

Grids & HighTEA discussion





Plot: J. Gäßler







- Grids at NNLO for DIS jets:
 - Eur. Phys. J. C 81 (2021) 10, 957 & Eur. Phys. J. C 79 (2019) 10, 845
- Grids at NNLO for pp jets:
 - Eur. Phys. J. C 82 (2022) 10, 930
- All grids public @ PloughShare







Ingredients



Theory: Interface to



- **NNLOJET:** T. Gehrmann et al., RADCOR2017 PoS (2018) 074, arXiv:1801.06415.
- Inclusive jets: J. Currie et al, PRL 118 (2017) 072002; JHEP 10 (2018) 155.
- **Dijets:** J. Currie et al., PRL 119 (2017) 152001; A. Gehrmann-de Ridder et al., PRL 123 (2019) 102001.
- **Full-colour NNLO:** X. Chen et al., JHEP09 (2022) 025. (Not yet included \rightarrow Lucas)

fastNLO

- Tools:
 - **APPLfast interface:** D. Britzger et al., EPJC 79 (2019) 845, arXiv:1906.05303.
 - fastNLO: D. Britzger et al., Proc. DIS2012 (2012) 217, arXiv:1208.3641.
 - **APPLgrid:** T. Carli et al., EPJC 66 (2010) 503, arXiv:0911.2985.
 - xfitter: S. Alekhin et al., EPJC 75 (2015) 304, arXiv:1410.4412.





Typical total runtime of a grid production





Return on investment



Relative numerical uncertainty of NNLO 3D dijet cross section Dominated by RRa and RV channels Numerical uncertainty provided inside grids



Grid closure vs. NNLOJET





Closure deteriorates somewhat towards phase space limits; exceptionally may exceed 1 ‰ at phase space edges ATLAS inclusive jets at 7 TeV

Generally aim at closure better than 1 ‰ at each level, LO, NLO, NNLO





Scale dependence



ATLAS inclusive jets at 7 TeV

Scale uncertainty bands: LO, NLO, NNLO



Alternative scale possible: p_{Tjet} instead of HT_{part}

From Snowmass report: arXiv:2203.13923

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ATLAS inclusive jets at 7 TeV

PDF uncertainty bands for selection of 9 PDF sets



Observation for \triangle PDF: CT14 \rightarrow CT18 larger NNPDF 3.1 \rightarrow 4.0 much smaller

Summer student project 2022 ETE

Christiane Mayer: - Establish grid production workflow (LAW) on Ixplus (with A. Huss, KR) - New result for Z+X @ NNLO to compare with CMS



Summer student project 2022 ETE

Christiane Mayer: - Nicely agrees with CMS data (with A. Huss, KR) - Slightly lower than FEWZ













Backup Slides









Implemented in APPLgrid & fastNLO

Use interpolation kernel

- Introduce set of n discrete x-nodes, x_i's being equidistant in a function f(x)
- Take set of Eigenfunctions E_i(x) around nodes x_i
- \rightarrow Interpolation kernels
- Actually a rather old idea, see e.g.
- C. Pascaud, F. Zomer (Orsay, LAL), LAL-94-42
- \rightarrow Single PDF is replaced by a linear combination of interpolation kernels

$$f_a(x) \cong \sum_i f_a(x_i) \cdot E^{(i)}(x)$$

- \rightarrow Then the integrals are done only once
- → Afterwards only summation required to change PDF

Tabulate the convolution of the perturbative coefficients with the interpolation kernel









- Seven inclusive jet datasets from ATLAS & CMS, 2D in p_T and y
 - Four centre-of-mass energies, three jet radii R
 - Two central scales for μ_{R/F}

Sample plots in this talk

Data	\sqrt{s} [TeV]	\mathcal{L} $[\mathrm{fb}^{-1}]$	no. of points	anti- $k_{ m T}$ R	kinematic range [GeV]	fiducial cuts	$\mu_{ m R/F}$ -choice
CMS [30]	2.76	0.00543	81	0.7	$p_{\rm T}^{\rm jet} \in [74, 592]$	y < 3.0	$p_{\rm T}^{\rm jet}, \hat{H}_{\rm T}$
ATLAS [28]	7.0	4.5	140	0.6	$p_{\rm T}^{\rm jet} \in [100, 1992]$	y < 3.0	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$
CMS [31]	7.0	5.0	133	0.7	$p_{\rm T}^{\rm jet} \in [114, 2116]$	y < 3.0	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$
ATLAS [32]	8.0	20.3	171	0.6	$p_{\rm T}^{\rm jet} \in [70, 2500]$	y < 3.0	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$
CMS [33]	8.0	$5.6 \\ 19.7$	248	0.7	$p_{\rm T}^{\rm jet} \in [21, 74]$ $p_{\rm T}^{\rm jet} \in [74, 2500]$	y < 4.7	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$
ATLAS [34]	13.0	3.2	177	0.4	$p_{\rm T}^{\rm jet} \in [100, 3937]$	y < 3.0	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$
CMS [35]	13.0	$36.3 \\ 33.5$	2×78	$\begin{array}{c} 0.4 \\ 0.7 \end{array}$	$p_{\rm T}^{\rm jet} \in [97, 3103]$	y < 2.0	$p_{\mathrm{T}}^{\mathrm{jet}}, \hat{H}_{\mathrm{T}}$





- Four dijet datasets from ATLAS & CMS, 2D in m₁₂ and y* or y_{max}, or 3D in <p_{T12}>, y*, y_b
 - Three centre-of-mass energies, three jet radii R
 - One central scale for $\mu_{R/F}$, except for 3D data with two

Sample plots in this talk

Data	\sqrt{s} [TeV]	\mathcal{L} [fb ⁻¹]	no. of points	anti- k_{T} R	kinematic range $[{ m GeV}]$	fiducial cuts	$\mu_{ m R/F}$ -choice
ATLAS [55]	7.0	4.5	90	0.6	$m_{12} \in [260, 5040]$	$ y_1 , y_2 < 3.0$ $[p_{T,1}, p_{T,2}] > [100, 50] \text{GeV}$ $y^* < 3.0$	m_{12}
CMS [31]	7.0	5.0	54	0.7	$m_{12} \in [197, 5058]$	y < 5.0 $[p_{T,1}, p_{T,2}] > [60, 30] \text{GeV}$ $ y_{\text{max}} < 2.5$	m_{12}
CMS [49]	8.0	19.7	122	0.7	$\langle p_{{\rm T}1,2} \rangle \in [133, 1784]$	y < 5.0 $p_{T,1}, p_{T,2} > 50 \text{GeV}$ $ y_1 , y_2 < 3.0$	$p_{T,1} \exp(0.3 y^*)$ m_{12}
ATLAS [34]	13.0	3.2	136	0.4	$m_{12} \in [260, 9066]$	$ y_1 , y_2 < 3.0$ $p_{T,1}, p_{T,2} > 75 \text{GeV}$ $\langle p_{T1,2} \rangle > 100 \text{GeV}$ $y^* < 3.0$	m_{12}



K factor robustness



Dependence of K_{NNLO} on: α_s – negligible most PDF sets – ~ 0.5%

exceptionally (HERAPDF) $- \sim 1\%$





α_s dependence



ATLAS inclusive jets at 7 TeV



Scale uncertainty versus α_s dependence (0.108 - 0.124)at each order

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Total inclusive jet cross section



- Closest possible definition with most cms energies
 - ATLAS: R=0.4, p_T > 100 GeV, |y| < 3</p>
 - CMS: R=0.7, p_T > 97 GeV, |y| < 2</p>

Only 13 TeV grid used here with E_{cms} extrapolation



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Les Houches, 15.06.2023

Scale dependence for CMS



Triple-differential dijets



Most measurements done with respect to dijet mass and either max. rapidity $|y|_{max}$ (CMS) or rapidity separation y^{*} (ATLAS). One CMS result 3D in p_{T12} , y^{*}, y_b:



Illustration of dijet event topologies



13 parameter fits – NLO vs. NNLOETE

Gluon from 13-parameter PDF fit with xfitter for two central scale choices



Left: NLO Significant differences between central scale definitions Right: NNLO Much improved agreement between scales

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Scale varied fits & PDF+\alpha_s fit

Gluon from 13-parameter PDF fit with scale variation band at NNLO

Gluon from 14-parameter PDF fit at NNLO with free α_s





Much reduced scale dependence

Consistent results between scales

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Demo plot using Python extension

Python extension available

🔹 … [--enable-pyext]

Easy example plotting 2D scale dependence:



#! /usr/bin/env python2 **Setup Python** with fastNLO from fastnlo import fastNLOLHAPDF import matplotlib import matplotlib.pyplot as plt from matplotlib import cm from mpl toolkits.mplot3d import axes3d import numpy as np Select table, fnlo = fastNLOLHAPDF('fnlotable.tab') fnlo.SetLHAPDFFilename('CT10nlo.LHgrid') PDF & mem. fnlo.SetLHAPDFMember(0) **Define** μ_r , μ_f mufs = np.arange(0.1, 1.5, 0.10)murs = np.arange(0.1, 1.5, 0.10)xs = np.zeros((mufs.size, murs.size)) ranges for i, muf in enumerate(mufs): Loop over for j, mur in enumerate(murs): fnlo.SetScaleFactorsMuRMuF(mur, muf) μ_r, μ_f fnlo.CalcCrossSection() xs[i][j] = np.array(fnlo.GetCrossSection())[0] fig = plt.figure(figsize=(13,13)) **Plot** ... plotting details ax.set_ylabel('Scale factor \$\mu_F\$') ax.set_xlabel('Scale factor \$\mu_R\$') ax.set zlabel('Cross Section [pb/GeV]') plt.show() ... plotting details



Grids allow plotting full 2D (μ_R , μ_F) dependence

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Extra slide: ATLAS dijet mass

Central scale: µ = pT_{max}

Outer y* bin!



Central scale: $\mu = pT_{max} \cdot exp(0.3 y^*)$



Grids allow plotting full 2D (μ_R , μ_F) dependence

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DIS interpolation grids





Interpolation grids available on:

https://ploughshare.web.cern.ch

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