Neural-Network-based extractions of unpolarized TMDs

Matteo Cerutti

NSTAR - Seville - 07/09/2026

Transverse Momentum Distributions (TMDs)

3D Map of the internal structure of the proton

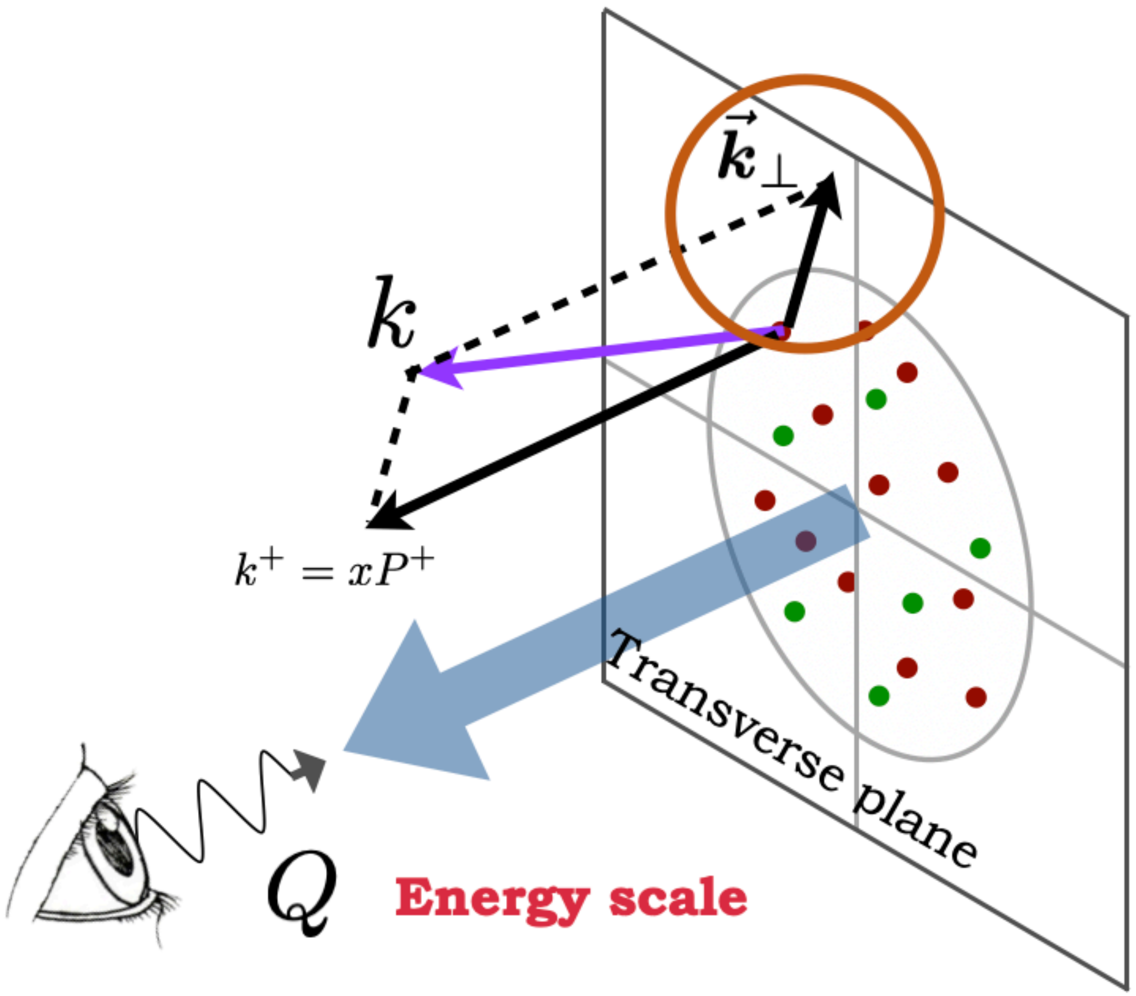
Non-Collinear framework

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

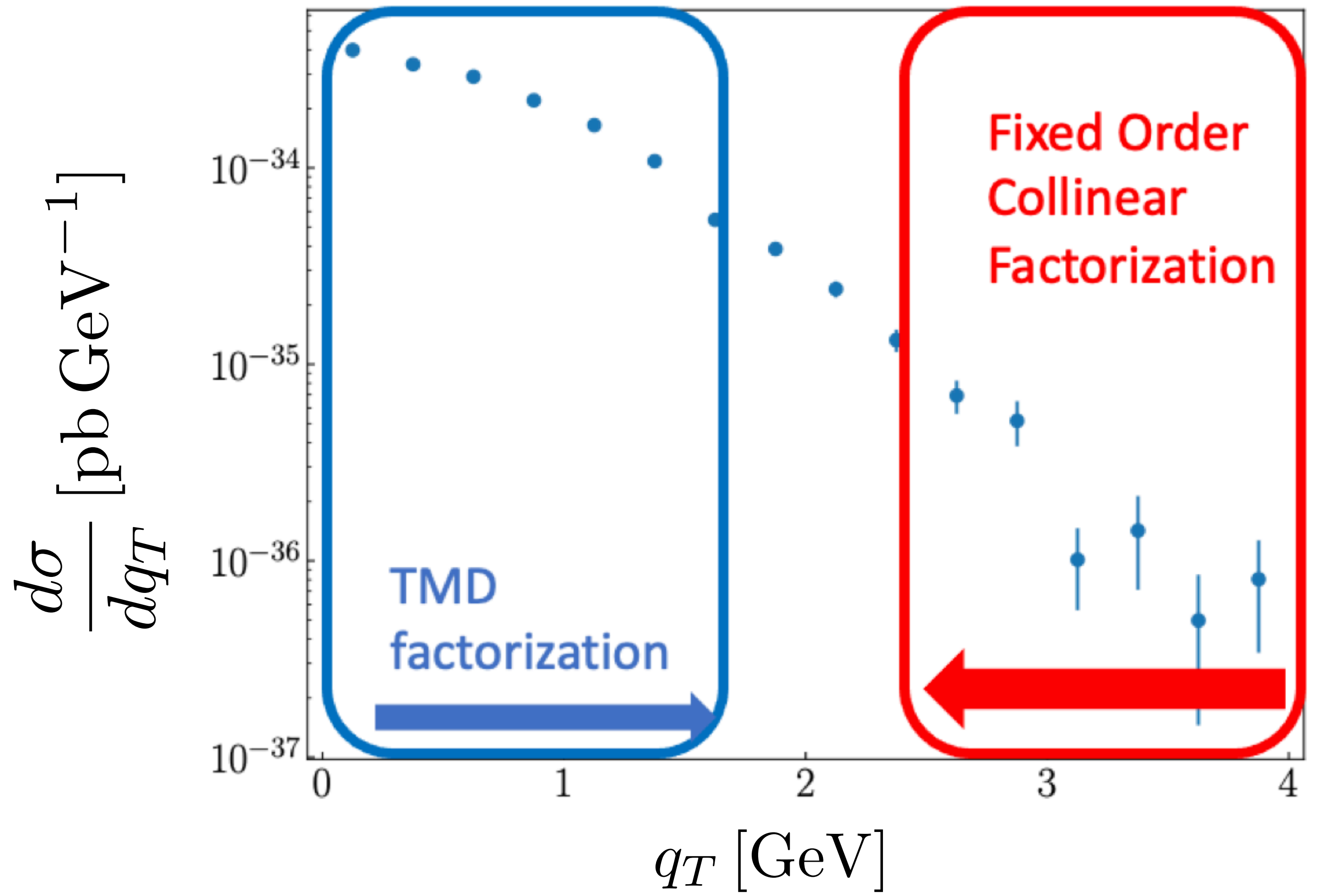


TMD PDFs

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

How to get information on TMDs

Cross section differential in transverse momentum



TMD factorisation: $Q^2 \gg M^2$

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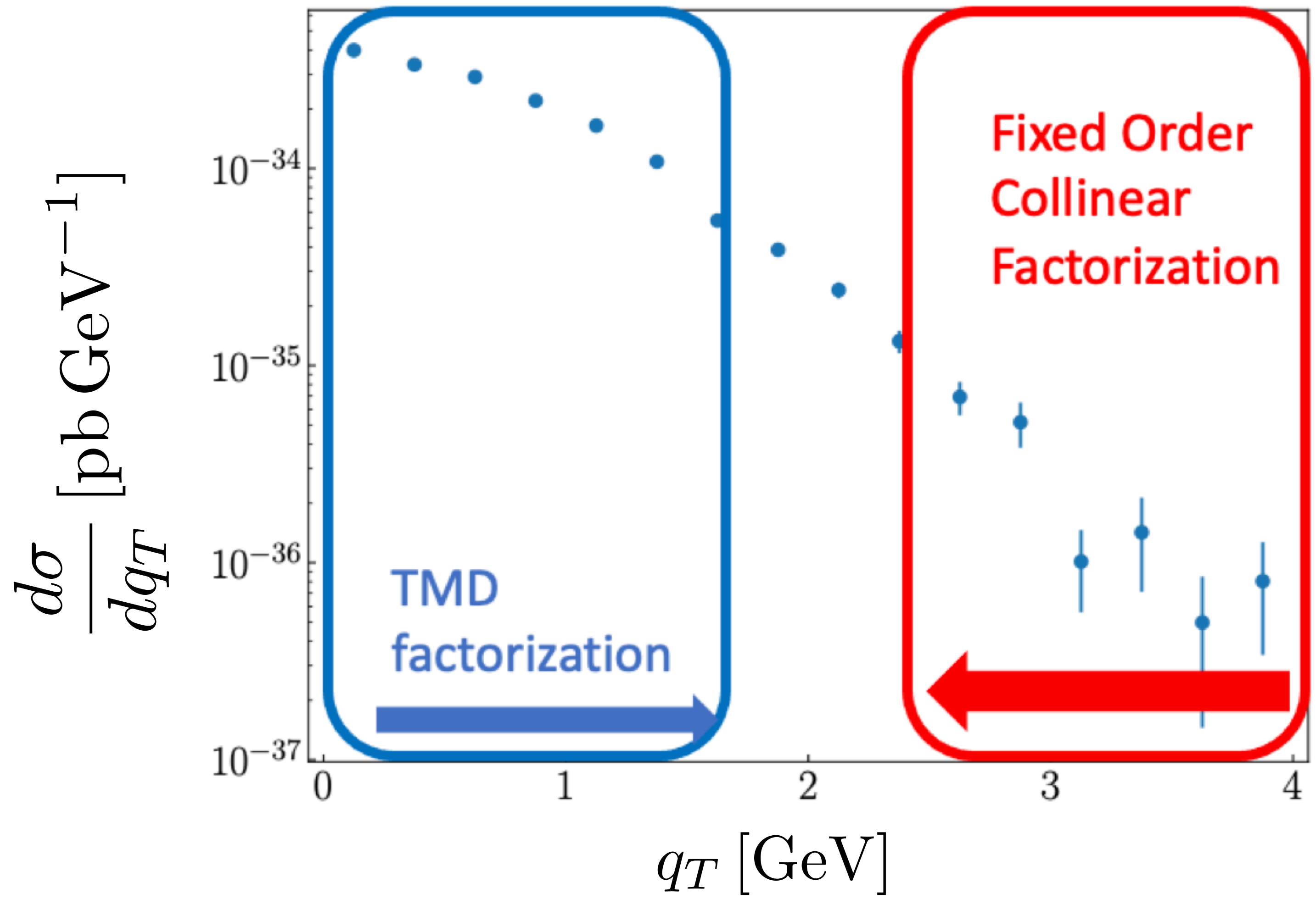

TMD factorisation:

$$Q^2 \gg M^2$$

$$\boxed{q_T^2 \ll Q^2}$$

The intricate expression of TMDs

TMD in Fourier space

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

J. Collins, "Foundation of Perturbative QCD"

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Perturbative TMD at the initial scale

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Non-perturbative part of the TMD

J. Collins, “Foundation of Perturbative QCD”

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Parameterization

J. Collins, “Foundation of Perturbative QCD”

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Parameterization

GLOBAL FITs

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TMD factorisation: universality

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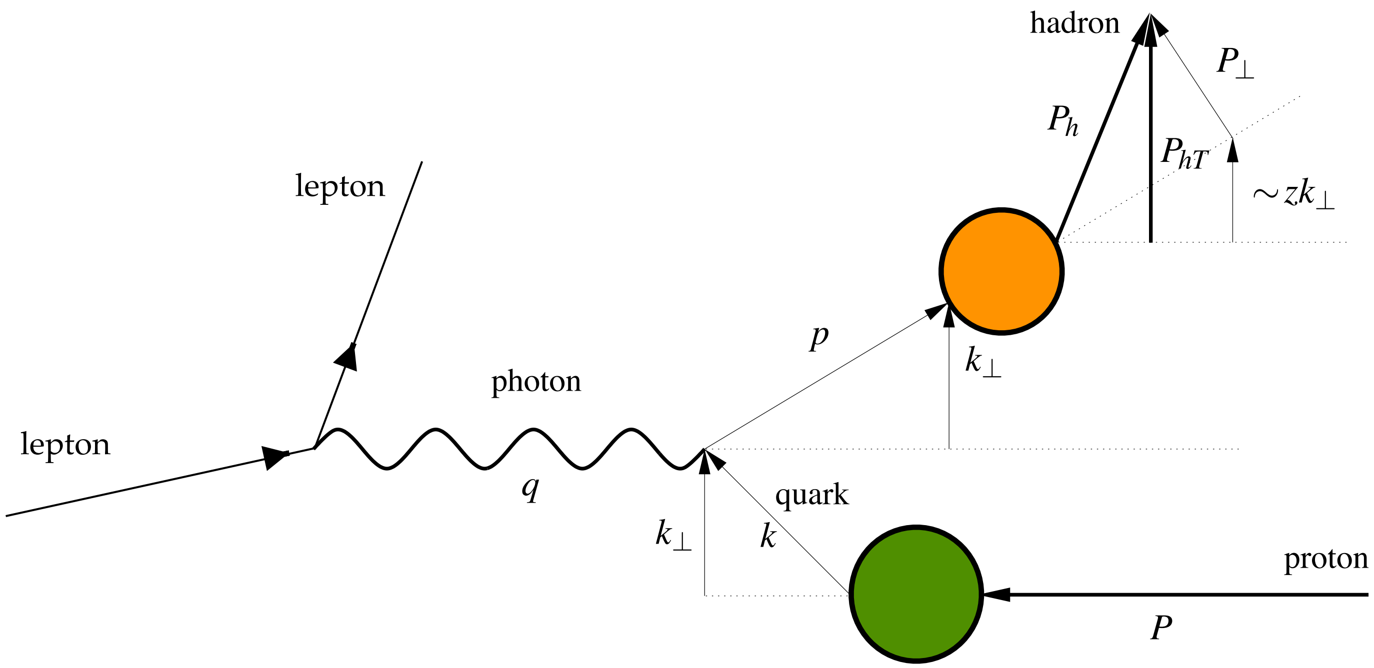
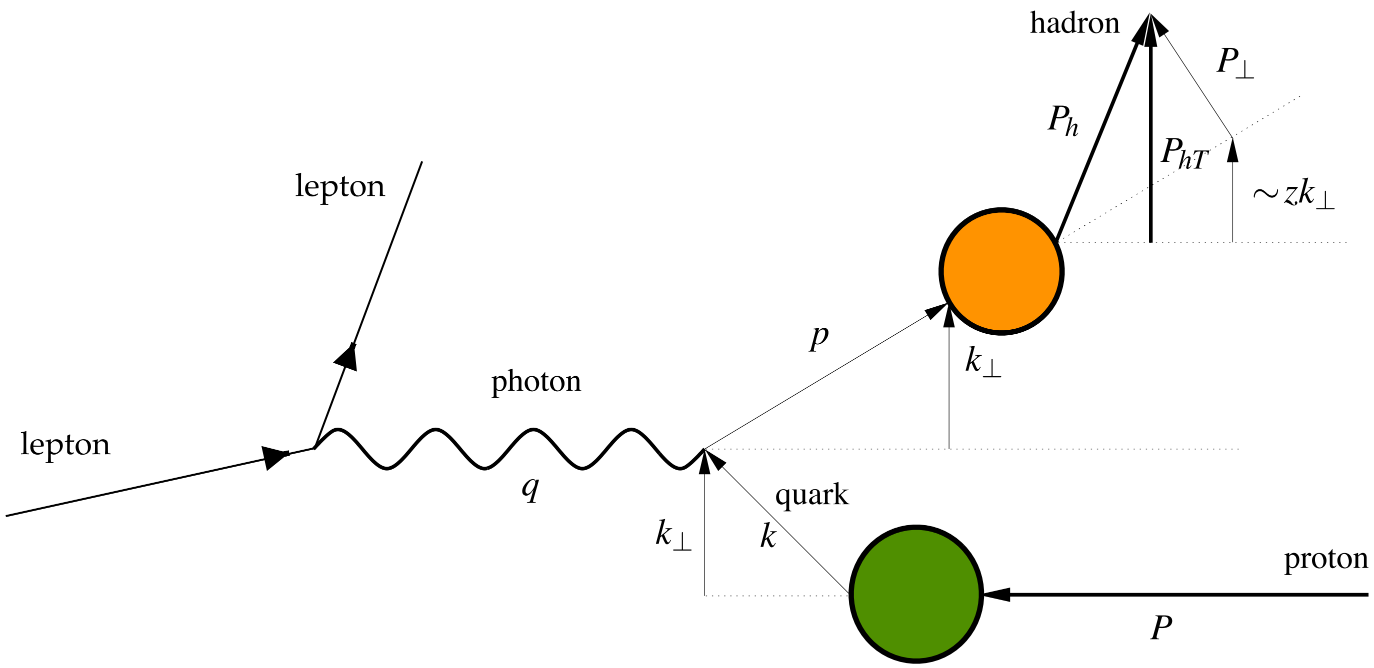
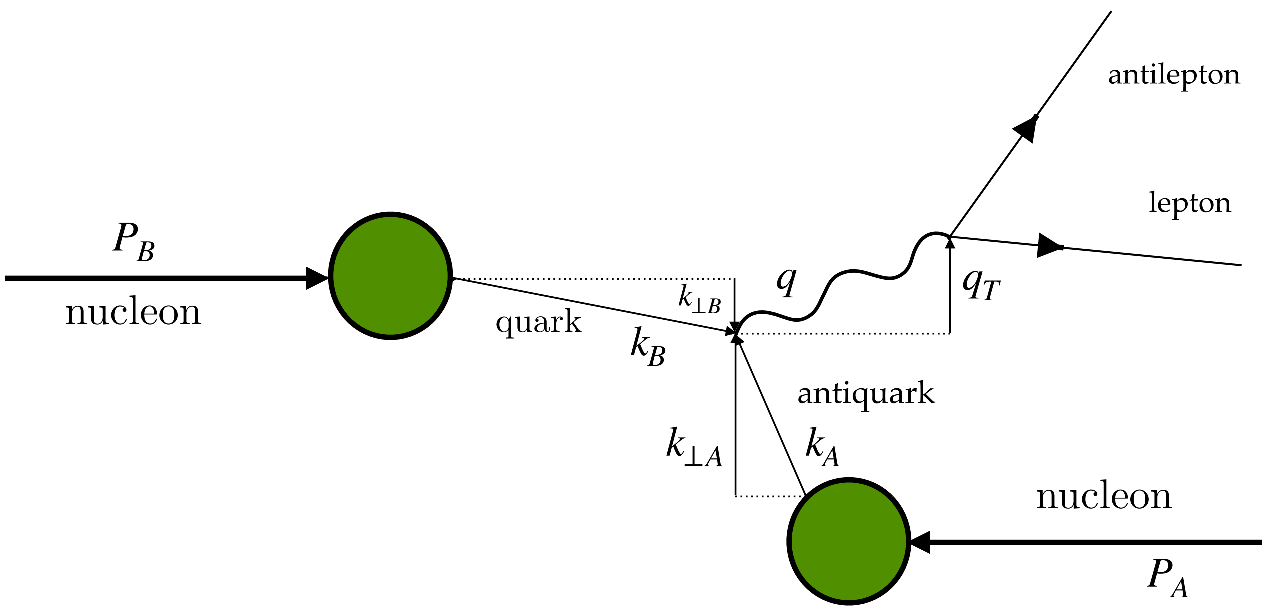


$$\boxed{q_T^2 \ll Q^2}$$

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

TMD factorisation: universality





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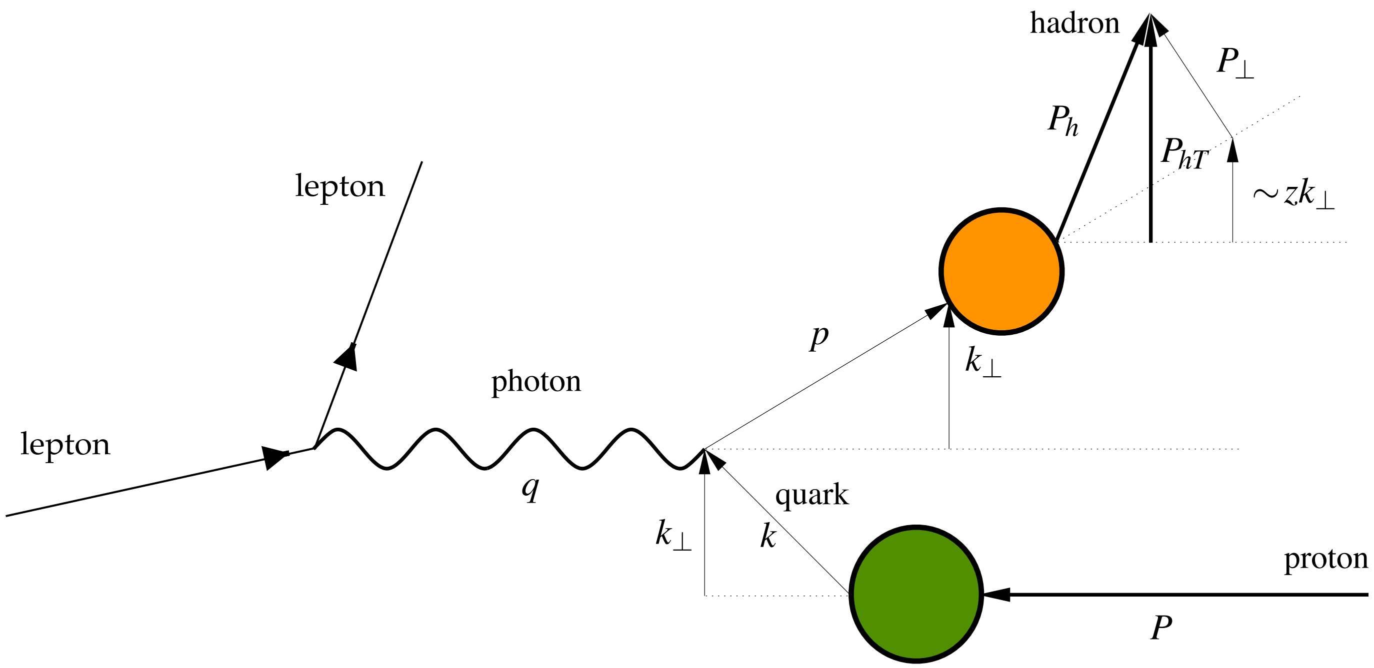

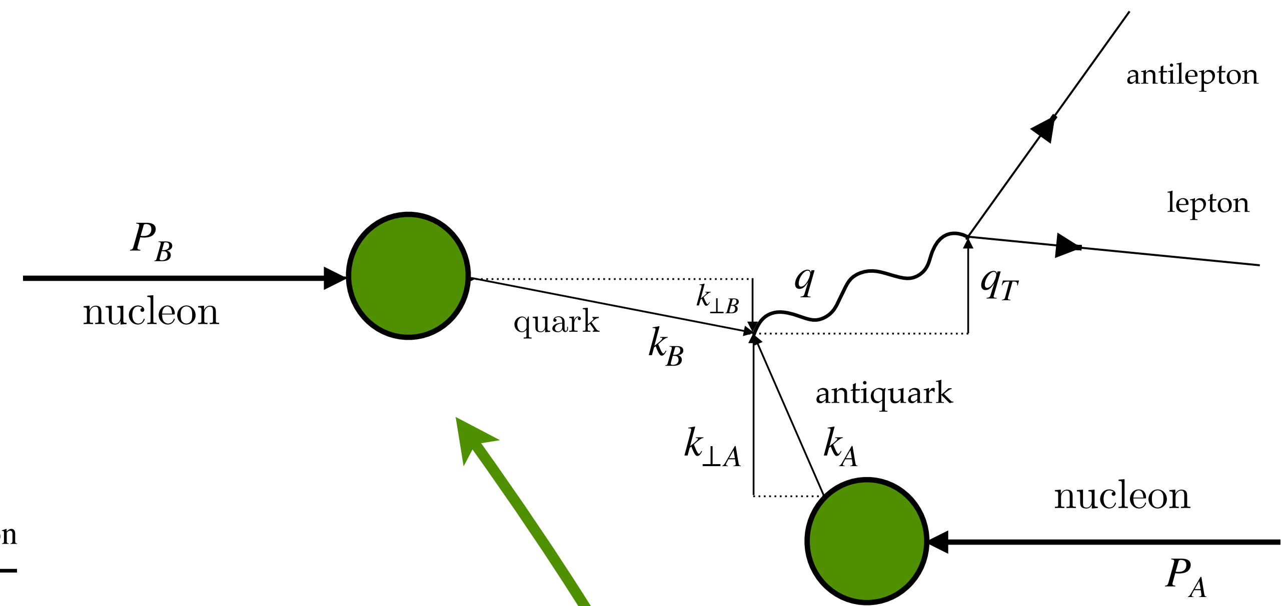

same functions

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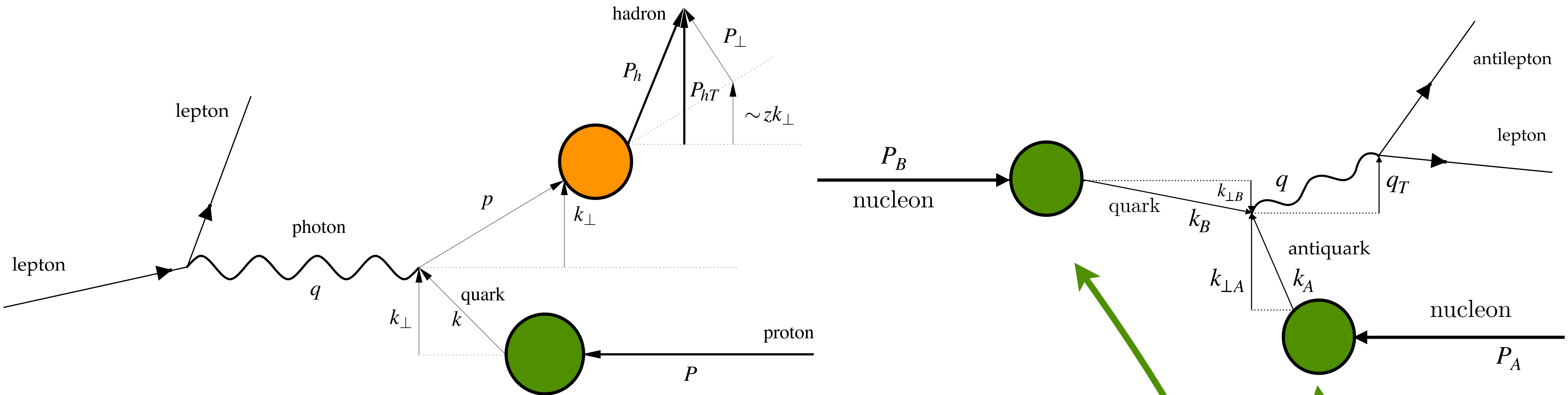

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GLOBAL FITS

TMD frameworks

Available TMD frameworks

- https://github.com/MapCollaboration/NangaParbat — MAP Collab.

  MAP Collaboration, PRL 135 (2025)

- https://teorica.fis.ucm.es/artemide/ — Madrid group

  Moos, Scimemi, et al., JHEP 11 (2025)

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Others…

Barry, Prokudin, et al, arXiv:2510.13771

Zaccheddu, Gamberg, et al, arXiv:2605.06606

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new optimised, general-purpose framework is under development and will be publicly available soon

Bertone, Bissolotti, Cerutti, Rodini, in preparation

TMDs *Form Factors*

ὄρος

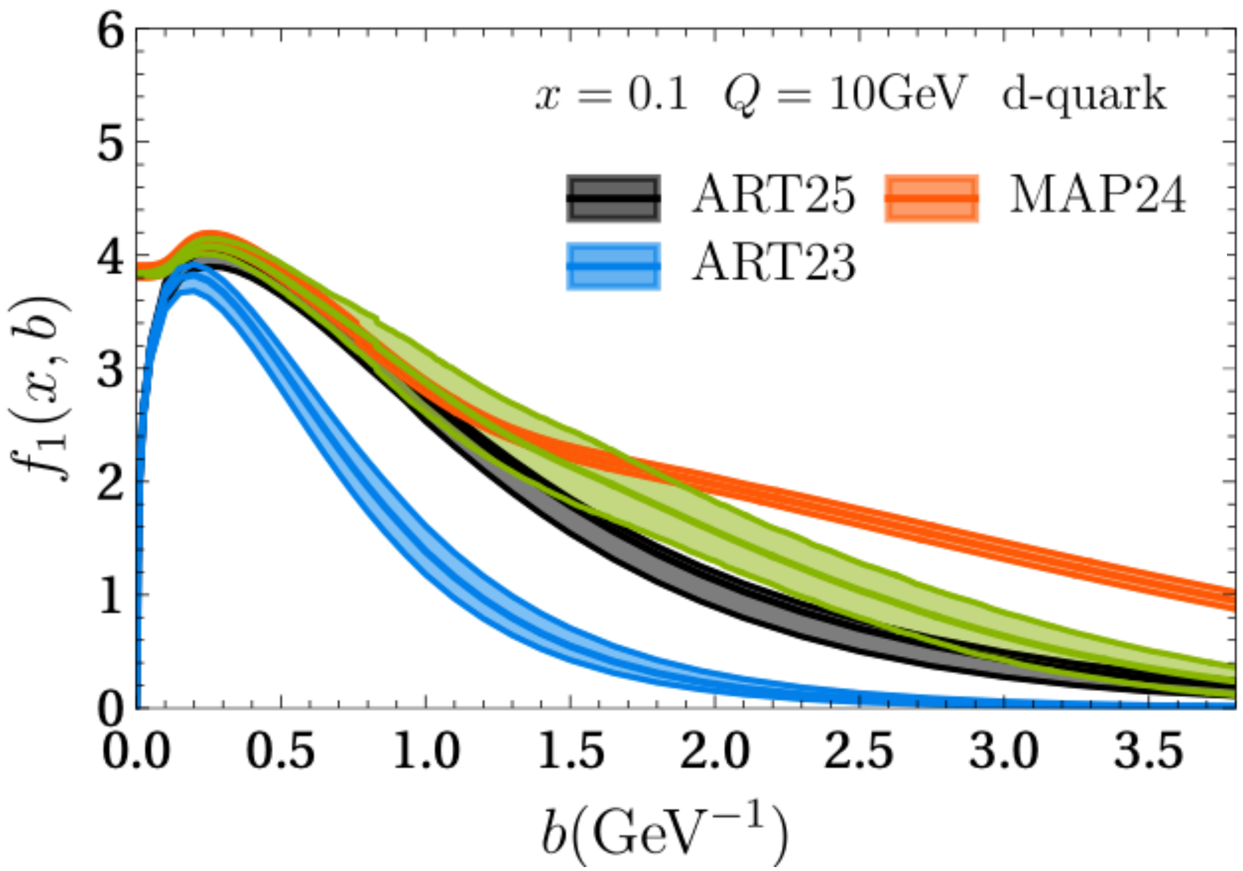
GPDs *PDFs/FFs*

Available global fits

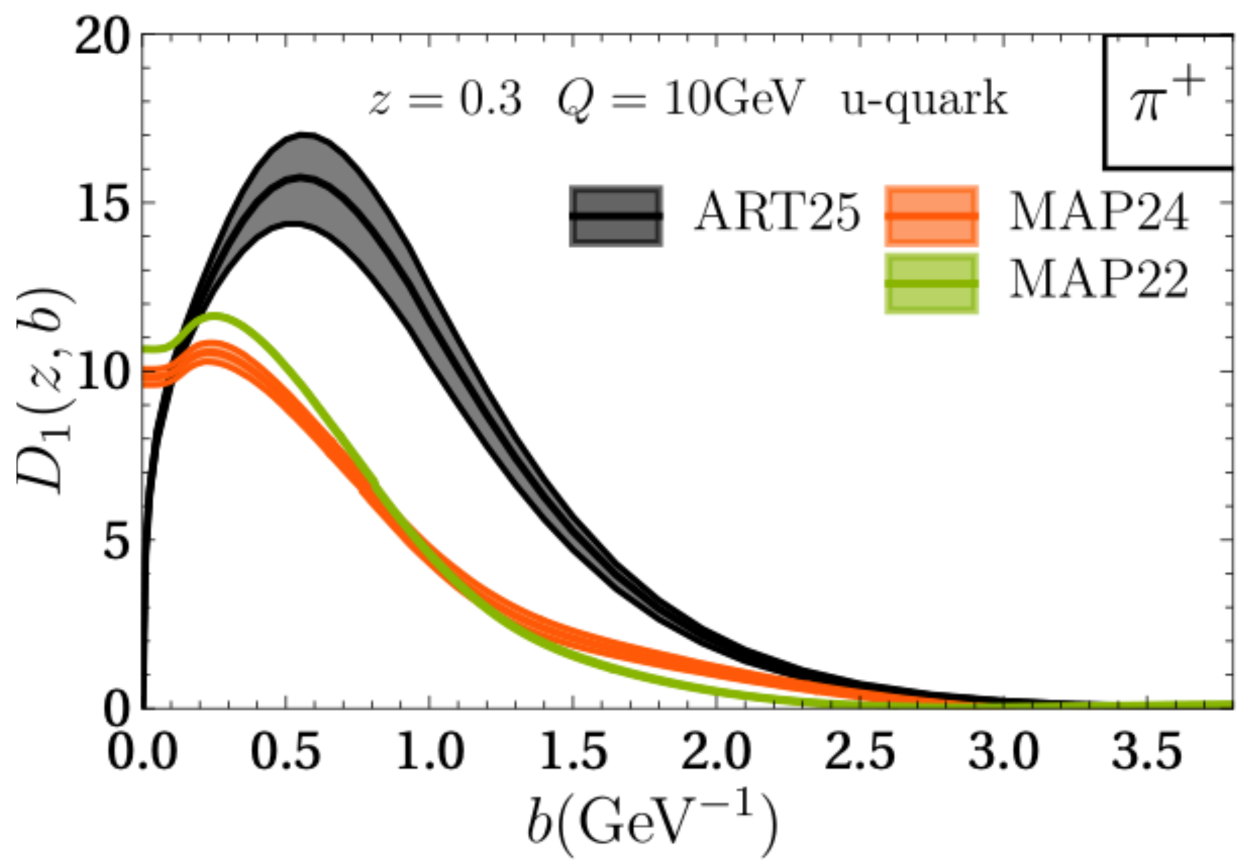
	Accuracy	*SIDIS*	*DY*	*N of points*	χ^2/N_{data}	*Flavor Dependence*
Pavia 2017 Bacchetta, Delcarro, et al., JHEP 06 (2017)	NLL	✔	✔	8059	1.55	✘
SV 2019 Scimemi, Vladimirov, JHEP 06 (2020)	N^3LL^-	✔	✔	1039	1.06	✘
MAPTMD22 Bacchetta, Bertone, et al., JHEP 10 (2022)	N^3LL^-	✔	✔	2031	1.06	✘
MAPTMD24 Bacchetta, Bertone, et al., JHEP 08 (2024)	N^3LL	✔	✔	2031	1.08	✔
ART25 Moos, Scimemi, et al., JHEP 11 (2025)	N^3LL^+	✔	✔	1209	1.05	✔

Comparison of different extractions

TMD PDFs



TMD FFs



Extracted TMDs from different analyses show incompatibilities

Moos, Scimemi, et al., JHEP 11 (2025)

Why Neural Networks?

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Why Neural Networks?

- Current extractions of TMDs show incompatibilities
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GOAL:

Reduce the parametrisation bias

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

Is this approach applicable to this complexity?

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

The parameterisation bias

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

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MAP Collaboration, JHEP 08 (2024)

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

MAP fits

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

Moos, Scimemi, et al., JHEP 11 (2025)

$$f_{NP}^f(x,b) = \frac{1}{\cosh\left(\left(\lambda_1^f(1-x)+\lambda_2^f x\right)b\right)}$$

ART fits

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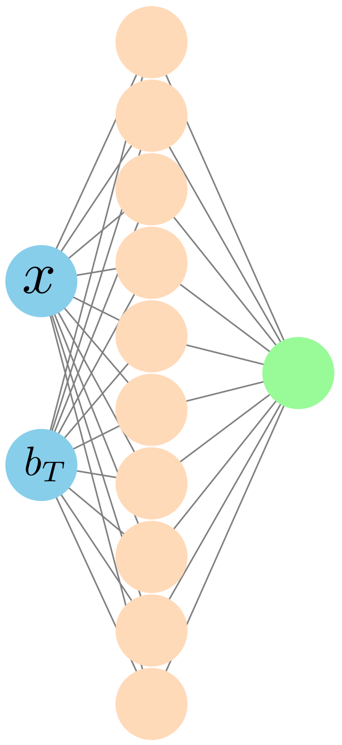
then *"by experience"*

Try to reduce the parametrisation bias!

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



MAP Collaboration, PRL 135 (2025)

NN-based model

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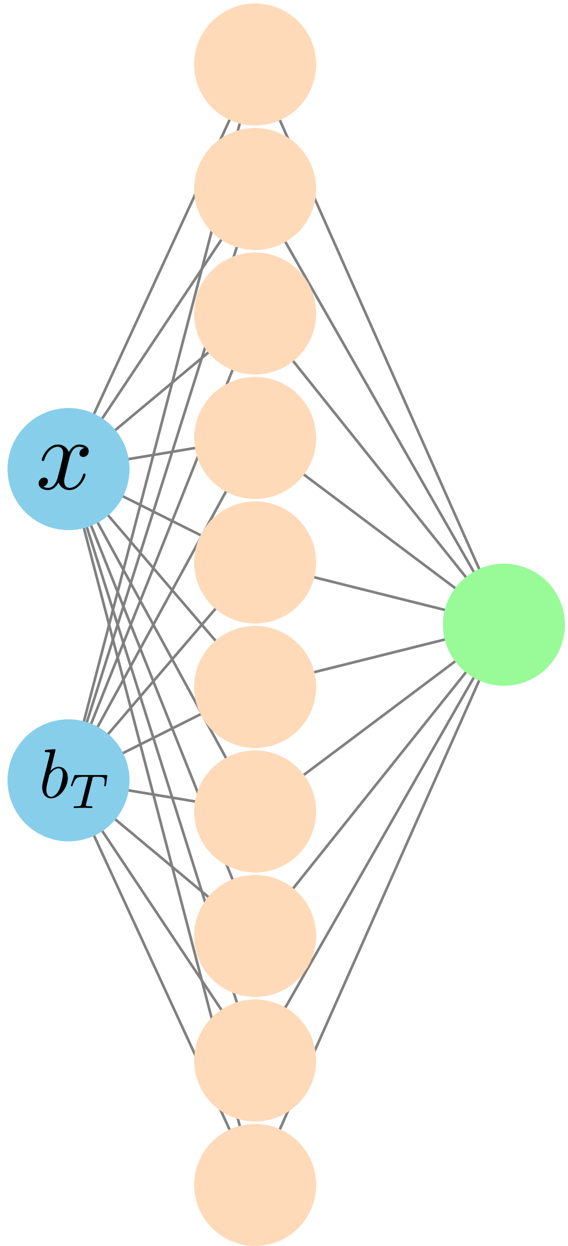

$\mathbb{NN}(x, b_T)$

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

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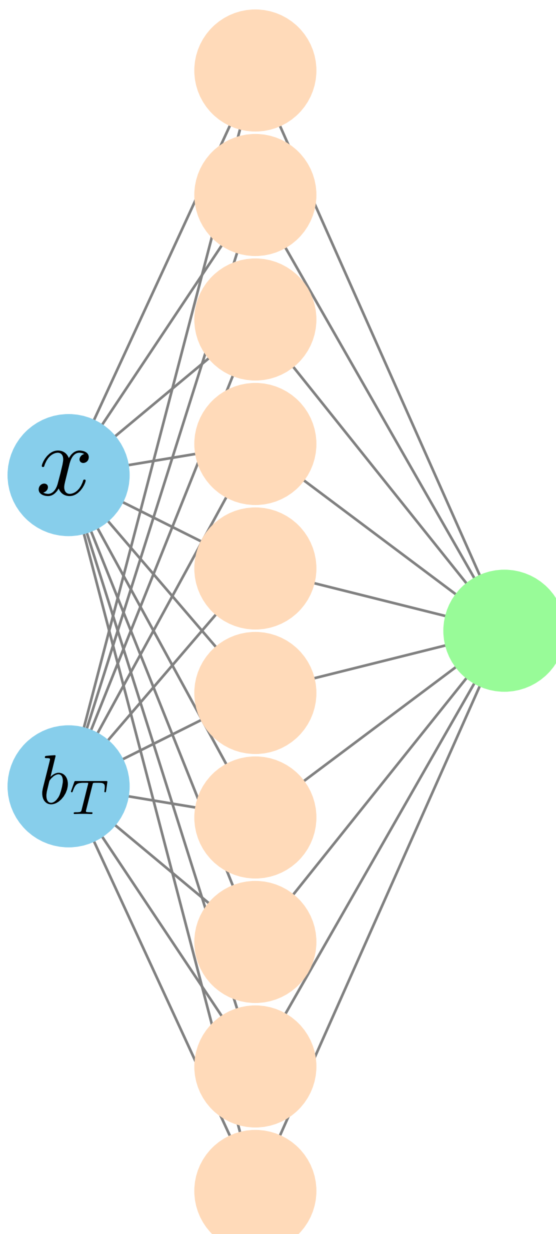

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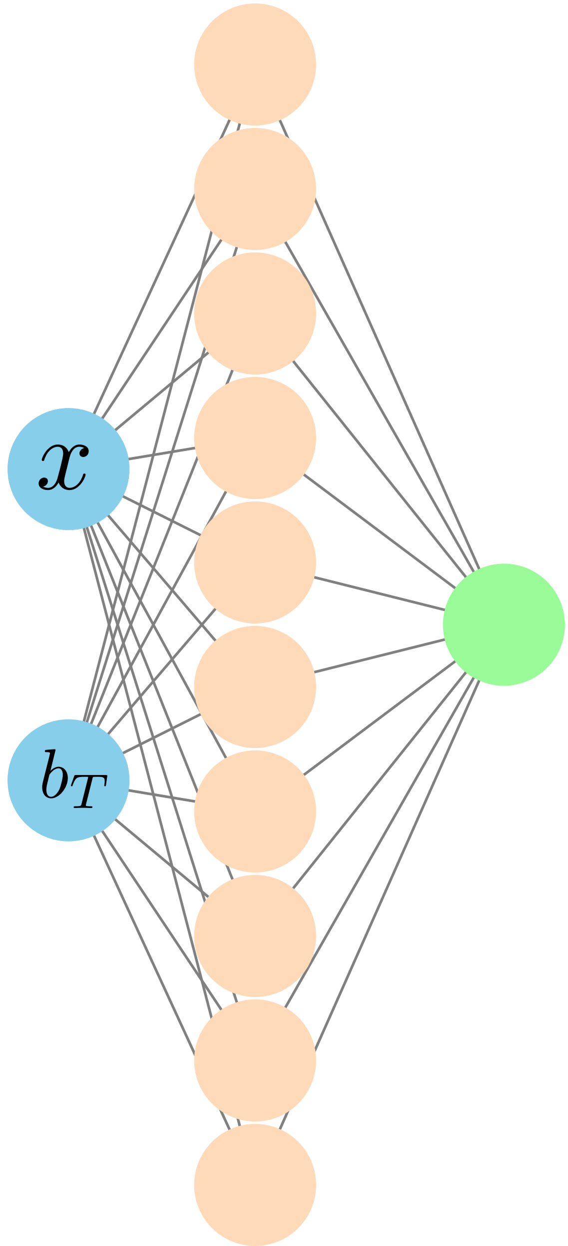

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$f_{\mathrm{NP}} \to 1$ for $b_T \to 0$

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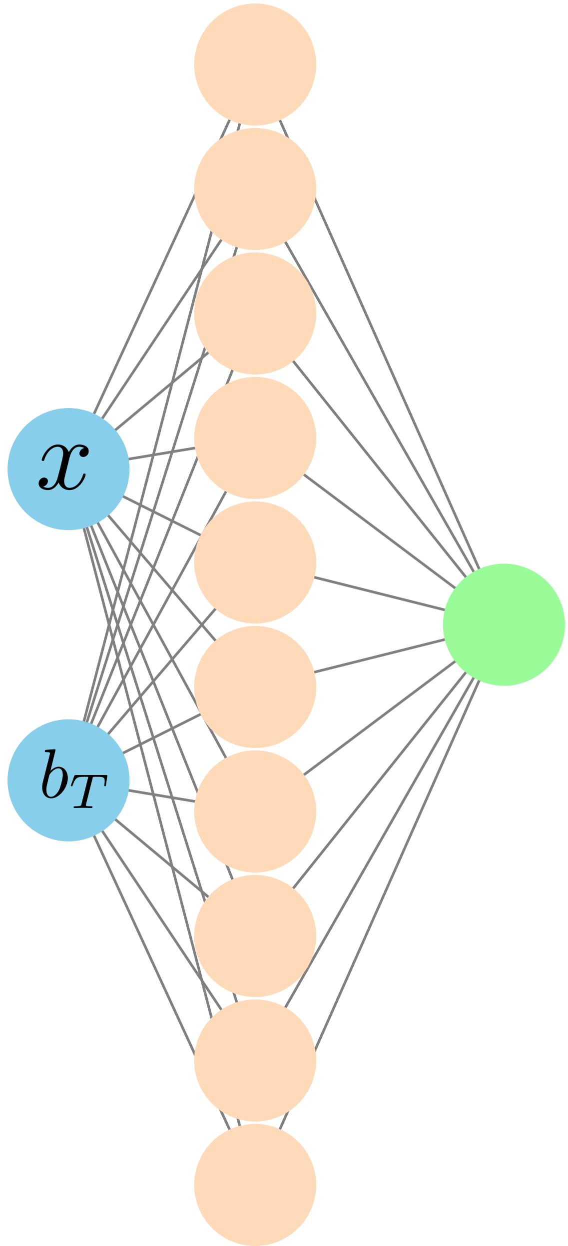

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Included data sets

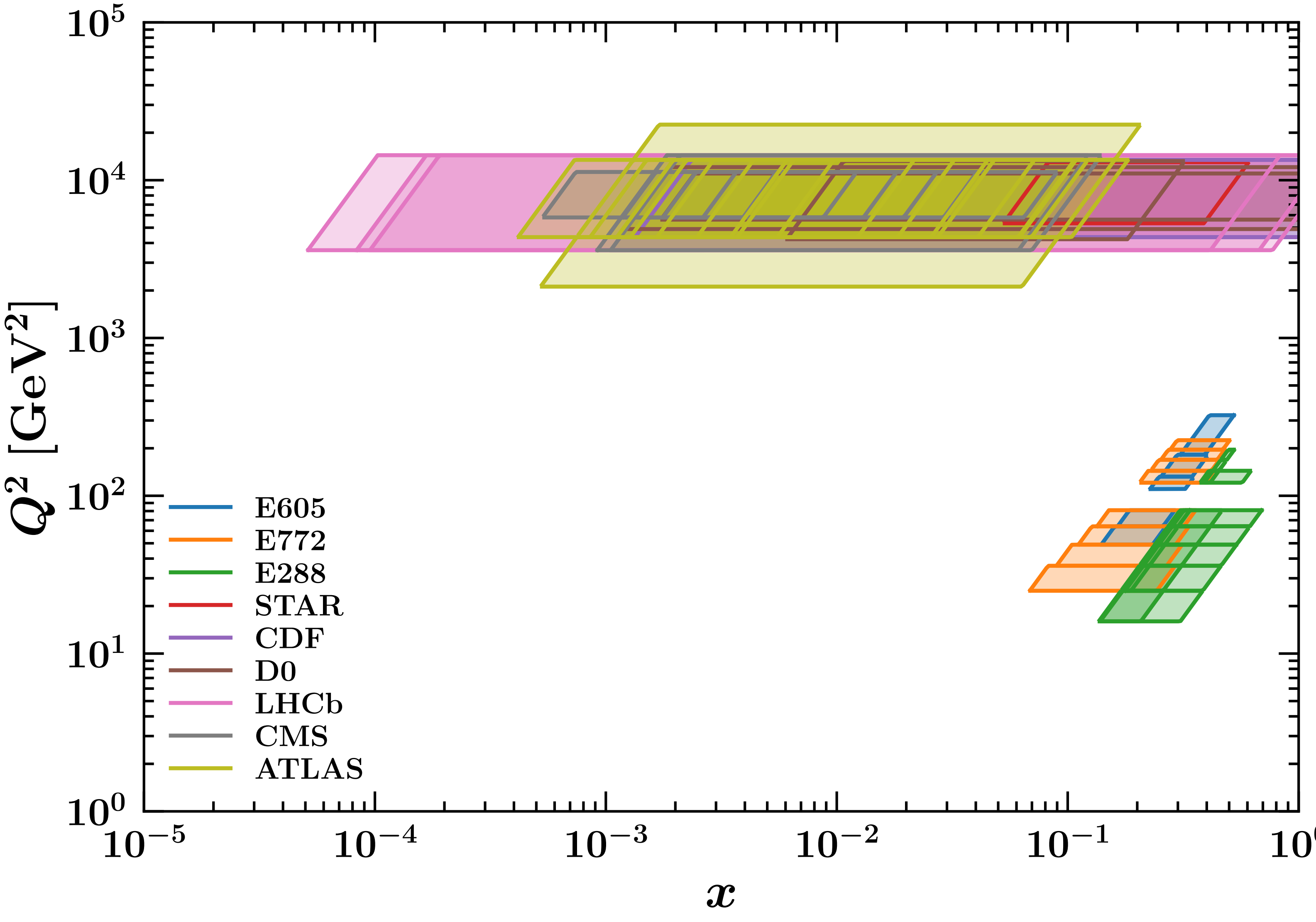
Drell-Yan data

Fixed-target:

E288, E605, E772

Collider mode:

RHIC, Tevatron, LHC



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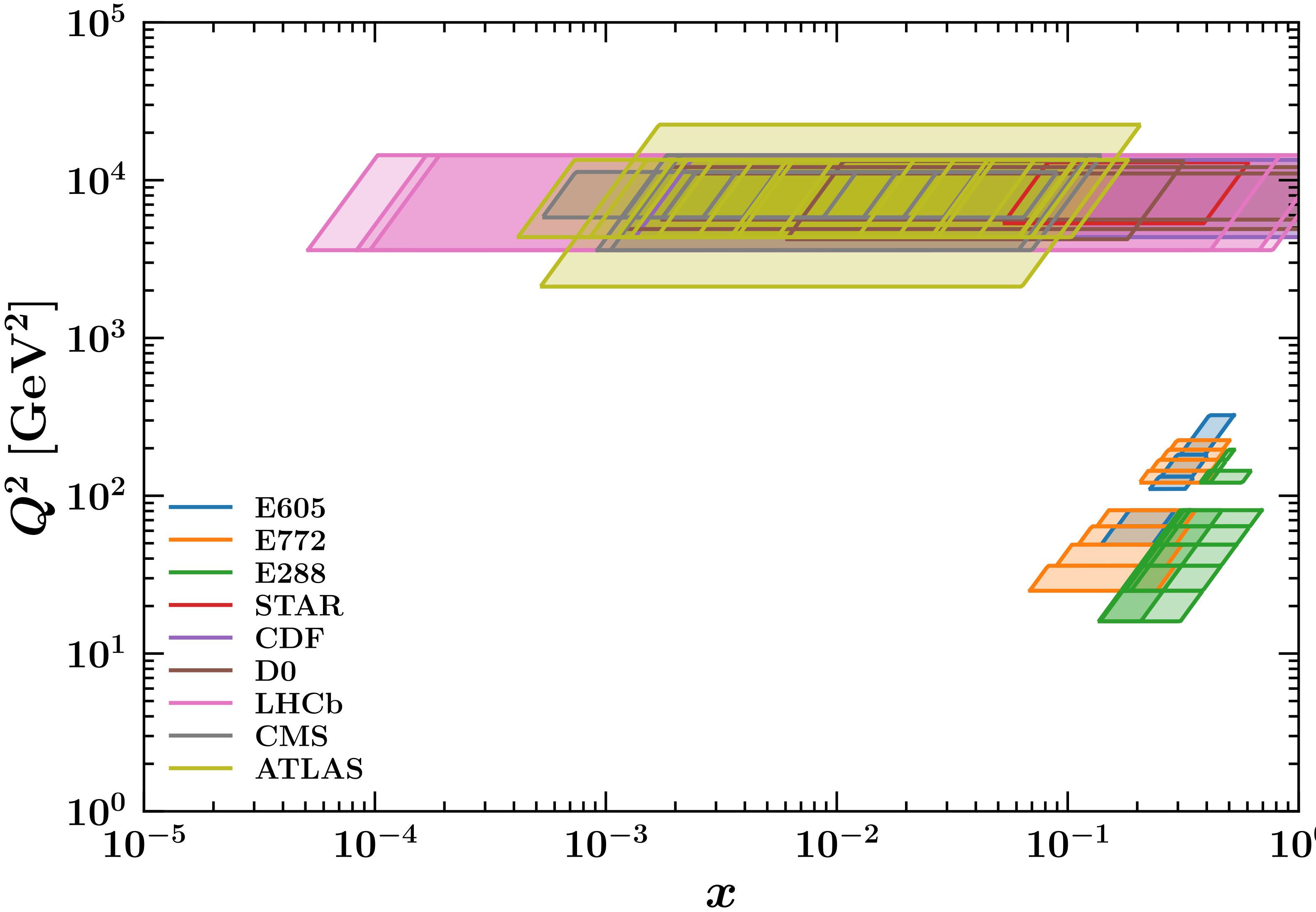

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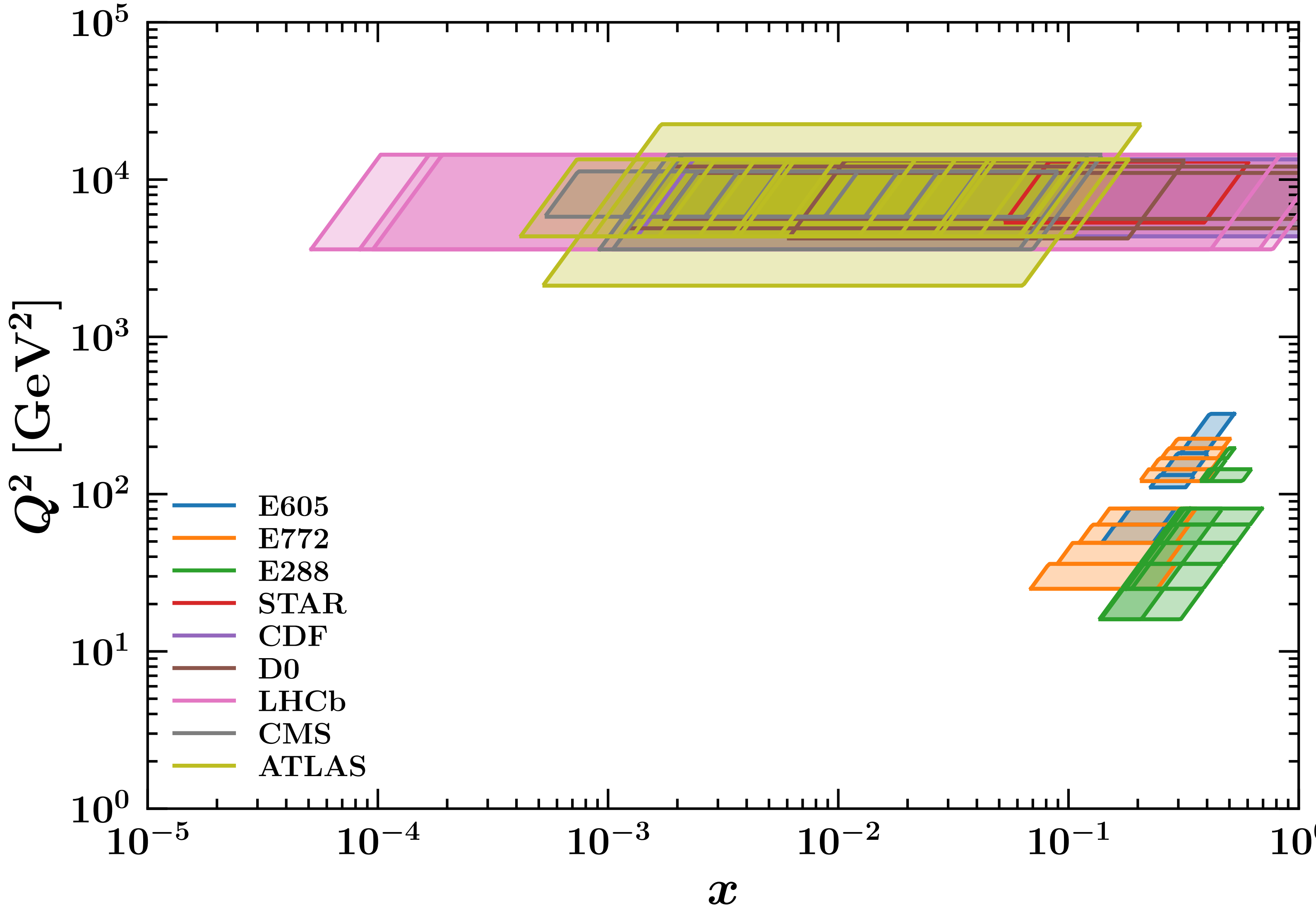

Total number of data: 482

Validation of the methodology

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**

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

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

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

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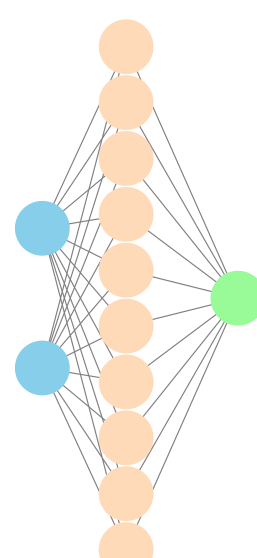
fit with NN



can we recover the DWS result?

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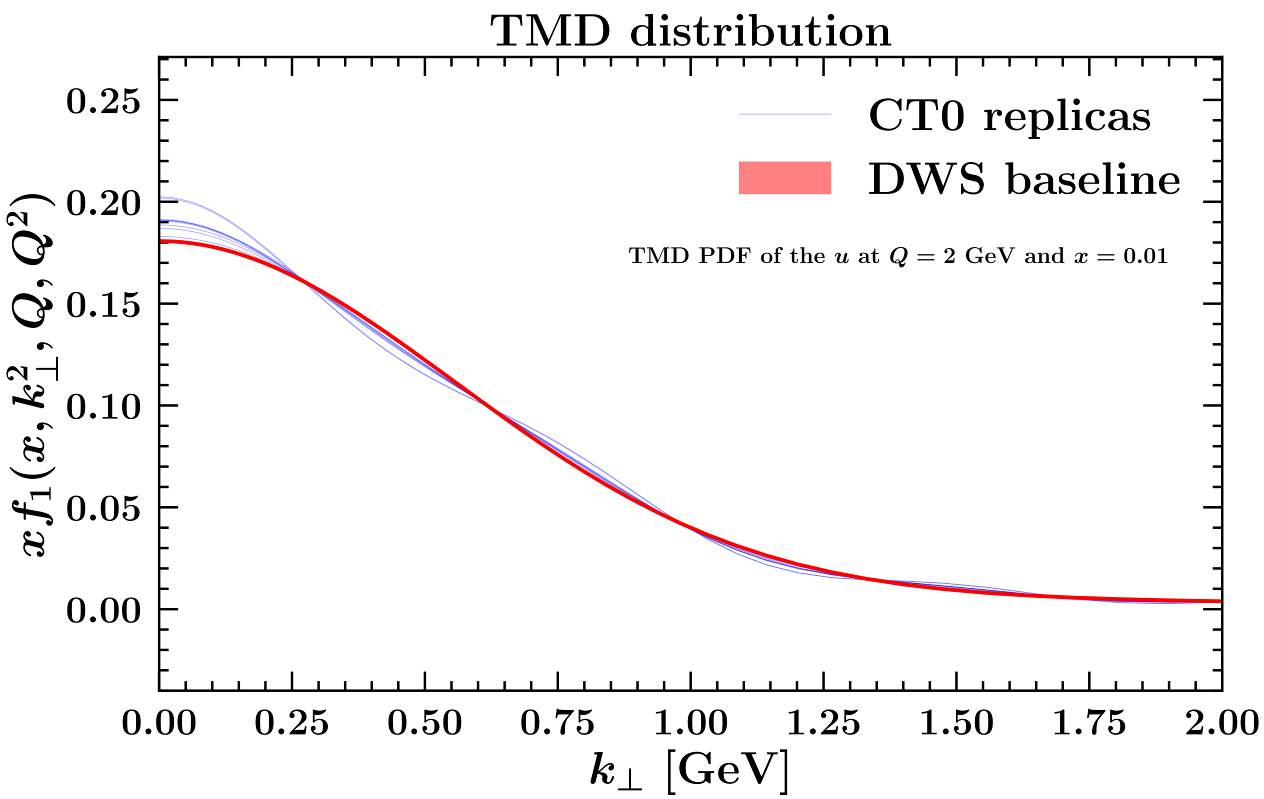

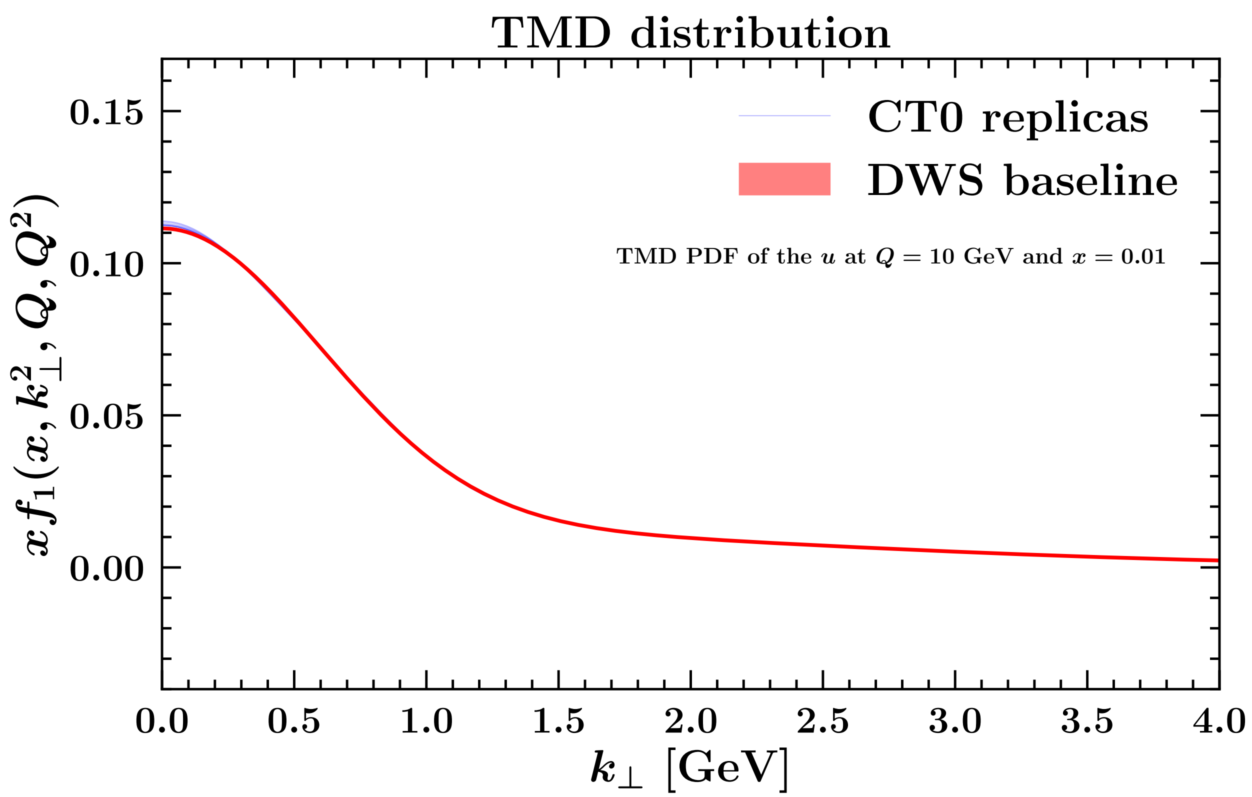

$$\chi^2 \sim 10^{-6}$$

Closure test successful!

Comparison to a traditional fit

MAP22 fit

MAP Collaboration, JHEP 08 (2024)

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

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11+1 parameters

Results of the analysis

MAP Collaboration, PRL 135 (2025)

Data / Theory agreement

MC replica method to propagate experimental uncertainties

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

Experiment	$N_{\rm dat}$	$\overline{\chi}^2$ $(\overline{\chi}_D^2 + \overline{\chi}_\lambda^2)$ NN	MAP22
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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	$0.40\ (0.38 + 0.02)$	$0.41\ (0.35 + 0.06)$
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Total	482	$0.97\ (0.86 + 0.11)$	$1.28\ (1.09 + 0.20)$

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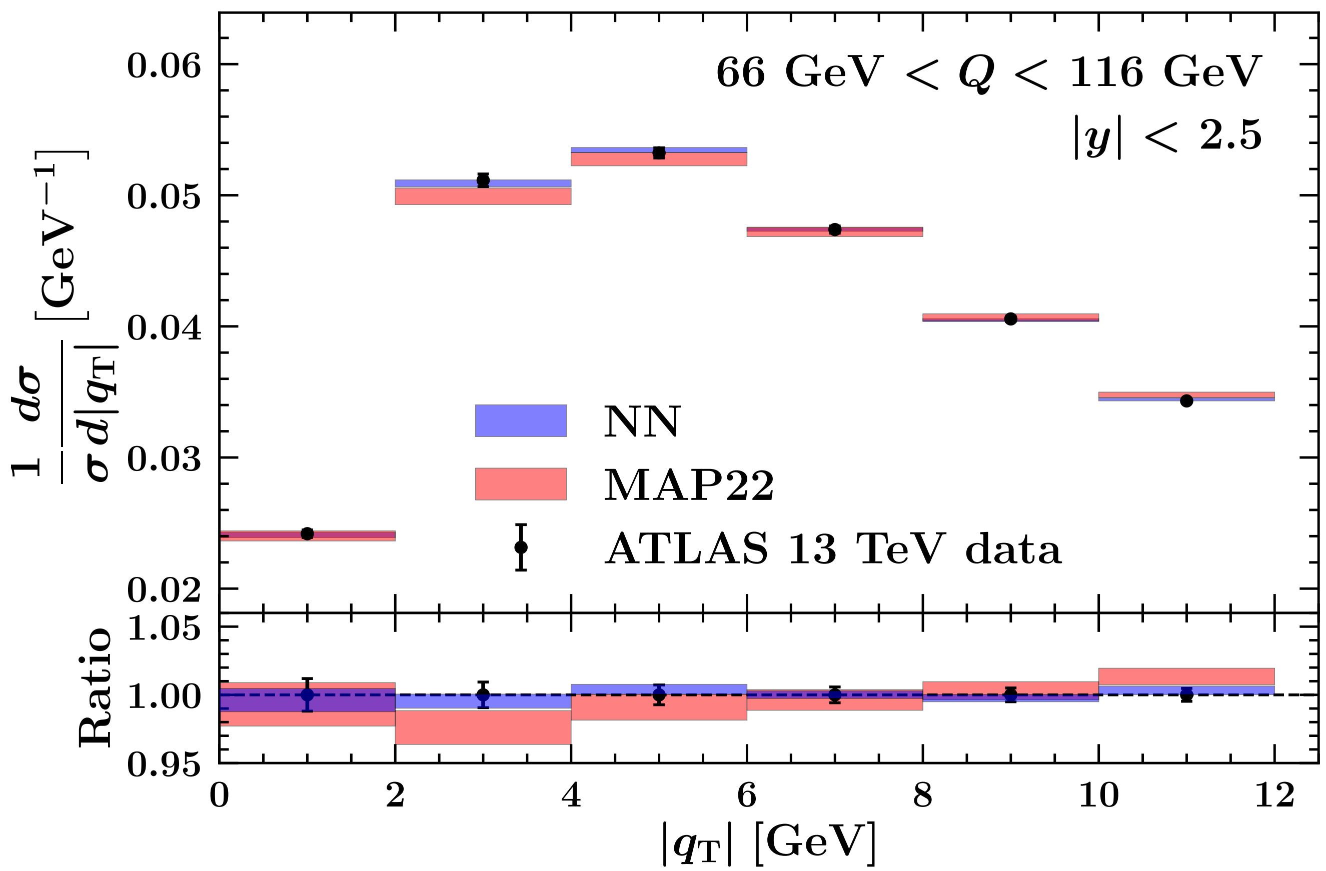

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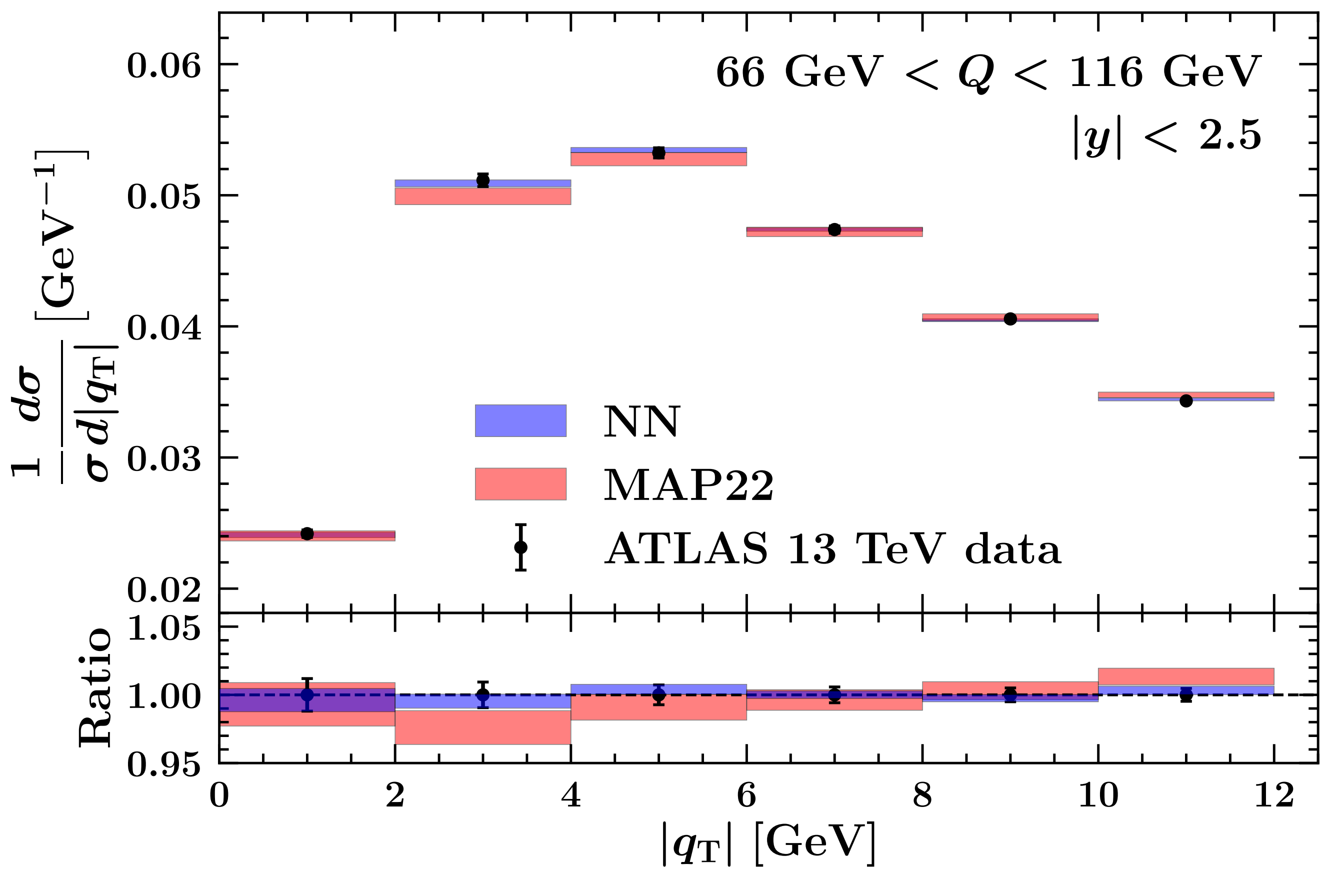

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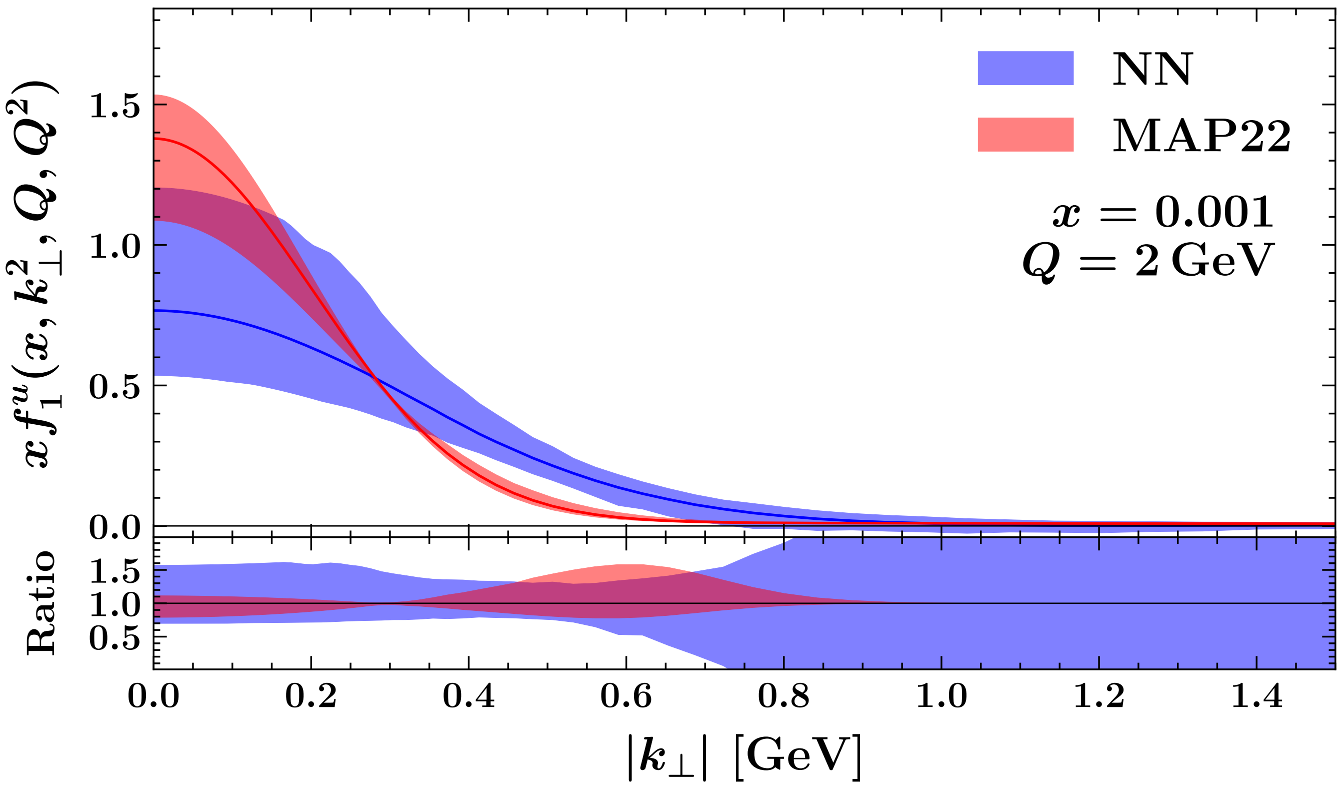
Significant improvement for ATLAS data

MAP22 relies more on systematic shifts ⇒ large error bands

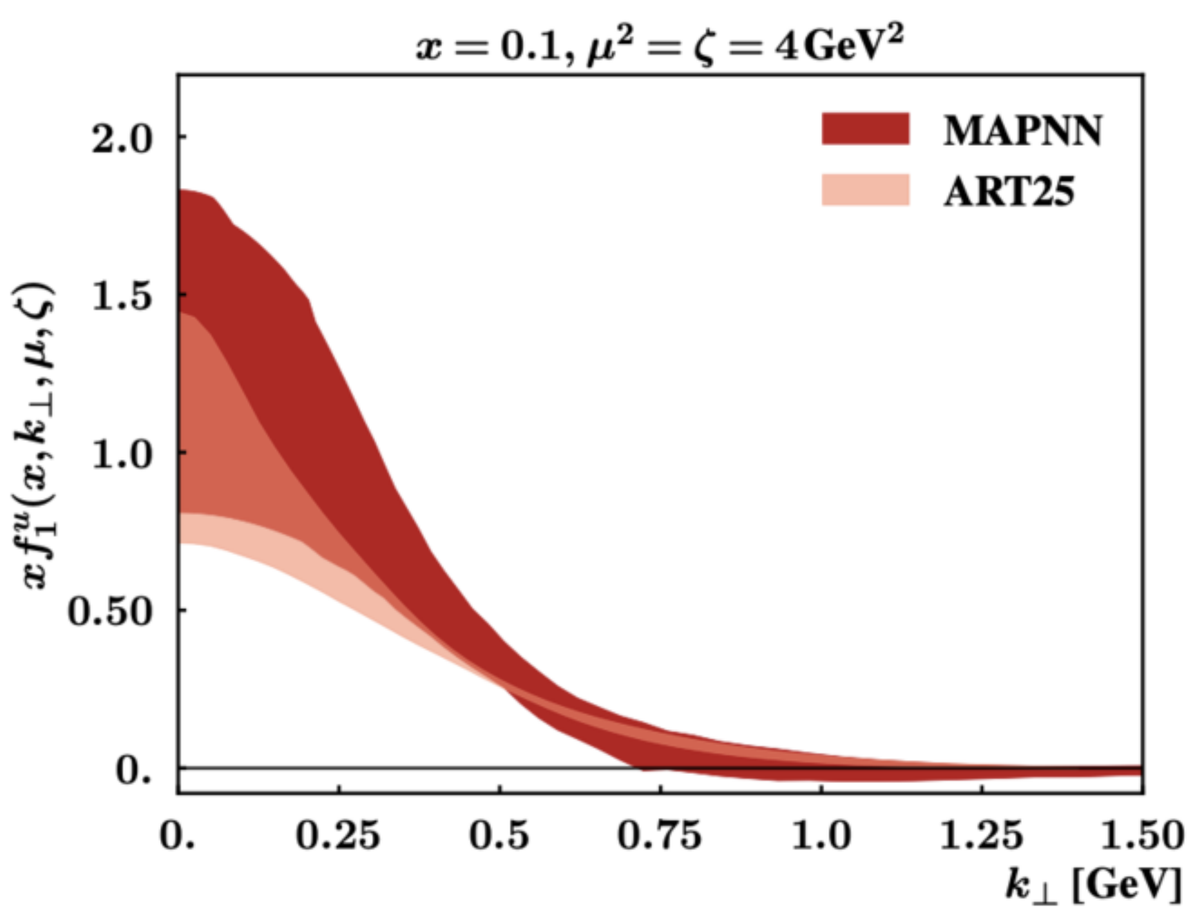
Fit results

Extracted TMDs

MAP Collaboration, PRL 135 (2025)



NN fit has larger bands



more conservative estimates of uncertainties

Lorcé, Metz, Pasquini, Barbara, Schweitzer, arXiv:2507.12664

Fit results

MAP Collaboration, PRL 135 (2025)

Extracted nonperturbative evolution (Collins-Soper kernel)

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Kernel of the rapidity evolution equation

$$\frac{\partial \ln \hat{f}_1(x, b_T; \mu, \zeta)}{\partial \ln \sqrt{\zeta}} = K(b_T, \mu)$$

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MAP Collaboration, PRL 135 (2025)

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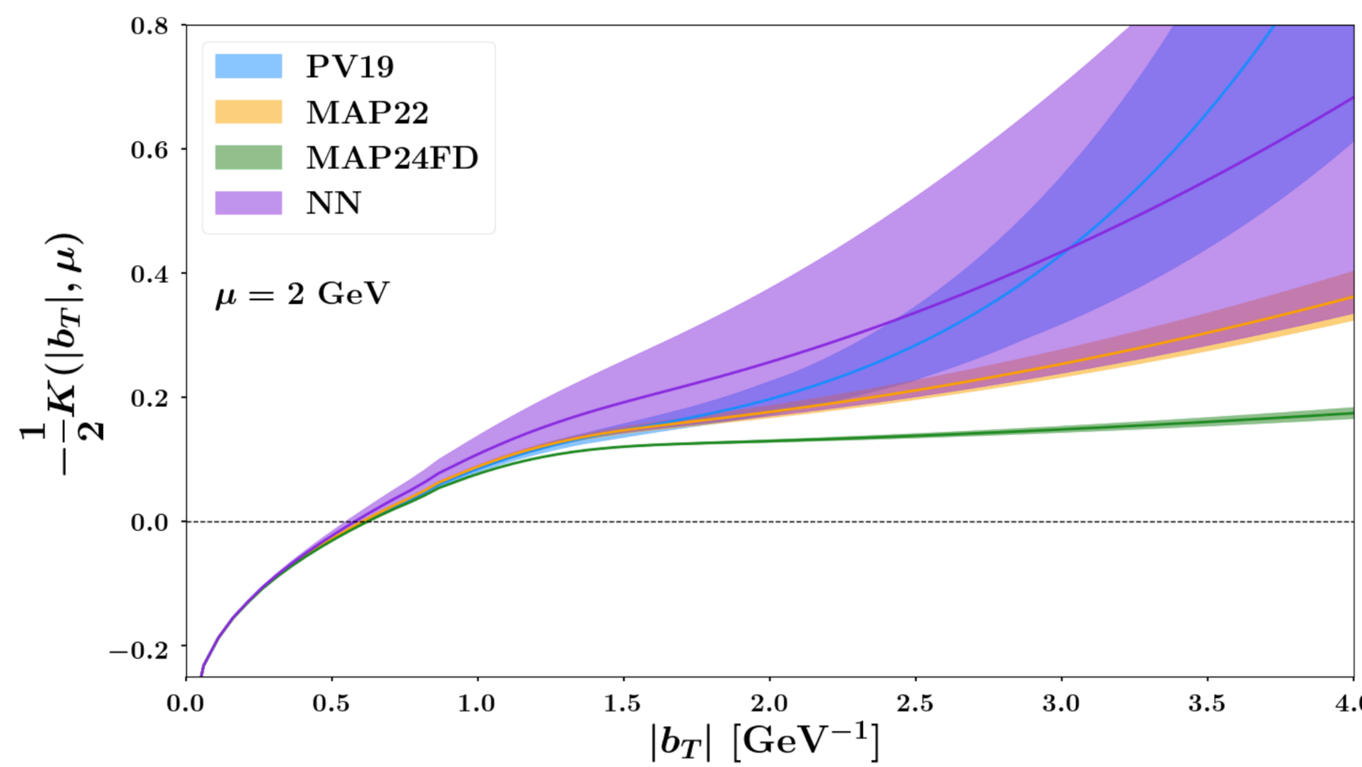
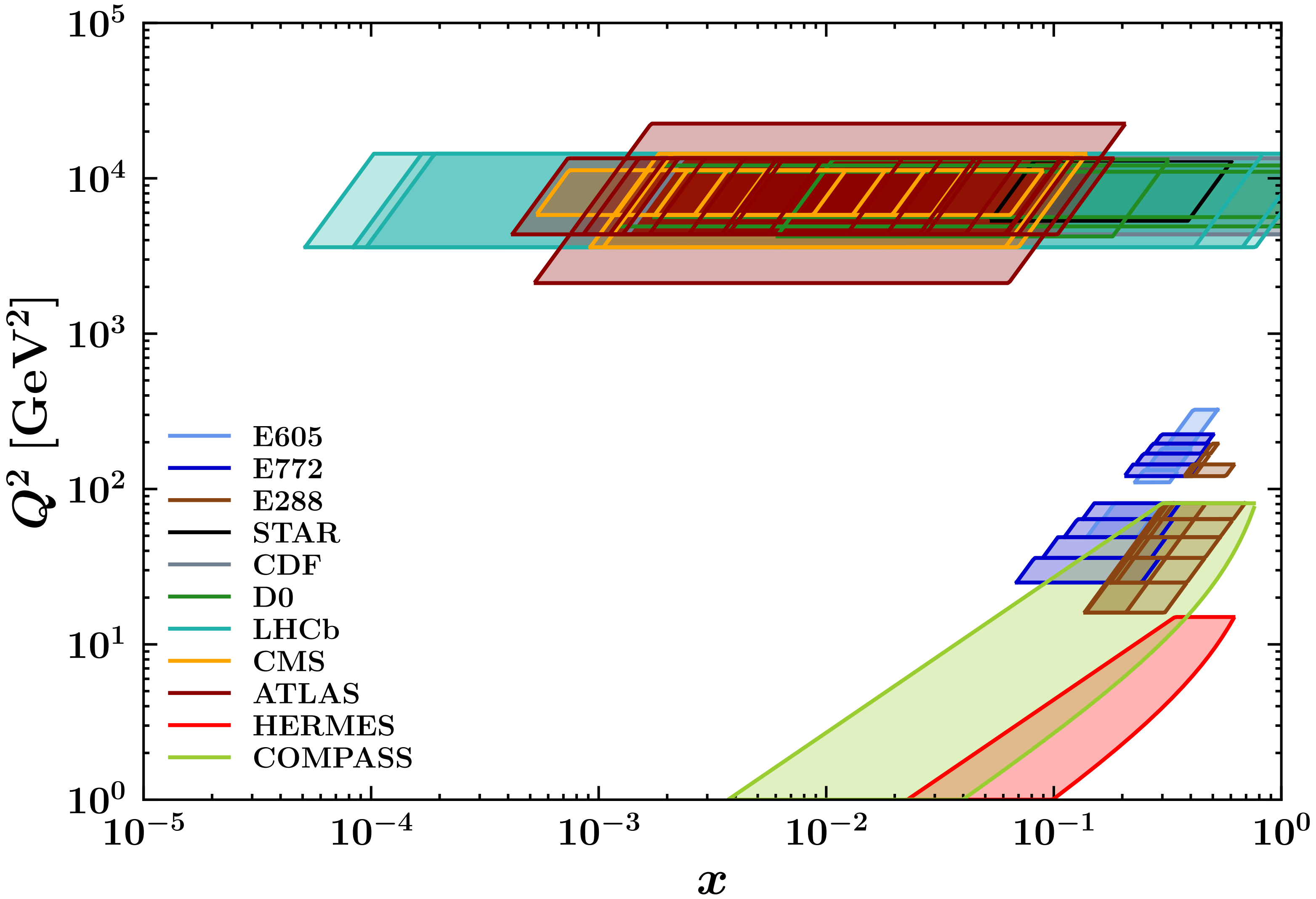


more reliable estimate of uncertainties

Moving towards a global fit

- Fitting framework: NangaParbat
- Perturbative accuracy: N3LL
- Dataset: DY + SIDIS



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$Q > 1.4$

$0.2 < z < 0.7$

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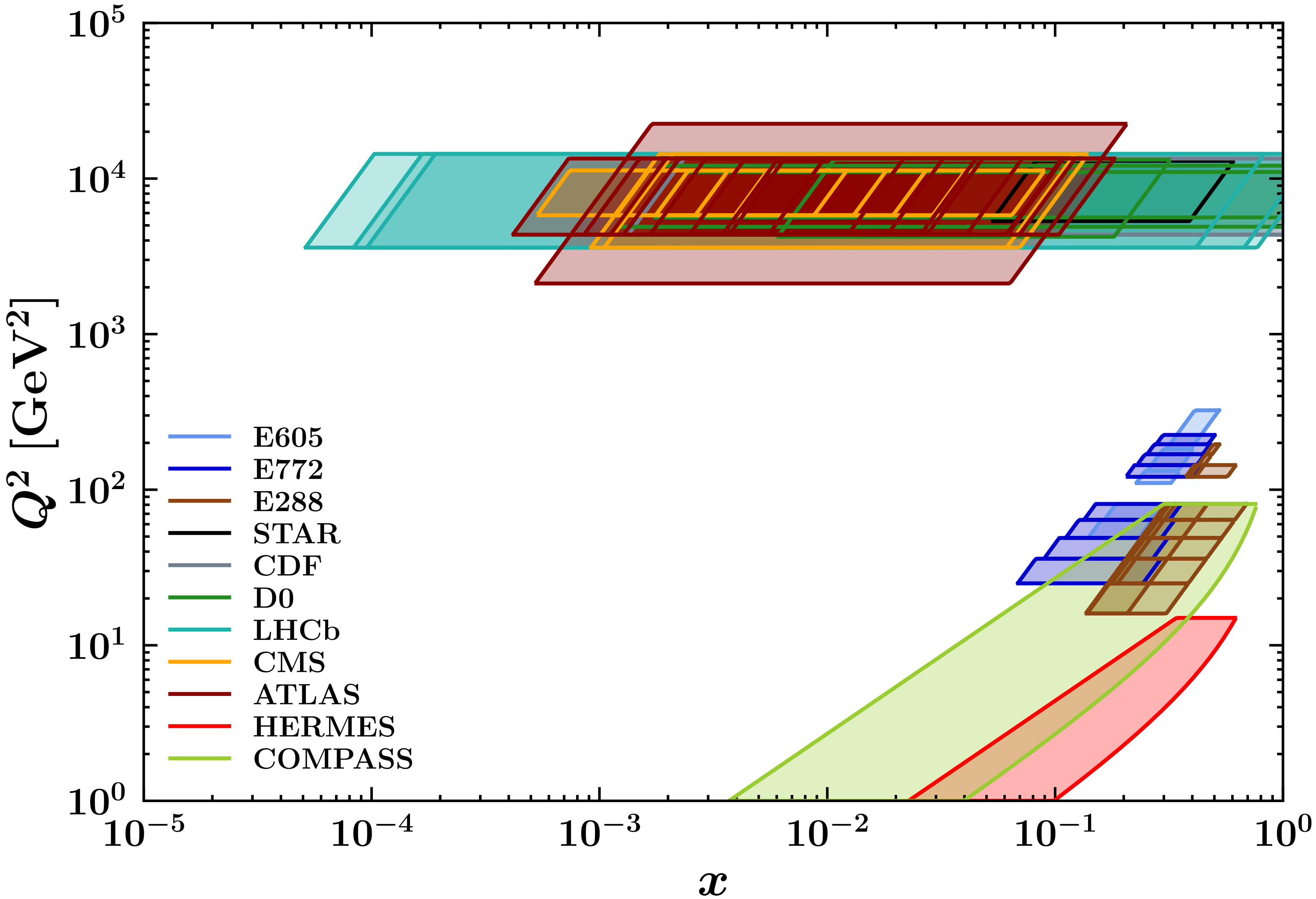

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482 + 1547 exp data

Extending the NN-based model

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

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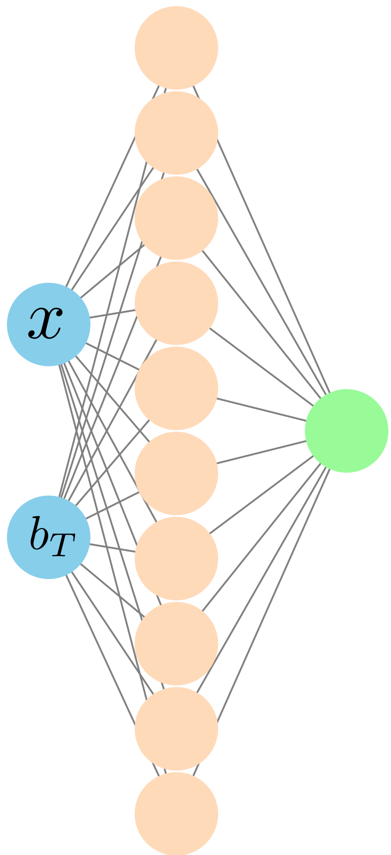

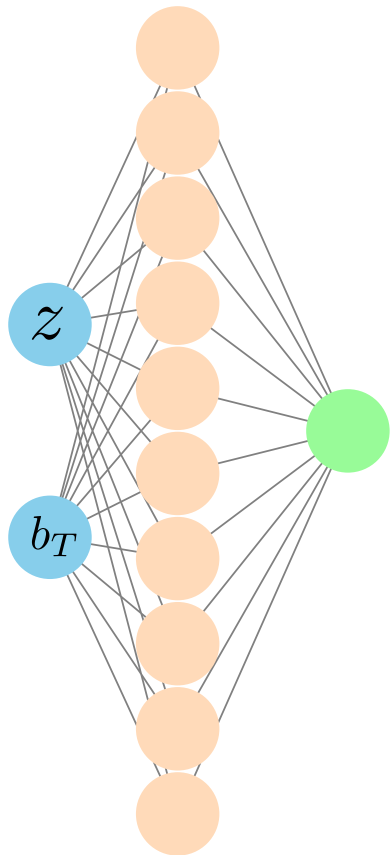

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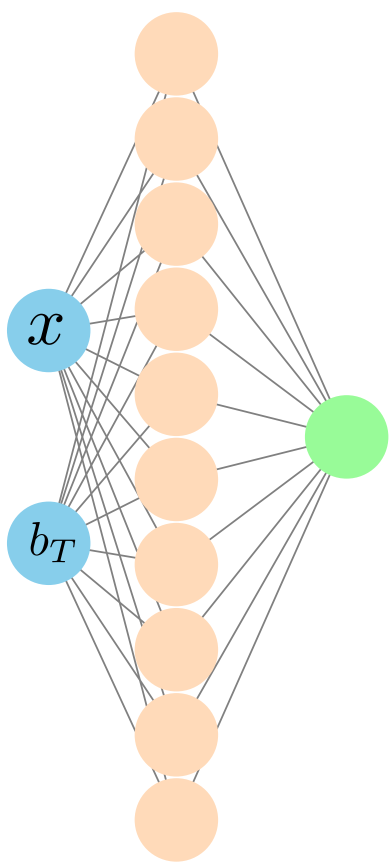
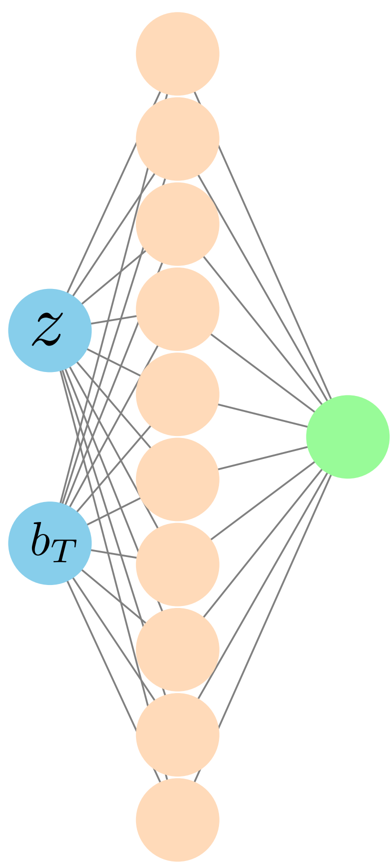
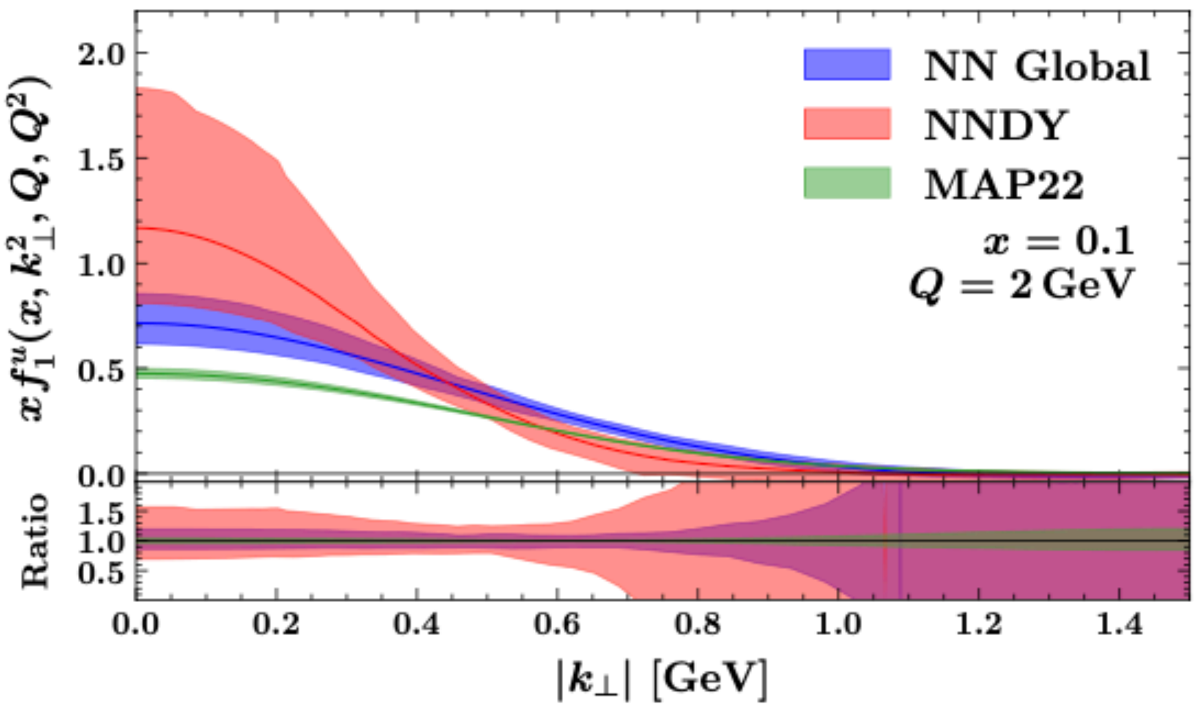


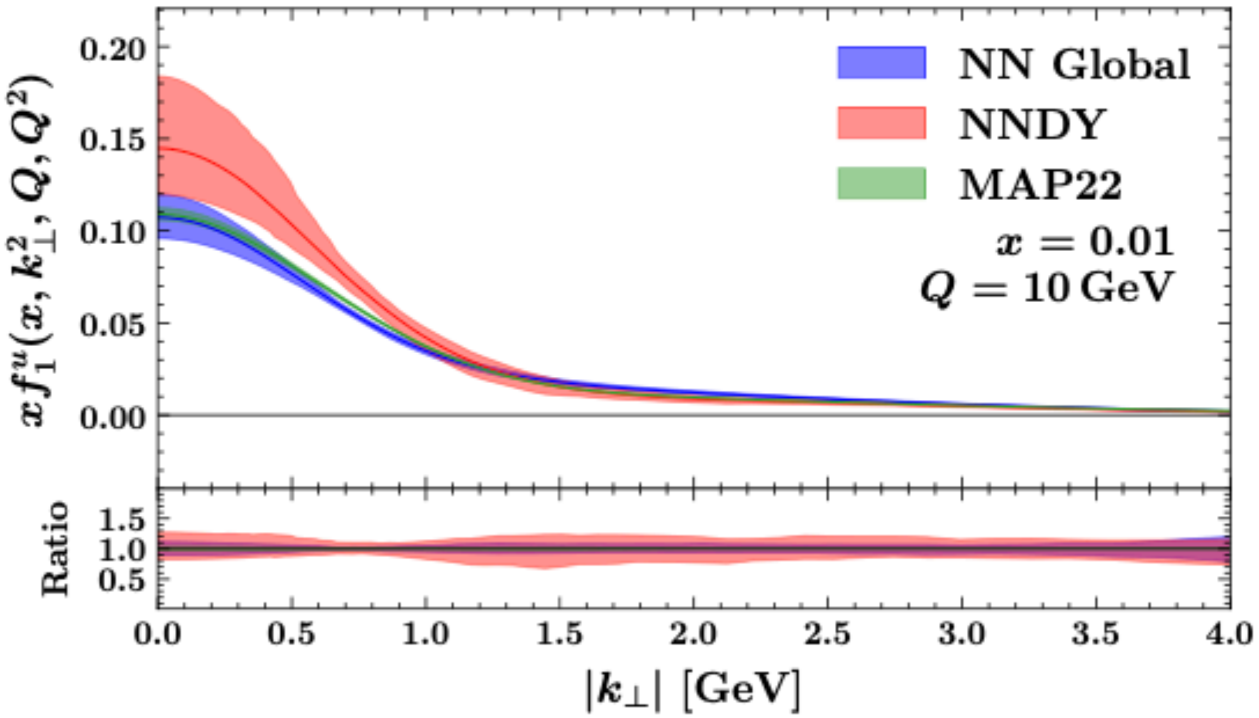


41 + 41+1 parameters

Global fit results

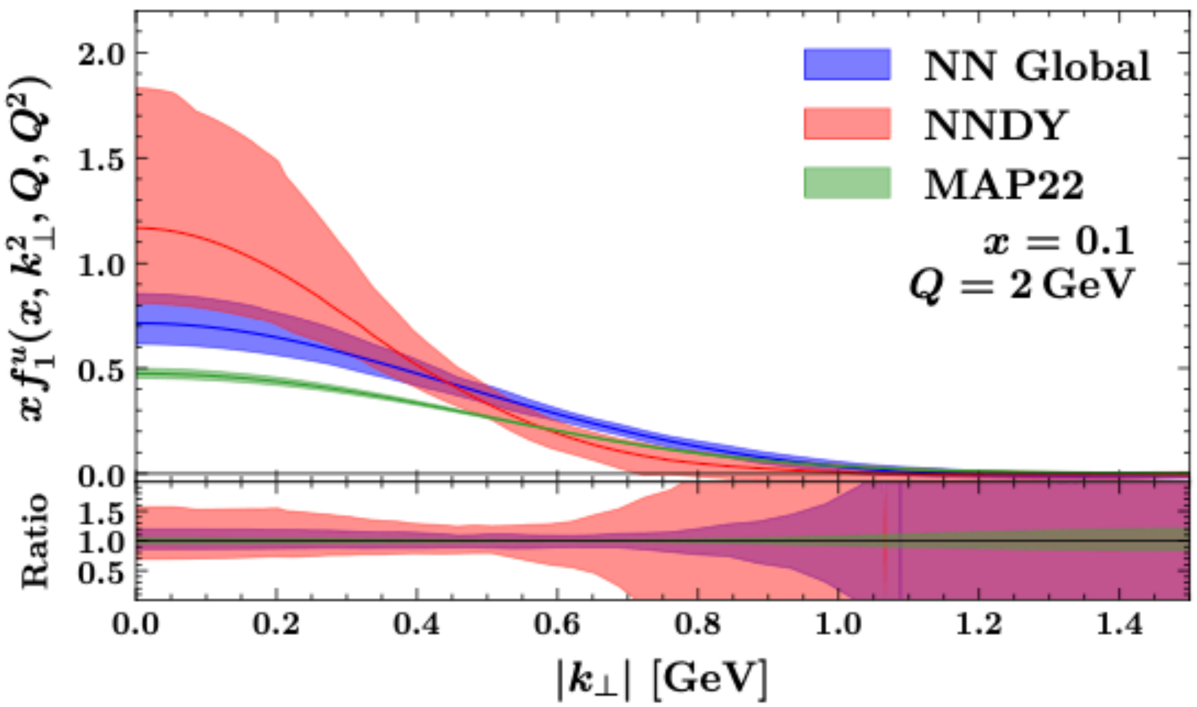
Extracted TMDs

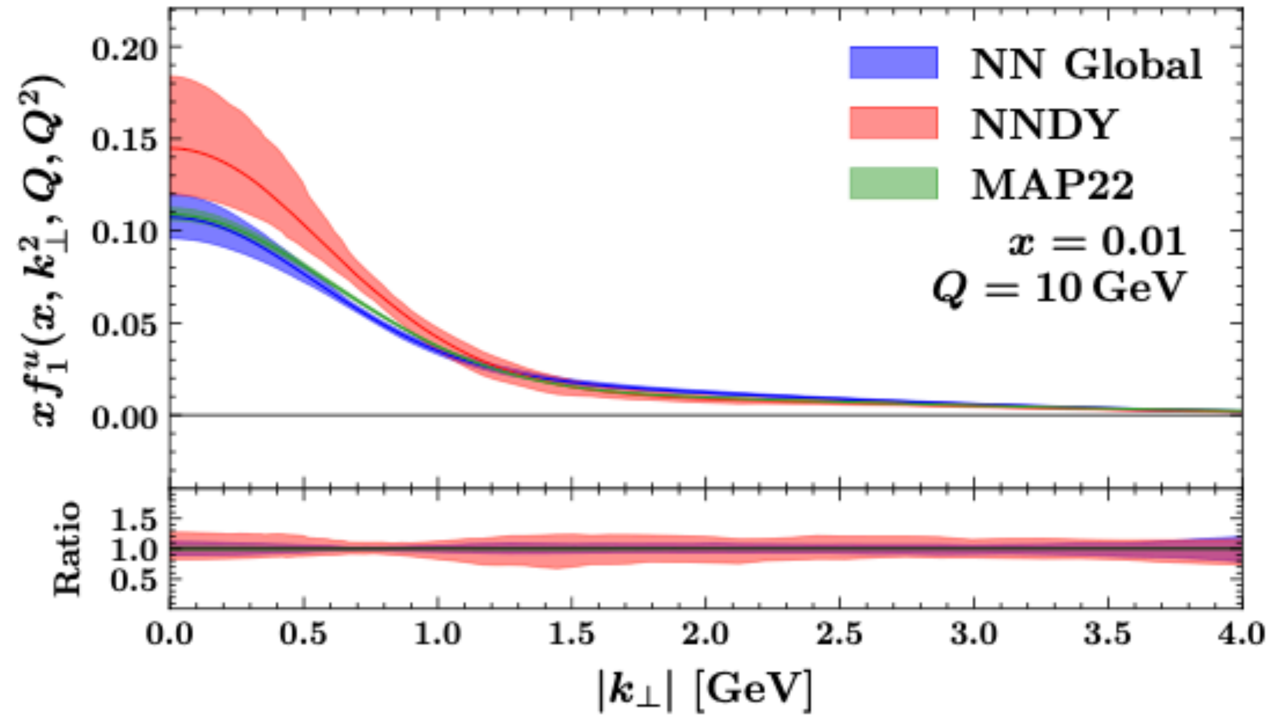




Global fit results

Extracted TMDs





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effect of the tensions?

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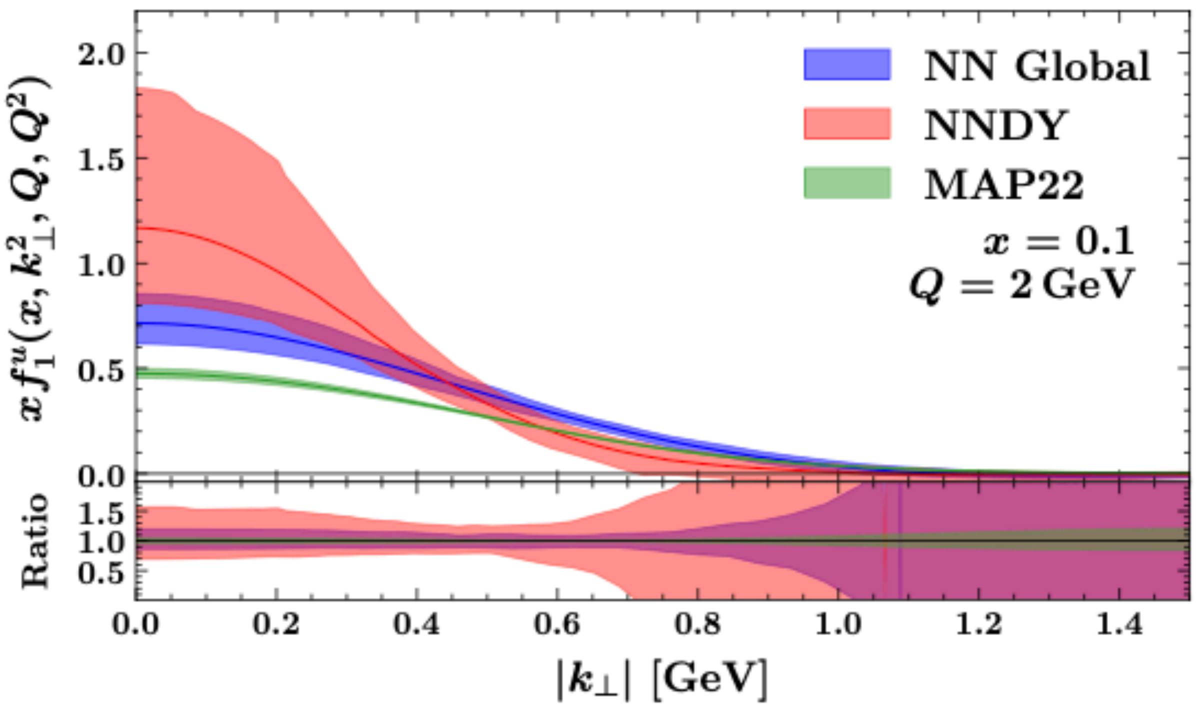

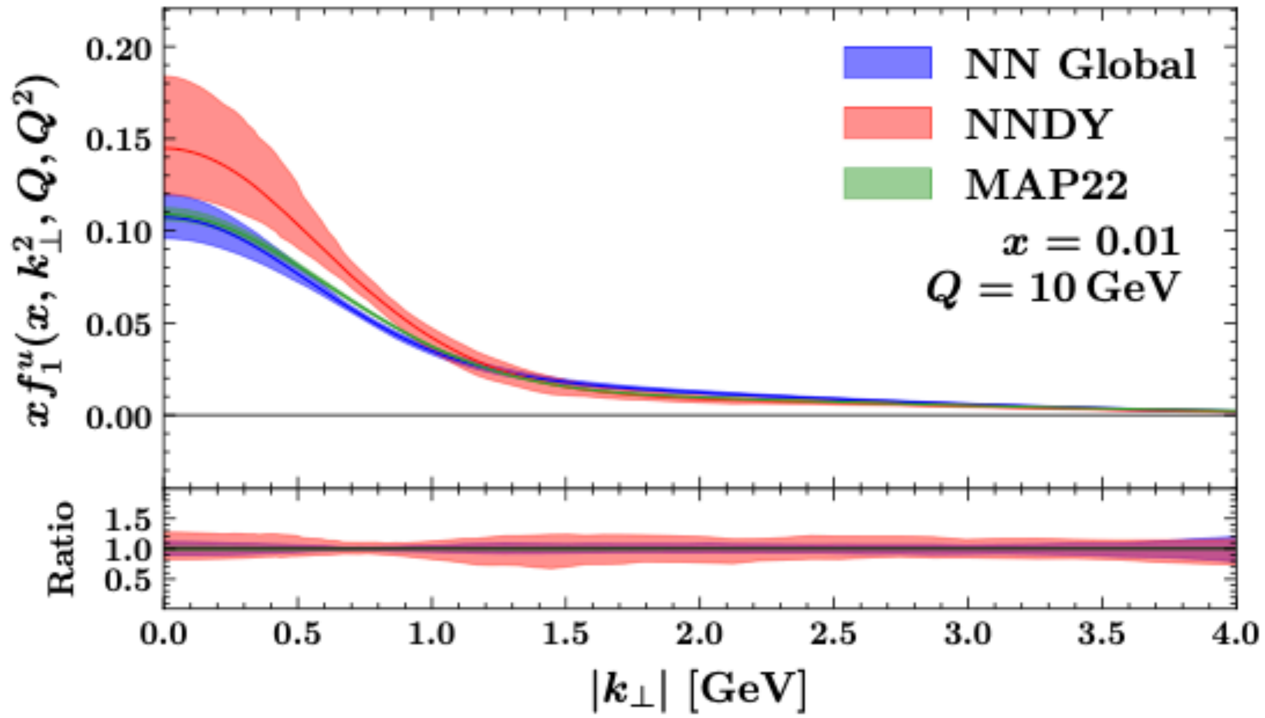

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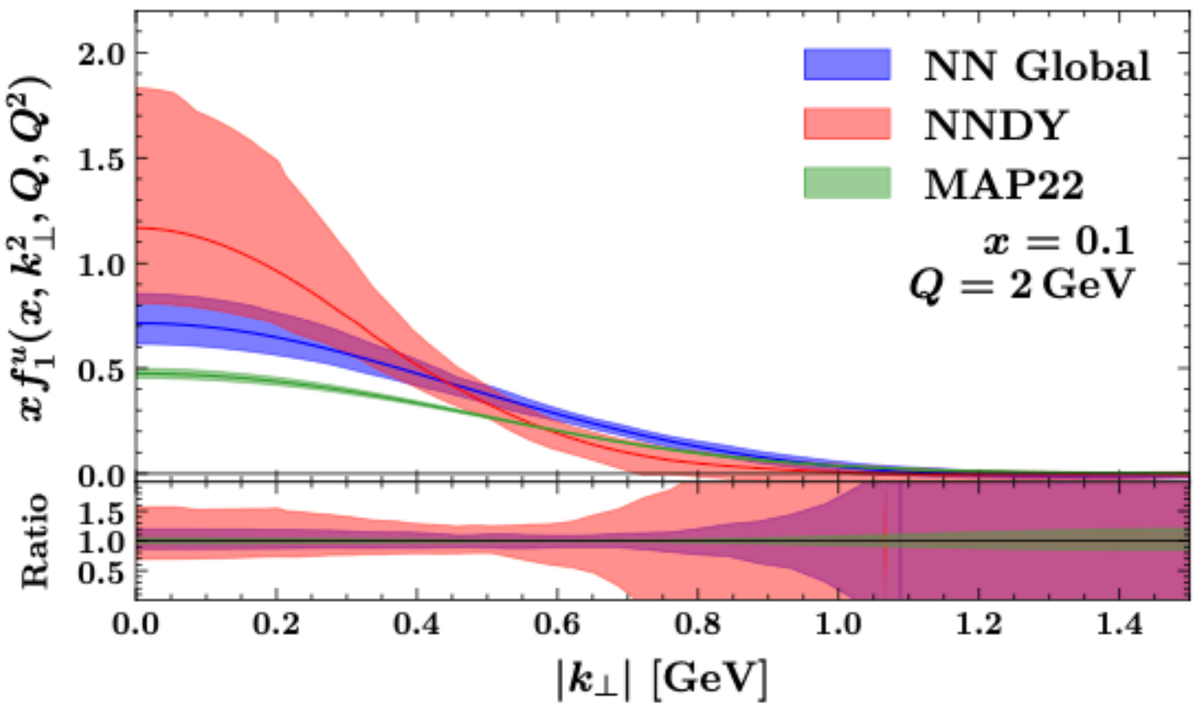

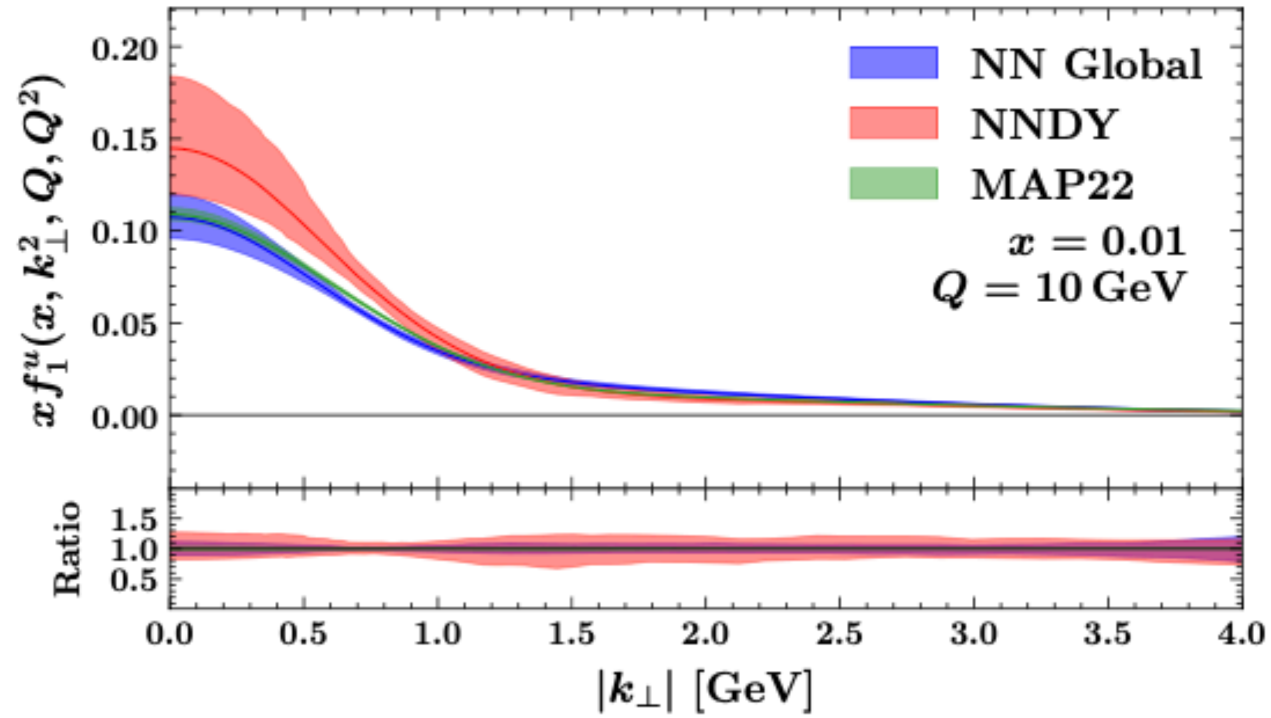

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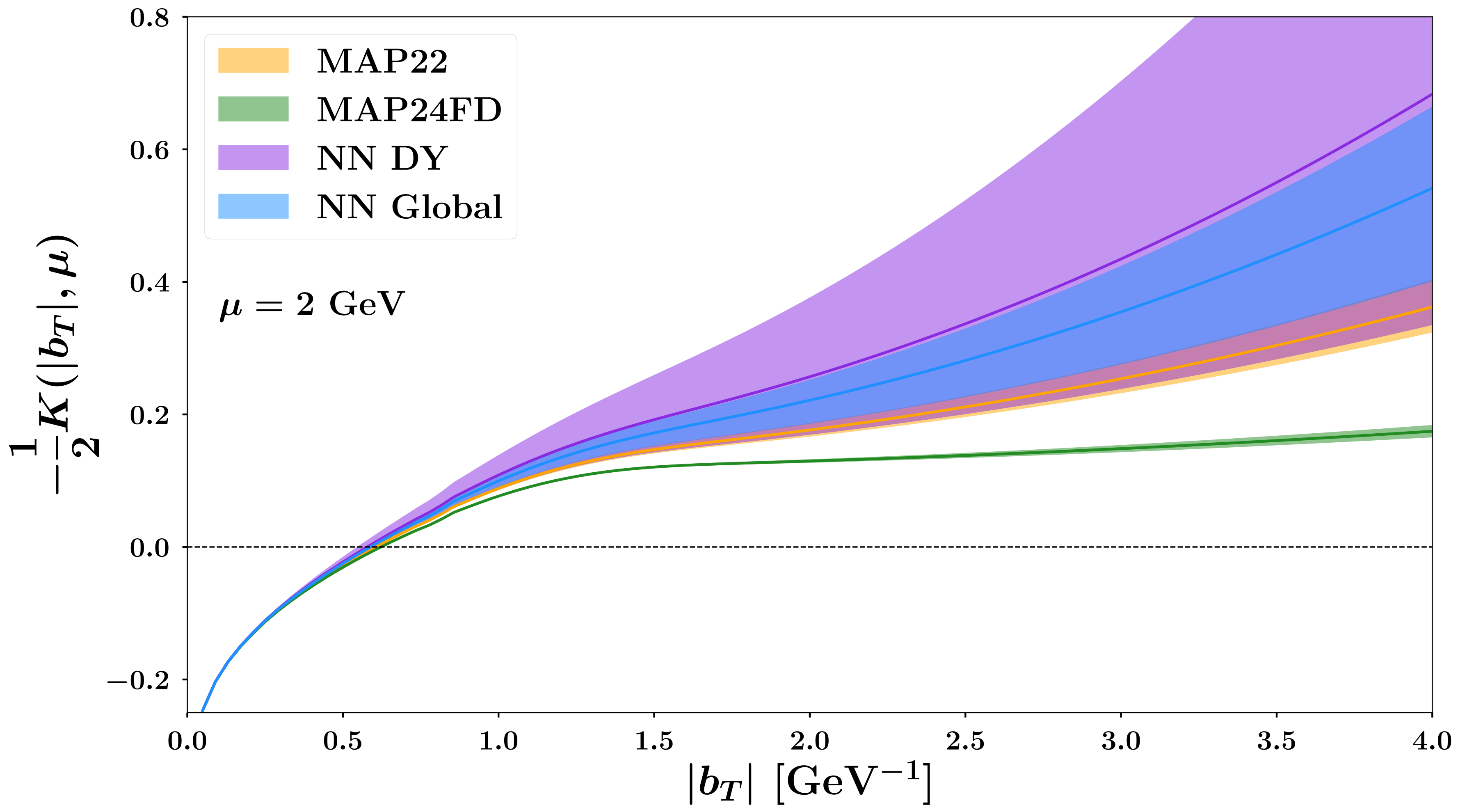
- But still larger than MAP22 — **more faithful representation of errors**

Global fit results

Collins-Soper kernel



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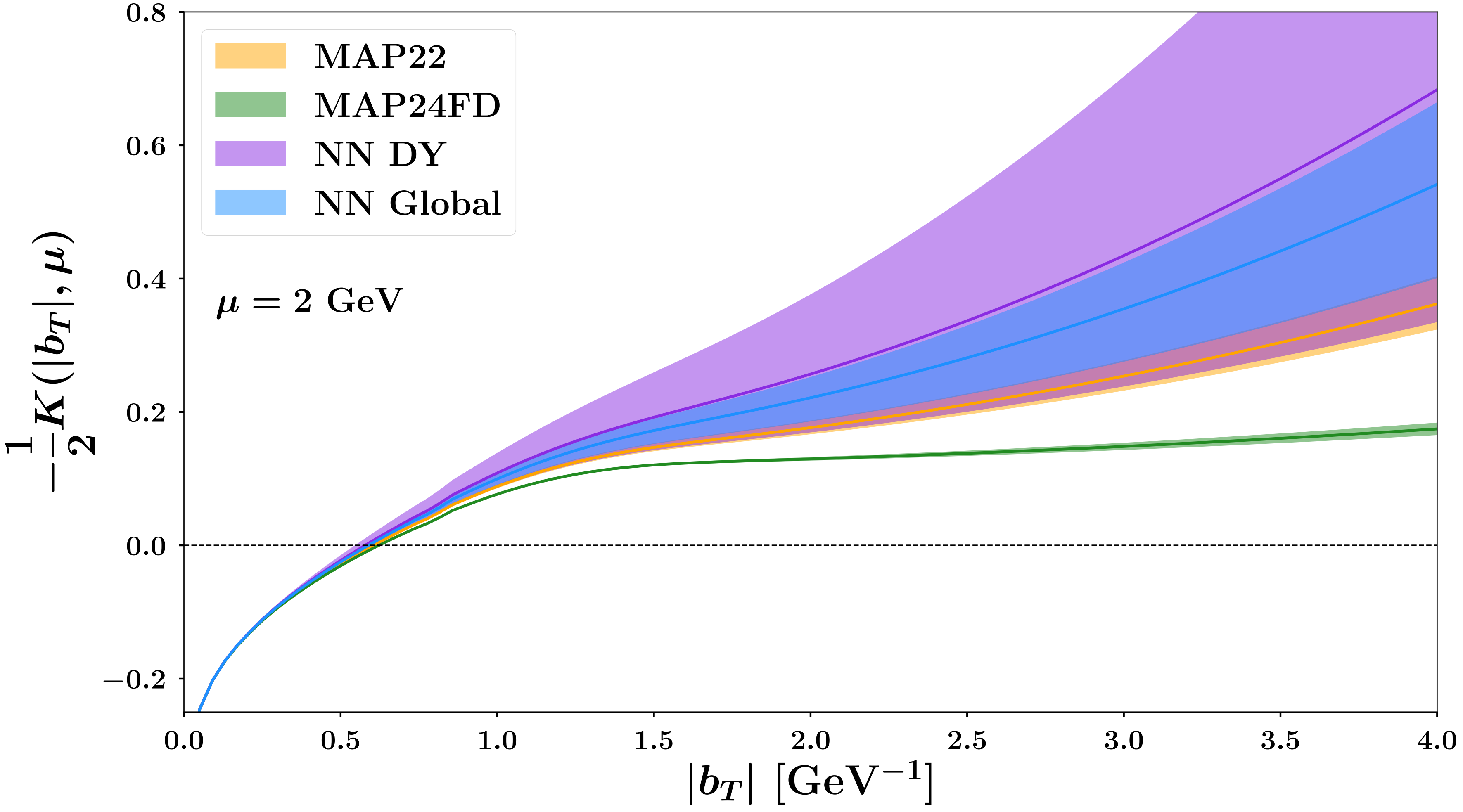

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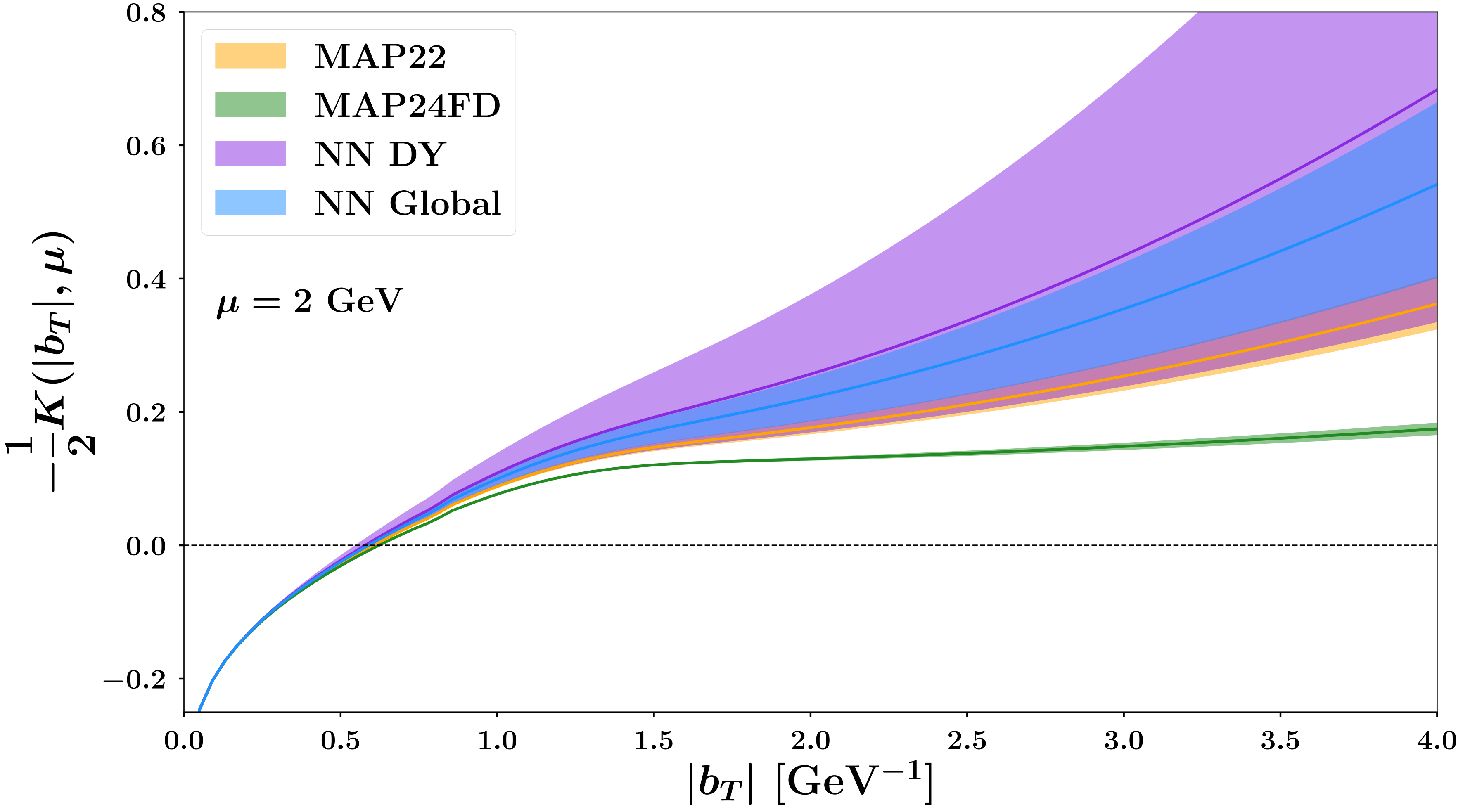

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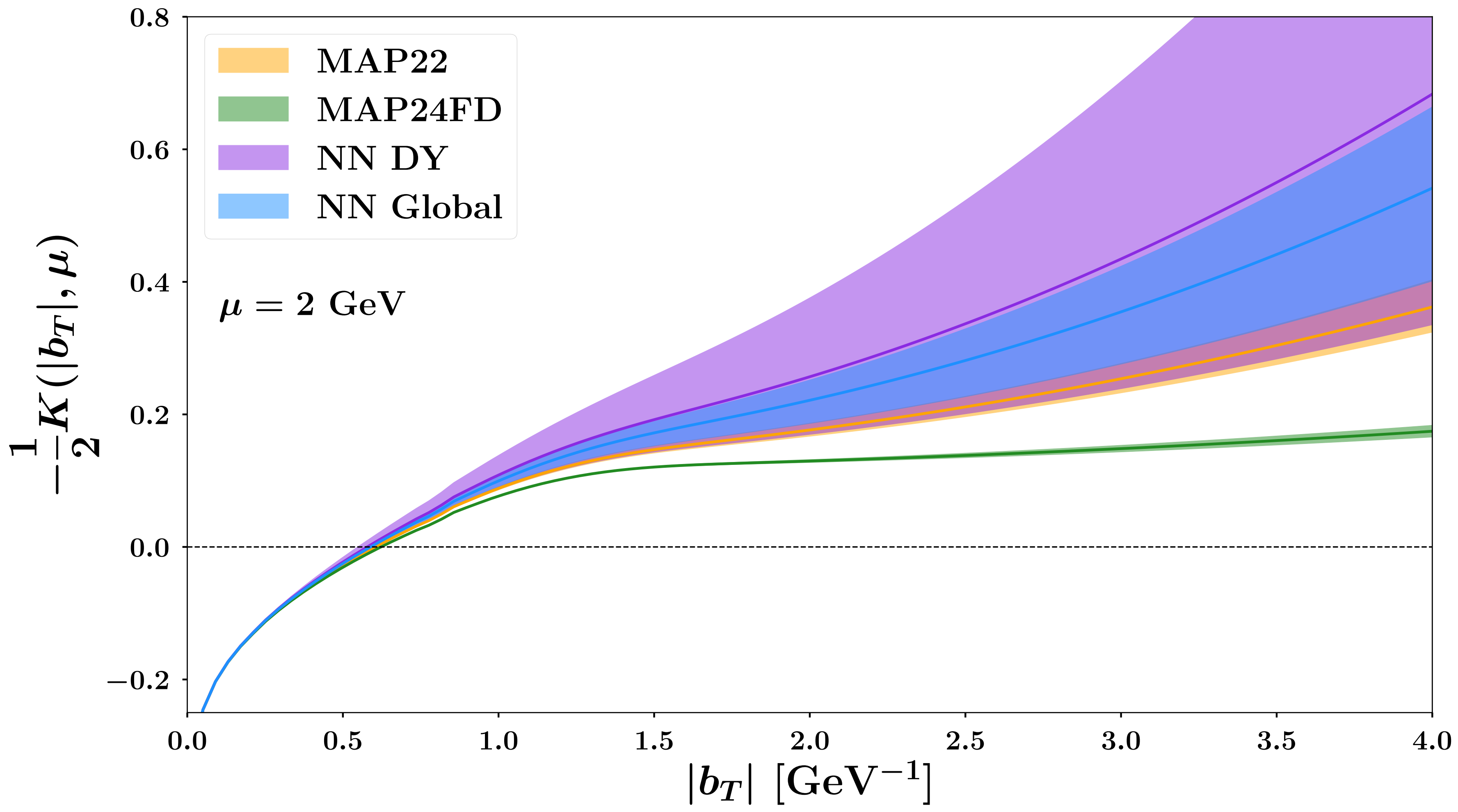

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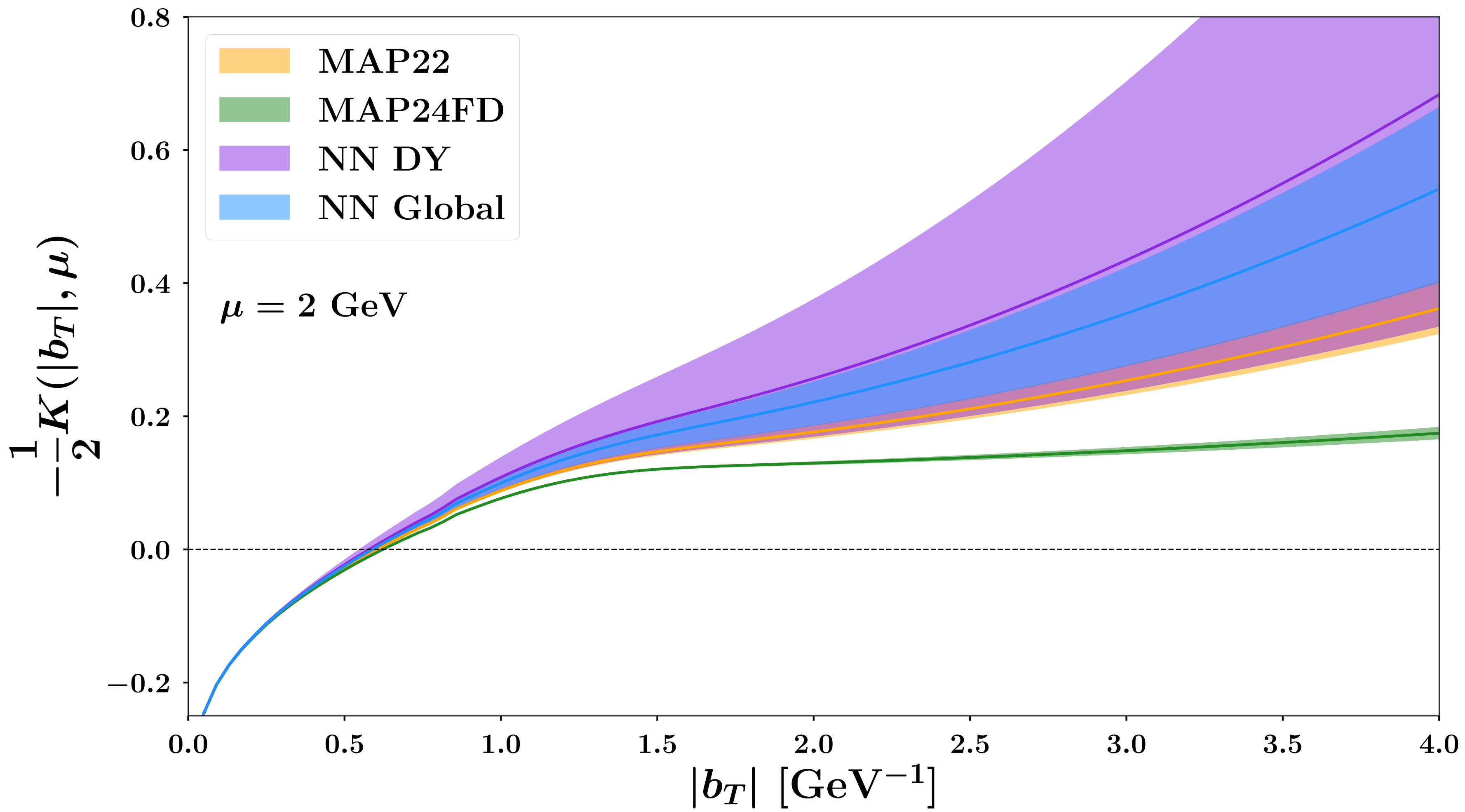

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  (Compatible with MAP literature! ART?)

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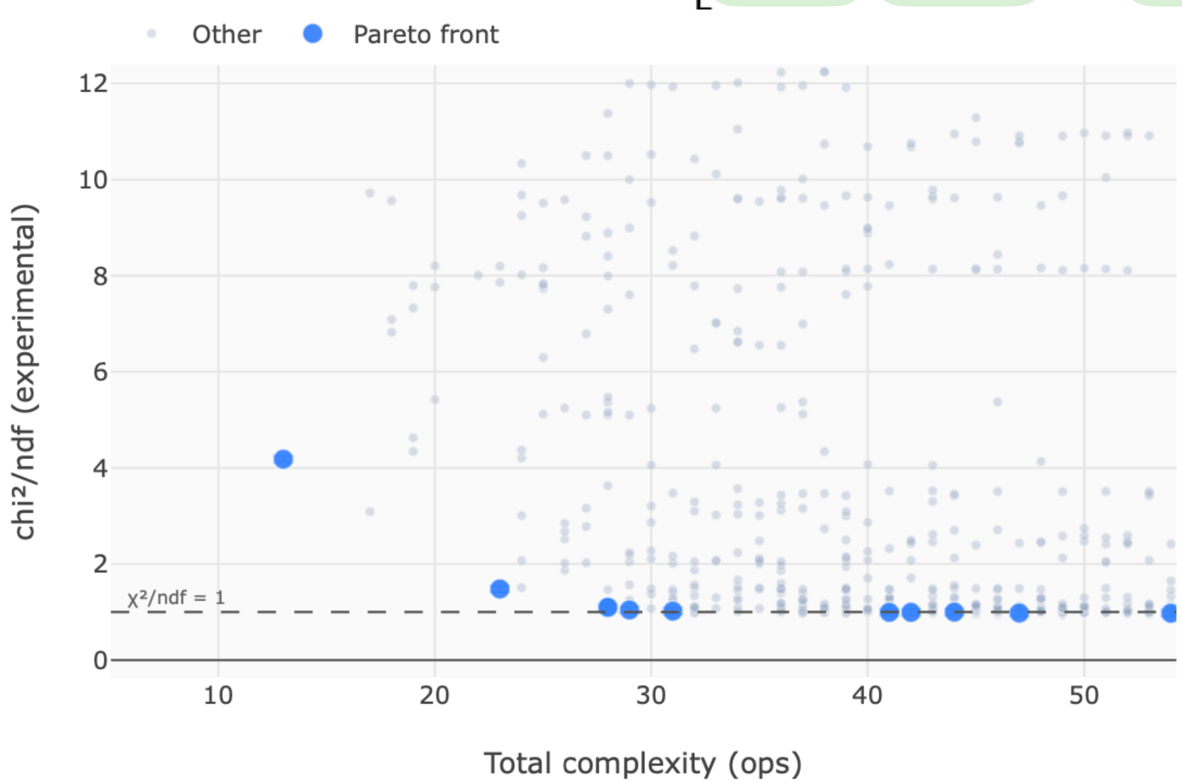
- First application of Symbolic Regression (PySR)
  Granger, Bacchetta, et al., arXiv:2607.24710

$$f_{\rm NP}(x, b_T, \zeta) = \exp\left[-g_2^2(b_T)\, b_T^2\, \ln(\zeta/Q_0^2)\right]$$
$$\exp\left[h_x(x)\, h_b(b_T) + h_{xb}(x, b_T)\right]$$



Fit with 4 NNs (~100 params) $\chi^2/\text{ndf} = 0.941$

complexity-χ^2 Pareto front

9-param. functional form $\chi^2/\text{ndf} = 1.040$

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  - ✓ Parametrisation bias
  - ○ Power-suppressed corrections — In progress
- **First application of Neural Networks in unpol. TMD fits**
  - ✓ The approach has been successfully tested on Drell-Yan data
  - ✓ NN provides more reliable uncertainty bands — MAP Collaboration, PRL 135 (2025)
  - ✓ The approach has been extended to global fits — Cerutti, arXiv:2606.28218
  - ○ Robust methodology validation tests are in progress — In progress

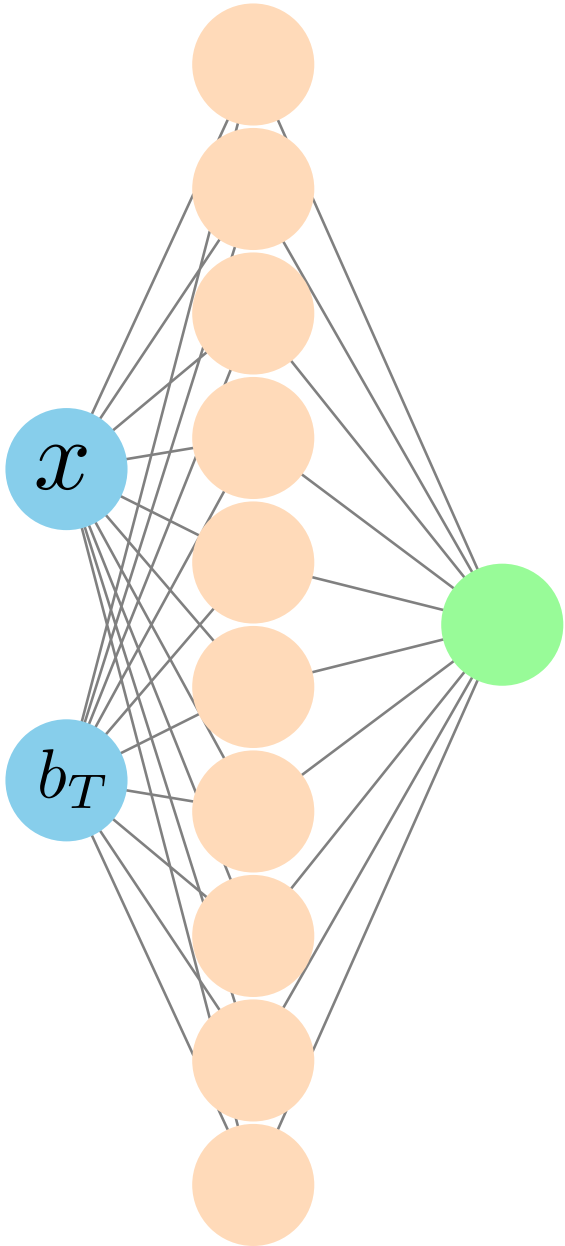
Backup

Parameterization: NN

MAP Collaboration, PRL 135 (2025)

$$\mathrm{NN}\left(x, b_T\right) = \sum_{j=1}^{10} v_j\, \sigma(w_{j1}\, x + w_{j2}\, b_T + b_j) + c$$

41+1 parameters



w_{j1}, w_{j2} Weights of the level 2->10

b_j Bias of the 10 hidden neurons

v_j Weight of the level 10->1

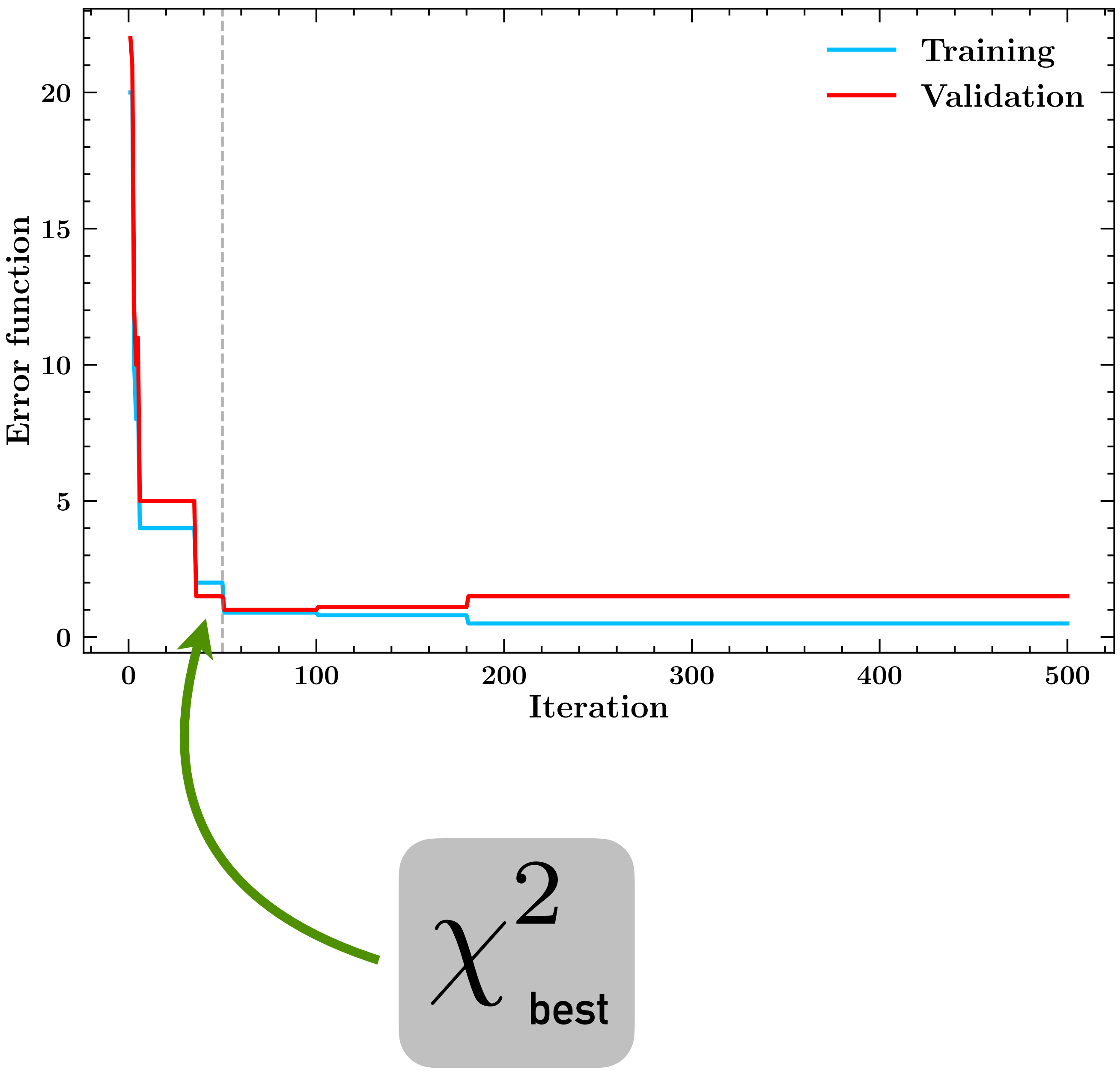
c Final bias

activation function

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

Fitting procedure

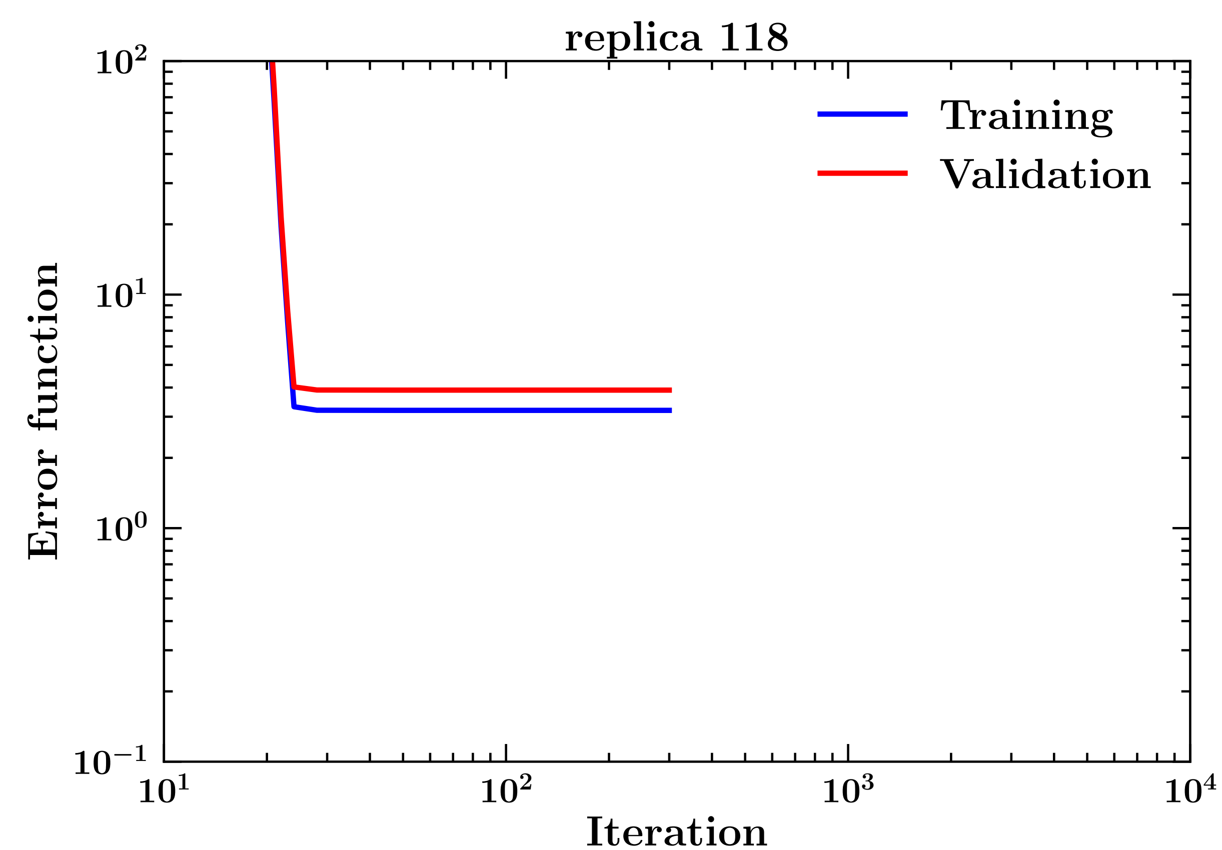
Splitting the dataset into training / validation subsets



random splitting

50% - 50%

dataset by dataset



How can we improve global analyses

- Improve phenomenological framework

  → increase theoretical accuracy (need N3LO) Moos, Scimemi, et al., JHEP 05 (2024)

  → improve control of theoretical uncertainties

  - model uncertainties (Neural Networks) MAP Collaboration, PRL 135 (2025)
  - fit setup (dependence on collinear set, b_* prescription) Cerutti, Simonelli, EPJ C 86 (2026)
  - scale variations, power corrections, … In progress

- Add new experimental data

  → LHC (low-mass DY data)

  → Jefferson Lab and EIC SIDIS future measurements

  → electron-positron annihilation (Belle? ALEPH? Key for TMD FFs)

We have studied the impact of pseudodata on current global analyses!

Cerutti, Chen, et al., accepted on PRC (2026)
Cerutti, D'Alesio, Gao, et al, PAC approved Jefferson Lab Run-group Experiment with E12-10-006 and E12-11-007 (2025)