TBA

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Heavy Ions: Experiment Confront Theory Niels Bohr Institute (Copenhagen) November 7-9, 2011

NNPDF for the LHC and a couple of comments on Nuclear (NN)PDFs

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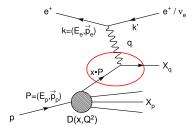
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What are Parton Distribution Functions?

• Consider a process with one hadron in the initial state



According to the Factorization Theorem we can write the cross section as

$$d\sigma = \sum_{a} \int_{0}^{1} \frac{d\xi}{\xi} D_{a}(\xi, \mu^{2}) d\hat{\sigma}_{a}\left(\frac{x}{\xi}, \frac{\hat{s}}{\mu^{2}}, \alpha_{s}(\mu^{2})\right) + \mathcal{O}\left(\frac{1}{Q^{p}}\right)$$



What are Parton Distribution Functions?

- The absolute value of PDFs at a given x and Q² cannot be computed in QCD Perturbation Theory (Lattice? In principle yes, but ...)
- ... but the scale dependence is governed by DGLAP evolution equations

$$\frac{\partial}{\ln Q^2} q^{NS}(\xi, Q^2) = P^{NS}(\xi, \alpha_s) \otimes q^{NS}(\xi, Q^2)$$
$$\frac{\partial}{\ln Q^2} \begin{pmatrix} \Sigma \\ g \end{pmatrix} (\xi, Q^2) = \begin{pmatrix} P_{qq} & P_{qg} \\ P_{gq} & P_{gg} \end{pmatrix} (\xi, \alpha_s) \otimes \begin{pmatrix} \Sigma \\ g \end{pmatrix} (\xi, Q^2)$$

 ... and the splitting functions P can be computed in PT and are known up to NNLO

[LO - Dokshitzer; Gribov, Lipatov; Altarelli, Parisi; 1977] [NLO - Floratos, Ross, Sachrajda; Gonzalez-Arroyo, Lopez, Yndurain; Curci, Furmanski, Petronzio, 1981] [NNLO - Moch, Vermaseren, Vogt; 2004]

Problem

Faithful estimation of errors on PDFs

- Single quantity: 1- σ error
- Multiple quantities: 1-σ contours
- Function: need an "error band" in the space of functions (*i.e.* the probability density *P*[*f*] in the space of functions *f*(*x*))

Expectation values are Functional integrals

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



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Determine a function from a finite set of data points



• Introduce a simple functional form with enough free parameters

$$q(x, Q^2) = x^{\alpha}(1-x)^{\beta} P(x; \lambda_1, ..., \lambda_n).$$

• Fit parameters minimizing χ^2 .



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Open problems:

- Error propagation from data to parameters and from parameters to observables is not trivial.
- Theoretical bias due to the chosen parametrization is difficult to assess.



Shortcomings of the Standard approach

What is the meaning of a one- σ uncertainty?

 Standard Δχ² = 1 criterion is too restrictive to account for large discrepancies among experiments in a global fit.

[Collins & Pumplin, 2001]





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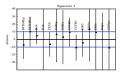
• Standard $\Delta \chi^2 = 1$ criterion is too restrictive to account for large discrepancies among experiments in a global fit.

[Collins & Pumplin, 2001]

• Introduce a **TOLERANCE** criterion, i.e. take the envelope of uncertainties of experiments to determine the $\Delta \chi^2$ to use for the global fit (CTEQ).

[Tung et al., 2006]







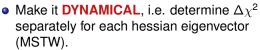
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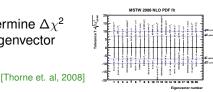
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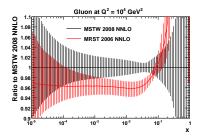




Shortcomings of the standard approach

What determines PDF uncertainties?

- Uncertainties in standard fits often increase when adding data (i.e. when adding information) even if they are compatible with the old data.
- **Reason**: need change the parametriztion in order to accomodate the new data.



Larger small-*x* uncertainty due to extrat free parameter.

Smaller high-x gluon (and slightly smaller α_S) results in larger small-x gluon – now shown at NNLO.

[R. Thorne, PDF4

THE NNPDF METHODOLOGY

[R. D. Ball, V. Bertone, F. Cerutti, L. Del Debbio, S. Forte, J. I. Latorre, A. Piccione, J. Rojo, M. Ubiali and AG]



NNPDF Methodology

Main Ingredients

Monte Carlo determination of errors

- No need to rely on linear propagation of errors
- Possibility to test for the impact of non gaussianly distributed errors
- Possibility to test for non-gaussian behaviour in fitted PDFs $(1 \sigma \text{ vs. 68\% CL})$

Neural Networks

• Provide an unbiased parametrization

• Stopping based on Cross-Validation

• Ensures proper fitting avoiding overlearning



NNPDF Methodology

- Generate *N_{rep}* Monte-Carlo replicas of the experimental data (sampling of the probability density in the space of data)
- Fit a set of Parton Distribution Functions on each replica (sampling of the probability density in the space of PDFs)
- Expectation values for observables are Monte Carlo integrals

$$\langle \mathcal{F}[f_i(x, Q^2)]
angle = rac{1}{N_{rep}} \sum_{k=1}^{N_{rep}} \mathcal{F}\Big(f_i^{(net)(k)}(x, Q^2)\Big)$$

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

NNPDF Methodology

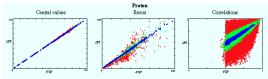
Monte Carlo replicas generation

Generate artificial data according to distribution

$$O_{i}^{(art)(k)} = (1 + r_{N}^{(k)} \sigma_{N}) \left[O_{i}^{(exp)} + \sum_{p=1}^{N_{sys}} r_{p}^{(k)} \sigma_{i,p} + r_{i,s}^{(k)} \sigma_{s}^{i} \right]$$

where r_i are univariate (gaussianly distributed) random numbers

• Validate Monte Carlo replicas against experimental data (statistical estimators, faithful representation of errors, convergence rate increasing *N*_{rep})



O(1000) replicas needed to reproduce correlations to percent accuracy

Neural Networks

... a suitable basis of functions

• We use Neural Networks as functions to represent PDFs at the starting scale

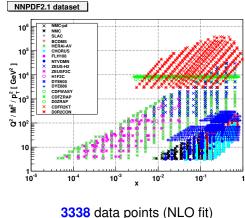
• They provide a parametrization which is **redundant** and **robust** against variations

• We employ Multilayer Feed-Forward Neural Networks trained using a Genetic Algorithm

- Very efficient for complex parameter spaces
- Reduces the probability of being trapped in local minima
- Stopping of the fit for each replica is determined by cross-validation method
 - Ensures proper proper fitting avoiding overlearning







(3330 - LO and 3445 - NNLO)

[R. D. Ball et. al, arXiv:1101.1300] - **NLO** [R. D. Ball et. al, arXiv:1107.2652] - **LO/NNLO**

OBS	Data set		
Deep Inelastic Scattering			
F_2^d/F_2^p	NMC-pd		
F_2^p	NMC, SLAC, BCDMS		
F_2^d	SLAC, BCDMS		
σ_{NC}^{\pm}	HERA-I, ZEUS (HERA-II)		
$\frac{\sigma_{NC}^{\pm}}{\sigma_{CC}^{\pm}}$	HERA-I, ZEUS (HERA-II)		
F _L	H1		
$\sigma_{\nu}, \sigma_{\bar{\nu}}$	CHORUS		
dimuon prod.	NuTeV		
F_2^c	ZEUS, H1		
Drell-Yan & Vector Boson prod.			
$d\sigma^{ m DY}/dM^2 dy$	E605		
$d\sigma^{\rm DY}/dM^2 dx_F$	E866		
W asymm.	CDF		
Z rap. distr.	D0/CDF		
Inclusive jet prod.			
Incl. $\sigma^{(jet)}$	CDF (k _T) - Run II		
Incl. $\sigma^{(jet)}$	D0 (cone) - Run II		

NNPDF2.1 ... based on the NNPDF Methodology

Parton Distributions Combination

NN architechture

Singlet $(\Sigma(x))$	\implies	2-5-3-1 (<mark>37</mark> pars)
Gluon $(g(x))$	\implies	2-5-3-1 (37 pars)
Total valence $(V(x) \equiv u_V(x) + d_V(x))$	\implies	2-5-3-1 (37 pars)
Non-singlet triplet ($T_3(x)$)	\implies	2-5-3-1 (37 pars)
Sea asymmetry $(\Delta_S(x) \equiv \overline{d}(x) - \overline{u}(x))$	\implies	2-5-3-1 (37 pars)
Total Strangeness $(s^+(x) \equiv (s(x) + \bar{s}(x))/2)$	\implies	2-5-3-1 (37 pars)
Strange valence $(s^-(x) \equiv (s(x) - \overline{s}(x))/2)$	\implies	2-5-3-1 (<mark>37</mark> pars)

 $\begin{array}{c} \textbf{259 parameters} \\ \textbf{Standard fits have} \sim \textbf{25 parameters in total} \end{array}$

No change in the parametrization since NNPDF1.2 ... despite substantial enlargement of the dataset.



NNPDF2.1

... including Heavy Flavour contributions (FONLL)

• We adopt the FONLL General Mass-Variable Flavour Number Scheme

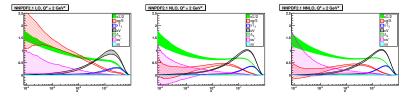
[M. Cacciari, M. Greco and P. Nason, (1998)] [S. Forte, P. Nason E. Laenen and J. Rojo, (2010)]

- FONLL gives a prescription to combine FFN (Massive) and ZM-VFN (Massless) computations, at any given order, avoiding double counting.
- With available computations three implementations of FONLL are possibile:
 - FONLL-A: $\mathcal{O}(\alpha_s)$ Massless + $\mathcal{O}(\alpha_s)$ Massive (NLO fit)
 - FONLL-B: $\mathcal{O}(\alpha_s)$ Massless + $\mathcal{O}(\alpha_s^2)$ Massive
 - FONLL-C: $\mathcal{O}(\alpha_s^2)$ Massless + $\mathcal{O}(\alpha_s^2)$ Massive (NNLO fit)
- Fixed Flavour Number Scheme (3-, 4-, 5-) fits available.





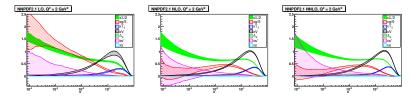
• At the starting scale (2 GeV²) ...



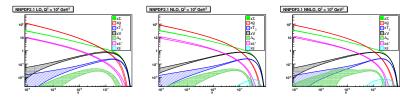




• At the starting scale (2 GeV²) ...

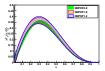


... and at the typical EW scale (100 GeV²)





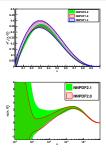








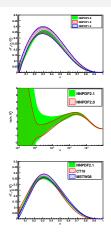
 When uncertainties increase we know it is not a parametrzation effect







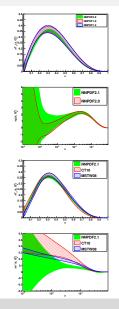
- When uncertainties increase we know it is not a parametrzation effect
- Uncertainties on PDFs have size comparable to those obtained by other groups when there are significant contraints from data ...





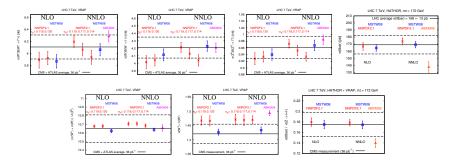


- When uncertainties increase we know it is not a parametrzation effect
- Uncertainties on PDFs have size comparable to those obtained by other groups when there are significant contraints from data ...
- ... but no functional bias in kinematic regions where there are little or no experimental constraints.





• Predictions for LHC Standard Candles compared to LHC data



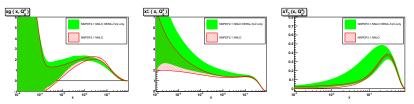
 LHC data will soon be precise enough to distinguish between different predictions.



NNPDF2.1: fits to reduced datasets

Collider-only fit

- The (proton) fit we would love to have ...
 - Only high energy data: minimize effects of higher-twist contribiutions
 - Only proton data: no assumptions based on models for nuclear corrections
- Based on HERA and Tevatron (inclusive jets and W/Z prduction) data



 LHC (and HERA-II combined) data are crucial in order to improve collider-only fit

LHC4PDFs

... the data we would love to have from the LHC

- Medium- and large-x gluon
 - Prompt photons
 - Inclusive Jets
 - *t*-quark distributions (p_{\perp}, y) (?)

• Light flavour separation at medium- & small-x

- Low-mass Drell-Yan
- High-mass W prduction
- Z rapidity distribution
- W(+jets) asymmetry

Strangeness & Heavy Flavours

- *W* + *c*
- Z + c, $\gamma + c$
- *Z* + *b*

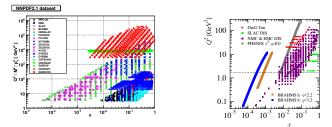
A QUICK LOOK IN THE NUCLEAR TERRITORY



Nuclear NNPDFs

The case for having them

 Nuclear PDFs are determined from a much more restricted dataset than proton ones



- In the standard approach to PDF extractions (used by EPS, HKN and nDS sets) uncontrolled theoretical assumption on the functional form of PDFs can be a source of large bias
- The NNPDF methodology is ideally suited to provide a reliable estimation of the uncertanties in a situation where experimental constraints are very loose

A. Guffanti (NBIA & Discovery Center)

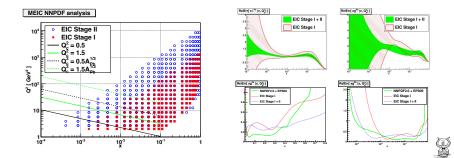


Nuclear NNPDFs

EIC White Book - the first NNPDF steps in the nuclear territory

[A. Accardi, V. Guzey and J. Rojo, arXiv:1106.3839]

- One of the phyiscs goal of the proposed Electron Ion Collider (EIC) is the determination of nuclear PDFs
- The NNPDF methodology has been used to extract the Singlet and gluon PDFs from a fit to simulated EIC e-Pb pseudodata



Conclusions & Outlook

- A set of PDF with a **reliable** estimation of **uncertainties** is crucial in order to exploit the full physics potential of the LHC experiments (both for *pp* and *AA*).
- The NNPDF2.1 family of PDF sets fulfills the requirement of an ideal parton densities set for precision (*pp*) phenomenology at the LHC
- The NNPDF Methodology is ideally suited to tackle problems that affect standard global (nuclear) fits (loose constraints from data, parametrization bias, etc.)
- ... moreover, plenty of new data will come from the LHC probing different nPDF combinations and providing more stringent constraints

