Neural network fits of parton distributions

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The NNPDF Collaboration:
Luigi Del Debbio, Stefano Forte, José I. Latorre,
Andrea Piccione and Juan Rojo,
(2007: +) Richard D. Ball, Alberto Guffanti and Maria Ubiali.

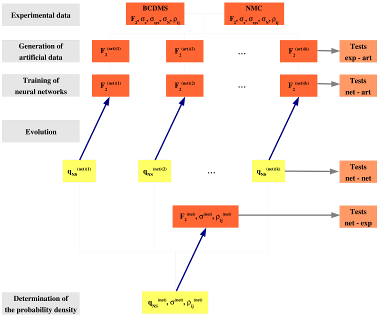
1. JHEP **02** (2002) 062 [arXiv:hep-ph/0204232].
2. JHEP **05** (2005) 080 [arXiv:hep-ph/0501067].
3. *Neural network determination of parton distributions: the nonsinglet case*, **JHEP 07 (2007) 039 [arXiv:hep-ph/0701127]**.

The neural Monte Carlo approach

Basic Idea: Monte Carlo sampling coupled to Neural Network interpolation

- Generate a set of Monte Carlo replicas $\sigma^{(k)}(p_i)$ of the original data set $\sigma^{(\mathrm{data})}(p_i)$, representation of $\mathcal{P}[\sigma(p_i)]$ at discrete set of points p_i
- Train a neural net for each pdf on each replica, obtaining a representation of the pdfs $q_i^{(\mathrm{net})(k)}$
- The set of neural nets is a representation of the probability density:

$$\langle \sigma\left[q_i\right] \rangle = \frac{1}{N_{\mathrm{rep}}} \sum_{k=1}^{N_{\mathrm{rep}}} \sigma\left[q_i^{(\mathrm{net})(k)}\right]$$



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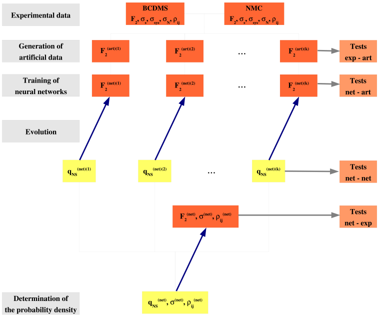

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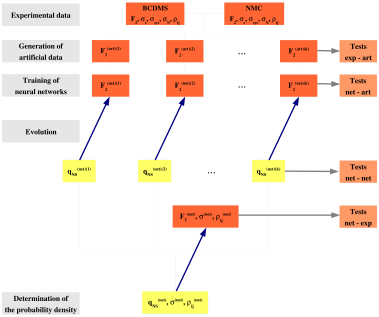

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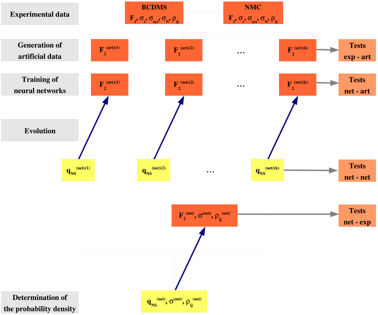

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Methodological issues

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Many different ingredients in the neural Monte Carlo approach to parton distributions: artificial data generation, neural network training, genetic minimization, preprocessing, result validation ...

Let us concentrate on a couple of the newest ones:

- Stopping criterion
- Stability estimators

N.B. Unless otherwise specified, results shown belong to hep-ph/0701127

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When to stop a fit?

In a standard fit, look for minimum χ^2 for given parametrization. However ...

- If basis too large $\rightarrow$ convergence never reached
- If basis too small $\rightarrow$ parametrization bias

How can one obtain an unbiased compromise? For neural nets, smoothness decreases as fit quality improves...

$\rightarrow$ Stop before fitting statistical noise (overlearning).

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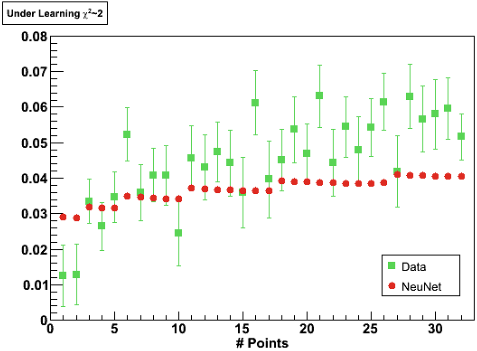

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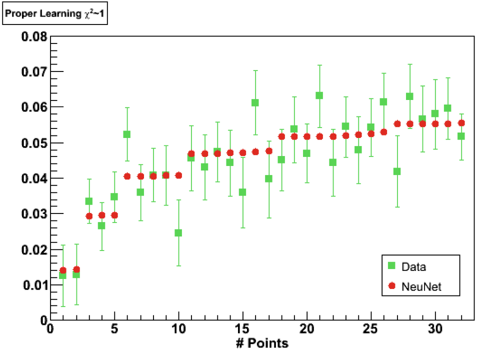
Proper learning



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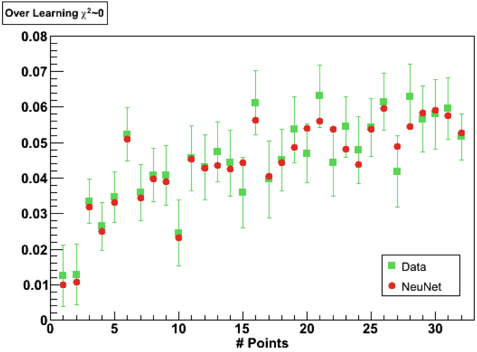

The neural stopping criterion

So stop the fit before overlearning sets in ... How does this work in practice?

At each Genetic Algorithm generation, χ^2 either decreases or unchanged

1. Divide the data set into training and validation sets
2. Minimize χ^2 of training set, monitor χ^2 of validation set
3. Stop minimization when validation χ^2 begins to rise

N.B. This stopping criterion could also be applied using standard polynomials (but impractical, a very large number of parameters required).

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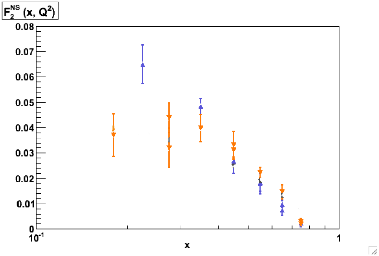
An explicit example

Let us see in practice how the overlearning stopping criterion works:

On your marks, get ready ...



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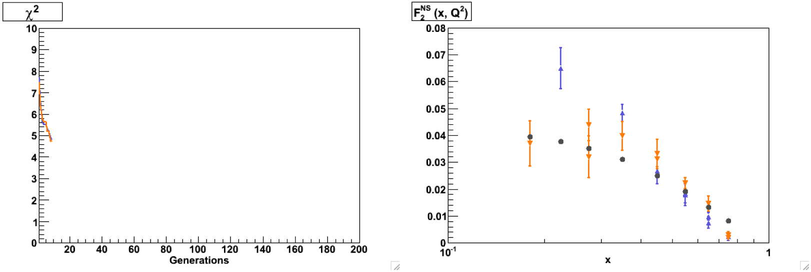

Underlearning, continue the minimization

An explicit example

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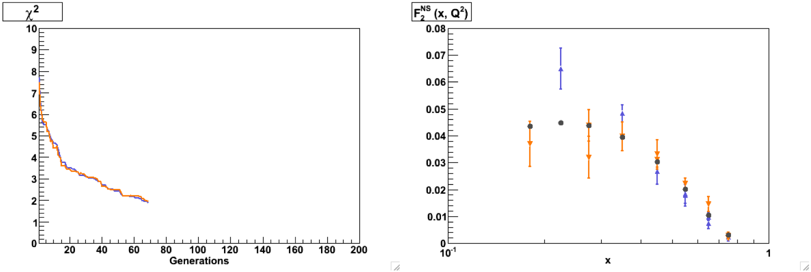
Stop!

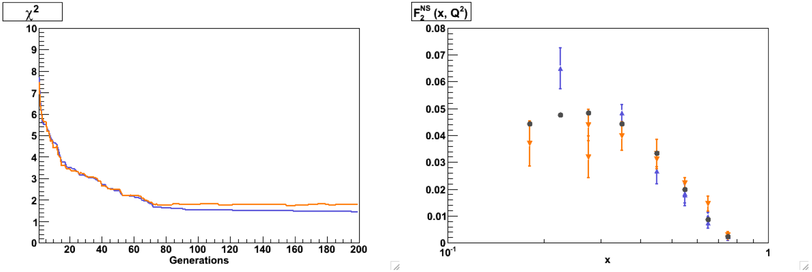


Onset of overlearning, stop the minimization.

An explicit example

Let us see in practice how the overlearning stopping criterion works:

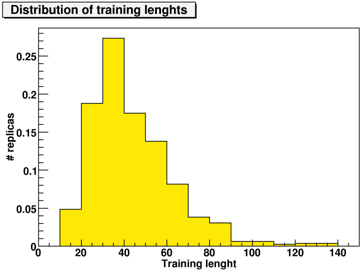
Too late!

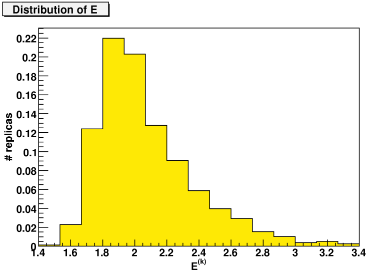


Deep in the overlearning region, fitting statistical noise ...

Does it work?

Distribution of χ^2 of pseudo-data and training lenghts





1. Poissonian distribution of training lenghts
2. For best fit, average χ^2 of replicas ~ 2, while when averaging over replicas $\chi^2 \sim 1$.
3. Total training time is optimized (never underlearn nor overlearn) $\longrightarrow$ efficient neural fitting.

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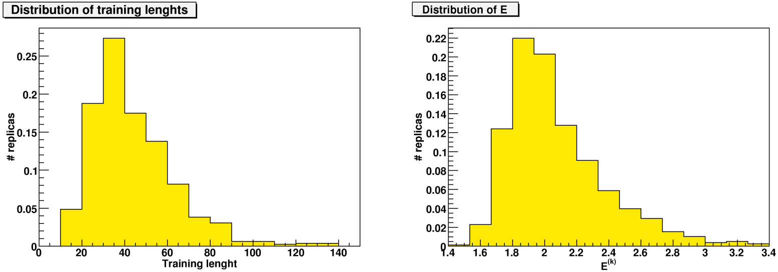

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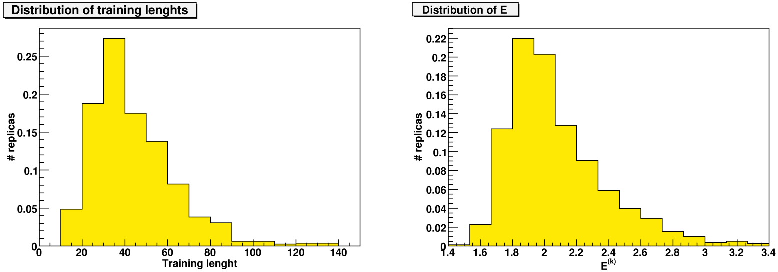

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Stability

Check stability and accuracy of our results (both for central values and for errors) when parameters of fit modified

Define RMS distance

$$\langle d[q] \rangle = \sqrt{\left\langle \frac{\left(\langle q_i \rangle_{(1)} - \langle q_i \rangle_{(2)}\right)^2}{\sigma^2[q_i^{(1)}] + \sigma^2[q_i^{(2)}]} \right\rangle_{\rm dat}}$$

where $\sigma[q_i] =$ error on $\langle q_i \rangle =$ error on $q_i/\sqrt{N_{\rm rep}}$.

Compute $\langle d[q] \rangle$ and $\langle d[\sigma] \rangle$ both in data region and in extrapolation region.

Statistical expectations:

- For statistically equivalent fits (different set of MC replicas, different net architecture) we expect $\langle d[q] \rangle \sim 1$, $\langle d[\sigma] \rangle \sim 1$.
- For statistically nonequivalent fits (different perturbative order, different α_s value) we expect (e.g. for central values)

$$\langle d[q] \rangle \sim \sqrt{\frac{N_{\rm rep}}{2}} \left\langle \frac{\left| \langle q_i \rangle_{(1)} - \langle q_i \rangle_{(2)} \right|}{\sigma[q_i]} \right\rangle_{\rm dat}$$

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Great expectations?

Indeed we observe the expected behavior:

Architecture	2-4-3-1 vs. 2-5-3-1
$\langle d\,[q]\rangle_{\rm dat}$	0.9
$\langle d\,[q]\rangle_{\rm extra}$	0.9
$\langle d\,[\sigma_q]\rangle_{\rm dat}$	0.9
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The nonsinglet case

Summary of the analysis

1. Data: $F_2^p(x,Q^2) - F_2^d(x,Q^2)$ from NMC and BCDMS (483 points with $Q^2 \geq 3$ GeV^2)
2. Determination of $q^{\mathrm{NS}}(x,Q_0^2) \equiv \left(u+\bar{u}-(d+\bar{d})\right)(x,Q_0^2)$ at $Q_0^2=2$ GeV^2 at L0, NLO, NNLO, and for different values of $\alpha_s(M_Z^2)$.
3. New fast and efficient implementation of NNLO parton evolution (mixed x/N space), benchmarked with the LH tables.

$$F_2^{\mathrm{NS}}(x,Q^2) = \frac{1}{6}x\int_x^1 \frac{dy}{y}\tilde{\Gamma}\left(y,\alpha_s\left(Q^2\right),\alpha_s\left(Q_0^2\right)\right) q_{\mathrm{NS}}\left(\frac{x}{y},Q_0^2\right) .$$

Results available from `http://sophia.ecm.ub.es/nnpdf`

See hep-ph/0701127 for all the technical details ...

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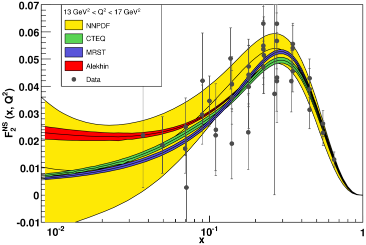
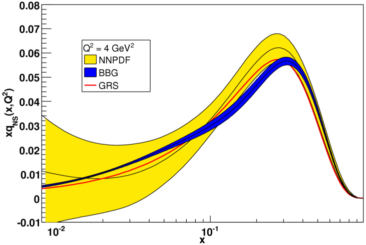
Comparison to other approaches





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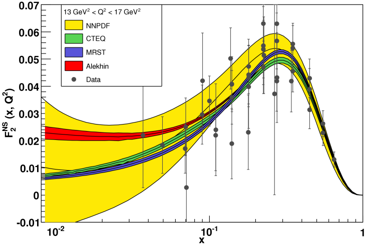

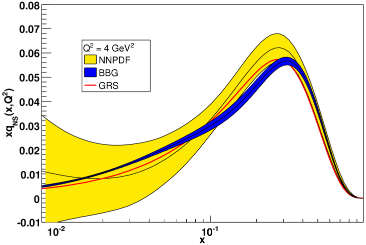

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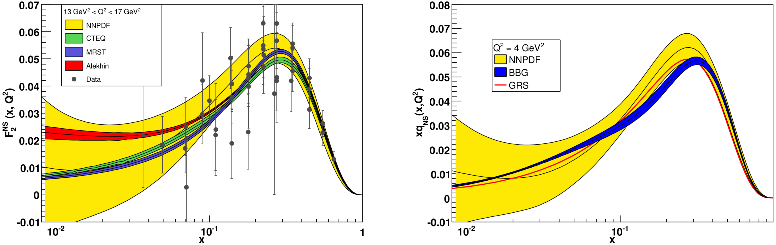

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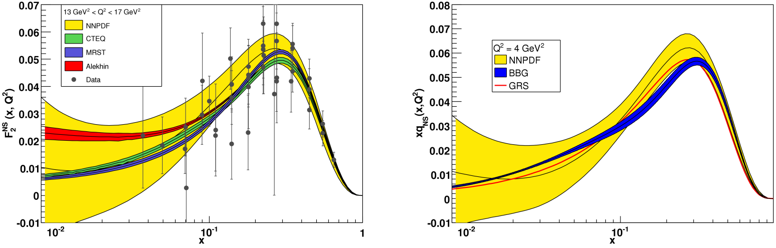

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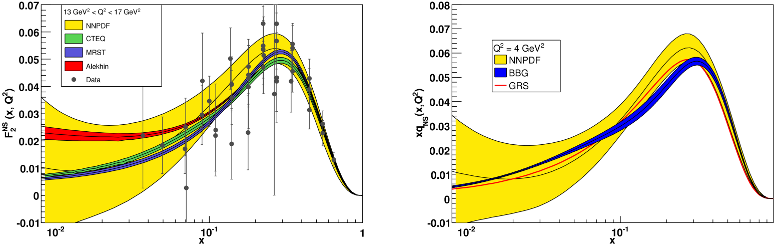

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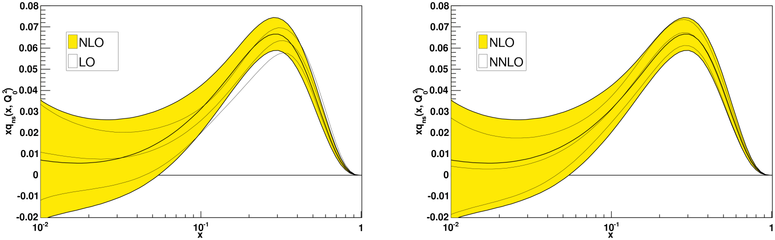

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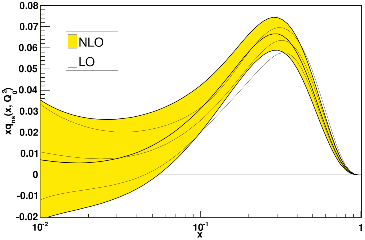

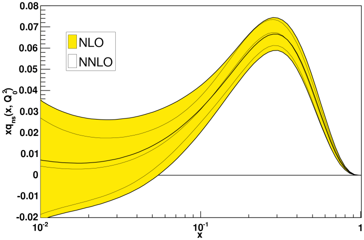

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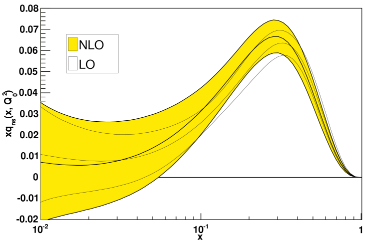

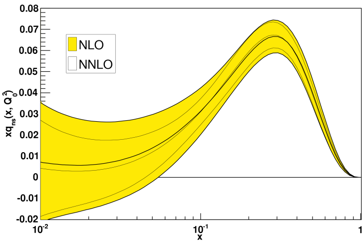

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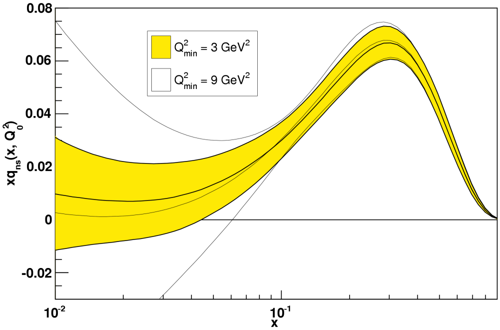
Kinematical cuts



Uncertainty in extrapolation region (small x) increases when kinematical cut in Q^2 is raised (as it should be!).

Status of the singlet case

The singlet case

- Data sets: SLAC, NMC, BCDMS structure function $F_2(x, Q^2)$ and HERA reduced cross sections $\widetilde{\sigma}^{NC}(x, Q^2)$ and $\widetilde{\sigma}^{CC}(x, Q^2)$.
- Fitted parton distributions (neural nets):

$$\Sigma(x, Q_0^2)\ , \quad q_{\rm NS}(x, Q_0^2)\ , \quad g(x, Q_0^2)$$

- ZM-VFN treatment of heavy flavors.
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- October 2006 - February 2007: Nonsinglet code extended to the singlet sector (data generation, evolution, neural parton fitting, validation)
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EXTRA SLIDES

Statistical estimators

	Total	NMC	BCDMS
$\chi^2_{\rm tot}$	0.75	0.72	0.78
$\langle E \rangle$	2.27	1.99	2.52
$r\left[F_2^{\rm NS}\right]$	0.81	0.66	0.95
$\left\langle \sigma^{(\exp)} \right\rangle_{\rm dat}$	0.011	0.017	0.006
$\left\langle \sigma^{(\rm net)} \right\rangle_{\rm dat}$	0.006	0.009	0.004
$r\left[\sigma^{(\rm net)}\right]$	0.59	-0.04	0.86
$\left\langle \rho^{(\exp)} \right\rangle_{\rm dat}$	0.11	0.39	0.16
$\left\langle \rho^{(\rm net)} \right\rangle_{\rm dat}$	0.46	0.42	0.50
$r\left[\rho^{(\rm net)}\right]$	0.15	0.25	0.04
$\left\langle {\rm cov}^{(\exp)} \right\rangle_{\rm dat}$	$8.6\ 10^{-6}$	$1.0\ 10^{-5}$	$7.2\ 10^{-6}$
$\left\langle {\rm cov}^{(\rm net)} \right\rangle_{\rm dat}$	$2.1\ 10^{-5}$	$3.8\ 10^{-5}$	$6.9\ 10^{-6}$
$r\left[{\rm cov}^{(\rm net)}\right]$	0.24	0.23	0.57

Determination of $\alpha_s(M_Z^2)$

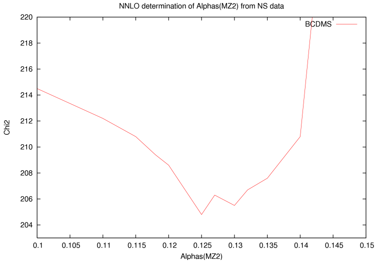
We do not fit $\alpha_s(M_Z^2)$ with $q_{\rm NS}(x, Q_0^2)$ (although technically possible), but take it from world average: $\alpha_s(M_Z^2)_{\rm NNLO} = 0.115$.

$\alpha_s(M_Z^2)$	0.116	0.118	0.120
χ^2	0.743	0.750	0.744
$\langle d\,[q]\rangle_{\rm dat}$	3.8	0	4.1
$\langle d\,[q]\rangle_{\rm extra}$	0.8	0	0.7
$\langle d\,[\sigma_q]\rangle_{\rm dat}$	1.6	0	2.4
$\langle d\,[\sigma_q]\rangle_{\rm extra}$	1.4	0	1.5

Fit results not sensible to $\alpha_s(M_Z^2)$ variation within world average uncertainty.

Determination of $\alpha_s(M_Z^2)$ II

More dedicated NNLO analysis in preparation:
Repeat the NNLO determination of $q_{NS}(x)$ scanning the $\alpha_s(M_Z^2)$ space:



Preliminary results: rather large value $\alpha_s(M_Z^2) = 0.124$ preferred by data, with large uncertainties (Similar conclusions in S. Forte et al., hep-ph/0205286).

Higher Twist

No evidence for Higher Twist found in experimental data:

Fit	$Q^2_{\rm min} = 3\ \mathrm{GeV}^2$+HT	$Q^2_{\rm min} = 5\ \mathrm{GeV}^2$	$Q^2_{\rm min} = 5\ \mathrm{GeV}^2$+HT
χ^2	0.76	0.79	0.78
$\langle d\,[q]\rangle_{\rm dat}$	2.9	0.8	3.2
$\langle d\,[q]\rangle_{\rm extra}$	1.4	0.8	0.9
$\langle d\,[\sigma_q]\rangle_{\rm dat}$	1.2	1.5	1.9
$\langle d\,[\sigma_q]\rangle_{\rm extra}$	1.3	1.8	2.3