

Neural Networks and the Structure of the Proton

Andrea Piccione

Milano, 12 Ottobre 2005

The NNPDF Collaboration

Luigi Del Debbio¹, Stefano Forte²,
José I. Latorre³, A. P.⁴ and Joan Rojo³

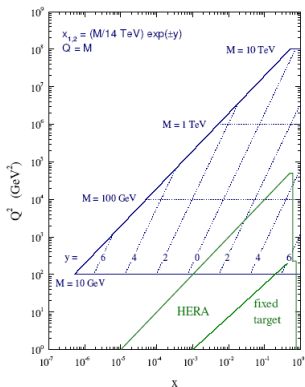
¹ Theory Division, CERN

² Dipartimento di Fisica, Università di Milano and INFN, Sezione di Milano

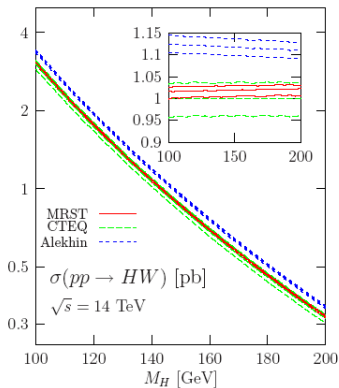
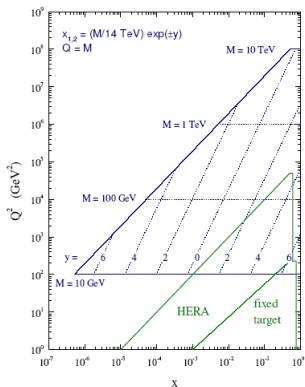
³ Departament d'Estructura i Constituents de la Matèria, Universitat de Barcelona

⁴ Dipartimento di Fisica Teorica, Università di Torino and INFN, Sezione di Torino

What do we need for the LHC?



What do we need for the LHC?



[Djouadi and Ferrag 2003]

Deep Inelastic Scattering

- ▶ The cross section

$$\frac{d^2\sigma}{dx dQ^2} = \frac{4\pi\alpha^2}{Q^4} \left[[1 + (1-y)^2] F_1 + \frac{1-y}{x} (F_2 - 2xF_1) \right]$$

- ▶ The structure function

$$F_2(x, Q^2) = x \left[\sum_{q=1}^{n_f} e_q^2 C^q \otimes q_q(x, Q^2) + 2n_f C^g \otimes g(x, Q^2) \right]$$

- ▶ Parton distribution evolution is described by DGLAP equations

$$Q^2 \frac{d}{dQ^2} q(x, Q^2) = \frac{\alpha_s(Q^2)}{2\pi} (P \otimes q)(x, Q^2)$$

Deep Inelastic Scattering and QCD

- ▶ The cross section

$$\frac{d^2\sigma}{dx dQ^2} = \frac{4\pi\alpha^2}{Q^4} \left[[1 + (1-y)^2] F_1 + \frac{1-y}{x} (F_2 - 2xF_1) \right]$$

- ▶ The structure function

$$F_2(x, Q^2) = x \left[\sum_{q=1}^{n_f} e_q^2 C^q \otimes q_q(x, Q^2) + 2n_f C^g \otimes g(x, Q^2) \right]$$

- ▶ Parton distribution evolution is described by DGLAP equations

$$Q^2 \frac{d}{dQ^2} q(x, Q^2) = \frac{\alpha_s(Q^2)}{2\pi} (P \otimes q)(x, Q^2)$$

The problem

- ▶ For a single quantity \rightarrow 1 sigma error
- ▶ For a pair of numbers \rightarrow 1 sigma ellipse
- ▶ For a function \rightarrow We need an “error band” in the space of functions (*i.e.* the probability density $\mathcal{P}[f]$ in the space of functions $f(x)$)

Expectation values \rightarrow Functional integrals

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

Determine an infinite-dimensional object (a function) from finite set of data points \rightarrow Mathematically ill-posed problem

The problem

- ▶ For a single quantity \rightarrow 1 sigma error
- ▶ For a pair of numbers \rightarrow 1 sigma ellipse
- ▶ For a function \rightarrow We need an “error band” in the space of functions (*i.e.* the probability density $\mathcal{P}[f]$ in the space of functions $f(x)$)

Expectation values \rightarrow **Functional integrals**

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

Determine an infinite-dimensional object (a function) from finite set of data points \rightarrow **Mathematically ill-posed problem**

The standard approach

1. Choose a simple functional form with enough free parameters

$$q(x, Q_0^2) = x^\alpha (1-x)^\beta P(x; \lambda_1, \dots, \lambda_n)$$

2. Fit parameters by minimizing χ^2

Problem:

- ▶ Which is the theoretical bias due to the parametrization?

The standard approach

1. Choose a simple functional form with enough free parameters

$$q(x, Q_0^2) = x^\alpha (1-x)^\beta P(x; \lambda_1, \dots, \lambda_n)$$

2. Fit parameters by minimizing χ^2

Problem:

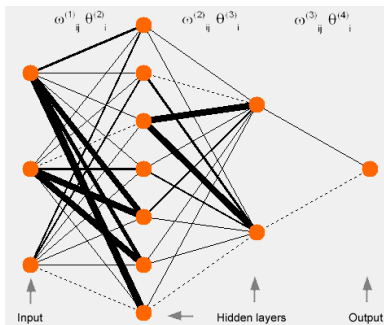
- ▶ Which is the theoretical bias due to the parametrization?

The NNPDF approach

- ▶ Determination of the Structure Functions:
this is the easiest case, since no evolution is required, but only data fitting. A good application to test the technique → Done
- ▶ Determination of the Parton Distributions:
the real stuff → Working on it ...

What are Neural Networks?

Neural networks are algorithms providing robust, universal, unbiased approximants to incomplete or noisy data



▶ Activation function:

$$\xi_i^{(l)} = g \left(\sum_{j=1}^{n_j-1} \omega_{ij}^{(l-1)} \xi_j^{(l-1)} - \theta_i^{(l)} \right)$$

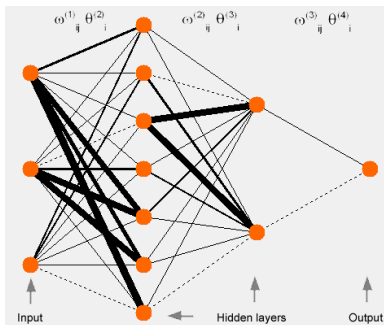
$$g(x) = \frac{1}{1 + e^{-x}}$$

▶ Parameters: weights $\omega_{ij}^{(l)}$ and thresholds $\theta_i^{(l)}$

▶ Assumption: smoothness and convergence criterium

What are Neural Networks?

Neural networks are algorithms providing robust, universal, unbiased approximants to incomplete or noisy data



▶ Activation function:

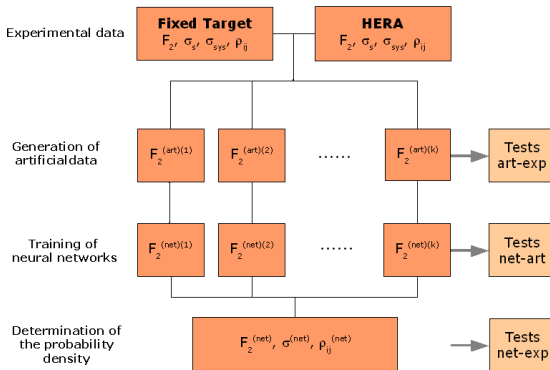
$$\xi_i^{(l)} = g \left(\sum_{j=1}^{n_{l-1}} \omega_{ij}^{(l-1)} \xi_j^{(l-1)} - \theta_i^{(l)} \right)$$

$$g(x) = \frac{1}{1 + e^{-x}}$$

▶ Parameters: weights $\omega_{ij}^{(l)}$ and thresholds $\theta_i^{(l)}$

▶ Assumption: smoothness and convergence criterium

General strategy



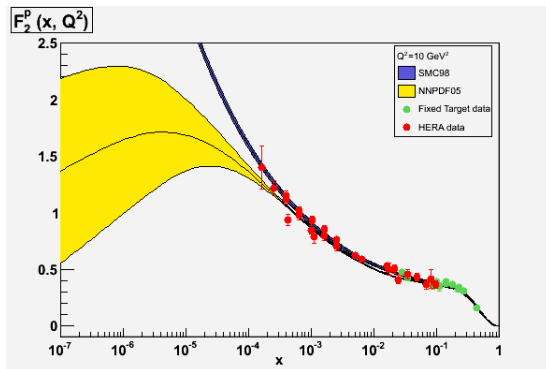
Credits

- ▶ S. Forte, L. Garrido, J. I. Latorre and A. P., “*Neural network parametrization of deep-inelastic structure functions,*” JHEP05 (2002) 062 [arXiv:hep-ph/0204232]
- ▶ L. Del Debbio, S. Forte, J. I. Latorre, A. P. and J. Rojo [NNPDF Collaboration], “*Unbiased determination of the proton structure function F_2^p with faithful uncertainty estimation*”, JHEP03 (2005) 080 [arXiv:hep-ph/0501067]

Source code, driver program and graphical web interface for F_2 plots and numerical computations available @

<http://sophia.ecm.ub.es/f2neural>

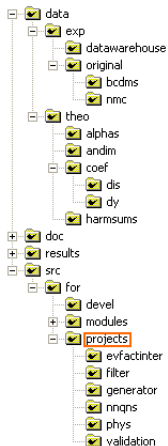
Fit of $F_2^p(x, Q^2)$ [NNPDF 2005]



Same strategy, but much more complex!

Same strategy, but much more complex!

CVS tree:

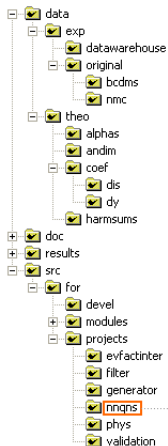


Languages: F77, C++, ShellScript
 Libraries: CERN, LHAPDF
 #code lines: 9K
 #files: 320
 #folders: 115
 #bytes: 14M

The NNPDF approach

Same strategy, but much more complex!

CVS tree:

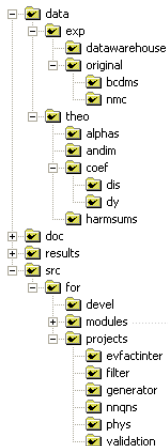


Languages: F77, C++, ShellScript
 Libraries: CERN, LHAPDF
 #code lines: 9K
 #files: 320
 #folders: 115
 #bytes: 14M



Same strategy, but much more complex!

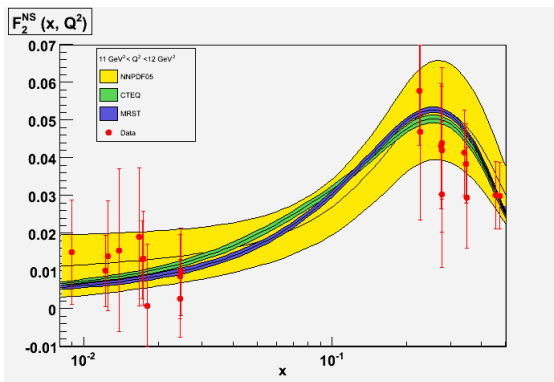
CVS tree:



Languages: F77, C++, ShellScript
 Libraries: CERN, LHAPDF
 #code lines: 9K
 #files: 320
 #folders: 115
 #bytes: 14M



Non-Singlet



Outlook

- ▶ NN fit of other structure functions (e. g. $F_3(x, Q^2)$)
- ▶ Construct full set of NNPDF parton distributions from all available data
- ▶ Assess impact of uncertainties of PDFs for relevant observables at LHC
- ▶ Make formalism compatible with standard interfaces (LHAPDF, PDFLIB) → NNPDF partons available for use in Monte Carlo generators

Outlook

- ▶ NN fit of other structure functions (e. g. $F_3(x, Q^2)$)
- ▶ Construct full set of NNPDF parton distributions from all available data
- ▶ Assess impact of uncertainties of PDFs for relevant observables at LHC
- ▶ Make formalism compatible with standard interfaces (LHAPDF, PDFLIB) → NNPDF partons available for use in Monte Carlo generators