NNPDF: Faithful Partons

- Parton Fitting: Problems and Solutions
- DIS fits: NNPDF 1.0 – 1.2
- Global fitting: NNPDF 2.0

RDB, Luigi Del Debbio, Stefano Forte, Alberto Guffanti,
Jose Latorre, Andrea Piccione, Juan Rojo, Maria Ubiali
(Barcelona, Edinburgh, Freiburg, Milan)

Cambridge June 2009

PDFs for LHC

To fully exploit LHC data, we need:

- Precise reliable faithful PDFs
- No theoretical bias (beyond NLO pQCD, etc.)

    No bias due to functional form

    No bias due to improper statistical procedure

- Genuine statistical confidence level

    Full inclusion of correlations in exp systematics

    No rescaling of experimental errors

    Uniform treatment of uncertainties

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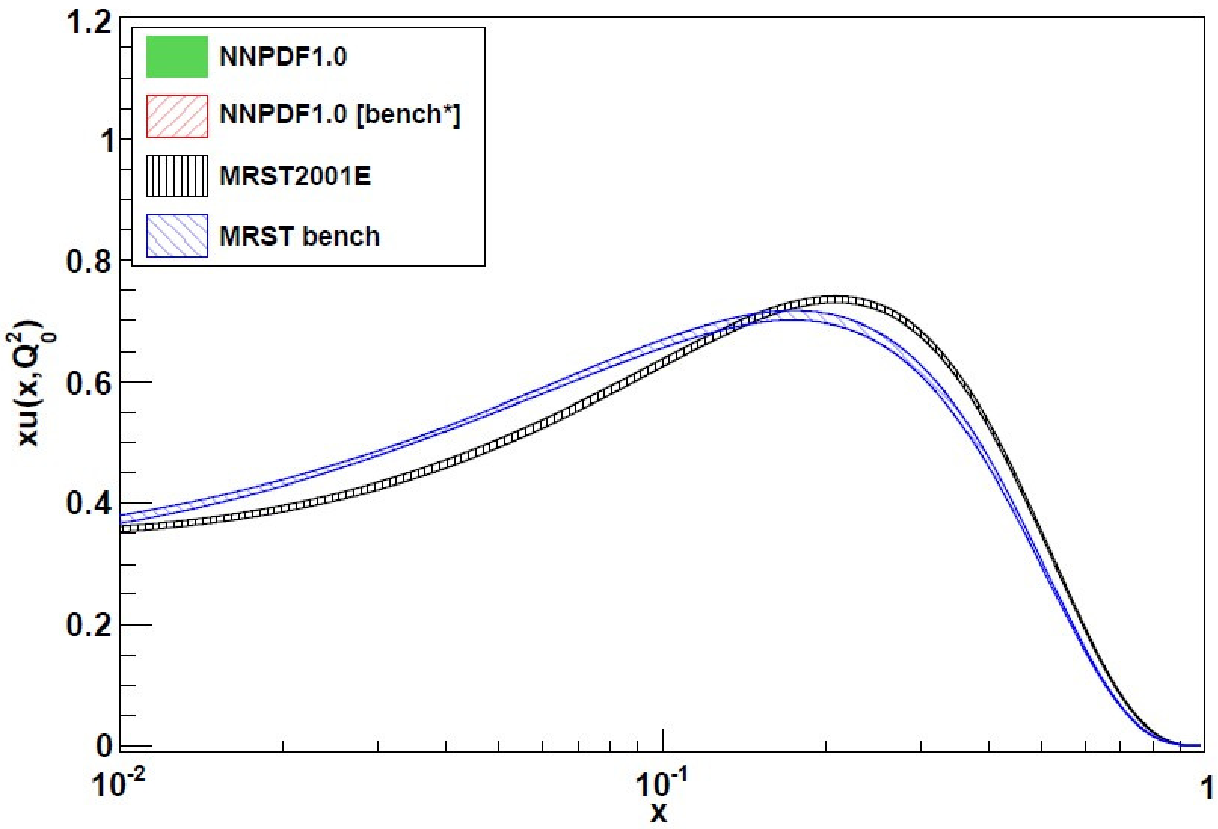
Zero Tolerance!

HERA-LHC Benchmark

hep-ph/0511119

3163 DIS data → 773 data

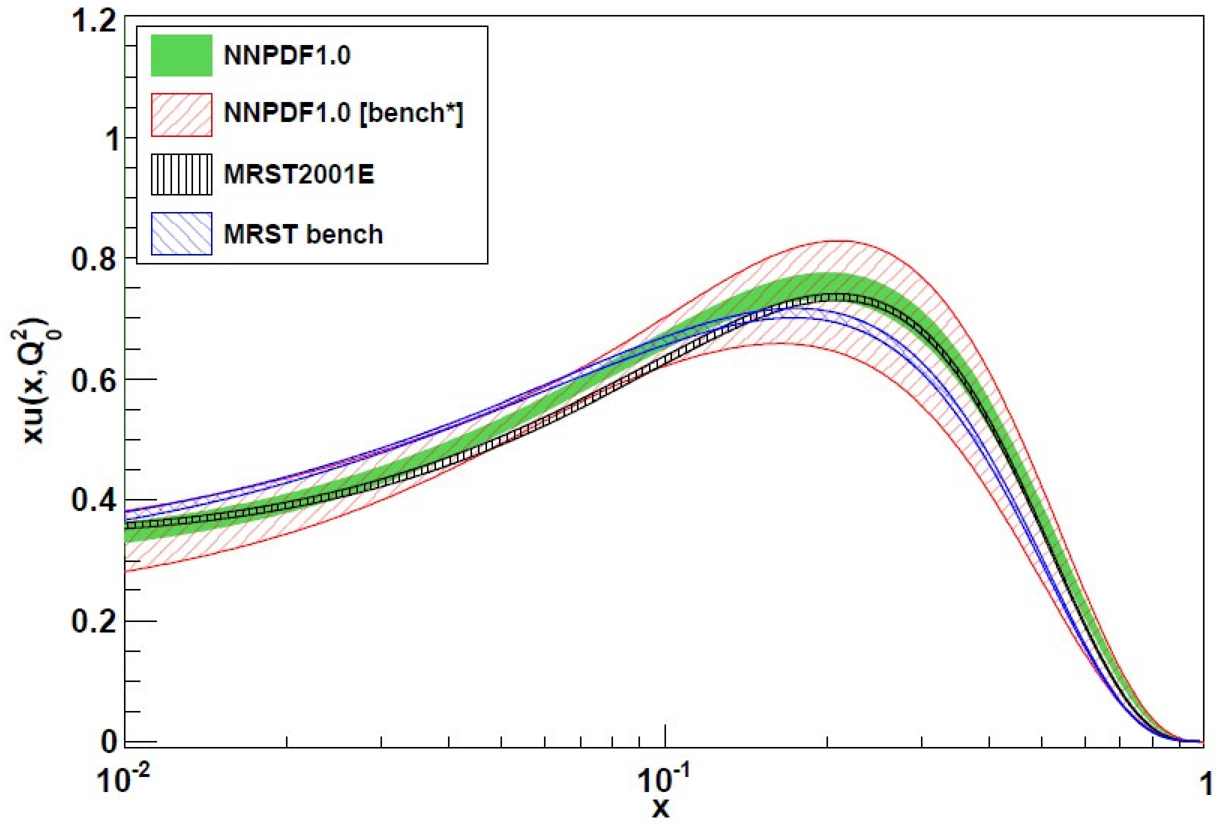
- Benchmark partons and global partons disagree!
- $\Delta \chi^2_{global}$=50 but $\Delta \chi^2_{bench}$=1: statistical treatment tuned



HERA-LHC Benchmark

3163 DIS data $\rightarrow$ 773 data

- NNPDF: benchmark partons and global partons agree!
- NNPDF: $\Delta\chi^2_{global}=\Delta\chi^2_{bench}=1$: statistical treatment consistent



Theory

PDF Ensembles

Given an observable $\mathcal{O}[f]$ (eg xsec), f a set of PDFs, want

$$\langle \mathcal{O}[f] \rangle = \int \mathcal{D}f \, \mathcal{P}[f] \, \mathcal{O}[f],$$

where $\mathcal{P}[f]$ is the probability density for the PDFs.

4052

Importance sampling: find PDF ensemble $\{f_k\}$ such that

$$\langle \mathcal{O}[f] \rangle \approx \frac{1}{N} \sum_{k=1}^{N} \mathcal{O}[f_k],$$

at least for large enough N.

232

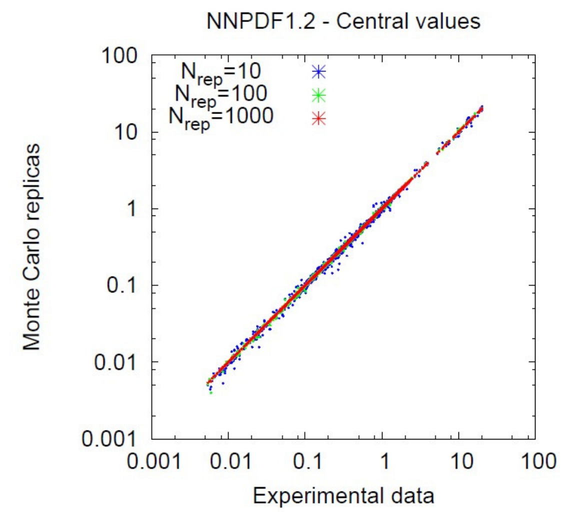
NNPDF delivers the ensemble $\{f_k\}$: N = 100, 1000

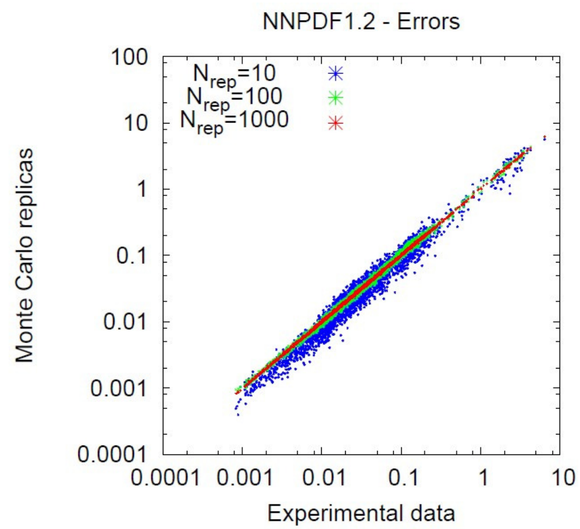
Note: $\mathcal{O}[f]$ can be a xsec, or a variance, or a correlation, or....

Producing the PDF Ensembles

- Generate by Monte Carlo N replicas of the experimental data sets, distributed according to the experimental uncertainties.

  N.B. use **all** known correlated uncertainties





Producing the PDF Ensembles

- Generate by Monte Carlo N replicas of the experimental data sets, distributed according to the experimental uncertainties.

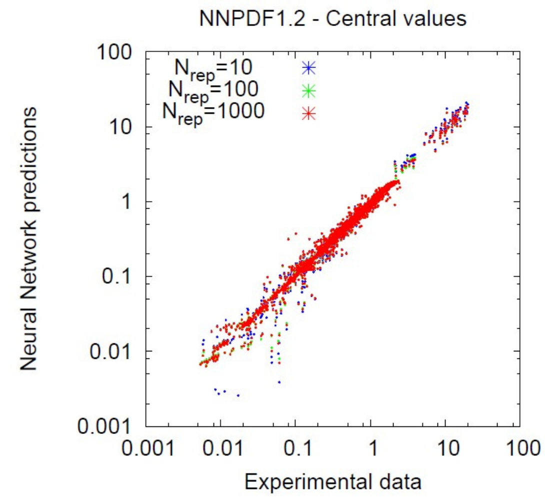
  N.B. use **all** known correlated uncertainties

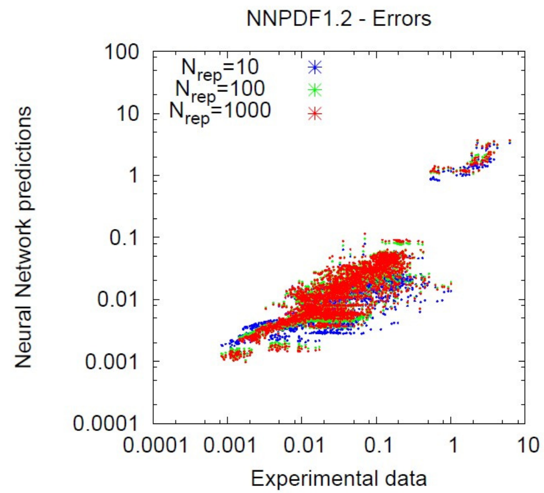
- Fit a pdf to each replica. The resulting ensemble of pdfs must then reproduce the data with combined uncertainties providing the fitting is itself unbiased.

  Unbiased fitting requires

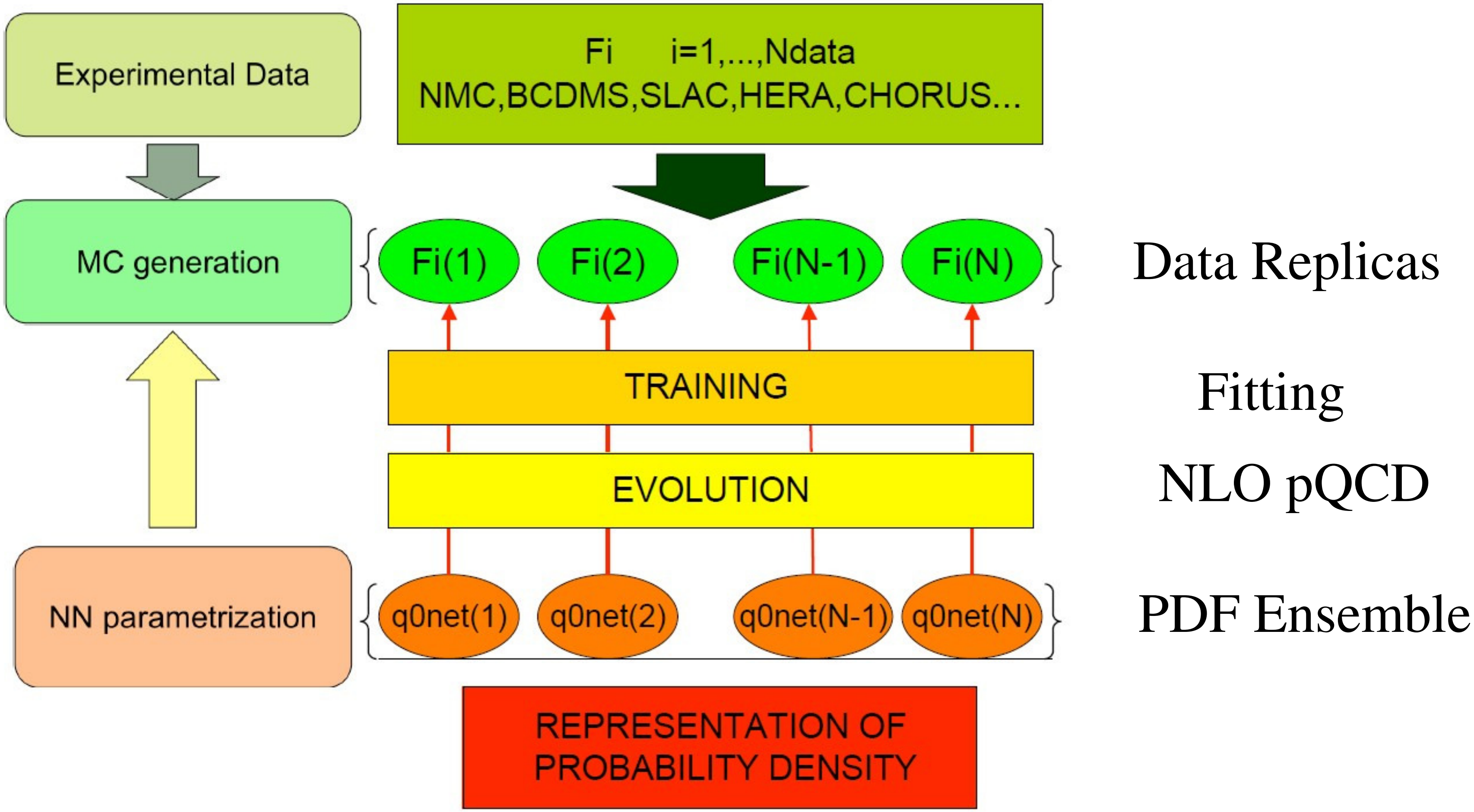
  (a) a redundant parametrization (large numbers of 'flat' directions): neural nets

  (b) a stopping criterion (so as not to fit statistical fluctuations)





Flow chart


Experimental Data
Fi i=1,...,Ndata
NMC,BCDMS,SLAC,HERA,CHORUS...
MC generation
Fi(1)
Fi(2)
Fi(N-1)
Fi(N)
TRAINING
EVOLUTION
NN parametrization
q0net(1)
q0net(2)
q0net(N-1)
q0net(N)
REPRESENTATION OF
PROBABILITY DENSITY
Data Replicas
Fitting
NLO pQCD
PDF Ensemble

Why Neural Networks?

In a standard fit, minimise a χ^2 with a given parametrization

- If the basis is too large, the fit never converges
- If the basis is too small, the fit is biased

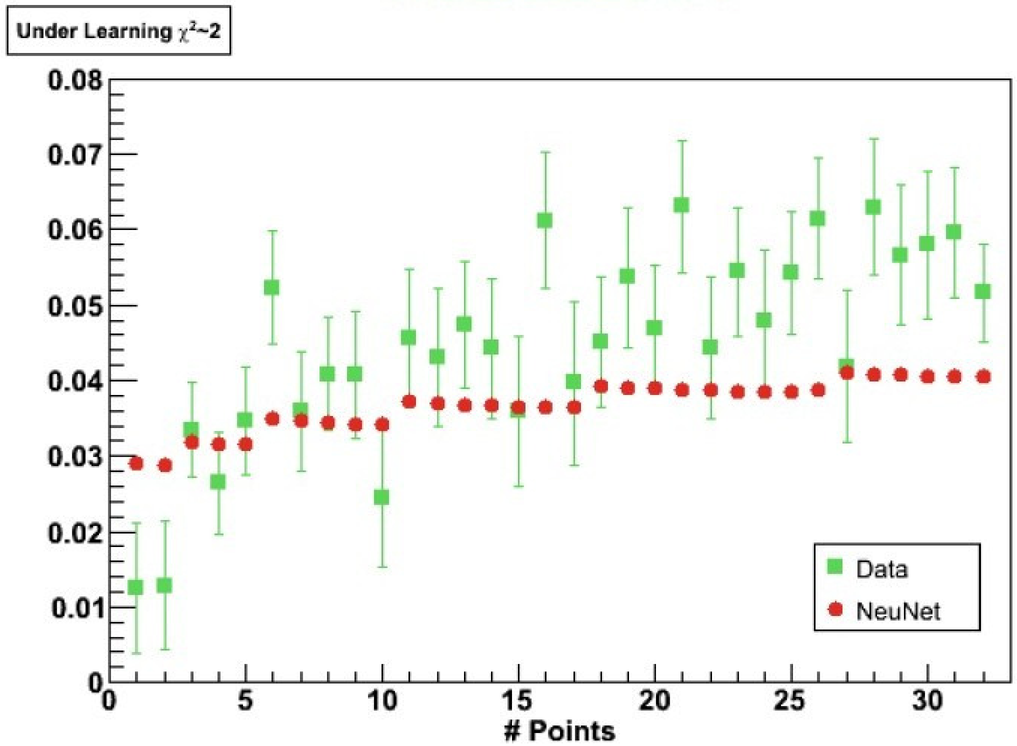
Q. How can we be sure that the compromise is unbiased?

A. Use a neural network: smoothness decreases as fit quality improves

UNDERLEARNING

Model

$\chi^2 \sim 2$



Why Neural Networks?

In a standard fit, minimise a χ^2 with a given parametrization

- If the basis is too large, the fit never converges
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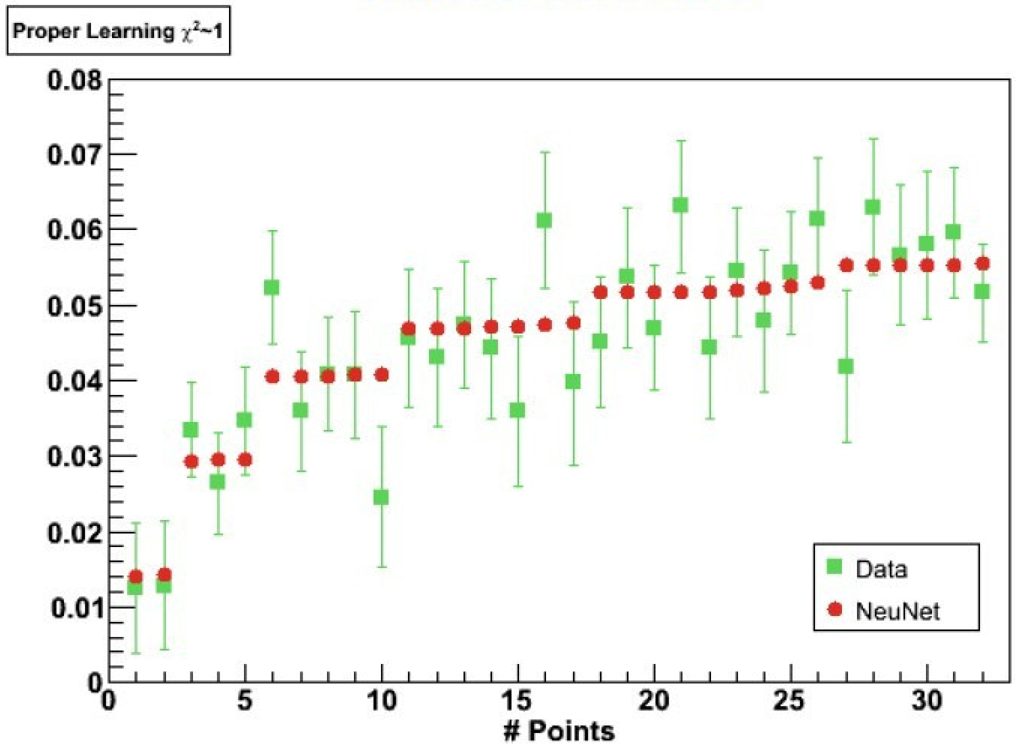
Q. How can we be sure that the compromise is unbiased?

A. Use a neural network: smoothness decreases as fit quality improves

Model

$\chi^2 \sim 1$

PROPER LEARNING



Why Neural Networks?

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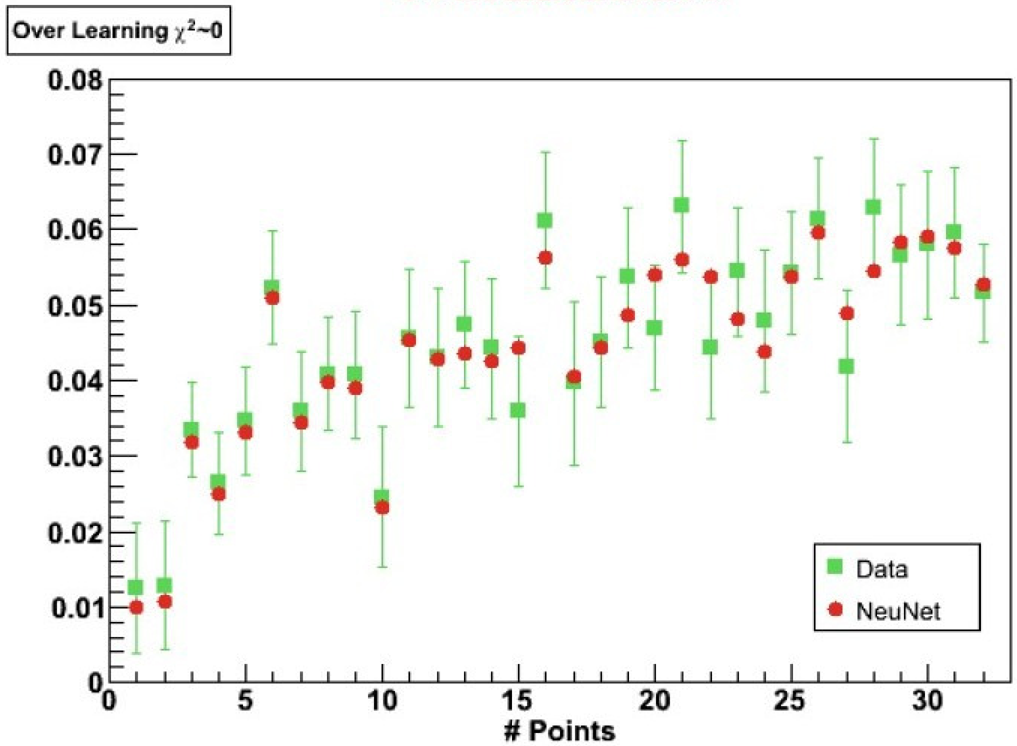
A. Use a neural network: smoothness decreases as fit quality improves

OVERLEARNING

Model

$\chi^2 \sim 0$

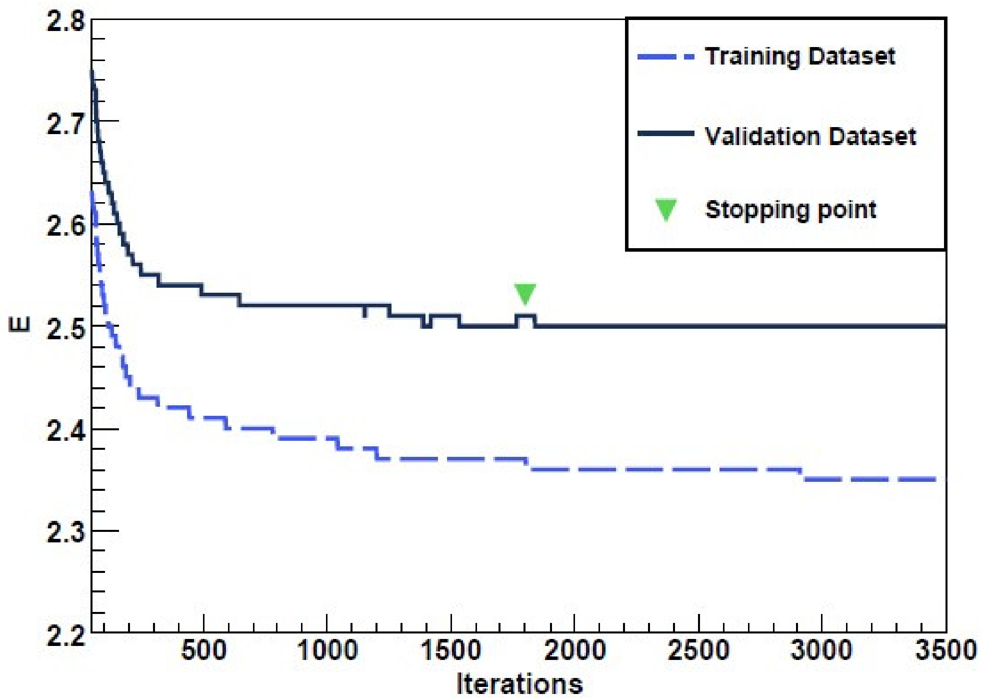


Stopping

Q. How do we know when to stop the fitting ('training')

A. Use cross-validation

- Divide data (randomly) into 'training' and 'validation' sets
- Train net on 'training' set, monitoring fit to 'validation' set
- When fit to 'training' set better than fit to 'validation' set .



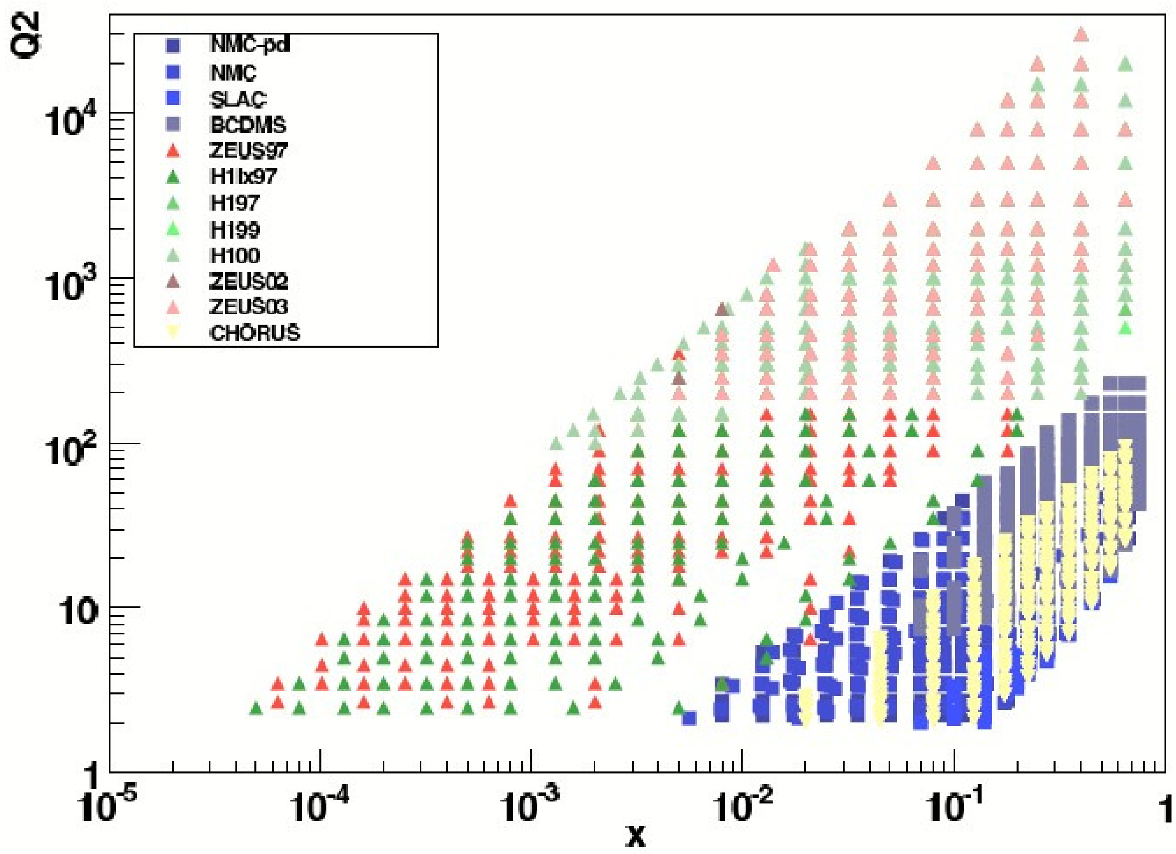
High final χ^2 means
data errors underestimated

Low final χ^2 means
data errors overestimated

Results

NNPDF1.0

Aug 2008



DIS data:

- Fixed Target
- HERA NC & CC
- Neutrino (CHORUS)

3161 data pts

Cuts:

$Q^2 > 2$ GeV^2

$W^2 > 12.5$ GeV^2

NLO pQCD

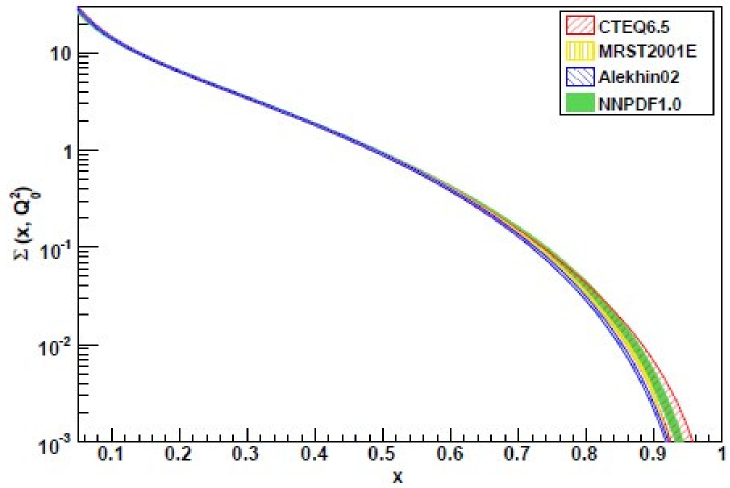
ZM-VFNS

Fit 5 PDFs at $Q_0{}^2 = 2$ GeV^2: $g,\ u,\ d,\ \bar{u},\ \bar{d}$

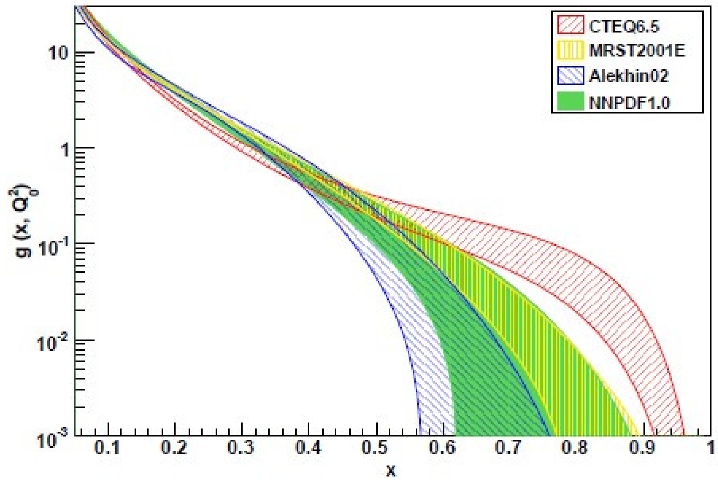
Assume $s = \bar{s} = \frac{1}{4}(\bar{u} + \bar{d})$

$5 \times 37 = 185$ parameters!

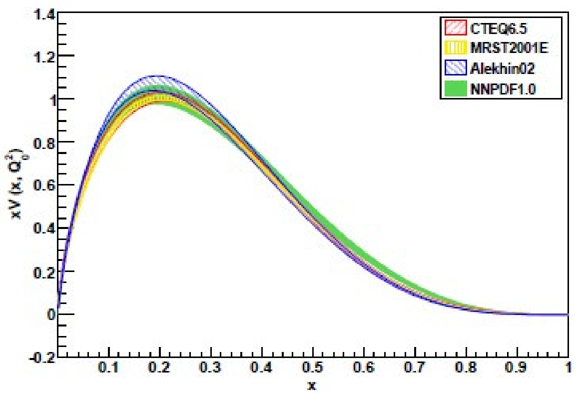
Singlet: $\Sigma = u + \bar{u} + d + \bar{d} + s + \bar{s}$



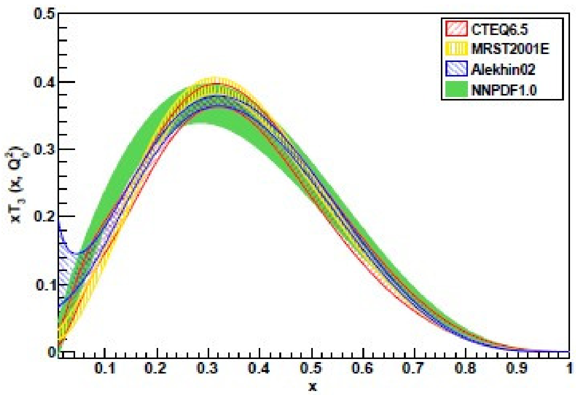
Gluon: g



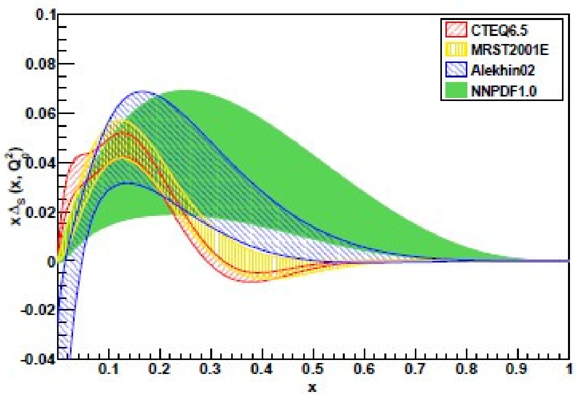
Valence: $V = u - \bar{u} + d - \bar{d}$

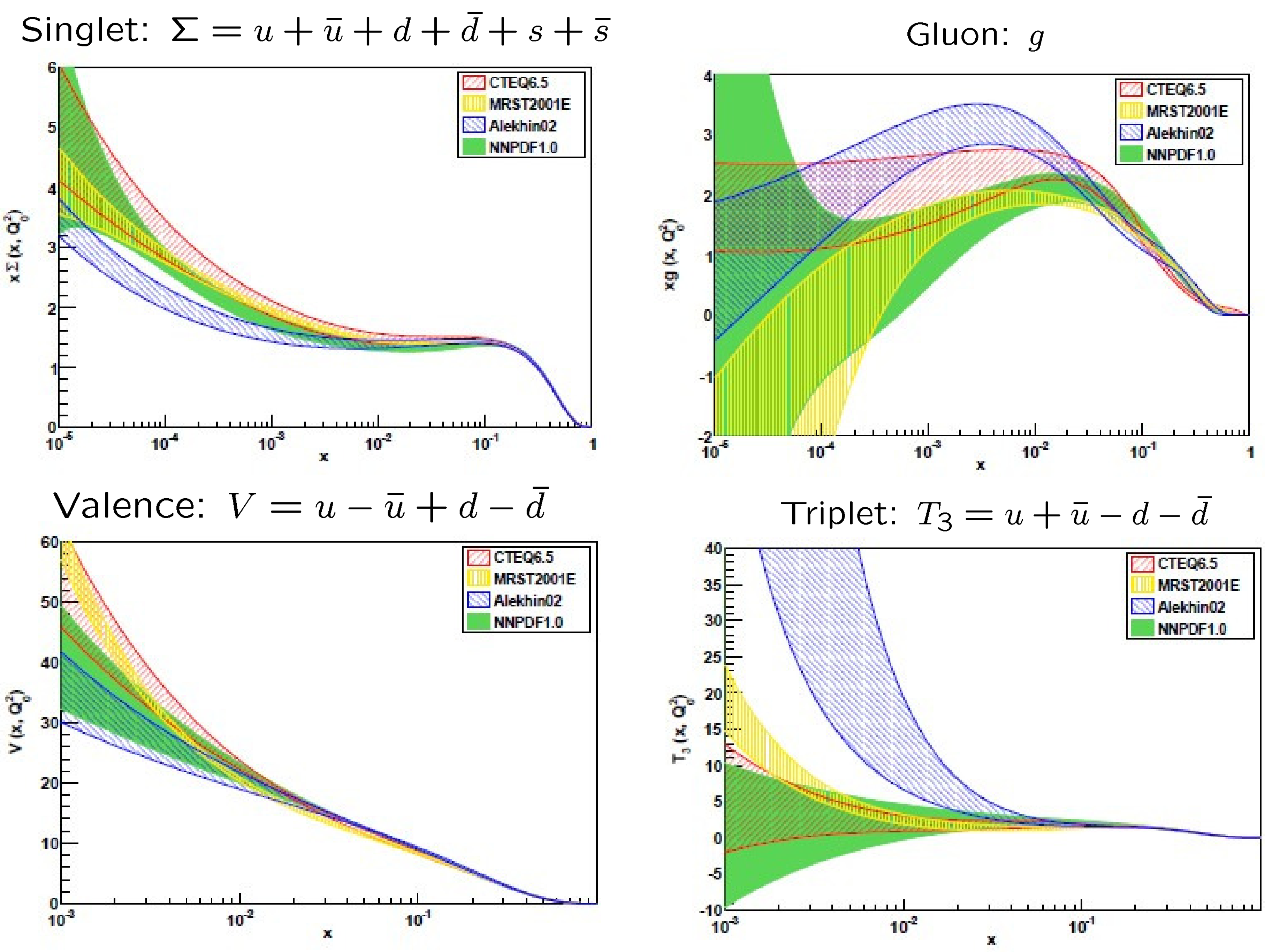


Triplet: $T_3 = u + \bar{u} - d - \bar{d}$



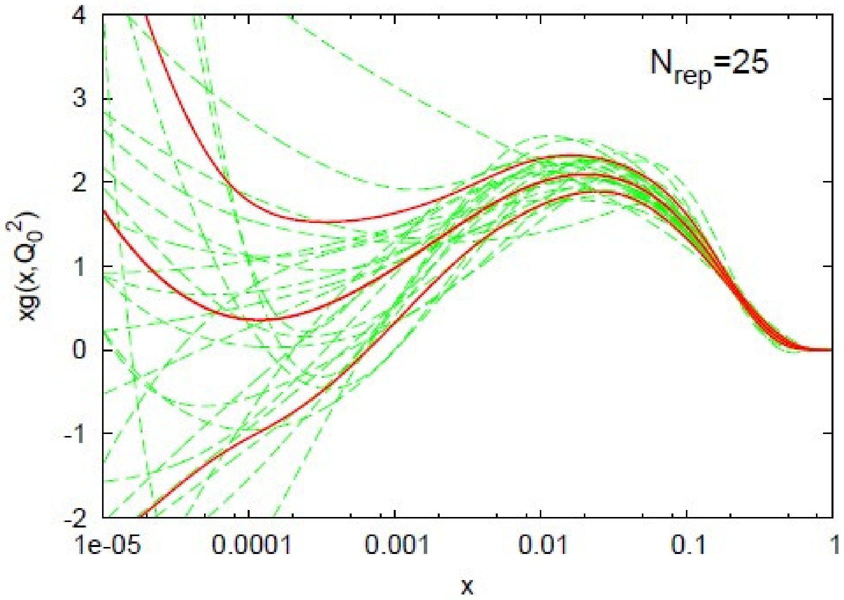
Asymmetry: $\Delta_s = \bar{d} - \bar{u}$

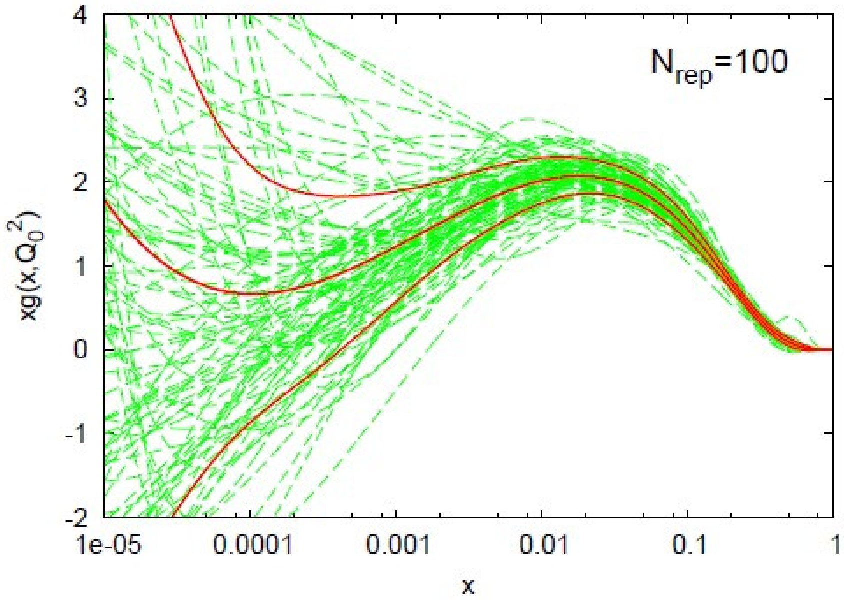




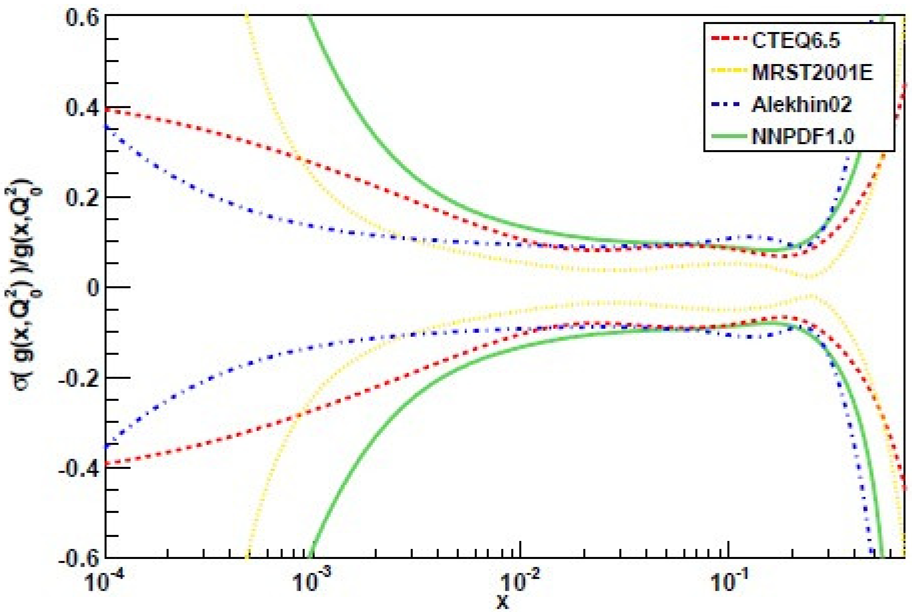
Singlet: $\Sigma = u + \bar{u} + d + \bar{d} + s + \bar{s}$
Gluon: g
Valence: $V = u - \bar{u} + d - \bar{d}$
Triplet: $T_3 = u + \bar{u} - d - \bar{d}$
CTEQ6.5
MRST2001E
Alekhin02
NNPDF1.0
$x\Sigma(x, Q_0^2)$
$xg(x, Q_0^2)$
$V(x, Q_0^2)$
$T_3(x, Q_0^2)$
x

Gluons : individual replicas





… and relative uncertainty

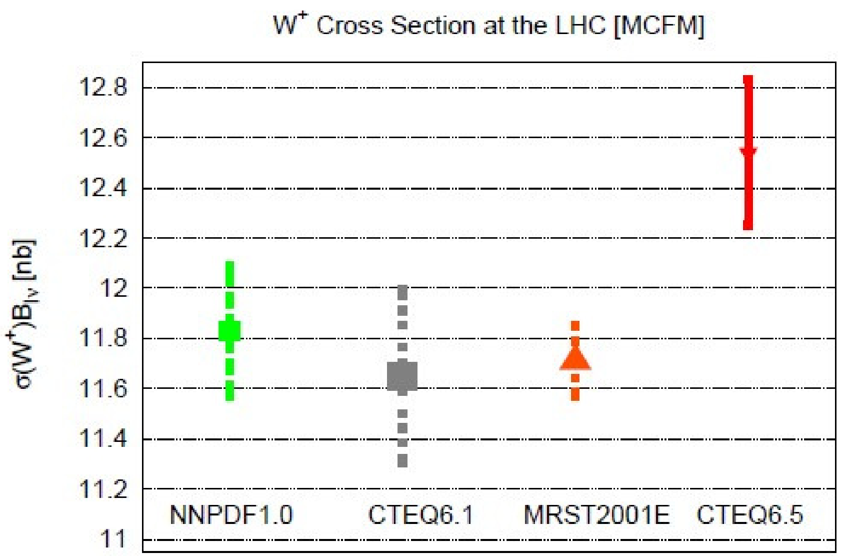


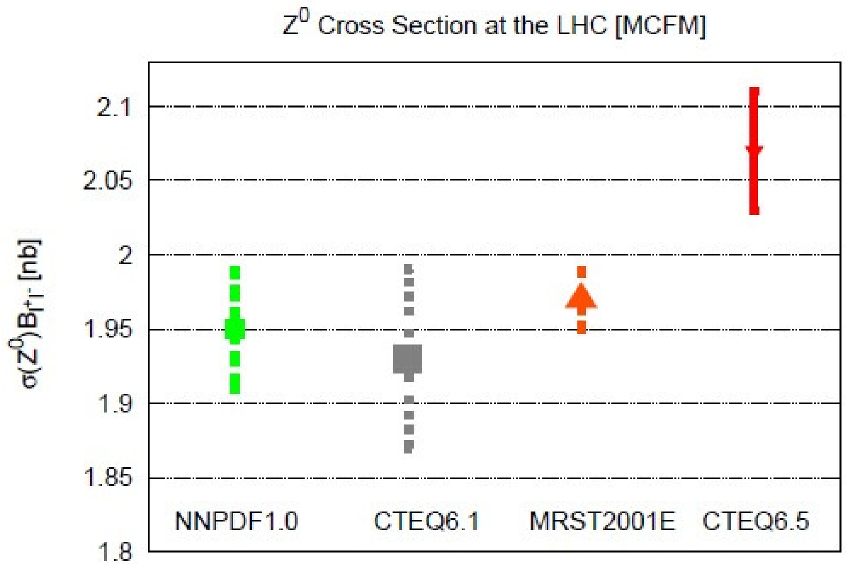
- NNPDF : Genuine 68% CL
- Error not artificially inflated

  Zero Tolerance!
- Error naturally large

  in extrapolation region

Standard Candles at LHC



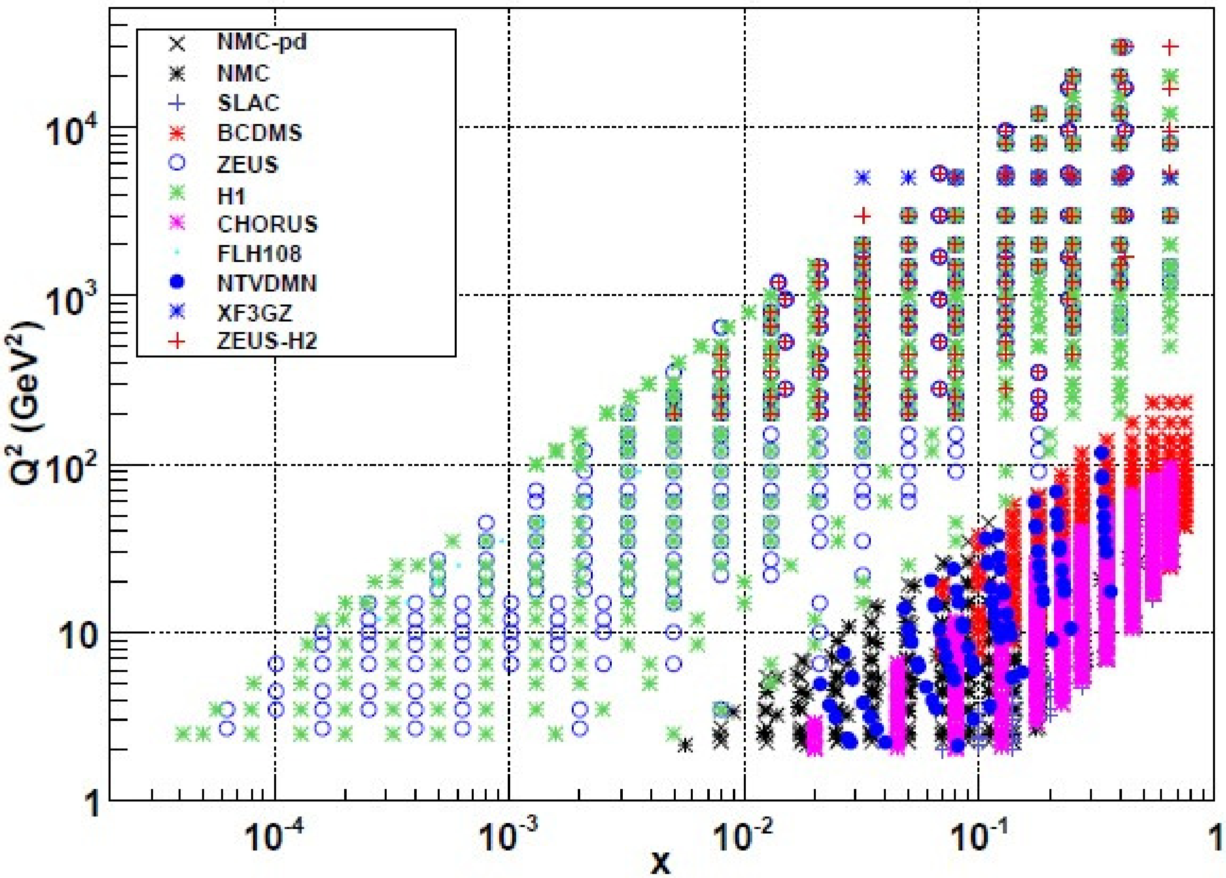


	$\sigma_{W+}\mathcal{B}_{l+\nu_l}$	$\Delta\sigma_{W+}/\sigma_{W+}$	$\sigma_{W-}\mathcal{B}_{l-\nu_l}$	$\Delta\sigma_{W-}/\sigma_{W-}$	$\sigma_Z\mathcal{B}_{l+l-}$	$\Delta\sigma_Z/\sigma_Z$
NNPDF1.0	11.83 ± 0.26	2.2%	8.41 ± 0.20	2.4%	1.95 ± 0.04	2.1%
CTEQ6.1	11.65 ± 0.34	2.9%	8.56 ± 0.26	3.0%	1.93 ± 0.06	3.1%
MRST01	11.71 ± 0.14	1.2%	8.70 ± 0.10	1.1%	1.97 ± 0.02	1.0%
CTEQ6.5	12.54 ± 0.29	2.3%	9.19 ± 0.22	2.4%	2.07 ± 0.04	1.9%

Includes heavy quark mass effects

Jun 2009

NNPDF1.2



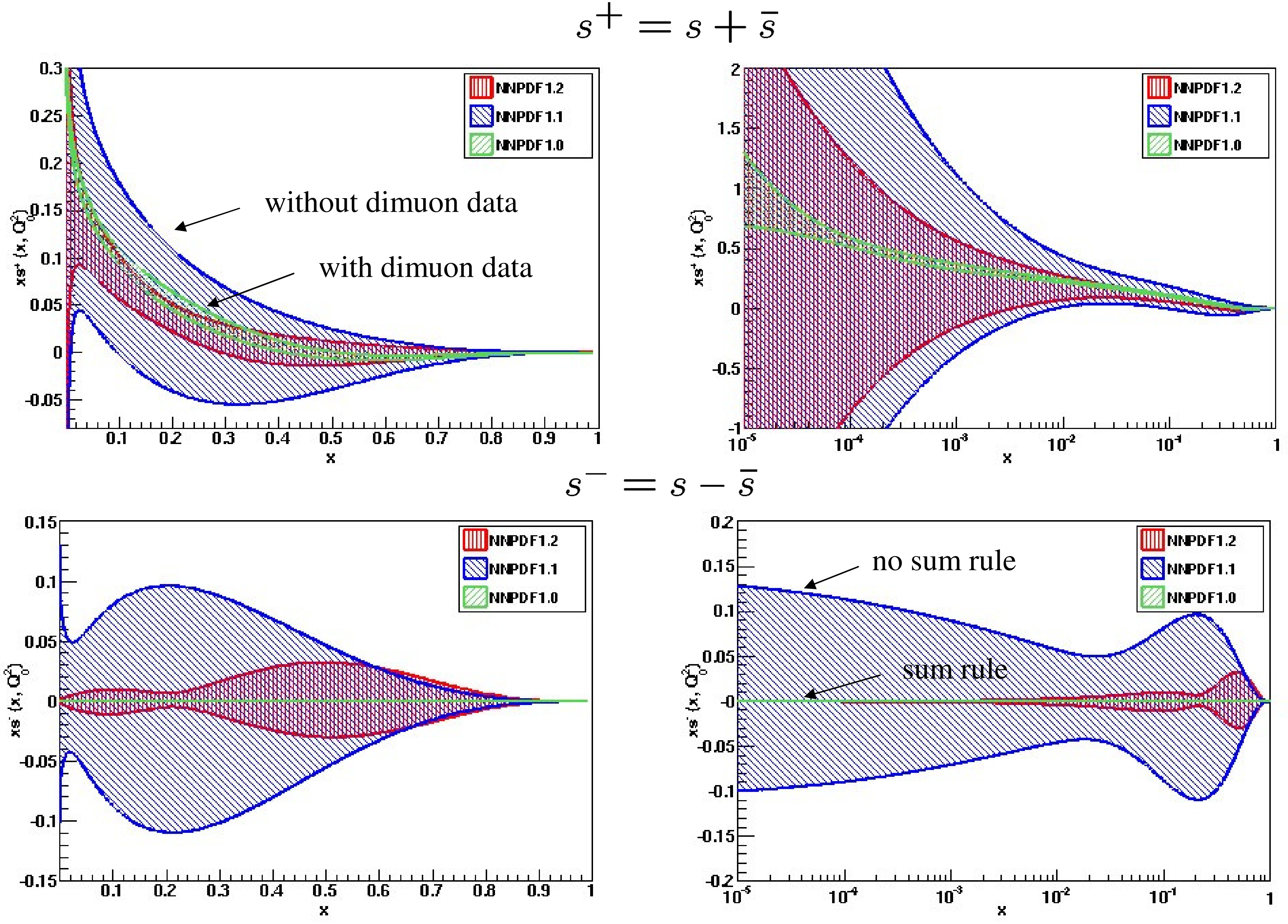
Add to DIS data NuTev dimuon data: sensitive to strangeness

3372 data pts

Use I-ZMVFNS (slow rescaling etc) for dimuon xsec (sensitive to charm mass)

Fit 7 PDFs at $Q_0^2 = 2$ GeV^2: $g,\ u,\ d,\ \bar{u},\ \bar{d},\ s,\ \bar{s}$

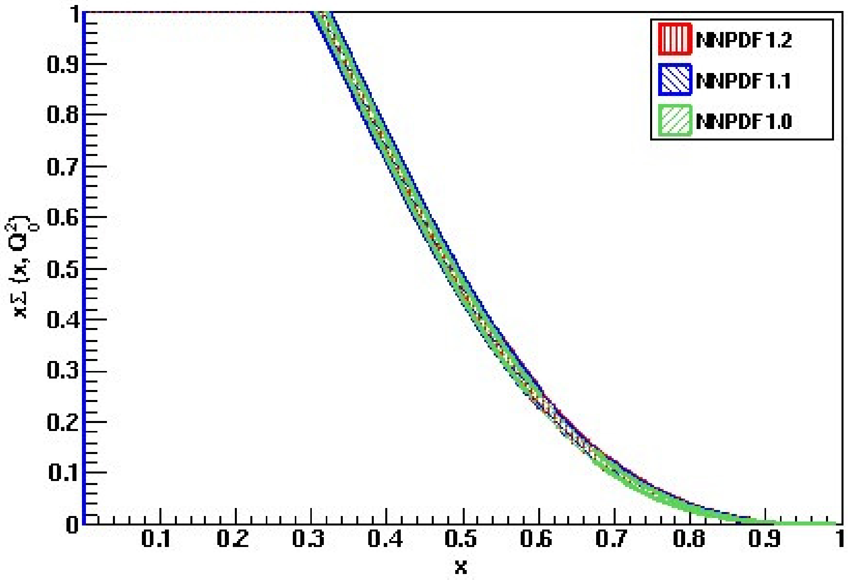
$7 \times 37 = 259$ parameters!

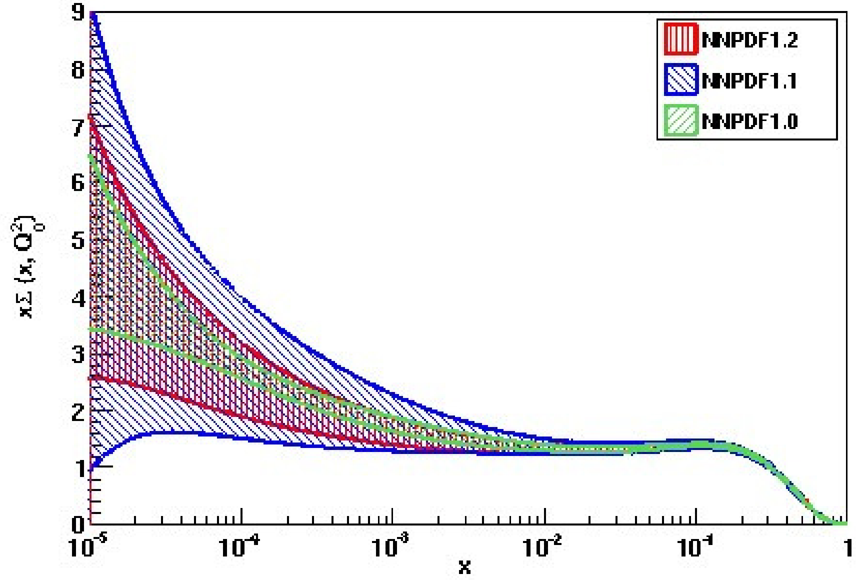


$s^+ = s + \bar{s}$
NNPDF1.2
NNPDF1.1
NNPDF1.0
without dimuon data
with dimuon data
$xs^+(x, Q_0^2)$
x
$s^- = s - \bar{s}$
$xs^-(x, Q_0^2)$
no sum rule
sum rule

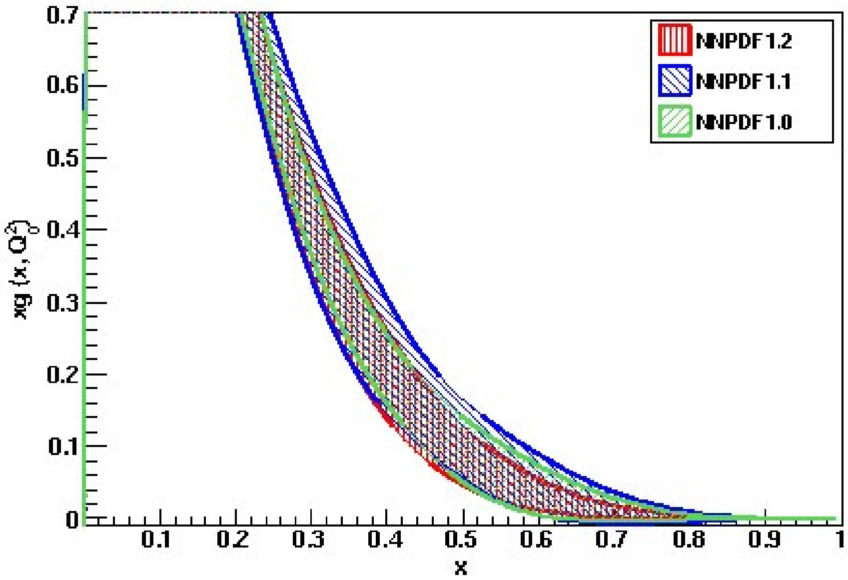
Stability

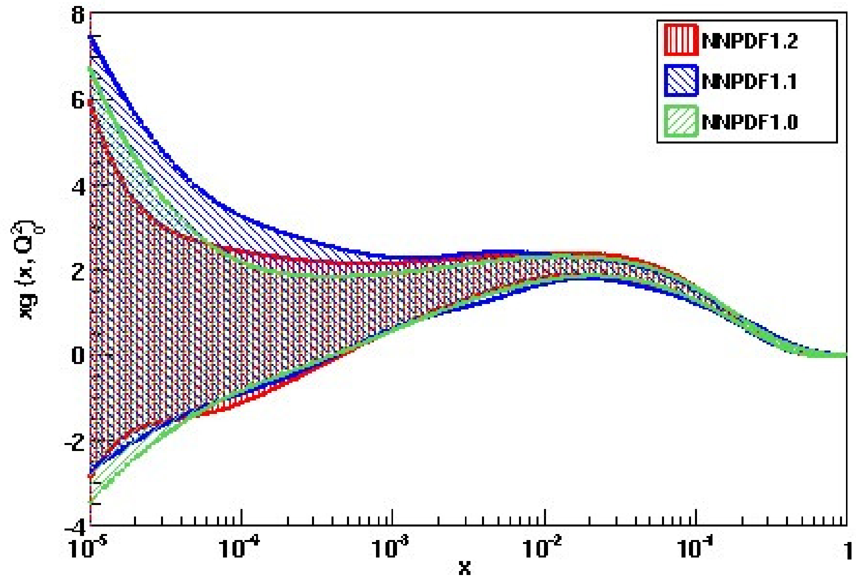
Singlet

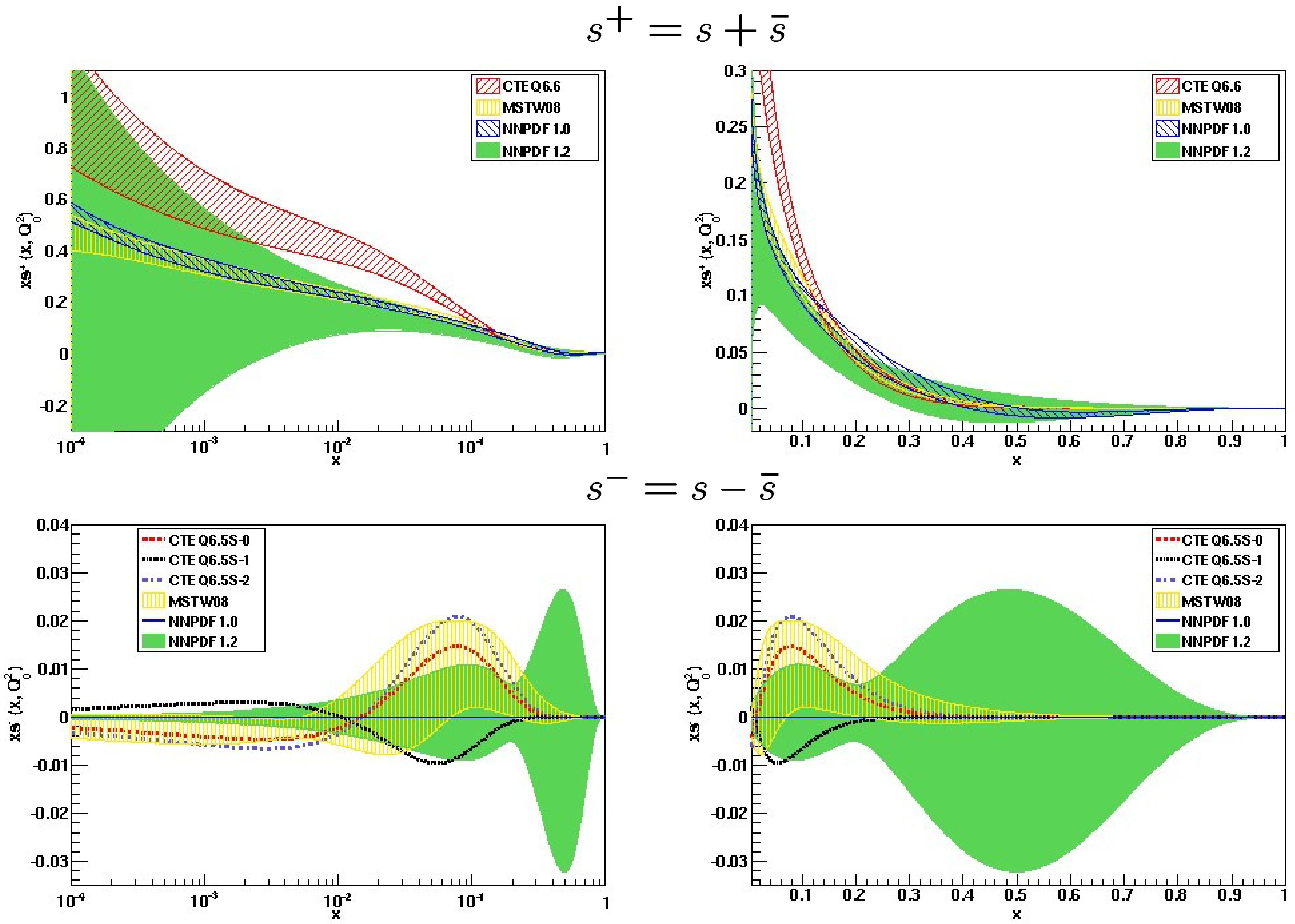




Gluon



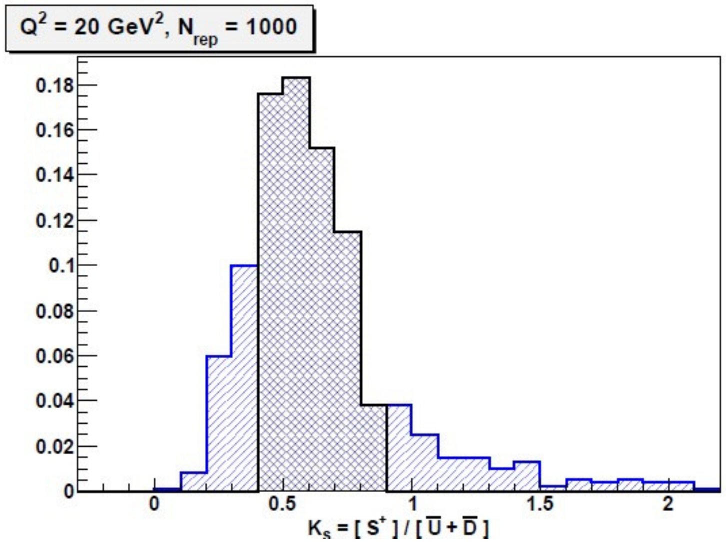




$s^+ = s + \bar{s}$
CTEQ6.6
MSTW08
NNPDF 1.0
NNPDF 1.2
$xs^+(x, Q_0^2)$
x
$s^- = s - \bar{s}$
CTEQ6.5S-0
CTEQ6.5S-1
CTEQ6.5S-2
MSTW08
NNPDF 1.0
NNPDF 1.2
$xs^-(x, Q_0^2)$
x

Strange momentum fraction

$$K_s = \frac{\int_0^1 dx\, x\,(s+\bar{s})}{\int_0^1 dx\, x\,(\bar{u}+\bar{d})}$$

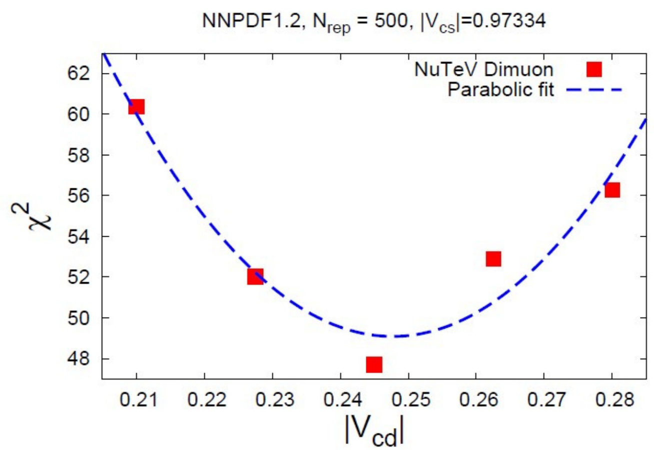


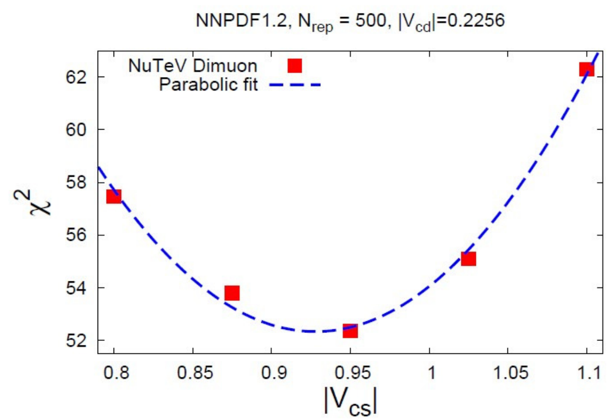
Analysis	$K_S\,(Q^2 = 20\,\mathrm{GeV}^2)$
NNPDF1.2	$0.71^{+0.20}_{-0.31}$
MSTW08	0.56 ± 0.03
CTEQ6.6	0.72 ± 0.05
AKP08	0.59 ± 0.08

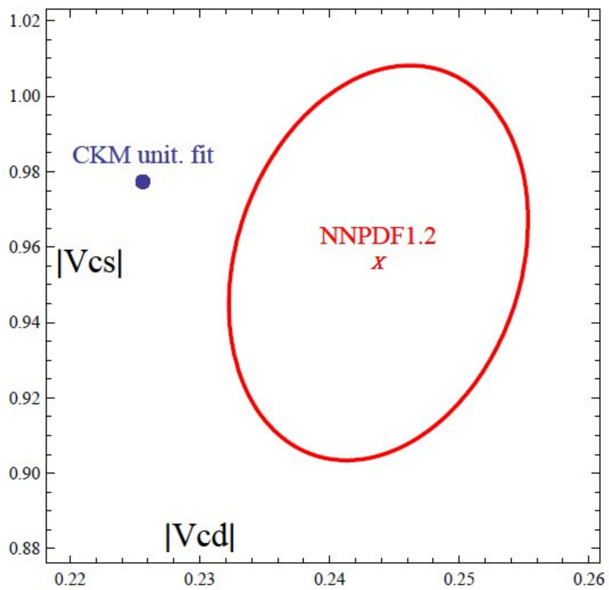
Complete probability distribution: large asymmetric error

CKM elements V_{cs} and V_{cd}

Despite large uncertainty in s^+, can still determine V_{cs}







$$|V_{cs}| = 0.96 \pm 0.05(data) \pm 0.07(syst)$$
$$|V_{cd}| = 0.24 \pm 0.01(data) \pm 0.02(syst)$$

Best direct determination of V_{cs}

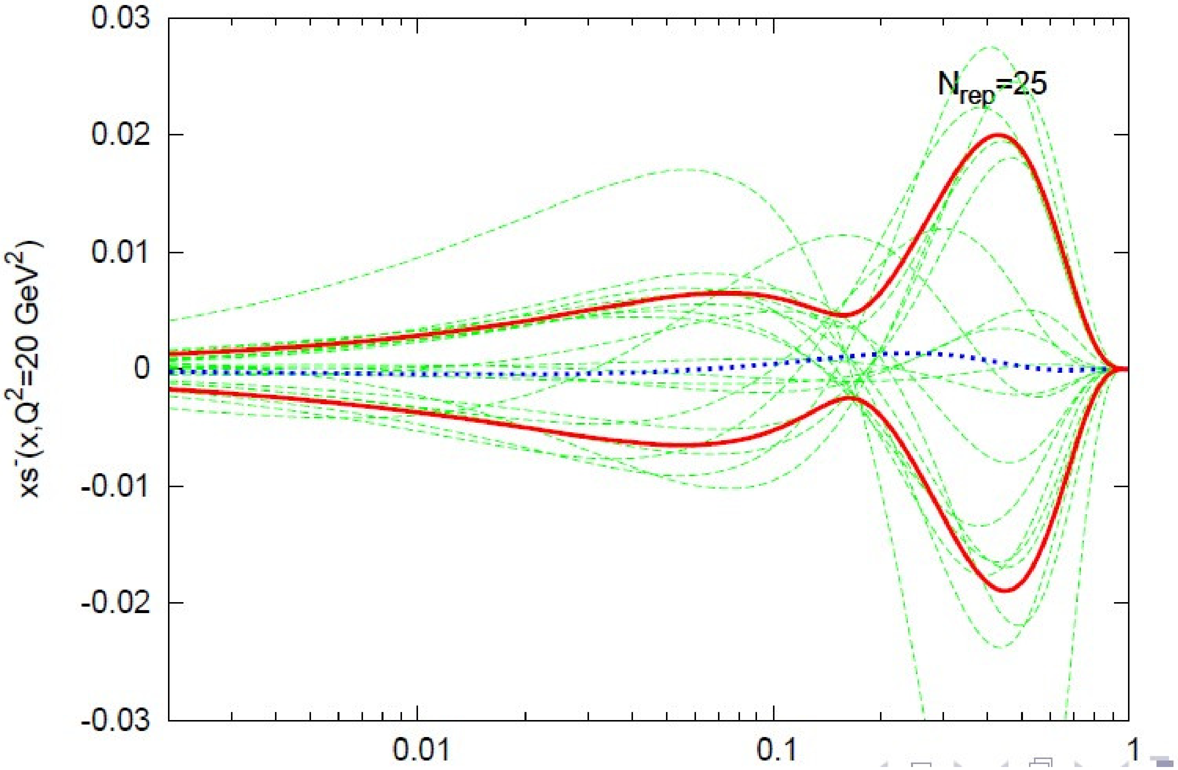
From D decays $|V_{cs}| = 1.04 \pm 0.06$ (PDG)

Valence Strangeness

$\int_0^1 dx(s - \bar{s}) = 0$

Parametrization very free:
≥ 1 crossing

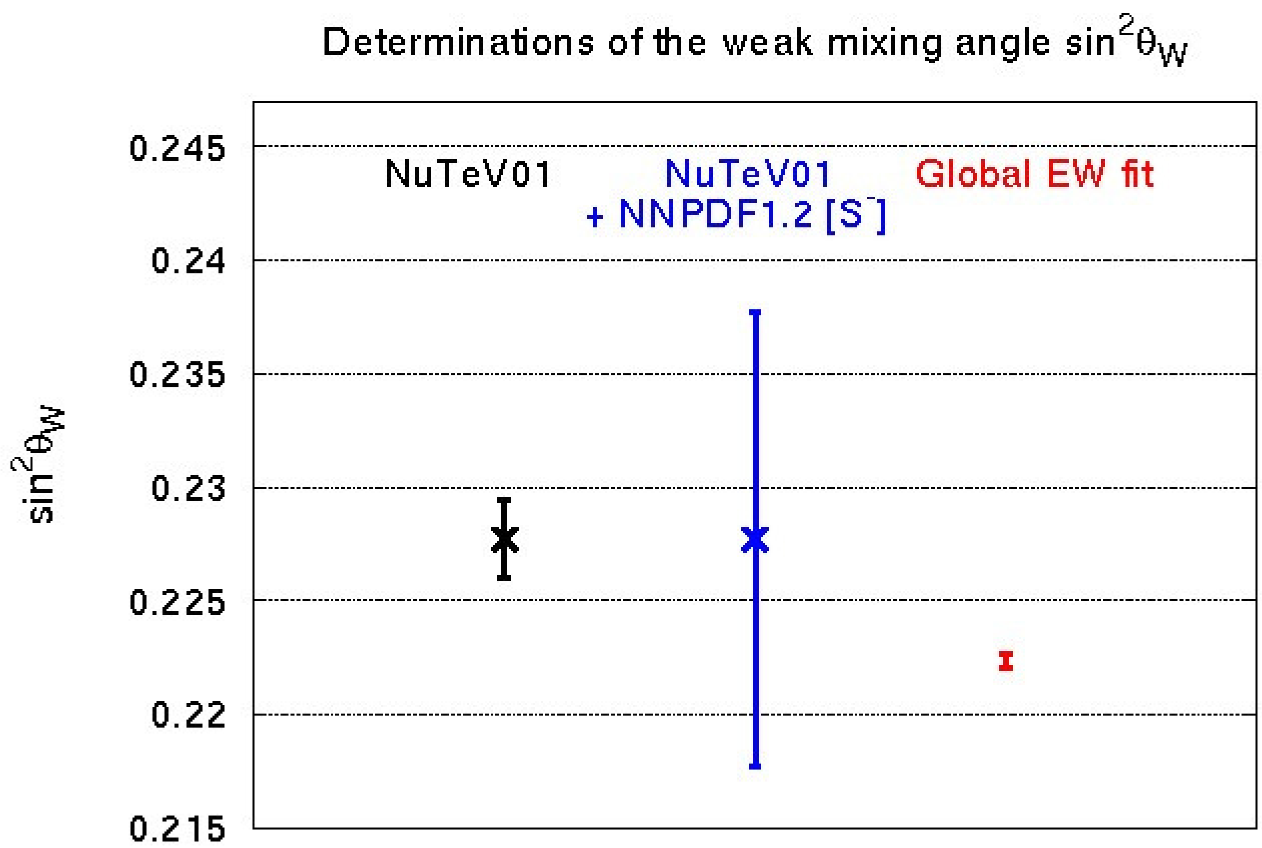
Very large uncertainty



Analysis	$[S^-]\ (Q^2 = 20\,\mathrm{GeV}^2)\cdot 10^3$
NNPDF1.2	0 ± 9
MSTW08	1.4 ± 1.2
CTEQ6.5s	1.2 ± 1.1
AKP08	1.0 ± 1.3
NuTeV07	1.3 ± 0.8

NuTeV Anomaly

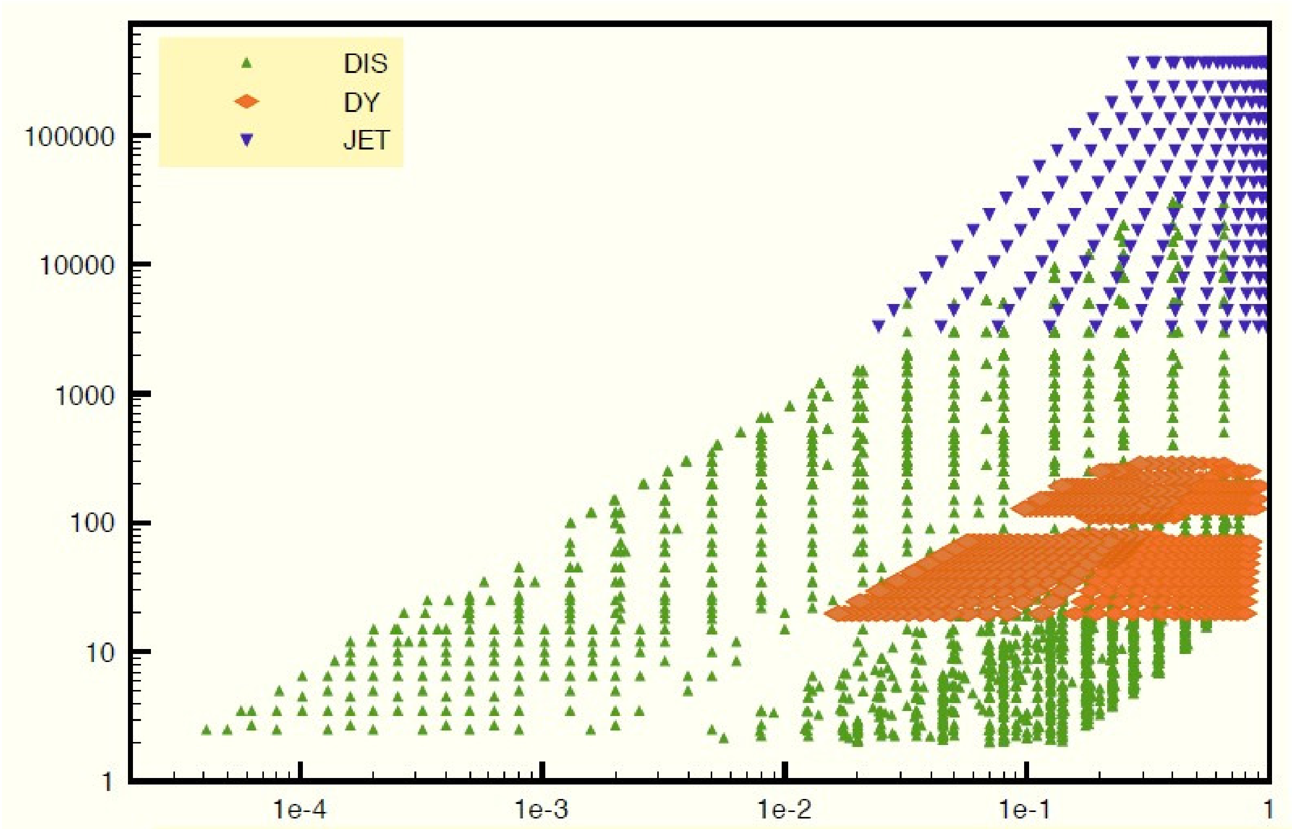
$$\sin^2\theta_W|_{NuTeV} = 0.2277 \pm 0.0014(stat) \pm 0.0009(syst) \pm 0.0100(PDF)$$



GONE!

Preliminary

NNPDF2.0 (truly global fit)



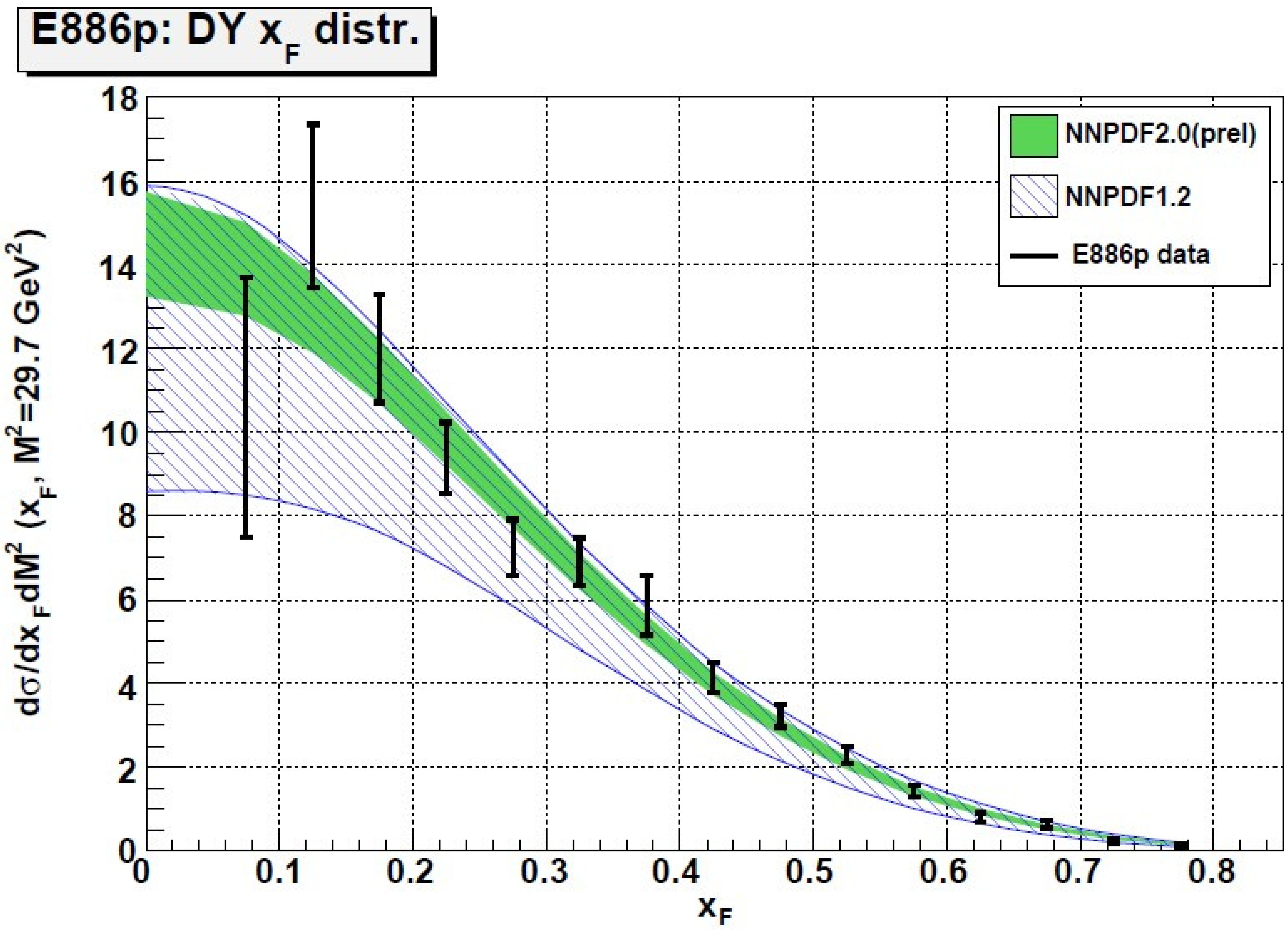
Add to DIS data dimuon data:

- DY data .
- W/Z asymm data
- Inclusive jets .

No K-factors: Use FastNLO for jets

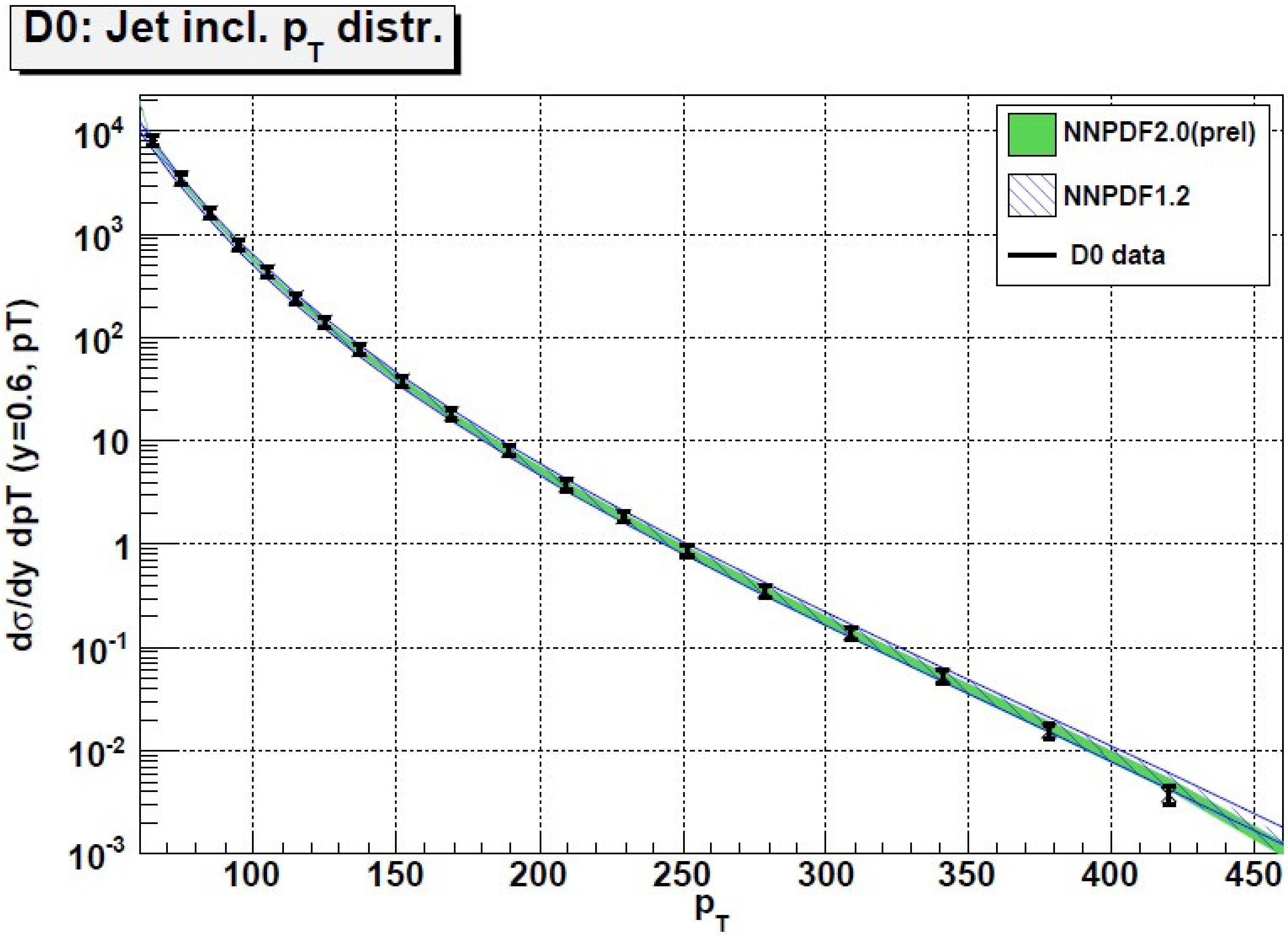
Have new FastNLO-type code for DY

Preliminary



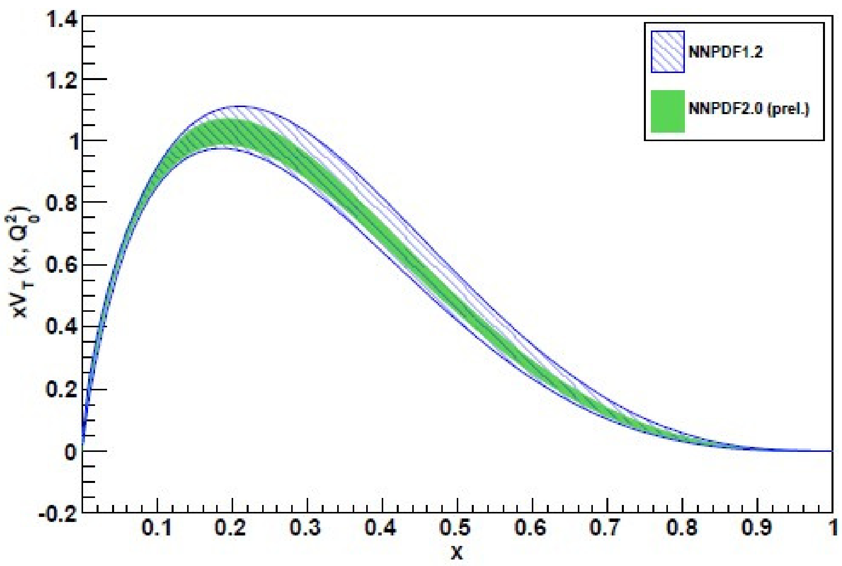
NB: NNPDF 1.2 fit already good…

Preliminary

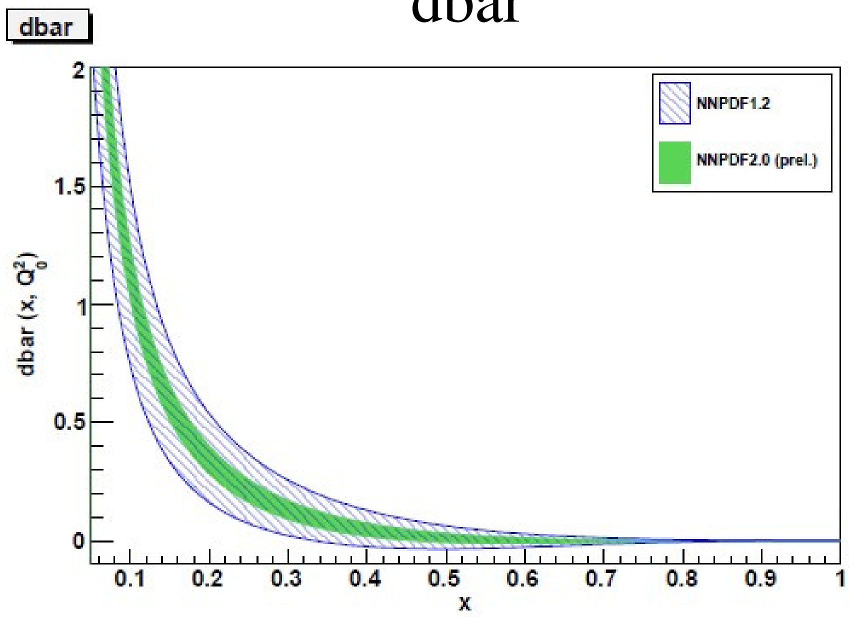


Preliminary

Valence



dbar



Reduced uncertainties in valence sector

Summary & Outlook

- NNPDF works : 1.0 (DIS), 1.2 (+dimuon)

  See for yourself: http://projects.hepforge.org/lhapdf
- New direct determination of V_{cs}: no NuTeV anomaly
- Global fits : 2.0 (+DY+W/Z+jets)

  ETA: Sep 2009
- For the future:

  heavy quarks, resummation, NNLO, etc, etc,

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Watch this space!

Papers

- Unbiased Determination of the Proton Structure Function F2p with Faithful Uncertainty Estimation
  JHEP 0503(2005)080; hep-ph/0501067

- Neural Network Approach to Parton Distribution Fitting
  Nucl.Instr.Meth. A559(2006)203; hep-ph/0509067

- Neural Network Determination of Parton Distributions: The Nonsinglet Case
  JHEP 0703(2007)039; hep-ph/0701127

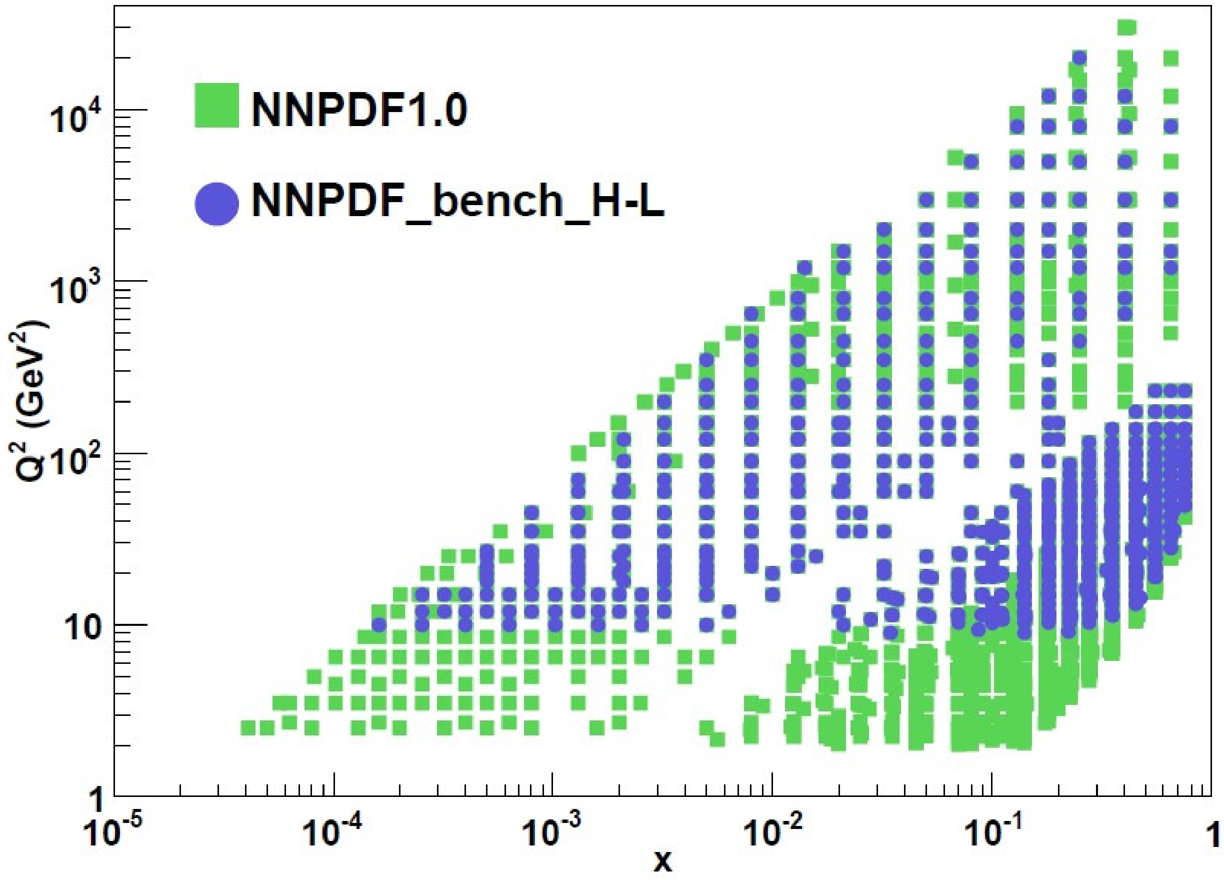
- A Determination of Parton Distributions with Faithful Uncertainty Estimation [NNPDF1.0]
  Nucl. Phys. B809(2009)1; arXiv:08081231

- Update on Neural Network Parton Distributions [NNPDF1.1]
  arXiv:0811.2288

- Precision Determination of Electroweak Parameters and the Strange Content of the Proton from Neutrino Deep Inelastic Scattering [NNPDF1.2]
  arXiv:0609??? (imminent)

Extra slides

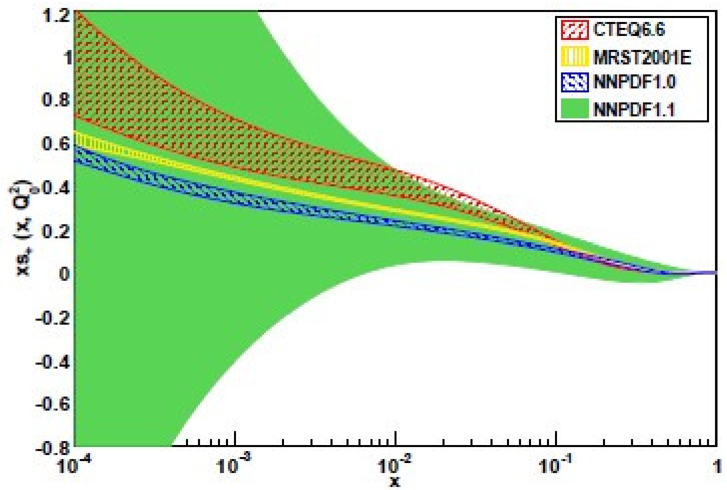
NNPDF1.0 Benchmark



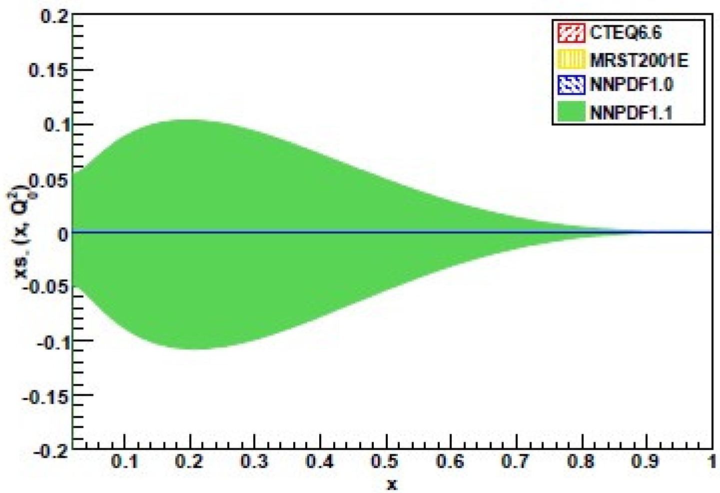
Strangeness: NNPDF1.1

Same data: add two more pdfs

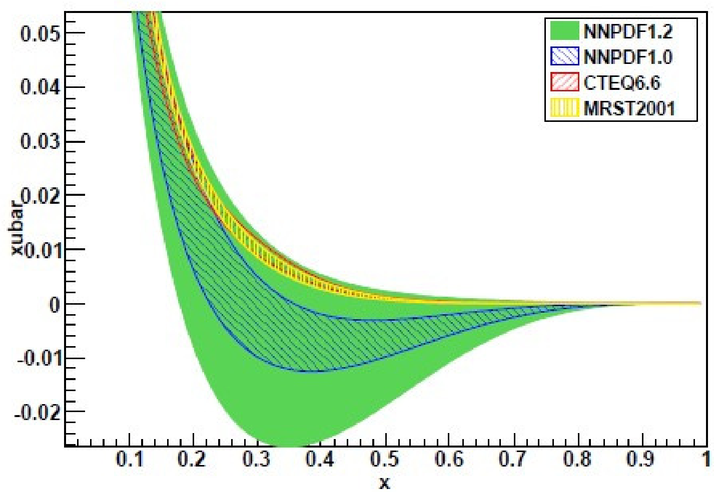
$s^+ = s + \bar{s}$



$s^- = s - \bar{s}$



Preprocessing: $PDF(x) = x^a(1-x)^b NN(x)$: vary a and b randomly

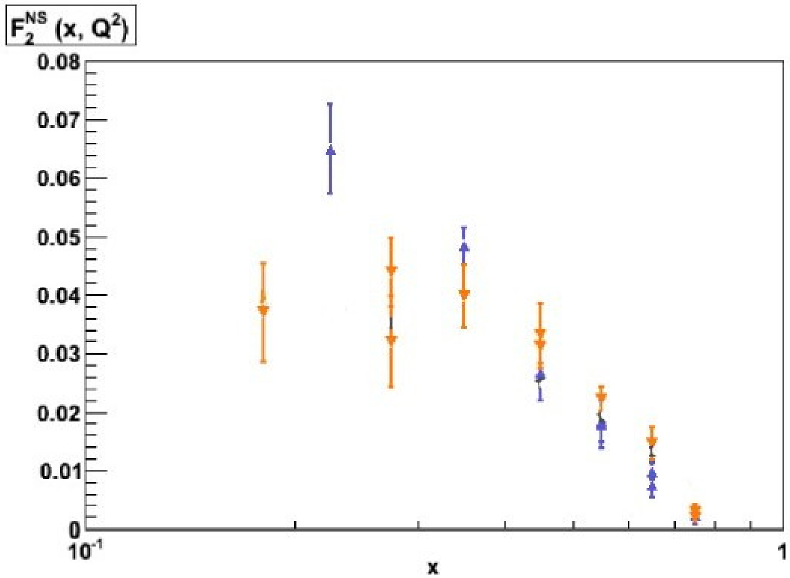


Stopping

Q. How do we know when to stop the fitting (‘training’)?

A. Use cross-validation

- Divide data (randomly) into ‘training’ and ‘validation’ sets



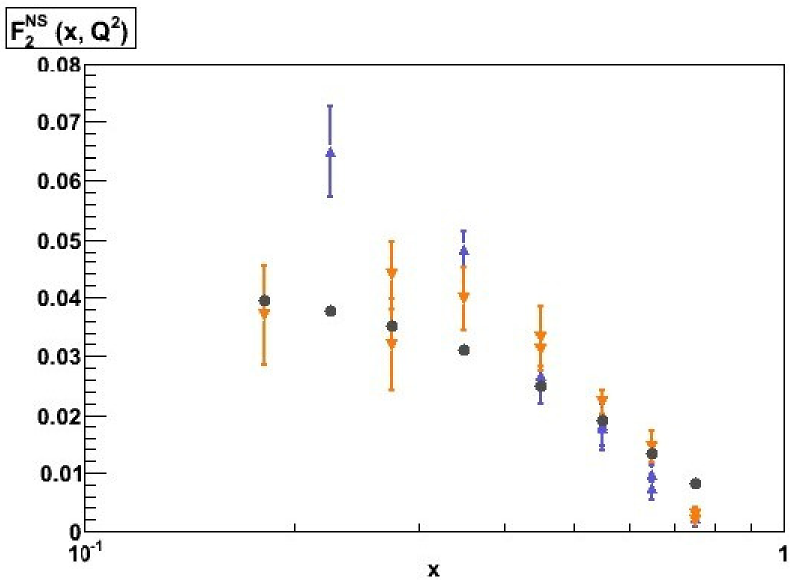
Real F_2 data

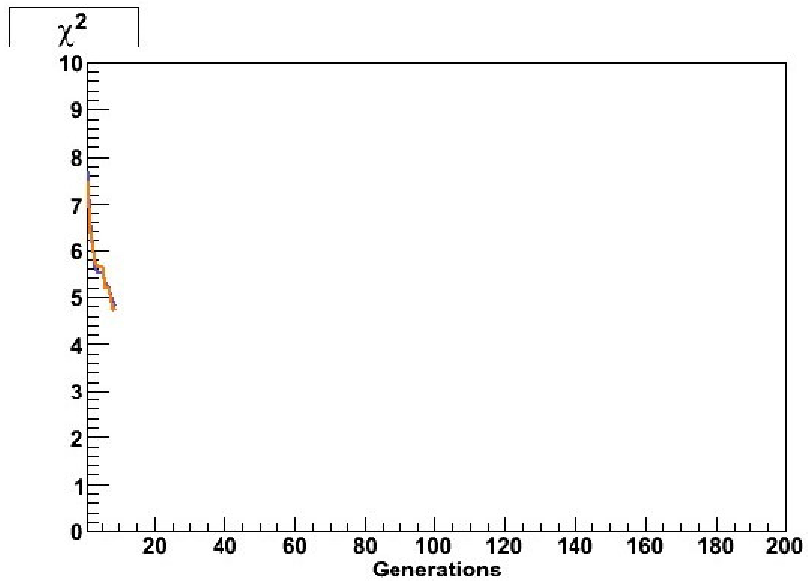
Stopping

Q. How do we know when to stop the fitting ('training')

A. Use cross-validation

- Divide data (randomly) into 'training' and 'validation' sets
- Train net on 'training' set, monitoring fit to 'validation' set





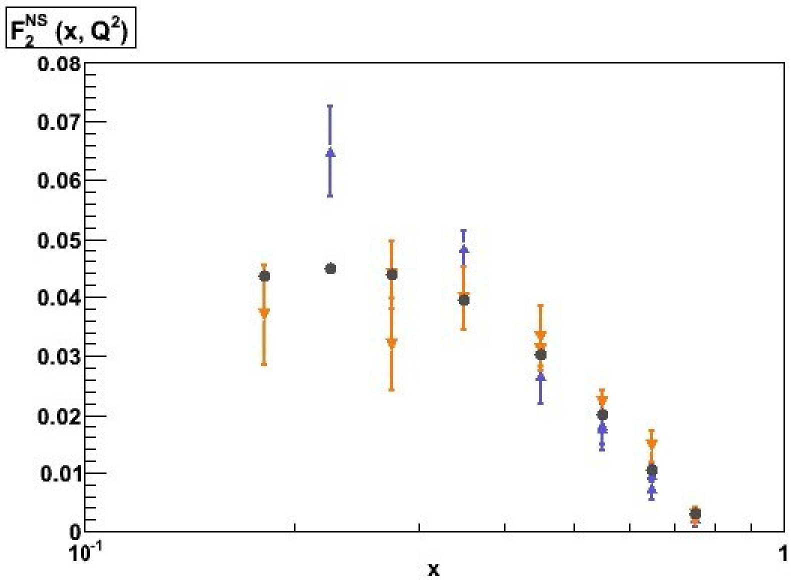
GO!

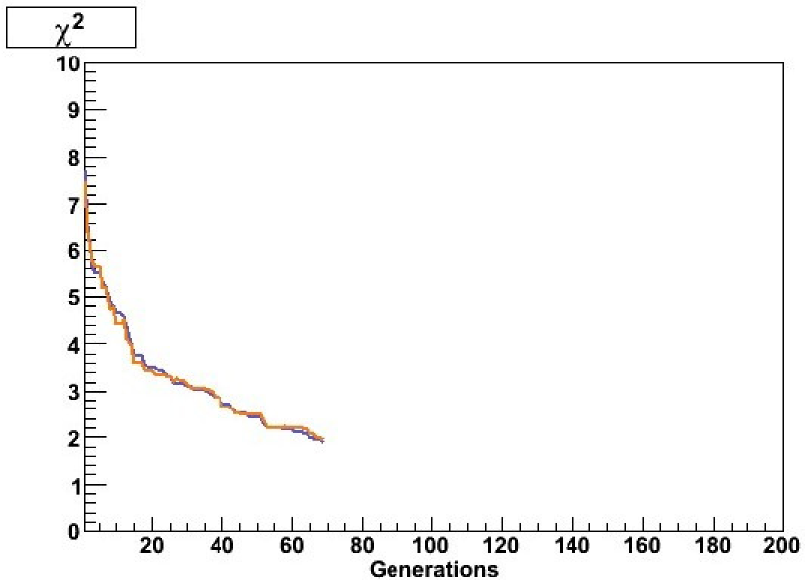
Stopping

Q. How do we know when to stop the fitting ('training')

A. Use cross-validation

- Divide data (randomly) into 'training' and 'validation' sets
- Train net on 'training' set, monitoring fit to 'validation' set
- When fit to 'training' set better than fit to 'validation' set...





STOP

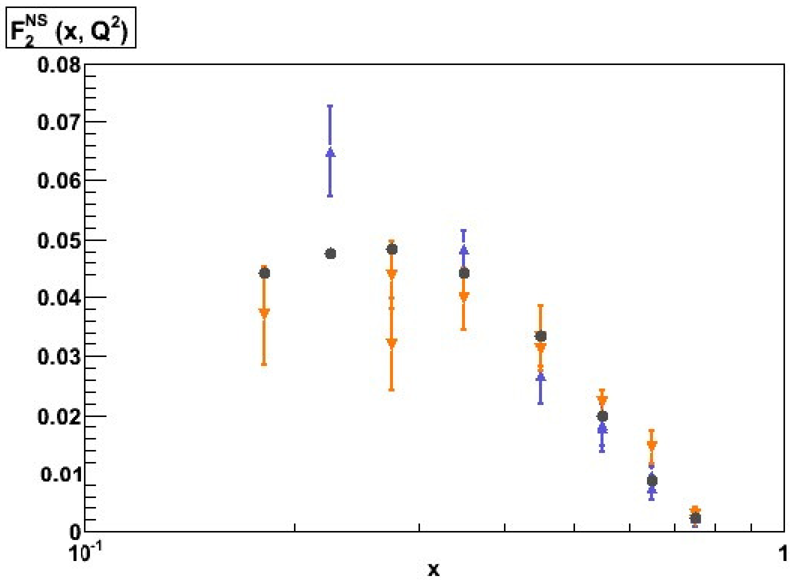
Stopping

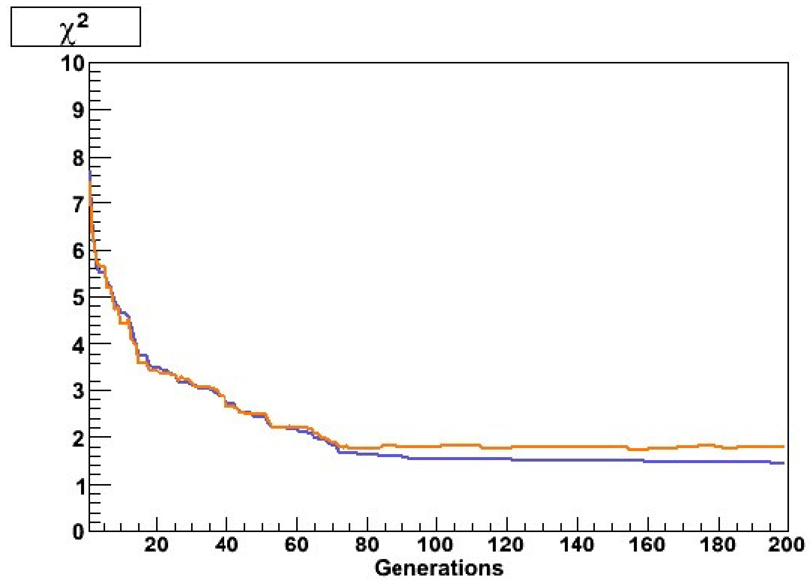
Q. How do we know when to stop the fitting (‘training’)

A. Use cross-validation

- Divide data (randomly) into ‘training’ and ‘validation’ sets
- Train net on ‘training’ set, monitoring fit to ‘validation’ set
- When fit to ‘training’ set better than fit to ‘validation’ set .

High χ^2 means bad data, not bad fit





Too Late!