Decorrelation of Dijets at Low x and Q^2 and a Fit of the Unintegrated Gluon Density

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Outline

$\Rightarrow$ Motivation & Selection

$\Rightarrow$ Unfolding of $\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$, $\frac{d^2\sigma}{dQ^2d\Delta\phi^*}$ and $\frac{d^3\sigma}{dx_{bj}dQ^2d\Delta\phi^*}$

$\Rightarrow$ Fit of the Unintegrated Gluon Density

$\Rightarrow$ Summary

Motivation

DGLAP: Gluon collinear with proton in LO

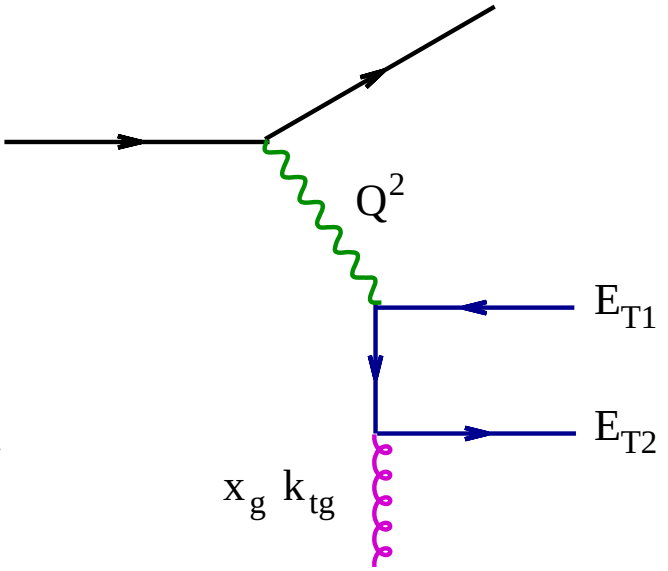
$\Rightarrow$ Jets back-to-back in HCM

Higher order QCD radiation

$\Rightarrow k_{tg} \neq 0$ and $\Delta\phi^* < 180^\circ$

Gluon propagators ordered in virtuality

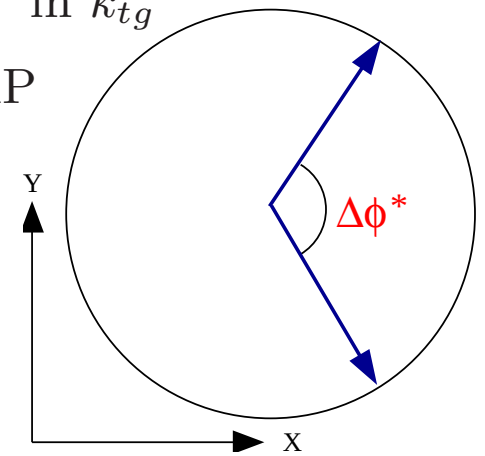
$\Rightarrow k_{tg}$ ordered



Small-x: New dynamics (BFKL, CCFM): 'random walk' in k_{tg}

$\Rightarrow$ Broader $\Delta\phi^*$ spectrum compared to DGLAP

uPDF $\Rightarrow \Delta\phi^* < 180^\circ$ already in LO



Azimuthal Decorrelations:

$\Rightarrow$ Sensitive to different parton dynamics

$\Rightarrow$ Sensitive to unintegrated gluon density

Selection

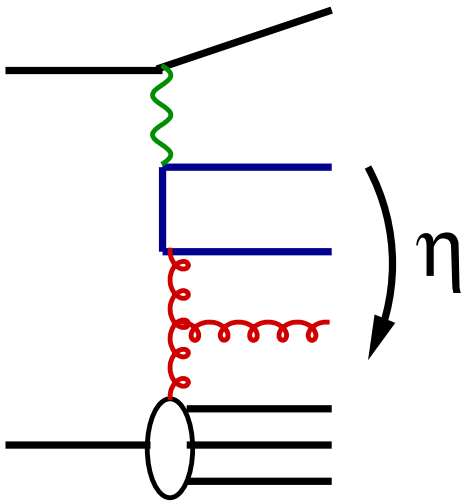
Using 1999/2000 e^+p data, $\mathcal{L} \simeq 64$ pb^{-1}

DIS Cuts

5 GeV^2 $<$	Q^2	$<$ 100 GeV^2
0.1 $<$	y	$<$ 0.7
9 GeV$<$	E_e	
156° $<$	θ_e	$<$ 175°
35 GeV$<$	$E - p_z$	$<$ 70 GeV
	$\lvert z_{vtx} \rvert$	$<$ 35 cm
	R_{clus}	$<$ 3.5 cm
	E_{had}	$<$ 0.5 GeV
	E_{veto}	$<$ 1.0 GeV

Dijet Cuts

-1 $<$	η_j	$<$ 2.5
5 GeV$<$	$E^*_{\perp j1,2}$	
	Sort in η	



Bayes Unfolding

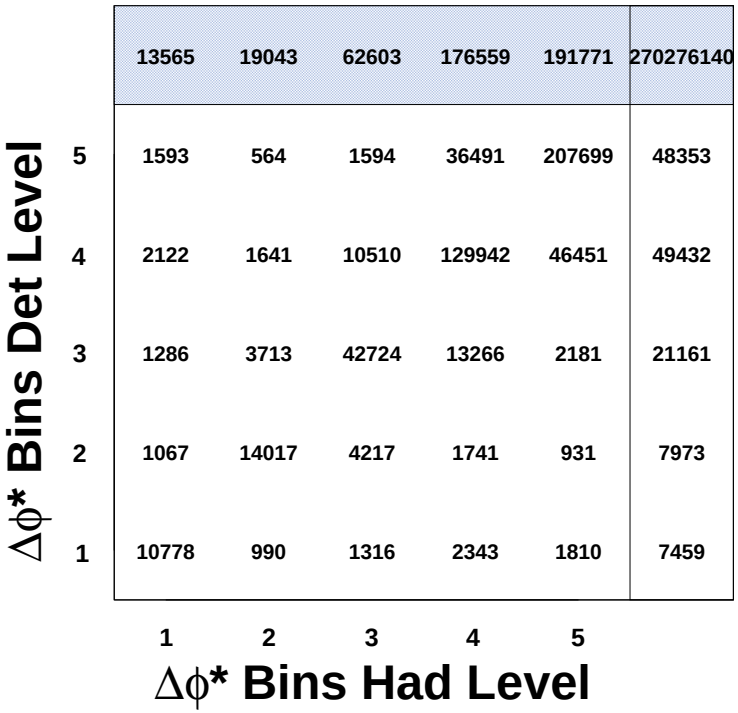
- Based on Bayes theorem

$$P(C_i|E_j) = \frac{P(E_j|C_i) \cdot P(C_i)}{\sum_{l=1}^{n_C} P(E_j|C_l) \cdot P(C_l)}$$

- $P(C_i|E_j)$: Probability that Effect j was produced by Cause i
- $P(E_j|C_i)$: Probability that Cause i will produce Effect j
  Smearing Matrix - Describes detector responce
  Estimated using Monte Carlo
- $P(C_i)$: Probability of Cause i. Is unknown.
  Make a first guess, then iterate unfolding and update $P(C_i)$ in each iteration
- Properly takes into account migration effects

Bayes Unfolding

⇒ Example of Smearing Matrix $P(E_j|C_i)$:



Large fluctuations because of many events in background bins

Excluded in Bayes unfolding - Correct for these using bin-by-bin method

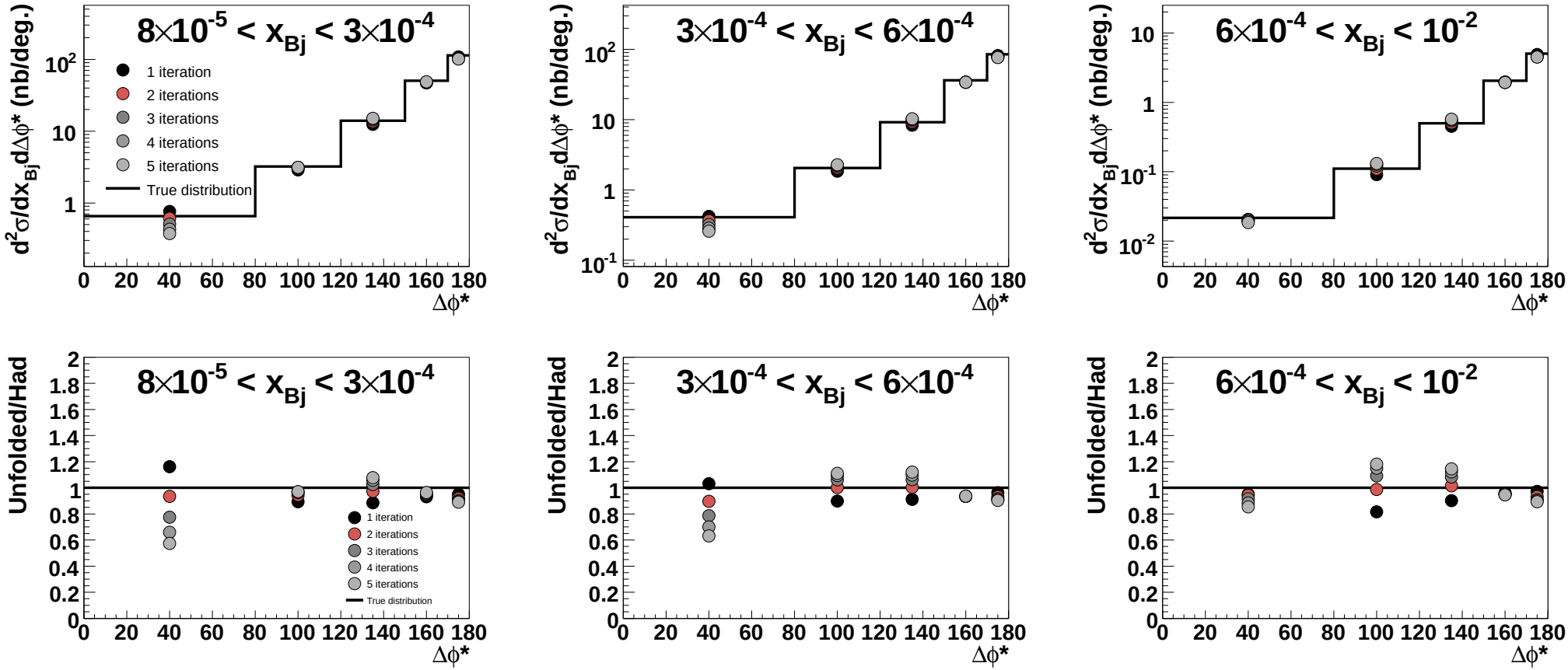
Also QED effects corrected bin-by-bin

⇒ First guess of $P(C_i)$: Hadron level distribution of MC used for unfolding

Bayes Unfolding

Must determine best number of iterations:

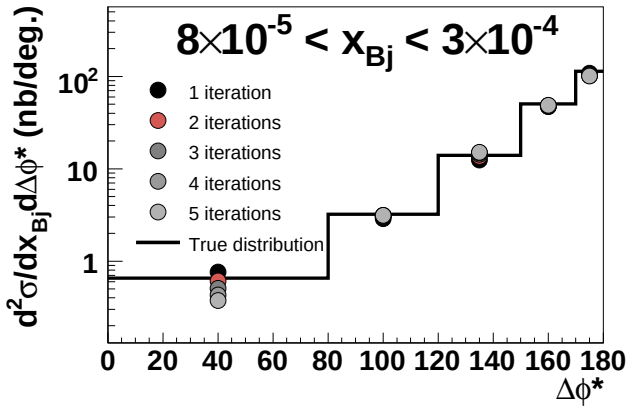
Unfold Rapgap using Django and compare to Rapgap hadron level

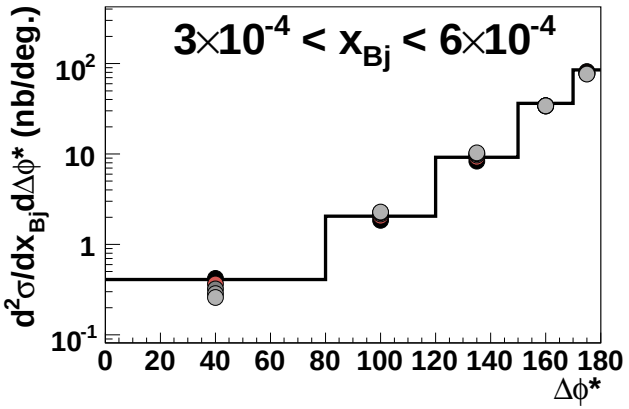


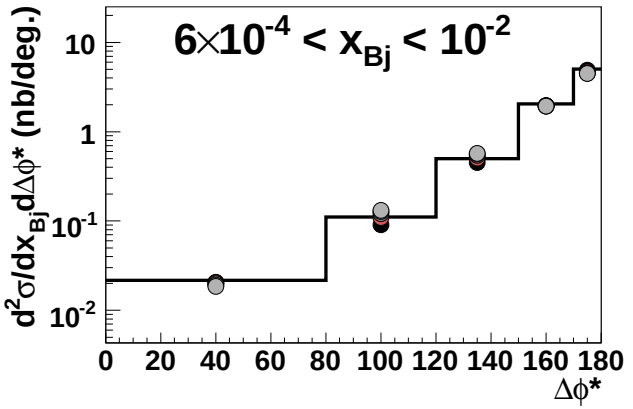
Bayes Unfolding

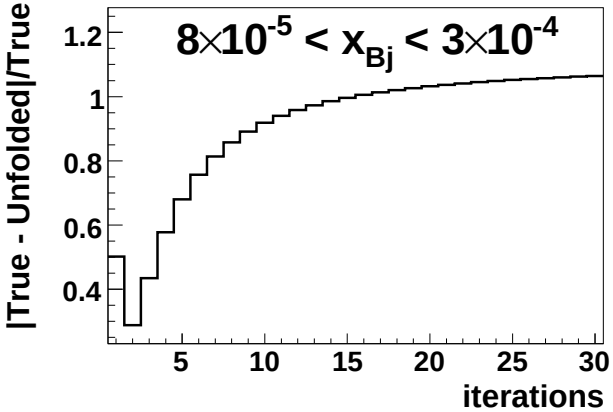
Calculate $\sum_{bins} \frac{|true - unfolded|}{true}$ for each iteration

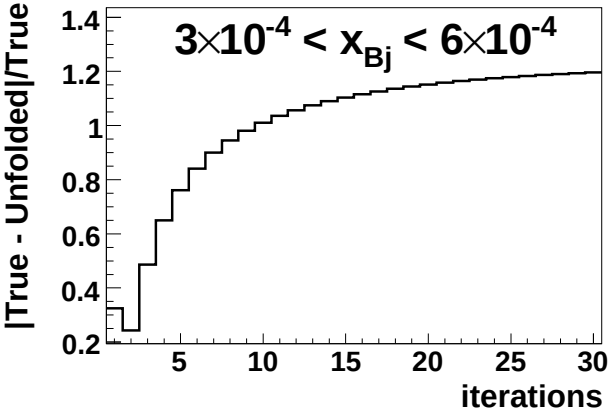
$\Rightarrow$ Best agreement after 2 iterations

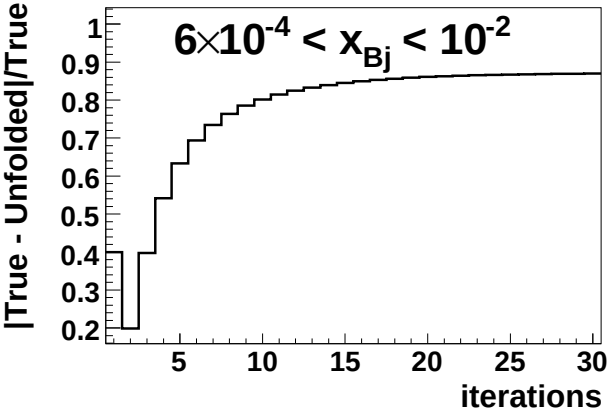












Similar result if unfolding Django using Rapgap, and for $\frac{d^2\sigma}{dQ^2 d\Delta\phi^*}$ and $\frac{d^3\sigma}{dx_{bj} dQ^2 d\Delta\phi^*}$

Systematic Uncertainties

Estimated using Rapgap, except:

Model Dependence: $\frac{|C_{Rapgap} - C_{Django}|}{2}$

Unfolding Bias: Unfold Rapgap using Django and compare to true Rapgap distribution ($\Rightarrow \Delta\sigma_{Rapgap}$) and vice versa

Source	Uncertainty	Typical $\Delta\sigma$		
		$\frac{d^2\sigma}{dx_{bj}\,d\Delta\phi^*}$	$\frac{d^2\sigma}{dQ^2\,d\Delta\phi^*}$	$\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$
Electron Energy	$\pm$ 1%	0.5-2%	0.5-2%	1-3%
Electron Polar Angle θ_e	$\pm$ 1 mrad	<1%	<1%	0.5-2%
LAr Hadronic Energy	$\pm$ 4%	2-7%	2-7%	2-10%
Track Momentum	$\pm$ 3%	$\ll$ 1%	$\ll$ 1%	$\ll$ 1%
Model Dependence	$\frac{\lvert C_{Rapgap} - C_{Django}\rvert}{2}$	0.5-2%	0.5-2%	1-4%
Unfolding Bias	$\frac{\Delta\sigma_{Rapgap} + \Delta\sigma_{Django}}{2}$	1-7%	1-7%	4-10%

Systematic Uncertainties

Estimated using Rapgap, except:

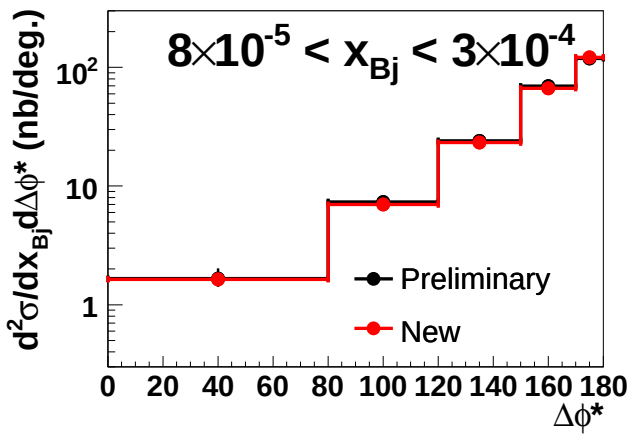
Model Dependence: $\frac{|C_{Rapgap} - C_{Django}|}{2}$

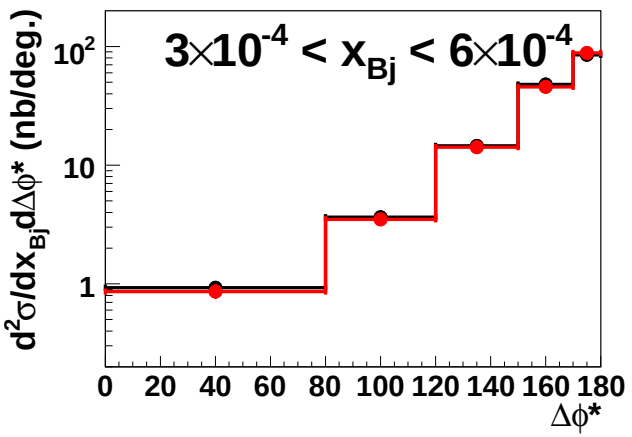
Unfolding Bias: Unfold Rapgap using Django and compare to true Rapgap distribution ($\Rightarrow \Delta\sigma_{Rapgap}$) and vice versa

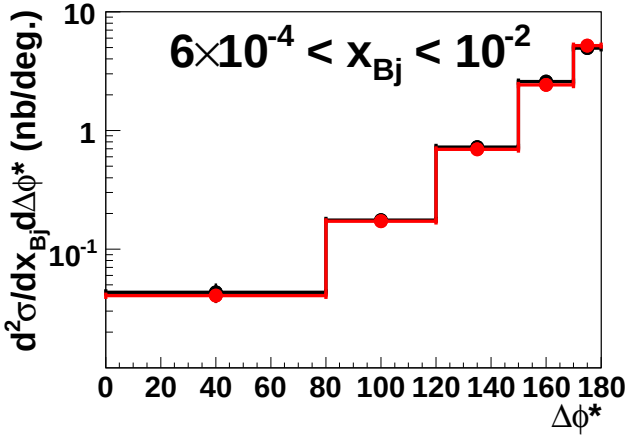
Source	Uncertainty	Correlated or Uncorrelated		
		$\frac{d^2\sigma}{dx_{bj}\,d\Delta\phi^*}$	$\frac{d^2\sigma}{dQ^2\,d\Delta\phi^*}$	$\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$
Electron Energy	$\pm$ 1%	Correlated		
Electron Polar Angle θ_e	$\pm$ 1 mrad	Correlated		
LAr Hadronic Energy	$\pm$ 4%	$\frac{1}{\sqrt{2}}$ correlated $\oplus$ $\frac{1}{\sqrt{2}}$ uncorrelated		
Track Momentum	$\pm$ 3%	Uncorrelated		
Model Dependence	$\frac{\lvert C_{Rapgap} - C_{Django}\rvert}{2}$	$\frac{1}{\sqrt{2}}$ correlated $\oplus$ $\frac{1}{\sqrt{2}}$ uncorrelated		
Unfolding Bias	$\frac{\Delta\sigma_{Rapgap} + \Delta\sigma_{Django}}{2}$	$\frac{1}{\sqrt{2}}$ correlated $\oplus$ $\frac{1}{\sqrt{2}}$ uncorrelated		

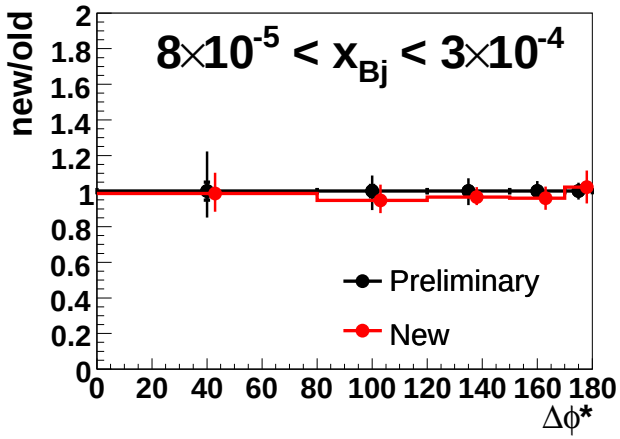
$d\sigma/dx_{bj}d\Delta\phi^*$

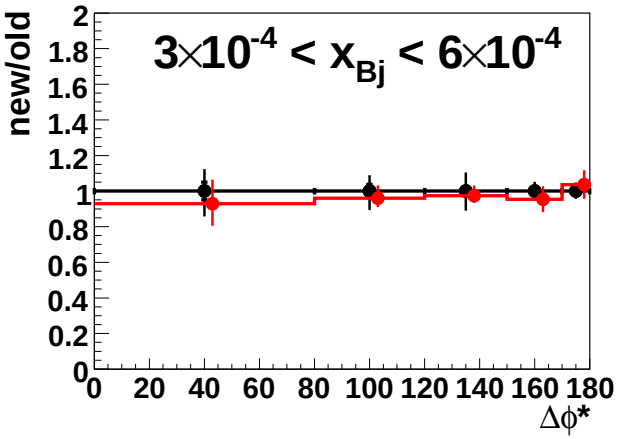
New Cross sections compared to preliminary (DIS06)

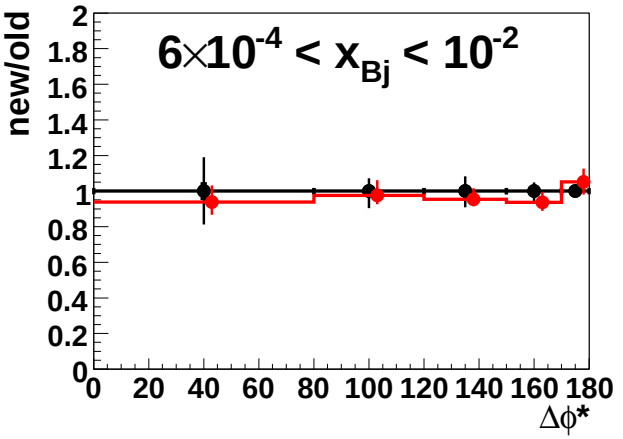






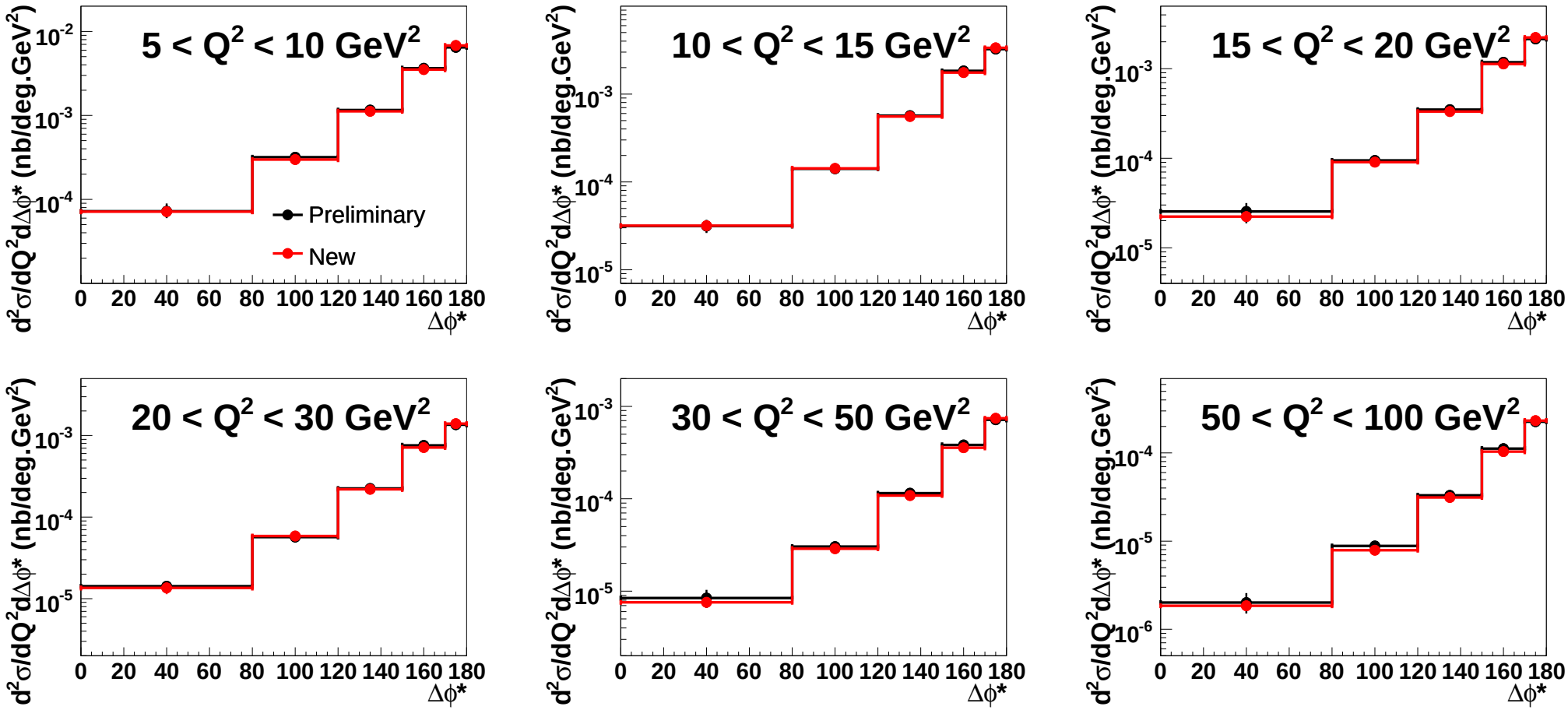






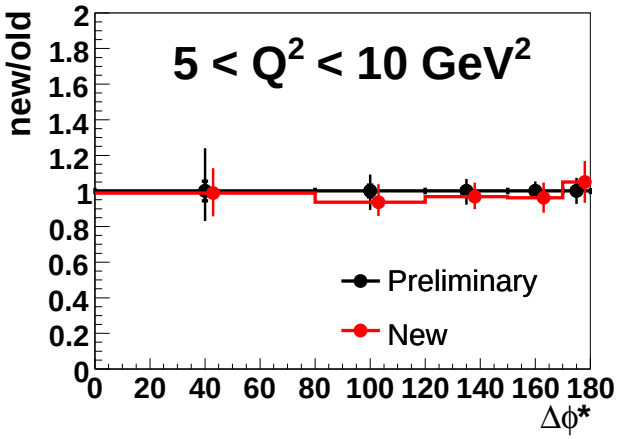
$d\sigma/dQ^2 d\Delta\phi^*$

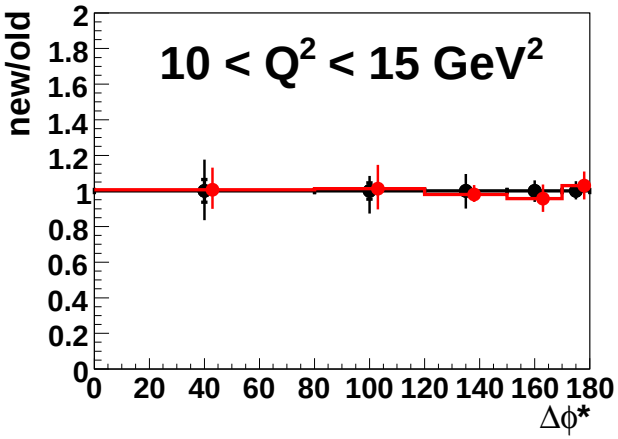
New Cross sections compared to preliminary (DIS06)

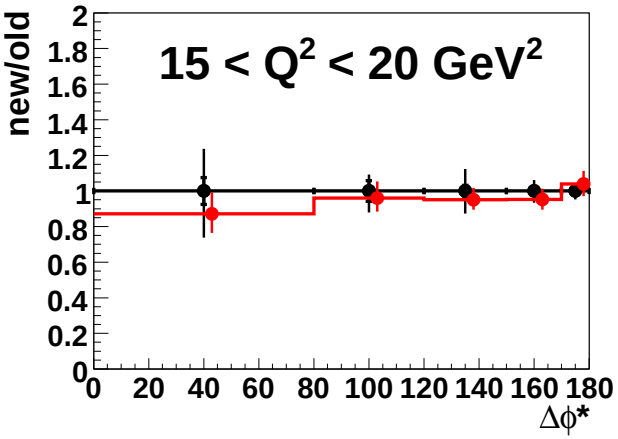


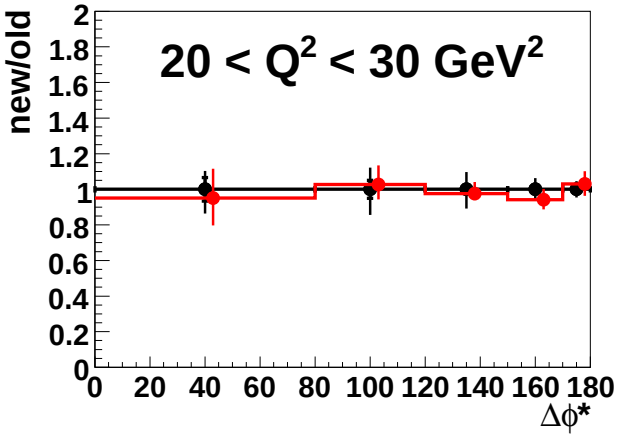
$d\sigma/dQ^2 d\Delta\phi^*$

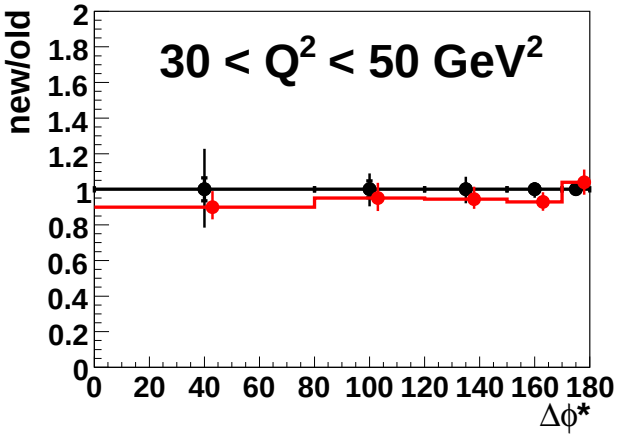
New Cross sections compared to preliminary (DIS06)

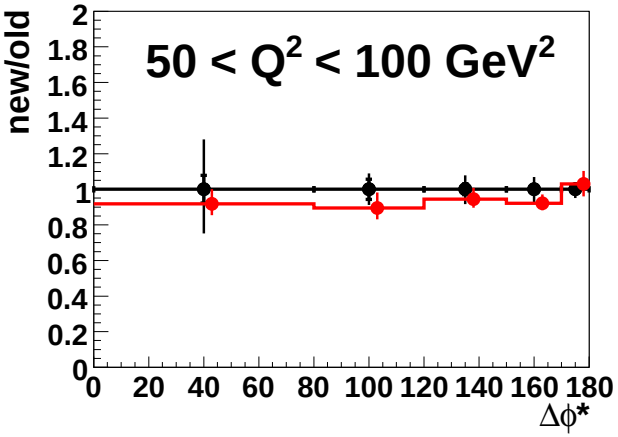


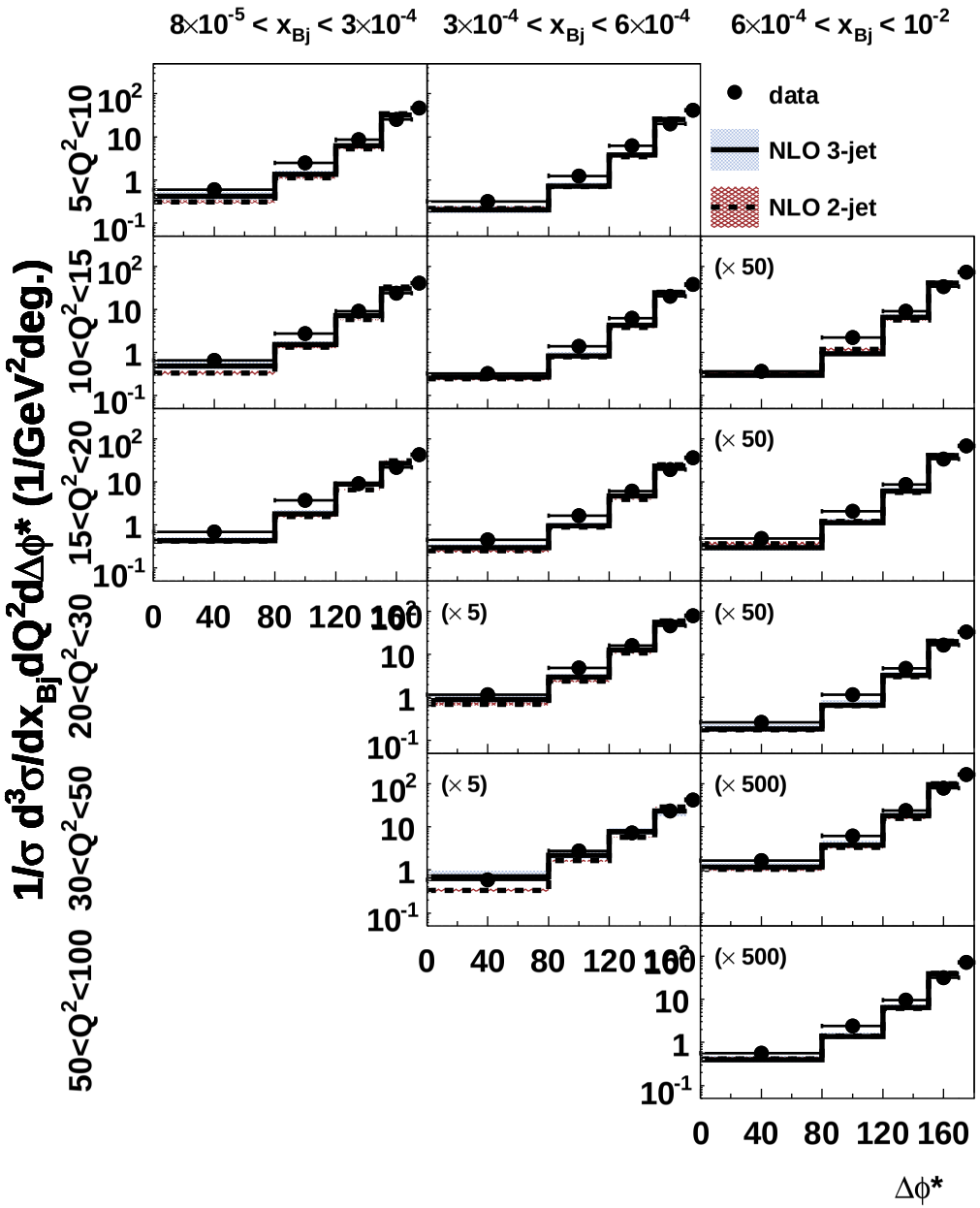


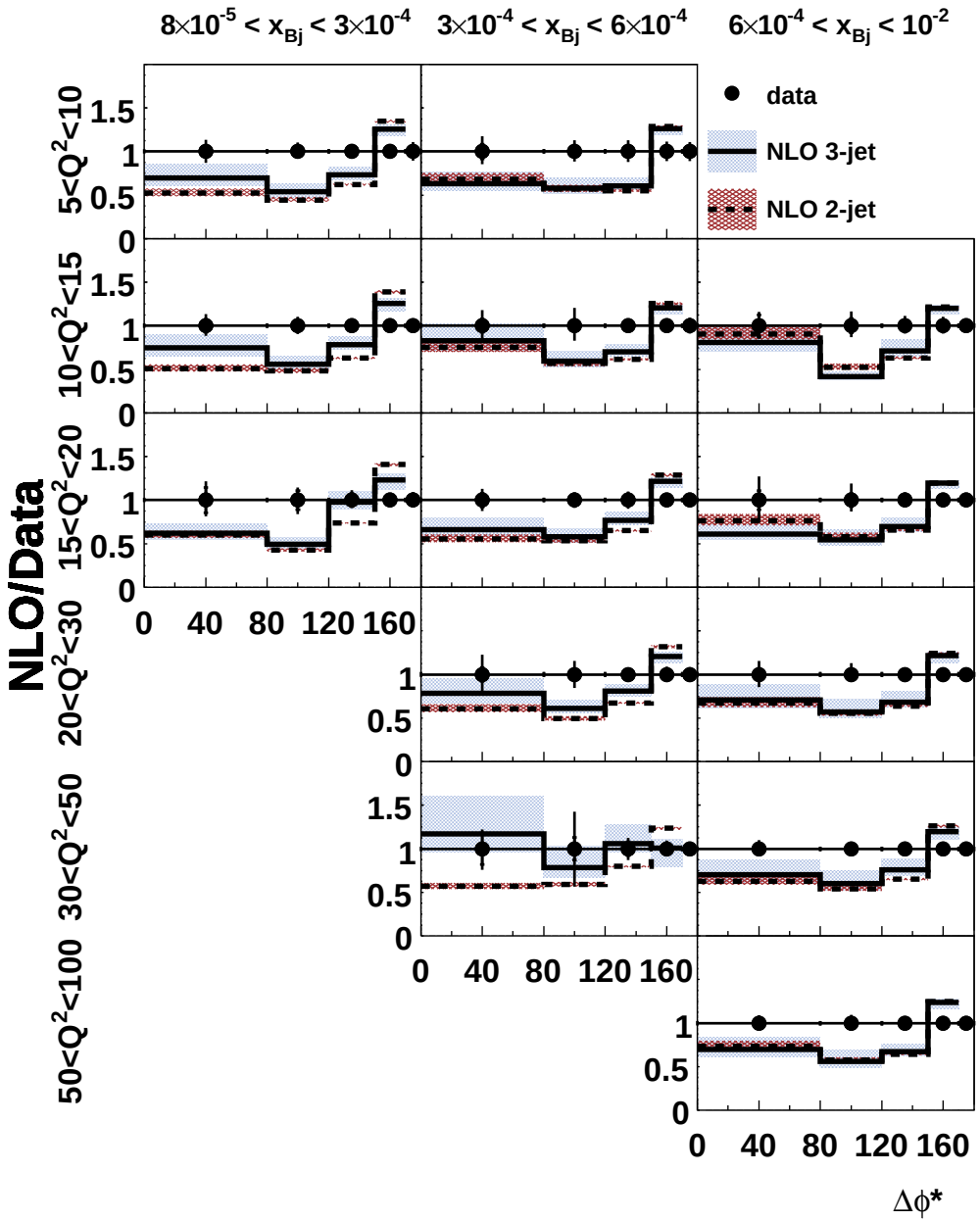









8×10^-5 < x_Bj < 3×10^-4
3×10^-4 < x_Bj < 6×10^-4
6×10^-4 < x_Bj < 10^-2
data
NLO 3-jet
NLO 2-jet
1/σ d^3σ/dx_Bj dQ^2 dΔφ* (1/GeV^2 deg.)
5<Q^2<10
10<Q^2<15
15<Q^2<20
20<Q^2<30
30<Q^2<50
50<Q^2<100
(× 50)
(× 5)
(× 500)
0 40 80 120 160
Δφ*


8×10^-5 < x_Bj < 3×10^-4
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6×10^-4 < x_Bj < 10^-2
data
NLO 3-jet
NLO 2-jet
NLO/Data
5<Q^2<10
10<Q^2<15
15<Q^2<20
20<Q^2<30
30<Q^2<50
50<Q^2<100
0 40 80 120 160
Δφ*

Fit Procedure

- Only use gluon densities
- Select starting distribution $x\mathcal{A}_0(x, k_\perp, \bar{q}_0)$
- Simulate events using CASCADE MC generator,
  uPDF is evolved using CCFM according to

$$x\mathcal{A}(x, k_\perp, \bar{q}) = \int dx' \mathcal{A}_0(x', k_\perp, \bar{q}_0) \cdot \frac{x}{x'} \tilde{\mathcal{A}}(\frac{x}{x'}, k_\perp, \bar{q})$$

- Minimize χ^2 by varying parameters in starting distribution $x\mathcal{A}_0(x, k_\perp, \bar{q}_0)$
  using HZTOOL and MINUIT

Fit Procedure

- Starting distribution:

$$x\mathcal{A}_0(x, k_\perp, \bar{q}_0) = N \cdot x^{-B} \cdot (1-x)^4 \cdot exp(-(k_\perp - \mu)^2/\sigma)$$

  where N, B, μ and σ are free parameters

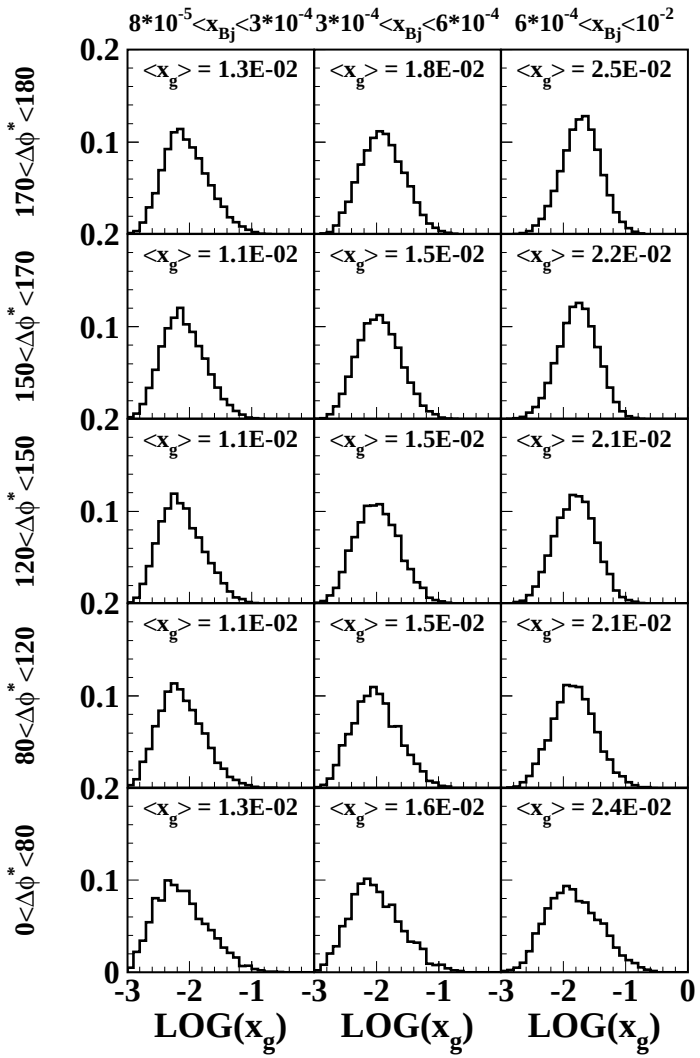
- Using full splitting function, i.e. including non-singular terms
- One-loop α_s with $\lambda^{[4]}_{QCD} = 0.13$ GeV
- Starting scale of evolution: $\bar{q}_0 = 1.2$ GeV
- $\chi^2 = \sum_i \left(\frac{(T_i - D_i)^2}{\sigma^2_{T,i} + \sigma^2_{D,i}} \right)$
- Use two data sets:

  1) $\frac{d^2\sigma}{dx_{bj} d\Delta\phi^*}$

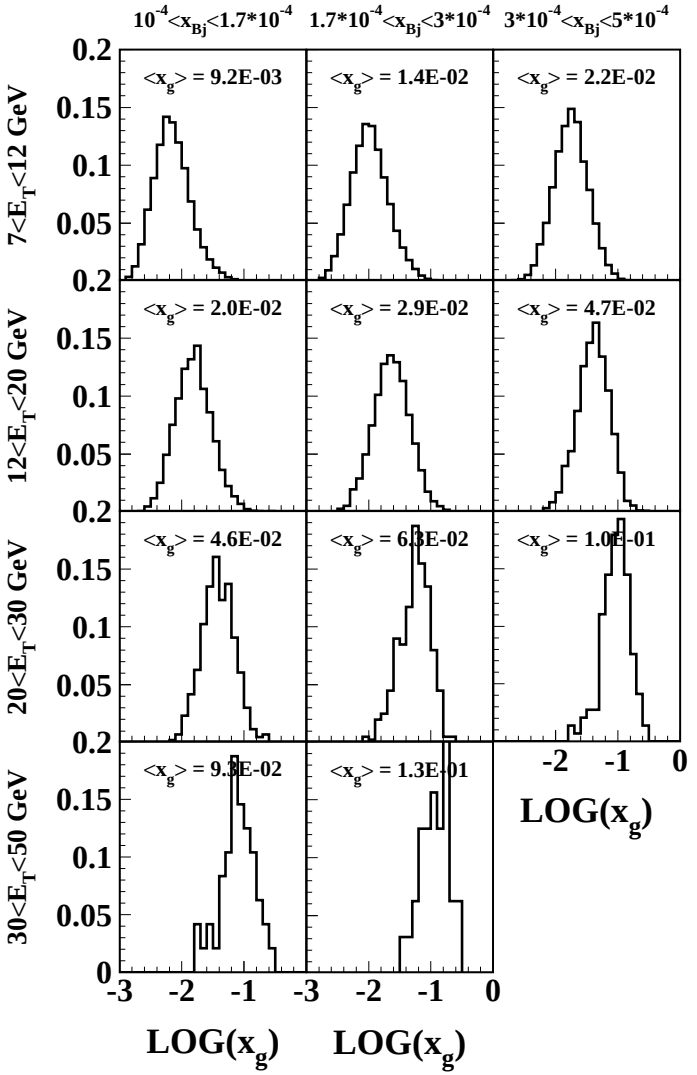
  2) $\frac{d^3\sigma}{dx_{bj} dQ^2 dE^*_{T,Max}}$: H1 1996/97 data (DESY-03-160)

Sensitivity to uPDF: x_g

$$\frac{d^2\sigma}{dx_{bj}\,d\Delta\phi^*}$$

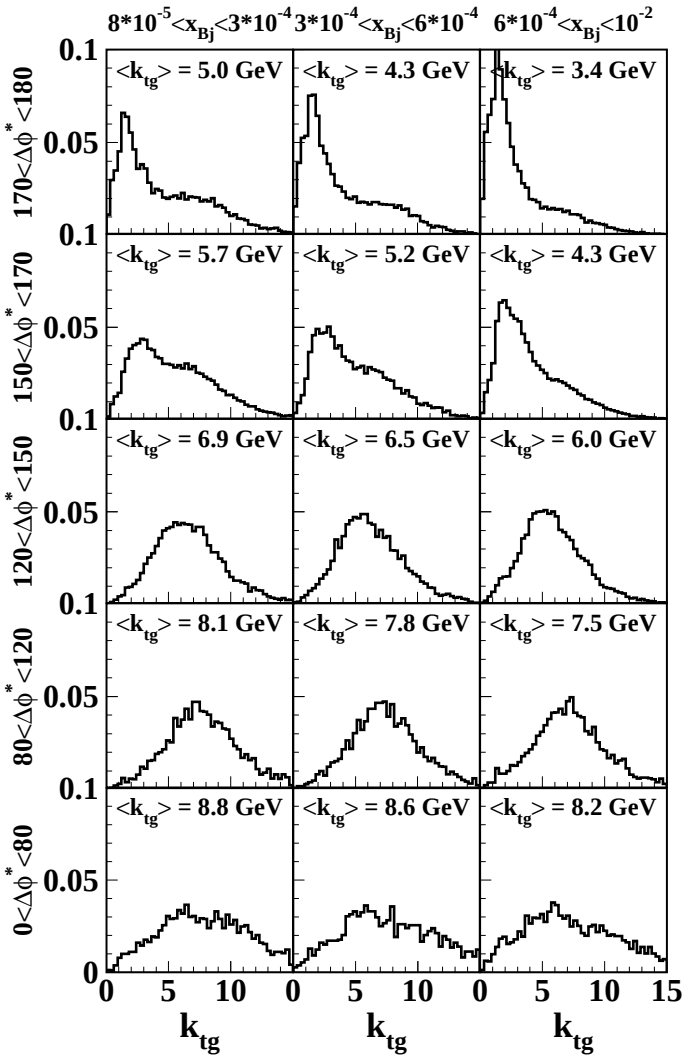


$$\frac{d^3\sigma}{dx_{bj}\,dQ^2\,dE^*_{T,Max}}$$

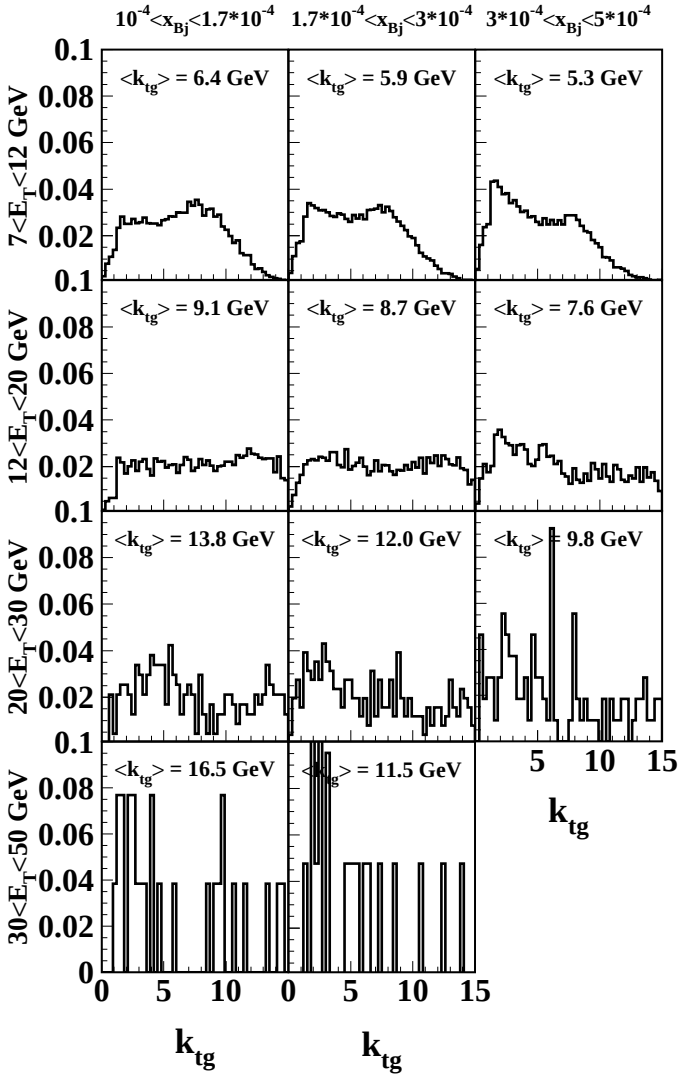


Sensitivity to uPDF: k_{tg}

$$\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$$



$$\frac{d^3\sigma}{dx_{bj}dQ^2dE^*_{T,Max}}$$

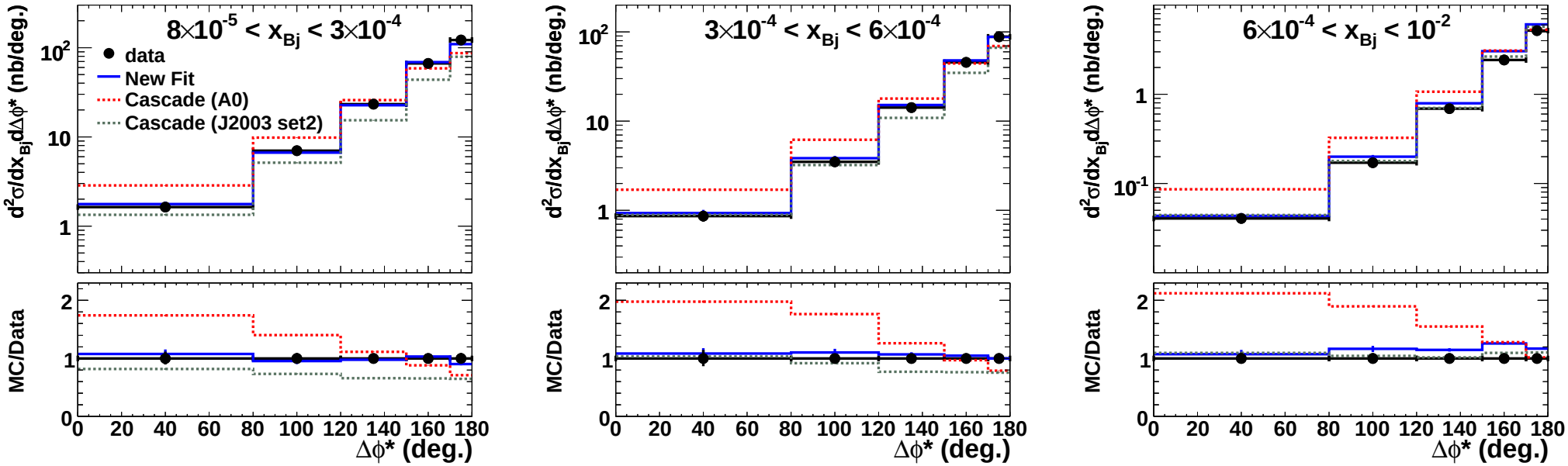


uPDF Fit

Parameters of Best Fit:

χ^2/ndf	N	B	μ	σ
1.85	0.2566	0.2920	1.5000	1.5000

Fit Compared to Data and Cascade predictions
using A0 and J2003Set2 uPDFs



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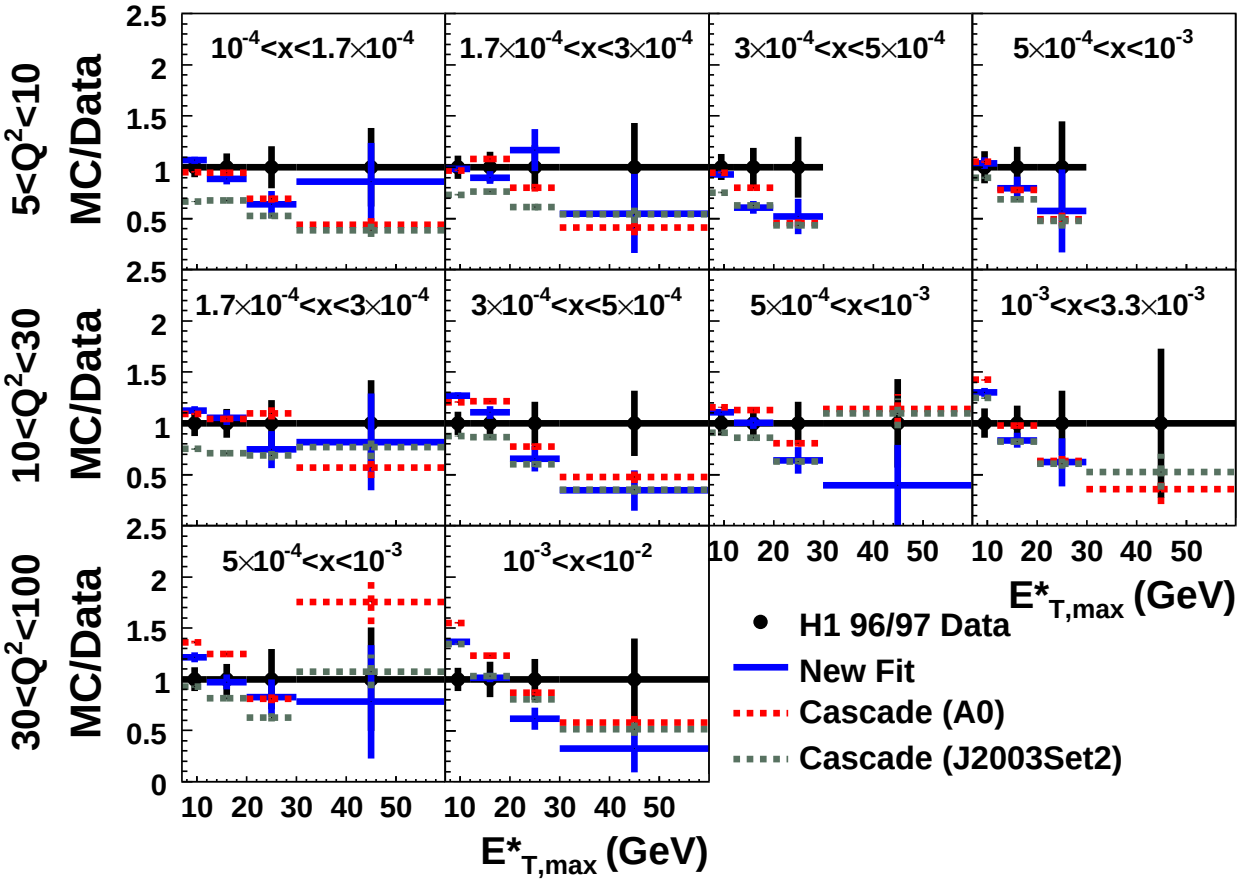


Summary

- $\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$, $\frac{d^2\sigma}{dQ^2d\Delta\phi^*}$ and $\frac{d^3\sigma}{dx_{bj}dQ^2d\Delta\phi^*}$ unfolded using Bayes method

  $\Rightarrow$ $\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$ and $\frac{d^2\sigma}{dQ^2d\Delta\phi^*}$ in agreement with preliminary cross sections

  $\Rightarrow$ Systematic uncertainties generally smaller at low $\Delta\phi^*$ and larger at high $\Delta\phi^*$ compared to preliminary

- uPDF fitted to $\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$ and $\frac{d^3\sigma}{dx_{bj}dQ^2dE^*_{T,Max}}$

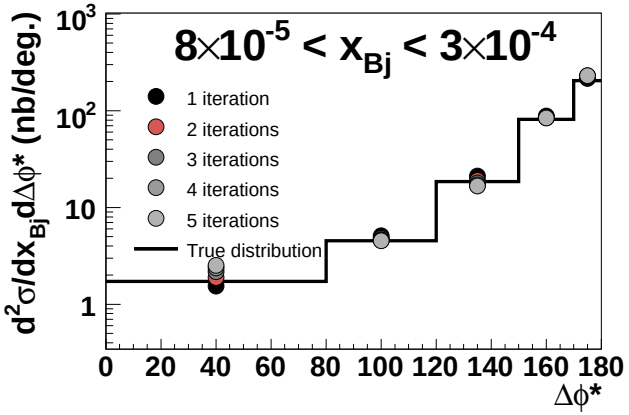
  $\Rightarrow$ improved description of $\frac{d^2\sigma}{dx_{bj}d\Delta\phi^*}$

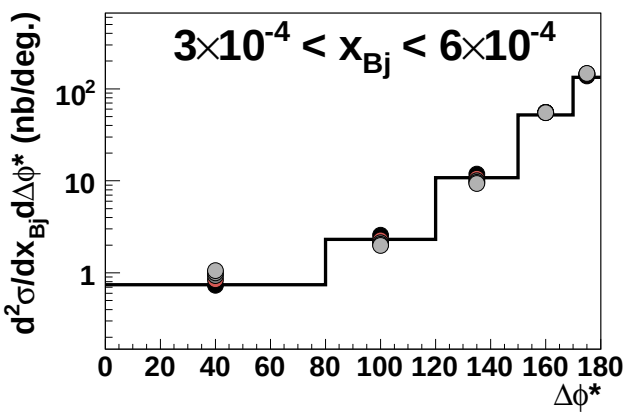
  $\Rightarrow$ $\frac{d^3\sigma}{dx_{bj}dQ^2dE^*_{T,Max}}$ better described at low x and Q^2

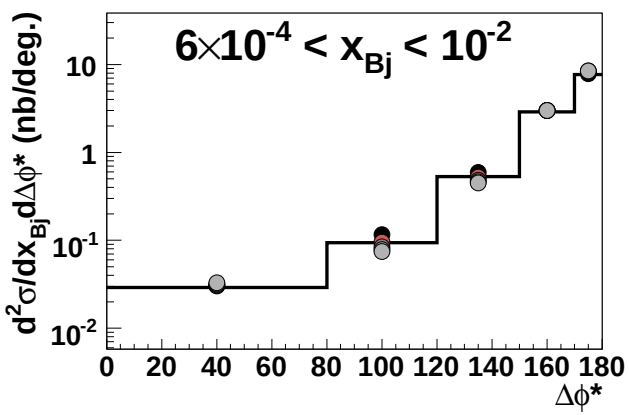
  $\Rightarrow$ Fit suggests $\mu = \sigma = 1.5$ GeV for Gaussian intrinsic k_T

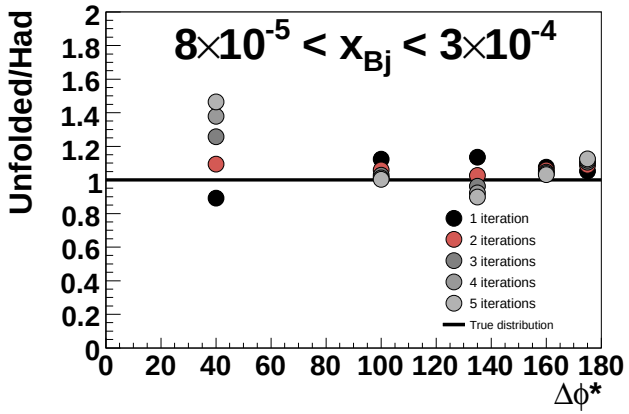
BACKUP PLOTS

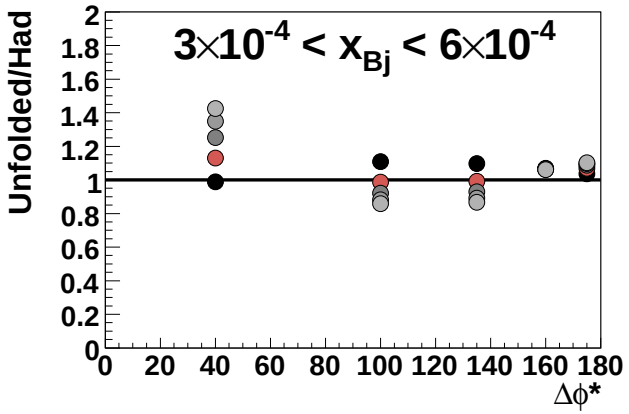
Bayes Unfolding - Unfold Django using Rapgap

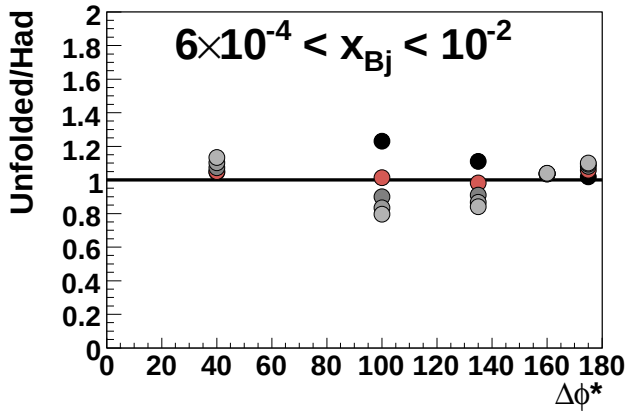




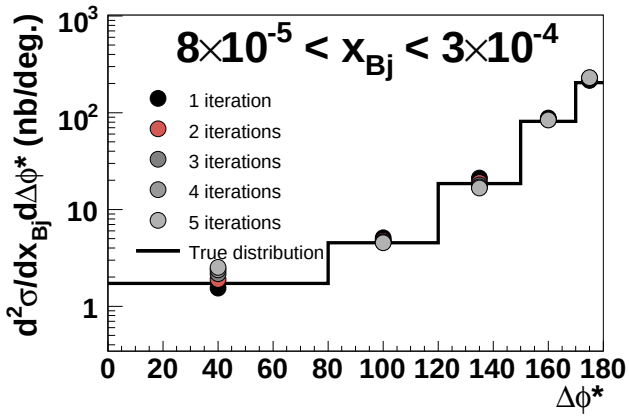


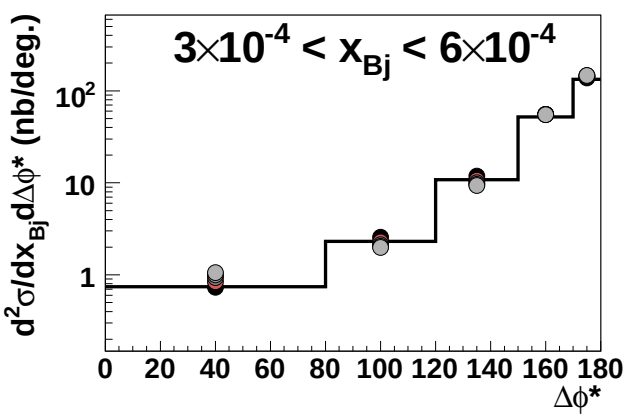


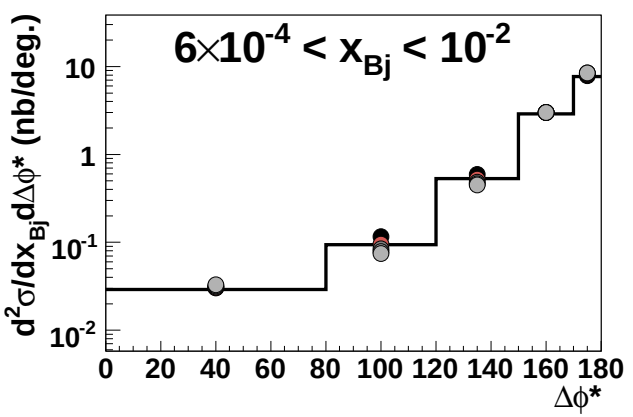


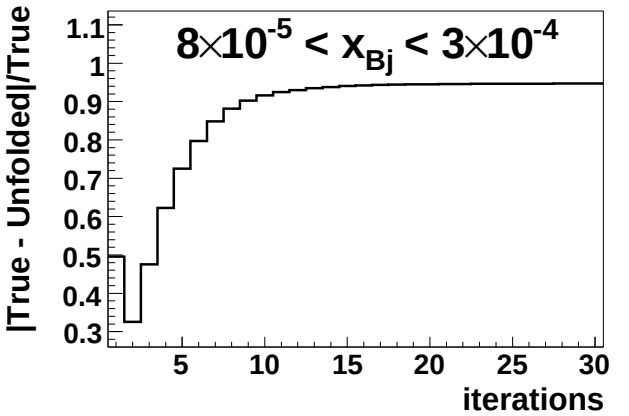


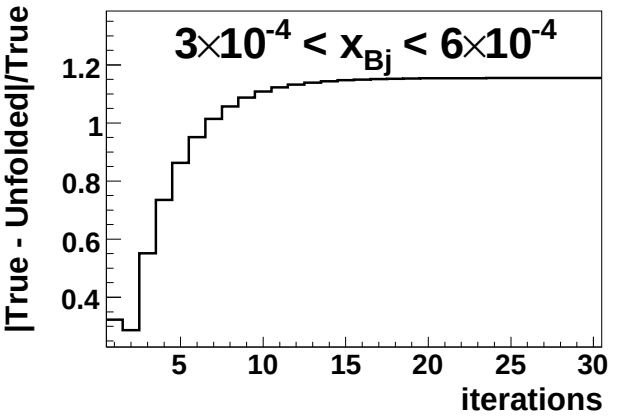
Bayes Unfolding - Unfold Django using Rapgap

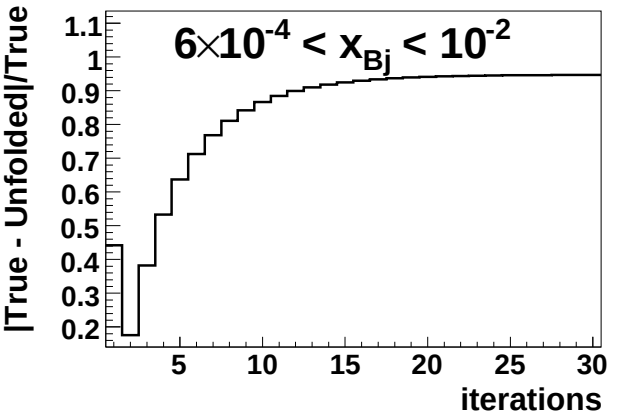




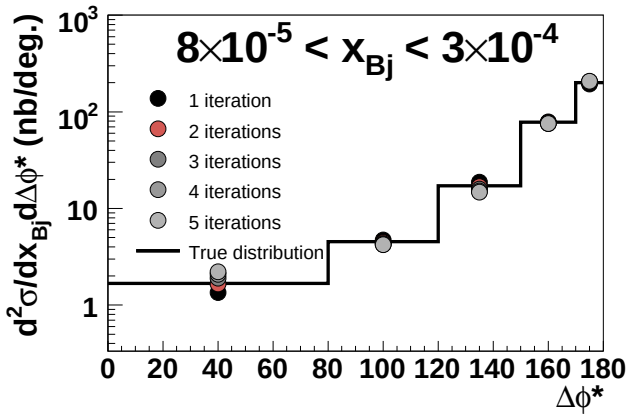


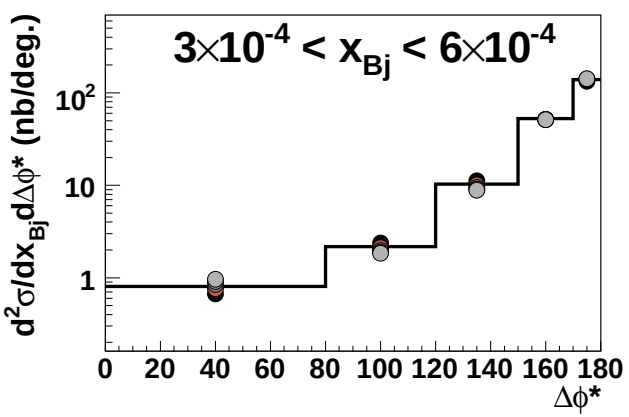


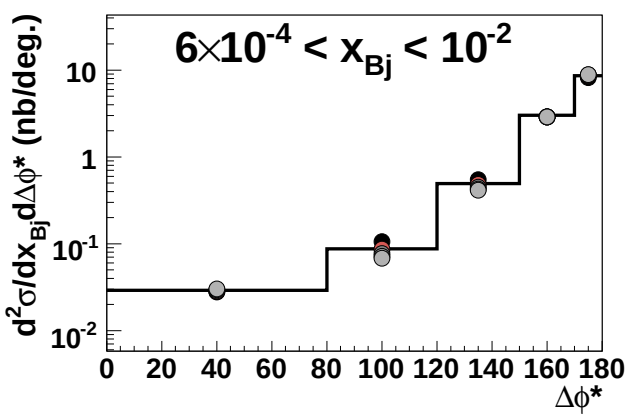


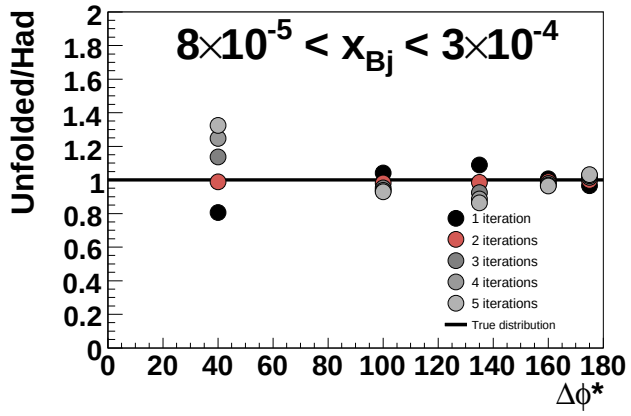


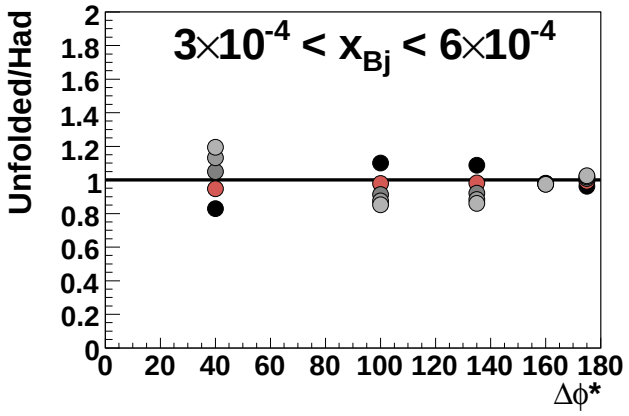
Bayes Unfolding - Unfold Django using Rapgap NRad

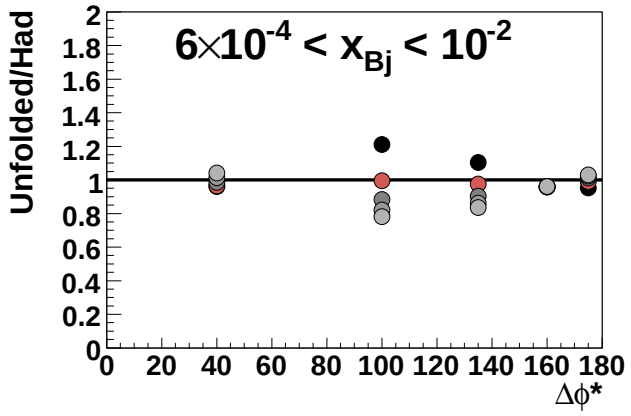




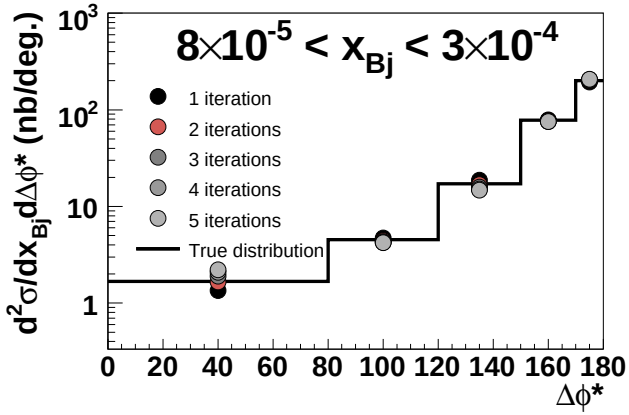


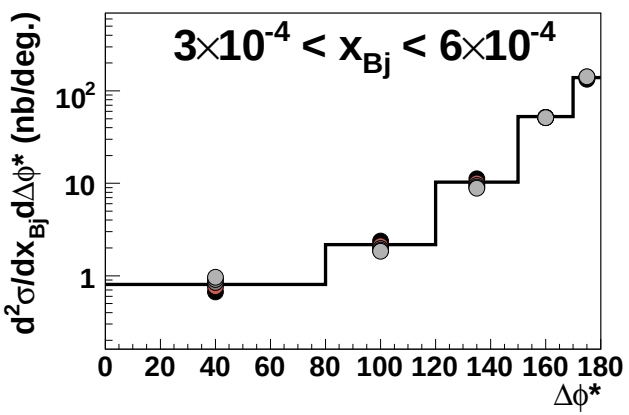


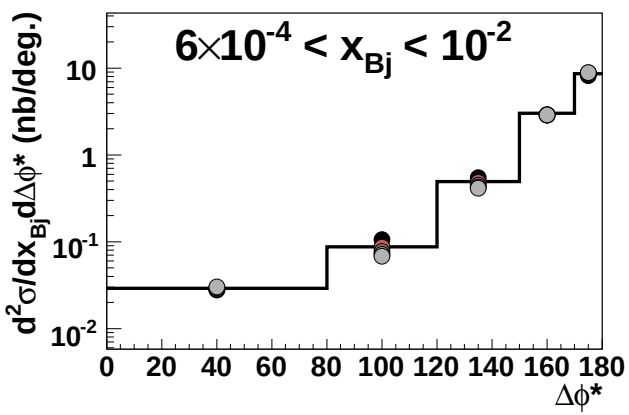


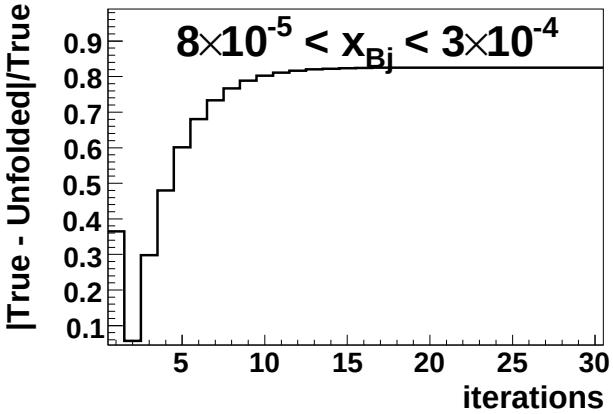


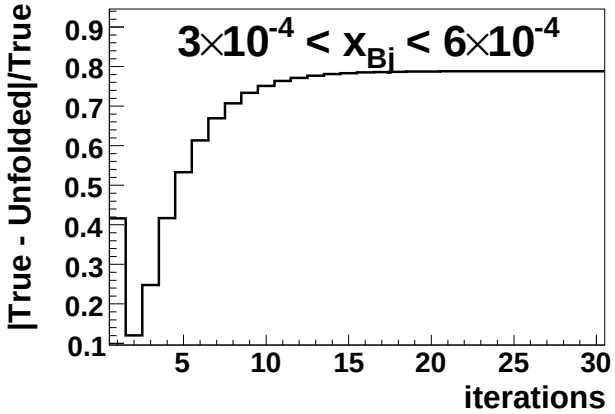
Bayes Unfolding - Unfold Django using Rapgap NRad

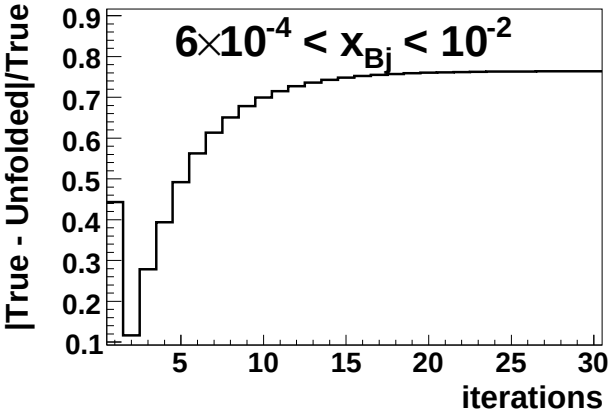




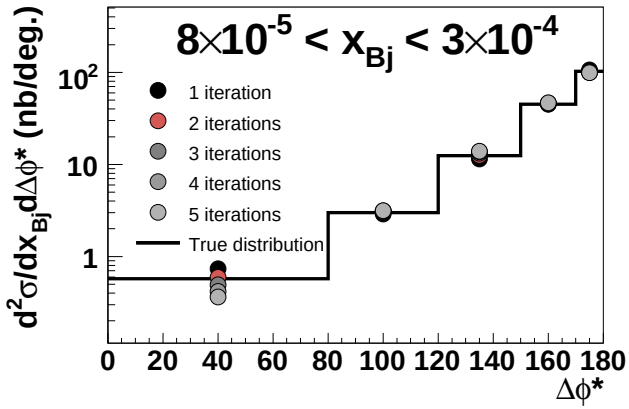


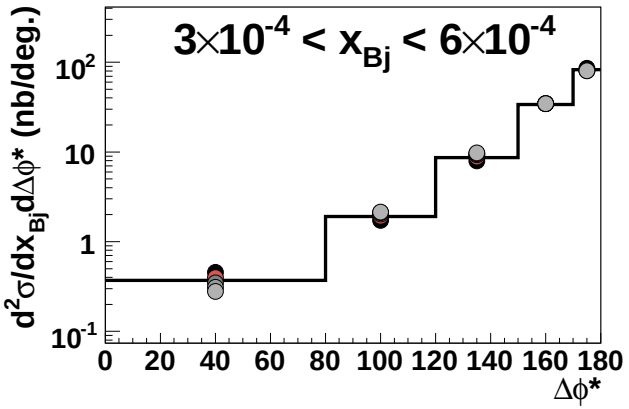


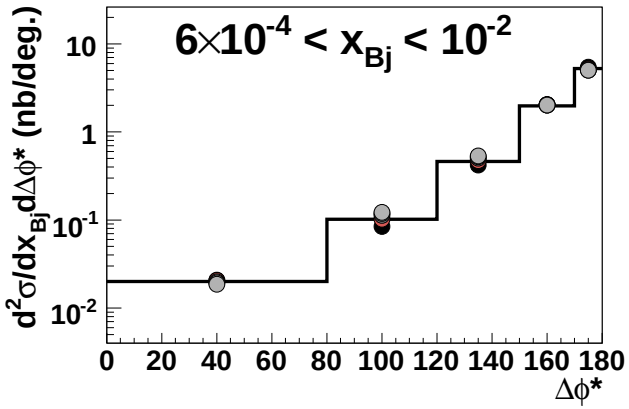


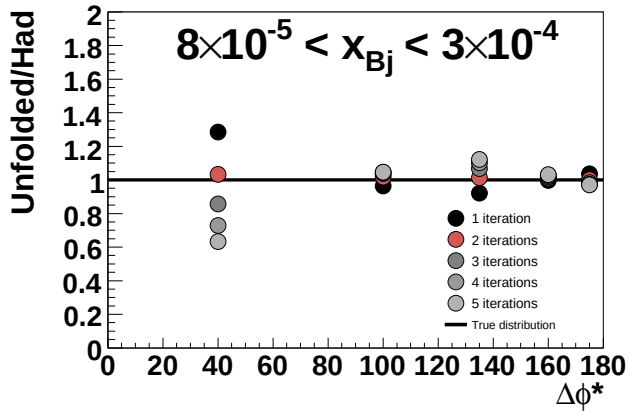


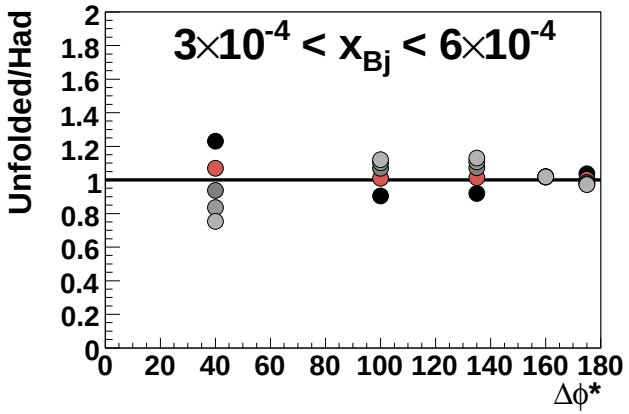
Bayes Unfolding - Unfold Rapgap using Django NRad

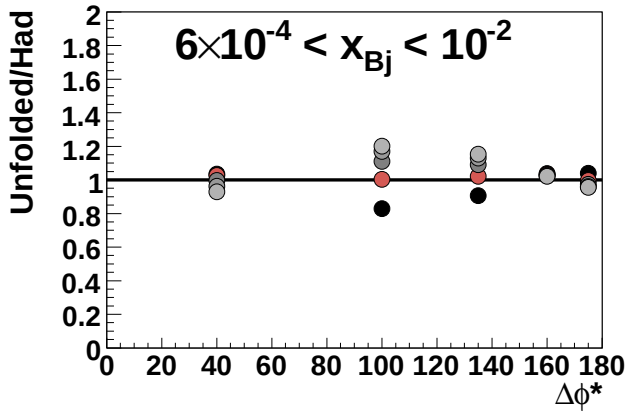




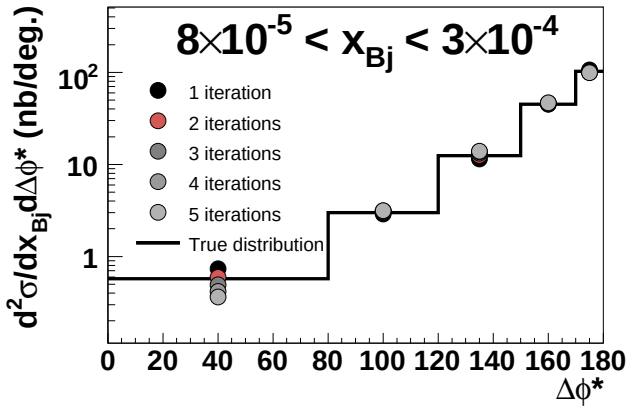


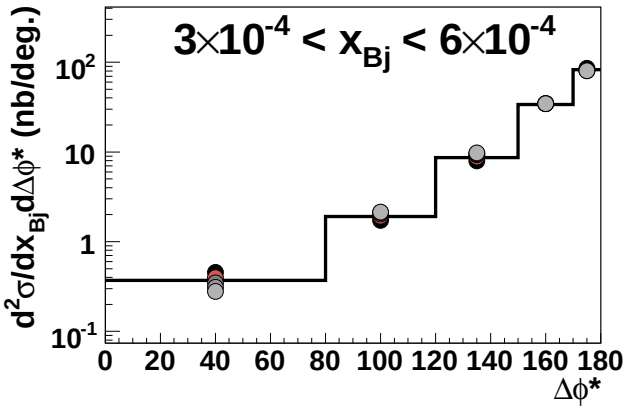


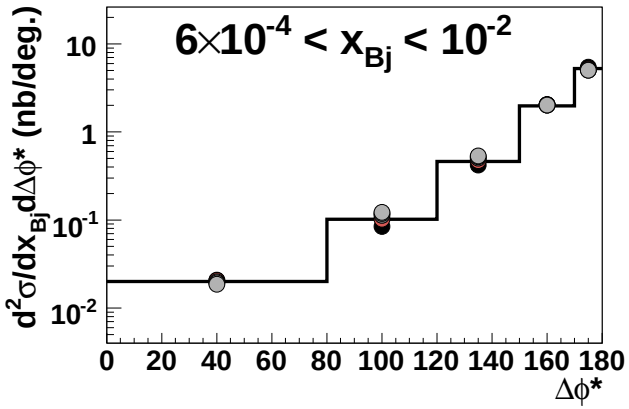


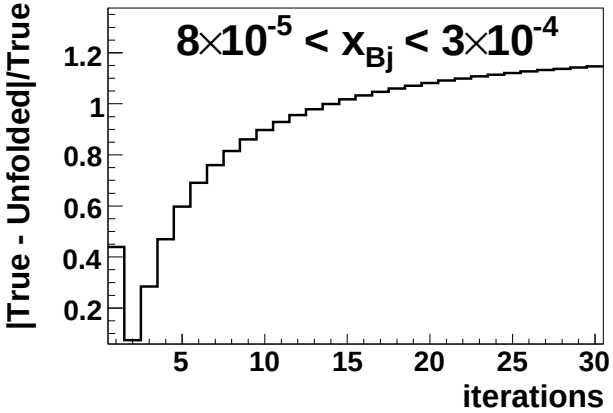


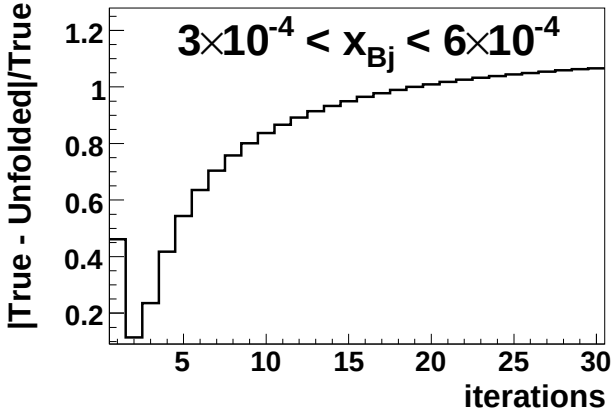
Bayes Unfolding - Unfold Rapgap using Django NRad

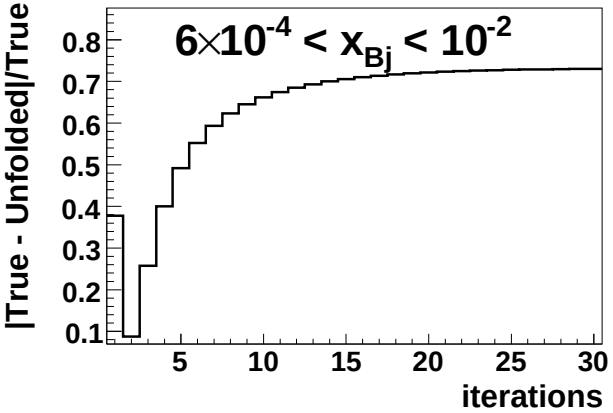




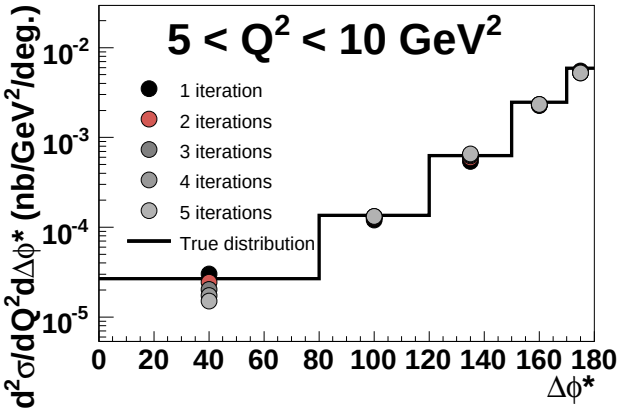


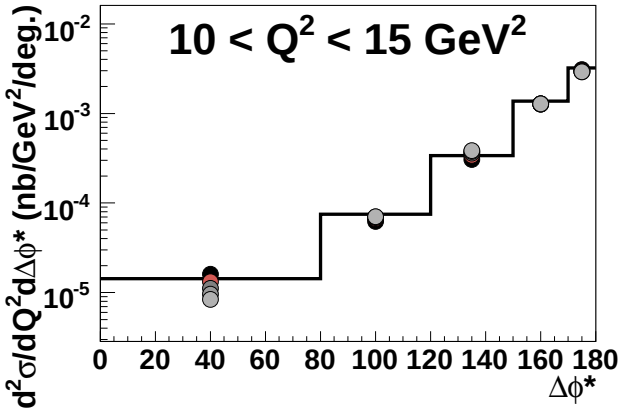


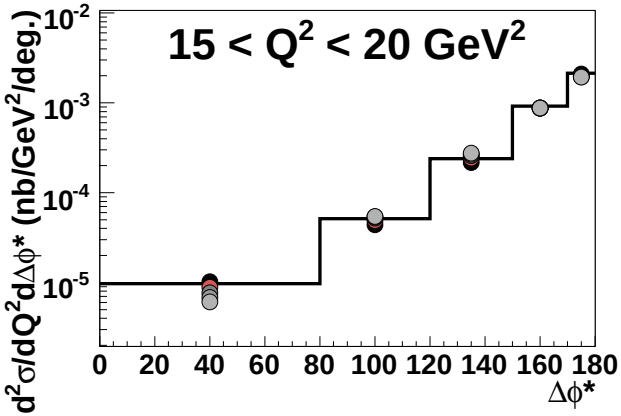


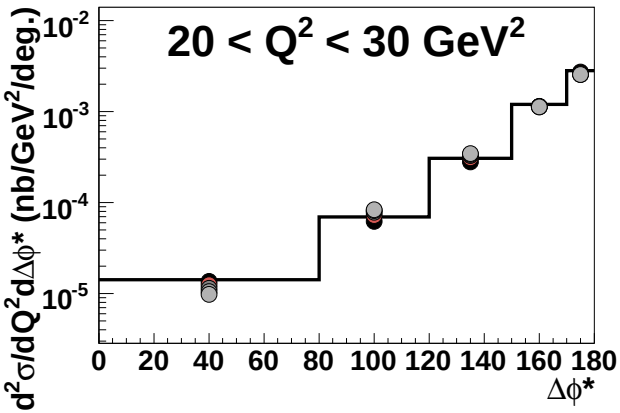


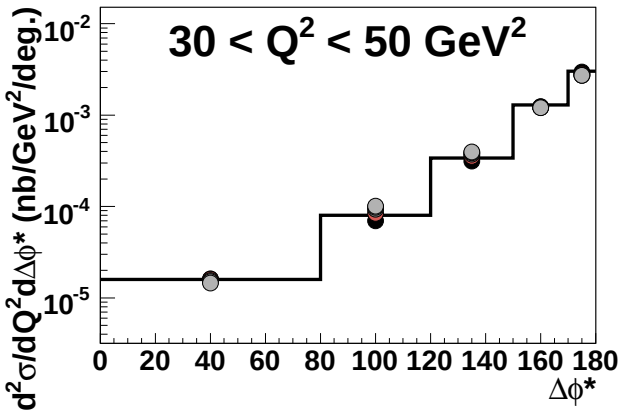
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^2\sigma}{dQ^2\,d\Delta\phi^*}$

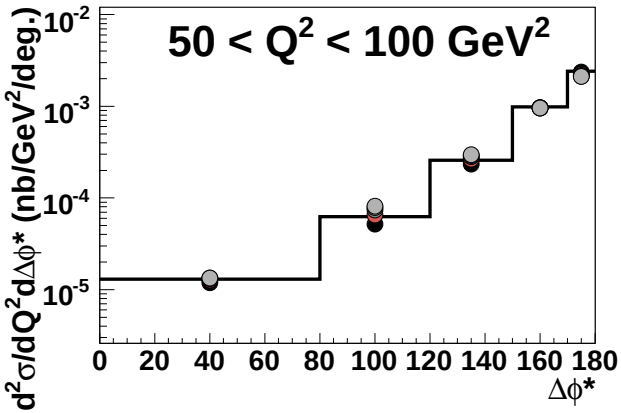




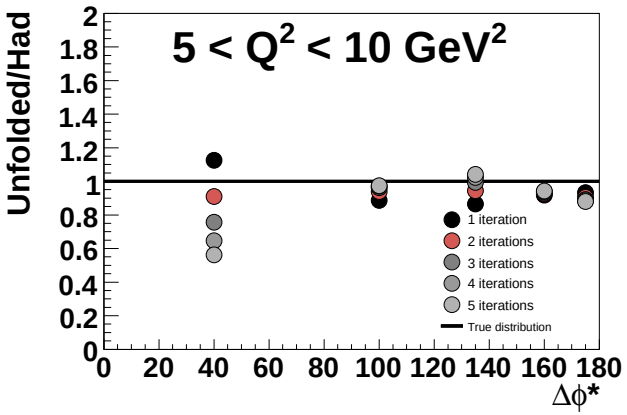


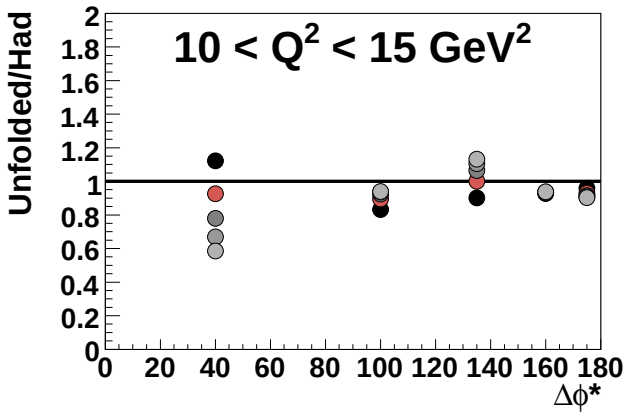


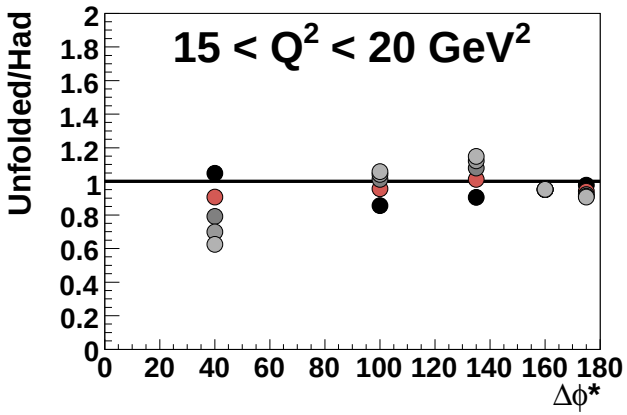


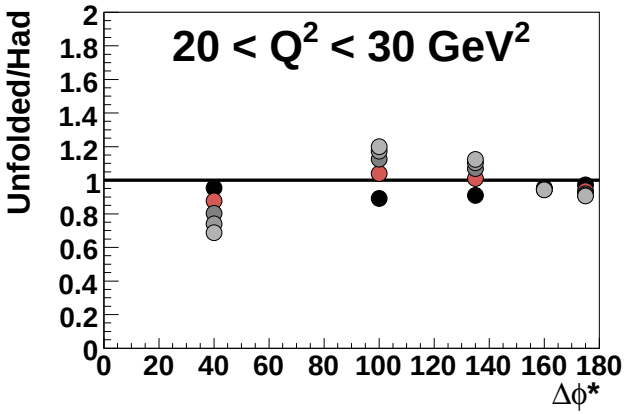


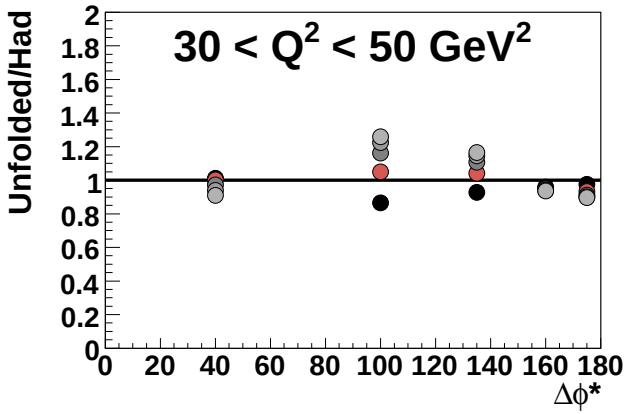
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^2\sigma}{dQ^2\,d\Delta\phi^*}$

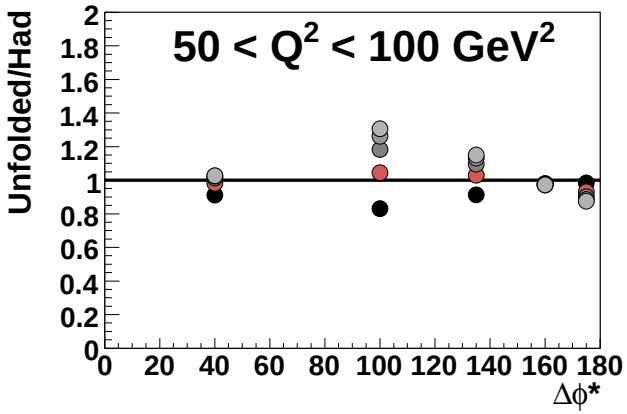




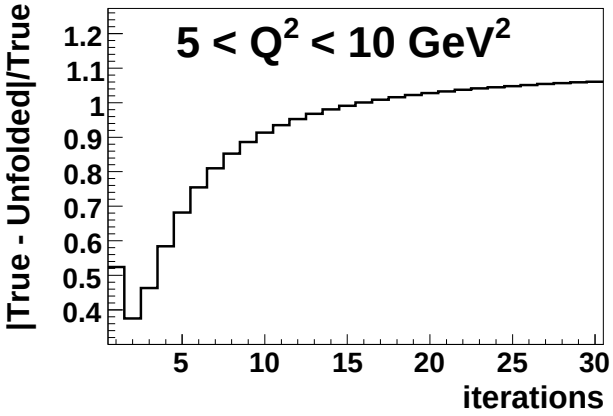


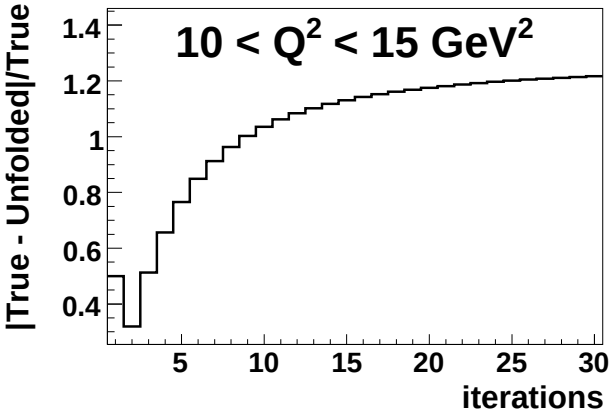


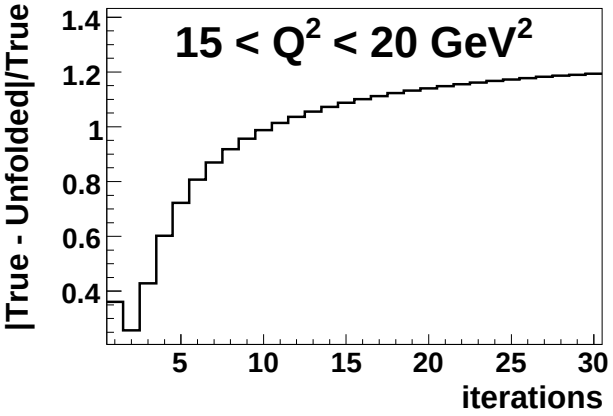


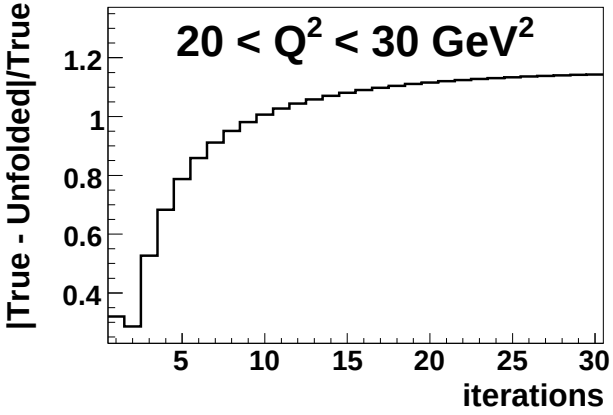


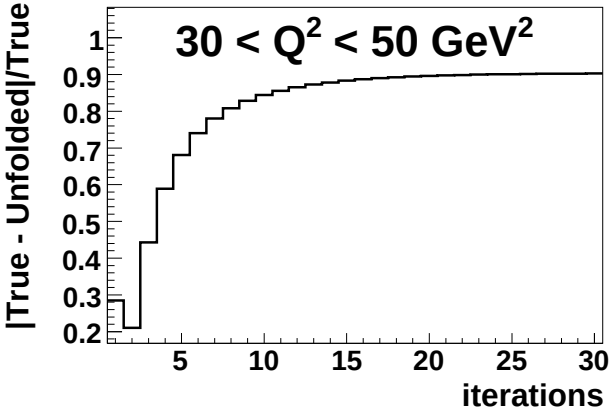
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^2\sigma}{dQ^2\,d\Delta\phi^*}$

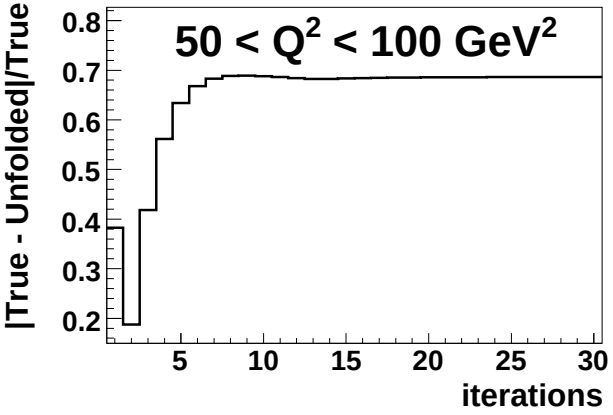




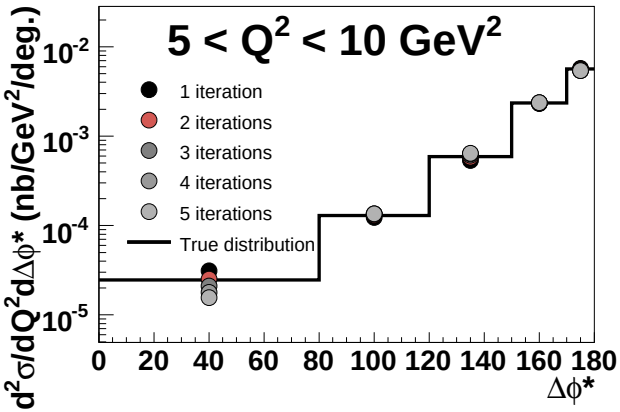


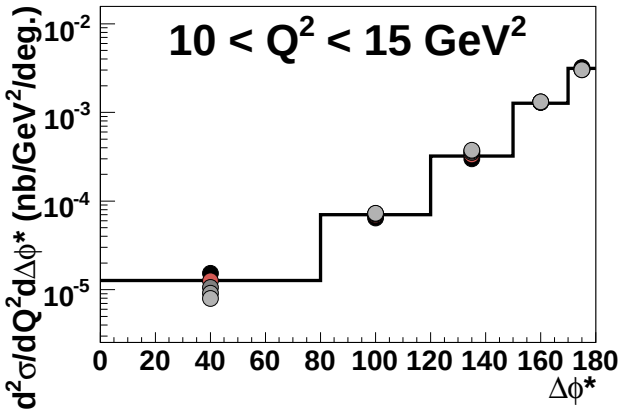


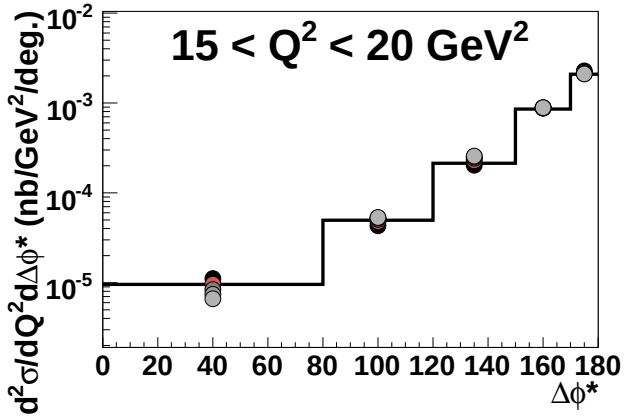


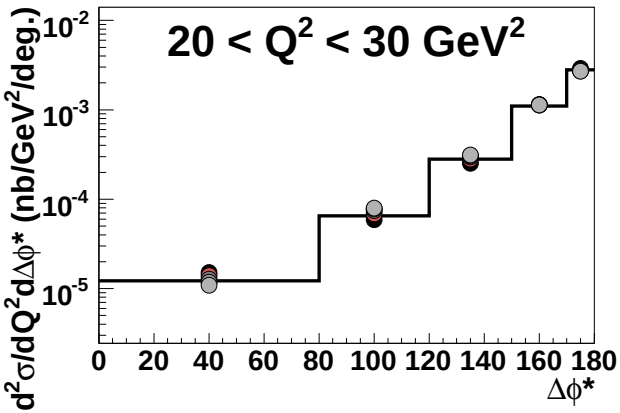


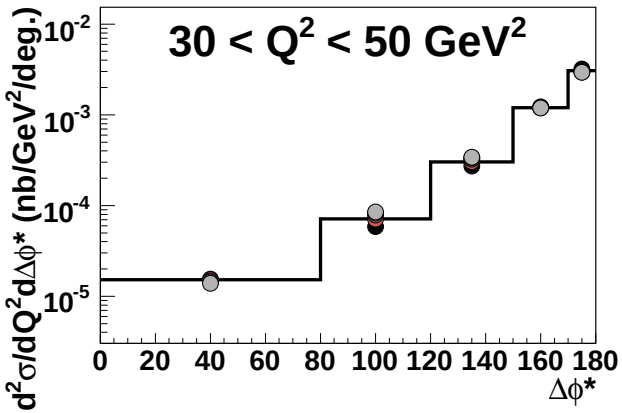
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^2\sigma}{dQ^2 d\Delta\phi^*}$

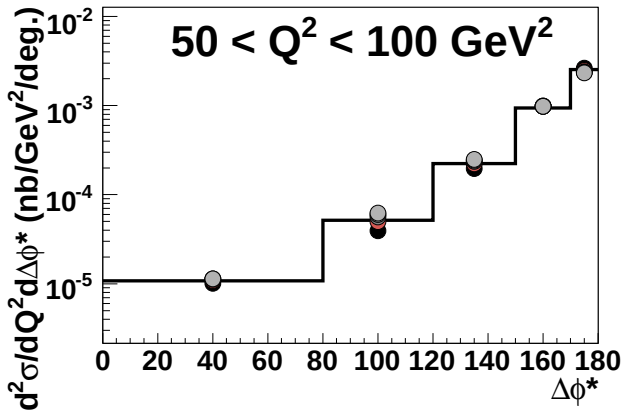




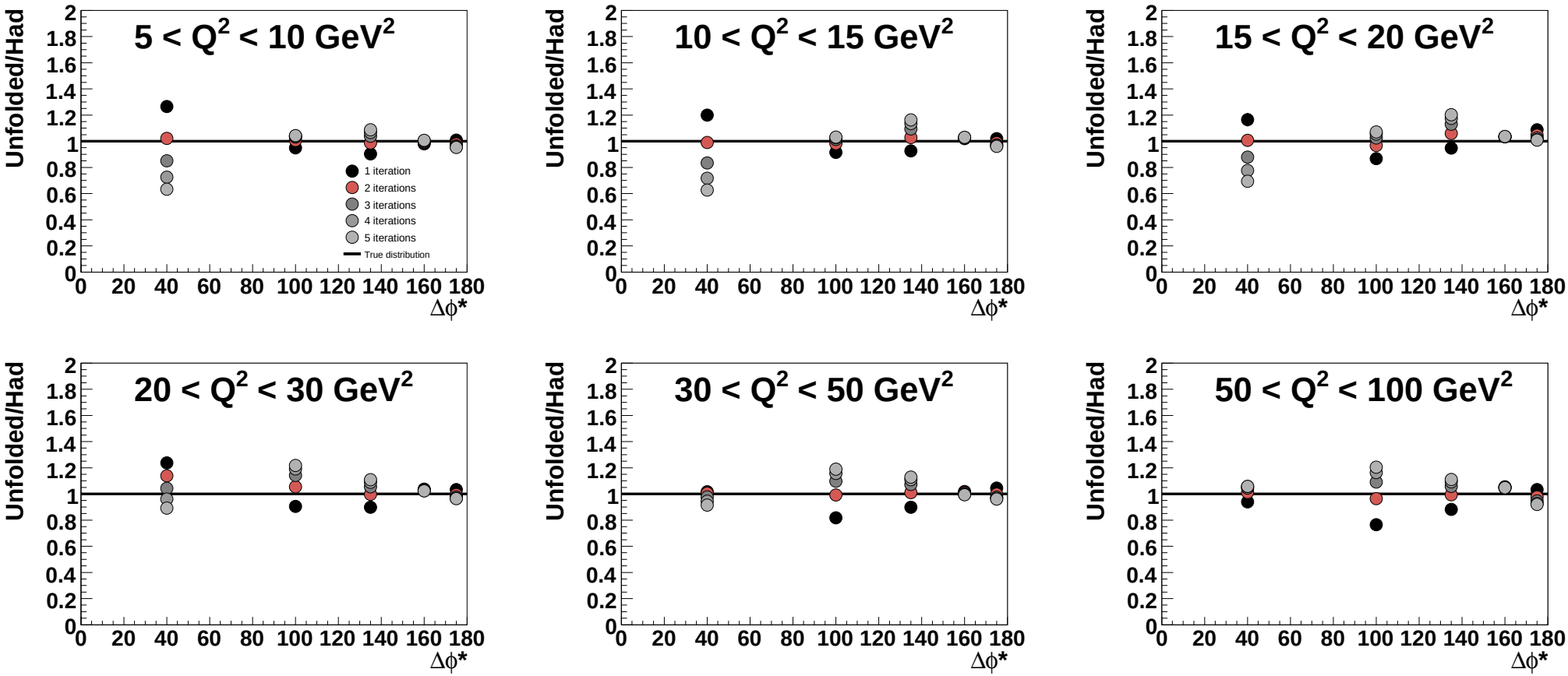




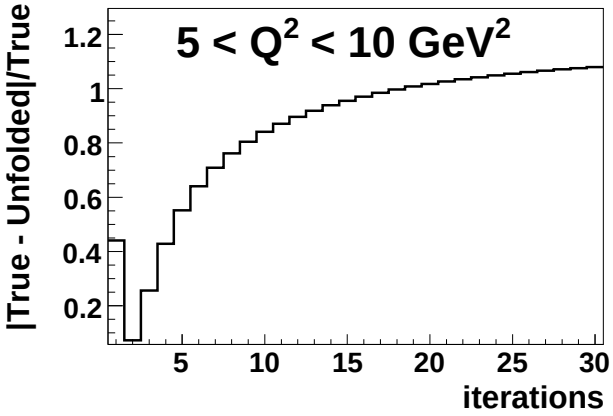


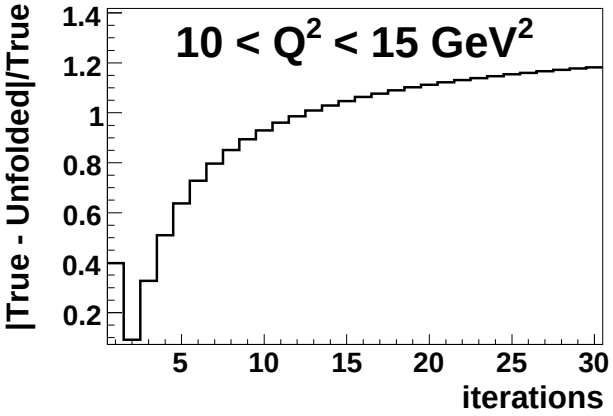


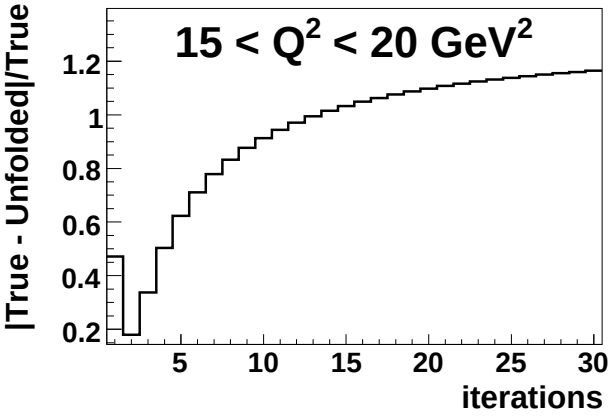
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^2\sigma}{dQ^2 d\Delta\phi^*}$

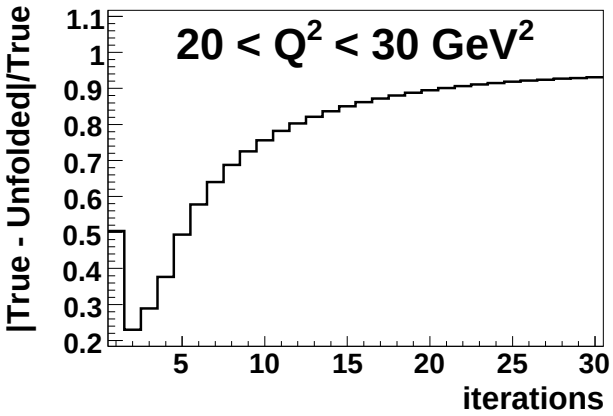


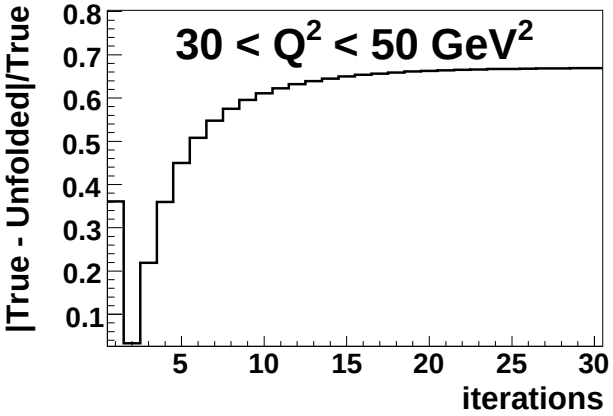
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^2\sigma}{dQ^2 d\Delta\phi^*}$

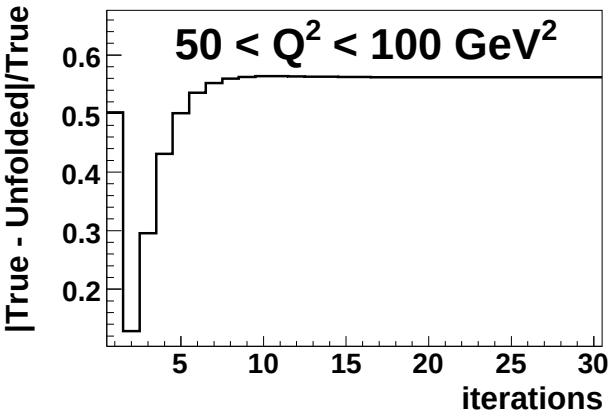




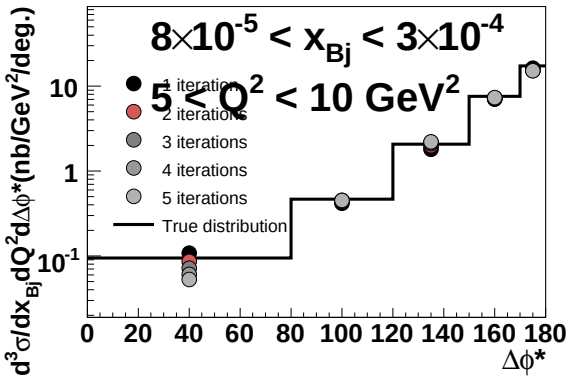


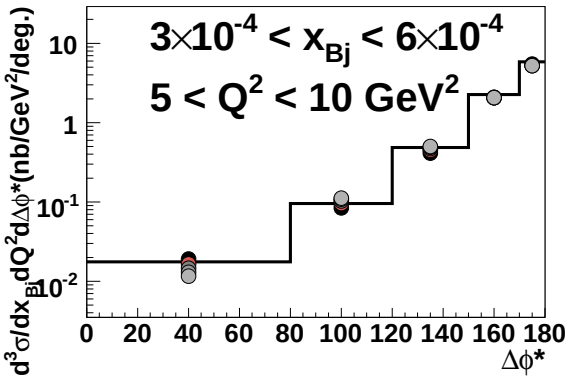


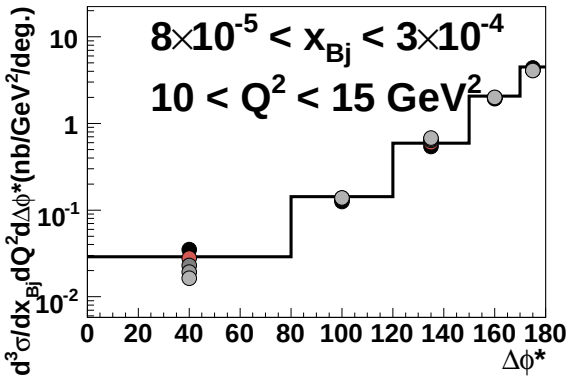


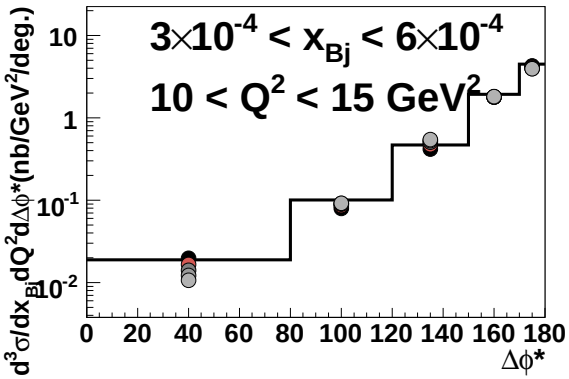


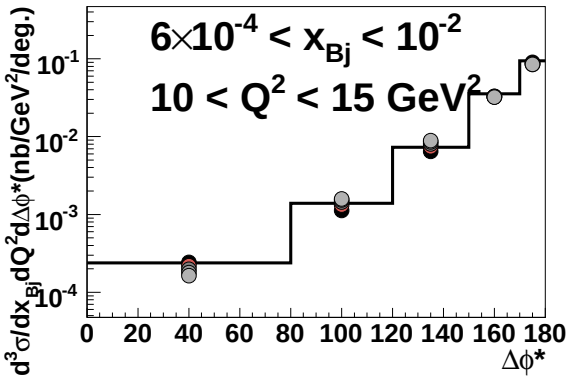
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

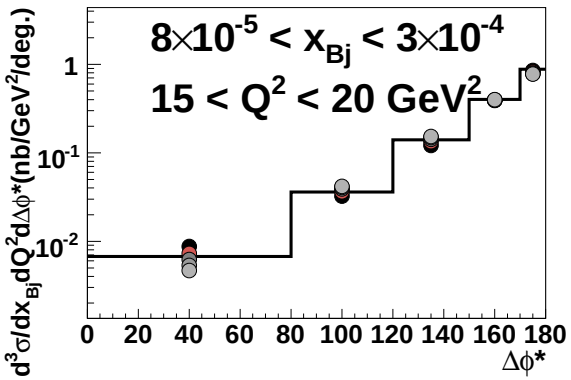


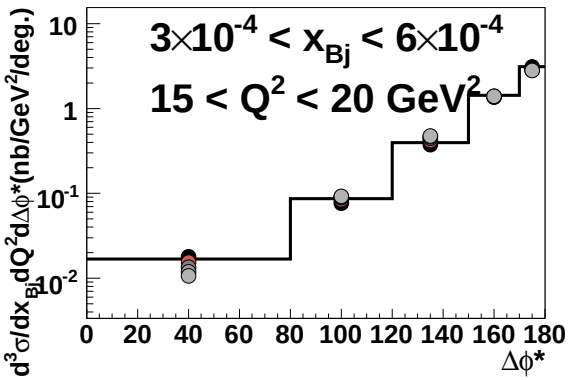


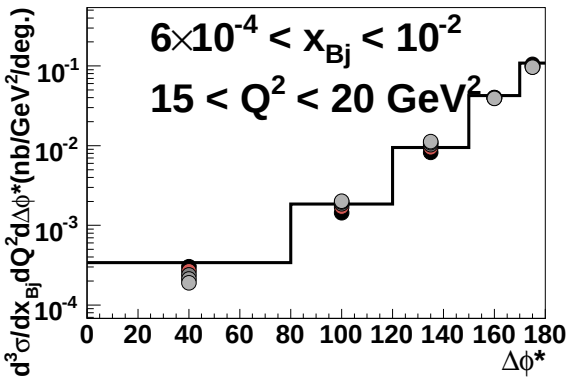




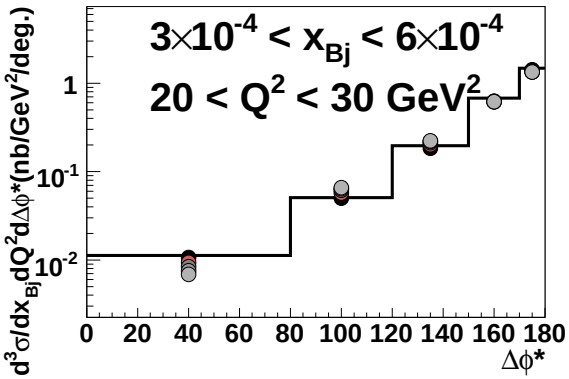


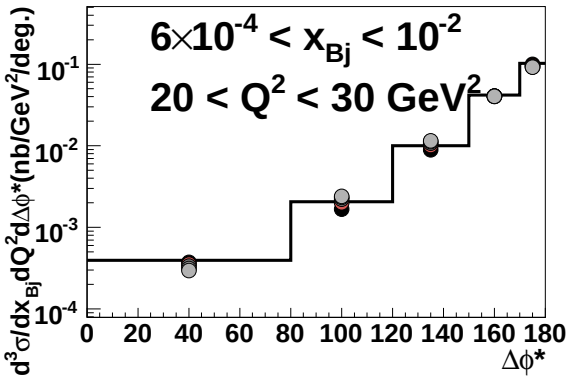


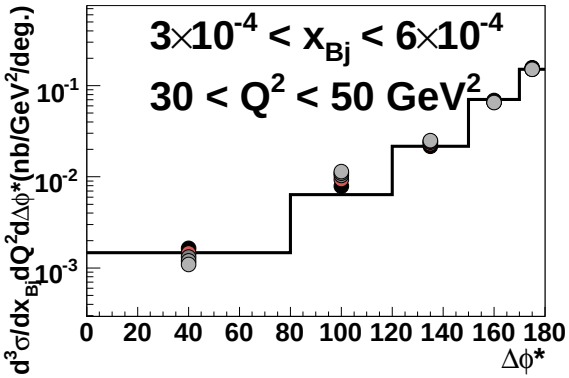


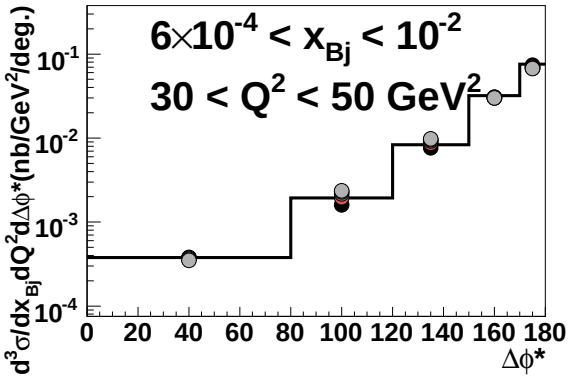


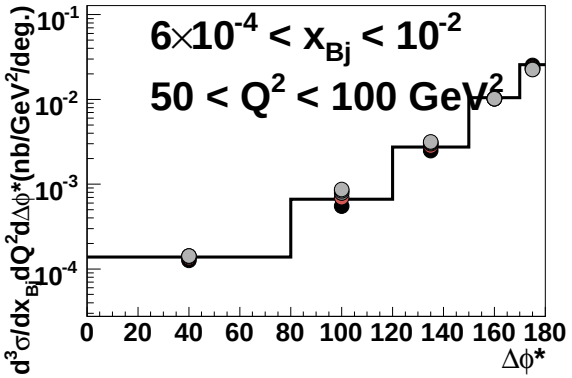
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$



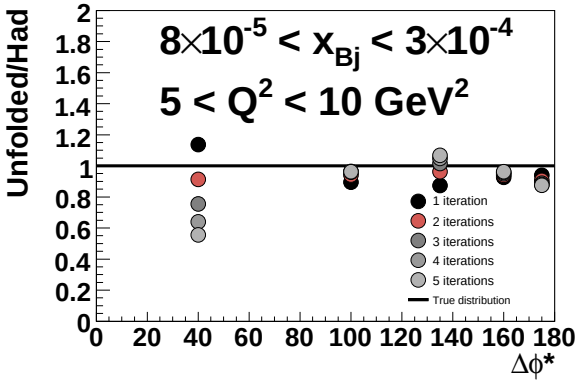


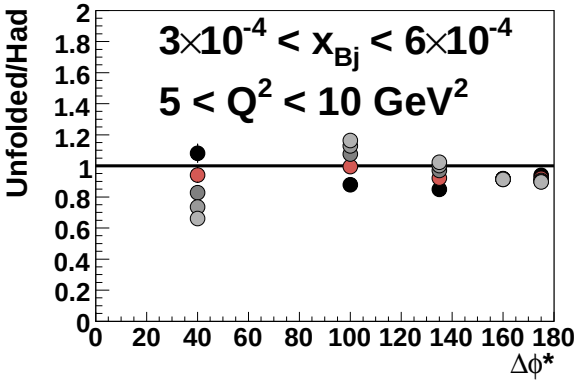


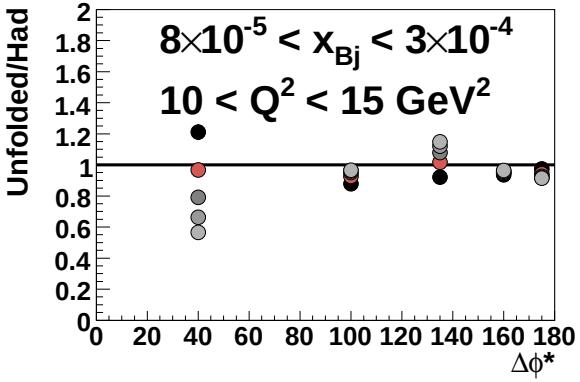


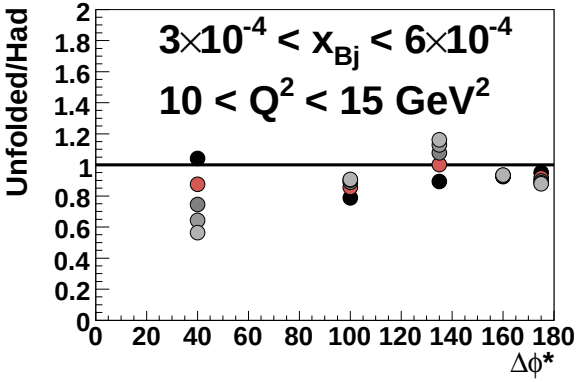


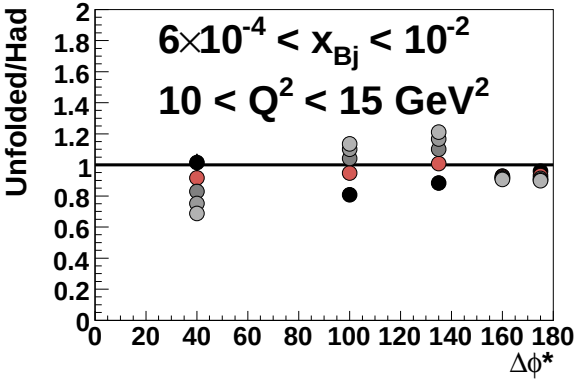
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

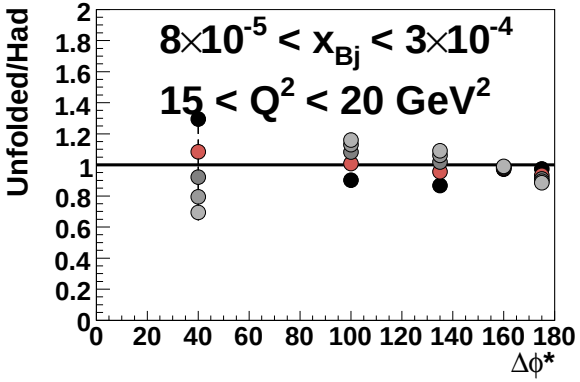


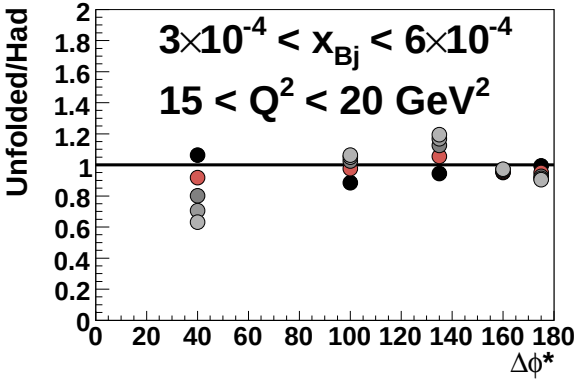


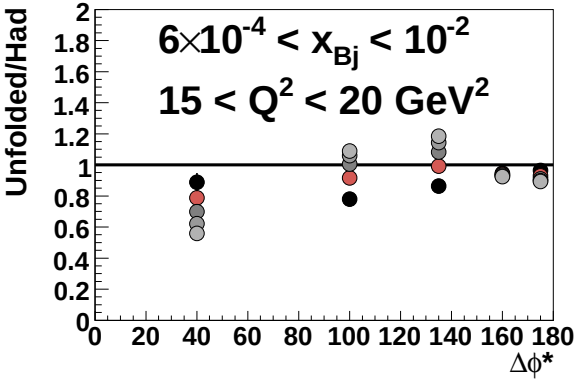




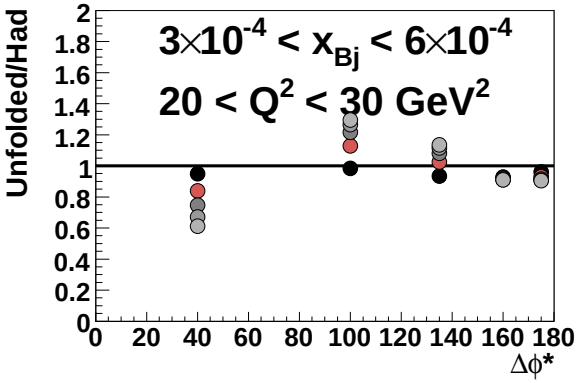


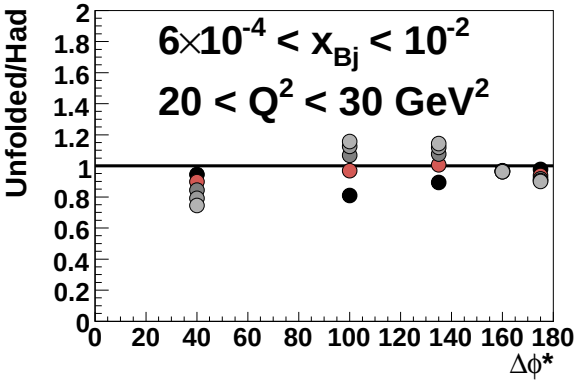


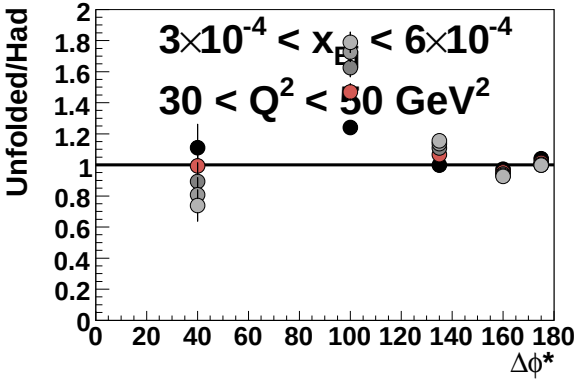


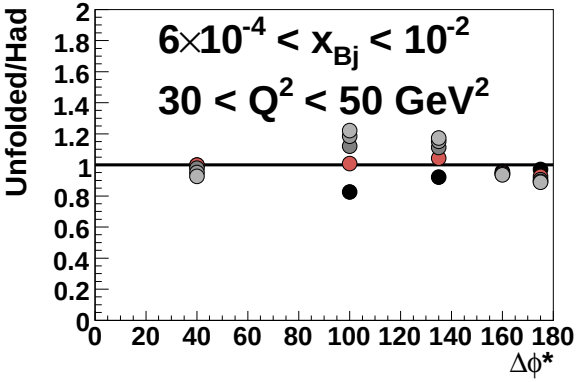


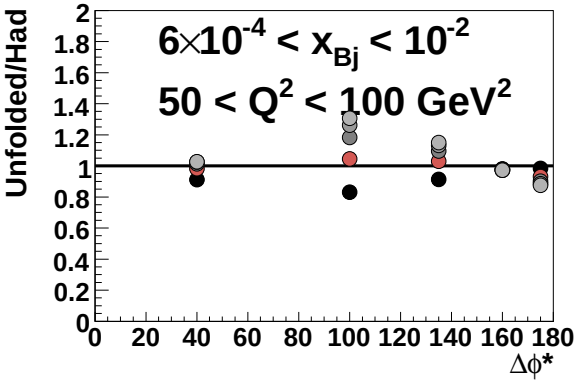
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$



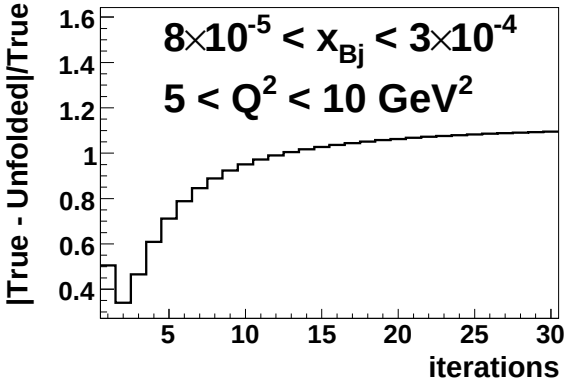


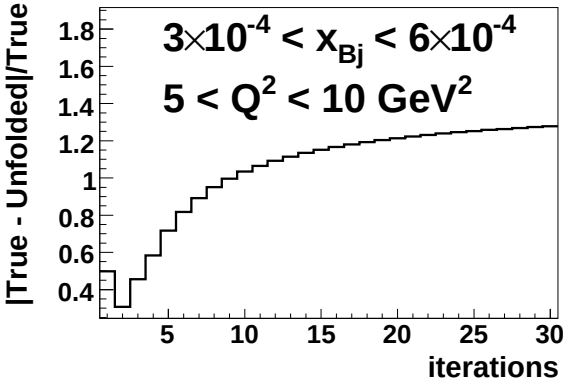


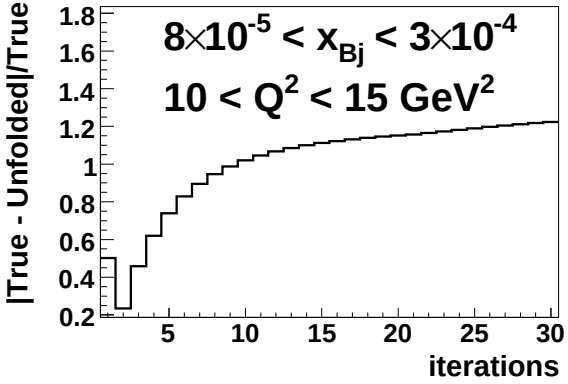


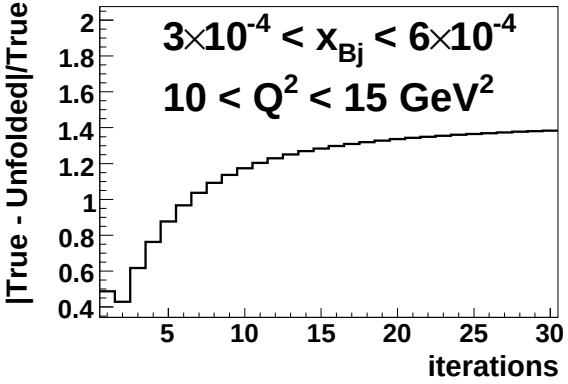


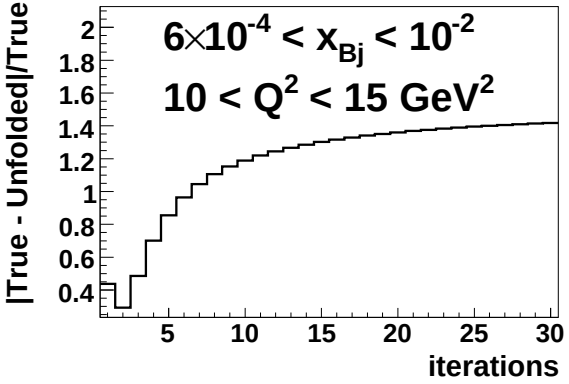
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

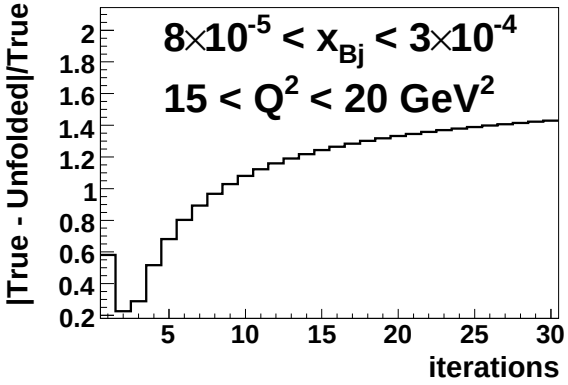


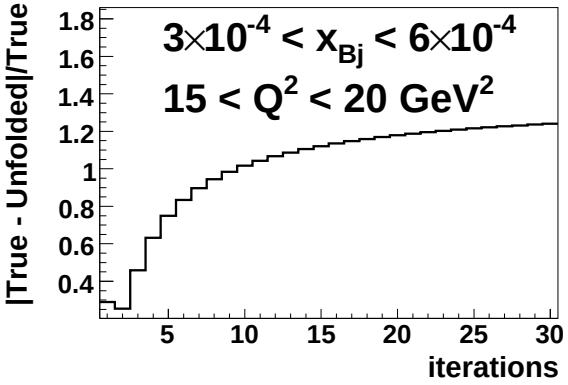


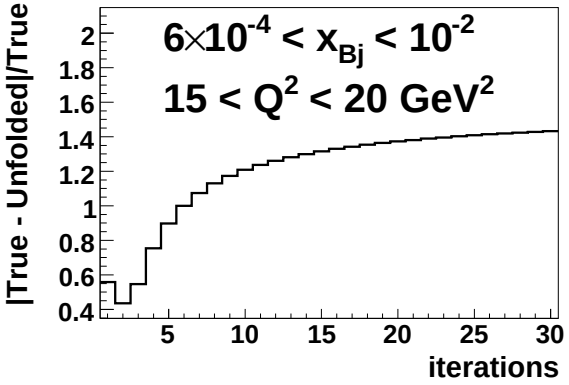




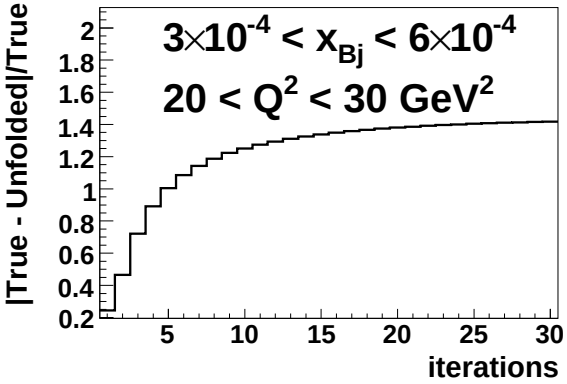


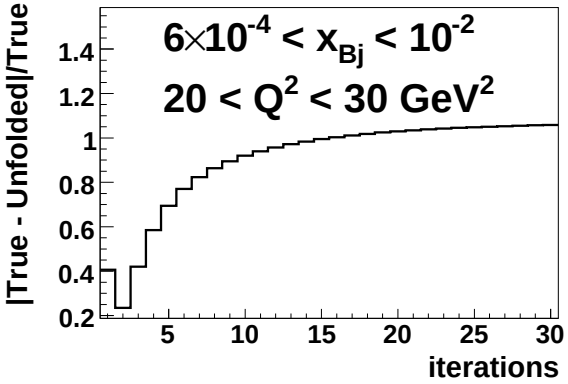


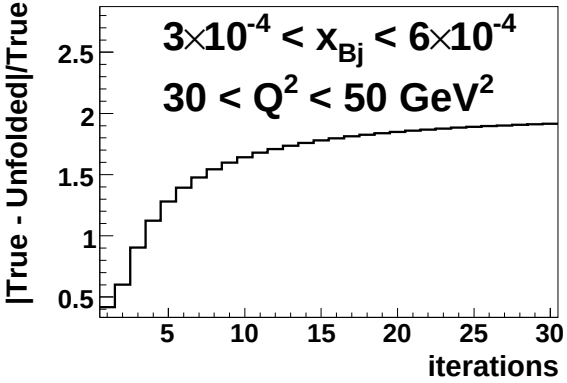


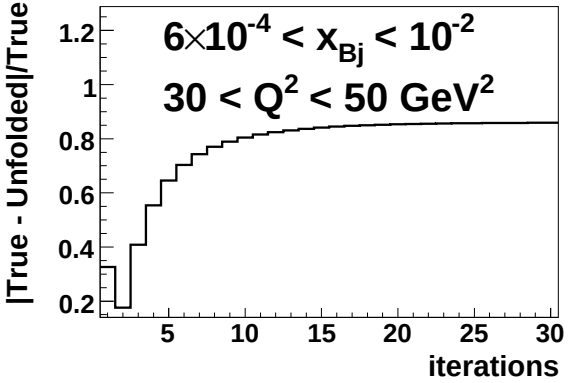


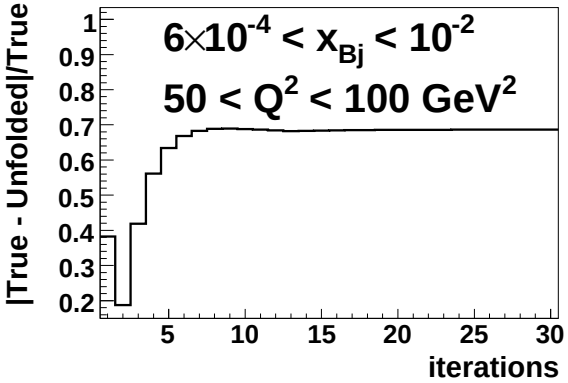
Bayes Unfolding - Unfold Rapgap using Django - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$



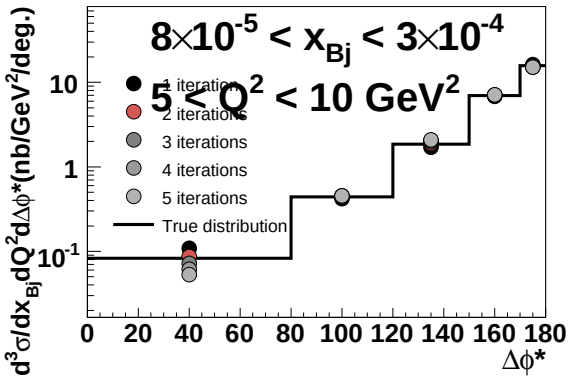


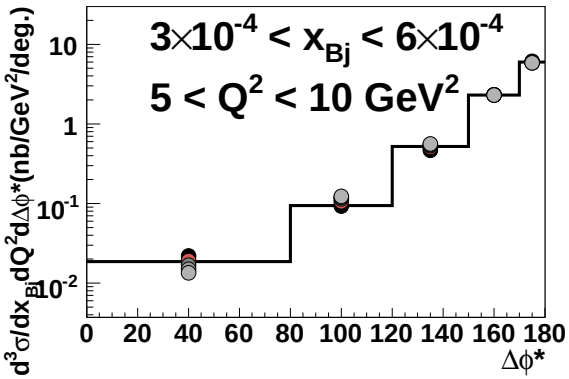


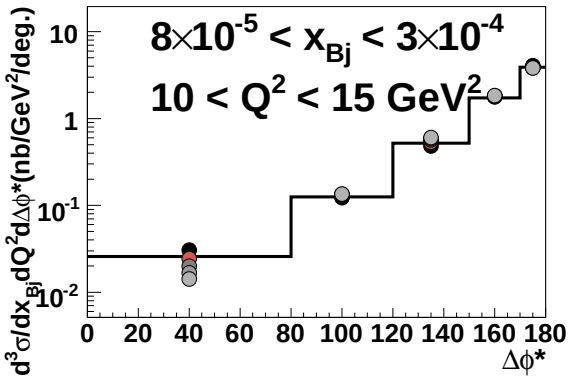


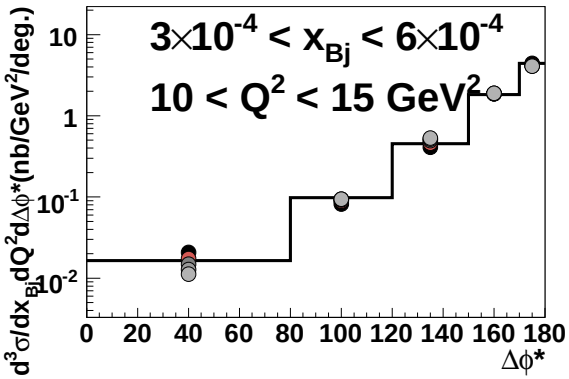


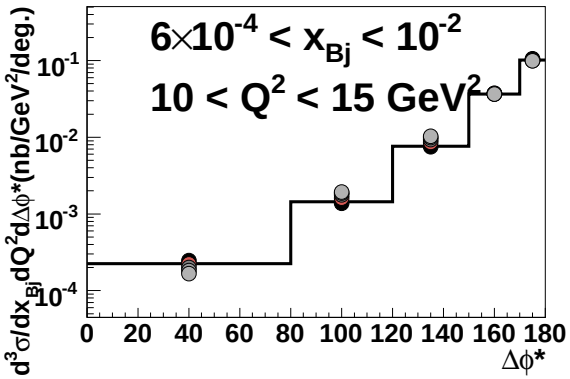
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

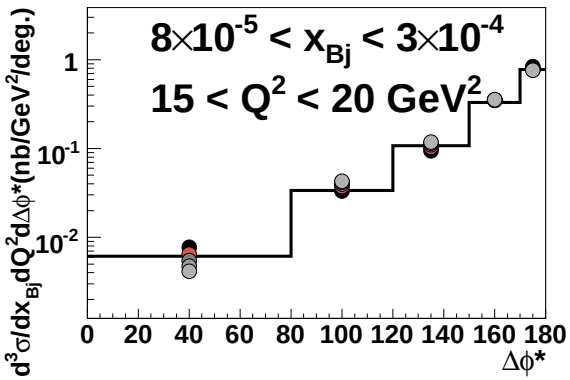


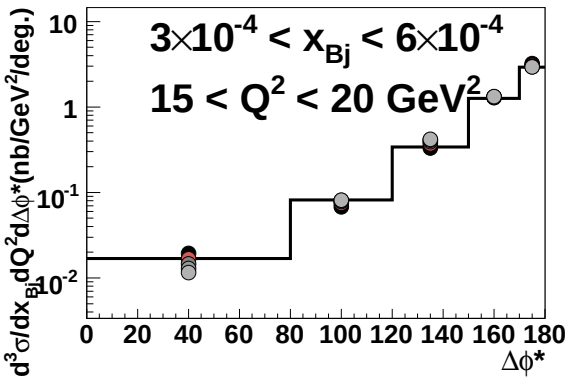


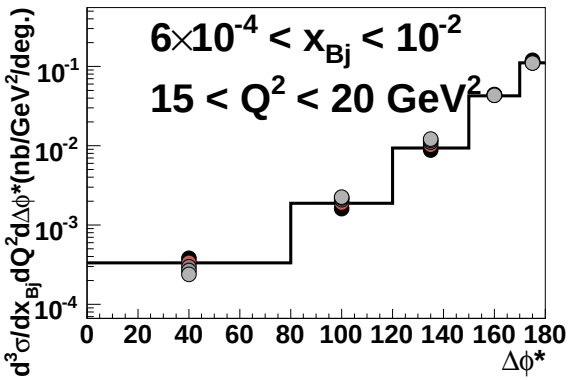




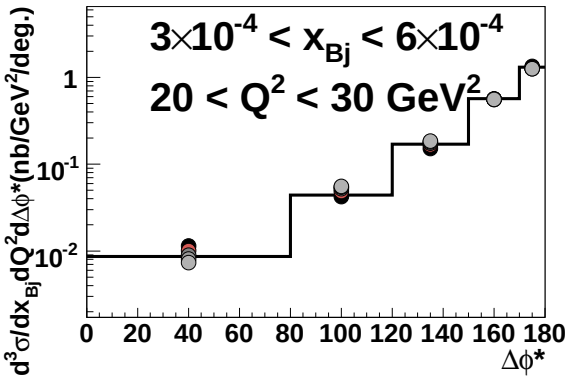


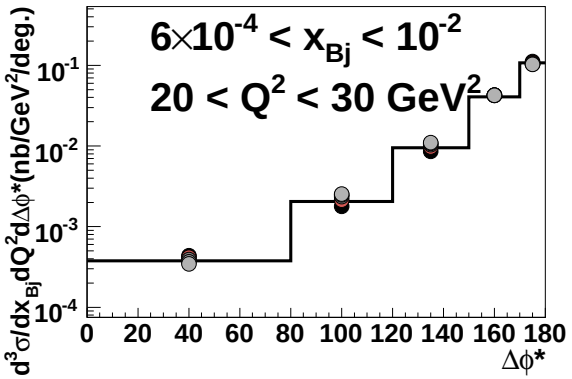


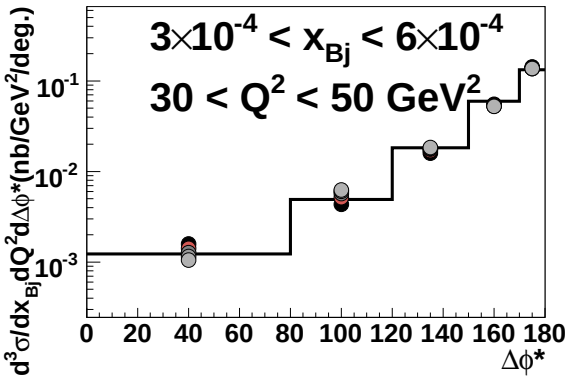


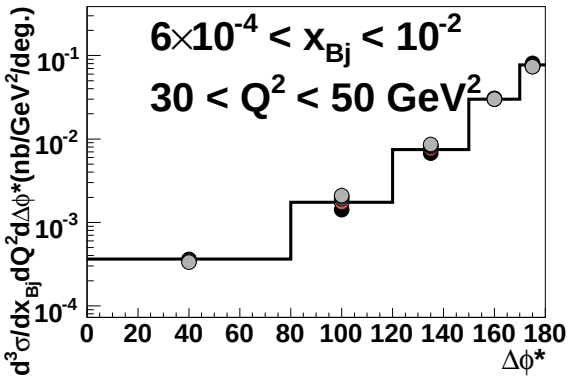


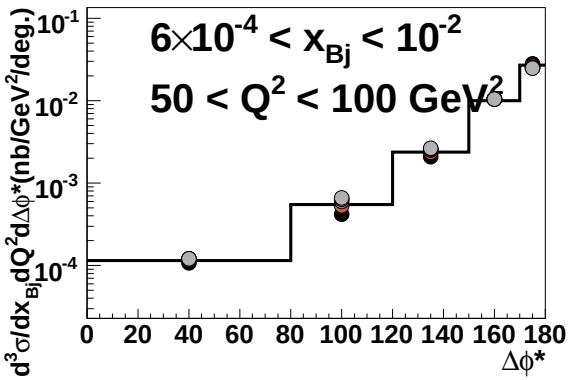
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$



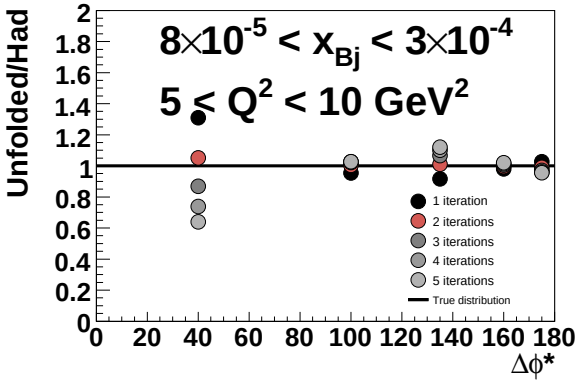


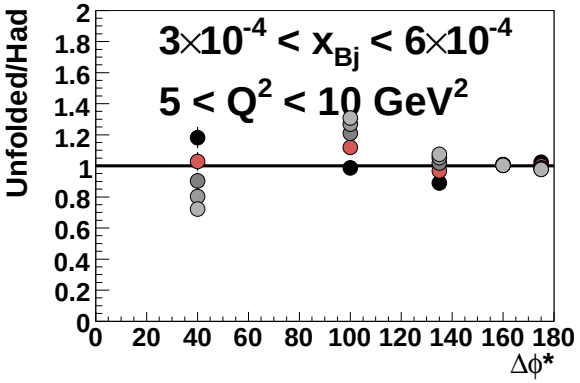


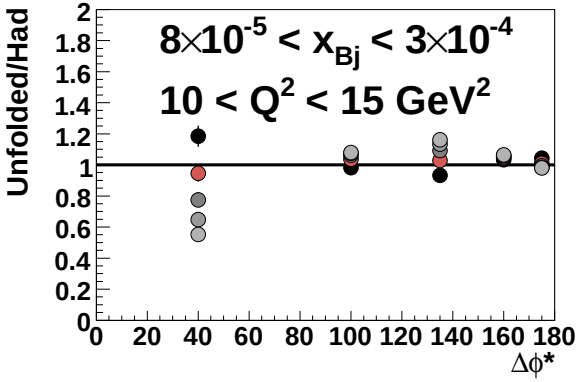


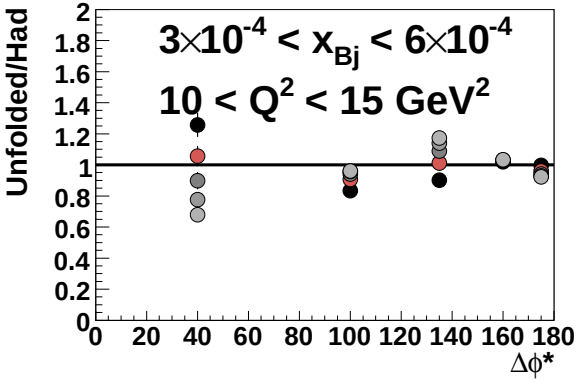


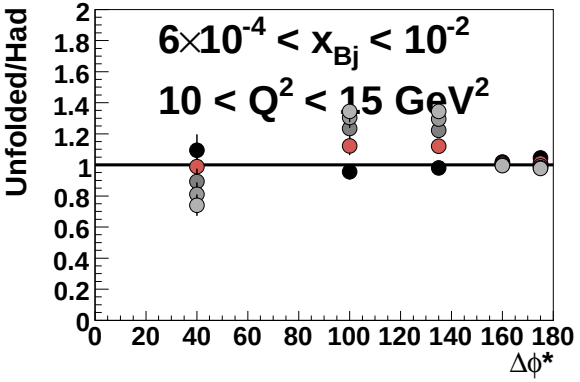
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

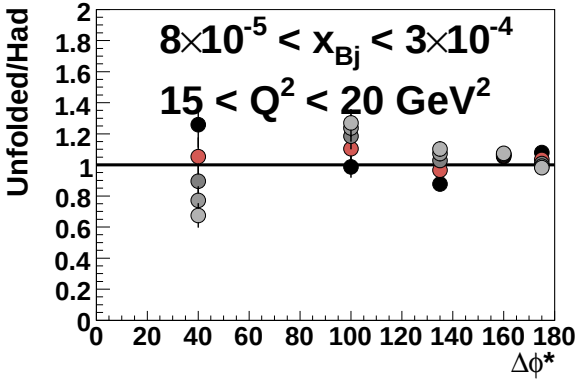


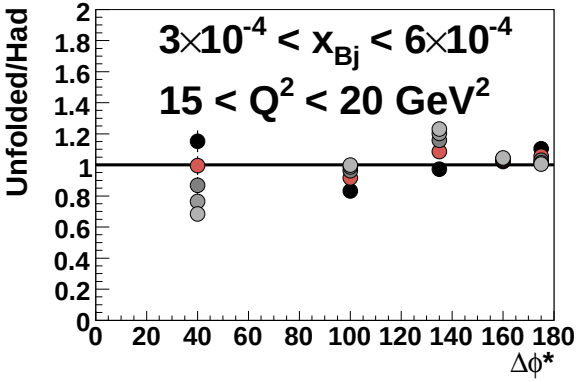


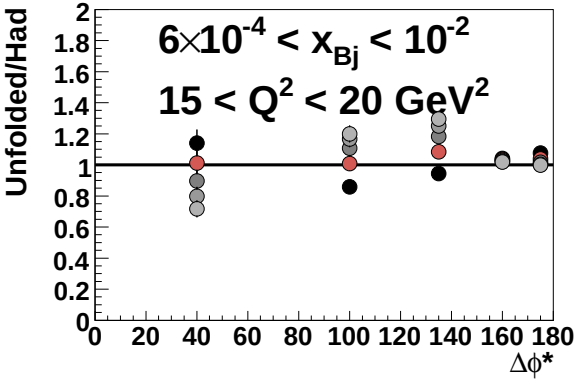




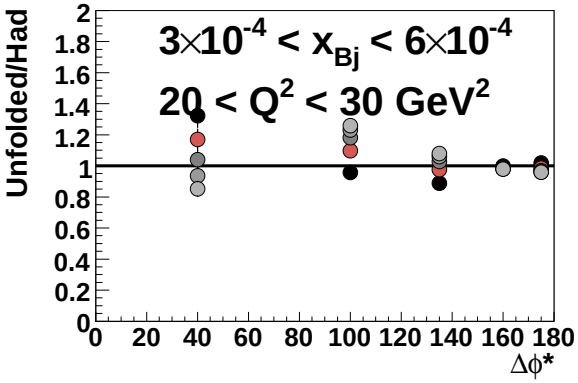


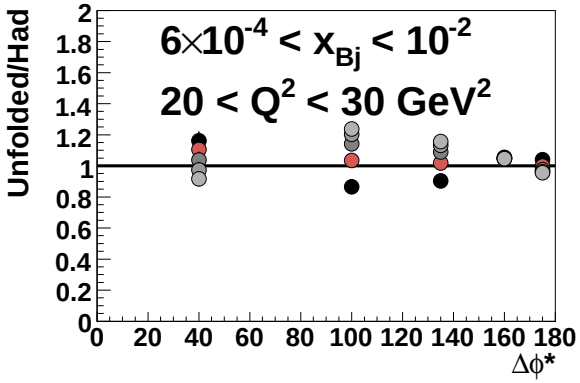


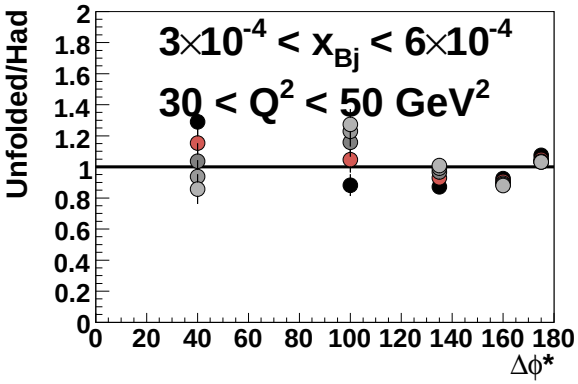


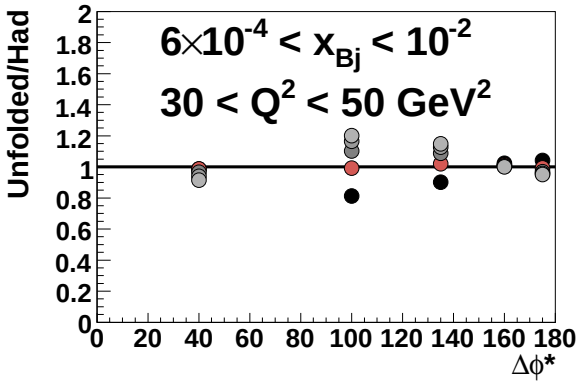


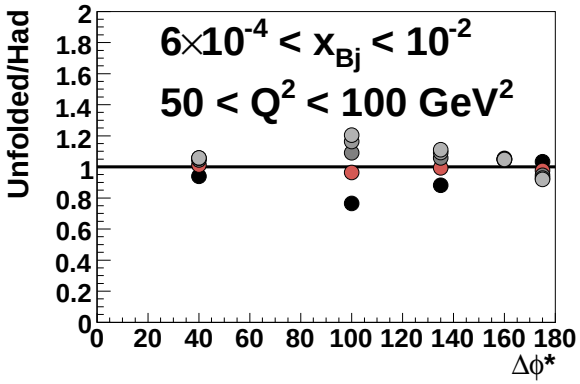
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$



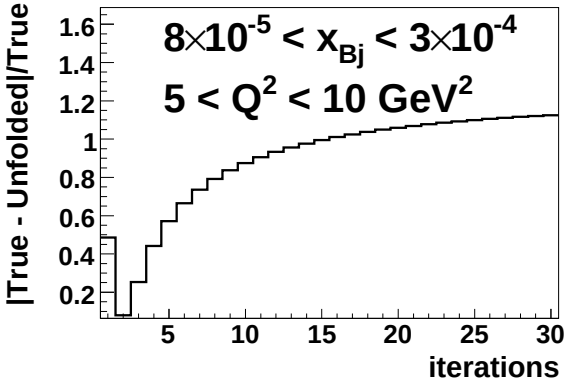


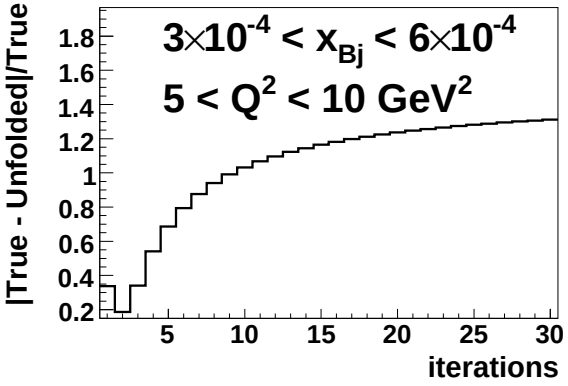


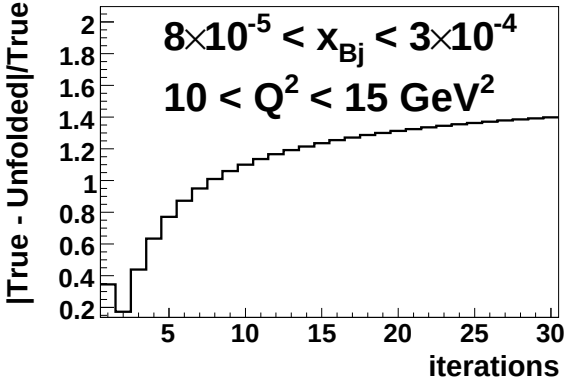


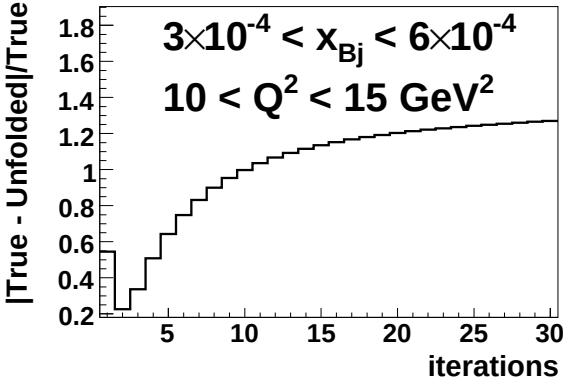


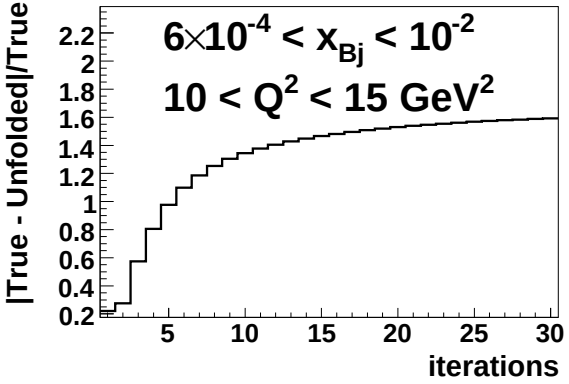
Bayes Unfolding - Unfold Rapgap using Django NRad - $\frac{d^3\sigma}{dx_{bj}\,dQ^2\,d\Delta\phi^*}$

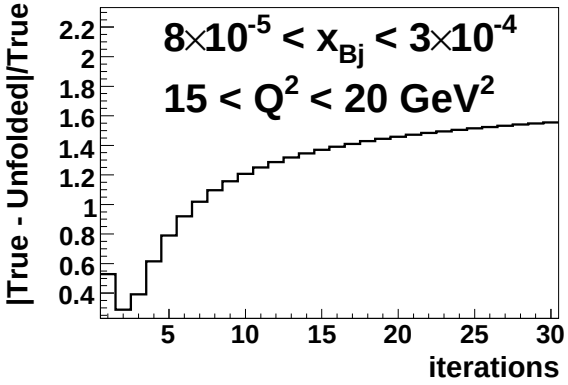


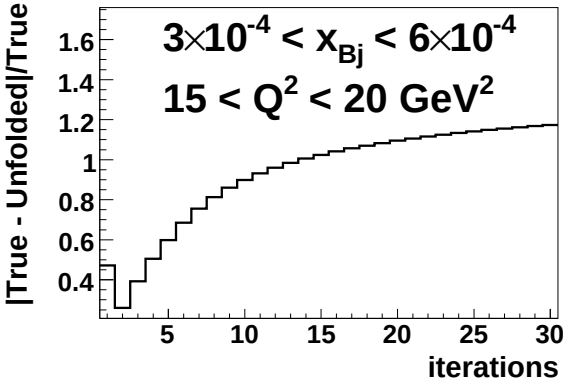


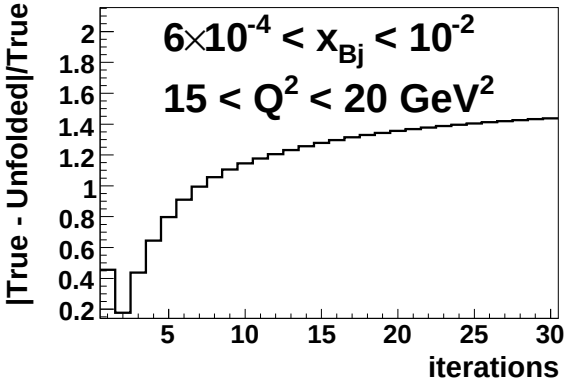












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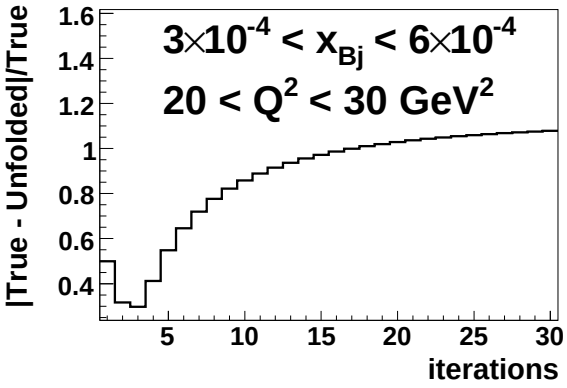

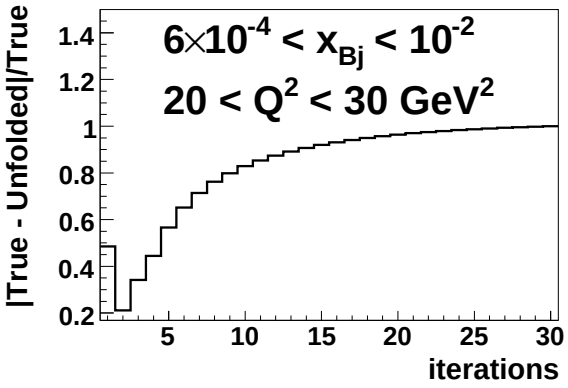

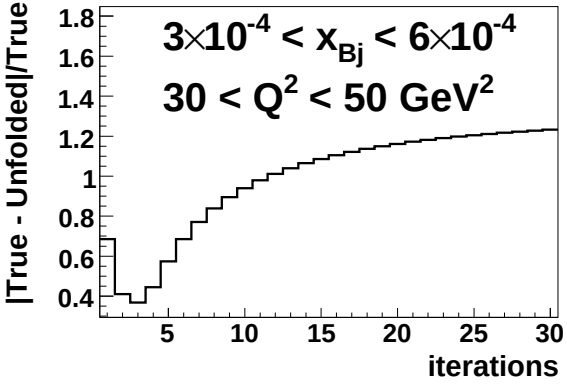

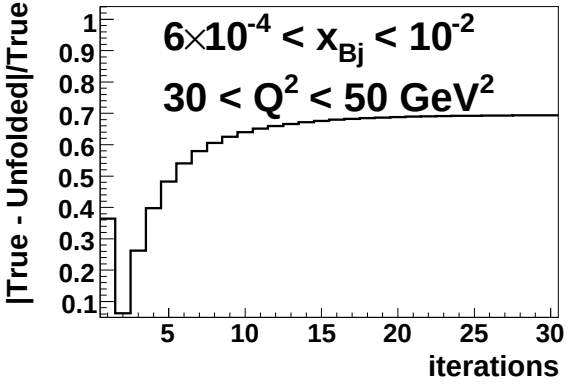

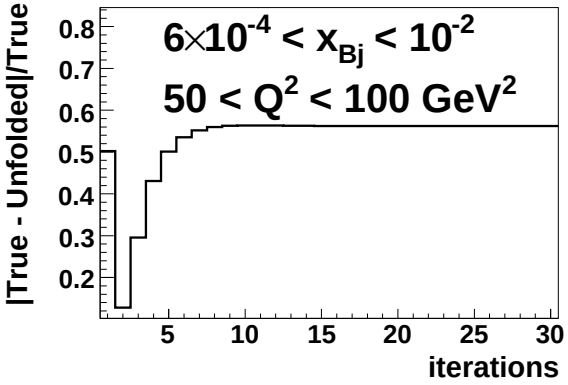

uPDF Fit

Parameters of Best Fit:

χ^2/ndf	N	B	μ	σ
1.85	0.2566	0.2920	1.5000	1.5000