PDF Constraint using LHCb data Z, W^{\pm} and Drell-Yan

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PDF4LHC, 23th October 2009

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Outline

² [Analysis](#page-11-0) **• [Hessian method](#page-12-0)**

• [NNPDF method](#page-18-0)

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Outline

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• Trigger low p_T muons $p_T > 1$ GeV

- Unique rapidity coverage $1.9 < \eta < 4.9$
- Possible to reach very small value of x
	- Up to $\sim 5 \cdot 10^{-5}$ with Z and W^{\pm}
	- Up to $\sim 10^{-6}$ with low mass drell-yan
- At nominal luminosity it will collect about 2 fb^{-1} of data in 1 year

LHC parton kinematics

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Warning!

Uncertainties

• Big uncertainties at high rapidity

- Big uncertainties at low mass
- Potentiality for LHCb to constraint PDFs using rapidity distribution for different channels
	- \bullet 7
	- \circ W^{\pm}
	- D-Y 2.5-5 GeV

(dominant but difficult experimentally)

- D-Y 5-10 GeV
- D-Y 10-20 GeV
- D-Y 20-40 GeV
- Combinations

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Analysis

- Hessian methods provide a central value and a set of ortogonal eigenvectors
- An observable, f, which is a function of PDF eigenvectors and rapidity, y , can be written:

$$
f(y) = f_0(y) + \sum_i \lambda_i \delta_i(y)
$$

where f_0 is the observable evaluated at the central value, λ_i are unknown numbers and δ_i are the deviations of f from f_0 obtained when changing the *ith* eigenvector by one unit of uncertainty. All theoretically consistent values of f can be found by sampling λ_i from a multinormal distribution.

- Since f_0 and δ_i are known it is possible to fit for the λ_i
- Considering rapidity distribution we minimize the χ^2

$$
\chi^2 = \sum_{bin} \left(\frac{N_{bin} - \lambda_0 (f_0 + \sum \lambda_i \delta_i)}{\Delta_{bin}} \right)^2 + \sum_{\langle \square \rangle \rightarrow \langle \bigoplus^2 \rangle} \lambda_i^2
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Analysis

- λ_i are the eigenvalues (function of the PDFs)
- Before fit: uncertainty on λ_i is $\Delta \lambda_i = 1$
- After fit: $\Delta \lambda_i < 1$ → better constraint of the PDF
- Uncertainties are calculated:

$$
\delta F = \sqrt{\sum_{ij} \frac{\partial F}{\partial \lambda_i} V_{ij} \frac{\partial F}{\partial \lambda_j}}
$$

After:

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V_{ij} = \left(\begin{array}{cccc} <1 & \neq 0 & \cdots & \neq 0 \\ \neq 0 & <1 & \cdots & \neq 0 \\ \vdots & \vdots & \ddots & \vdots \\ \neq 0 & \neq 0 & \cdots & <1 \end{array} \right)
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• NNPDF provides Montecarlo replicas of the PDFs

• Generating rapidity distributions with each replica we can compare the prediction of a single replica with the central value

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\chi_i^2 = \sum_{bin} \left(\frac{N_{bin}^c - \lambda_0 f_i(y)}{\Delta_{bin}} \right)^2
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where *i* is the index of the replica, N_{bin}^c is the prediction of the central value for that rapidity-bin and $f_i(y)$ is the value of the rapidity distribution generated with the *ith* replica

• We recalculate the central value and the uncertainty rejecting replicas with χ^2 probability smaller than 1%

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Analysis Why selection at 1%

- If we perform 1000 psuedo-experiments generated from a given replica, and calculate the χ^2 compared to the SAME replica, we get a flat probability distribution.
- Only 1% of the time we reject replicas that were actually consistent irrespective of the amount of data.
- On the other hand, incorrect replicas may or may not be consistent. In general, with more data, more incorrect replicas can be rejected.

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Percentage of replicas with χ^2 probability $>$ 1%

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NNPDF1.0 Drell-Yan

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Model comparison

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Luminosity dependence Drell-Yan $2.5 - 5$ GeV

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Conclusion

- LHCb will improve PDF in an unexplored region of (x, Q^2)
- Possible improvement up to 96% in some region with low mass Drell-Yan
- Size of the reduction of uncertainty depends on the model

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