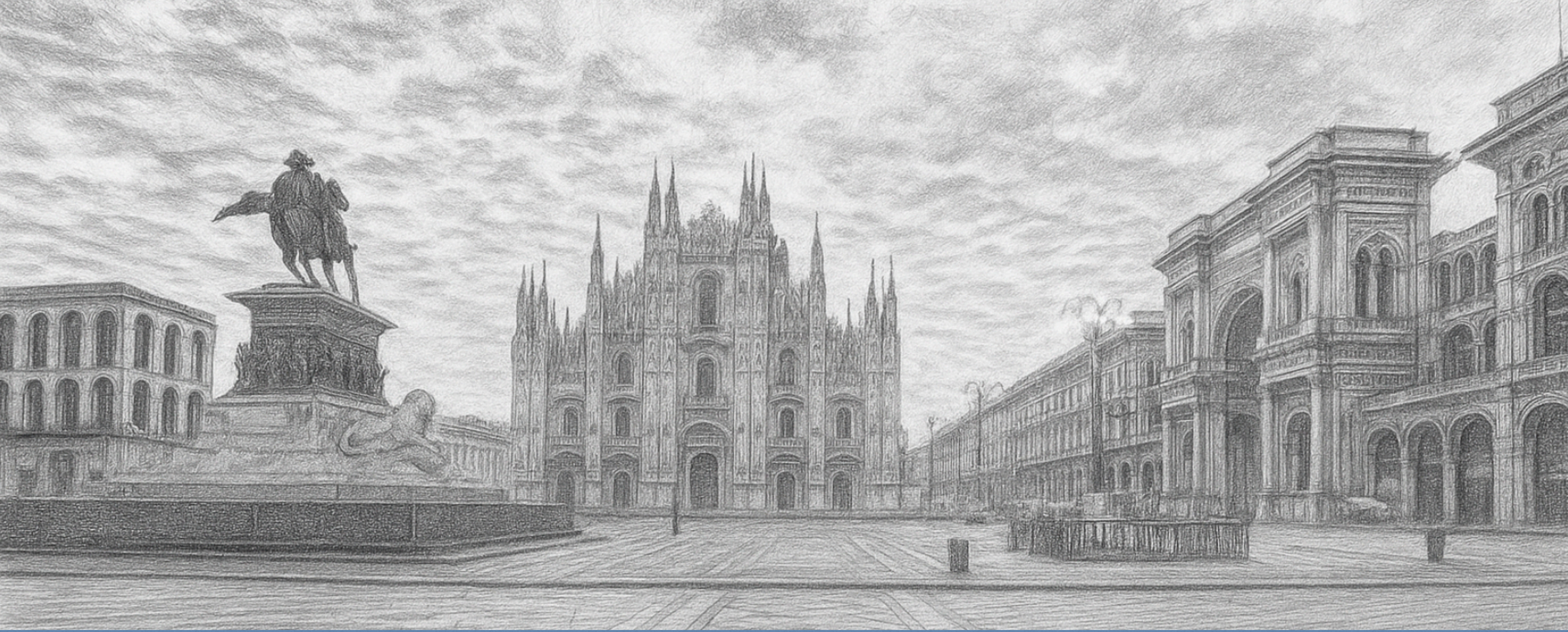


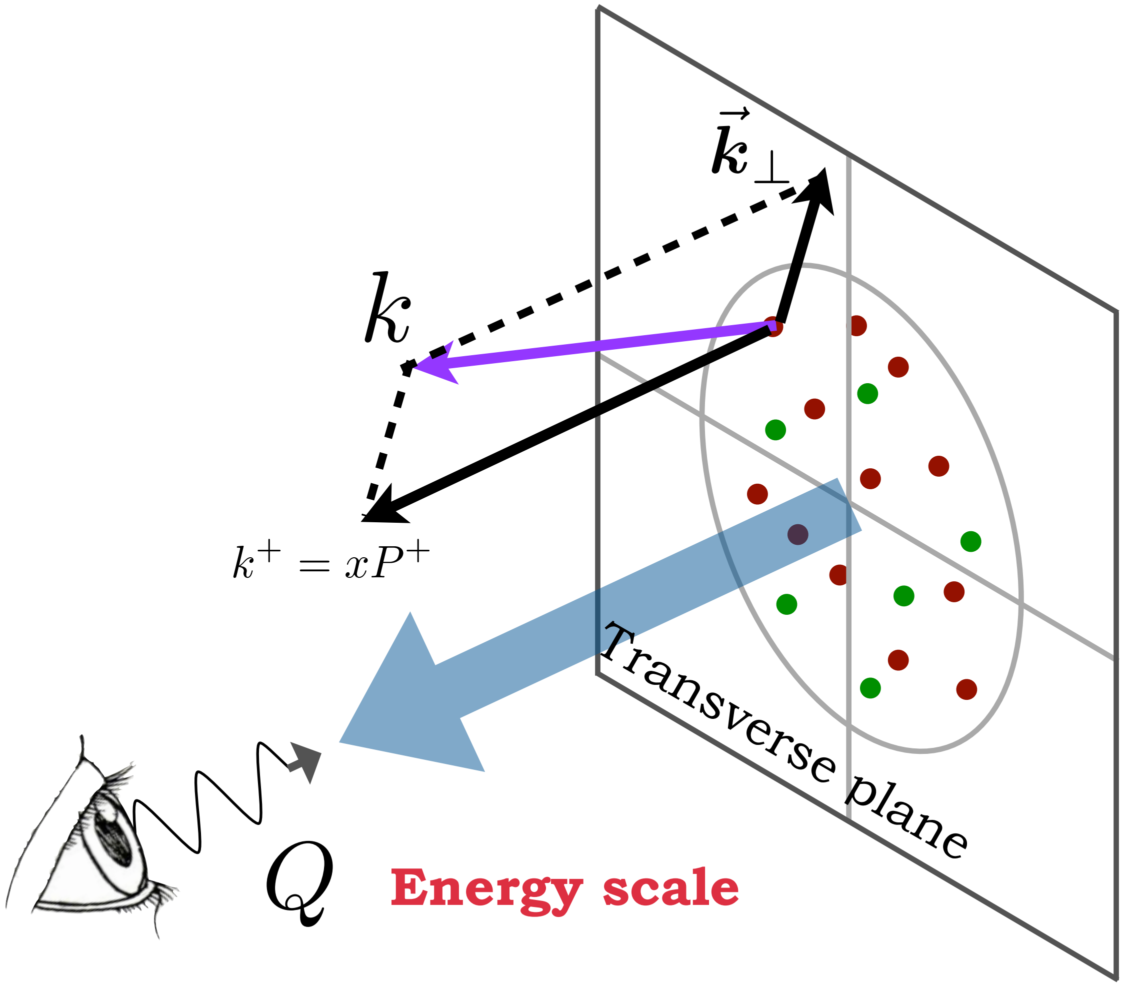
First Neural-Network Extraction of Unpolarized Transverse-Momentum-Dependent Distributions

Matteo Cerutti
MAP Collaboration, PRL 135 2025

Transverse-Momentum Distributions (TMDs)

3-***dimensional*** ***map*** of the internal structure of the nucleon

Non-collinear framework



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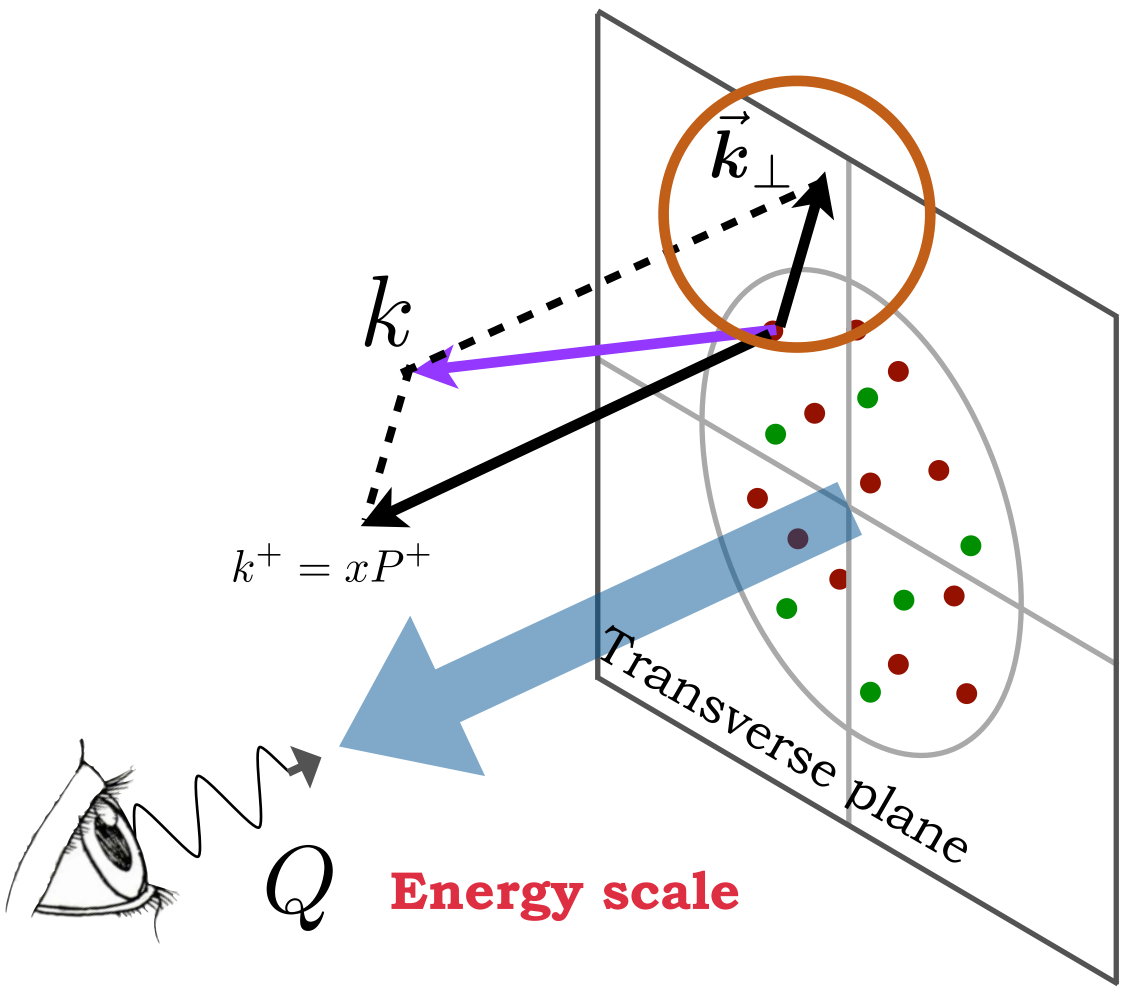

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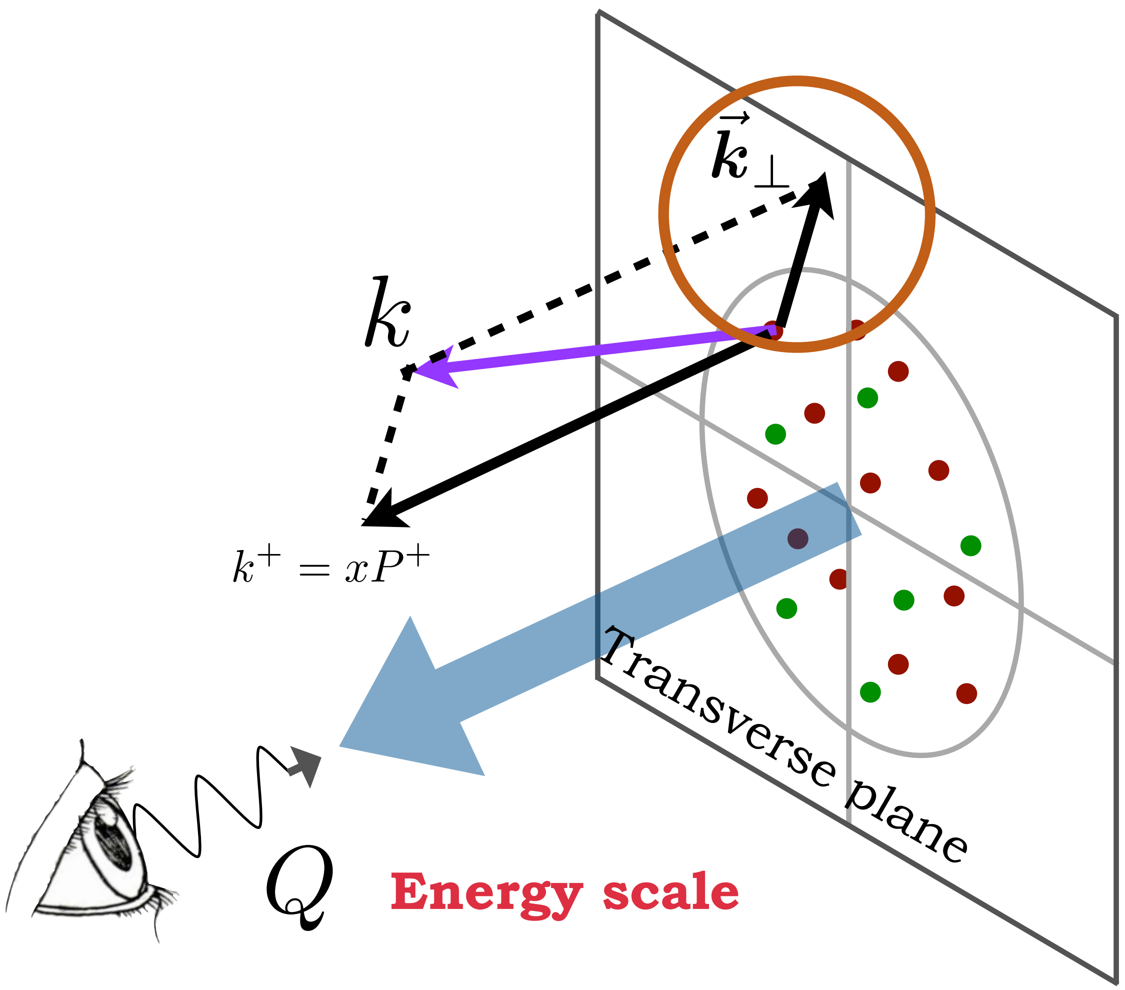

Quark Polarization

Nucleon Pol.

	U	L	T
U	f_1		$h_1^\perp$
L		g_1	$h_{1L}^\perp$
T	$f_{1T}^\perp$	g_{1T}	h_1 $h_{1T}^\perp$

Time-reversal odd

Time-reversal even

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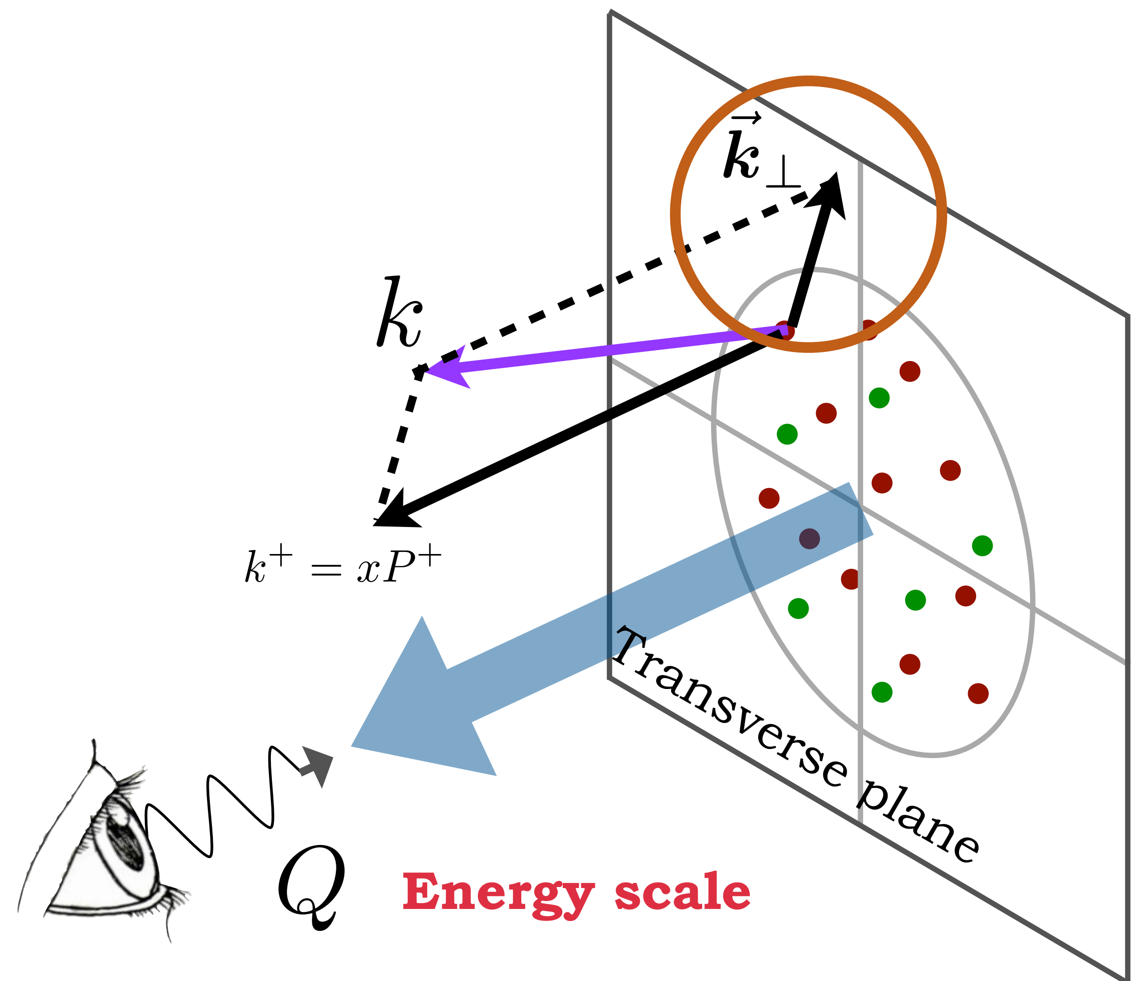
T	$f_{1T}^{\perp}$	g_{1T}	$h_1 \, h_{1T}^{\perp}$

Time-reversal odd   Time-reversal even

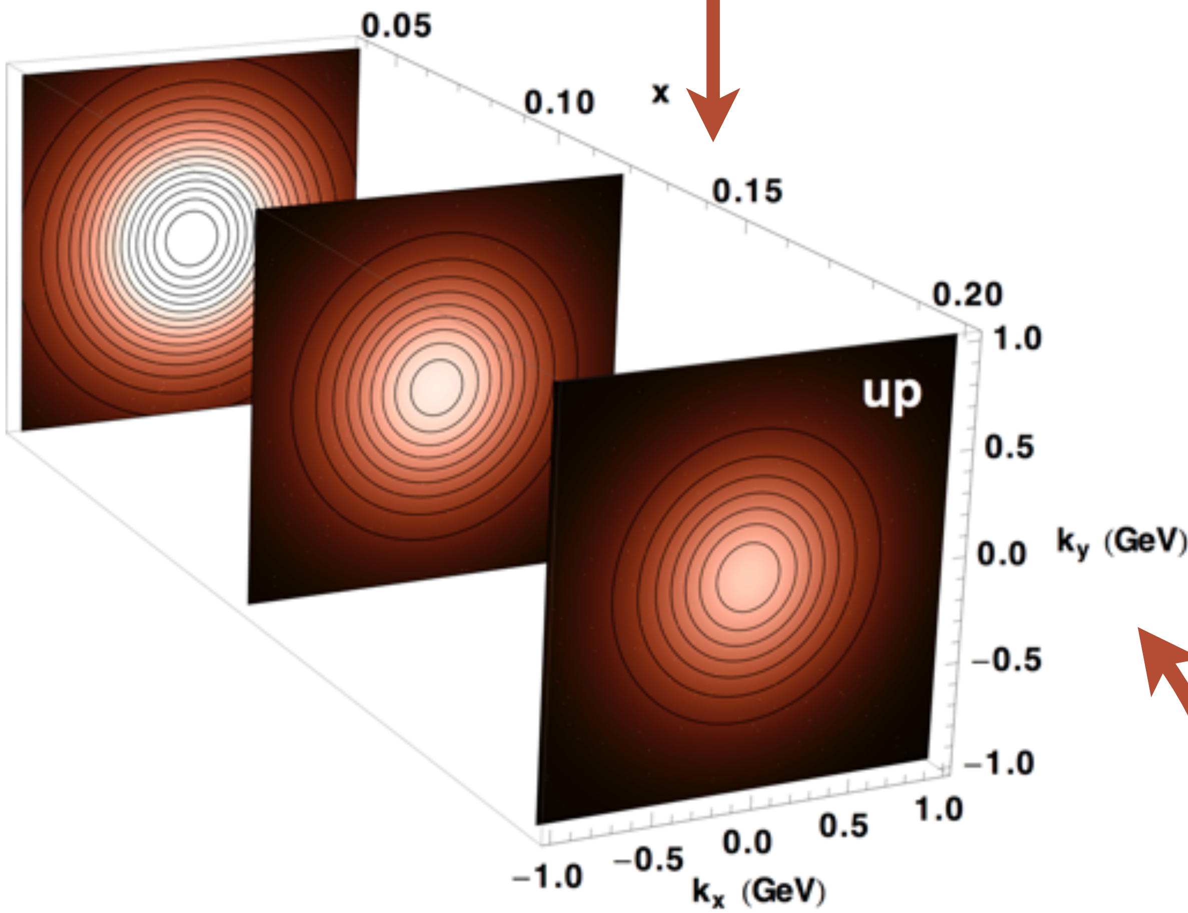


TMD PDFs

$$F(x, \boldsymbol{k}_{\perp}^2, \mu, \zeta)$$

Transverse-Momentum Distributions (TMDs)

Fraction of
longitudinal momentum



Transverse momentum

TMDs map the distribution of partons inside the nucleon in 3D in momentum space.

They can be extracted through ***global fits***
There are attempts to calculate them in lattice QCD

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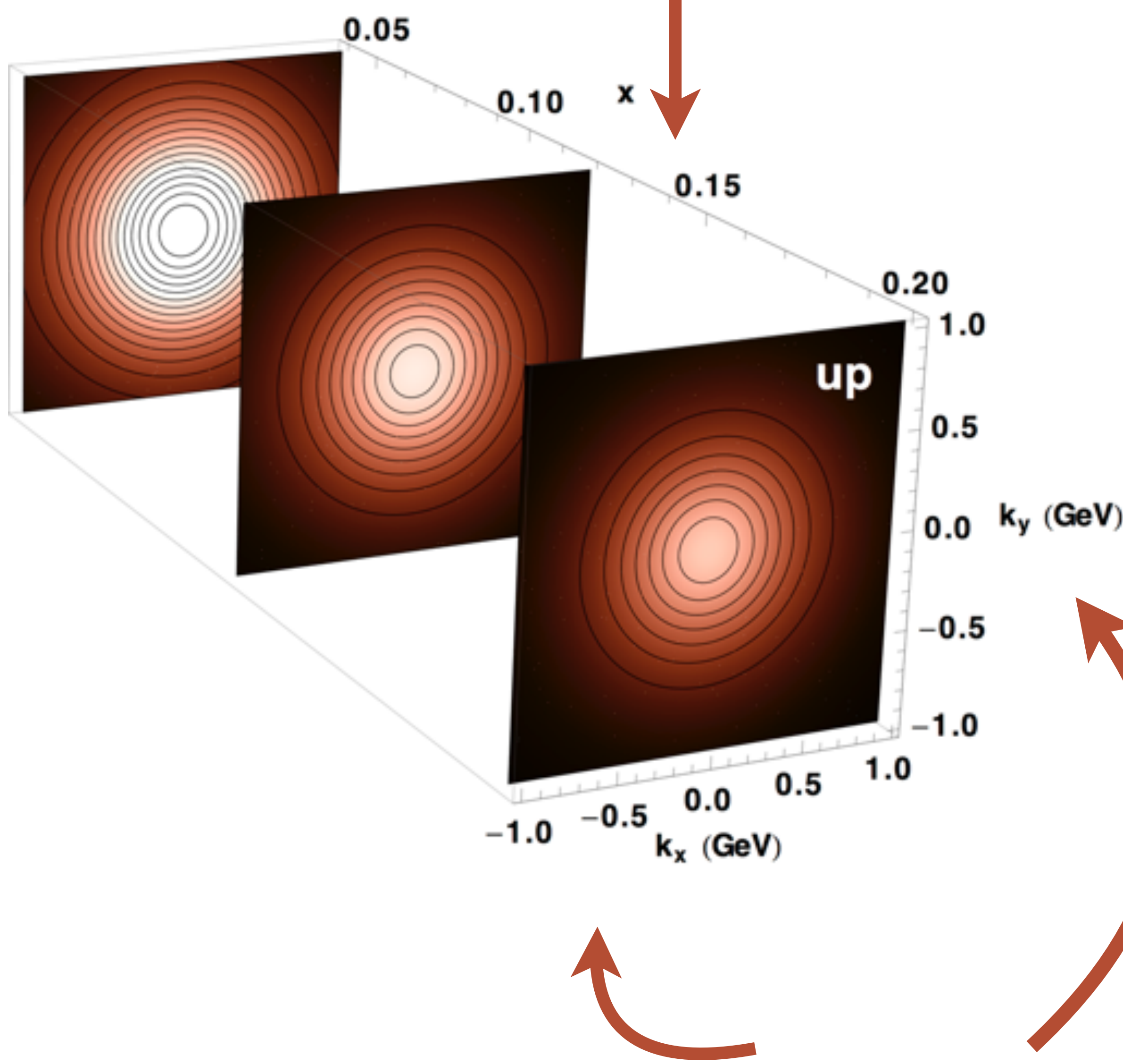

Transverse momentum

TMDs map the distribution of partons inside the nucleon in 3D in momentum space.

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Are TMDs universal?

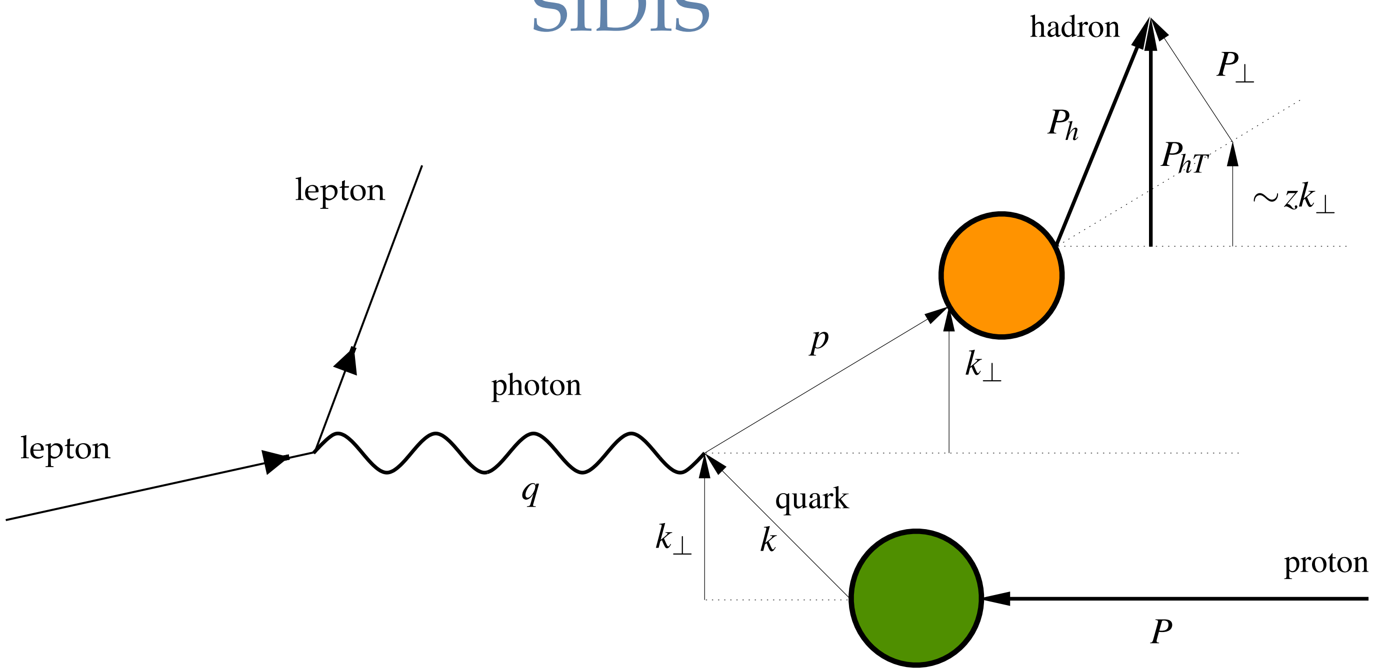
Do they depend on x?

Do they depend on the quark flavor?

TMD factorization: Universality

TMD factorization: Universality

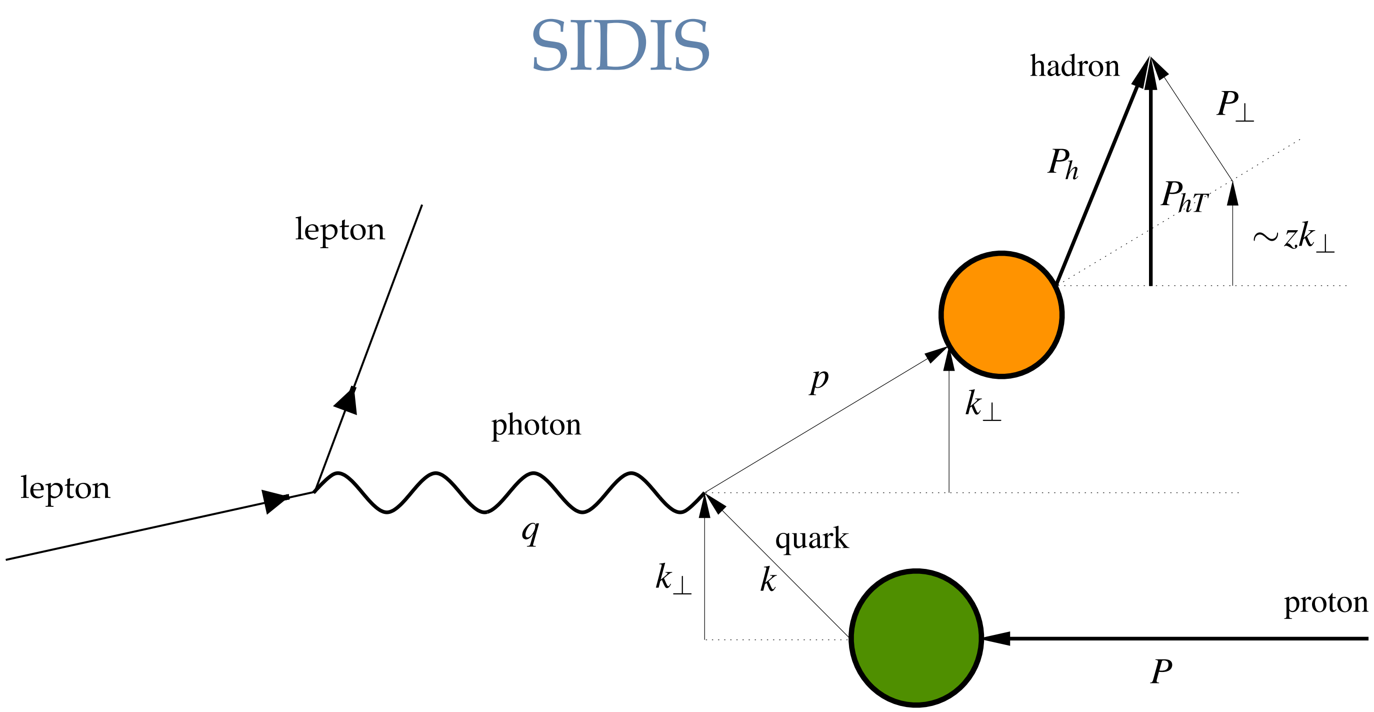
SIDIS

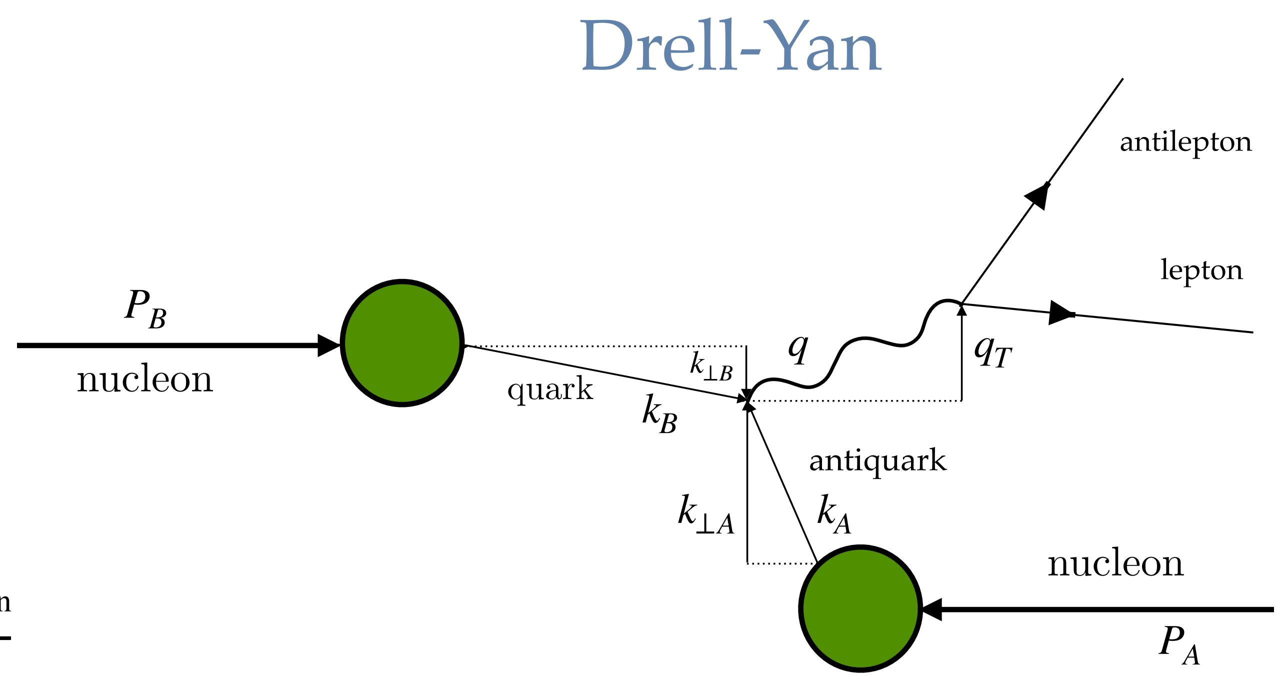


If $q_T^2 \ll Q^2$

$$F_{UU,T}\big(x, z, |\boldsymbol{q}_T|, Q\big) \sim \int_0^{+\infty} d|\boldsymbol{b}_T||\boldsymbol{b}_T| J_0\big(|\boldsymbol{b}_T||\boldsymbol{q}_T|\big)\, \hat{f}_1^a(x, b_T^2; \mu, \zeta_A)\, \hat{D}_1^{a\to h}(z, b_T^2; \mu, \zeta_B)$$

TMD factorization: Universality





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TMD factorization: Universality

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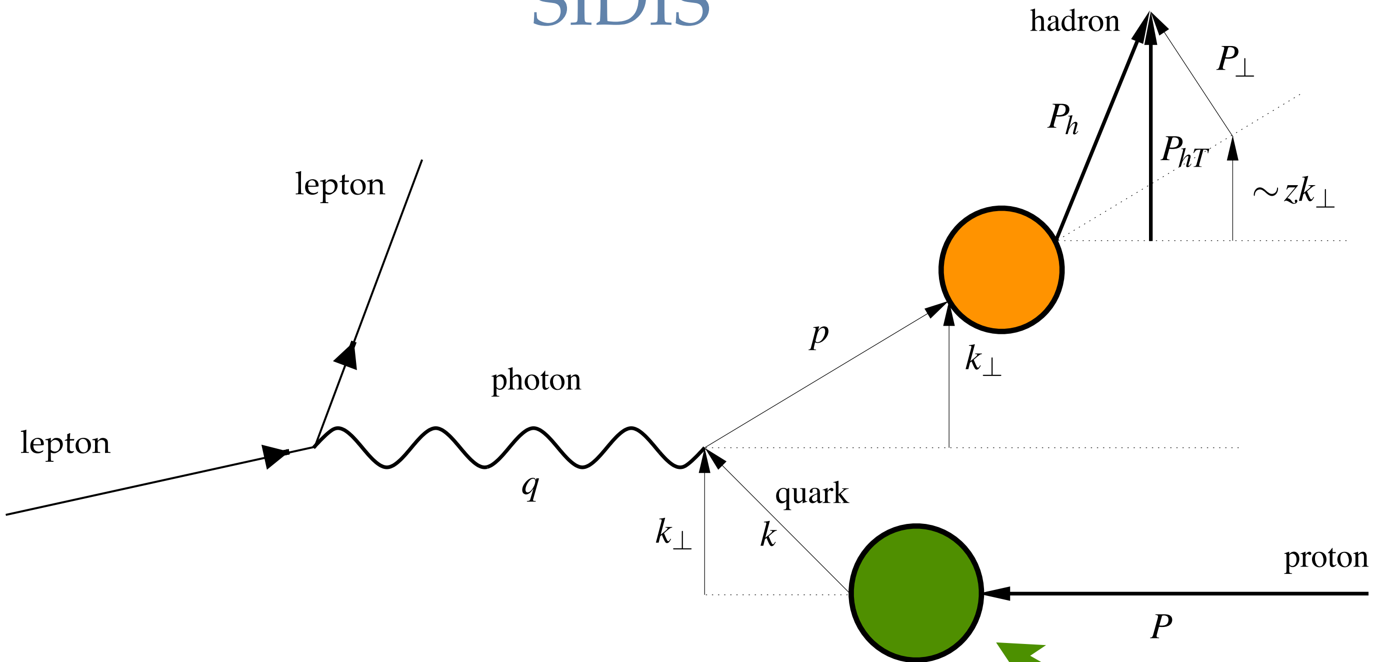
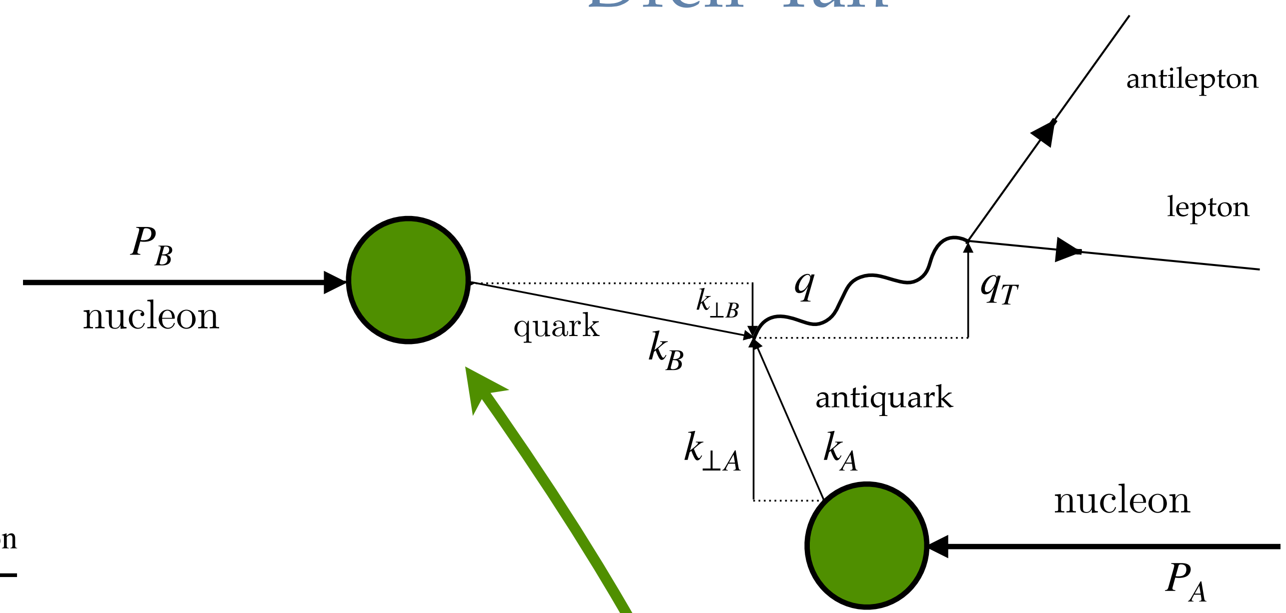


Drell-Yan



Same functions

If $q_T^2 \ll Q^2$

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TMD factorization: Universality

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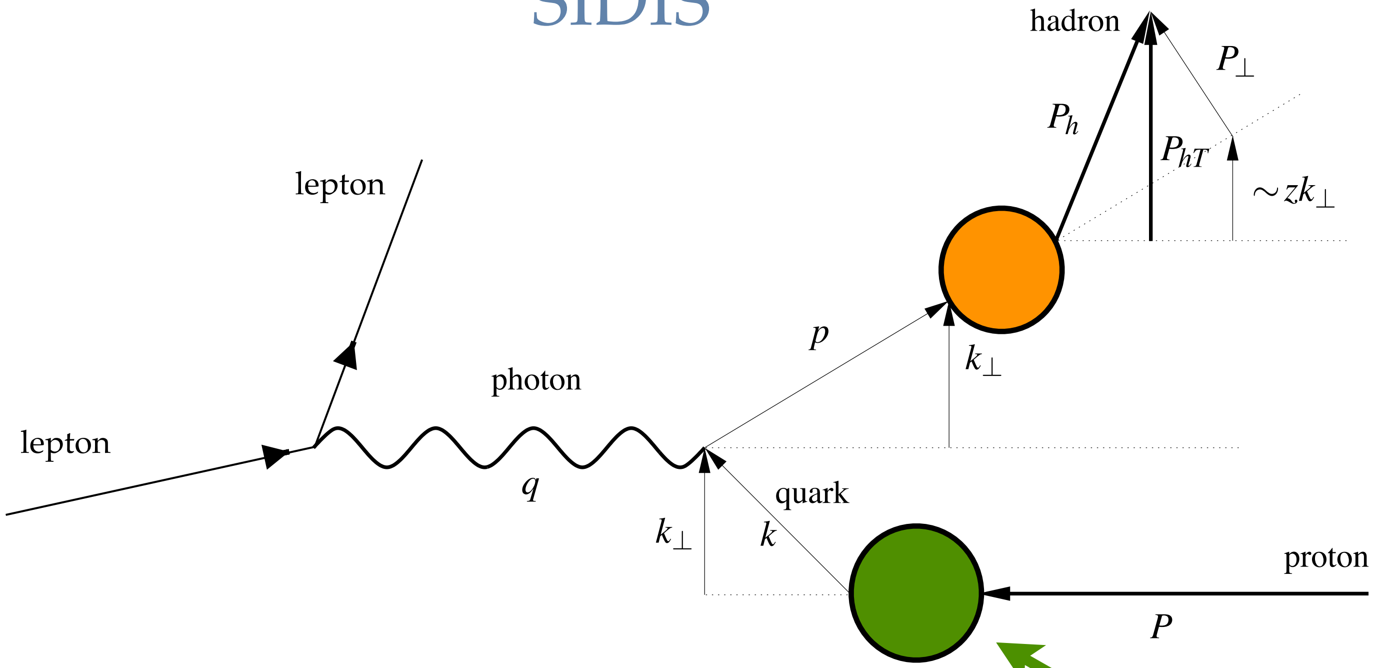

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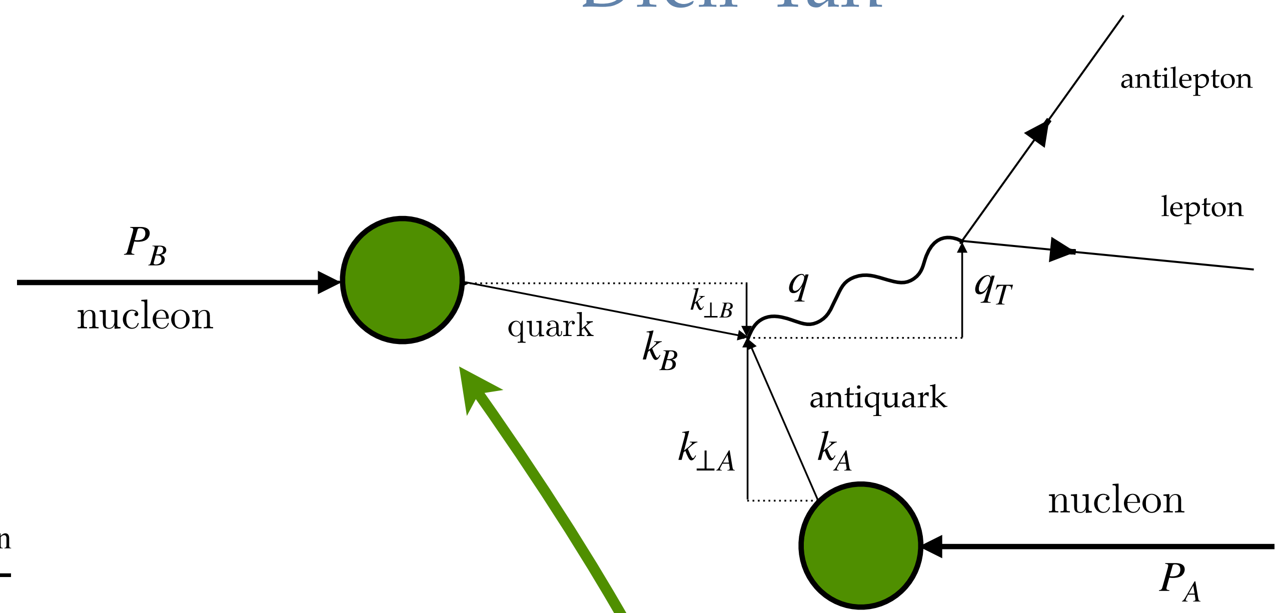

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GLOBAL FITs

Structure of a TMD

TMD in Fourier space

$$\hat{F}(x, b_T^2; \mu, \zeta) = \int \frac{d^2\boldsymbol{k}_\perp}{(2\pi)^2} e^{i\boldsymbol{b}_T \cdot \boldsymbol{k}_\perp} F(x, k_\perp^2; \mu, \zeta)$$

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J. Collins, “Foundation of Perturbative QCD”

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Perturbative TMD at the initial scale

J. Collins, “Foundation of Perturbative QCD”

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Perturbative TMD at the initial scale

$$\times \exp\left\{ K(b_*; \mu_{b_*}) \ln \frac{\sqrt{\zeta}}{\mu_{b_*}} + \int_{\mu_{b_*}}^{\mu} \frac{d\mu'}{\mu'} \left[\gamma_F - \gamma_K \ln \frac{\sqrt{\zeta}}{\mu'} \right] \right\} \qquad : \mathrm{B}$$

Evolution to final scale (of the process)

J. Collins, "Foundation of Perturbative QCD"

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Evolution to final scale (of the process)

$$\times f_{NP}(x, b_T^2) \exp\left\{g_K(b_T^2) \ln\frac{\sqrt{\zeta}}{\sqrt{\zeta_0}}\right\} \qquad : \mathrm{C}$$

Non-perturbative part of the TMD

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Non-perturbative part of the TMD

Parameterization

J. Collins, "Foundation of Perturbative QCD"

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Non-perturbative part of the TMD

Parameterization

GLOBAL FITs

J. Collins, "Foundation of Perturbative QCD"

Available Global Fits

	Accuracy	*SIDIS*	*DY*	*N of points*	*χ^2/N_{data}*	*Flavor Dependence*
Pavia 2017 Bacchetta, Delcarro, et al., JHEP 06 (2017)	NLL	✔	✔	8059	1.55	✘
SV 2019 Scimemi, Vladimirov, JHEP 06 (2020)	N^3LL^-	✔	✔	1039	1.06	✘
MAPTMD22 Bacchetta, Bertone, et al., JHEP 10 (2022)	N^3LL^-	✔	✔	2031	1.06	✘
MAPTMD24 Bacchetta, Bertone, et al., JHEP 08 (2024)	**N^3LL**	✔	✔	**2031**	**1.08**	✔
ART25 Moos, Scimemi, et al., arXiv:2503.11201	N^3LL^+	✔	✔	1209	1.05	✔

Motivation

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- Current extractions of TMDs show incompatibilities

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$\Rightarrow$ fit *for the first time* TMDs with Neural Networks

Motivation

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GOAL:

Reduce the parameterization bias

$\Rightarrow$ fit *for the first time* TMDs with Neural Networks

Is this approach applicable to this complex task?

Do they offer advantages in the description of the exp. data

Is the approach scalable?

TMD fitting framework

NangaParbat

https://github.com/MapCollaboration/NangaParbat

README.md

Nanga Parbat is a fitting framework aimed at the determination of the non-perturbative component of TMD distributions.

Download

You can obtain NangaParbat directly from the github repository:

https://github.com/MapCollaboration/NangaParbat

For the last development branch you can clone the master code:

```
git clone git@github.com:MapCollaboration/NangaParbat.git
```

Included data sets

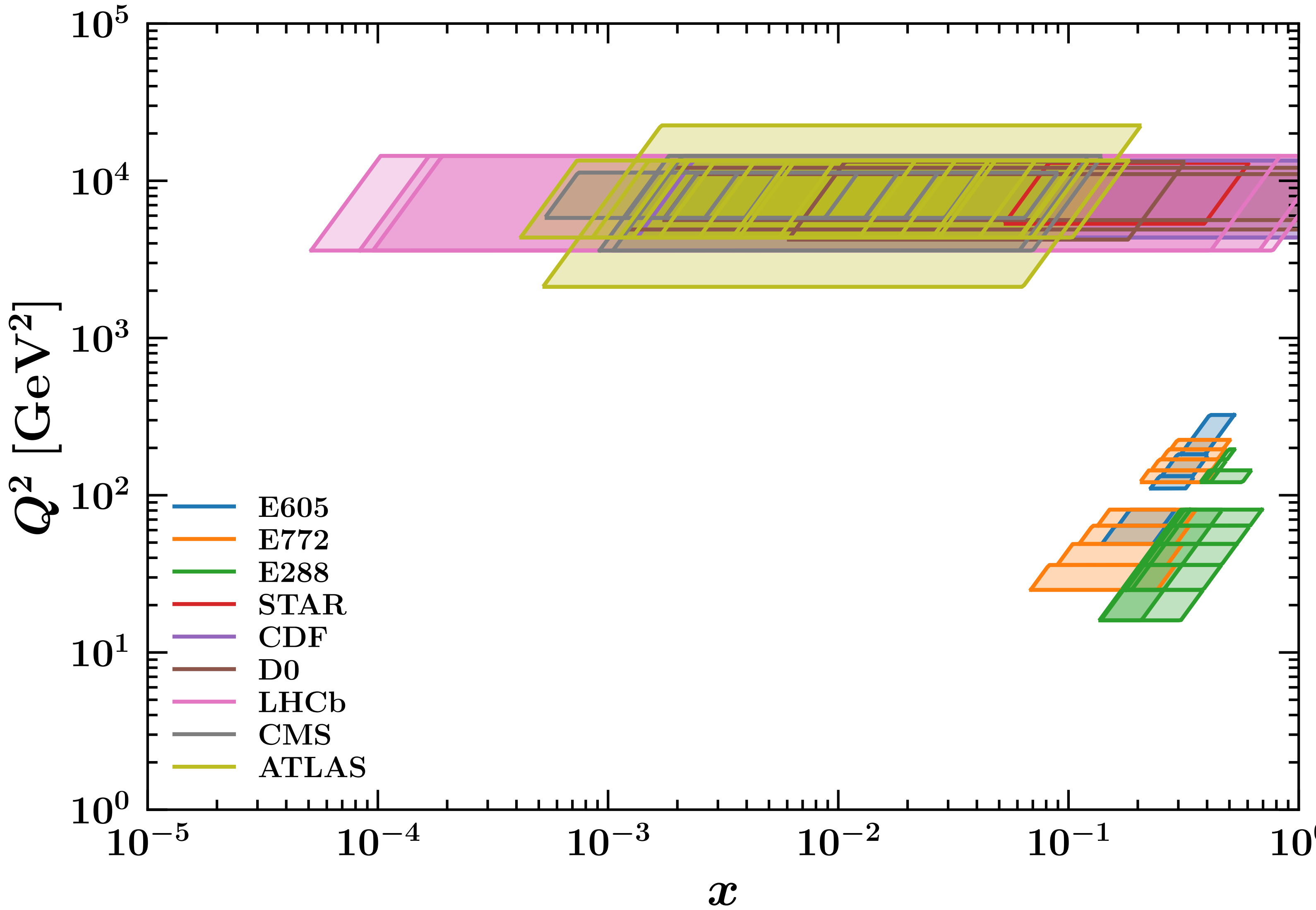
Drell-Yan data

Fixed-target:

E288, E605, E772

Collider mode:

RHIC, Tevatron, LHC



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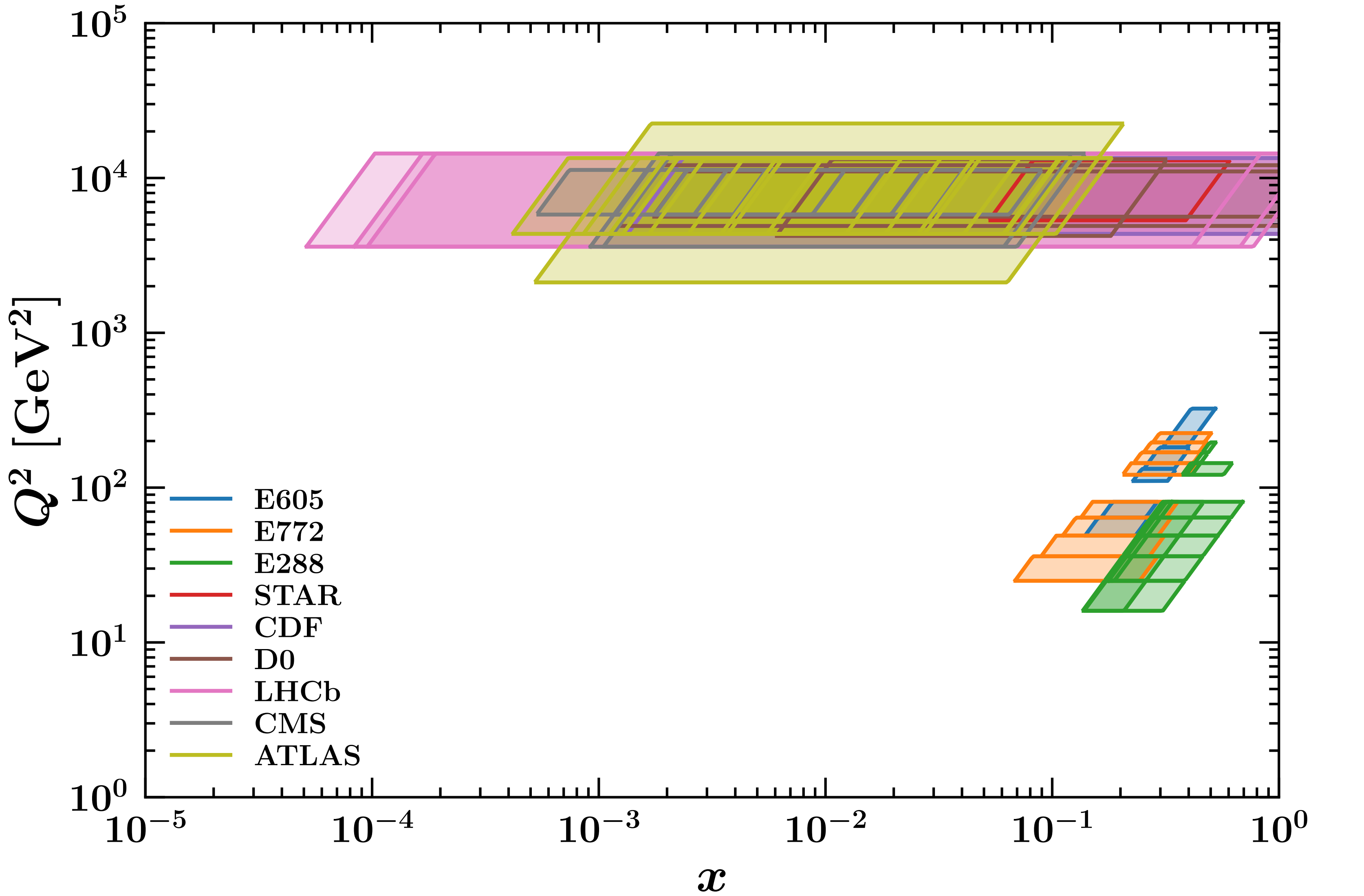
$q_T/Q < 0.2$



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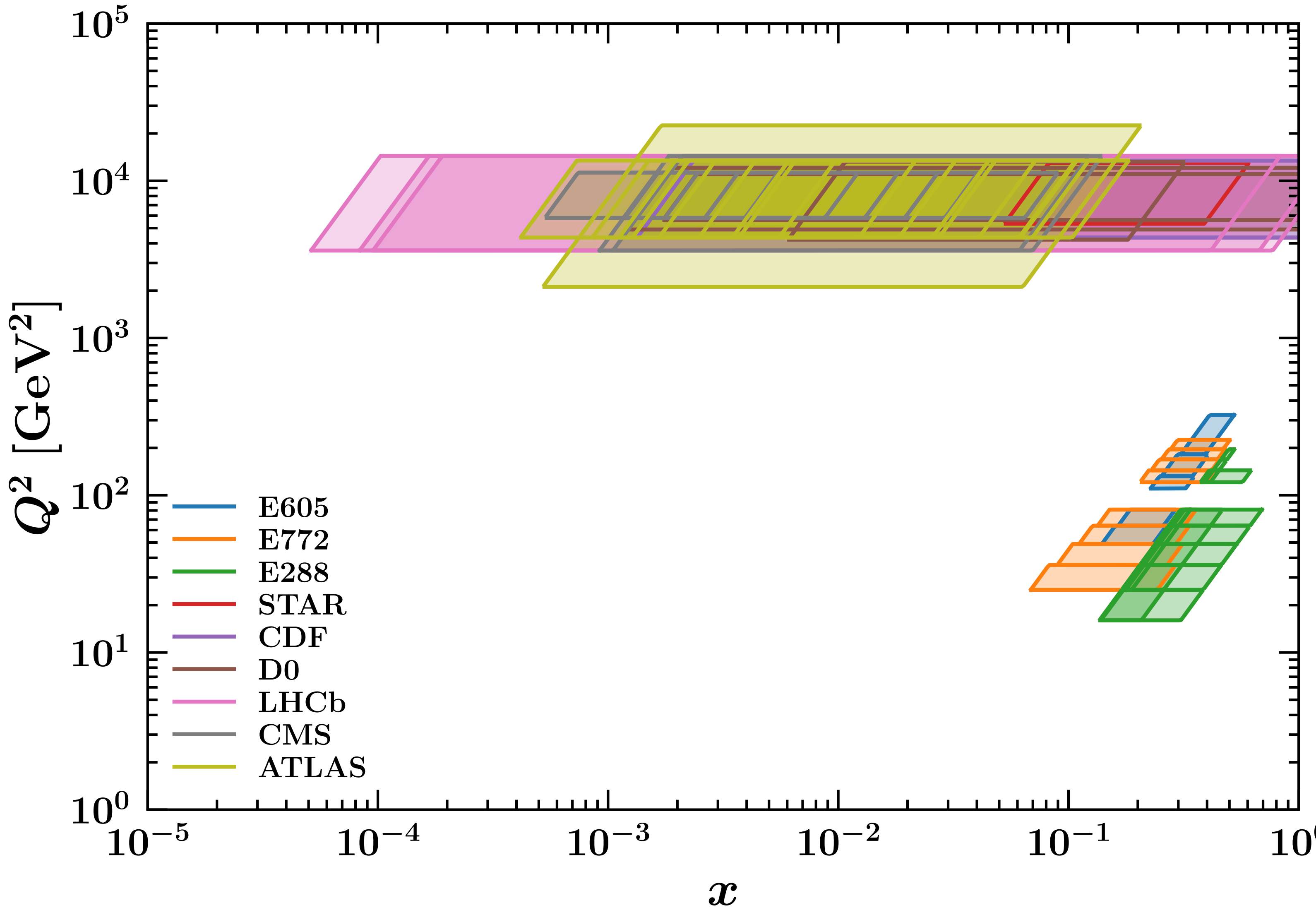

Total number of data: 482

Parameterization: NN

MAP Collaboration, PRL 135 (2025)

$$f_{\mathrm{NP}}(x, b_T; \zeta) \;=\; \frac{\mathbb{N}\mathbb{N}\big(x, b_T, \{p_i\}\big)}{\mathbb{N}\mathbb{N}\big(x, 0, \{p_i\}\big)} \;\exp\!\left[-\, g_2^2\, b_T^2\; \ln\!\left(\frac{\zeta}{Q_0^2}\right)\right]$$

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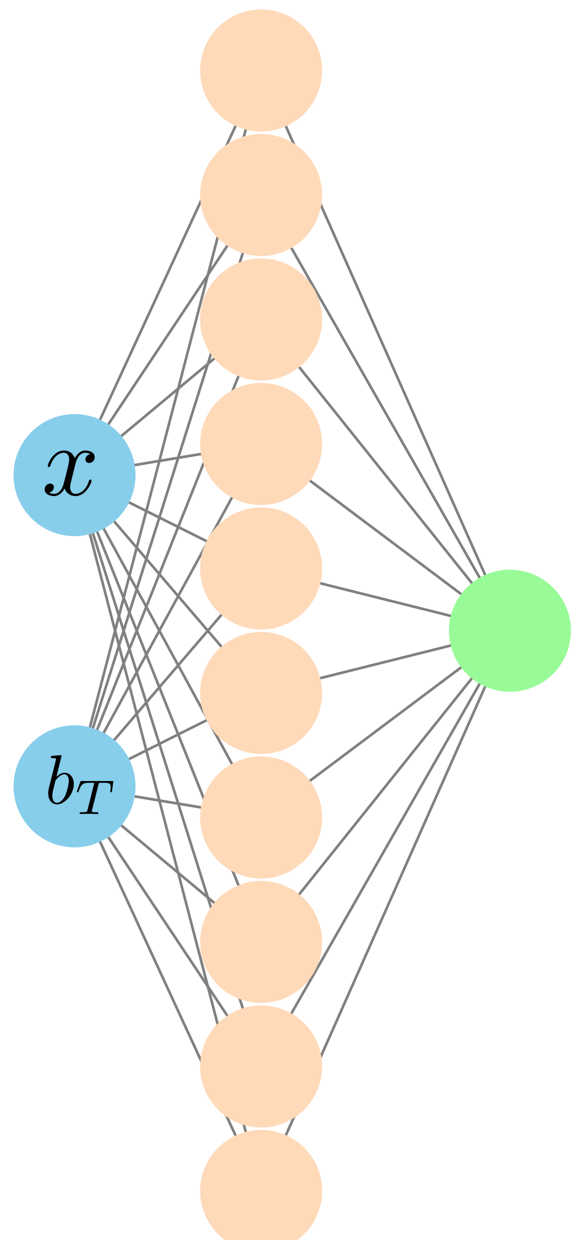

$$\mathbb{NN}(x, b_T)$$

only one output node because there is no flavor dependence (yet)

Parameterization: NN

MAP Collaboration, PRL 135 (2025)

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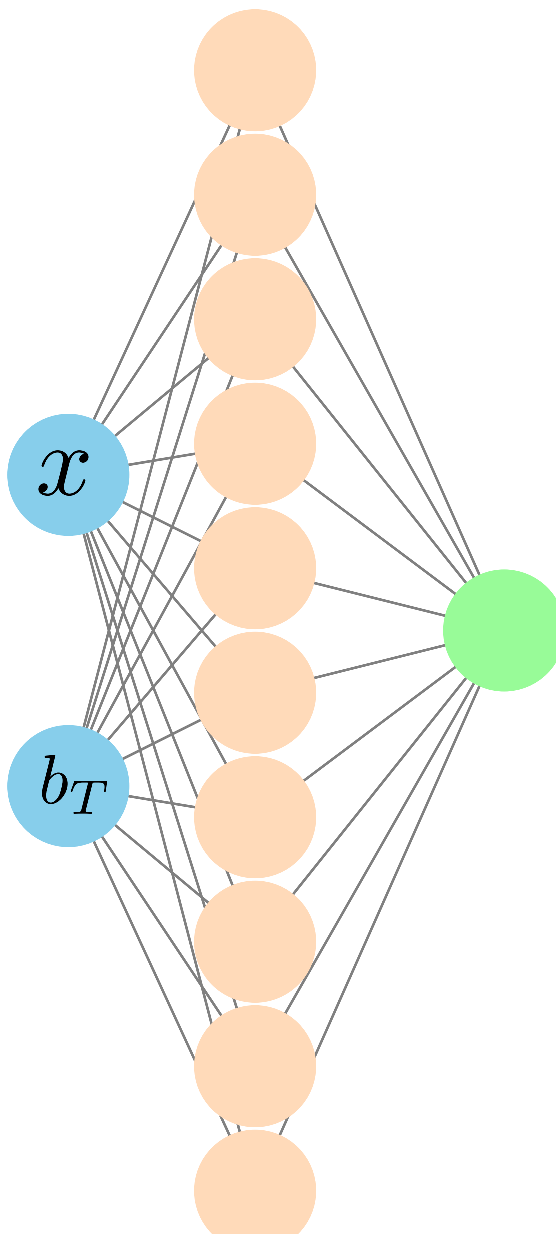


$$\mathbb{N}\mathbb{N}(x, b_T)$$

only one output node because there is no flavor dependence (yet)

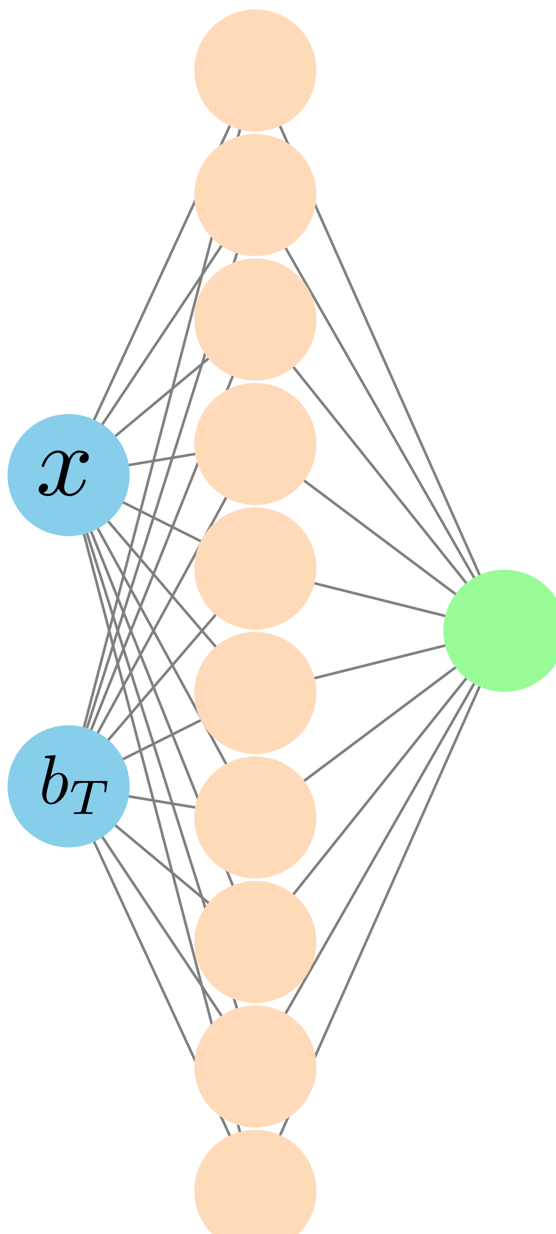
with activation function

$$\sigma(z) = \frac{1}{2}\left(1 + \frac{z}{1+|z|}\right)$$

Parameterization: NN

MAP Collaboration, PRL 135 (2025)

$$f_{\rm NP}(x, b_T; \zeta) = \frac{\mathbb{NN}\big(x, b_T, \{p_i\}\big)}{\mathbb{NN}\big(x, 0, \{p_i\}\big)} \exp\left[-g_2^2\, b_T^2\, \ln\left(\frac{\zeta}{Q_0^2}\right)\right]$$



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physically required constraints

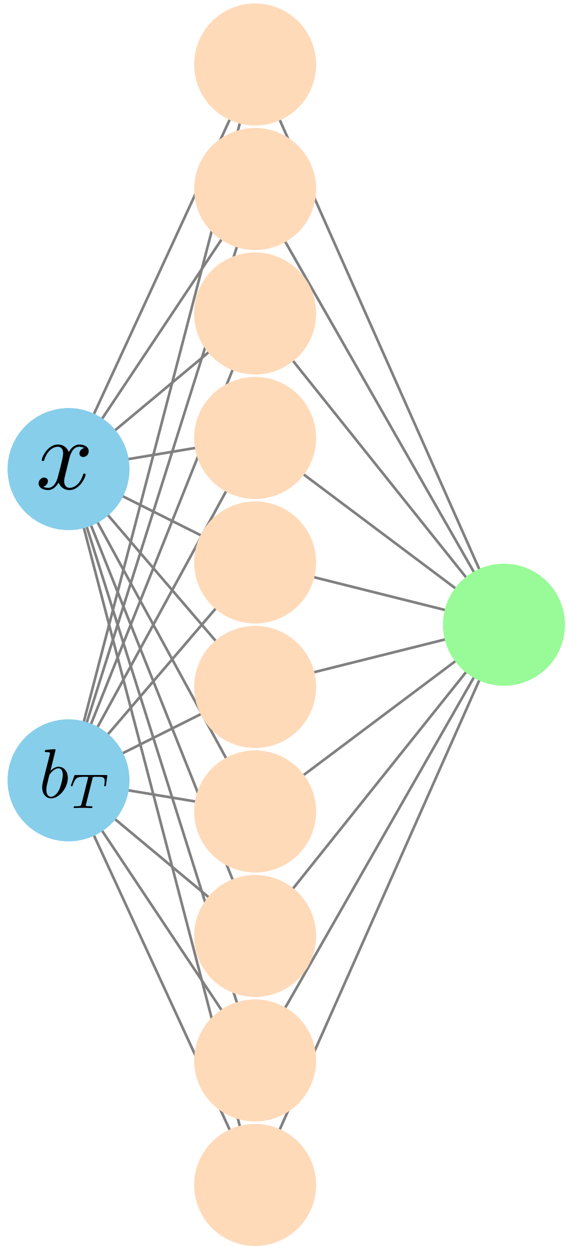
$f_{\rm NP} \to 1$ for $b_T \to 0$

Parameterization: NN

MAP Collaboration, PRL 135 (2025)

$$f_{\mathrm{NP}}(x, b_T; \zeta) = \frac{\mathbb{NN}(x, b_T, \{p_i\})}{\mathbb{NN}(x, 0, \{p_i\})} \exp\left[-g_2^2\, b_T^2\, \ln\left(\frac{\zeta}{Q_0^2}\right)\right]$$

41+1 parameters



$$\mathbb{NN}(x, b_T)$$

only one output node because there is no flavor dependence (yet)

with activation function

$$\sigma(z) = \frac{1}{2}\left(1 + \frac{z}{1+|z|}\right)$$

physically required constraints

$f_{\mathrm{NP}} \to 1$ for $b_T \to 0$

Validation of the methodology

Closure Tests

Validation of the methodology

Closure Tests

- Level 0: *pseudodata given by prediction of known model*

  no Monte Carlo noise added on top of pseudodata

  fit the same pseudo data set but with different initial parameters

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  fit of Monte Carlo replicas

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Closure Tests - level 0

Generation of pseudo data from a known model

Validation of the methodology

Closure Tests - level 0

Generation of pseudo data from a known model

1. central value compute with **DWS model**

$$f_{\mathrm{NP}}^{\mathrm{DWS}}(b_T, \zeta) = \exp\left[-\frac{1}{2}\left(g_1 + g_2 \ln\left(\frac{\zeta}{2Q_0^2}\right)\right) b_T^2\right]$$

$$g_1 = 0.304$$
$$g_2 = 0.028$$

Bacchetta, Bertone, et al., JHEP 07 (2020)

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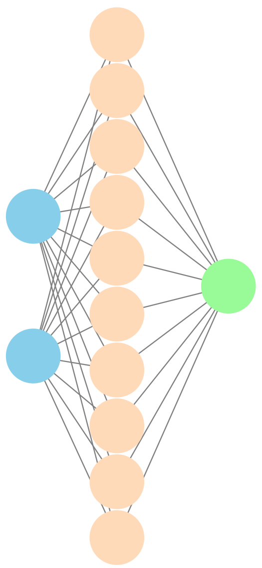
2. pseudodata errors from real DY data

fit with NN



can we recover the DWS result?

Validation of the methodology

Closure Tests - level 0

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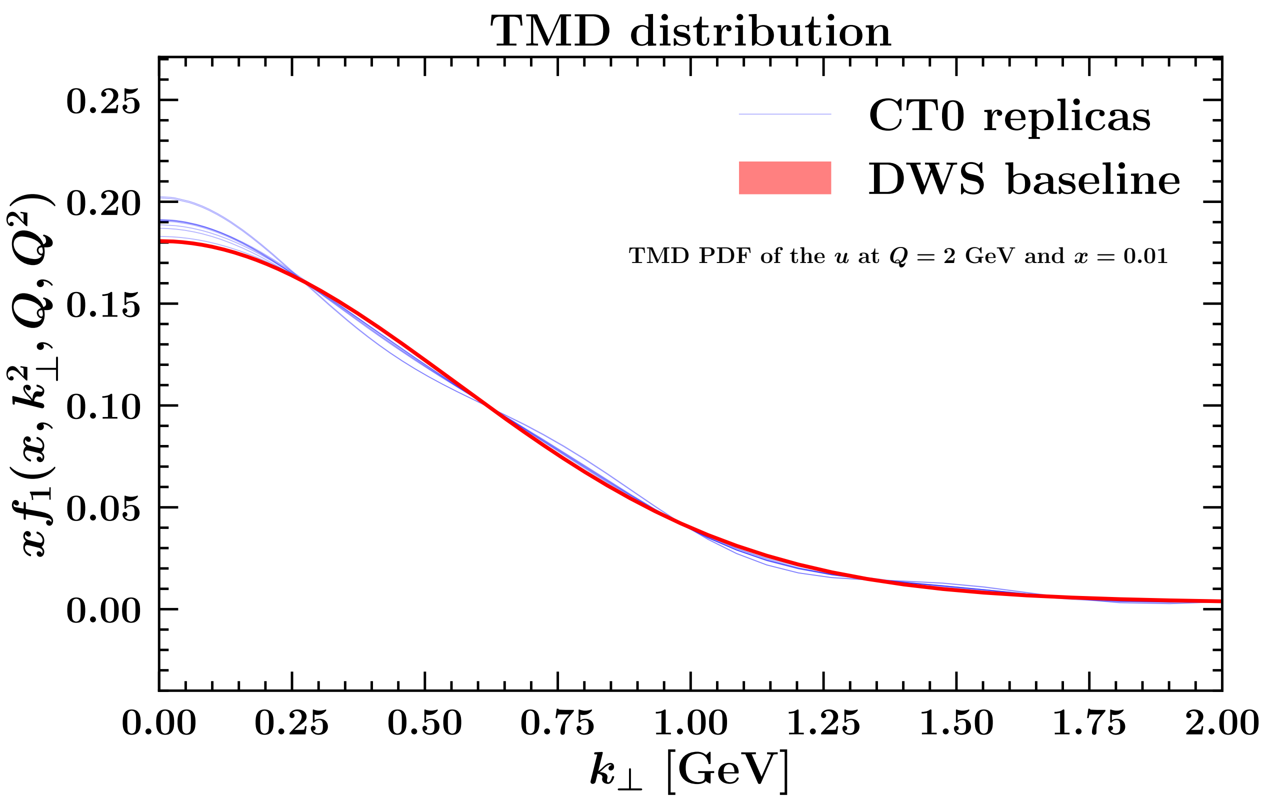
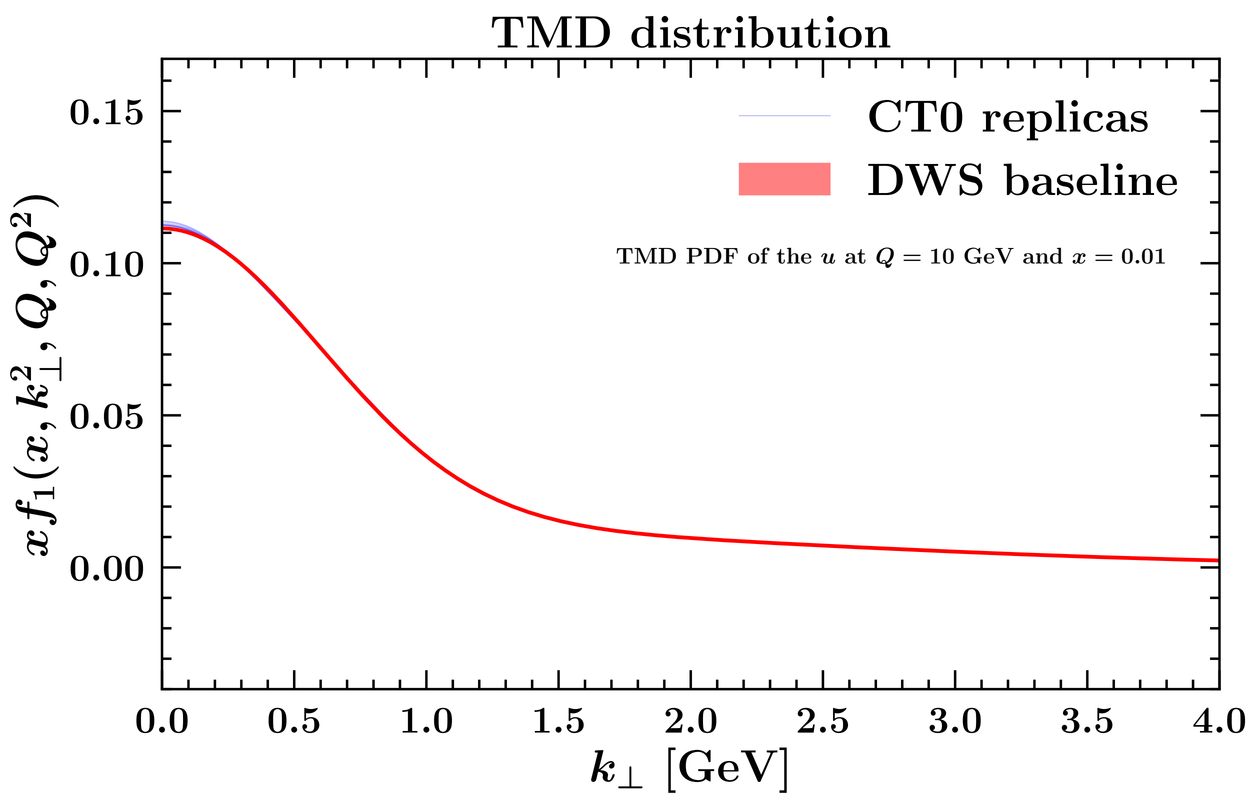




$$\chi^2 \sim 10^{-6}$$

Closure test successful!

Parameterization: MAP22

Bacchetta, Gamberg, Goldstein, et al., PLB 659 (2008)
Bacchetta, Conti, Radici, PRD 78 (2008)
Pasquini, Cazzaniga, Boffi, PRD 78 (2008)
Matevosyan, Bentz, Cloet, Thomas, PRD 85 (2012)

$$f_{1\mathrm{NP}}(x, b_T^2) \propto \text{F.T. of } \left(e^{-\frac{k_\perp^2}{g_{1A}}} + \lambda_B k_\perp^2 e^{-\frac{k_\perp^2}{g_{1B}}} + \lambda_C e^{-\frac{k_\perp^2}{g_{1C}}} \right)$$

$$g_1(x) = N_1 \frac{(1-x)^\alpha \; x^\sigma}{(1-\hat{x})^\alpha \; \hat{x}^\sigma}$$

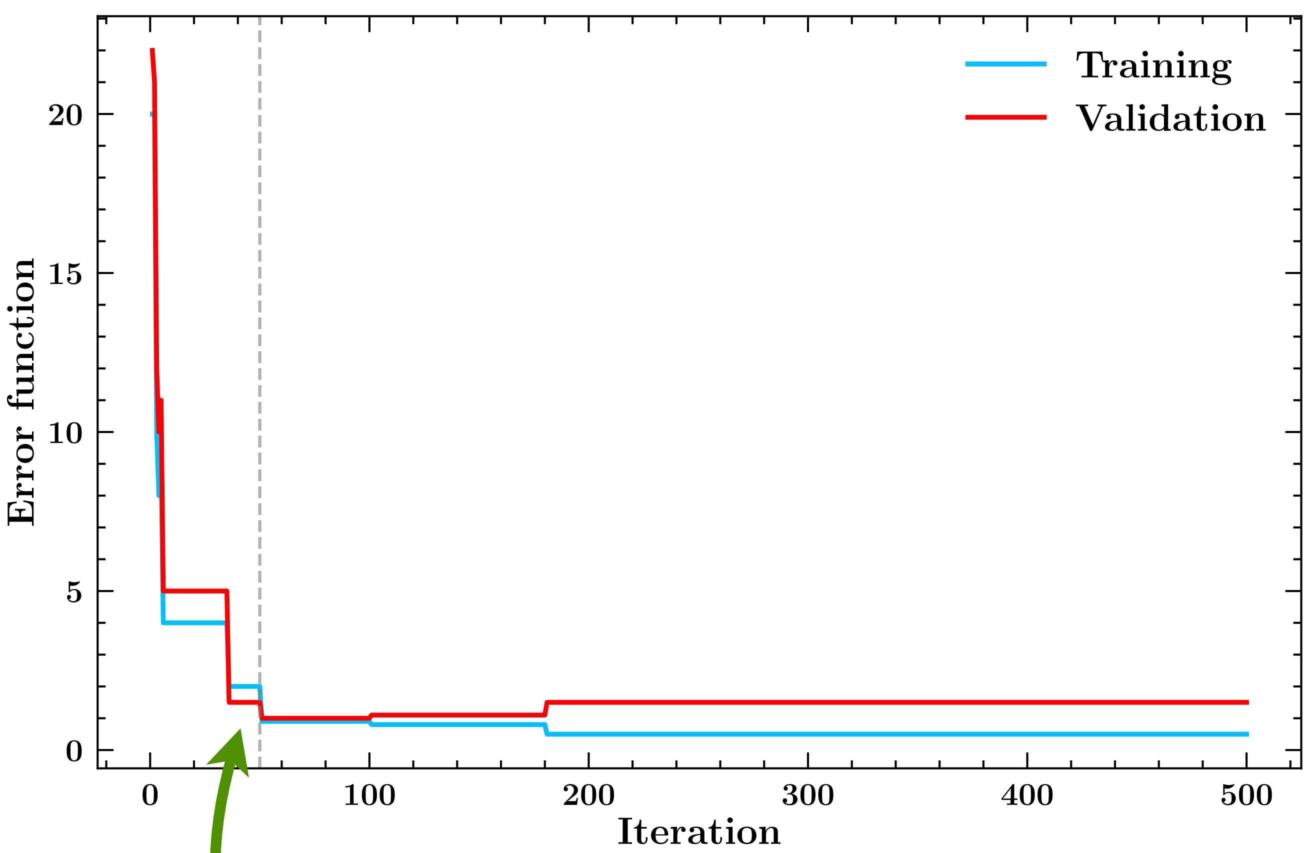
11+1 parameters

$$g_K(b_T^2) = -g_2^2 \frac{b_T^2}{4}$$

Gaussians and weighted-Gaussians: are they enough flexible?

Fitting procedure

Splitting the dataset into training / validation subsets

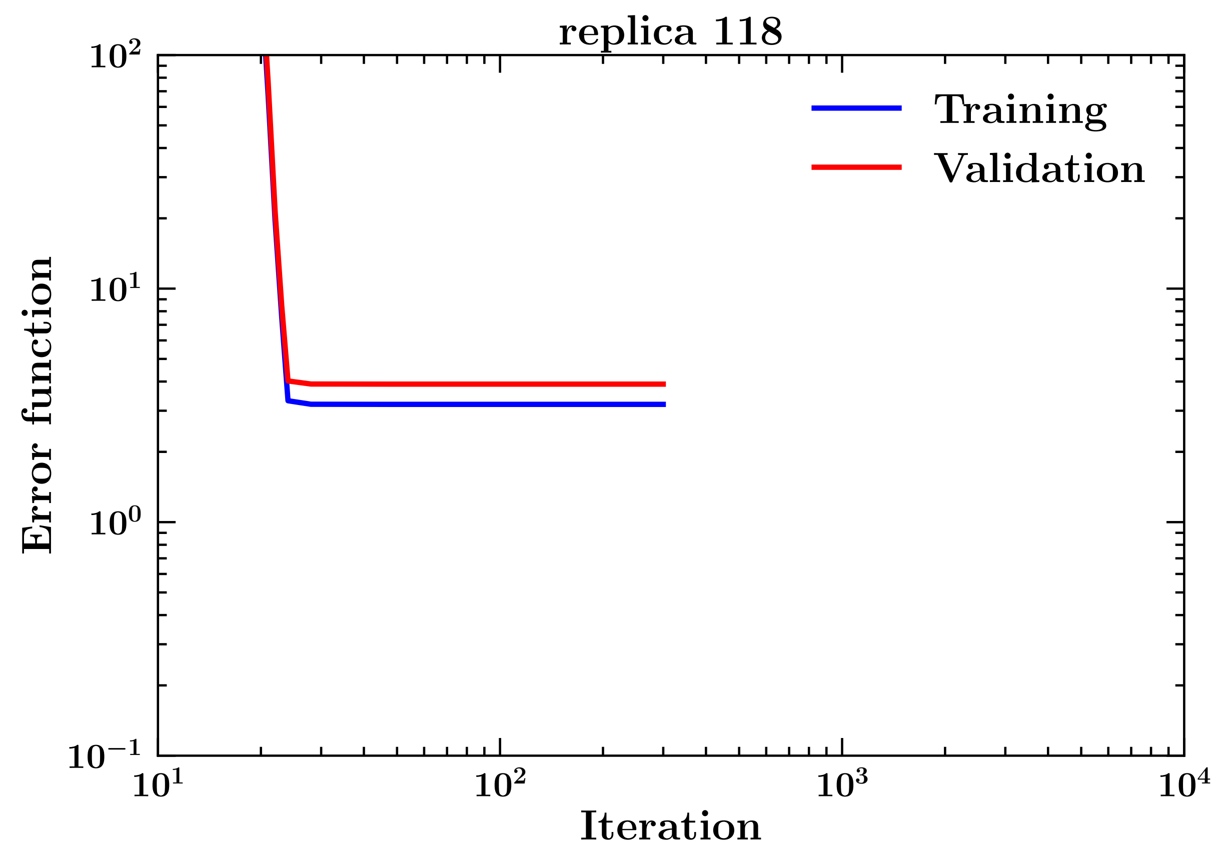


χ^2_{best}

random splitting

50% - 50%

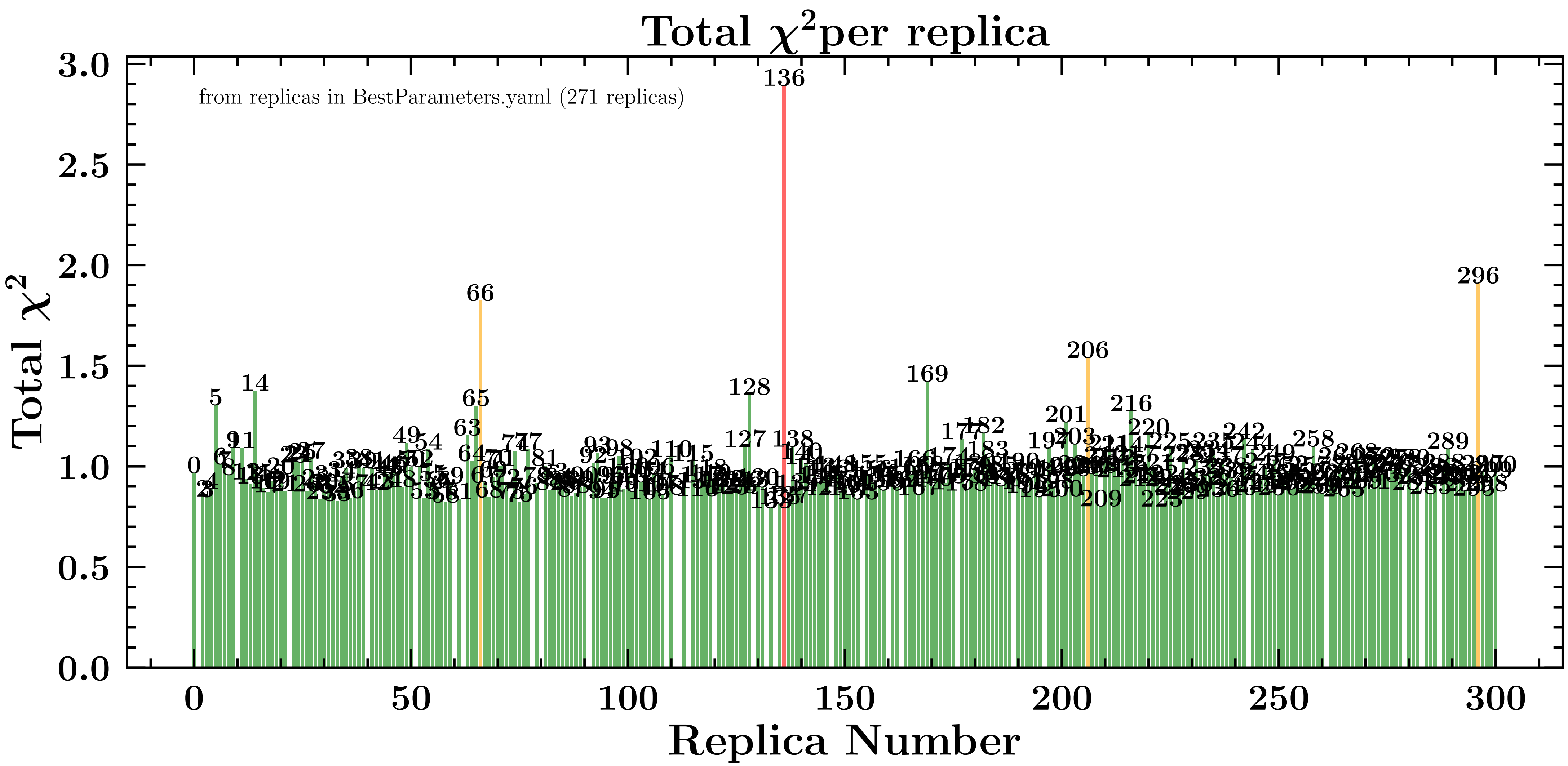
dataset by dataset



Fitting procedure

Error propagation: generation of Monte Carlo replicas

a fit runs in ~15 mins



Results of the analysis

Data / Theory agreement

$$\chi^2 = \sum_{i=1}^{n} \left(\frac{m_i - \bar{t}_i}{s_i} \right)^2 + \sum_{\alpha=1}^{k} \lambda_\alpha^2$$

Experiment	N_{dat}	$\overline{\chi}^2$ $(\overline{\chi}^2_D + \overline{\chi}^2_\lambda)$	
		NN	MAP22
Fixed-target	233	1.08 $(0.98 + 0.10)$	0.91 $(0.70 + 0.21)$
RHIC	7	1.11 $(1.03 + 0.07)$	1.45 $(1.37 + 0.08)$
Tevatron	71	0.80 $(0.73 + 0.06)$	1.20 $(1.17 + 0.04)$
LHCb	21	0.98 $(0.88 + 0.10)$	1.25 $(1.05 + 0.20)$
CMS	78	0.40 $(0.38 + 0.02)$	0.41 $(0.35 + 0.06)$
ATLAS	72	1.38 $(1.09 + 0.29)$	3.51 $(3.03 + 0.49)$
Total	482	0.97 $(0.86 + 0.11)$	1.28 $(1.09 + 0.20)$

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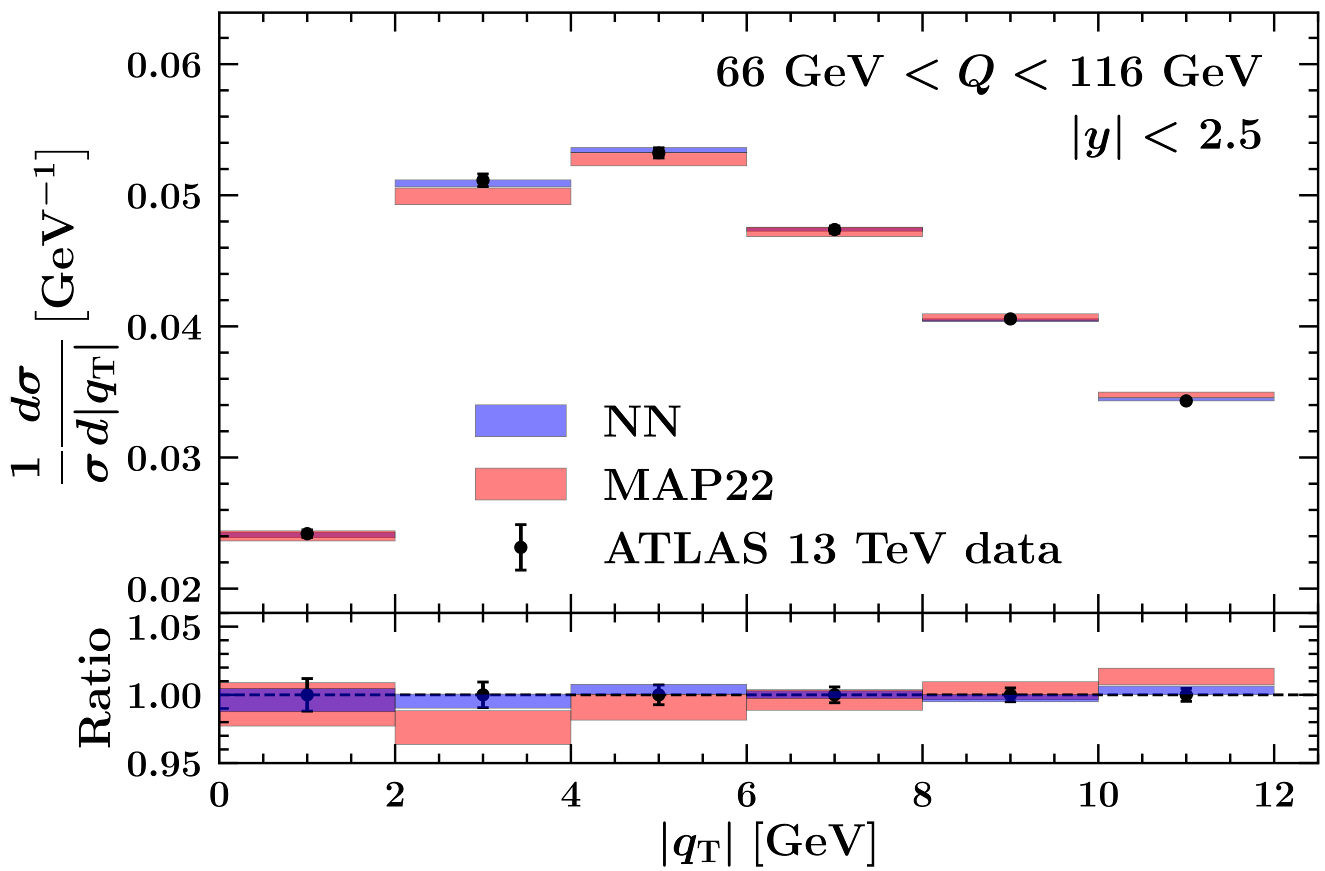

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Significant improvement for ATLAS data

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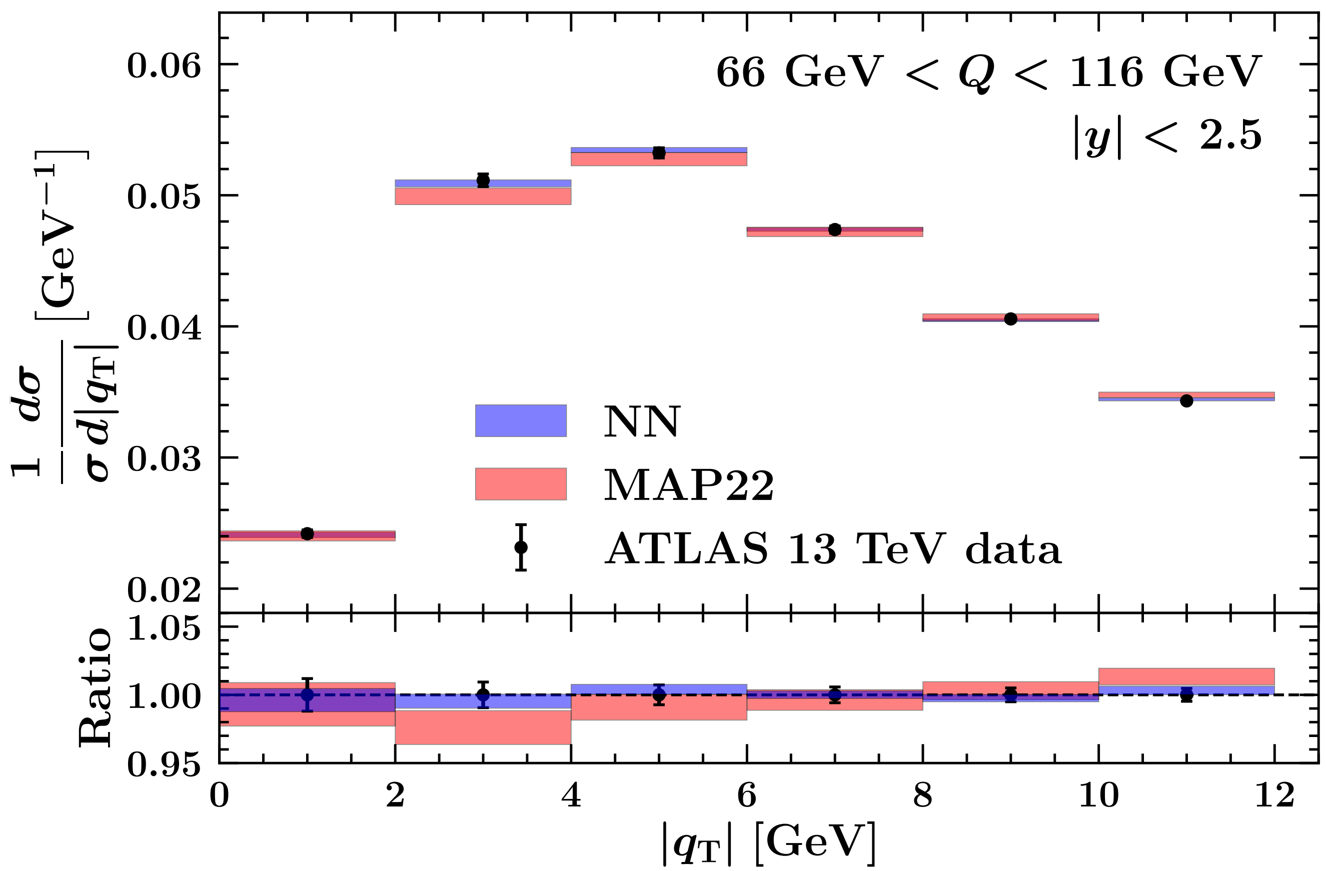

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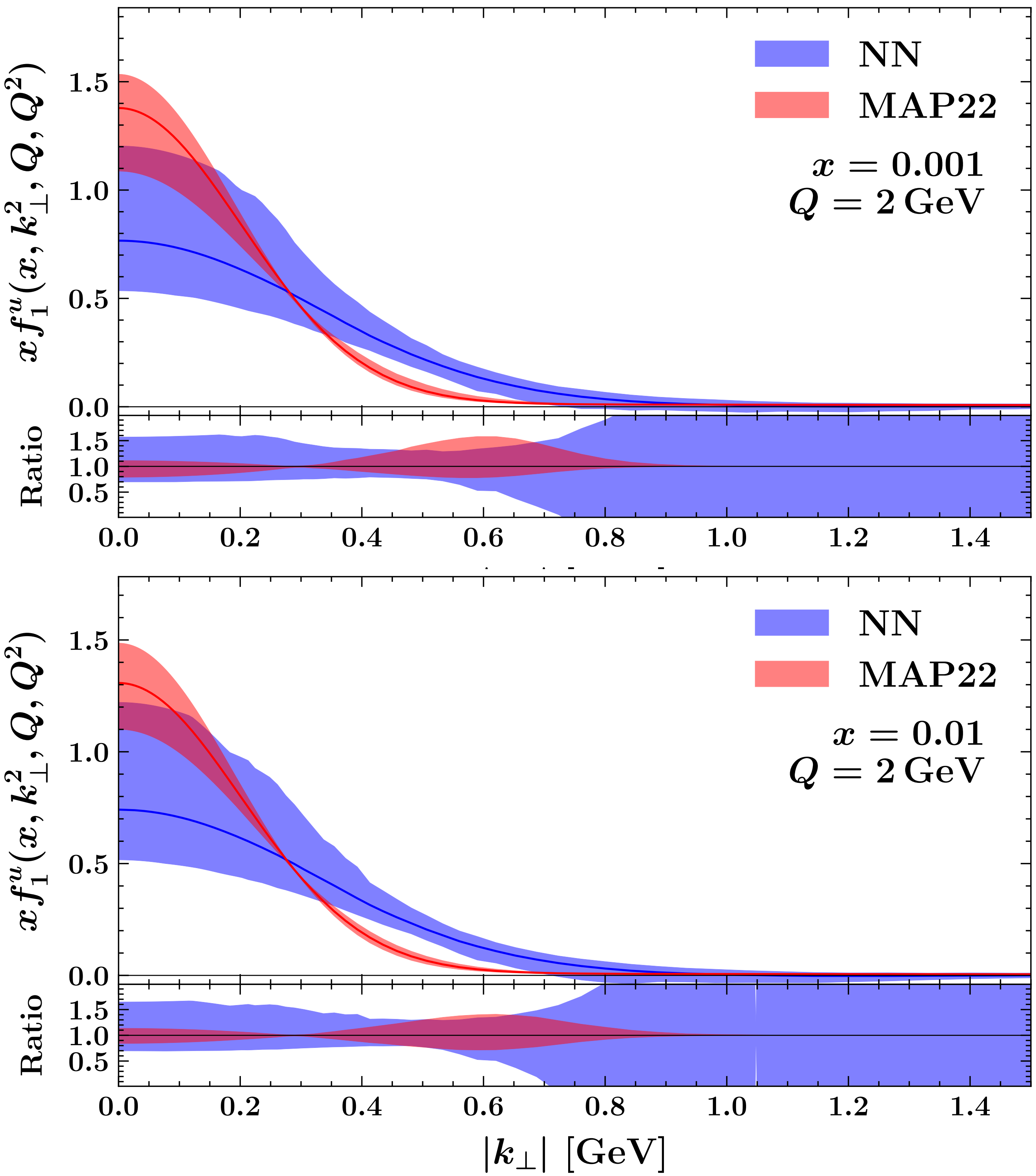
Significant improvement for ATLAS data

MAP22 relies more on systematic shifts ⇒ large error bands

Results of the analysis

Extracted TMDs

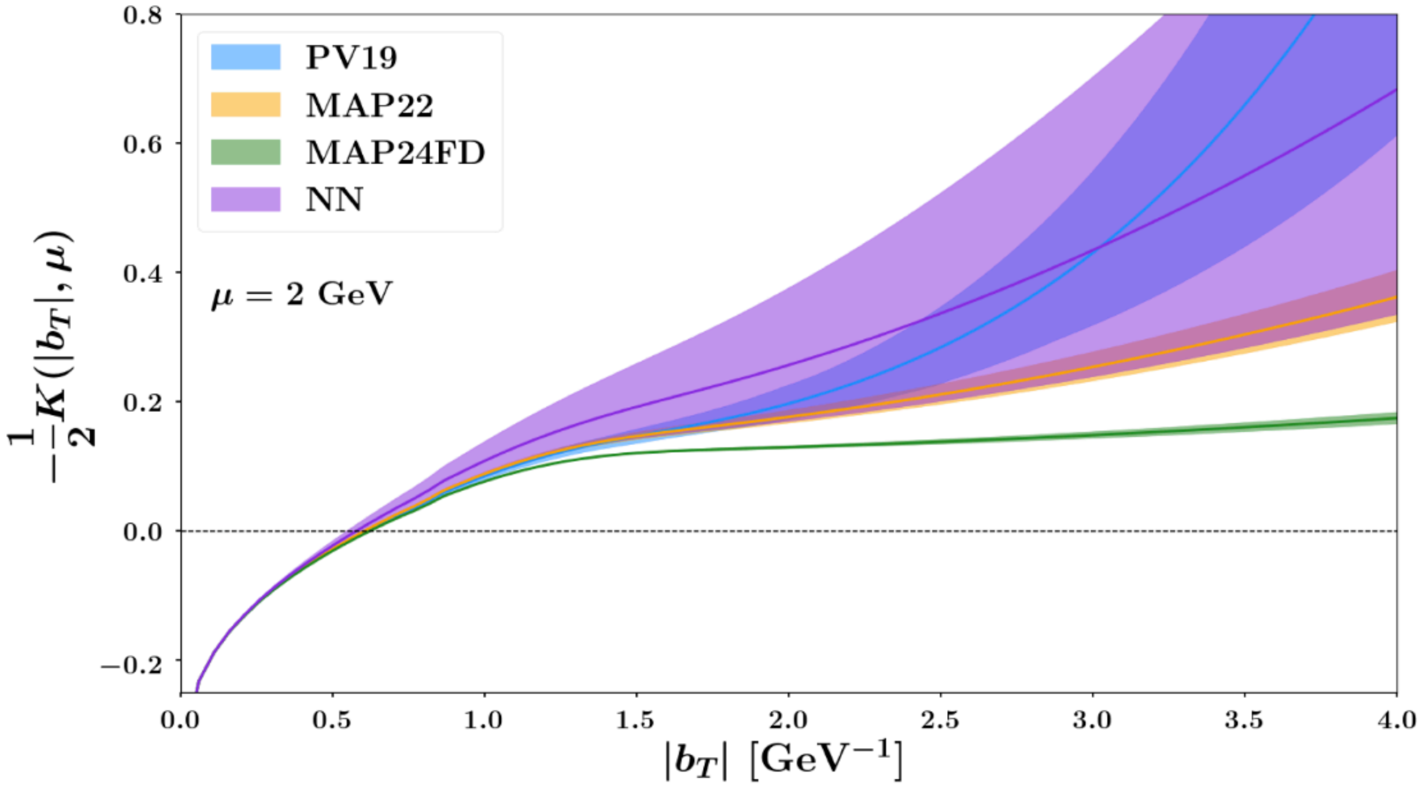


NN fit has larger bands

more reliable estimation of uncertainties

Results of the analysis

Extracted nonperturbative evolution (Collins-Soper kernel)



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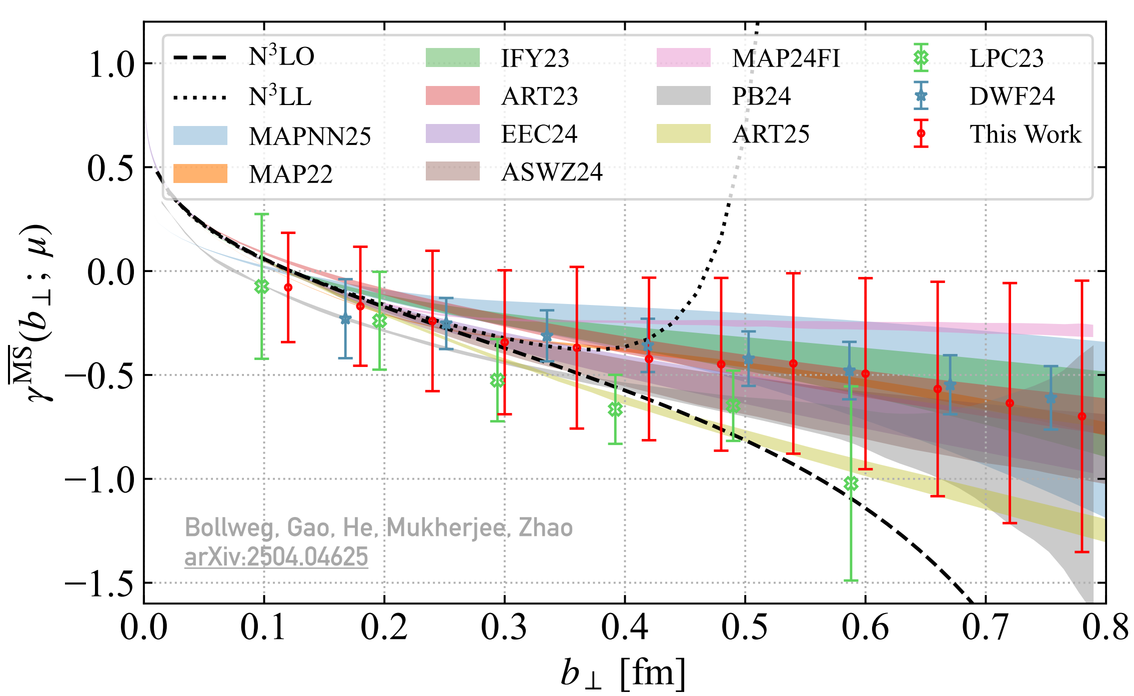

Is it possible to apply information from lattice to the extraction of the CS kernel?

Conclusions

- The Neural Network approach can be applied to TMD phenomenology

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Joint effort lattice+pheno for CS kernel

New advanced computational framework for QCD global fits

Detailed study on extracted TMD FFs from global fits

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Backup

Structure of a TMD: NP content

$$f_{NP}(x, b_T^2)\exp\left\{g_K(b_T^2)\ln\frac{\sqrt{\zeta}}{\sqrt{\zeta_0}}\right\} \quad : \mathrm{C}$$

$$\boxed{\mu_b > \mu} \quad \infty \xleftarrow{b_T \ll 1} \mu_b = \frac{2e^{-\gamma_E}}{|\boldsymbol{b}_T|} \xrightarrow{b_T \gg 1} 0 \quad \boxed{\alpha_S(\mu_b) \to +\infty}$$

b$_*$-prescription

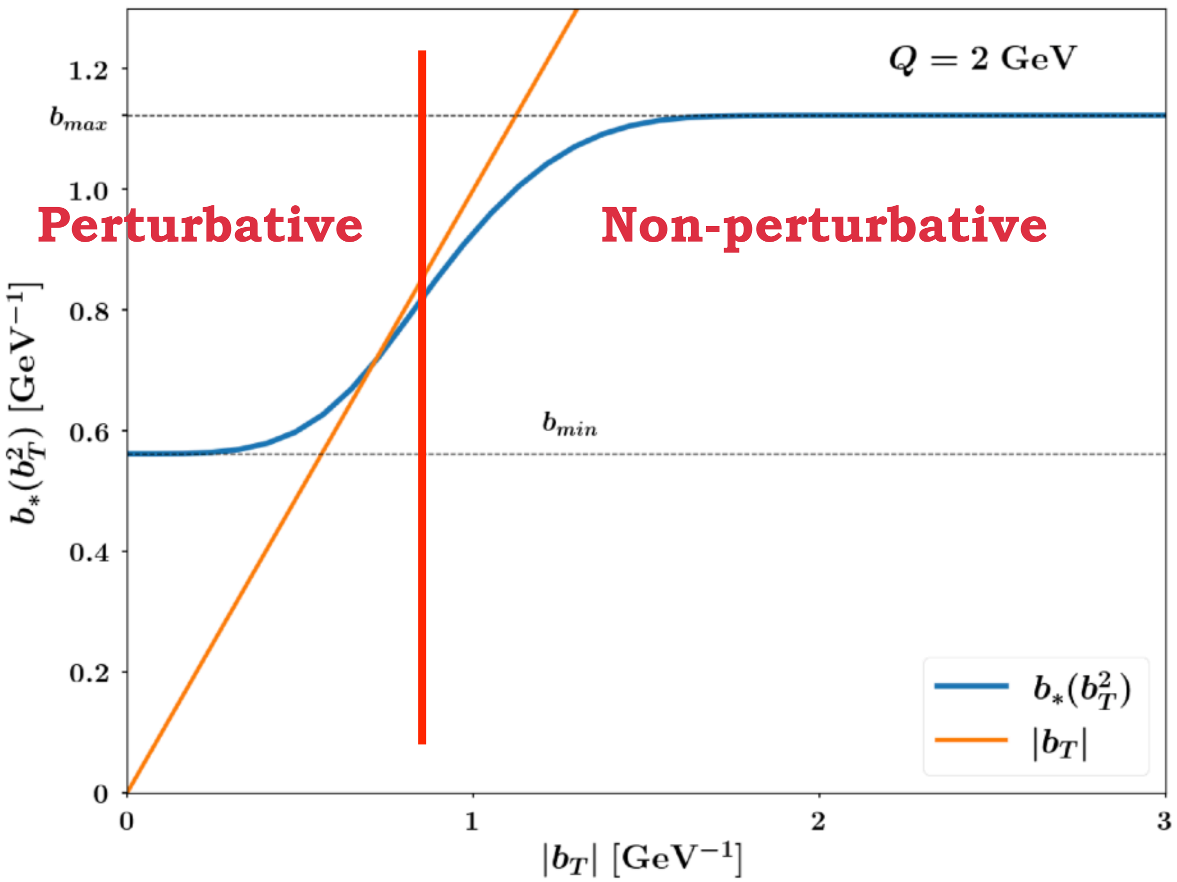
$$b_{\max} = 2e^{-\gamma_E}$$

$$b_{\min} = \frac{2e^{-\gamma_E}}{\mu}$$

Collins, Soper, Sterman, Nucl. Phys. B250 (1985)

Collins, Gamberg, et al., PRD (2016)

Bacchetta, Echevarria, Mulders, et al., JHEP 11 (2015)



$$\hat{f}_1(x, b_T^2; \mu, \zeta) = \left[\frac{\hat{f}_1(x, b_T^2; \mu, \zeta)}{\hat{f}_1(x, b_*(b_T^2); \mu, \zeta)}\right]\hat{f}_1(x, b_*(b_T^2); \mu, \zeta) \equiv \boxed{f_{\mathrm{NP}}(x, b_T^2; \zeta)}\hat{f}_1(x, b_*(b_T^2); \mu, \zeta)$$

Theory/data agreement

Decomposition of the χ^2

experimental data

$$m_i \pm \sigma_{i,\mathrm{unc}} \pm \sigma_{i,\mathrm{corr}}^{(1)} \pm \cdots \pm \sigma_{i,\mathrm{corr}}^{(k)}$$

uncorrelated

correlated

$$\chi^2 = \sum_{i=1}^{n} \left(\frac{m_i - \bar{t}_i}{s_i} \right)^2 + \sum_{\alpha=1}^{k} \lambda_\alpha^2$$

uncorrelated contribution

penalty term

nuisance parameters $\dfrac{\partial \chi^2}{\partial \lambda_\alpha} = 0$

$$\bar{t}_i = t_i + d_i$$

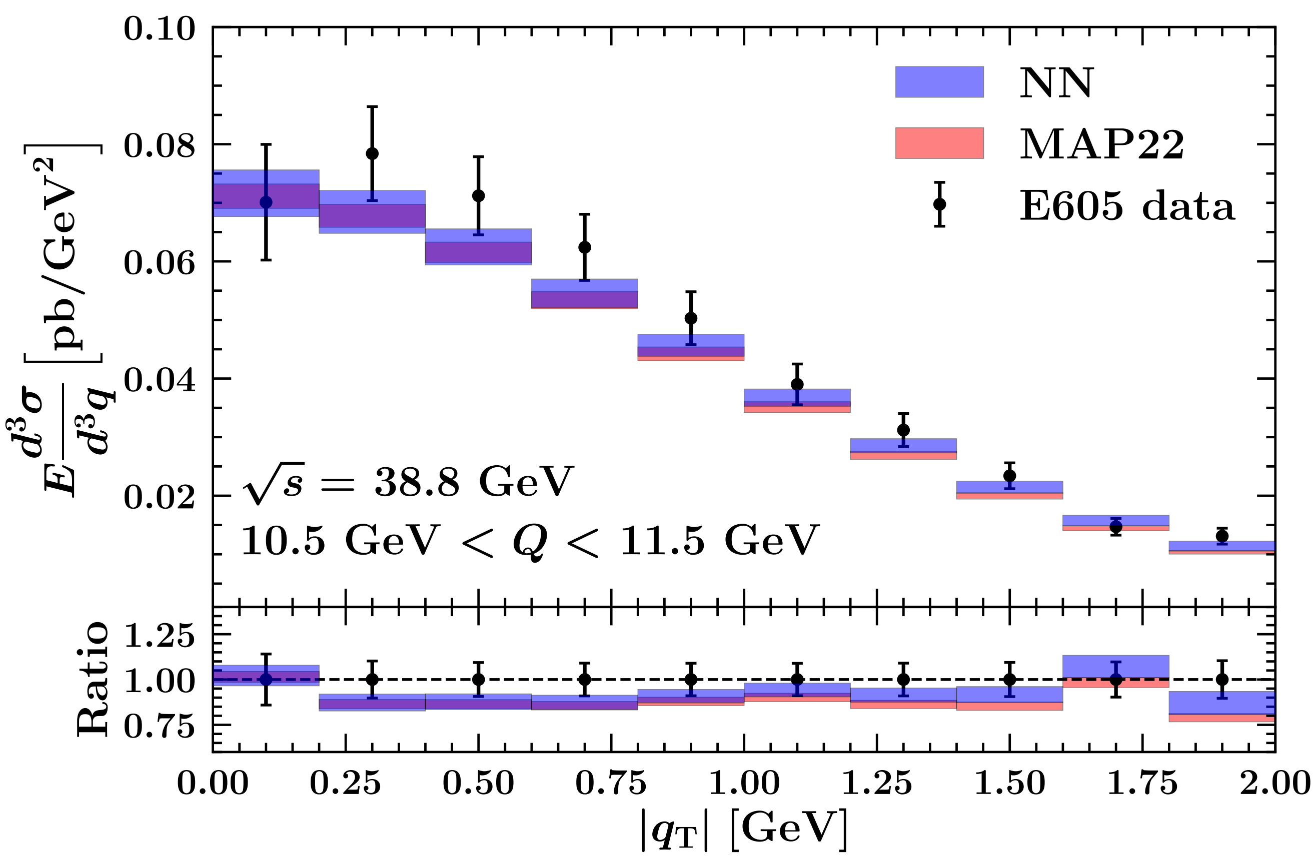
shifted prediction

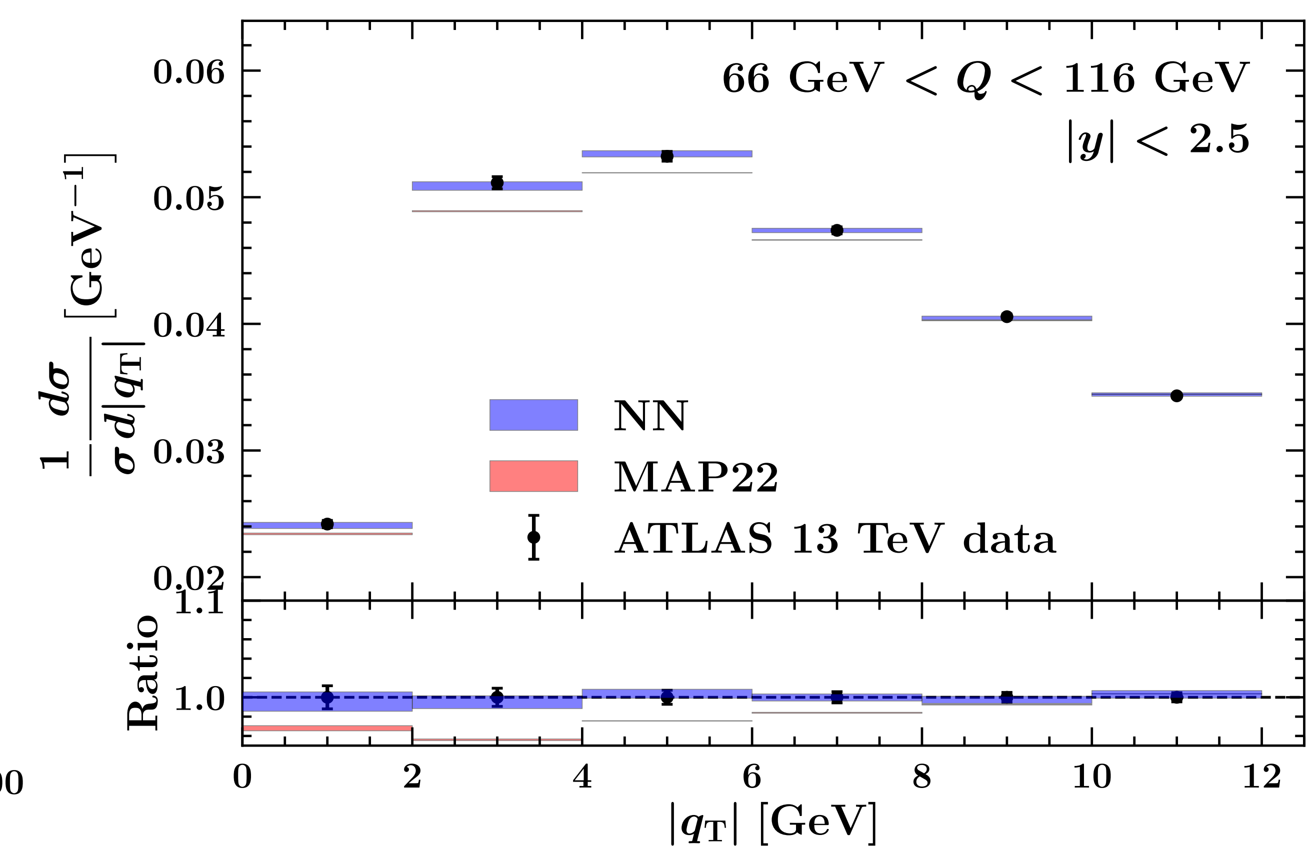
shift $d_i = \sum_{\alpha=1}^{k} \lambda_\alpha \sigma_{i,\mathrm{corr}}^{(\alpha)}$

Results of the analysis

Data / Theory comparison

without systematic shifts





The error bands comes directly from the uncertainty of the extracted TMDs