RESEARCH INTERESTS

Juan Rojo-Chacón

Exp/Th LPNHE/LPTHE meeting

November 29, 2006

CV - in brief

- Degree in Physics at the Universitat de Barcelona
- Ph.D. in Theoretical Physics at the Universitat de Barcelona (hep-ph/0607122) under the supervision of J.I. Latorre and S. Forte (Milan)
- October 2006 - October 2008 $\rightarrow$ Postdoctoral CNRS researcher at the LPTHE.

Research interests

- **Perturbative Quantum Chromodynamics**
  1. New approaches to global fits of **Parton Distribution Functions (The neural network approach)**, (hep-ph/0501067, hep-ph/0607199).
  2. Large and small-x resummations (hep-ph/0601048)
  3. B-physics, effective theories (hep-ph/0605248, hep-ph/0601229)
  4. Ultra-high energy neutrino physics (ICECUBE)
  5. Jet physics.
- **Other**
  1. Astroparticles: atmospheric neutrinos (Super Kamiokande) (hep-ph/0607324).
  2. Artificial intelligence, neural networks, genetic algorithms, data mining ...

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Parton distribution functions I

1. Parametrize the PDFs at a starting evolution scale Q_0^2 with a functional form
$$q_i(x, Q_0^2) = A_i x^{b_i}(1-x)^{c_i}\left(1 + d_i x + e_i x^2 + \ldots\right)$$
Large x: Counting rules, small x: Regge theory (not from QCD!)
2. Evolve each PDF (DGLAP equations) to the scale Q^2 of experimental data + add perturbative coefficients
$$F_i^{(QCD)} = C_{ij}(x, \alpha(Q^2)) \otimes q_j(x, Q^2)$$
3. Minimize a statistical estimator, like the diagonal χ^2 until convergence is achieved
$$\chi^2_{\mathrm{diag}} = \frac{1}{N_{\mathrm{dat}}} \sum_{i=1}^{N_{\mathrm{dat}}} \left(F_i^{(\exp)} - F_i^{(QCD)}\right)^2 / \sigma_i^2$$
4. Assess the uncertainties (theoretical and experimental) associated with this best fit set.

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Parton distribution functions II

Parton distributions carry different potential sources of (large) uncertainties:

1. Experimental uncertainties: experimental data has finite precision.
2. Theoretical uncertainties: perturbative calculations are always approximate.
3. Intrinsic uncertainties: functional form bias (see e.g hep-ph/0611254).

Moreover, PDFs uncertainties need to be propagated to observables in a faithful way.
Are PDFs uncertainties phenomenologically relevant?
For the LHC parton distributions are essential:

$$\sigma(Q^2) = C_{ij}\left(x, \alpha_s(Q^2)\right) \otimes q_i(x, Q^2) \otimes q_j(x, Q^2)$$

PDF uncertainties are dominant in many benchmark LHC processes (e.g. Higgs production, hep-ph/0508222)

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The neural network approach

The **NNPDF Collaboration**: L. del Debbio (Edinburgh), S. Forte (Milan), J.I. Latorre (Barcelona), A. Piccione (Torino) and J. Rojo (Paris).

We use a combination of Monte Carlo methods and neural networks as unbiased universal interpolants to construct a probability measure in the space of functions $\mathcal{P}\left[F(x, Q^2)\right]$ from experimental data.

1. Monte Carlo replica generation $\longrightarrow$ Faithful estimation of the uncertainties and non-linear error propagation.
2. Neural network training $\longrightarrow$ No bias due to fixed functional forms, faithful extrapolation

The probability measure $\mathcal{P}[F]$ contains all information from experimental data (central values, errors, correlations) with the only assumption of smoothness.

Expectation values $\longrightarrow$ Functional integrals over probability measure

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

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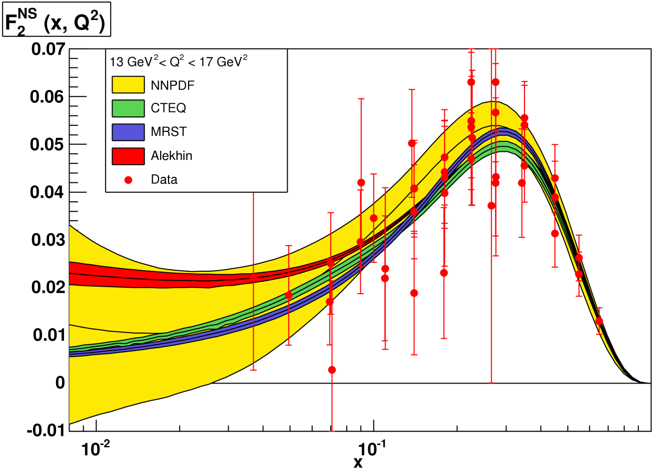
Results: the nonsinglet pdf



Future research

Perturbative Quantum Chromodynamics

1. Construct a global fit of parton distributions from all available data using the NNPDF approach.
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