PDF parametrizations

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& Université Catholique de Louvain

QCD at LHC, Trento

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The NNPDF Collaboration
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Outline

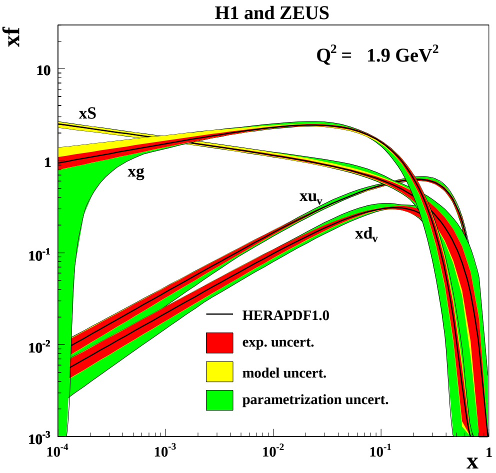
- Given a set of data points a set of functions with errors must be determined.
- We need an error band, i.e. a probability density $\mathcal{P}[f(x)]$ in the space of PDFs :

$$\langle \mathcal{F}[f(x)] \rangle = \int [\mathcal{D}f] \, \mathcal{F}[f(x)] \mathcal{P}[f(x)]$$

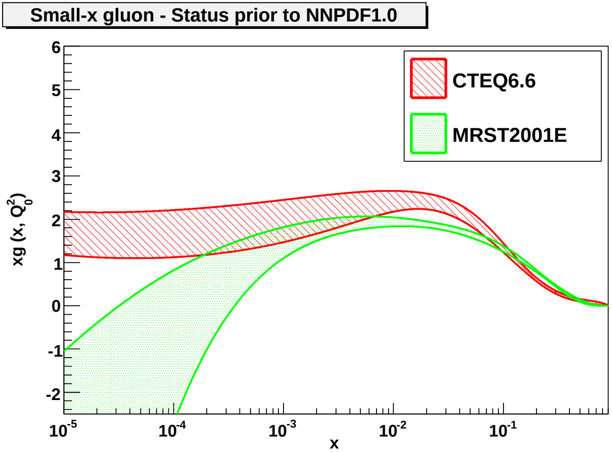
Standard approach

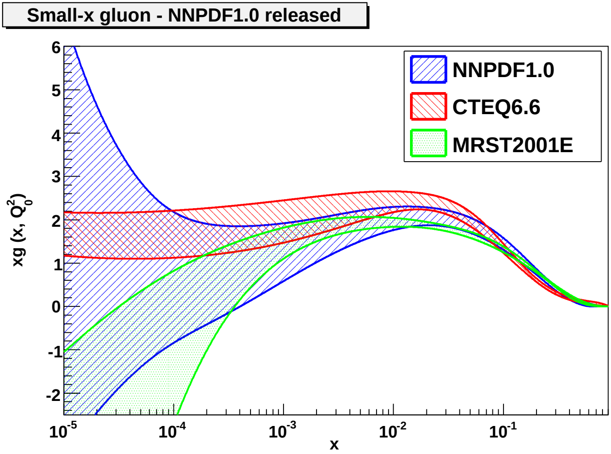
1. Choose a specific functional form
$$q_i(x, Q_0^2) = A_i x^{b_i} (1-x)^{c_i} (1 + \ldots).$$
2. Determine best-fit values of parameters which define the functions.
3. Errors determined via gaussian linear error propagation and tolerance $\Delta\chi^2 \gg 1$

* What is the error associated to the choice of parametrization?
* How can we know that it is flexible enough?
* Large tolerance $T = \sqrt{\Delta\chi^2}$ means that error on experimental measurements is inflated.



- HERAPDF analysis: computation of parametrization uncertainty on top of the model and experimental uncertainty.
- In many regions the parametrization uncertainty is dominating.


Small-x gluon - Status prior to NNPDF1.0
CTEQ6.6
MRST2001E
xg (x, Q_0^2)
6
5
4
3
2
1
0
-1
-2
10^{-5}
10^{-4}
10^{-3}
10^{-2}
10^{-1}
x


Small-x gluon - NNPDF1.0 released
NNPDF1.0
CTEQ6.6
MRST2001E
$xg(x, Q_0^2)$
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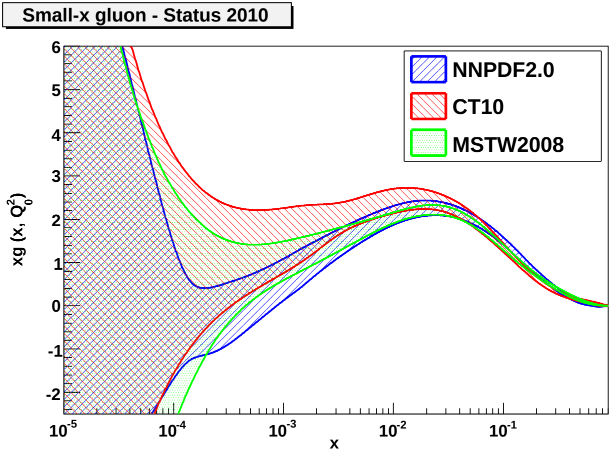
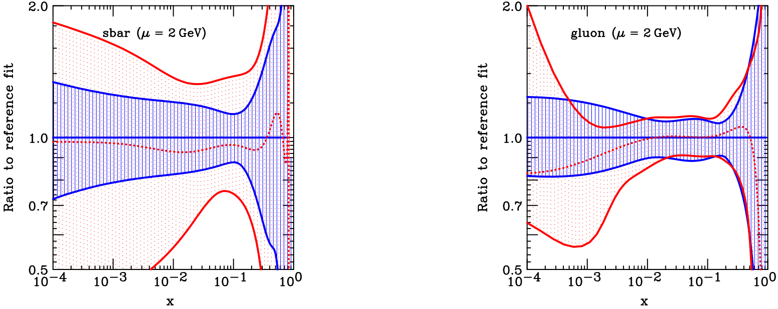
10^{-1}

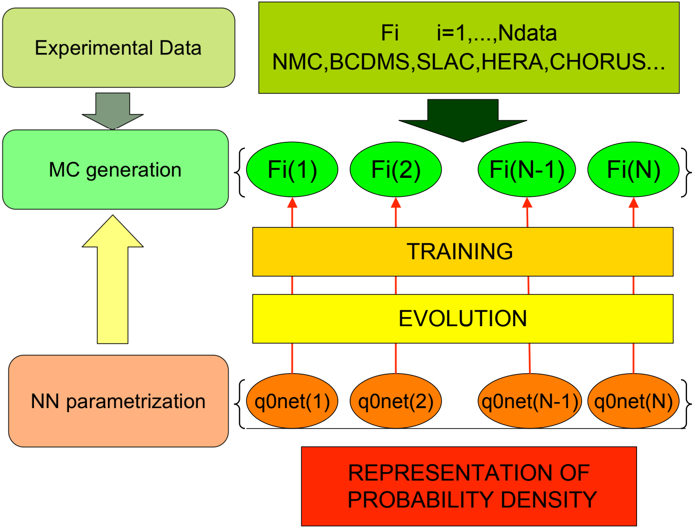
Introduction

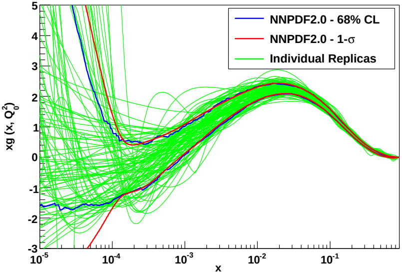
Increasingly flexible parametrizations

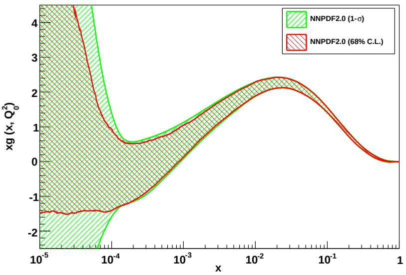




- Uncertainties often go up when data are added because of need to add parameters.
- CTEQ66 (22 free params) to CT10 (26 free params)


Experimental Data
Fi i=1,...,Ndata
NMC,BCDMS,SLAC,HERA,CHORUS...
MC generation
Fi(1)
Fi(2)
Fi(N-1)
Fi(N)
TRAINING
EVOLUTION
NN parametrization
q0net(1)
q0net(2)
q0net(N-1)
q0net(N)
REPRESENTATION OF
PROBABILITY DENSITY





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

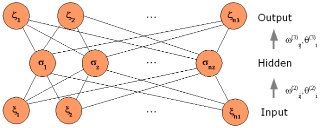
$$\sigma_{\mathcal{F}[f(x)]} = \sqrt{\langle \mathcal{F}[f(x)]^2 \rangle - \langle \mathcal{F}[f(x)] \rangle^2}$$

* The MC sampling in the functional space of PDFs is obtained from the MC sampling in the space of data.
* Individual replicas are allowed to fluctuate, average quantities are smooth as the size of the MC ensemble increases.

* Each independent PDF at the initial scale $Q_0^2 = 2\mathrm{GeV}^2$ is parameterized by an individual NN.

$\Sigma(x) \longmapsto \mathrm{NN}_\Sigma(x)$	2-5-3-1	37 pars
$g(x) \longmapsto \mathrm{NN}_g(x)$	2-5-3-1	37 pars
$V(x) \longmapsto \mathrm{NN}_V(x)$	2-5-3-1	37 pars
$T_3(x) \longmapsto \mathrm{NN}_{T3}(x)$	2-5-3-1	37 pars
$\Delta_S(x) \equiv \bar{d}(x) - \bar{u}(x) \longmapsto \mathrm{NN}_\Delta(x)$	2-5-3-1	37 pars
$s^+(x) \equiv (s(x) + \bar{s}(x))/2 \longmapsto \mathrm{NN}_{(s+)}(x)$	2-5-3-1	37 pars
$s^-(x) \equiv (s(x) - \bar{s}(x))/2 \longmapsto \mathrm{NN}_{(s-)}(x)$	2-5-3-1	37 pars

Total: 259 parameters



* Neural Networks are just functions, which adapt well to any functional behaviour.
For a (1-2-1) NN

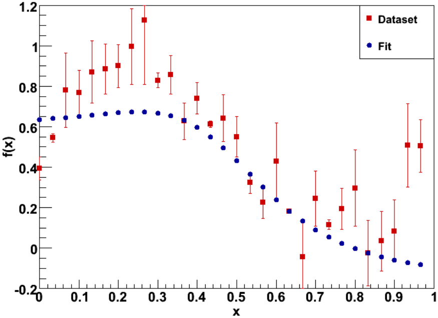
$$\xi_1^{(3)} = \frac{1}{1 + e^{\theta_1^{(3)} - \frac{\omega_{11}^{(2)}}{1+e^{\theta_1^{(2)} - \xi_1^{(1)}\omega_{11}^{(1)}}} - \frac{\omega_{12}^{(2)}}{1+e^{\theta_2^{(2)} - \xi_1^{(1)}\omega_{21}^{(1)}}}}}$$

* Instead of a set of basis functions with a small number of parameters $\mathcal{O}(20)$ pars, we have an unbiased basis of functions parameterized by a very large and redundant set of parameters $\mathcal{O}(200)$ pars.

Not trivial because ...

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

UNDERLEARNING→



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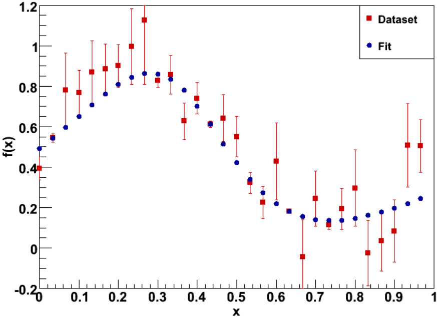
PROPER LEARNING→



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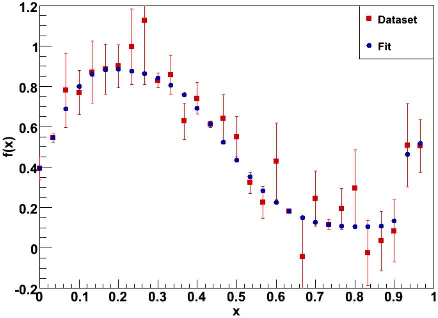
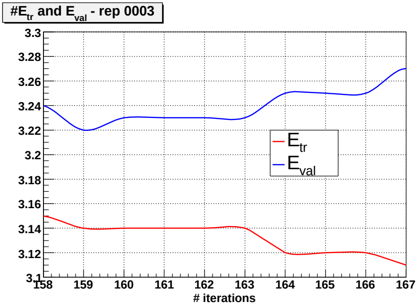
TOO LATE!→



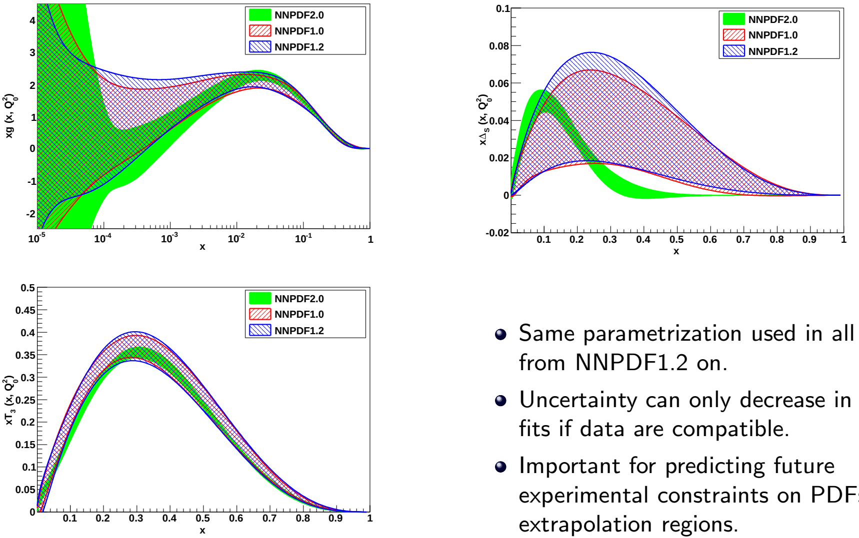
Cross-validation method

- 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 → STOP.



NNPDF results

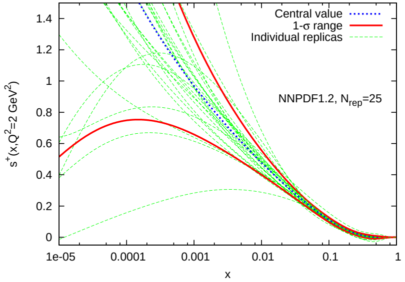
Uncertainty can only decrease #1

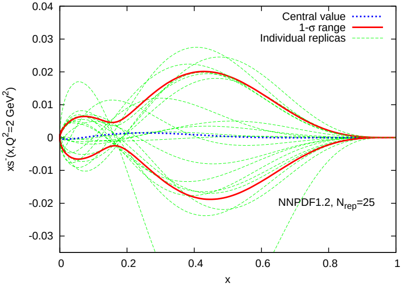


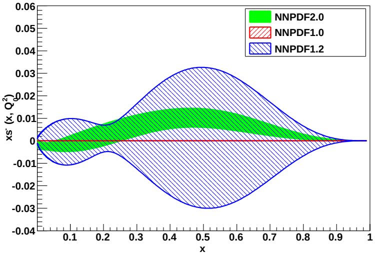
- Same parametrization used in all fits from NNPDF1.2 on.
- Uncertainty can only decrease in future fits if data are compatible.
- Important for predicting future experimental constraints on PDFs in extrapolation regions.

NNPDF results

Able to deal with unconstrained parton distributions: the strange case #2







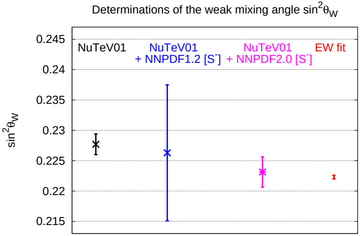
- In NNPDF1.2 analysis strange constrained by NuTeV dimuon data.
- 74 parameters for strangeness, s^+ and s^-, unbiased large parametrization.
- In NNPDF2.0 added constrain from Drell-Yan data.

* Control on PDFs uncertainties: NuteV anomaly solved AND precision studies at the same time.

- Discrepancy $\geq 3\sigma$ between indirect and direct determination from NuTeV measurement assuming $[S^-] = 0$ and isospin symmetry.
- Uncertainty reduced by addiction of DY data.
- Striking agreement with EW fits.

$$\delta_s \sin^2\theta_W \sim -0.240 \frac{[S^-]}{[Q^-]}$$

$$\delta_s \sin^2\theta_W = -0.0005 \pm 0.0096^{\mathrm{PDFs}} \pm sys$$

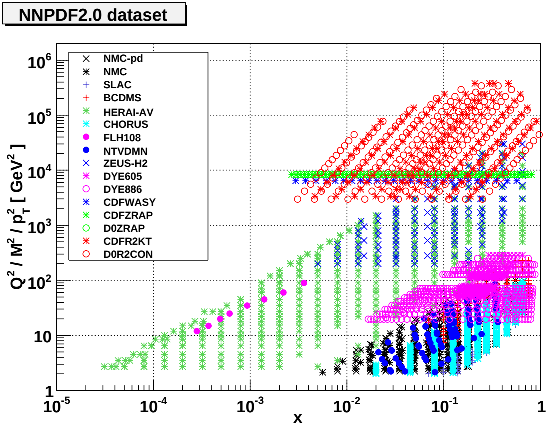


- **2005:** Structure functions [hep-ph/0501067]
- **2007:** Non-singlet PDF $q^{-} = u + d - (\bar{u} + \bar{d})$ [hep-ph/0701127]
- **2008:** DIS global analysis: NNPDF1.0 [arXiv:0808.1231]
- **2009:** Determination of the strange content: NNPDF1.2 [arXiv:0906.1958]
- **2010:** Global (DIS+DY+JET) analysis in ZM-VFN scheme for heavy quark masses: NNPDF2.0 [arXiv:1002.4407]
- **upcoming:** Global (DIS+DY+JET) analysis in GM-VFN scheme (FONLL) for heavy quark masses: NNPDF2.1 [arXiv:1007.0354]
- **upcoming:** LO parton set for leading order event generators based on NNPDF2.0 analysis.
- **upcoming:** Reweighting NNPDF: the W lepton asymmetry analysis.

PS: All sets are (will be) available in the LHAPDF interface

NNPDF2.1

NNPDF2.0 data sets



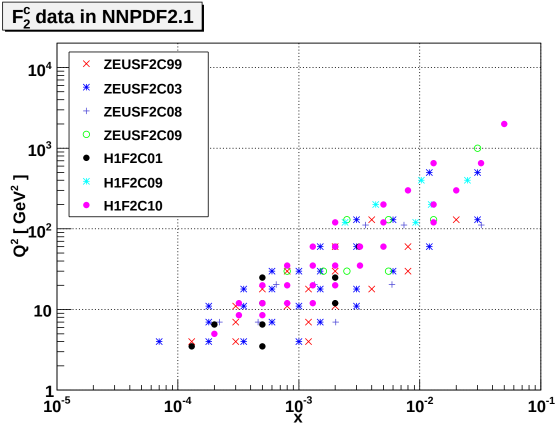
3477 data points

For comparison MSTW08 includes 2699 data points

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

- Kinematical cuts on DIS data
  $Q^2 > 2$ GeV^2
  $W^2 = Q^2(1-x)/x > 12.5$ GeV^2
- No cuts on hadronic data
- Improved treatment of normalizations (t_0 method)[arXiv:0912.2276]
- FastKernel (exact NLO analysis)

NNPDF2.1 data sets



3554 data points

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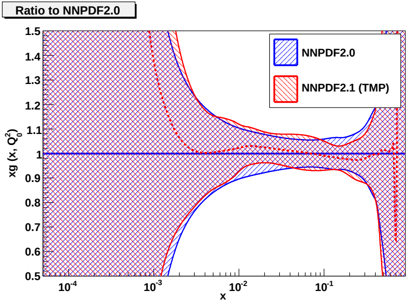
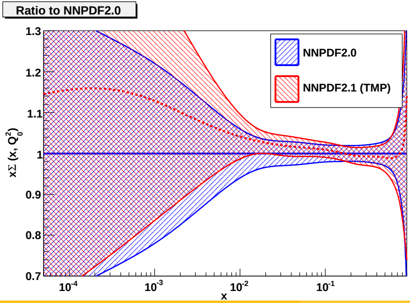
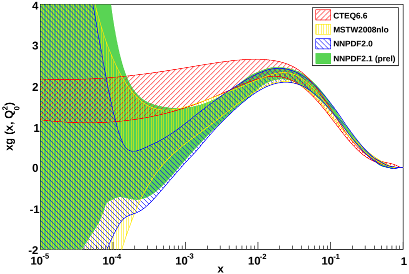
W asymmetry	CDF
Z rap. distr.	CDF,D0
incl. $\sigma^{(\rm jet)}$	D0(cone) Run II
incl. $\sigma^{(\rm jet)}$	CDF(k_T) Run II
F_2^c	**ZEUS (99,03,08,09)**
F_2^c	**H1 (01,09,10)**

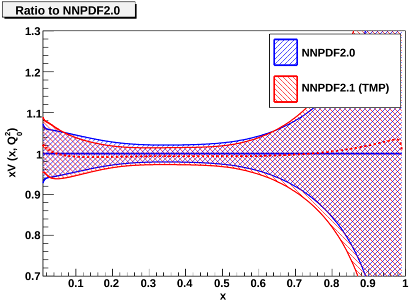
- F_2^b not included due to large uncertainty.
- HQ mass effects implemented according to the FastKernel method. Exact NLO analysis.

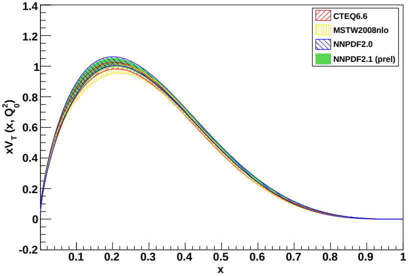


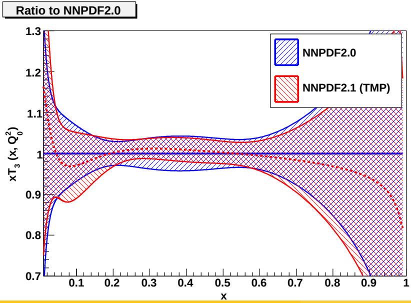




- Small and medium-x gluon and singlet are the most affected.
- Effect is within 1σ.
- Other PDFs unaffected.







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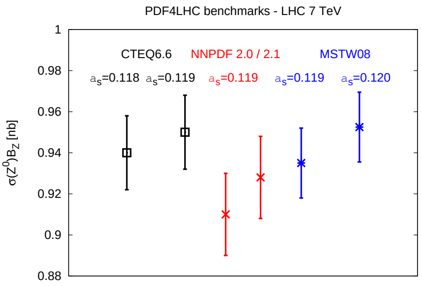
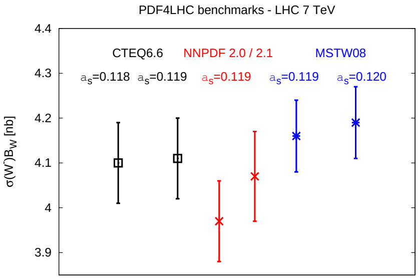
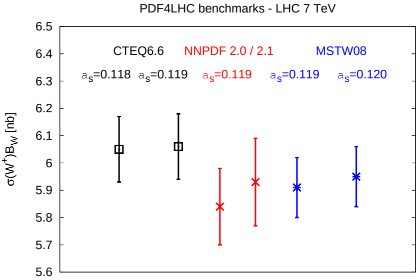






- Important to use the same value of α_s.
- Effect in predictions at 7 TeV is within 1σ.
- More in the talk on Wednesday afternoon.

PDF set	$\left(\chi^2_{\rm LO} - \chi^2_{\rm NLO}\right)/\chi^2_{\rm NLO}$
NNPDF2.0 LO	$\sim$ 7%
CT09	$\sim$ 30%
MRST07	$\sim$ 25%
MSTW08	$\sim$ 26%

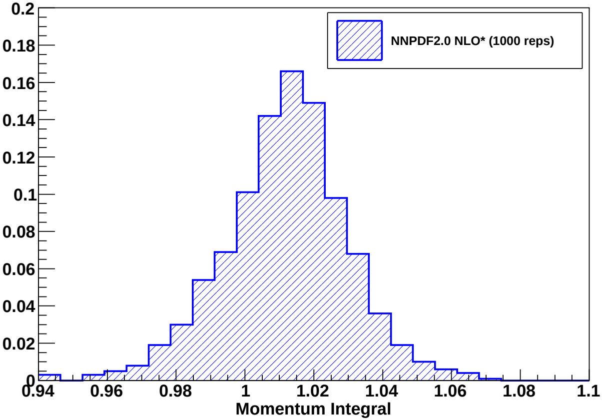
* The quality of the fit from NLO to LO does not deteriorate much.
* Flexible parametrization able to accommodate the lack of NLO theory?

* The quality of the fit does not change if momentum sum rules are relaxed or if $\alpha_s^{\rm NLO}$ is used.

PDF set	Pert. order	$\alpha_s\left(M_Z\right)$	MSR
LO	LO	0.1313	Yes
LOmod	LO	0.119	Yes
LOstar	LO	0.119	No
NLOstar	NLO	0.119	No

Experiment	LO	LOmod	LO*	NLO	NLO*
χ^2	1.30	1.29	1.31	1.21	1.22
$[M]$	1	1	1.078 ± 0.024	1.0000 ± 0.0001	1.01 ± 0.02

* The NLO fit without momentum sum rules imposed yields $\langle M \rangle$ consistent to the one redicted by pQCD.



Reweighting
General framework

- The $N_{\rm rep}$ replicas $\{f\}$ of a NNPDF fit give the probability density in the space of PDFs

$$\langle \mathcal{F}[f_i(x,Q^2)] \rangle = \frac{1}{N_{rep}} \sum_{k=1}^{N_{rep}} \mathcal{F}\left(f_i^{(k)}(x,Q^2) \right)$$

- The impact of including new data $\{x_i\}$ in the fit $(i = 1, \cdots, n_{\rm dat})$ can be assessed by updating the probability density distribution taking into account the new data,

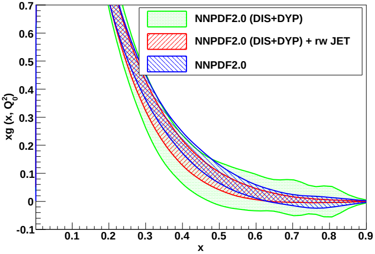
$$\mathcal{P}_{\rm new}(\{f\}) = \mathcal{N}_\chi P(\chi^2|\{f\}) \mathcal{P}_{\rm old}(\{f\}) \, , \qquad P(\chi^2|\{f\}) \propto [\chi^2(y,\{f\})]^{n_{\rm dat}/2-1} e^{-\frac{\chi^2(y,\{f\})}{2}}$$

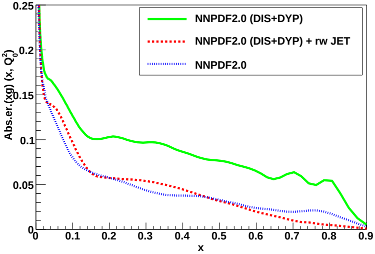
Statistical inference

- Monte Carlo integrals are given by weighted sums

$$\langle \mathcal{F}[f_i(x,Q^2)] \rangle = \sum_{k=1}^{N_{rep}} w_k \mathcal{F}\left(f_i^{(k)}(x,Q^2) \right) \qquad w_k = \mathcal{N}_\chi [\chi^2(y,f_k)]^{n_{\rm dat}/2-1} e^{-\frac{\chi^2(y,f_k)}{2}}$$

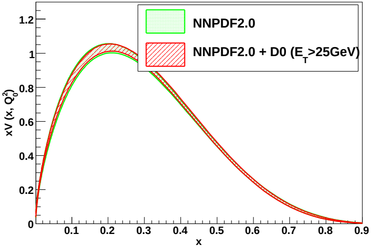
- $\mathcal{N}_\chi$ is fixed by normalising the new probability density, $\mathcal{N}_\chi = N_{\rm rep} / \sum_k w_k$.

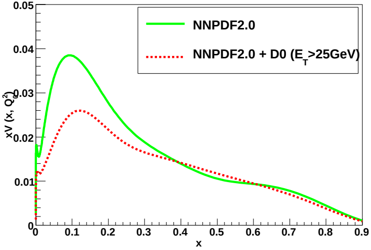




- Include JET data through re-fitting and through re-weighting
- Use (DIS+DY) 1000 replicas fit as a initial condition
- Re-weighting and re-fitting give same results within statistical fluctuations

- In the fit only CDF W asymmetry is included [arXiv:0901.216 [hep-ex]]
- We evaluated W electron asymmetry with 1000 replicas of NNPDF20 set using DYNNLO[arXiv:0903.2120 [hep-ph]].
- .. and included D0 W electron asymmetry data points [arXiv:0807.3367 [hep-ex]] through re-weighting.
- Main impact on reduction of middle-x Valence uncertainty. (more details on Thursday afternoon)
- No need of rifitting! Everybody can do it.
- Same method can be applied to pseudo-dato to predict future experiments'constrains on PDFs.





Conclusion and outlook

- Monte Carlo ensemble + Neural Network parametrization
  - Any statistical property of PDFs can be calculated using standard statistical methods.
  - Consistent statistical behaviour when adding/removing data.
  - No problem in dealing with unconstrained parametrization: strange analysis.
  - Ideal framework for reweighting analyses – useful tool for experimentalists.
- The NNPDF2.0 is the fist unbiased global NLO fit [FastKernel] – ZMVFNS.
- The NNPDF2.1 analysis includes F_2^c data and implements the FONLL scheme to include the effect of the masses of the heavy quarks.
  - Small and medium-x gluon and singlet are the most affected.
  - The effect of the heavy quark masses is within 1σ uncertainty in predictions for standard candles.
- The NNPDF2.0 LO parton set is ready for LO event generators
  - The quality of the fit deteriorates less than for other collaboration when switching to LO fit.
  - Prescriptions like LOmod or LO* have little effect on quality of the fit.

BACKUP

FastKernel

- The NLO computation of hadronic observables too slow for parton global fits.
- Often higher order corrections are included as (local) K factors rescaling the LO cross section
- K-factor depends on PDFs and it is not always a good approximation.

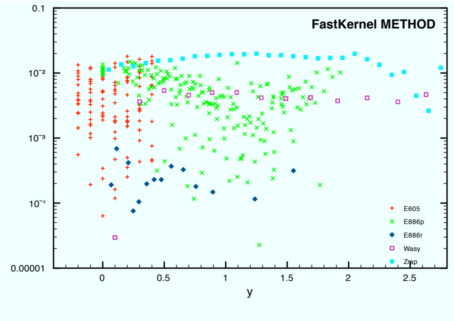
* NNPDF2.0 includes full NLO calculation of hadronic observables.
* Use available fastNLO interface for jet inclusive cross-sections.[hep-ph/0609285]
* Built up our own **FastKernel** computation of DY observables.

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

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

- New strategy to solve DGLAP evolution equation
- Implementation benchmarked against the Les Houches tables
- Gain in speed by a factor 30 (for a fit to 3000 datapoints)

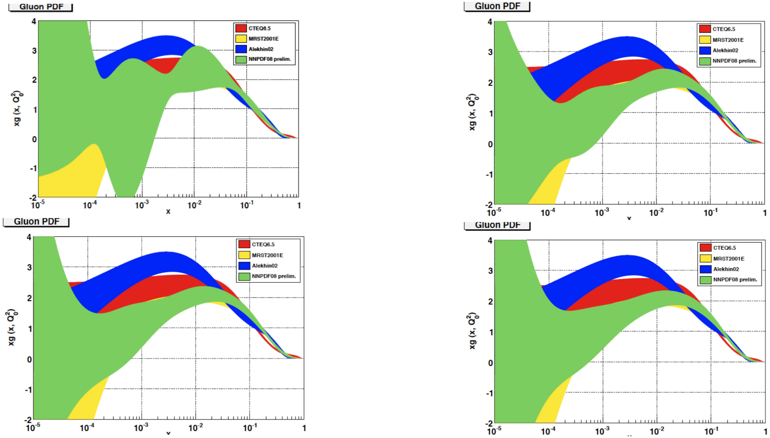
x (50 pts)	$e_{\rm rel}(u_V)$	$e_{\rm rel}(\Sigma)$	$e_{\rm rel}(g)$
$1 \cdot 10^{-7}$	$2.1 \cdot 10^{-4}$	$2.7 \cdot 10^{-5}$	$4.7 \cdot 10^{-6}$
$1 \cdot 10^{-6}$	$8.9 \cdot 10^{-5}$	$3.0 \cdot 10^{-5}$	$2.1 \cdot 10^{-5}$
$1 \cdot 10^{-5}$	$9.3 \cdot 10^{-5}$	$2.3 \cdot 10^{-5}$	$2.0 \cdot 10^{-5}$
$1 \cdot 10^{-4}$	$4.5 \cdot 10^{-5}$	$4.4 \cdot 10^{-5}$	$4.2 \cdot 10^{-5}$
$1 \cdot 10^{-3}$	$3.0 \cdot 10^{-5}$	$4.0 \cdot 10^{-5}$	$3.5 \cdot 10^{-5}$
$1 \cdot 10^{-2}$	$7.9 \cdot 10^{-5}$	$4.5 \cdot 10^{-5}$	$5.8 \cdot 10^{-5}$
$1 \cdot 10^{-1}$	$1.7 \cdot 10^{-4}$	$1.6 \cdot 10^{-5}$	$3.9 \cdot 10^{-5}$
$3 \cdot 10^{-1}$	$9.1 \cdot 10^{-6}$	$1.1 \cdot 10^{-5}$	$1.9 \cdot 10^{-7}$
$5 \cdot 10^{-1}$	$2.4 \cdot 10^{-5}$	$2.2 \cdot 10^{-5}$	$2.2 \cdot 10^{-5}$
$7 \cdot 10^{-1}$	$9.1 \cdot 10^{-5}$	$7.8 \cdot 10^{-5}$	$1.2 \cdot 10^{-4}$
$9 \cdot 10^{-1}$	$1.0 \cdot 10^{-3}$	$8.0 \cdot 10^{-4}$	$2.8 \cdot 10^{-3}$



- Drell–Yan fast computation exploits linear interpolation
- Accuracy below 1% for all points included in the fit
- Increasing number of points in the grid one can improve accuracy;

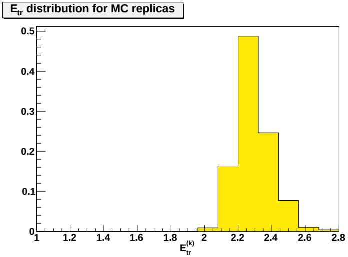
A truly NLO analysis

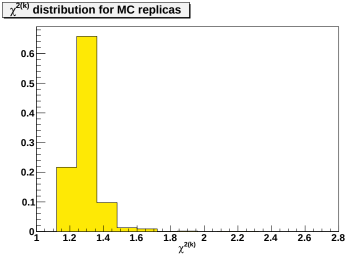
Parametrization and statistics

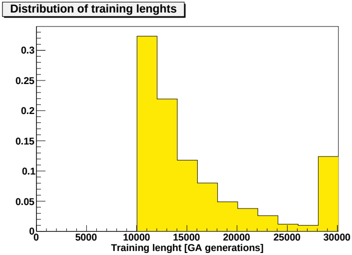


- Irregular or knotty shapes are allowed if data fluctuate
- Statistics shows whether the effect is real

NNPDF2.0: global χ^2

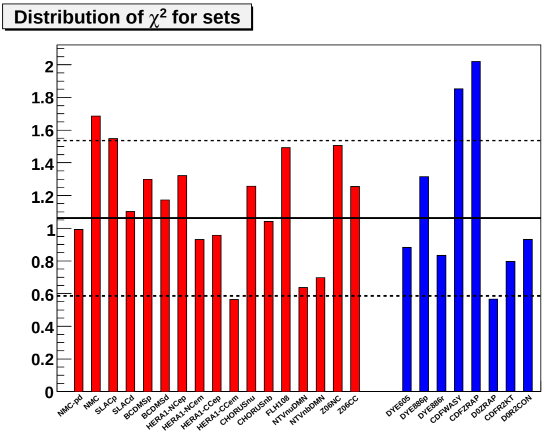






$\chi^2_{\rm tot}$	1.21
$\langle E \rangle \pm \sigma_E$	2.32 $\pm$ 0.10
$\langle E_{\rm val} \rangle \pm \sigma_{E_{\rm val}}$	2.29$\pm$ 0.11
$\langle E_{\rm val} \rangle \pm \sigma_{E_{\rm val}}$	2.35$\pm$ 0.12
$\langle TL \rangle \pm \sigma_{TL}$	16175 $\pm$ 6275
$\langle \chi^{2(k)} \rangle \pm \sigma_{\chi^2}$	1.29$\pm$ 0.09
$\langle \sigma^{(\rm exp)} \rangle_{\rm dat}(\%)$	11.4
$\langle \sigma^{(\rm net)} \rangle_{\rm dat}(\%)$	6.0

NNPDF2.0: individual experiments χ^2



- No obvious signs of mutual tensions between hadronic and DIS data.
- Some internal inconsistencies (NMC data, Z and W rapidity distributions).
- Reasonable distribution of χ^2

NNPDF2.0: A quantitative assessment of compatibility

- A quantitative assessment is possible

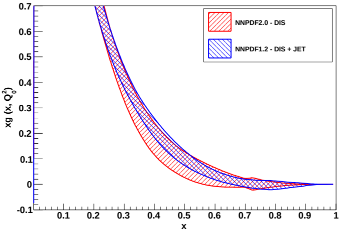
$$d(q_j) = \sqrt{\left\langle \frac{\left(\langle q_j\rangle_{(1)} - \langle q_j\rangle_{(2)}\right)^2}{\sigma_1^2[q_j] + \sigma_2^2[q_j]} \right\rangle_{N_{\rm part}}}$$

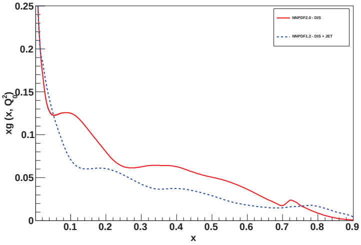
$$d(\sigma_j) = \sqrt{\left\langle \frac{\left(\langle \sigma_j\rangle_{(1)} - \langle \sigma_j\rangle_{(2)}\right)^2}{\sigma_1^2[\sigma_j] + \sigma_2^2[\sigma_j]} \right\rangle_{N_{\rm part}}}$$

- 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 $d \sim 1$
- Compatibility can be tested by comparing fits to different datasets.

1. Add JETS to DIS data
2. Add JETS to DIS+DY data
3. Add DY data to DIS data
4. Add DY data to DIS+JET data

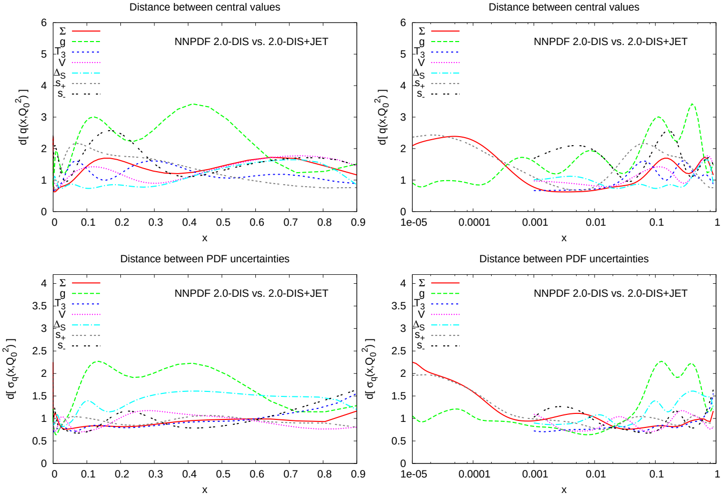
Fit	2.0 DIS	2.0 DIS+JET	NNPDF2.0
$\chi^2_{\rm tot}$	1.20	1.18	1.21
NMC-pd	0.85	0.86	0.99
NMC	1.69	1.66	1.69
SLAC	1.37	1.31	1.34
BCDMS	1.26	1.27	1.27
HERAI	1.13	1.13	1.14
CHORUS	1.13	1.11	1.18
FLH108	1.51	1.49	1.49
NTVDMN	0.71	0.75	0.67
ZEUS-H2	1.50	1.49	1.51
DYE605	*7.32*	*10.35*	0.88
DYE866	*2.24*	*2.59*	1.28
CDFWASY	*13.06*	*14.13*	1.85
CDFZRAP	*3.12*	*3.31*	*2.02*
D0ZRAP	*0.65*	*0.68*	0.47
CDFR2KT	*0.91*	0.79	0.80
D0R2CON	*1.00*	0.93	0.93





- JET data well reproduced even if not fitted.
- JET data provide a valuable constrain to large-x gluon.
- Other PDFs unaffected.

NNPDF2.0:A quantitative assessment of compatibility: DIS + JETS



Fit	2.0 DIS	2.0 DIS+JET	NNPDF2.0
$\chi^2_{\rm tot}$	1.20	1.18	1.21
NMC-pd	0.85	0.86	0.99
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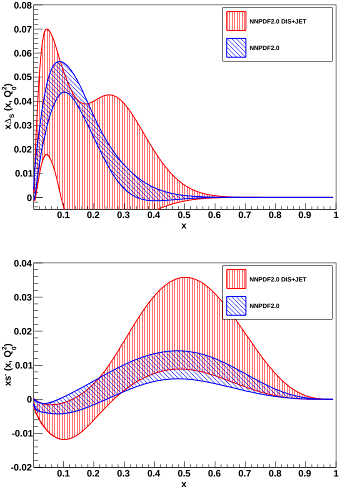
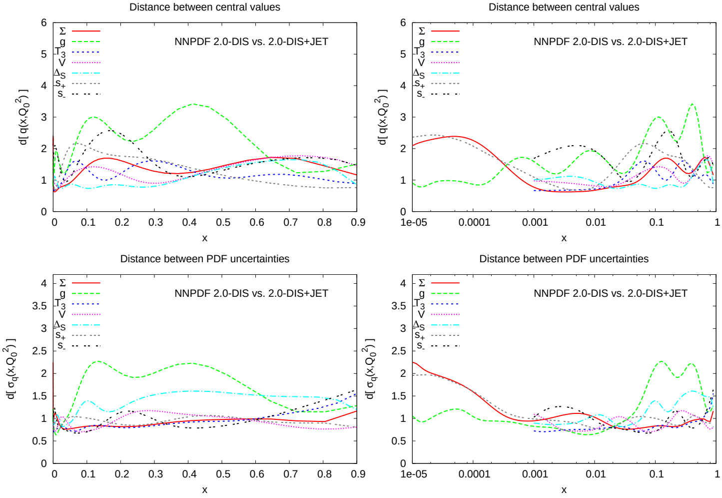
HERAI	1.13	1.13	1.14
CHORUS	1.13	1.11	1.18
FLH108	1.51	1.49	1.49
NTVDMN	0.71	0.75	0.67
ZEUS-H2	1.50	1.49	1.51
DYE605	7.32	*10.35*	0.88
DYE866	2.24	*2.59*	1.28
CDFWASY	13.06	*14.13*	1.85
CDFZRAP	3.12	*3.31*	2.02
D0ZRAP	0.65	*0.68*	0.47
CDFR2KT	0.91	0.79	0.80
D0R2CON	1.00	0.93	0.93

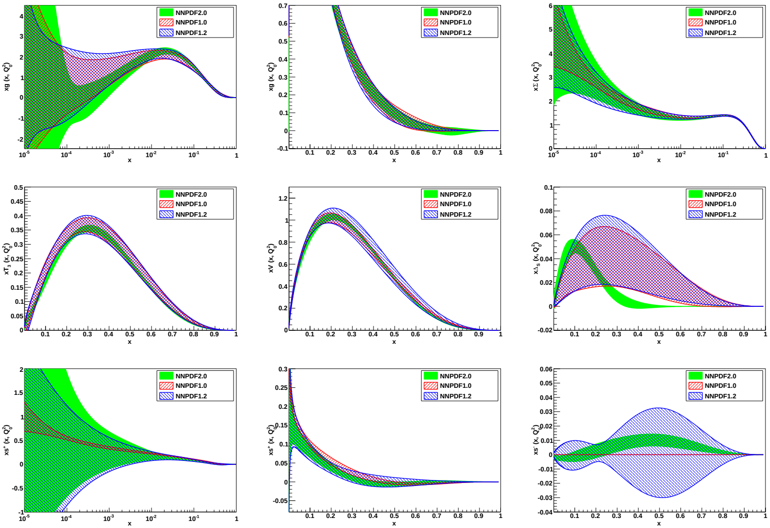


- Substantial improvement when DY data are include.
- All valence-type PDF combinations are affected and uncertainty reduced.

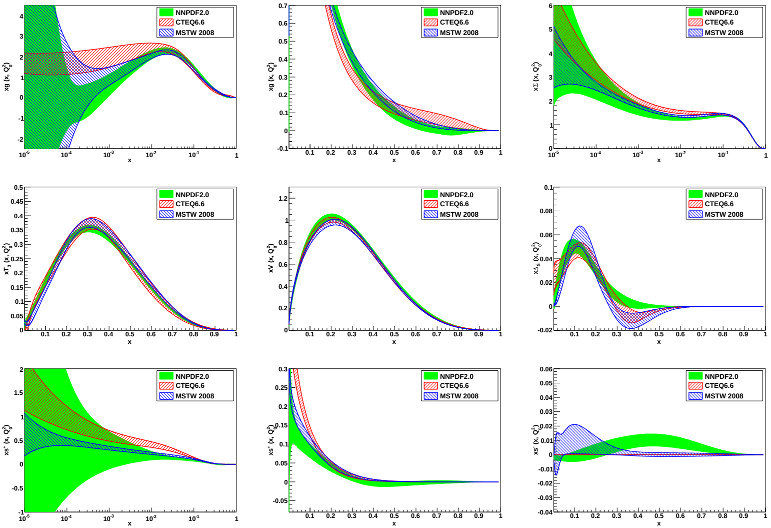
NNPDF2.0: A quantitative assessment of compatibility: DIS+JETS+DY



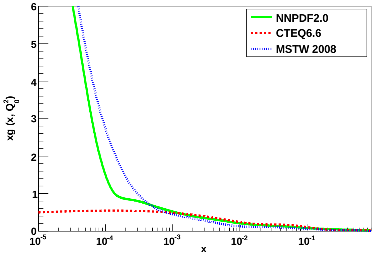
NNPDF2.0 Partons

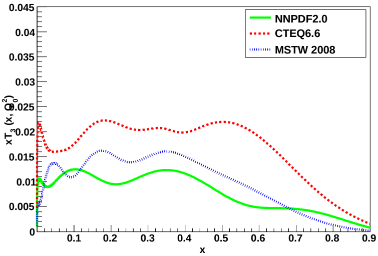


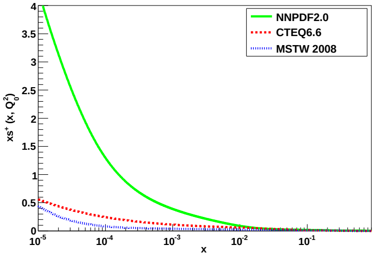
NNPDF2.0 Partons



NNPDF2.0 Partons

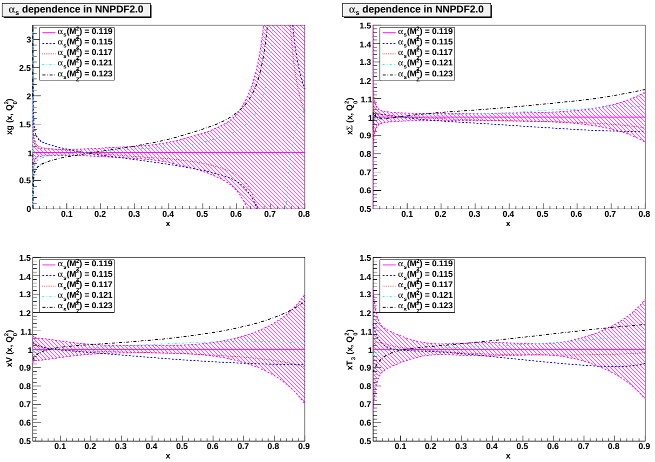






- Reduction of uncertainties with respect to older NNPDF sets (consistency).
- Uncertainties competitive with results from other groups.
- Smaller for some PDFs, larger when parametrization is too rigid.

NNPDF2.0: Impact of α_s



- Greater sensitivity to α_s than NNPDF1.2
- Greater NLO corrections for Drell-Yan observables.

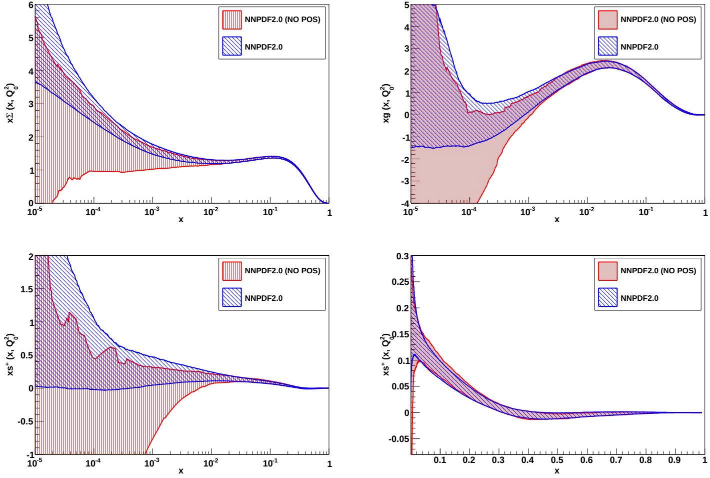
Positivity constraints

- We want the fitting procedure to explore only the subspace of acceptable physical solutions.
- We want
  - F_L positive.
  - Dimuon cross–section positive.
  - Momentum and valence sum rules.
- Modify the training function witha ddition of a Lagrangian multiplier:

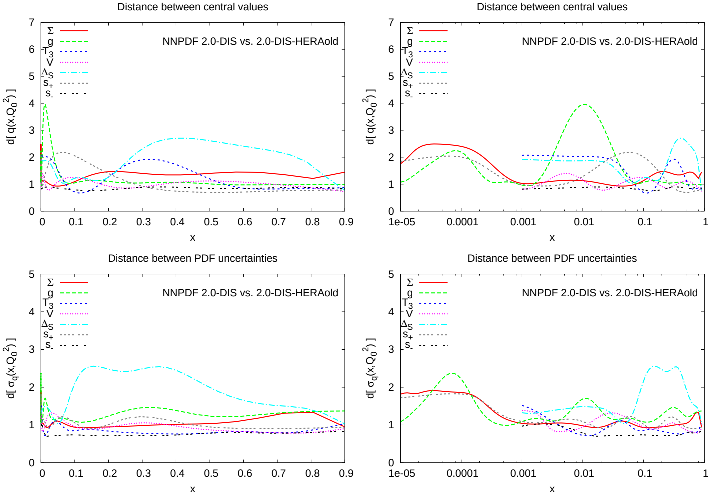
$$E^{(k)} \longrightarrow E^{(k)} - \lambda_{\rm pos} \sum_{l=1}^{N_{\rm dat,pos}} \Theta\left(F_l^{(net)(k)}\right) F_l^{(net)(k)}$$

- $N_{\rm dat,pos}$: number of pseudodata points used to implement positivity constraints.
- $\lambda_{\rm pos}$: associated Lagrangian multiplier (10^{10})

Impact of positivity



HERA-I combined dataset

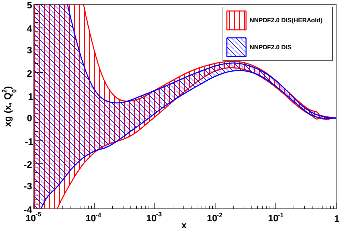


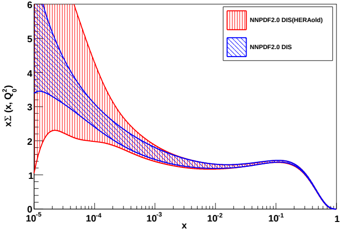
HERA-I combined dataset

Fit	NNPDF1.2	NNPDF1.2+IGA	NNPDF1.2+IGA+t_0	2.0 DIS	2.0 DIS+JET	NNPDF2.0
$\chi^2_{\rm tot}$	1.32	1.16	1.12	1.20	1.18	1.21
$\langle E \rangle$	2.79	2.41	2.24	2.31	2.28	2.32
$\langle E_{\rm tr} \rangle$	2.75	2.39	2.20	2.28	2.24	2.29
$\langle E_{\rm val} \rangle$	2.80	2.46	2.27	2.34	2.32	2.35
$\langle \chi^{2(k)} \rangle$	1.60	1.28	1.21	1.29	1.27	1.29
NMC-pd	1.48	0.97	0.87	0.85	0.86	0.99
NMC	1.68	1.72	1.65	1.69	1.66	1.69
SLAC	1.20	1.42	1.33	1.37	1.31	1.34
BCDMS	1.59	1.33	1.25	1.26	1.27	1.27
HERAI	1.05	0.98	0.96	1.13	1.13	1.14
CHORUS	1.39	1.13	1.12	1.13	1.11	1.18
FLH108	1.70	1.53	1.53	1.51	1.49	1.49
NTVDMN	0.64	0.81	0.71	0.71	0.75	0.67
ZEUS-H2	1.52	1.51	1.49	1.50	1.49	1.51
DYE605	*11.19*	*22.89*	*8.21*	*7.32*	*10.35*	0.88
DYE866	*53.20*	*4.81*	*2.46*	*2.24*	*2.59*	1.28
CDFWASY	*26.76*	*28.22*	*20.32*	*13.06*	*14.13*	1.85
CDFZRAP	*1.65*	*4.61*	*3.13*	*3.12*	*3.31*	2.02
D0ZRAP	*0.56*	*0.80*	*0.65*	*0.65*	*0.68*	0.47
CDFR2KT	*1.10*	*0.95*	*0.78*	*0.91*	0.79	0.80
D0R2CON	*1.18*	*1.07*	*0.94*	*1.00*	0.93	0.93

HERA-I combined dataset

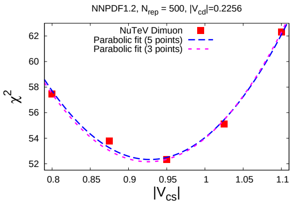
- HERA-I combined more precise:cross-calibration $\chi^2 = 1.12$ vs $\chi^2 = 1.21$
- Quality of other data unchanged
- Overall fit quality to the whole dataset is good ($\chi^2 = 1.13$)
    - $\sigma^+_{\rm NC}$ dataset has relatively high $\chi^2 \sim 1.3$
    - $\sigma^-_{\rm CC}$ dataset has very low $\chi^2 \sim 0.55$
- Same χ^2-pattern observed in the HERAPDF1.0 analysis
- Impact on PDFs, mainly Singlet and Gluon at small-x

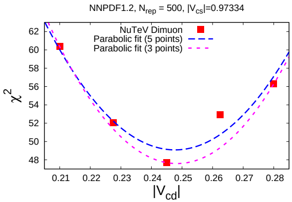




V_{cs} determination

* Control on PDFs uncertainties: NuteV anomaly solved AND precision studies at the same time





CKM fit

$$V_{cs} = 0.97334 \pm 0.00023, \;\; \Delta V_{cs} \sim 0.02\%$$

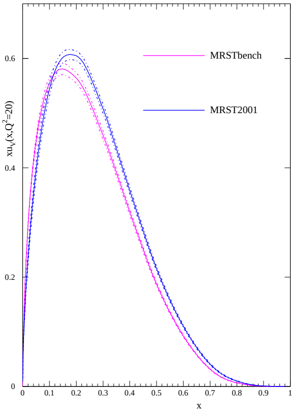
Direct Determination

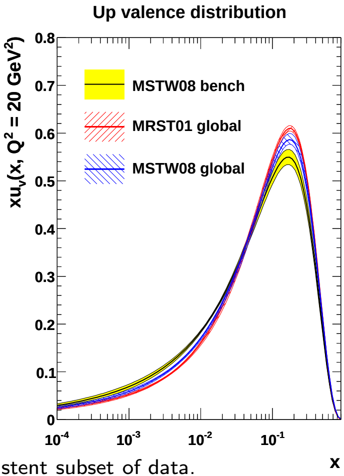
V_{cs}	$=$	$1.04 \pm 0.06, \;\; \Delta V_{cs} \sim 6\%$	D/B decays
V_{cs}	$>$	0.59	DIS fit

NNPDF1.2 analysis

$$V_{cs} = 0.97 \pm 0.07, \;\; \Delta V_{cs} \sim 6\%$$

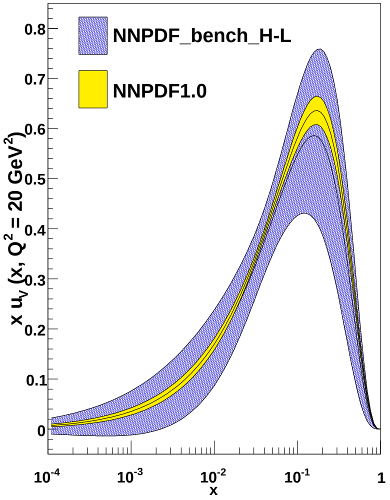
HERALHC benchmark analysis

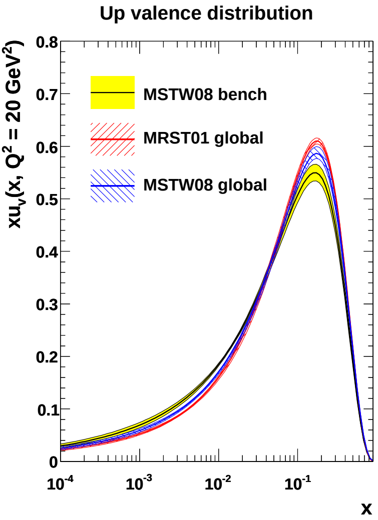


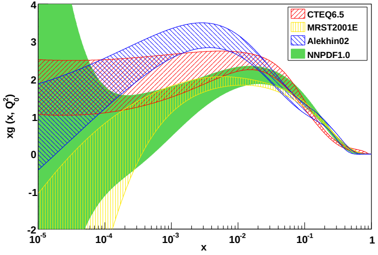


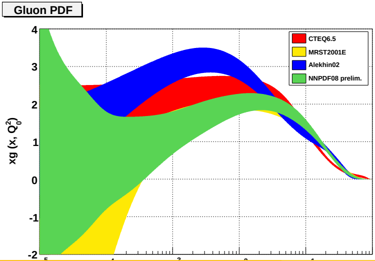
- Benchmark partons: perform a fit on a consistent subset of data.
- MRST2001: partons from global fit and from benchmark fit do not agree within uncertainty.
- MSTW08: with a more general parametrization situation improves.
- Both parametrization and statistical treatment need to be tuned to experimental data.

HERALHC benchmark analysis









- The independence of the choice of the parametrization can be statistically measured

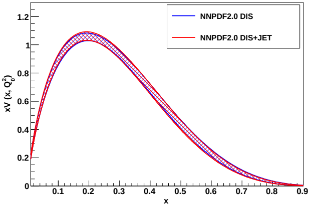
$$d(q_j) = \sqrt{\left\langle \frac{\left(\langle q_j\rangle_{(1)} - \langle q_j\rangle_{(2)}\right)^2}{\sigma_1^2[q_j] + \sigma_2^2[q_j]} \right\rangle_{N_{\rm part}}}$$

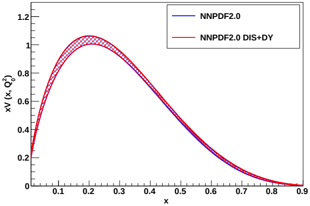
$$d(\sigma_j) = \sqrt{\left\langle \frac{\left(\langle \sigma_j\rangle_{(1)} - \langle \sigma_j\rangle_{(2)}\right)^2}{\sigma_1^2[\sigma_j] + \sigma_2^2[\sigma_j]} \right\rangle_{N_{\rm part}}}$$

	Data	Extrapolation
$g(x, Q_0^2)$	$5\ 10^{-4} \leq x \leq 0.1$	$10^{-5} \leq x \leq 10^{-4}$
$\langle d[f]\rangle$	1.07	0.87
$\langle d[\sigma]\rangle$	0.86	0.78

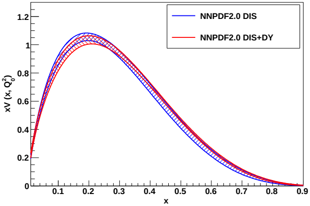
185 pars $\rightarrow$ **155 pars**

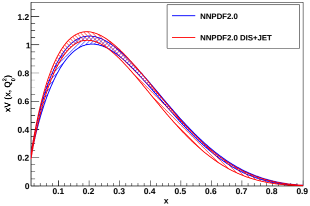
- Adding JETS data to DIS data and to DIS+Drell-Yan data...





- Adding Drell-Yan data to DIS data and to DIS+JET data



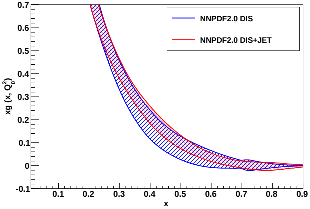


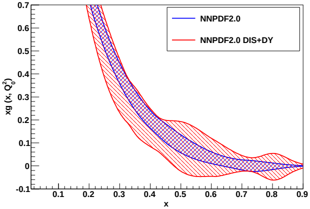
- The impact of a dataset in independent of the data it is added to.

NNPDF results

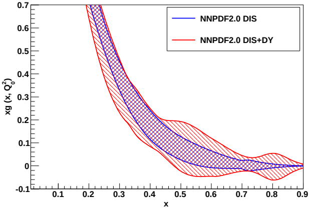
Commutative properties... #5

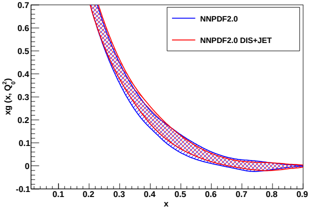
- Adding JETS data to DIS data and to DIS+Drell-Yan data...





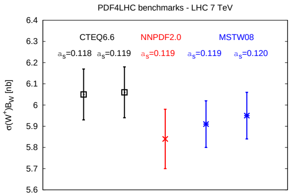
- Adding Drell-Yan data to DIS data and to DIS+JET data

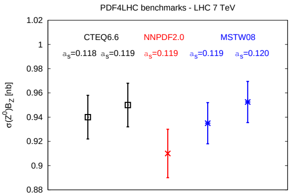


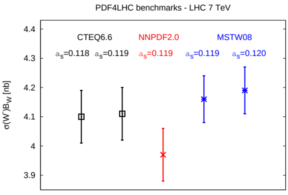


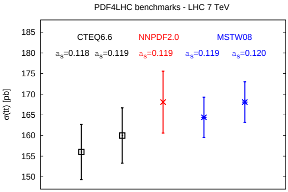
- The impact of a dataset in independent of the data it is added to.

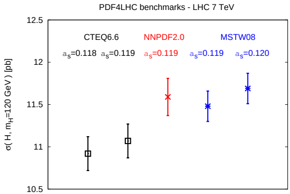
LHC standard candles











- The value of α_s is important when comparing standard candles.
- Good agreement between global parton sets.

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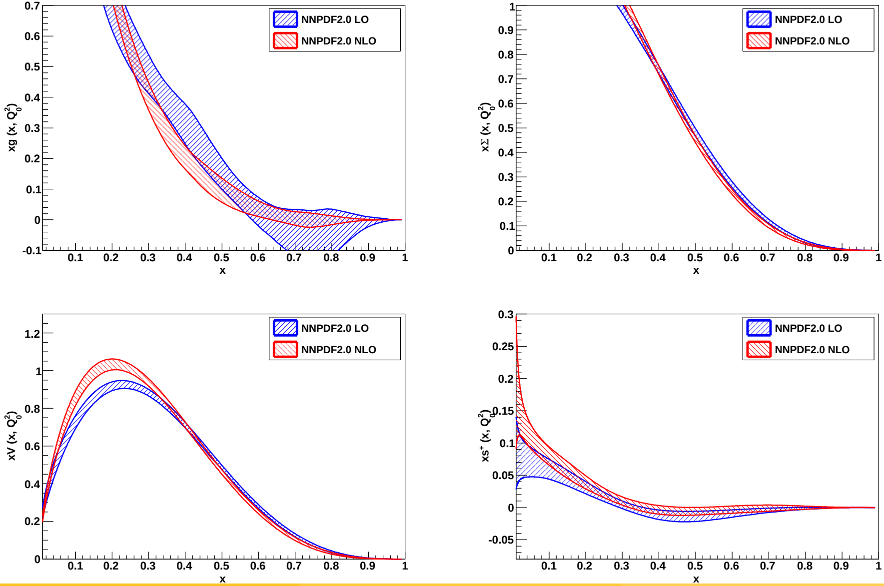
LO partons



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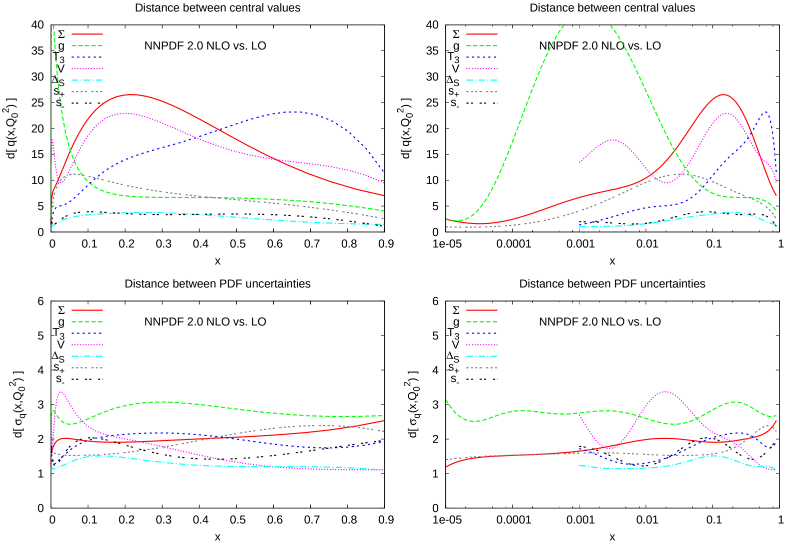

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LO partons