An alternative approach to fitting the unintegrated gluon density (Status report)

HERA-LHC Working Group Week, DESY, 29/10-2/11-2007

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(Thanks to Magnus Hansson (Lund) for help and data!)

Outline

Intro to the unintegrated gluon

•The Data

•The fitting

Results

•Summary/Outlook

The unintegrated PDF

The uPDF starting distribution:

$$xA_0(x, k_T, \bar{q}_0) = N \cdot x^{-B} \cdot (1-x)^C \cdot exp(-\frac{(k_T - \mu)^2}{2\sigma^2})$$

N: Normalization (fitted) B: Small x behaviour (fitted) C=4: Large x behaviour (kept fixed) $\mu = \sigma$ =1.5: Determines the shape of the intrinsic k_T of the gluon below k_T = 1.2 GeV (for simplicity kept fixed at the moment)

 q_0 is the starting scale of the distribution. The uPDF is calculated for higher scales by emissions of gluons according to the CCFM evolution scheme.

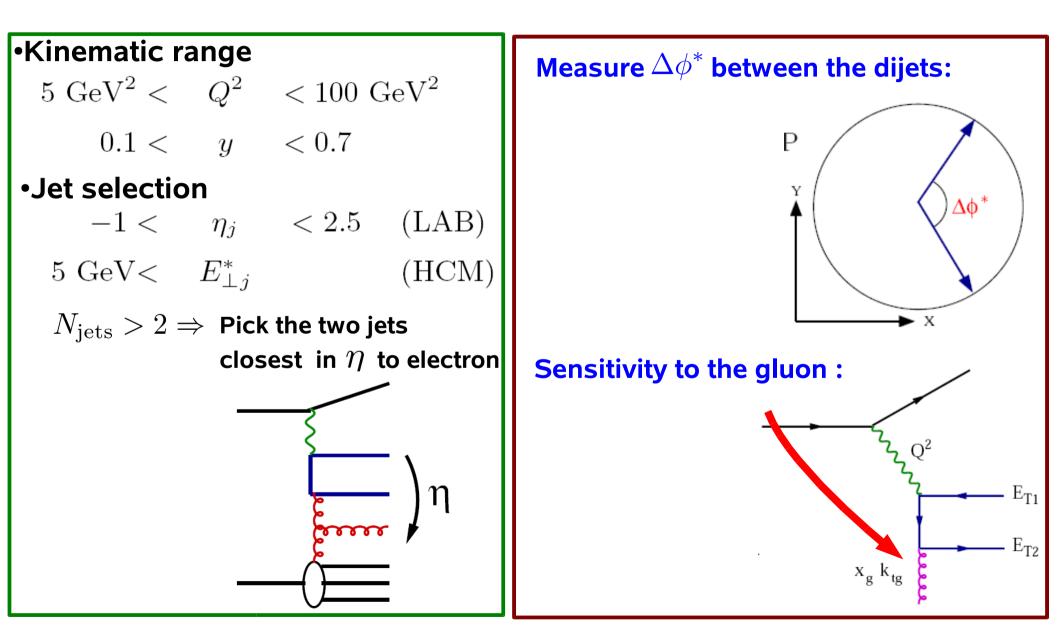
The parameters N,B,C, μ , $\!\sigma\!$, $\,$ are not theoretically calculable.



We need to fit the uPDF to experimental data.

The Data – Dijets and azimuthal decorrelations

For testing and development we fit to a double differential dijet cross-section, which is expected to be sensitive to the gluon.

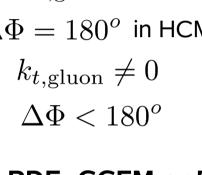


The Data – Dijets and azimuthal decorrelations

Integrated PDF: DGLAP

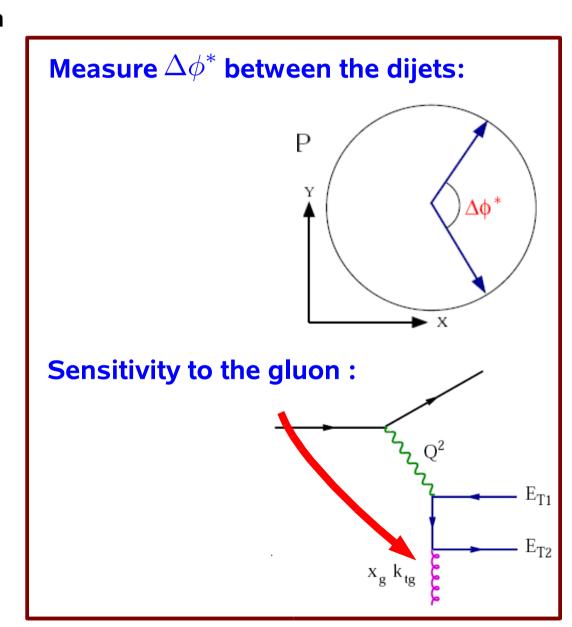
LO: Gluon collinear with proton $k_{t,\text{gluon}} = 0$ $\Delta \Phi = 180^o$ in HCM $k_{t,\text{gluon}} \neq 0$ $\Delta \Phi < 180^{\circ}$

Higher orders:



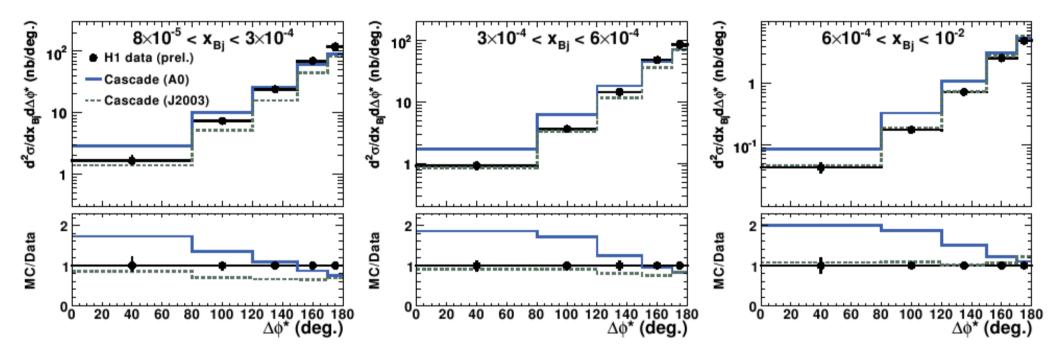
Unintegrated PDF: CCFM or BFKL

 $k_{t,\text{gluon}} \neq 0$ $\Delta \Phi < 180^{\circ}$ already at LO



The Data – Dijets and azimuthal decorrelations

Double differential cross-section (H1 preliminary):



The uPDF has been fitted before (to other, more inclusive, data). Here compared to the same data as we use,

A0: Only non-signular terms in the CCFM gluon splitting function J2003: Both singular and non-singular terms in the splitting function

The conventional fitting method:

- 1. Calculate cross-section using CASCADE for a given set of parameter values
- 2. Compare to data, calculate Chi2 and feed it to MINUIT
- 3. MINUIT (e.g. the simplex method) estimates new parameter values
- 4. Iterate 1. 3. until Chi2 is minimized

This means that if MINUIT needs 100 iterations to minimize Chi2, CASCADE is run 100 times, not simultaneously:

If one CASCADE run takes 1 hour, the minimization takes 100hours.

To fit uPDF one needs exclusive measurements (like the azimuthal dijet measurement)

A lot of statistics. Minimization >> 100h.

Acknowledgement

New method!

The method was developed for tuning Monte Carlo models

Parameter Optimisation in Monte Carlo Event Generators

Hendrik Hoeth

(University of Wuppertal)

1st Mcnet School, IPPP Durham, 18-20th April 2007

We try to carry out the same method for fitting uPDFs.

- 1. Build up a grid in parameter cross section space using Monte Carlo.
 - If you have a CPU farm (or use the *GRID*) this ultimately
 - takes the time of running CASCADE once.

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- 2. Fit polynomials to the Monte Carlo grid.

$$\sigma_{\text{poly}} = A + \sum_{1}^{N} B_i \cdot p_i + \sum_{1}^{N} C_i \cdot p_i^2 + \sum_{1}^{N} D_i \cdot p_i p_{i-1} + H.O.$$

$$A, B, C \text{ and } D \text{ are determined}$$
by fitting the polynomial to the parameter-xsection grid.

This takes a *few seconds*.

Step 1. and 2. are done for each bin in the measurement.

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Step 1. and 2. are done for each bin in the measurement.

3. Determine PDF parameters, p_i , by fitting the polynomials to data Also this takes only a few seconds.

Step 2. and 3. are done by Chi2-minimization in for example minuit.

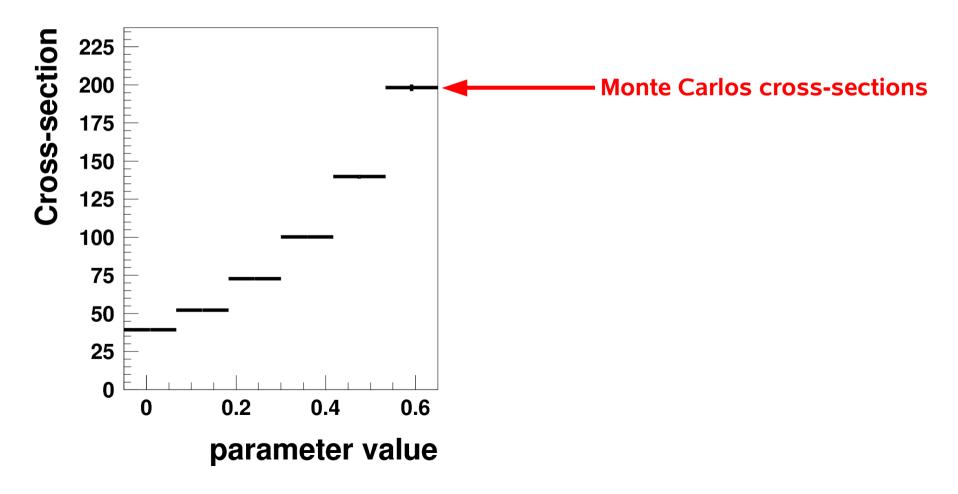
Simple Example

Simplest possible example

1 parameter, 1 data cross-section

(based on a sub-sample of the actual grid.)

1. Build up the grid



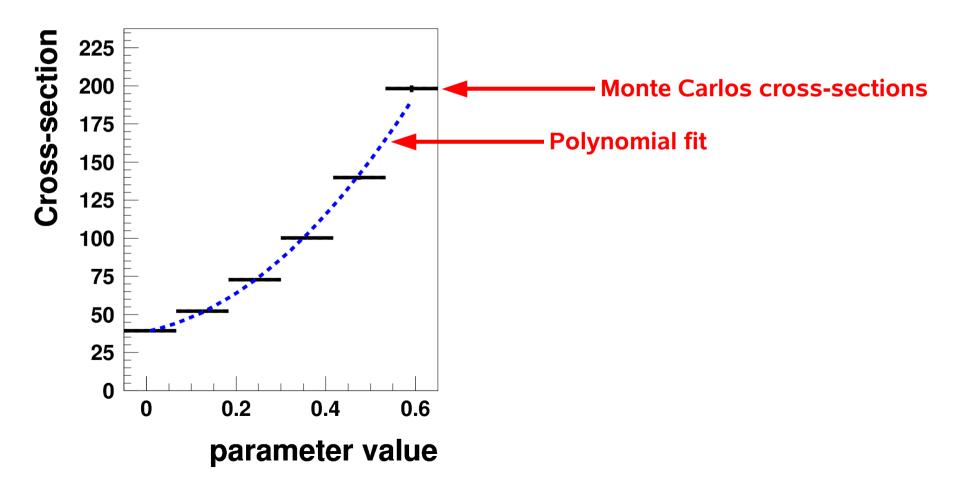
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2. Fit Ploynomial



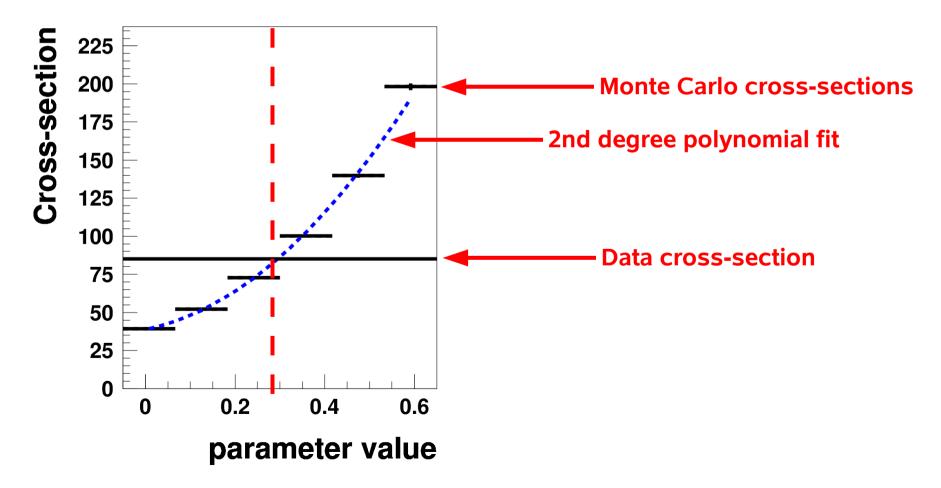
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1 parameter, 1 data cross-section

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3. Minimize Chi2 to data

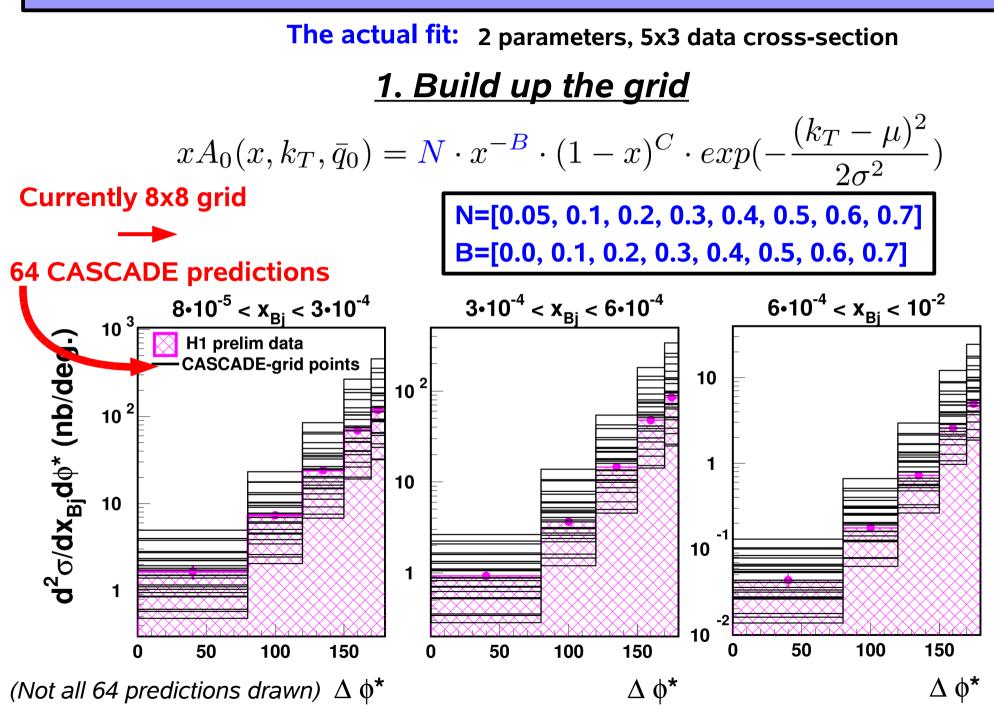


The actual fit: 2 parameters, 5x3 data cross-section

1. Build up the grid

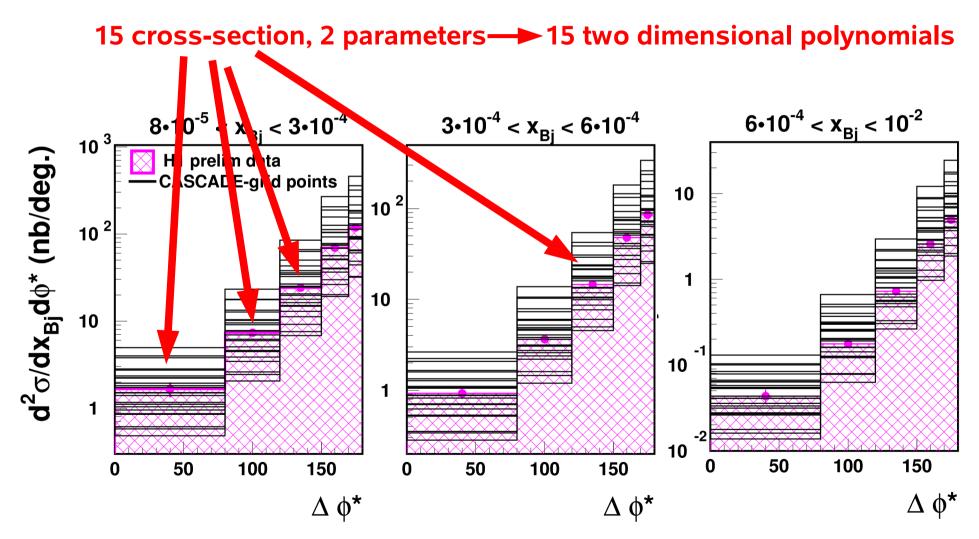
$$xA_0(x, k_T, \bar{q}_0) = N \cdot x^{-B} \cdot (1-x)^C \cdot exp(-\frac{(k_T - \mu)^2}{2\sigma^2})$$

N=[0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7] B=[0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7]



The actual fit: 2 parameters, 5x3 data cross-section

2. Determine polynomials



3. Fit polynomials to Monte Carlo grids

We try different orders of the fitted polynomials

Chi2/NDF for polynomial fits	Order:	2nd	3rd	4th	5th	6th
chi2/ndf for histo 1, bin chi2/ndf for histo 2, bin chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin	1 = = = = = = = = = = = = = = = = = = =	$ \begin{array}{r} 11.8\\34.7\\129.\\356.\\345.\\8.21\\24.1\\95.6\\293.\\283.\\9.33\\30.1\\130.\\467.\end{array} $	$\begin{array}{c} 2.1\\ 3.4\\ 10.\\ 30.\\ 30.\\ 1.9\\ 3.0\\ 7.8\\ 23.\\ 26.\\ 2.1\\ 5.6\\ 16.\\ 41. \end{array}$	$ \begin{array}{r} 1.9\\ 2.0\\ 3.4\\ 4.0\\ 3.4\\ 1.7\\ 1.8\\ 3.1\\ 4.0\\ 3.3\\ 2.2\\ 5.7\\ 14.\\ 17. \end{array} $	$ \begin{array}{r} 1.9\\ 2.3\\ 3.8\\ 4.0\\ 3.1\\ 1.6\\ 1.7\\ 2.7\\ 2.7\\ 2.7\\ 2.7\\ 2.4\\ 2.1\\ 5.9\\ 14.\\ 15. \end{array} $	1.7 2.0 3.1 3.4 2.8 1.5 1.9 2.5 2.1 2.3 2.3 6.0 14. 15. 12.
chi2/ndf for histo 3, bin	. 5 =	477.	41.	13.	12.	14.

$$\chi^2 = \sum \frac{(\sigma_{i,\text{poly}} - \sigma_{i,\text{MC}})^2}{err_{i,\text{MC}}^2}$$

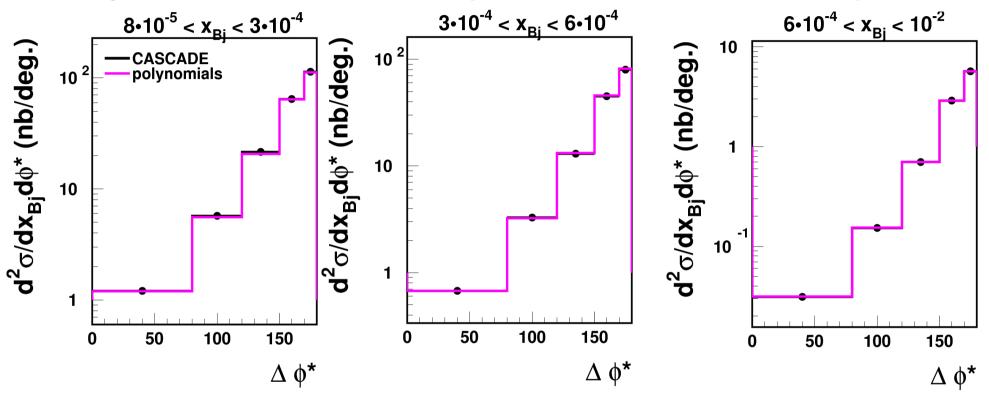
Improvement up to 4th degree.

4th, 5th and 6th describes MC parameter-xsection space equally well.

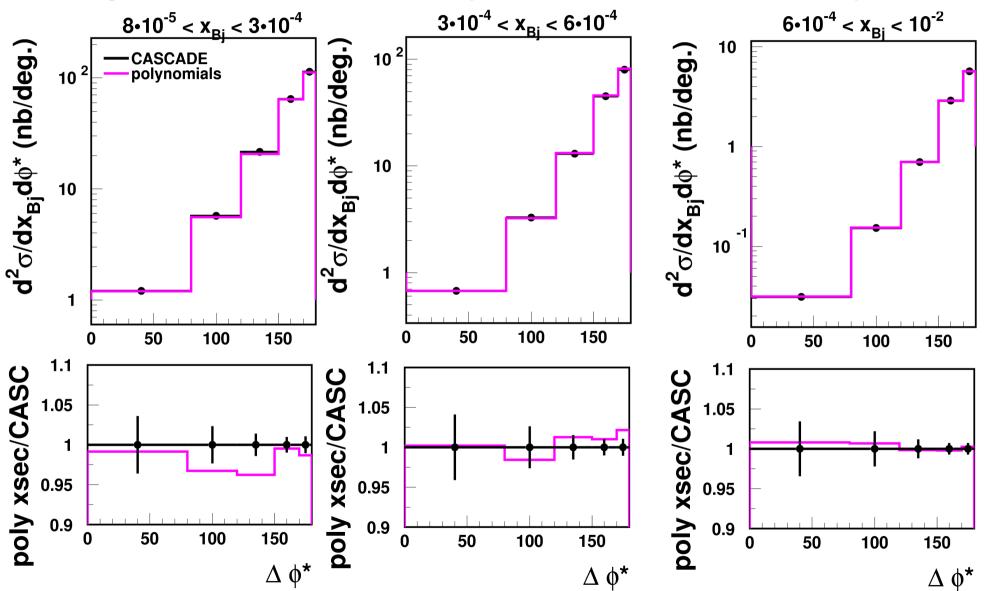
3. Fit Polynomials to data by varying parameters

Chi2/NDF for polyno	<u>mial fits</u>	Order:	2nd	3rd	4th	5th	6th
chi2/ndf for his chi2/ndf for his			$11.8 \\ 34.7$	2.1 3.4	1.9	1.9 2.3	1.7 2.0
chi2/ndf for his	to 1, bin	3 =	129.	10. 30.	3.4	3.84.0	3.1 3.4
chi2/ndf for his chi2/ndf for his	to 1, bin	5 =	345.	30.	3.4	3.1	2.8
chi2/ndf for his chi2/ndf for his		1 = 2 =	8.21 24.1	1.9 3.0	$1.7 \\ 1.8$	$1.6 \\ 1.7$	$1.5 \\ 1.9$
chi2/ndf for his	to 2, bin	3 =	95.6	7.8	3.1	2.7	2.5 2.1
chi2/ndf for his chi2/ndf for his		4 = 5 =	293. 283.	26.	4.0 3.3	2.7	2.3
	- 2 1.	$\frac{1}{2}$	9.33 30.1	2.1 5.6	2.2	2.1 5.9	2.3 6.0
$v^2 = \sum \frac{(O_{i,\text{Data}})}{(O_{i,\text{Data}})}$	$-o_{i,\mathrm{Poly}}$		130.	16. 41.	14.	14. 15.	14. 15.
$^{\Lambda}$ – $_$ err	$rac{-\sigma_{i, ext{Poly}}}{\sigma_{i, ext{Data}}^2}$	F	467. 477.	41.	17. 13.	12.	12.
		Order:	2nd	3rd	4th	5th	6th
Chi2/NDF for parameter fit 3.79 3.84 3.67 3.79 3.68					3.68		
	N	-value	0.119	0.110	0.115	0.109	0.110
	В	-value	0.537	0.530	0.520	0.535	0.534
We pick point with						/ -	
lowest Chi2:	22	N <i>T</i> ====	-B (1	C		, $(k_T$	$(-\mu)^2$
N=0.115	$xA_0 = x$	$\mathbf{v} \cdot x$	•(1	$-x)^{2}$	$\cdot exp($		$2\sigma^2$
B=0.520							20

Polynomial cross-sections compared to the actual CASCADE prediction

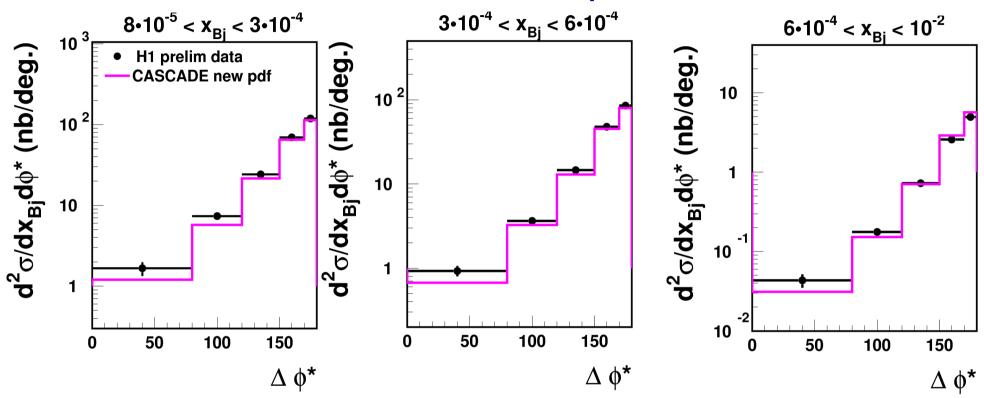


Polynomial cross-sections compared to the actual CASCADE prediction

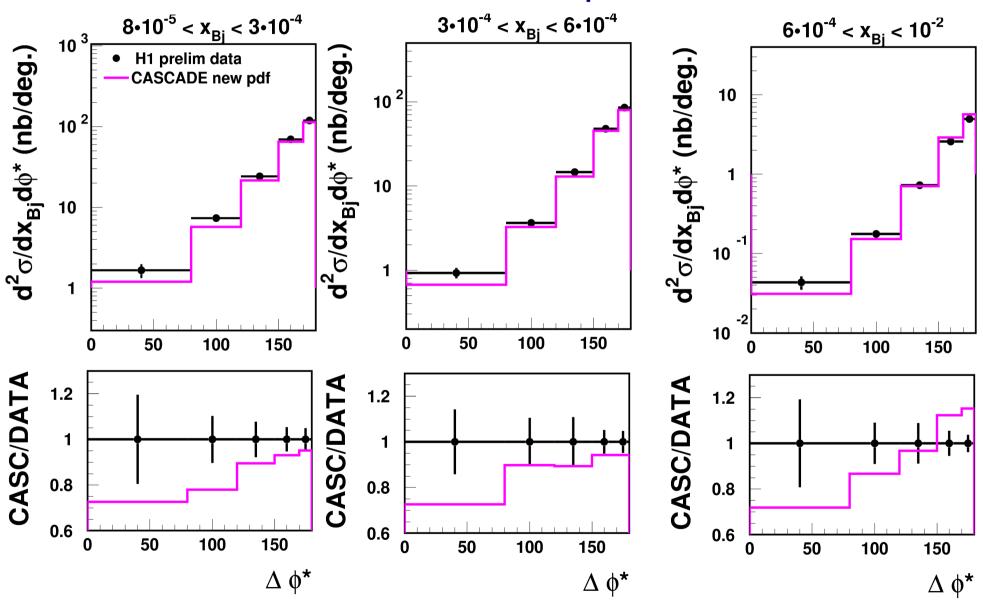


Room for improvements, but not very bad.

The results of the fit compared to data

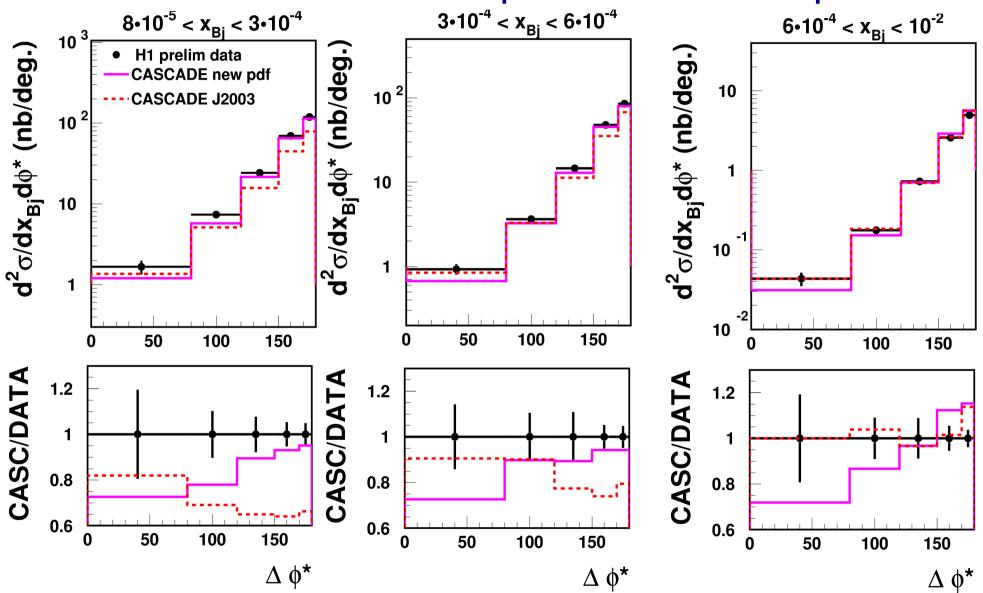


The results of the fit compared to data



Up to 30% deviation

The results of the fit compared to data and J2003-pdf



At low x and medium x in competition with J2003...

That one was fitted to other data.

Bad: We dont reconstruct the data we are fitting to.

Fitting the unintegrated uPDF

Chi2/NDF for polynomial fit	Degree:	2nd	3rd	4th	5th	6th
chi2/ndf for histo 1, bin chi2/ndf for histo 2, bin chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin	$ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 1 \\ 2 \\ 1 \\ 1 \\ 2 \\ 1 \\ 1 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1$	11.8 34.7 129. 356. 345. 8.21 24.1 95.6 293. 283 9.33 30.1	2.1 3.4 10. 30. 30. 1.9 3.0 7.8 23. 26 2.1 5.6	$ \begin{array}{r} 1.9\\ 2.0\\ 3.4\\ 4.0\\ 3.4\\ 1.7\\ 1.8\\ 3.1\\ 4.0\\ 2.2\\ 5.7\\ \end{array} $	$ \begin{array}{r} 1.9 \\ 2.3 \\ 3.8 \\ 4.0 \\ 3.1 \\ 1.6 \\ 1.7 \\ 2.7 \\ 2.7 \\ 2.7 \\ 2.7 \\ 2.1 \\ 5.6 \\ \end{array} $	$ \begin{array}{c} 1.7 \\ 2.0 \\ 3.1 \\ 3.4 \\ 2.8 \\ 1.5 \\ 1.9 \\ 2.5 \\ 2.1 \\ 2.3 \\ 2.3 \\ 2.3 \\ 0.0 \\ 14. \\ \end{array} $
chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin chi2/ndf for histo 3, bin	4 =	130. 467.	16. 41.	17. 13.	14. 15. 12.	$14. \\ 15. \\ 12. $

What happens if we excludes some bins?

We remove the ones where the polynomial fit is worst.

Fitting the unintegrated uPDF

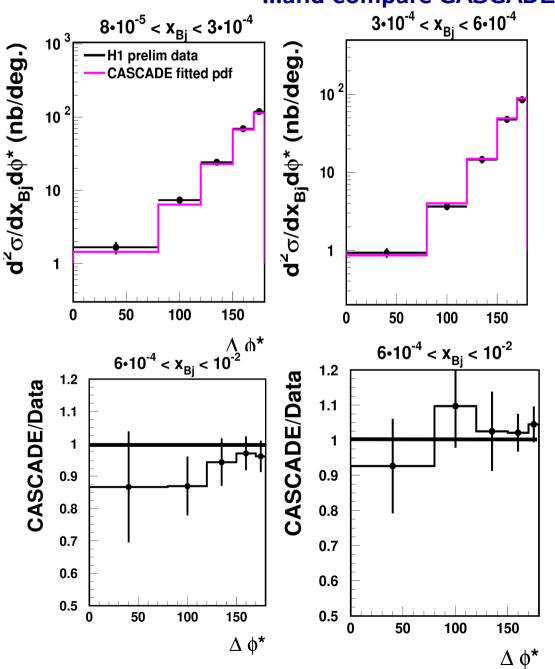
Chi2/NDF for polynomial	<u>mial fit</u> Degree:	2nd 3r	d 4th	5th	6th
chi2/ndf for histo chi2/ndf for histo	1, bin 1 = 1, bin 2 = 1, bin 3 = 1, bin 4 = 1, bin 5 = 2, bin 1 = 2, bin 2 = 2, bin 3 = 2, bin 4 = 2, bin 5 = 3, bin 1 = 3, bin 2 = 3, bin 3 = 3, bin 5 =	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{r} 1.9 \\ 2.3 \\ 3.8 \\ 4.0 \\ 3.1 \\ 1.6 \\ 1.7 \\ 2.7 \\ 2.7 \\ 2.7 \\ 2.7 \\ 2.7 \\ 2.1 \\ 5.6 \\ 14. \\ 15. \\ 12. \\ \end{array} $	1.7 2.0 3.1 3.4 2.8 1.5 1.9 2.5 2.1 2.3 2.3 0.0 14. 15. 12.

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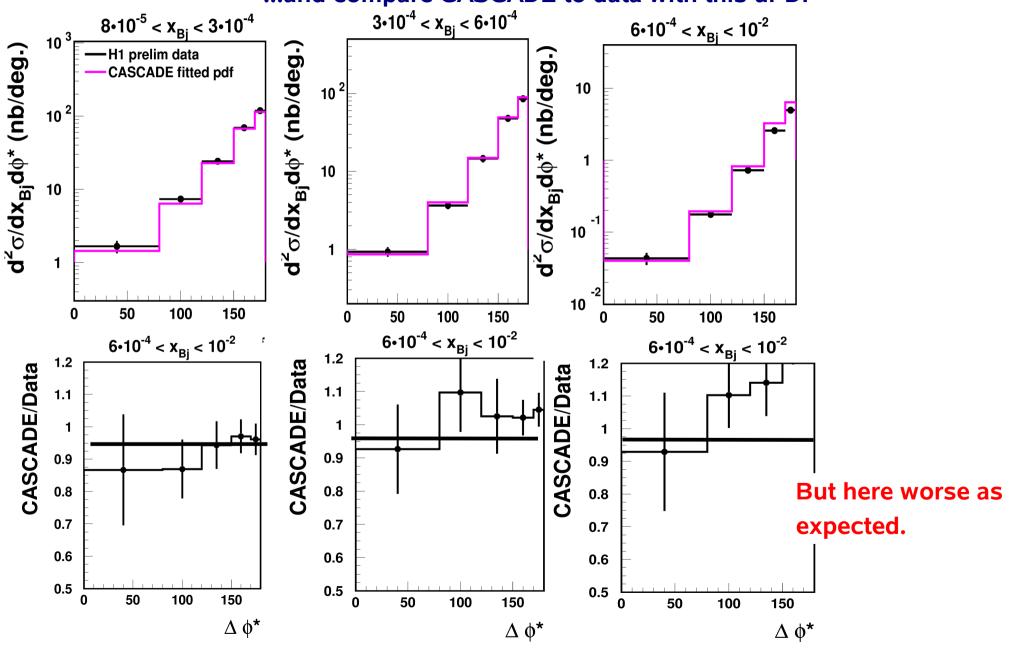
the remote the ones where the polynomial nets worst.						10150
	Degree:	2nd	3rd	4th	5th	6th
Chi2/NDF	for parameter fit	0.45	0.47	0.52	0.52	0.49
	N-value	0.23	0.24	0.22	0.22	0.21
(These parameters are cl	ose B-value	0.32	0.31	0.35	0.36	0.36
to Magnus Hanssons'. Conventianl fitting method.)	$xA_0 = N \cdot x^-$	$B \cdot (1$	$(-x)^{c}$	$r^{2} \cdot exp$	$p(-\frac{(k_2)}{k_2})$	$(r - \mu)^2 \over 2\sigma^2$

...and compare CASCADE to data with this uPDF



As expected much better description of the data in these bins.

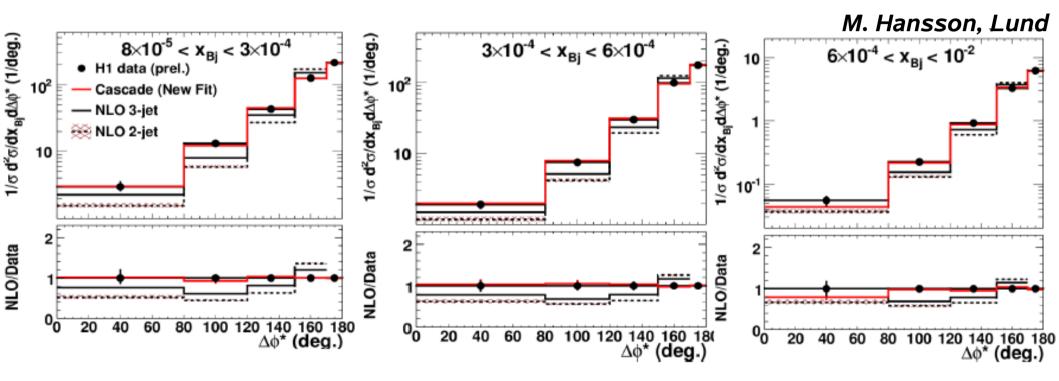
...and compare CASCADE to data with this uPDF



Previous fit

We know that there exists a better minimum.

In the end we should expect something like this...



Fit obtained using the conventional fitting method.

Singular Value Decomposition

As before, polynomial

 $\sigma_{\text{poly}}(p_1, p_2) = A + B_1 p_1 + B_2 p_2 + C_1 p_1^2 + C_2 p_2^2 + C_3 p_1 p_2 + H.O.$ i.e.

 $\begin{array}{lll} P_{n,m}X_m=\sigma_{n,poly} & \text{where} & X_n=(A,B_1,B_2,C_1,C_2,C_3,\ldots) \\ & P_n=(1,p_1,p_2,p_1^2,p_1p_2,p_2^2,\ldots) \\ & n=\textit{Grid points} \end{array}$

n > m — Over determined system

Approach based on SVD algorithm:

To obtain solution we minimize $r = |PX - \sigma|$ where r is a number as small as the machine accuracy allow us

Method soon implemented for the PDF fitting.

Tools Used

•CASCADE – for the physics

•MINUIT – for Chi2 minimizations

•HZTOOL – basic helper tool

•PAW – for visualizations

•(Additional Fortran coding)

Summary

•An alternative method for fitting of uPDF has been presented.

- •This method is much less time consuming.
- •The method is up and running.
- •...but the results are not satisfactory. More investigations needed. *Project still in testing state...*



- Singular Value Decomposition!
- Implement error handling of polynomial
- Investigate grid density
- Improve code to N_parameters > 2
- Increase number of data points (other variables/measurements)
- Final fit of uPDF