Parton Distribution Functions for the LHC

Present Status & Uncertainty determination

Alberto Guffanti

Niels Bohr International Academy & Discovery Center
Niels Bohr Institute - Copenhagen

Ph. D. course on Particle Physics Phenomenology

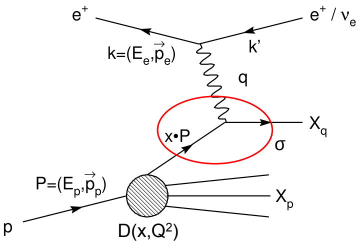
NBI Copenhagen

October 4, 2011

What are Parton Distribution Functions?

Definition - Factorization

- 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?

Definition - DGLAP equations

- The initial condition cannot be computed in Perturbation Theory
  (Lattice? In principle yes, but ...)

- ... but the energy scale dependence is governed by DGLAP evolution equations

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

- ... 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 $\mathcal{P}[f]$ in the space of functions $f(x)$)

Expectation values are **Functional integrals**

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

Problem

Faithful estimation of errors on PDFs

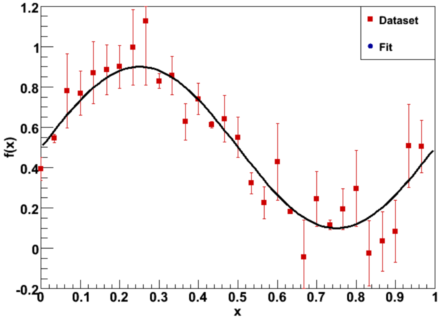
- Single quantity: **1-σ error**
- Multiple quantities: **1-σ contours**
- Function: need an **"error band" in the space of functions**
  (*i.e.* the probability density $\mathcal{P}[f]$ in the space of functions $f(x)$)

Expectation values are **Functional integrals**

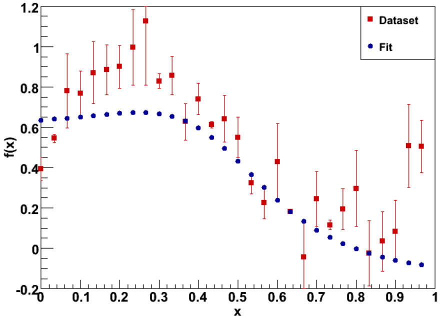
$$\langle \mathcal{F}[f(x)] \rangle = \int \mathcal{D}f \mathcal{F}[f(x)] \mathcal{P}[f(x)]$$

Determine a function from a finite set of data points

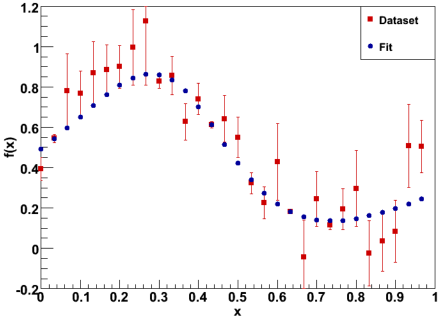
Proper Fitting avoiding Overlearning



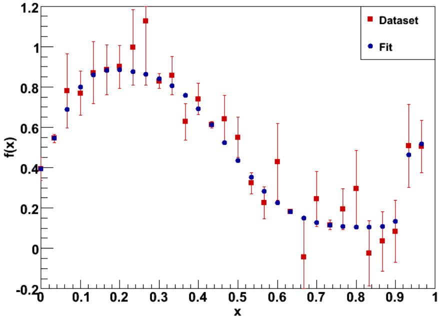
Proper Fitting avoiding Overlearning



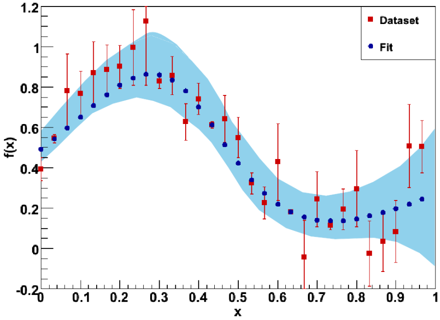
Proper Fitting avoiding Overlearning



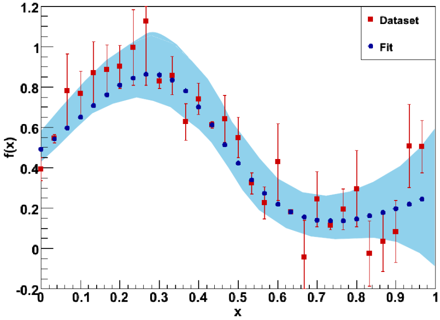
Proper Fitting avoiding Overlearning



Proper Fitting avoiding Overlearning



Proper Fitting avoiding Overlearning



- Need a **redundant parametrization** to avoid parametrization bias.
- Need a way of **stopping the fit before overlearning** sets in to avoid fitting statistical noise.
- Need a **reliable error estimation**.

DATA SET SELECTION

Choice of Dataset

Global vs. Restricted dataset

Restricted set Analyses

- **HERAPDF**: use only HERA DIS data
- **AB(K)M/JR**: use Fixed target DIS, HERA and Drell-Yan data
    - Focus on the most precise dataset(s)
    - Avoid possible incompatibilities
    - Limited flavour separation
    - Neglect important constraints (gluon at medium/large-x)

Global Analyses

- **CTEQ-TEA/MSTW/NNPDF**: HERA DIS, Fixed target DIS and Drell-Yan, Vector Boson and Inclusive jet production at colliders
    - Focus on completeness
    - Reliable flavour separation
    - Possible data incompatibilities

Choice of Dataset

Which data constrain which PDFs

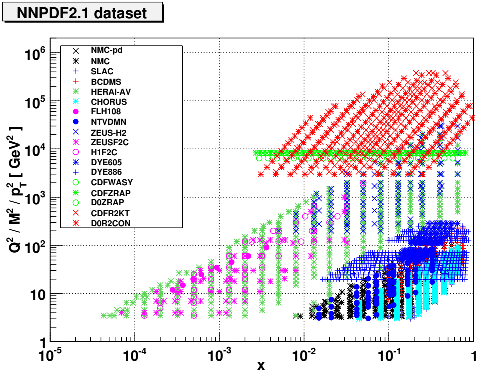
H1, ZEUS: $F_2^{e^\pm p}(x,Q^2)$
BCDMS: $F_2^{\mu p}(x,Q^2)$, $F_2^{\mu d}(x,Q^2)$
NMC: $F_2^{\mu p}(x,Q^2)$, $F_2^{\mu d}(x,Q^2)$, $\frac{F_2^{\mu n}(x,Q^2)}{F_2^{\mu p}(x,Q^2)}$
SLAC: $F_2^{\mu p}(x,Q^2)$, $F_2^{\mu d}(x,Q^2)$
E665: $F_2^{\mu p}(x,Q^2)$, $F_2^{\mu d}(x,Q^2)$
CCFR, NuTeV, CHORUS: $F_{2,3}^{\nu(\bar\nu)p}(x,Q^2)$

$\Rightarrow$ q, $\bar q$ at all x; g at moderate and small x

E605, E702, E866: $pN \to \mu\bar\mu + X$	$\Rightarrow$	$\bar q$, (g)
E605: Drell-Yan p, n asymmetry	$\Rightarrow$	$\bar u$, $\bar d$
CDF: W rapidity asymmetry	$\Rightarrow$	u/d ratio at high-x
CDF, D0: Inclusive jet data	$\Rightarrow$	g at high-x
CCFR, NuTeV: Dimuon data	$\Rightarrow$	s, $\bar s$ sea

NNPDF 2.1

Dataset



3338 data points

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
$\sigma_{NC}^{\pm}$	HERA-I, ZEUS (HERA-II)
$\sigma_{CC}^{\pm}$	HERA-I, ZEUS (HERA-II)
F_L	H1
$\sigma_{\nu}, \sigma_{\bar{\nu}}$	CHORUS
dimuon prod.	NuTeV
F_2^c	ZEUS (99,03,08,09)
F_2^c	H1 (01,09,10)
Drell-Yan & Vector Boson prod.	
$d\sigma^{\rm DY}/dM^2 dy$	E605
$d\sigma^{\rm DY}/dM^2 dx_F$	E866
W asymm.	CDF
Z rap. distr.	D0/CDF
Inclusive jet prod.	
Incl. $\sigma^{\rm (jet)}$	CDF (k_T) - Run II
Incl. $\sigma^{\rm (jet)}$	D0 (cone) - Run II

PDF PARAMETRIZATION

PDF parametrization

Theoretical Requirements - QCD Sum Rules

- **Valence Sum Rules**

$$\int_0^1 [u(x,Q^2) - \overline{u}(x,Q^2)]dx = 2, \qquad \int_0^1 [d(x,Q^2) - \overline{d}(x,Q^2)]dx = 1$$

$$\int_0^1 [s(x,Q^2) - \overline{s}(x,Q^2)]dx = 0$$

A proton has net quantum numbers of 2 up and 1 down quarks.

- **Momentum Sum Rule**

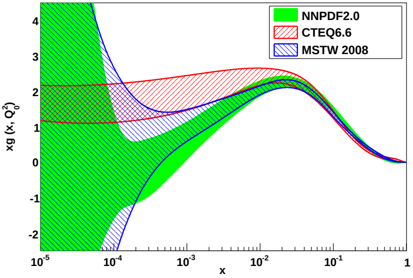
$$\sum_{a=q,\bar{q},g} \int_0^1 x f_a(x,Q^2) = 1$$

Momenta of all partons must add up to the proton momentum.

PDF parametrization

Theoretical Requirements - Positivity of Observables

- **Cross-sections must be positve**
  - Tipically realized imposing PDF positivity
  - ... but remember: PDFs are not **P**robability **D**ensity **F**unctions (nor are they observables)
  - **No probabilistic interpretation** beyond Leading Order
  - Might result in excessive constraints on PDFs.



PDF parametrization

Standard Approach (CTEQ-TEA/MSTW/ABKM/HERAPDF)

- Introduce a simple functional form with enough free parameters

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

- "Theoretically motivated"-form
  - $x \to 0 : q \propto x^{a_1}$ - Regge-like behaviour
  - $x \to 1 : q \propto (1-x)^{a_2}$ - quark counting rules
  - $P(x; \lambda_1, ..., \lambda_n)$: affects medium$-x$, just a convenient functional form

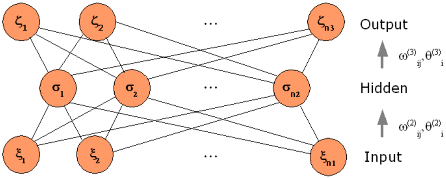
Parton Distributions Combination

$$
\begin{aligned}
xu_v(x,Q^2) &= A_u x^{\eta_1}(1-x)^{\eta_2}(1+\epsilon_u\sqrt{x}+\gamma_u x)\\
xd_v(x,Q^2) &= A_d x^{\eta_3}(1-x)^{\eta_4}(1+\epsilon_d\sqrt{x}+\gamma_d x)\\
xS(x,Q^2) &= A_S x^{\delta_S}(1-x)^{\eta_S}(1+\epsilon_S\sqrt{x}+\gamma_S x)\\
x\Delta(x,Q^2) &= A_\Delta x^{\eta_\Delta}(1-x)^{\eta_S+2}(1+\gamma_\Delta+\delta_\Delta x^2)\\
xg(x,Q^2) &= A_g x^{\delta_g}(1-x)^{\eta_g}(1+\epsilon_g\sqrt{x}+\gamma_g x)+A_{g'}x^{\delta_{g'}}(1-x)^{\eta_{g'}}\\
x(s+\bar{s})(x,Q^2) &= A_+ x^{\delta_S}(1-x)^{\eta_+}(1+\epsilon_S\sqrt{x}+\gamma_S x)\\
x(s-\bar{s})(x,Q^2) &= A_- x^{\delta_-}(1-x)^{\eta_-}(1+x/x_0)
\end{aligned}
$$

29 parameters

PDF parametrization

The NNPDF Approach - Neural Networks



- Neural Networks are **non-linear** statistical tools.
- Any continuous function can be approximated with neural network with one internal layer and non-linear neuron activation function.
- **Efficient minimization algorithms** for complex parameter spaces.
- They provide a parametrization which is **redundant** and **robust** against variations.

PDF parametrization

Neural Networks ... just another basis of functions

Multilayer feed-forward networks

- Each neuron receives input from neurons in preceding layer and feeds output to neurons in subsequent layer
- Activation determined by weights and thresholds

$$\xi_i = g\left(\sum_j \omega_{ij}\xi_j - \theta_i\right)$$

- Sigmoid activation function

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

PDF parametrization

Neural Networks ... just another basis of functions

Multilayer feed-forward networks

- Each neuron receives input from neurons in preceding layer and feeds output to neurons in subsequent layer
- Activation determined by weights and thresholds

$$\xi_i = g\left(\sum_j \omega_{ij}\xi_j - \theta_i\right)$$

- Sigmoid activation function

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

A 1-2-1 NN:

$$\xi_1^{(3)}(\xi_1^{(1)}) = \frac{1}{1+e^{\theta_1^{(3)} - \frac{\omega_{11}^{(2)}}{1+e^{\theta_1^{(2)} - \xi_1^{(1)}\omega_{11}^{(1)}}} - \frac{\omega_{12}^{(2)}}{1+e^{\theta_2^{(2)} - \xi_1^{(1)}\omega_{21}^{(1)}}}}}$$

PDF parametrization

NNPDF 2.1 Parametrization

Parton Distributions Combination		NN architechture
Singlet ($\Sigma(x)$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Gluon ($g(x)$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Total valence ($V(x) \equiv u_V(x) + d_V(x)$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Non-singlet triplet ($T_3(x)$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Sea asymmetry ($\Delta_S(x) \equiv \bar{d}(x) - \bar{u}(x)$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Total Strangeness ($s^+(x) \equiv (s(x) + \bar{s}(x))/2$)	$\Longrightarrow$	2-5-3-1 (37 pars)
Strange valence ($s^-(x) \equiv (s(x) - \bar{s}(x))/2$)	$\Longrightarrow$	2-5-3-1 (37 pars)

259 parameters

PDF UNCERTAINTIES

PDF Uncertainties

The Hessian Method

- The figure of merit to be minimized in the fit is the fully correlated χ^2

$$\chi^2 = \sum_{I,J=1}^{N_{dat}} (D_I - T_I(\{a\})) \left[(\mathrm{cov})^{-1}\right]_{IJ} (D_J - T_J(\{a\}))$$

where D_k and T_k are the **data** and **theory** values for each data point

- Important to properly **accout** for **correlated uncertainties**.
- Special care needed for **normalization uncertainties** (in general multiplicative uncertainties).

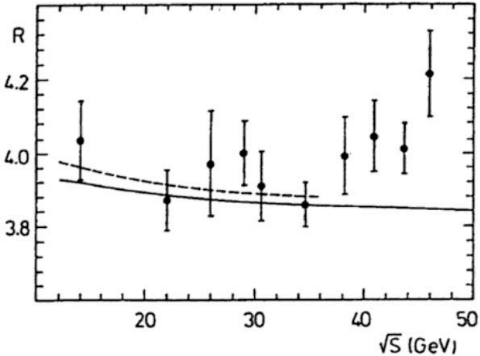
[R. D. Ball et al., arXiv:0912.2276]

PDF Uncertainties

Normailization Uncertainties

m-cov

R(e^+e^-)
CELLO 1987



Dashed line: data below 36 GeV
Solid line: all data

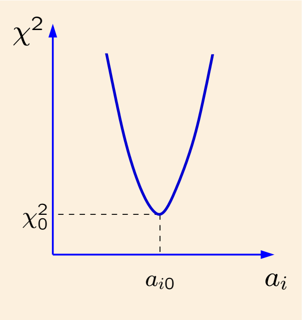
D'Agostini 1994

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



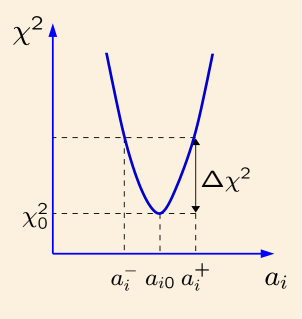
- Minimization of a likelihood function (χ^2) with respect to ~ 30 theoretical (mostly PDF) parameters $\{a_i\}$ and > 100 experimental systematical parameters

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



- Establish a confidence region for $\{a_i\}$ for a given tolerated increase in χ^2
- In the ideal case of perfectly compatible Gaussian errors, 68% c.l. on a physical observable X corresponds to $\Delta\chi^2 = 1$ independently of the number N of PDF parameters

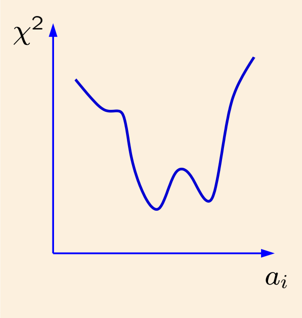
See, e.g., P. Bevington, K. Robinson, Data analysis and error reduction for the physical sciences

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



Pitfalls to avoid

- "Landscape"
  - disagreements between the experiments

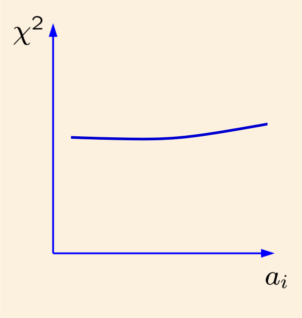
In the worst situation, significant disagreements between M experimental data sets can produce up to $N \sim M!$ possible solutions for PDF's, with $N \sim 10^{500}$ reached for "only" about 200 data sets

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



Pitfalls to avoid

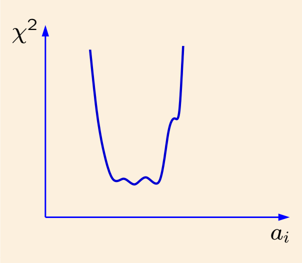
- Flat directions
  - unconstrained combinations of PDF parameters
  - dependence on free theoretical parameters, especially in the PDF parametrization
  - impossible to derive reliable PDF error sets

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



The actual χ^2 function shows

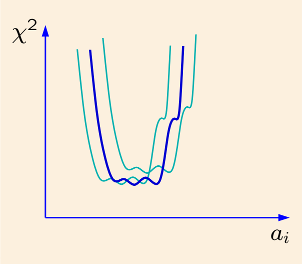
- a well pronounced global minimum χ^2_0
- weak tensions between data sets in the vicinity of χ^2_0 (mini-landscape)
- some dependence on assumptions about flat directions

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis

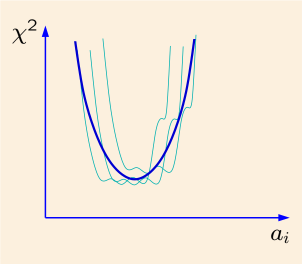


The actual χ^2 function shows

- a well pronounced global minimum χ_0^2
- weak tensions between data sets in the vicinity of χ_0^2 (mini-landscape)
- some dependence on assumptions about flat directions

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



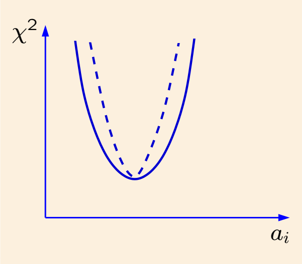
The actual χ^2 function shows

- a well pronounced global minimum χ_0^2
- weak tensions between data sets in the vicinity of χ_0^2 (mini-landscape)
- some dependence on assumptions about flat directions

The likelihood is approximately described by a quadratic χ^2 with a revised tolerance condition $\Delta\chi^2 \leq T^2$

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



The actual χ^2 function shows

- a well pronounced global minimum χ_0^2
- weak tensions between data sets in the vicinity of χ_0^2 (mini-landscape)
- some dependence on assumptions about flat directions

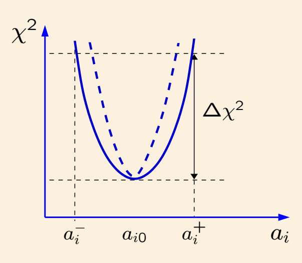
The likelihood is approximately described by a quadratic χ^2 with a revised tolerance condition $\Delta\chi^2 \leq T^2$

PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Multi-dimensional error analysis



The actual χ^2 function shows

- a well pronounced global minimum χ_0^2
- weak tensions between data sets in the vicinity of χ_0^2 (mini-landscape)
- some dependence on assumptions about flat directions

The likelihood is approximately described by a quadratic χ^2 with a revised tolerance condition $\Delta\chi^2 \leq T^2$

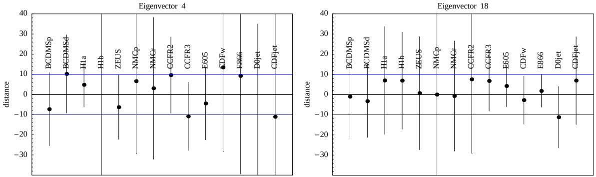
PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

CTEQ6 tolerance criterion (2001)

Acceptable values of PDF parameters must agree at ≈90% c.l. with all experiments included in the fit, *for a plausible range of assumptions about the PDF parametrization, scale dependence, experimental systematics, ...*



Can be crudely approximated (but does not have to) by assuming $T \approx 10$ for all PDF parameters

A somewhat stricter variant of this criterion is applied in the MSTW'08 analysis

PDF Uncertainties

The Hessian Method

- Used by most PDF fitters (CTEQ, MSTW, ABKM, HERAPDF).
- Given an observable which depends on a set of parameters $\{z\}$

$$X(\{z\}) = X_0 + z_i \partial_i X(\{z\})$$

  the variance is given by

$$\sigma_X^2 = \sigma_{ij} \partial_i X \partial_j X$$

  with σ_{ij} being the covariance matrix in parameter space.

- **Diagonalization**: choose the z_i as eigenvectors of σ_{ij} with unit eigenvalues so that

$$\sigma_X^2 = |\vec{\nabla} X|^2$$

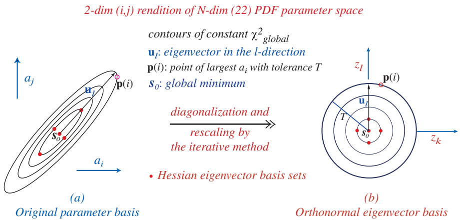
- Relies on **linear error propagation**, i.e. **Gaussian approximation**

PDF Uncertainties

The Hessian Method

[P. Nadolsky, CTEQ School 2009]

Tolerance hypersphere in the PDF space



A hyperellipse $\Delta\chi^2 \leq T^2$ in space of N physical PDF parameters $\{a_i\}$ is mapped onto a filled hypersphere of radius T in space of N orthonormal PDF parameters $\{z_i\}$

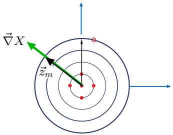
PDF Uncertainties

The Hessian Method

[P. Nadolsky, CTEQ School 2009]

Tolerance hypersphere in the PDF space

2-dim (i,j) rendition of N-dim (22) PDF parameter space



(b)
Orthonormal eigenvector basis

PDF error for a physical observable X is given by

$$\Delta X = \vec{\nabla} X \cdot \vec{z}_m = \left|\vec{\nabla} X\right| = \frac{1}{2}\sqrt{\sum_{i=1}^{N}\left(X_i^{(+)} - X_i^{(-)}\right)^2}$$

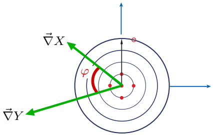
PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Tolerance hypersphere in the PDF space

2-dim (i,j) rendition of N-dim (22) PDF parameter space



(b)
Orthonormal eigenvector basis

Correlation cosine for observables X and Y:

$$\cos\varphi = \frac{\vec{\nabla}X \cdot \vec{\nabla}Y}{\Delta X \Delta Y} = \frac{1}{4\Delta X\, \Delta Y} \sum_{i=1}^{N} \left(X_i^{(+)} - X_i^{(-)}\right)\left(Y_i^{(+)} - Y_i^{(-)}\right)$$

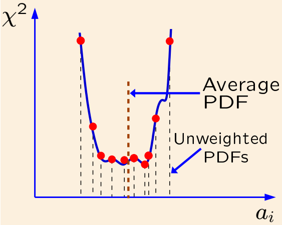
PDF Uncertainties

Multidimensional error Analysis

[P. Nadolsky, CTEQ School 2009]

Confidence intervals in global PDF analyses

Monte-Carlo sampling of the PDF parameter space



A very general approach that

- realizes stochastic sampling of the probability distribution *(Alekhin; Giele, Keller, Kosower; NNPDF)*
- can parametrize PDF's by flexible neural networks (NNPDF)
- does not rely on smoothness of χ^2 or Gaussian approximations

PDF Uncertainties

The Monte Carlo Method

- Used by NNPDF (and old Fermi and Alekhin sets).
- Generate N_{rep} Monte Carlo **replicas of the data**
  (Monte Carlo in the space of parameters is not a smart idea, because of flat directions)
- Fit a set of PDFs to each replica, the **ensemble of replicas** gives the **probability density** in the space of PDFs
- You get a set of N_{rep} replicas, compute central values, standard deviations, correlations as you would do for any Monte Carlo ensemble:

$$\langle \mathcal{F}[\{q\}] \rangle = \frac{1}{N_{\rm rep}} \sum_{k=1}^{N_{\rm rep}} \mathcal{F}[\{q^{(k)}\}]$$

$$\sigma_{\mathcal{F}} = \sqrt{\frac{N_{\rm rep}}{N_{\rm rep}-1} \left(\langle \mathcal{F}[\{q\}]^2 \rangle - \langle \mathcal{F}[\{q\}] \rangle^2 \right)}$$

PDF Uncertainties

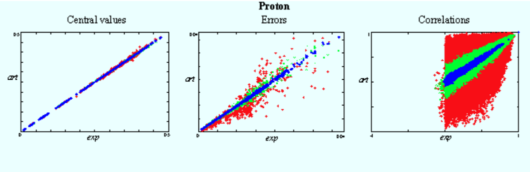
The Monte Carlo Method in practice

- **Generate artificial data** according to distribution

$$O_i^{(art)\,(k)} = (1 + r_N^{(k)}\,\sigma_N)\left[O_i^{(exp)} + \sum_{p=1}^{N_{sys}} r_p^{(k)}\,\sigma_{i,p} + r_{i,s}^{(k)}\,\sigma_s^i\right]$$

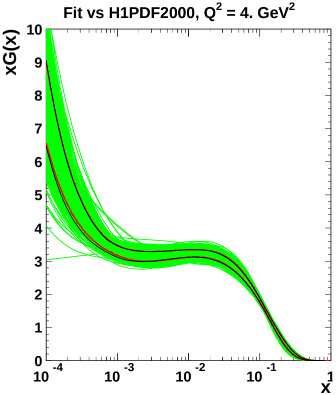
  where r_i are univariate (gaussian) random numbers

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



- $\mathcal{O}(1000)$ **replicas** needed to reproduce **correlations to percent accuracy**

- **Q**: Are the two methods equivalent?
  A: Hessian and MC method give the same results in the linear error propagation approximation
- **Q**: Nice, but what about in the real world?
  A: arXiV:0901.2504, pg. 41
- **Q**: Wait a minute, you assumed gaussian errors ...
  A: arXiV:0901.2504, pg. 42

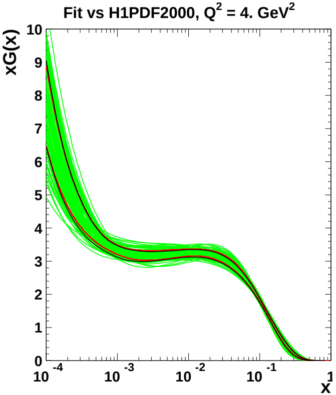


[S. Glazov and V. Radescu]

PDF Uncertainties

Hessian vs. Monte Carlo

- **Q**: Are the two methods equivalent?
  A: Hessian and MC method give the same results in the linear error propagation approximation
- **Q**: Nice, but what about in the real world?
  A: arXiV:0901.2504, pg. 41
- **Q**: Wait a minute, you assumed gaussian errors ...
  A: arXiV:0901.2504, pg. 42



[S. Glazov and V. Radescu]

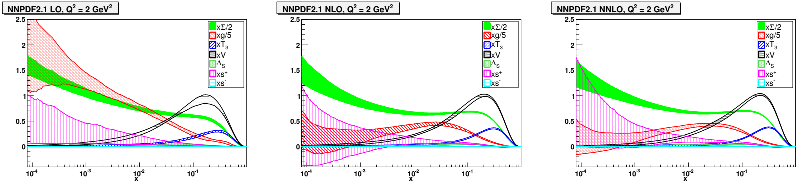
PDF fits status

The present status of PDF fits

The PDF sets Matrix

	Dataset	**Pert. Order**	**Heavy Flavours**	α_S	**Param.**	**Uncert.**
ABKM09	DIS (FT, HERA) Drell-Yan (FT)	NLO NNLO	FFN (BMSN)	fitted	6 indep. PDF Polynomial (25 param.)	Hessian ($\Delta\chi^2 = 1$)
CT10	DIS (FT, HERA) Drell-Yan (FT, Tev) Jets (Tevatron)	LO NLO	GM-VFNS (S-ACOT)	external	6 indep. PDF Polynomial (26 param.)	Hessian ($\Delta\chi^2 = 100$)
JR09	DIS (FT, HERA) Drell-Yan (FT) Jets (Tevatron)	NLO NNLO	FFN VFN	fitted	5 indep. PDF Polyinom. (15 param.)	Hessian ($\Delta\chi^2 = 1$)
HERAPDF1.5	DIS (HERA)	NLO NNLO	GM-VFNS (TR)	external	5 indep. PDF Polnom. (14 param.)	Hessian ($\Delta\chi^2 = 1$)
MSTW08	DIS (FT, HERA) Drell-Yan (FT, Tev) Jets (HERA, Tev)	LO NLO NNLO	GM-VFNS (TR)	fitted	7 indep. PDF Polynom. (20 param.)	Hessian ($\Delta\chi^2 \sim 25$)
NNPDF2.1	DIS (FT, HERA) Drell-Yan (FT, Tev) Jets (Tevatron)	LO NLO NNLO	GM-VFNS (FONLL)	external	7 indep. PDF Neural Netw. (259 param.)	Monte Carlo

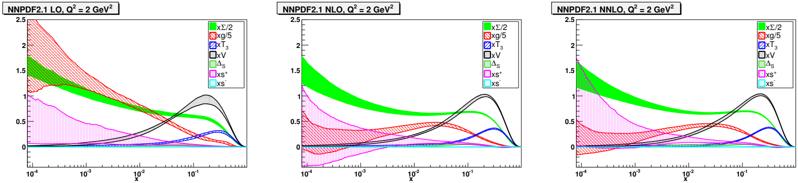
- At the starting scale (2 GeV^2) ...



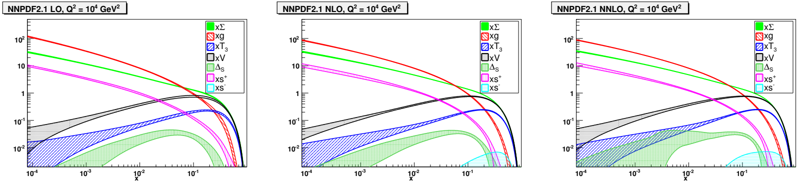
The present status of PDF fits

PDFs ... a family portrait

- At the starting scale (2 GeV^2) ...



- ... and at the typical EW scale (100 GeV^2)



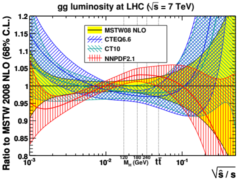
The present status of PDF fits

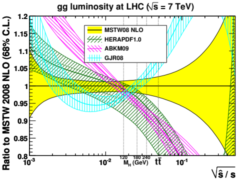
Comparison between Parton Luminosities

- When trying to understand **differences between PDF** sets it is useful to look at **parton luminosities**

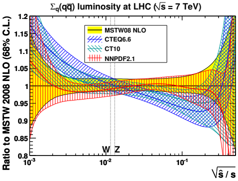
$$\Phi_{ij}(M_X^2) = \frac{1}{s}\int_{\tau}^{1}\frac{x_1}{x_1} f_i(x_1, M_X^2) f_j(\tau/x_1, M_X^2)$$

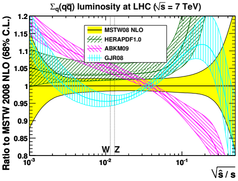
gg:





$q\bar{q}$:

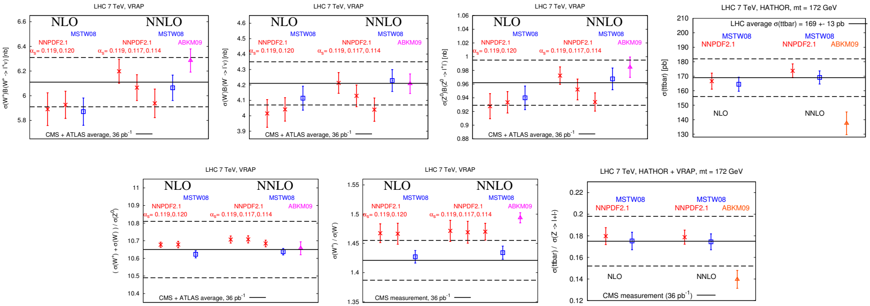




The present status of PDF fits

Comparisons to LHC data

- Predictions for **LHC Standard Candles** compared to **LHC data**



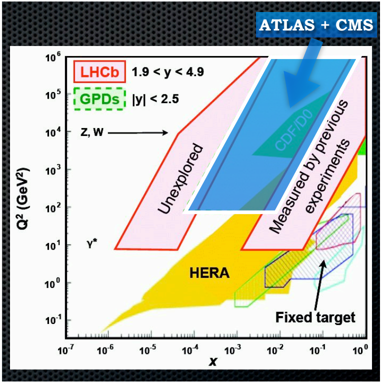
- LHC data will soon be precise enough to distinguish between different predictions.

The present status of PDF fits

W lepton asymmetry data at the LHC

$$A_W^l = \frac{\sigma(pp \to W^+ \to l^+\nu_l) - \sigma(pp \to W^- \to l^-\bar{\nu}_l)}{\sigma(pp \to W^+ \to l^+\nu_l) + \sigma(pp \to W^+ \to l^-\bar{\nu}_l)}$$

- ATLAS: muon charge asymmetry (31pb^{-1}) [ArXiv:1103:2929]
- CMS: muon charge asymmetry (36pb^{-1}) [ArXiv:1103:3470]

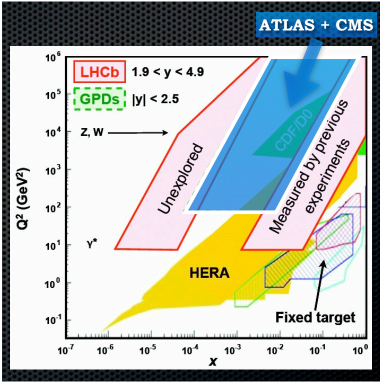


The present status of PDF fits

W lepton asymmetry data at the LHC

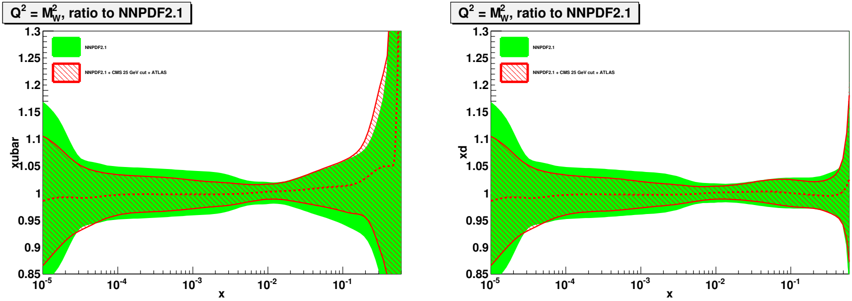
$$A_W^l \sim \frac{u(x_1, M_W^2)\bar{d}(x_2, M_W^2) - d(x_1, M_W^2)\bar{u}(x_2, M_W^2)}{u(x_1, M_W^2)\bar{d}(x_2, M_W^2) + d(x_1, M_W^2)\bar{u}(x_2, M_W^2)}$$

- ATLAS: muon charge asymmetry (31pb^{-1}) [ArXiv:1103:2929]
- CMS: muon charge asymmetry (36pb^{-1}) [ArXiv:1103:3470]



The present status of PDF fits

First contstraints on PDFs from LHC



- ATLAS and CMS data compatible with data included in global analysis
- The provide important constraint to PDFs in the small medium-x region
- Significant uncertainty reduction for light (anti-)flavour distributions

The present status of PDF fits

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