDF + \alpha_s$ uncertainty.

$$\langle \mathcal{F} \rangle_{\rm rep} = \frac{1}{N_{\rm rep}} \sum_{j=1}^{N_\alpha} \sum_{k_j=1}^{N_{\rm rep}^{\alpha_s^{(j)}}} \mathcal{F}\left({\rm PDF}^{(k_j,j)}, \alpha_s^{(j)} \right) \ ,$$

- $N_{\rm rep}^{\alpha_s^{(j)}}$ are determined by the probability distribution of values of α_s, with the constraint

$$N_{\rm rep} = \sum_{j=1}^{N_{\alpha_s}} N_{\rm rep}^{\alpha_s^{(j)}} \ .$$

NNPDF features

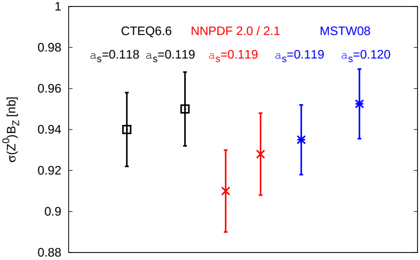
Theoretical side: α_s and m_Q

Add 1 or 2 plots about value of mc and mb (overlap with HQ talk!)

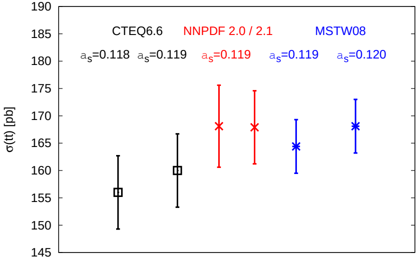
Benchmark

Observables (NNPDF2.1 Preliminary)

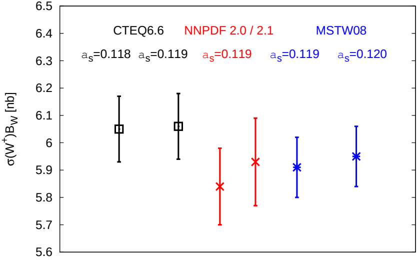
PDF4LHC benchmarks - LHC 7 TeV



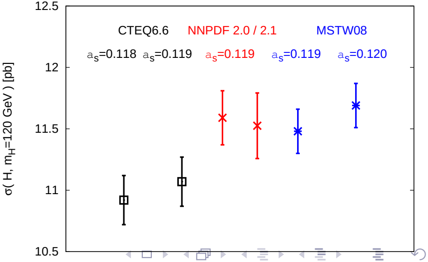
PDF4LHC benchmarks - LHC 7 TeV



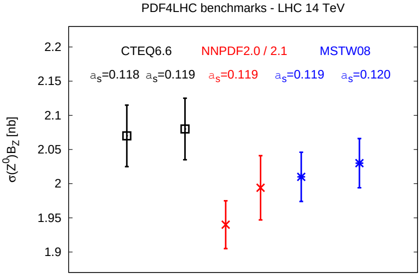
PDF4LHC benchmarks - LHC 7 TeV

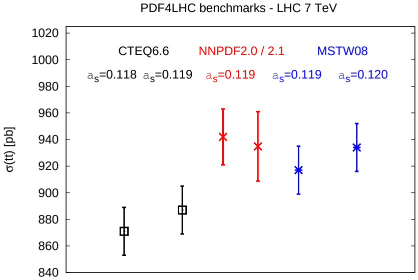


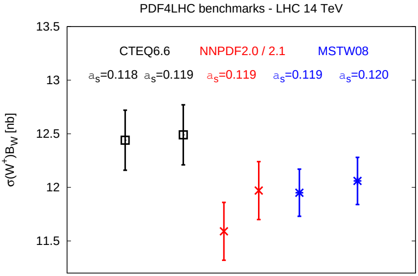
PDF4LHC benchmarks - LHC 7 TeV

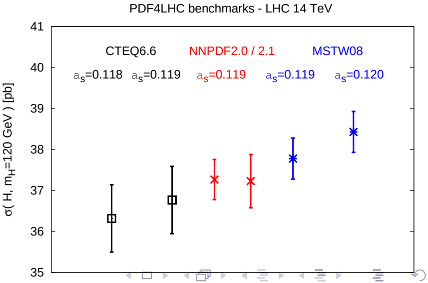


Observables (NNPDF2.1 Preliminary)









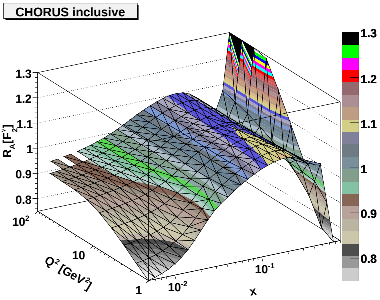
Conclusion

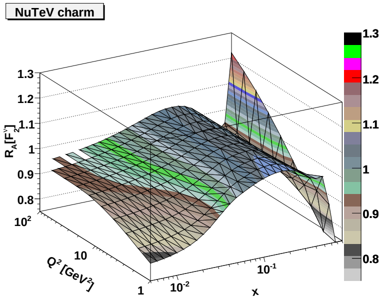
- The benchmark comparison strongly depends on the value of the strong coupling constant.
- For meaningful comparison use the same value of α_s.
- What about the values for m_c and m_b?
- Going from NNPDF2.0 to NNPDF2.1 results for LHC standard candles move within 1σ uncertainty.
- NNPDF2.1 closer to MSTW08 but a marginal agreement with CTEQ66.

BACKUP slides

Nuclear corrections

Kulagin-Petti parametrization, corrections on structure functions



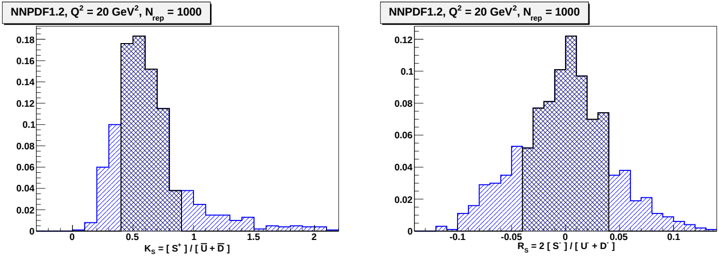


- Corrections are model-dependent.
- Tested the impact of nuclear corrections (NuTeV, A=49.6; CHORUS, A=206).
- Used both De Florian-Sassot model and Hirai et all model.
- Found that the impact of the nuclear corrections is small, within statistical fluctuations.
- Quantified with computation of distances $d \sim 1$

Nuclear corrections

	ZM		De Florian-Sassot		HKN07	
	Data	Extrapolation	Data	Extrap.	Data	Extrap. .
$\Sigma(x, Q_0^2)$	$5\ 10^{-4} \leq x \leq 0.1$	$10^{-5} \leq x \leq 10^{-4}$				
$\langle d[q] \rangle$	5.2	1.0	2.3	1.4	2.3	0.9
$\langle d[\sigma] \rangle$	2.5	1.6	1.5	1.2	1.2	1.1
$g(x, Q_0^2)$	$5\ 10^{-4} \leq x \leq 0.1$	$10^{-5} \leq x \leq 10^{-4}$				
$\langle d[q] \rangle$	1.4	1.5	1.2	1.0	1.4	1.1
$\langle d[\sigma] \rangle$	1.8	1.5	1.2	1.2	1.2	1.4
$T_3(x, Q_0^2)$	$0.05 \leq x \leq 0.75$	$10^{-3} \leq x \leq 10^{-2}$				
$\langle d[q] \rangle$	1.4	2.0	1.3	1.0	1.0	1.0
$\langle d[\sigma] \rangle$	2.9	0.9	1.4	1.5	1.1	1.1
$V(x, Q_0^2)$	$0.1 \leq x \leq 0.6$	$3\ 10^{-3} \leq x \leq 3\ 10^{-2}$				
$\langle d[q] \rangle$	1.2	1.2	1.3	1.2	0.8	0.7
$\langle d[\sigma] \rangle$	1.5	1.1	1.3	1.5	1.3	0.9
$\Delta_S(x, Q_0^2)$	$0.1 \leq x \leq 0.6$	$3\ 10^{-3} \leq x \leq 3\ 10^{-2}$				
$\langle d[q] \rangle$	2.1	2.3	0.8	1.0	1.1	1.0
$\langle d[\sigma] \rangle$	1.1	1.1	1.2	1.3	1.0	1.3
$s^+(x, Q_0^2)$	$5\ 10^{-4} \leq x \leq 0.1$	$10^{-5} \leq x \leq 10^{-4}$				
$\langle d[q] \rangle$	9.4	1.1	2.1	1.5	1.6	1.1
$\langle d[\sigma] \rangle$	3.4	1.6	1.5	1.0	1.5	1.0
$s^-(x, Q_0^2)$	$0.1 \leq x \leq 0.6$	$3\ 10^{-3} \leq x \leq 3\ 10^{-2}$				
$\langle d[q] \rangle$	0.9	0.9	1.0	1.1	1.3	1.1
$\langle d[\sigma] \rangle$	1.4	1.2	1.0	1.0	1.4	0.9

Nuclear corrections



	K_S (mean)	R_S
Reference	$0.71^{+0.19}_{-0.31}$	$(6 \pm 45) \cdot 10^{-3}$
Nuclear - dFS03	$0.74^{+0.21}_{-0.40}$	$(12 \pm 48) \cdot 10^{-3}$
Nuclear - HKN07	$0.68^{+0.24}_{-0.29}$	$(0 \pm 40) \cdot 10^{-3}$