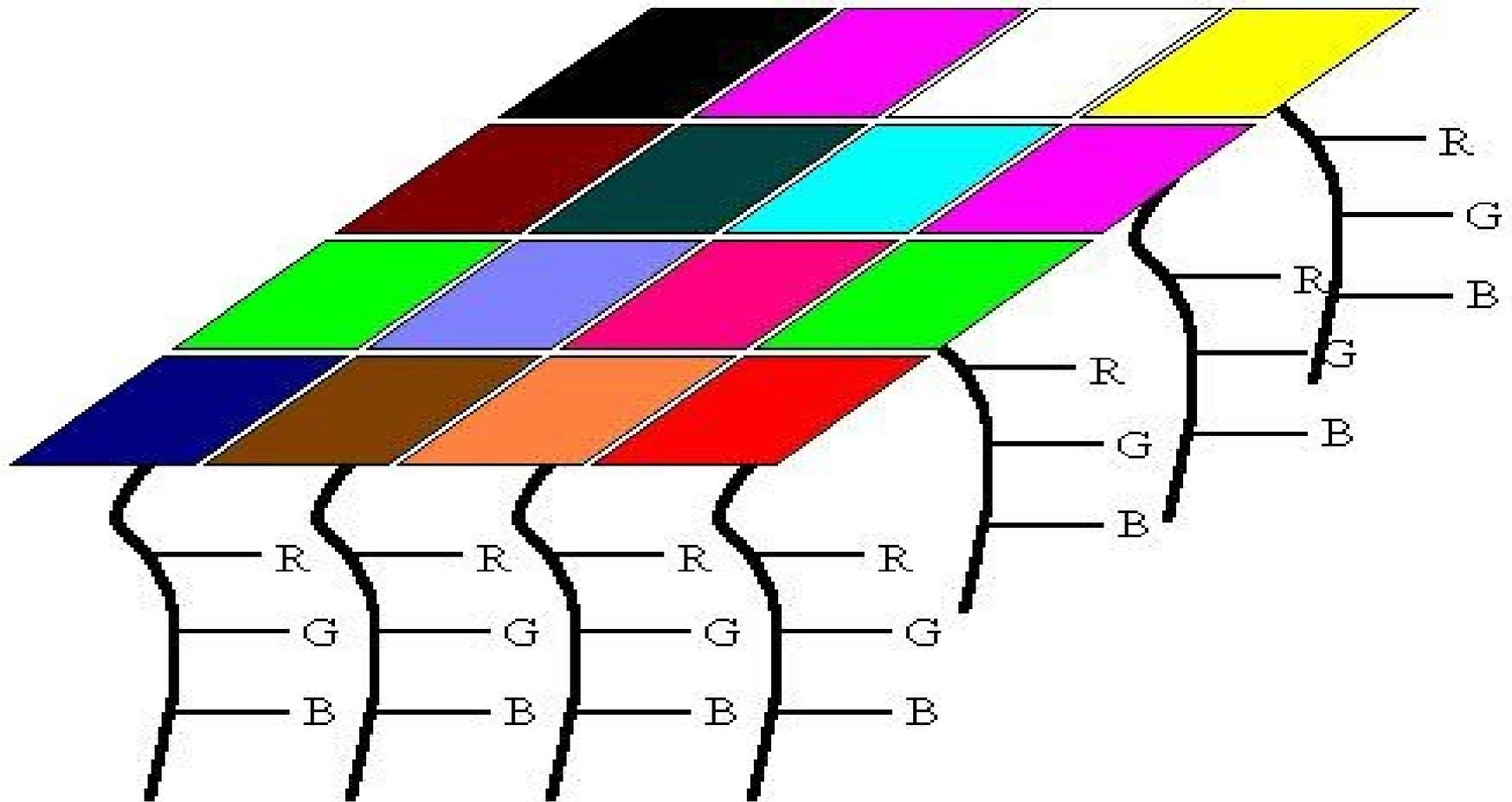


Use of Self Organizing Maps in Deep Inelastic Scattering

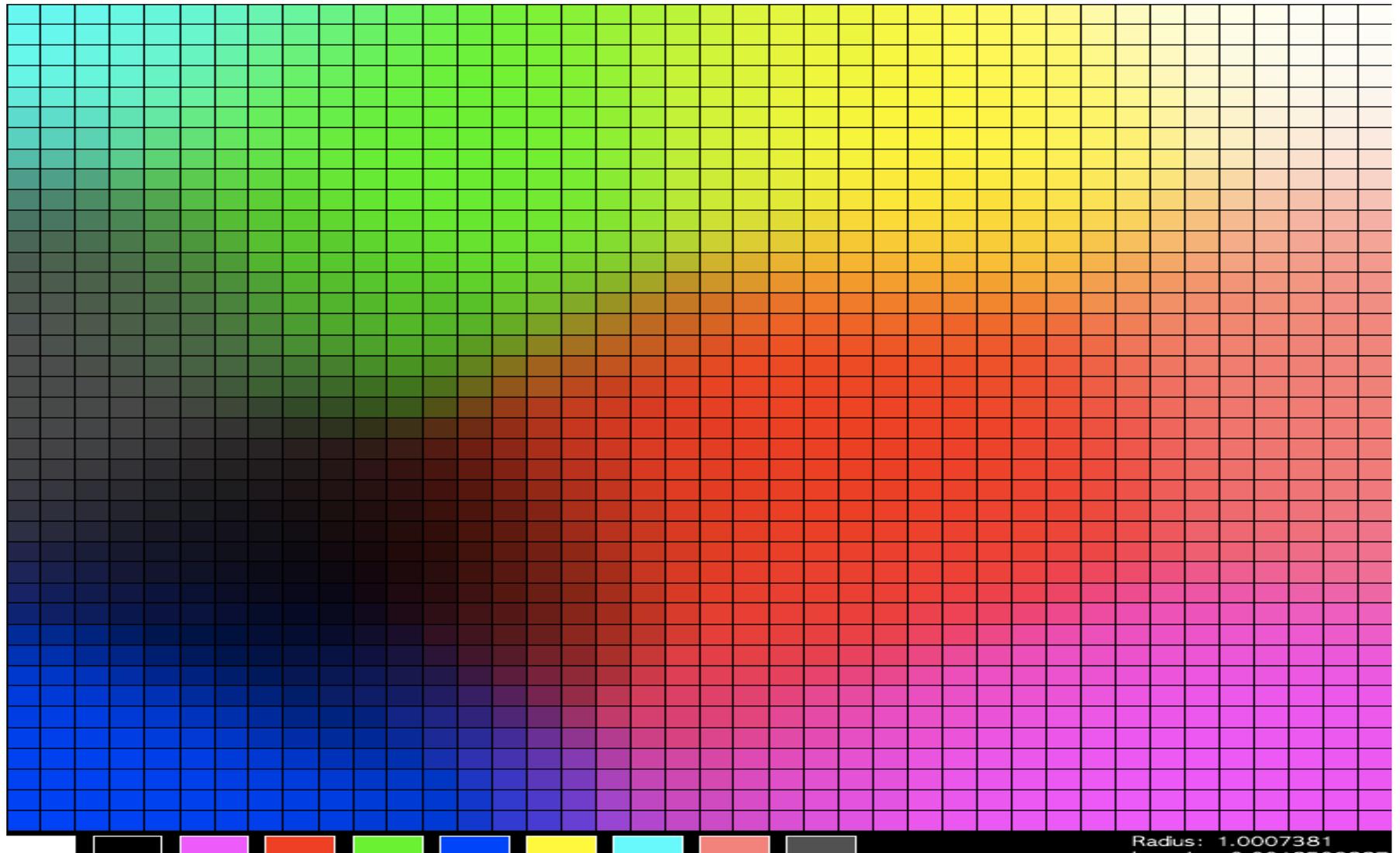
Self Organizing Maps

- Self Organizing Maps (SOM) are a type of neural network that uses *unsupervised learning*.
- Unsupervised learning refers to a type of neural network data evolution where an initial data set is molded to fit a final data set without the final data set being used as a reinforcement.
- A Self Organizing Map is a Map of Training Data on which an input set of training data, represented by an n dimensional vector, is placed.

SOM Color Example: a 4X4 Grid of Map Vectors That Comprise a Map



SOM Color Example After Self Organizing Process

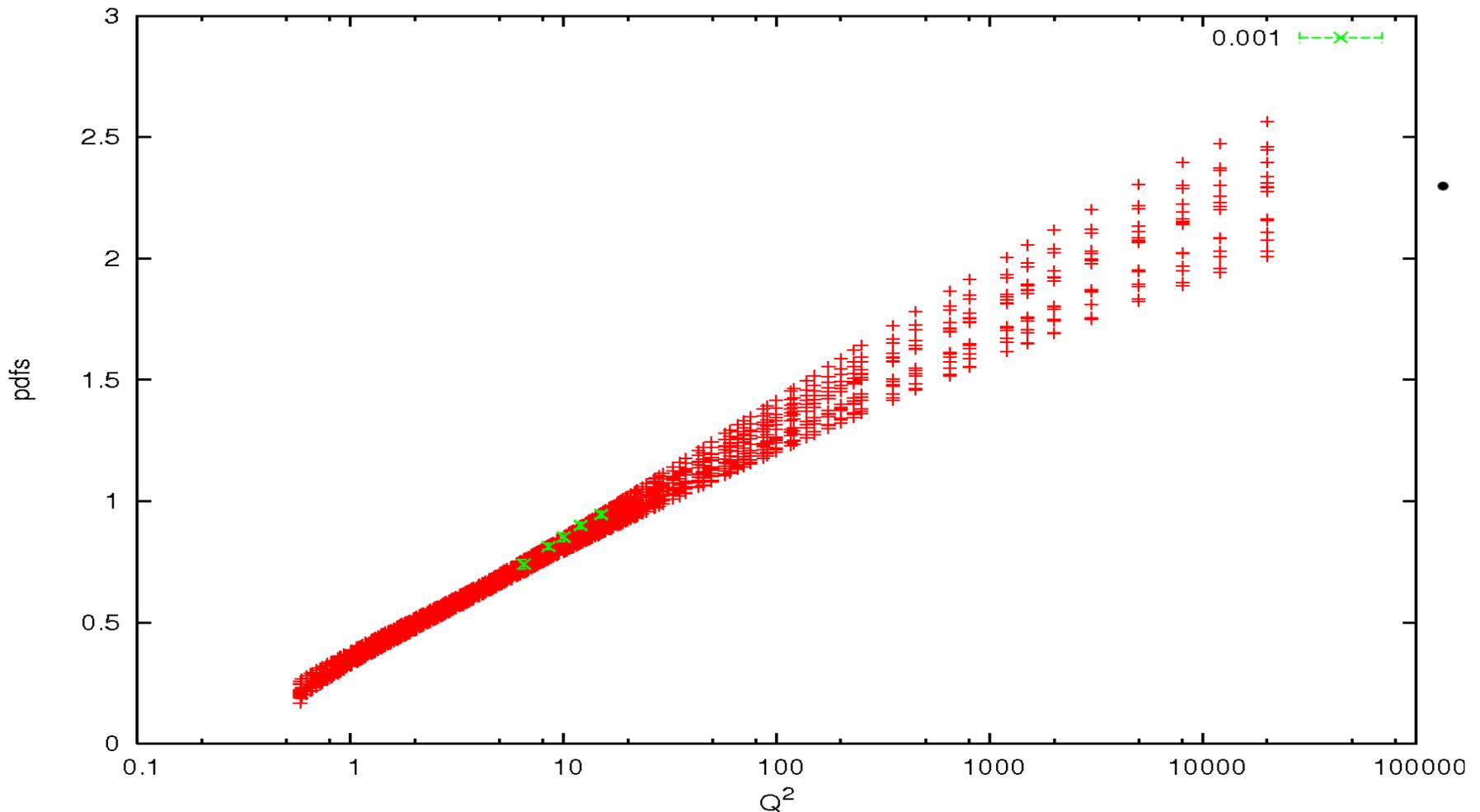


SOMPDF Methodology

- The SOM map training vectors formed from a parameterized set of Parton Distribution Functions, or PDFs, where the parameters are varied semi-randomly. The input training vector is also formed from a semi-randomly varied, parameterized PDF.
- The parameters for the PDF are “wiggled” for the map and the input vector.
- This way, after the map is trained, the χ^2 for the input PDFs, relative to the experimental data, can be minimized using the genetic algorithm.

Example of PDF envelope for $x = 0.001$

Red Dots = PDF Envelopes, Green Dots = Experimental data



Genetic Algorithm

- For a NXN map of PDFs, the training process was repeated for a given number of iterations.
- The training vectors with the best values of χ^2 were determined for each iteration.
- The best-matching training vectors were used to generate the next set of training vectors for the subsequent iteration.

PDFs and Their Purpose

- The cross section for deep inelastic scattering of a lepton off of a proton can be written in terms of a hard scattering cross section and $q_j(x, Q^2)$.
 - - $q_j(x, Q^2)$ refers to the Parton Distribution Functions
 - Q^2 is the square of the momentum of the virtual photon exchanged
 - x is the fraction of the proton momentum contained in the parton momentum
- At the moment, direct info about these parton distribution functions can only be obtained through experiment

Constraining the PDFs

- The parton distributions used are the PDFs for the 3 lightest quarks, up, down and strange, and the gluons.

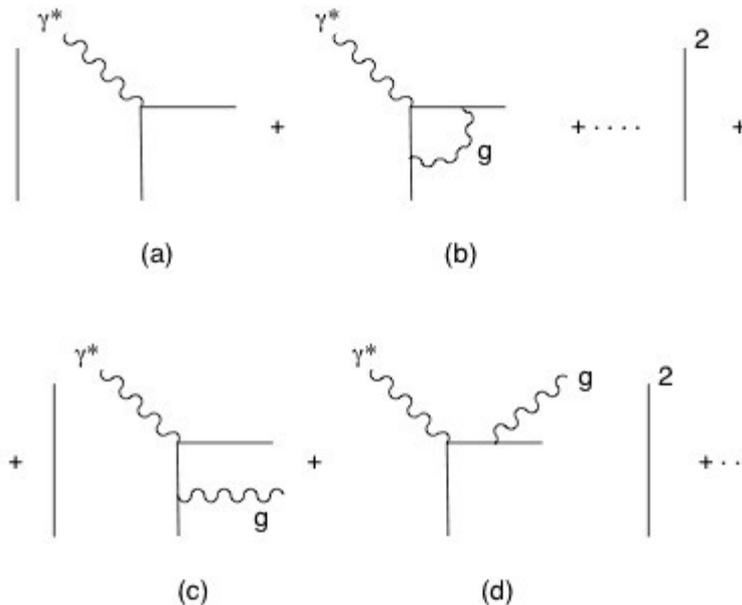
- For these PDFs, momentum conservation yields
$$\int_0^1 dx x (u + \bar{u} + d + \bar{d} + s + \bar{s} + g) = 1$$

- Then there are the sum rules for the up, down and strange quarks:

$$\int_0^1 dx (u - \bar{u}) = 2, \int_0^1 dx (d - \bar{d}) = 1 \quad \text{and} \\ \int_0^1 dx (s - \bar{s}) = 0$$

Momentum Evolution for the PDFs

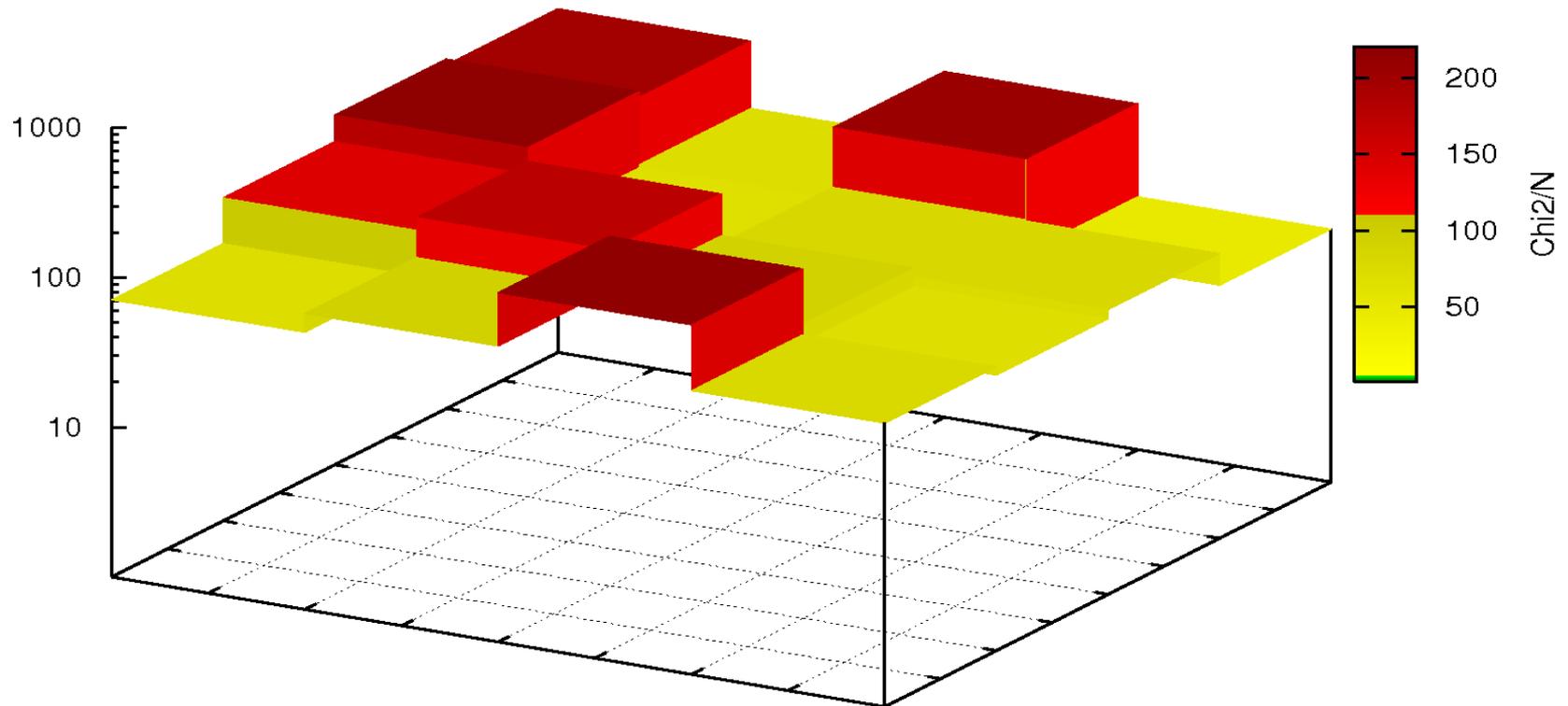
– Third Constraint



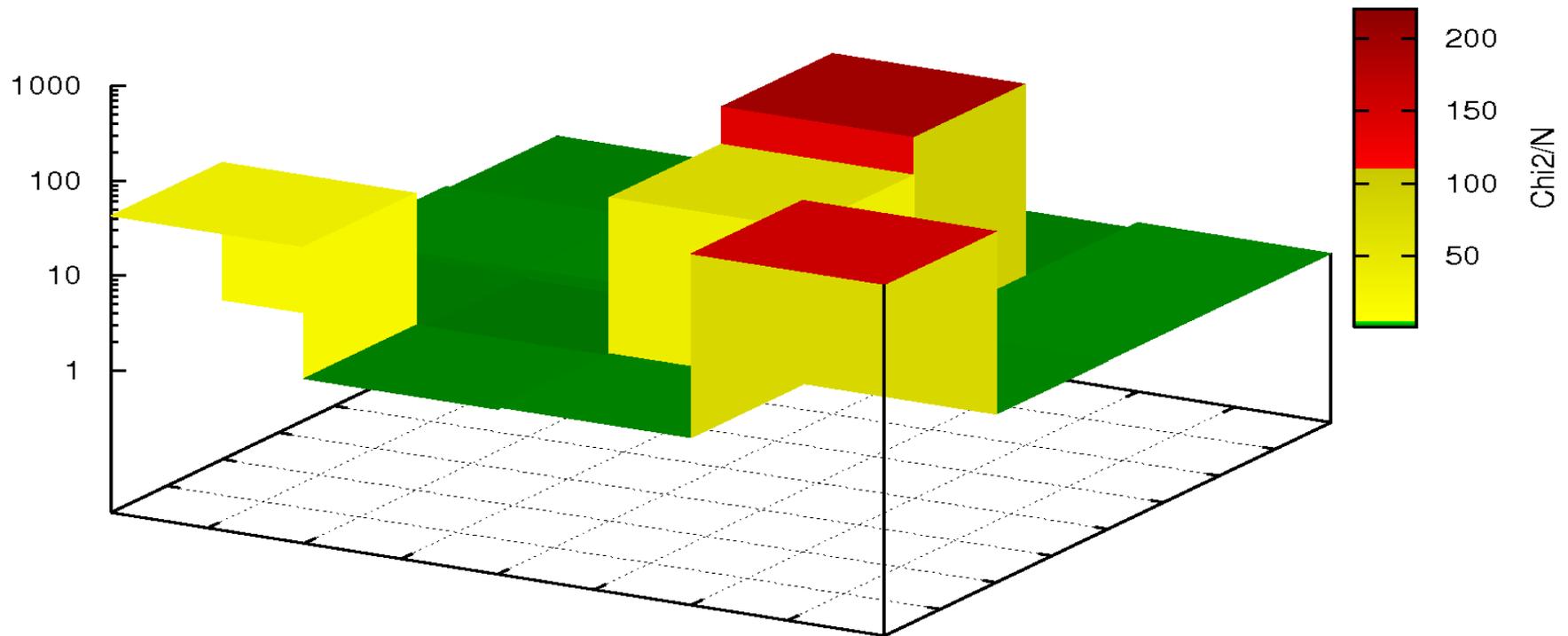
The integrals of the PDFs needed to be equal to the evolution factors, which are functions of $\ln(q^2)$.

The third condition was that the PDFs had to be normalized according to the momentum transfer evolution

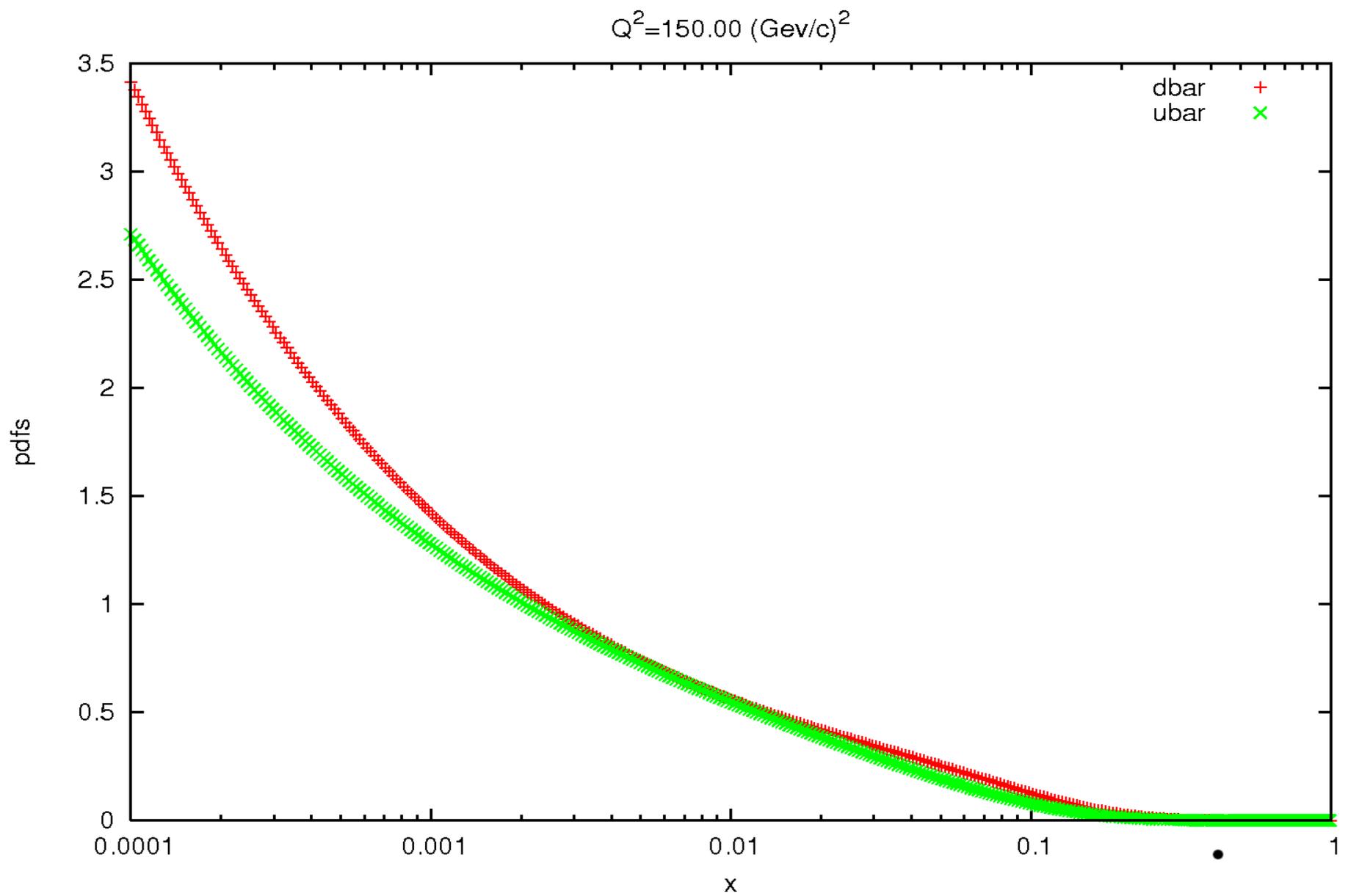
Map of χ^2 for the SOMPDF Initial Iteration



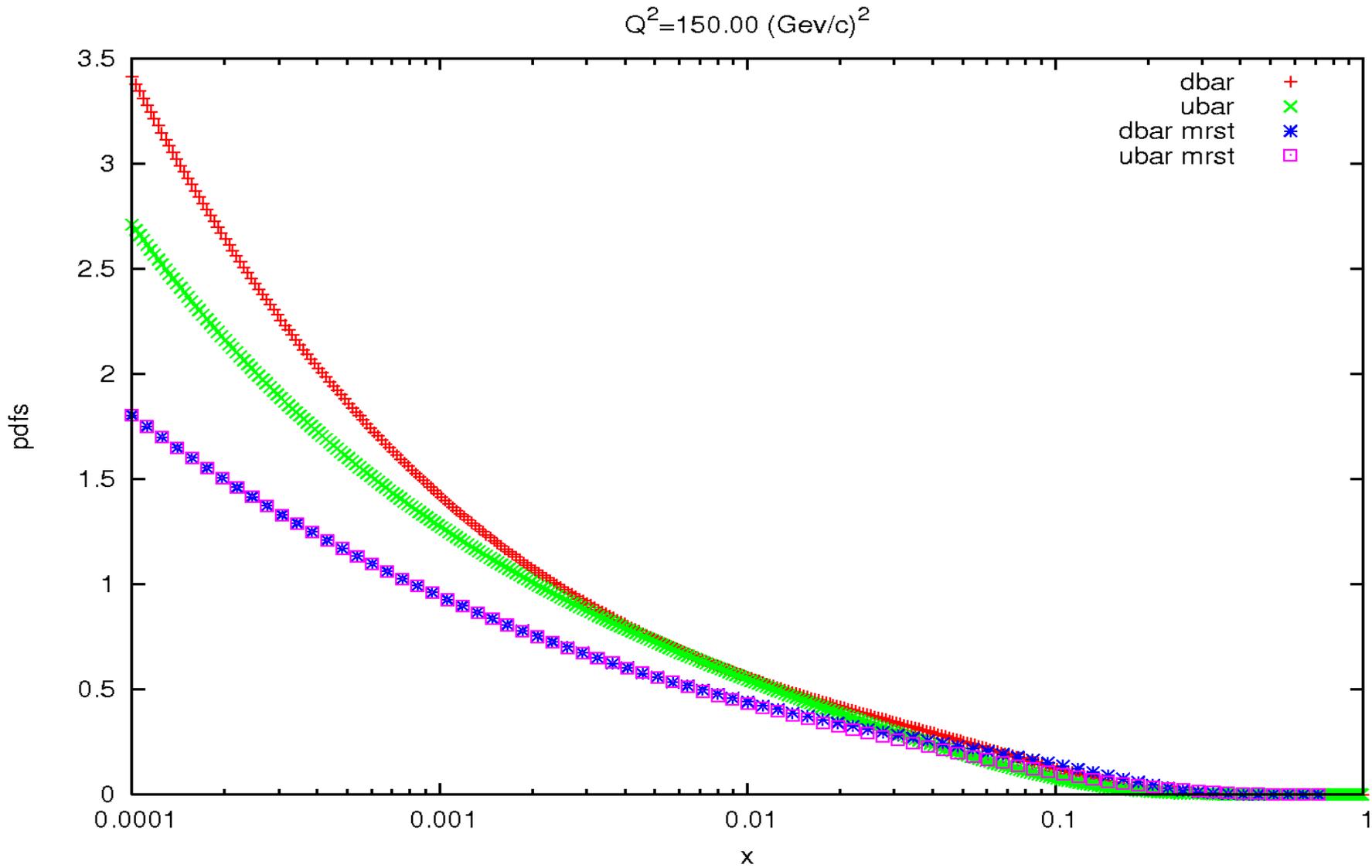
Map of χ^2 for the SOMPDF Final Iteration



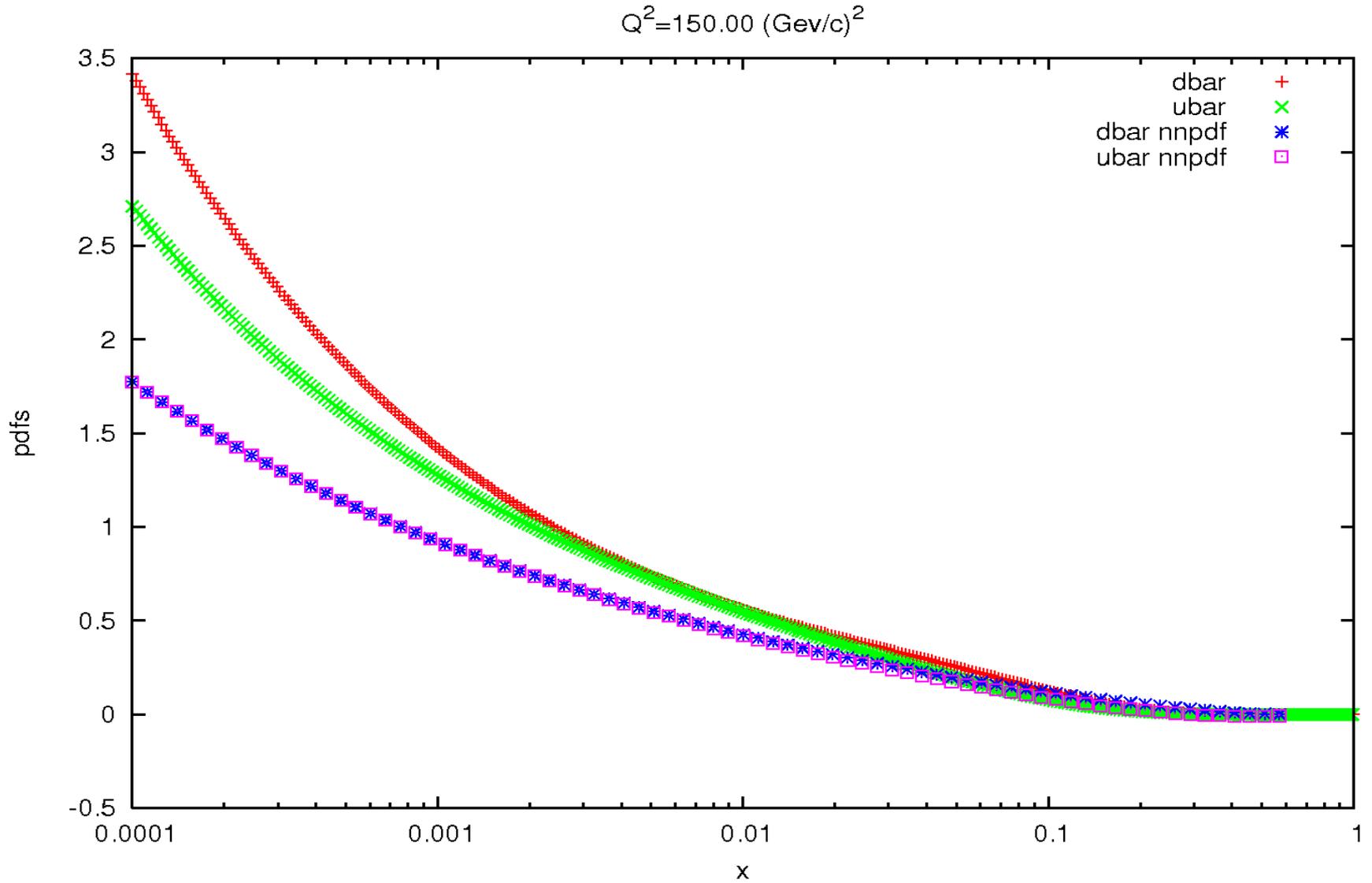
Ub and Db Plots for Proton Data, $\chi^2 = 1.92$



Comparison of Ub and Db Plots for Proton Data with MRST Experimental Data, $\chi^2 = 1.92$

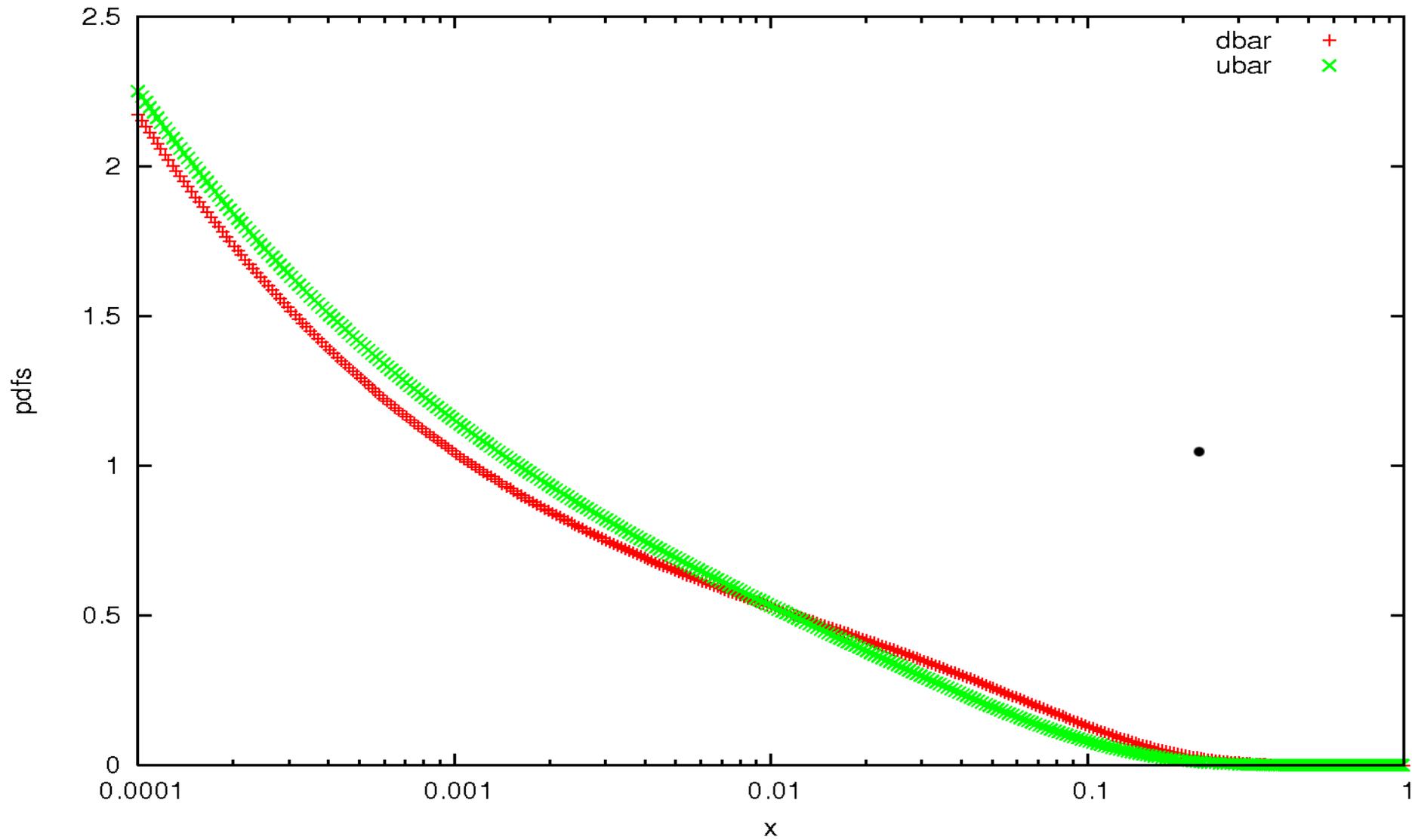


Comparison of Ub and Db Plots for Proton Data with NNPDF Experimental Data, $\chi^2 = 1.92$



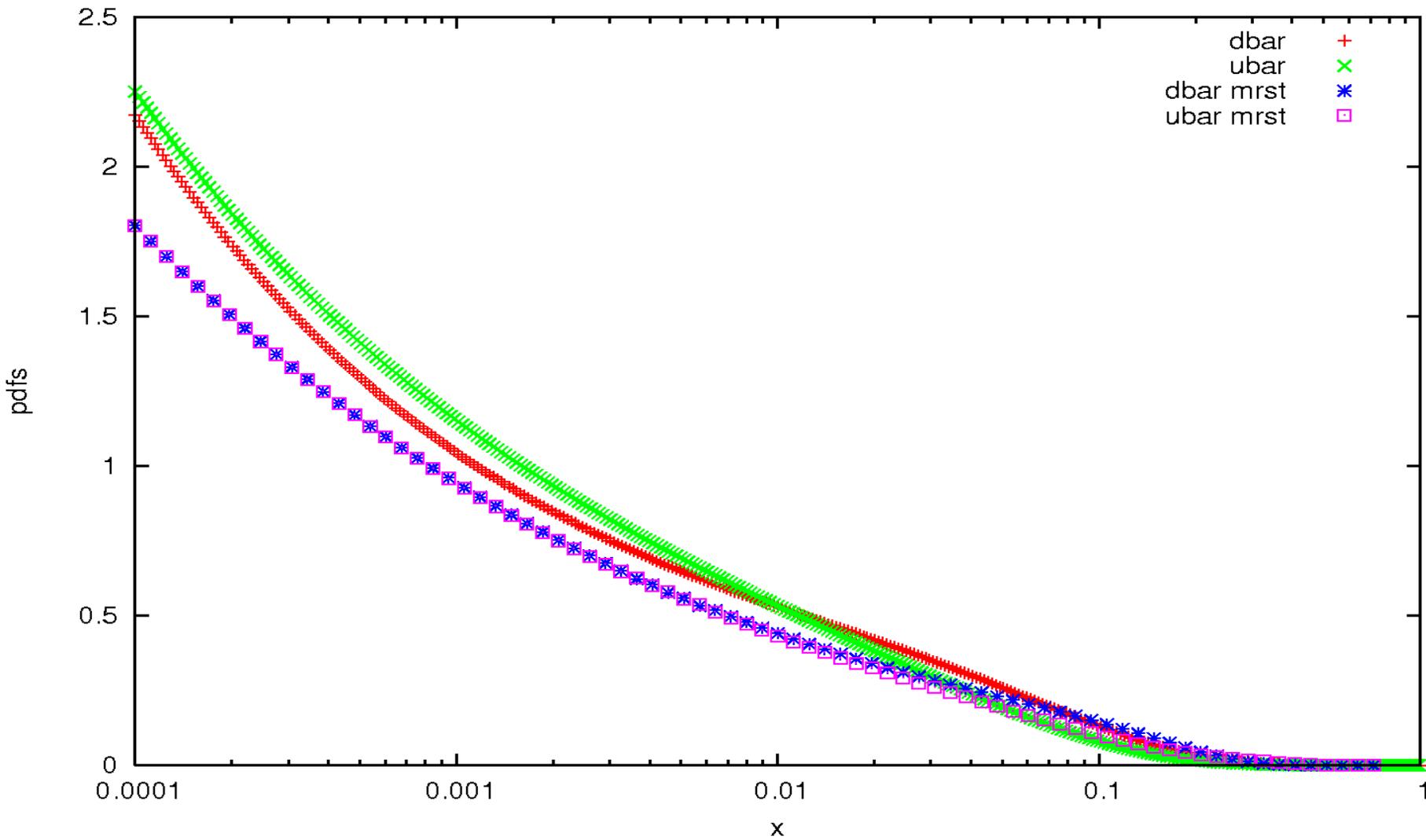
Ub and Db Plots for Deuteron Data, $\chi^2 = 1.92$

$Q^2 = 150.00 \text{ (Gev/c)}^2$



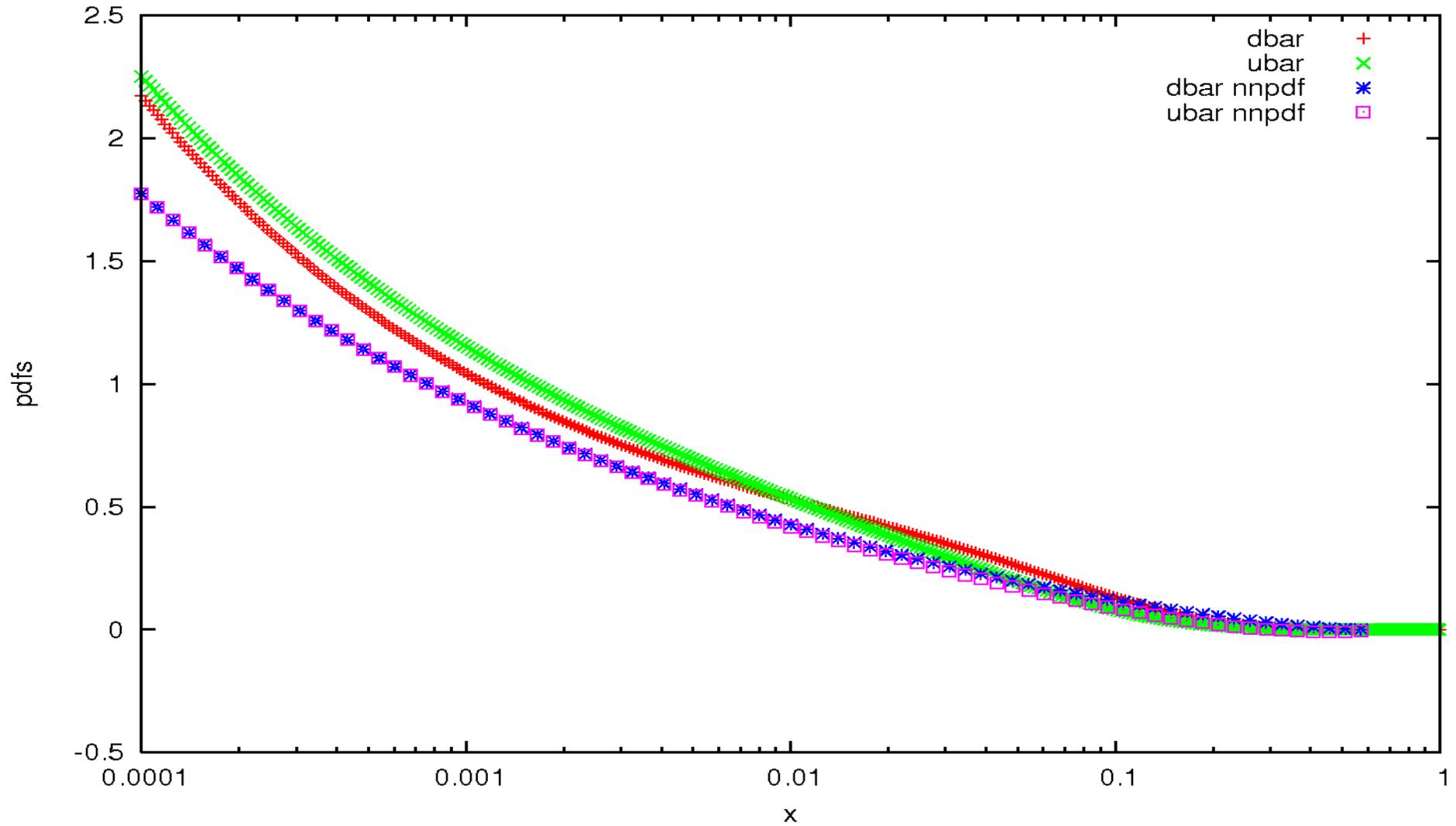
Comparison of Ub and Db Plots for Deuteron Data with MRST Experimental Data, $\chi^2 = 1.92$

$Q^2 = 150.00 \text{ (Gev/c)}^2$

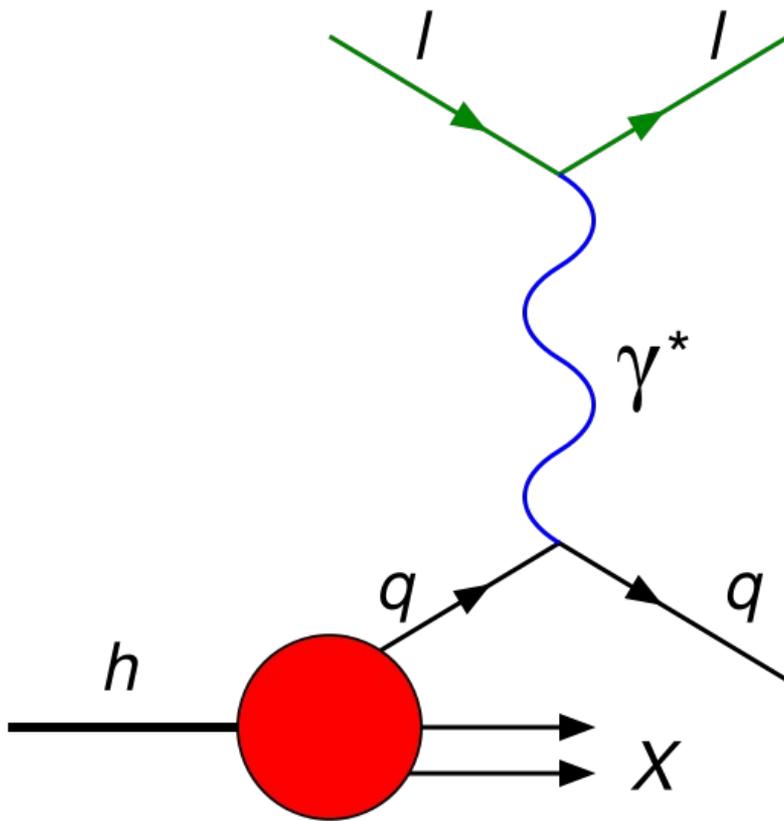


Comparison of Ub and Db Plots for Deuteron Data with NNPDF Experimental Data, $\chi^2 = 1.92$

$Q^2 = 150.00 \text{ (Gev/c)}^2$



Background on DIS



- Deep Inelastic Scattering is used to probe the structure of hadrons-including the proton.
- In this setup, an electron, muon or neutrino scatters off of a proton and exchanges a virtual photon with momentum q with a parton (quark) in the proton.
- This leads to a series of partons in the proton carrying fractions of the proton's initial momentum

The Need for Neural Networks

- Neural Networks are organized systems of data used to train and evolve a given data set to more closely match a known data set. Here they are used to train PDF data.
- The parameterized PDFs vary significantly from group to group.
- In order to fit them with the experimental values for the PDF we attempt to evolve the PDFs from an initial set of conditions using neural networks.
- Then we can analyze how well the PDFs that different groups have created can fit the experimental data.
- The neural network we attempt to use is the Self Organizing Map.