# Update on neural network parton distributions



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NNPDF2.3 PDFs PDF Benchmarking NNPDF2.3 MC

## NNPDF2.3

NNPDF2.3: Only publicly available PDF set which includes LHC data in the fit. [arXiv:1207.1303]

Global fit, includes all relevant LHC data which was available with full covariance matrix:

- ATLAS Inclusive Jets,  $36pb^{-1}$
- ATLAS W/Z lepton rapidity distributions, 36pb<sup>-1</sup>
- CMS W lepton asymmetry,  $840 {\rm pb}^{-1}$
- LHCb W rapidity distributions,  $36 \text{pb}^{-1}$



Outlook

NNPDF2.3 PDFs PDF Benchmarking NNPDF2.3 MC

# NNPDF2.3 PDFs

Impact of LHC data:

- Moderate effect from LHC data, generally less than half a sigma in central values.
- Largest impact is for Singlet and strange distributions.
- Expect more substantial improvements with 2011 and 2012 data.



NNPDF2.3 PDFs PDF Benchmarking NNPDF2.3 MC

# PDF Benchmarking

Comprehensive PDF benchmarking analysis in arXiv:1211.5142

• Compares PDFs, parton luminosities and observables for available NNLO sets at common  $\alpha_S$ .



- Good consistency between the three global PDF sets.
- Most recent NNPDF, MSTW and CT NNLO sets agree at least as well as for NLO, in some places better

NNPDF2.3: PDFs with LHC data

Other NNPDF developments Outlook NNPDF2.3 PDFs PDF Benchmarking NNPDF2.3 MC

# PDF Benchmarking



- HERAPDF1.5 NNLO consistent with global sets, although with larger uncertainties due to reduced dataset.
- Significant disagreement with ABM11 for some PDFs and cross sections, even at common  $\alpha_S$ .



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#### NNPDF2.3 set for MC event generators

- NLO event generators often require positive definite NLO PDFs.
- In NLO and NNLO NNPDF fits we impose positivity on observables, not on PDFs directly
- In practice, PDFs go negative in regions with few experimental constraints, and this has little effect on observables
- NNPDF2.3 MC set with exact PDF positivity, available through latest version of LHAPDF (v5.8.9, NNPDF2.3\_as\_0119\_mc.LHgrid etc.)
- Also investigating extending range of observables for which we impose positivity.



# Other NNPDF developments

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#### Study of theoretical uncertainties

Recent paper [arXiv:1303.1189] looks at the effects of three sources of theoretical uncertainties in the framework of NNPDF2.3.

- Fixed Flavor Number (FFN) scheme for heavy quark masses
  - NNPDF fit performed using FFN scheme and compared to default (GM-VFN)
  - Significant differences found for PDFs
    - Large change in gluon due to differences in scaling violations
    - Effect increase with evolution to LHC scales
  - These differences translate to observables, results in worse quality of fit and affects LHC cross sections



## Study of theoretical uncertainties

- Higher twist effects using same corrections as ABM
  - Negligible impact on PDFs or observables
  - Doubling size of corrections results in change less than half sigma in all PDFs
- Deuterium nuclear corrections
  - Moderate impact, confined to up-down separation for large x.
  - Theoretical knowledge of effects still poor.



• These results suggest that difference between ABM11 and the three global PDF sets is largely due to use of FFN scheme and an almost DIS-only dataset.

#### C++ development

We are currently in the process of developing a  $C{++}\xspace$  version of our fitting code.

Having a new more modular object-oriented code has several benefits:

- It has been possible to cleanly separate the theory, data and fitting element of the code.
- Easier to maintain and to add new improvements.
- Easier to add new LHC data, and to add cross-correlations between datasets.
- New code was developed with minimal reference to old code, so provides a cross-check for bugs.
- Have also gained a large speedup through structural changes.

Development should be complete in time for next major NNPDF release.

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# Outlook

Many things planned for NNPDF in the future

- NNPDF2.3QED: PDF set with QED corrections
  - see Stefano's talk up next.
- New strangeness analysis using recently released W+ charm data
- Further in the future, NNPDF3.0:
  - Based on C++ code
  - Including many new LHC processes
    - top pair production
    - double differential Drell-Yan
    - $Z p_T$  distributions
    - CMS jet data
    - prompt photon
    - + others...
  - Improved NNPDF methodology

# Summary

- NNPDF2.3: Only PDF fit which includes LHC data, shows that available LHC data already has a small but significant impact on PDF determination.
- New NNPDF2.3 NLO set specifically for use in NLO event generators.
- Looking ahead, lots of new LHC data coming out over the next months and years and we'll have a refined NNPDF methodology to fit it with.

NNPDF website: nnpdf.hepforge.org

Our PDFs are also available through the LHAPDF interface (lhapdf.hepforge.org)

Image: Second second

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## NNPDF approach - key features

- Global Fit
  - Use data from wide variety of processes (e.g DIS, W/Z cross sections from colliders, fixed target Drell-Yan, jet data)
- Fit PDFs at initial scale using neural networks
  - Provides a flexible and unbiased fitting basis
- $\bullet\,$  Perform  $\chi^2$  minimization to experimental data using genetic algorithm
  - Suitable for efficiently searching for minima in a large parameter space
- Monte Carlo approach to PDF uncertainties
  - Direct sample of probability distributions of PDFs without assumptions of Gaussianity

### Neural network PDFs

• We model 7 independent PDF combinations:

 $\begin{array}{ll} \mbox{Gluon} & g(x) & \mbox{Sea asymmetry} & \Delta_s(x) = \bar{d}(x) - \bar{u}(x) \\ \mbox{Singlet} & \Sigma(x) = \sum_i [f_i(x) + \bar{f}_i(x)] & \mbox{Total strangeness} & s^+(x) = s(x) + \bar{s}(x) \\ \mbox{Valence} & V(x) = \sum_i [f_i(x) - \bar{f}_i(x)] & \mbox{Strange valence} & s^-(x) = s(x) - \bar{s}(x) \\ \mbox{Triplet} & T(x) = [u(x) + \bar{u}(x)] - [d(x) + \bar{d}(x)] \\ \end{array}$ 

- Each PDF is parametrized by a neural network defined by 37 parameters per PDF, so 259 for the fit in total.
- Large number of parameters increases risk of overfitting fitting statistical noise in data as well as underlying pattern.
- We prevent this using Cross-Validation:
  - Data is split into *training* and *validation* sets.
  - The networks are trained on only the training set and the fit is stopped when quality of fit to validation set increases.

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# Monte Carlo replicas

We use a Monte Carlo approach to calculating PDF uncertainties:

- Generate a large number of replica datasets according to multigaussian probability distributions suggested by the experimental uncertainties.
- Perform a separate fit using each data replica.

Expectation values for any quantity dependent on PDFs can be determined directly using

$$\left\langle \mathcal{F}\right\rangle =\frac{1}{N_{rep}}\sum_{k=1}^{N_{rep}}\mathcal{F}\left(S_{k}\right)$$

and uncertainties, confidence intervals, correlations using similar formula.



# Results: Fit Quality

- Comparison of  $\chi^2$  to data for NNPDF2.1 and 2.3 sets.
- Improvement for NLO fit in most datasets due to methodological improvements.
- Inclusion of LHC data improves quality of their descriptions with little impact on other experiments – no sign of tension.
- Fit quality comparable between NLO and NNLO, with NLO slightly better.

	NNP	DF2.1	NNPDF2.3		
	NLO	NNLO	NLO	NNLO	
Total	1.145	1.167	1.121	1.153	
NMC-pd	0.97	0.93	0.93	0.94	
NMC	1.68	1.58	1.61	1.57	
SLAC	1.34	1.04	1.26	1.02	
BCDMS	1.21	1.29	1.19	1.29	
CHORUS	1.10	1.08	1.10	1.06	
NTVDMN	0.70	0.50	0.45	0.55	
HERAI-AV	1.04	1.04	1.00	1.01	
FLH108	1.34	1.23	1.28	1.20	
ZEUS-H2	1.21	1.21	1.20	1.22	
ZEUS $F_2^c$	0.75	0.81	0.82	0.90	
H1 $F_2^{c}$	1.50	1.44	1.58	1.52	
DYE605	0.94	1.09	0.88	1.02	
DYE886	1.42	1.76	1.28	1.62	
CDF W asy	1.87	1.63	1.54	1.70	
CDF Z rap	1.77	2.42	1.79	2.12	
D0 Z rap	0.57	0.68	0.57	0.63	
ATLAS W,Z	[1.58]	[2.22]	1.27	1.46	
CMS W e asy	[2.26]	[1.45]	1.04	0.96	
LHCb W,Z	[1.34]	[1.42]	1.21	1.22	
CDF RII kT	0.68	0.65	0.61	0.67	
D0 RII cone	0.90	0.98	0.84	0.93	
ATLAS jets	[1.65]	[1.48]	1.55	1.42	

## NNPDF2.3 PDFs: NLO



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### NNPDF2.3 PDFs: NNLO



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# FFN fit quality

$x_{\min}$	$x_{\max}$	$Q_{\min}^2$ (GeV)	$Q_{ m max}^2$ (GeV)	$\Delta\chi^2$ (DIS)	$N_{dat}^{DIS}$	$\Delta\chi^2$ (HERA-I)	$N_{dat}^{hera-I}$
$4 \cdot 10^{-5}$	1	3	$10^{6}$	72.2	2936	77.1	592
$4 \cdot 10^{-5}$	0.1	3	$10^{6}$	87.1	1055	67.8	405
$4 \cdot 10^{-5}$	0.01	3	$10^{6}$	40.9	422	17.8	202
$4 \cdot 10^{-5}$	1	10	$10^{6}$	53.6	2109	76.4	537
$4 \cdot 10^{-5}$	1	100	$10^{6}$	91.4	620	97.7	412
$4 \cdot 10^{-5}$	0.1	10	$10^{6}$	84.9	583	67.4	350
$4 \cdot 10^{-5}$	0.1	100	$10^{6}$	87.7	321	87.1	227

 $\Delta\chi^2\equiv\chi^2_{\rm FFN}-\chi^2_{\rm VFN}$  of the deep-inelastic data in different kinematic regions. The contribution from combined HERA-I data is also shown in the last column.

The difference is always positive, indicating that the  $\ensuremath{\mathsf{FFN}}$  fit is always worse.

See arXiv:1211.5142 for more details.

#### PDFs with Higher Twist corrections [arXiv:1211.5142]



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# Collider-only NNPDF2.3

- NNPDF fit only using HERA, Tevatron and LHC data
- Gluon is fairly well constrained.
- Large uncertainties in other PDFs e.g. T3
- Situation will change with more LHC data

