Participation funded by

Impact of SIDIS measurements at future facilities towards the next generation of TMD analyses

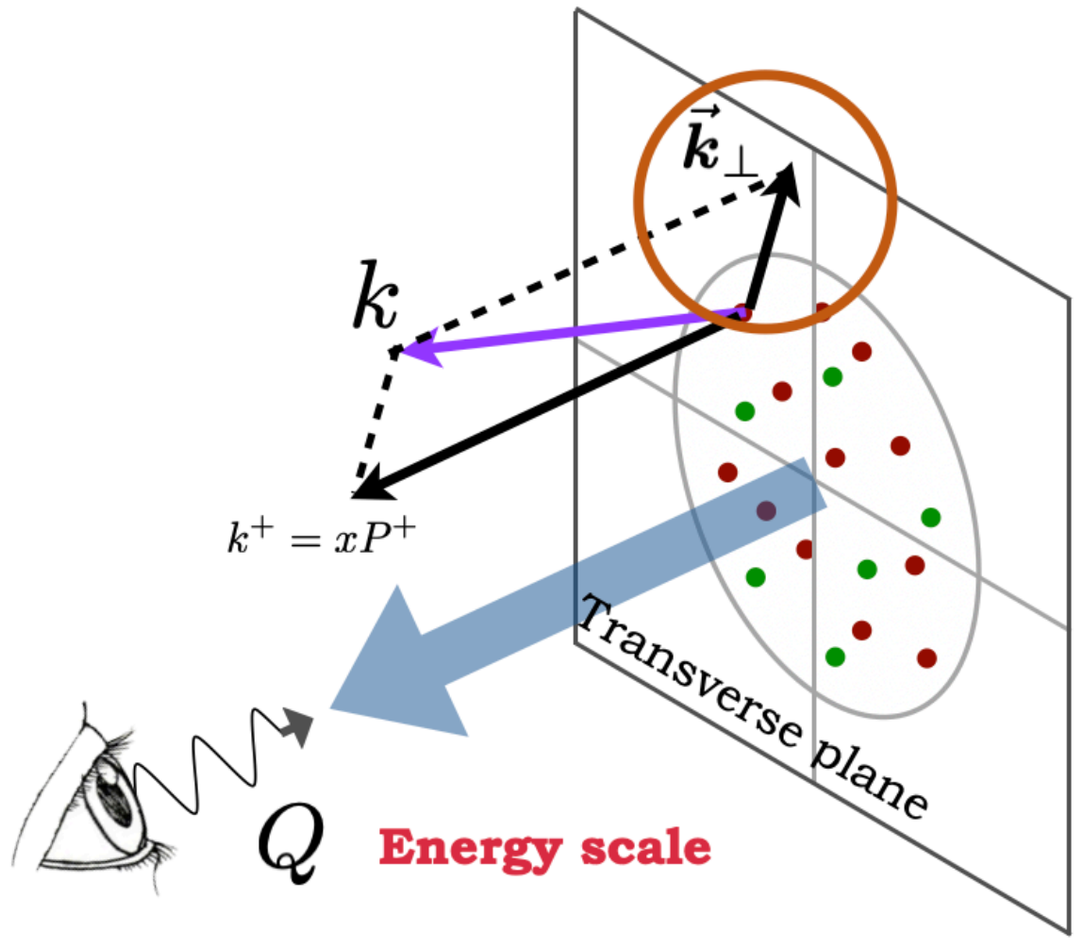
Matteo Cerutti

DIS2026 - Bologna (IT) - 05/05/2026

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

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

TMD factorisation: Universality

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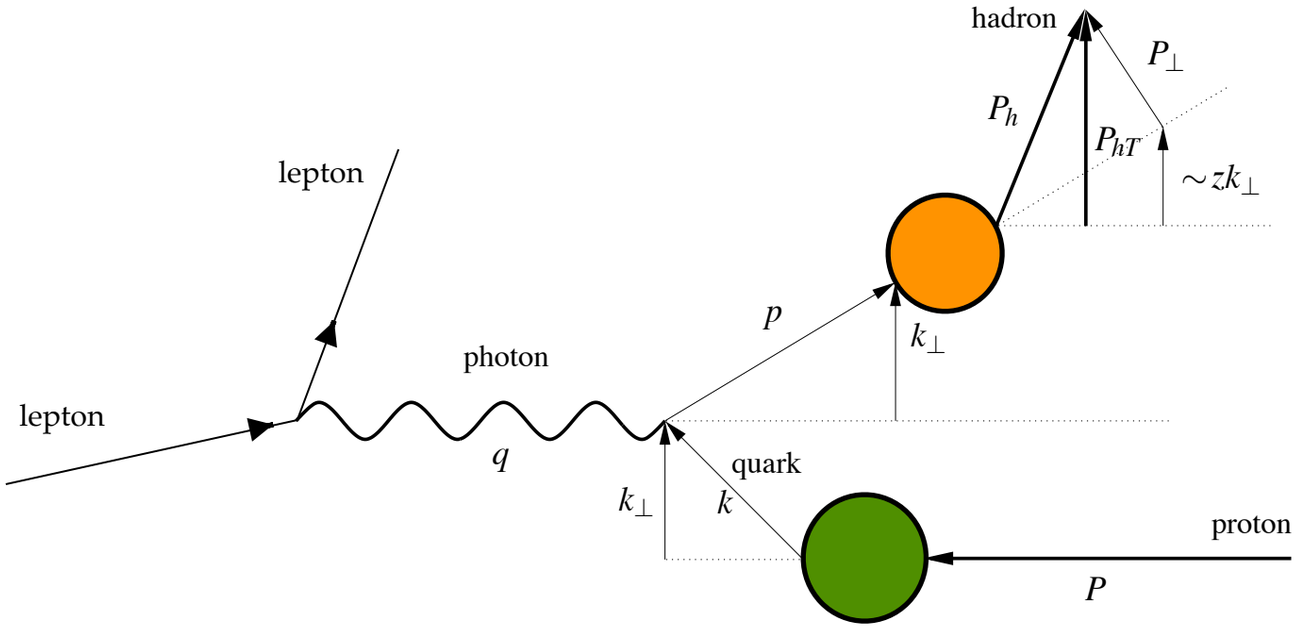
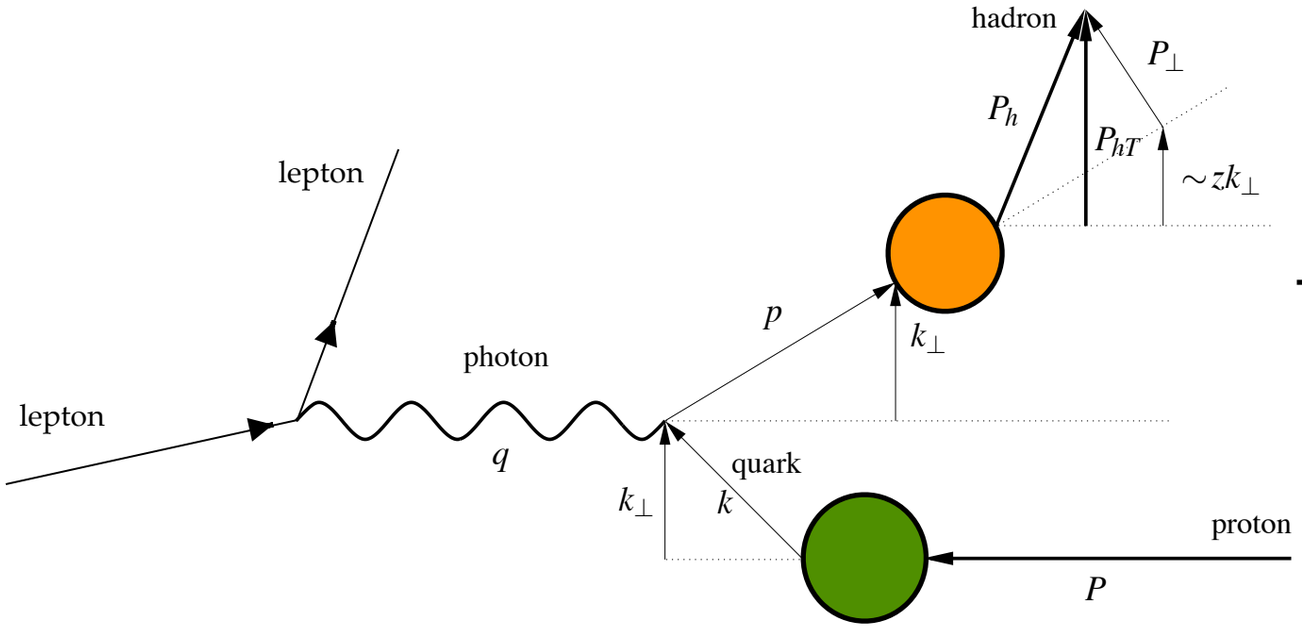
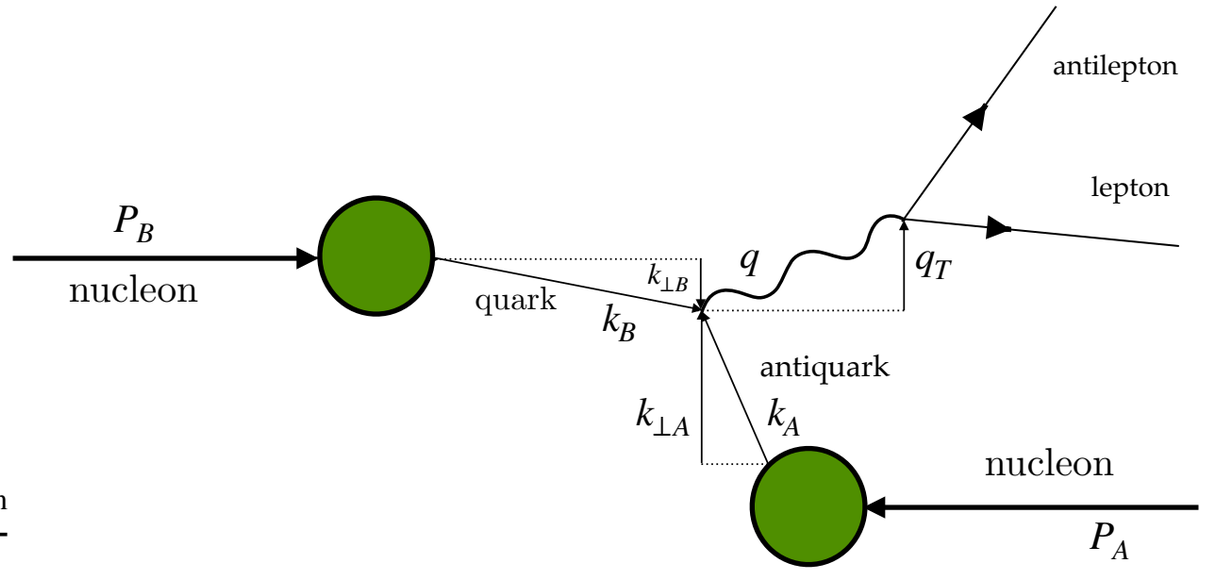


$$q_T^2 \ll Q^2$$

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

TMD factorisation: Universality





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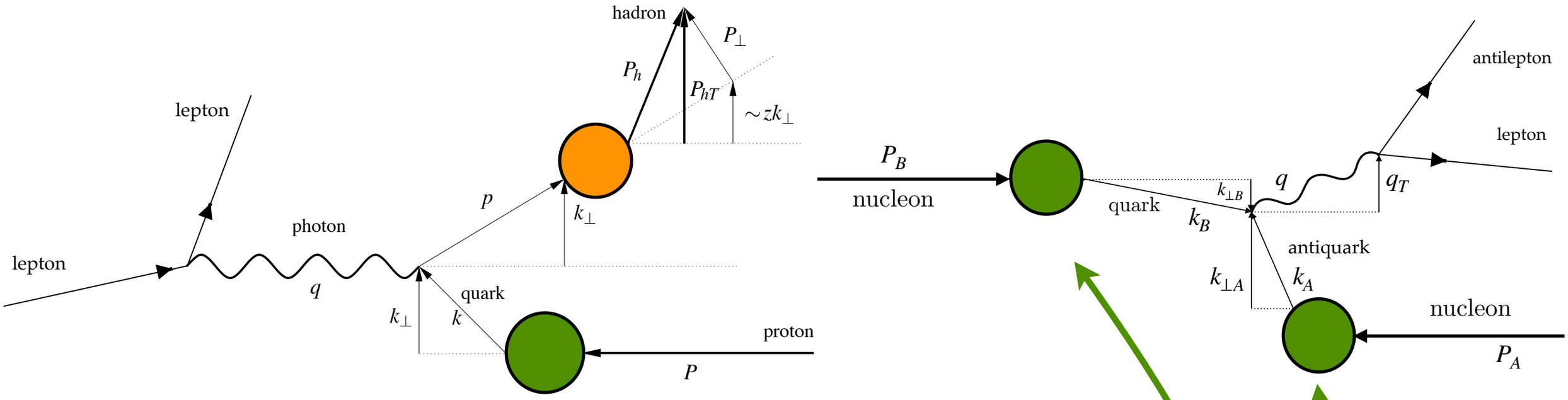

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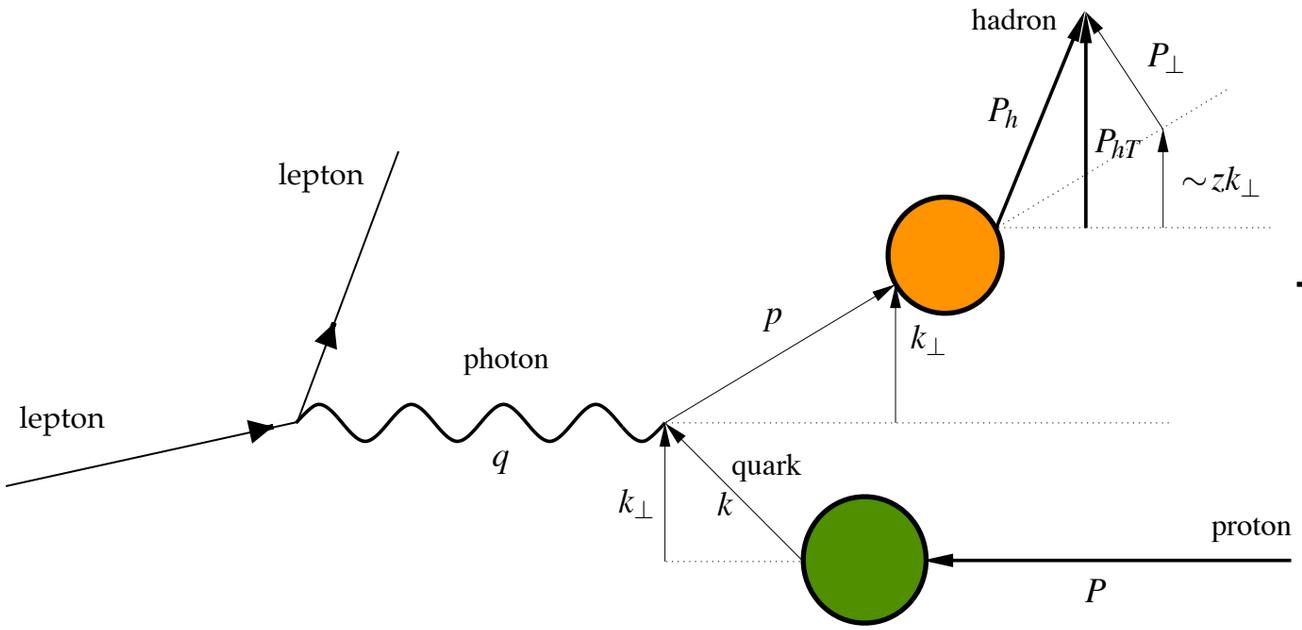

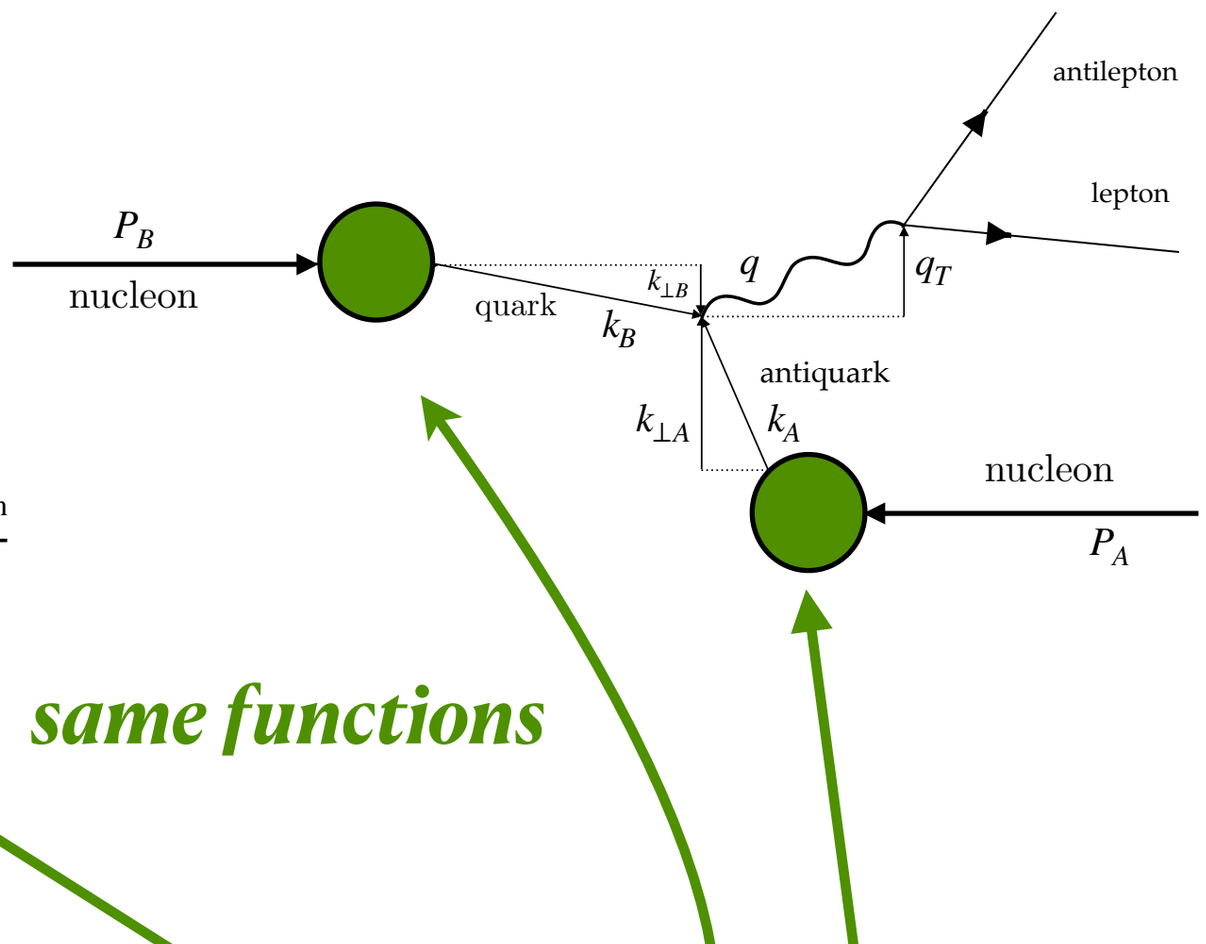

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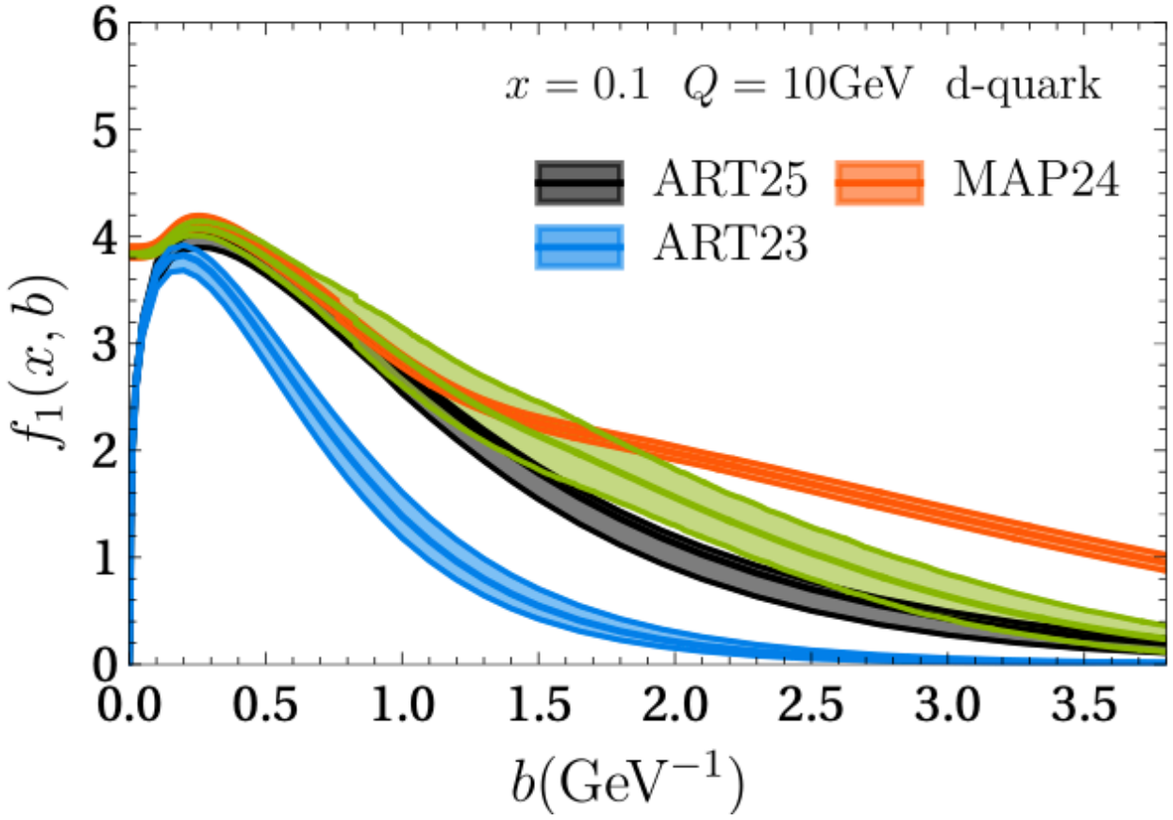
GLOBAL FITS

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 among different extractions

TMD PDFs



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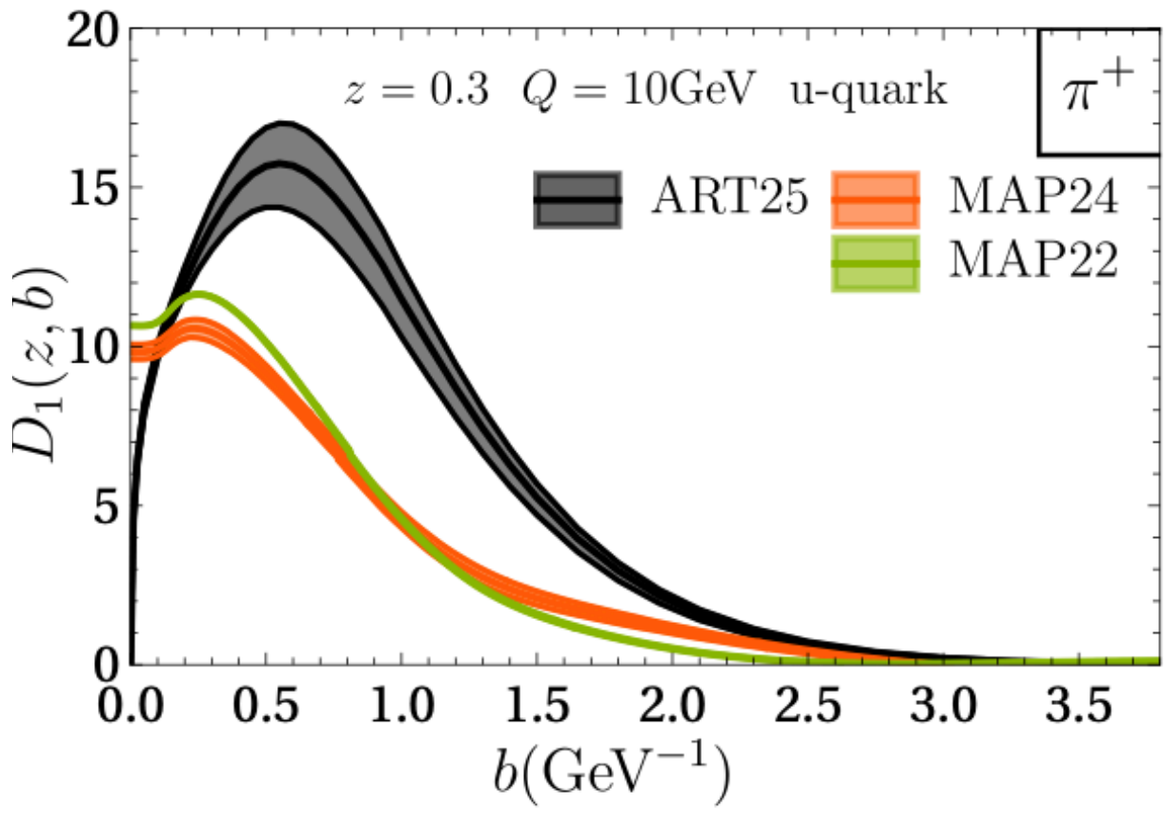


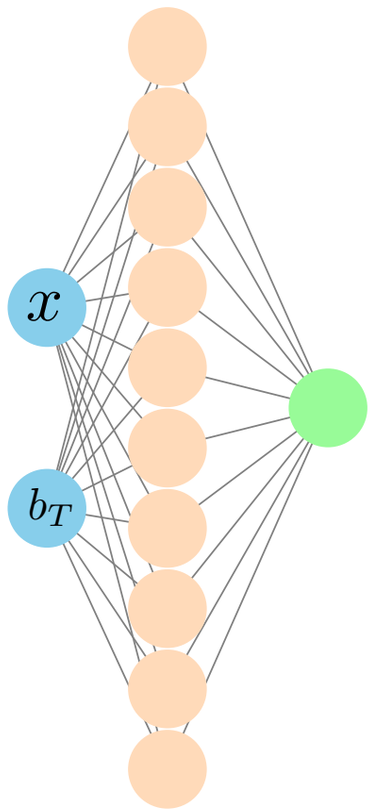
Extracted TMDs from different analyses show incompatibilities

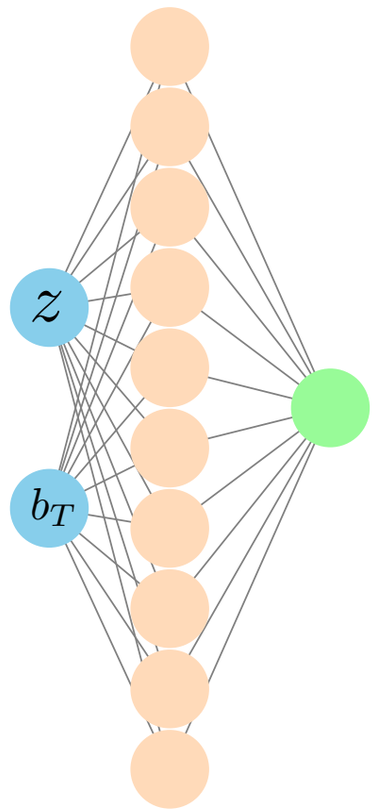
Moos, Scimemi, et al., JHEP 11 (2025)

NN-based parametrisation

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

$$D_{\rm NP}(z, b_T; \zeta) = \frac{\mathbb{NN}(z, b_T, \{p'_j\})}{\mathbb{NN}(z, 0, \{p'_j\})} \exp\left[-g_2^2 b_T^2 \ln\left(\frac{\zeta}{Q_0^2}\right)\right]$$





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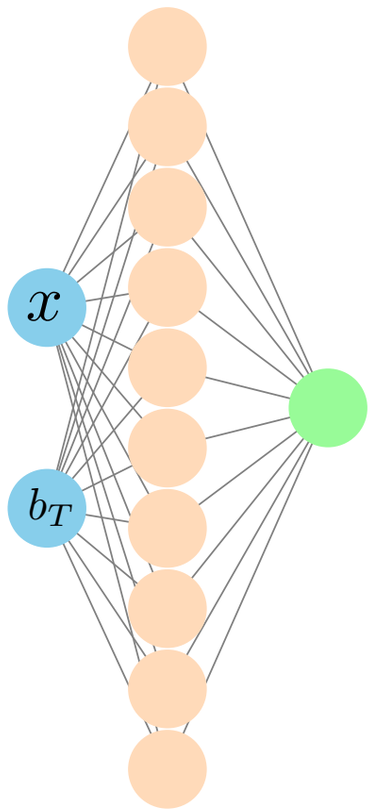

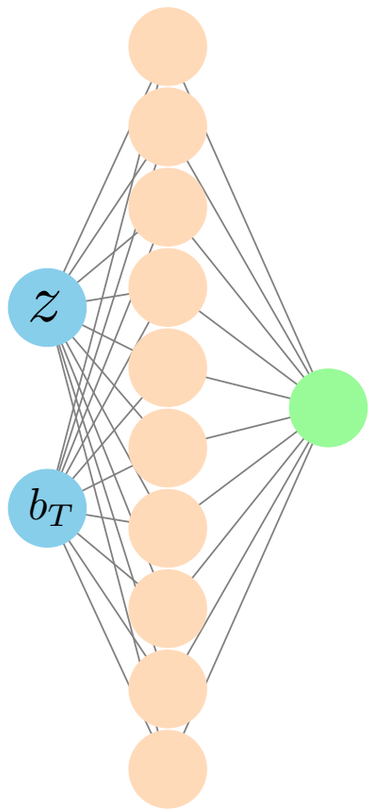

41 + 41+1 parameters

Fit results

Data/Theoy agreement

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

MAP Collaboration, PRL 135 (2025)

Experiment	$N_{\rm dat}$	$\overline{\chi}^2$ $(\overline{\chi}^2_D + \overline{\chi}^2_\lambda)$	
		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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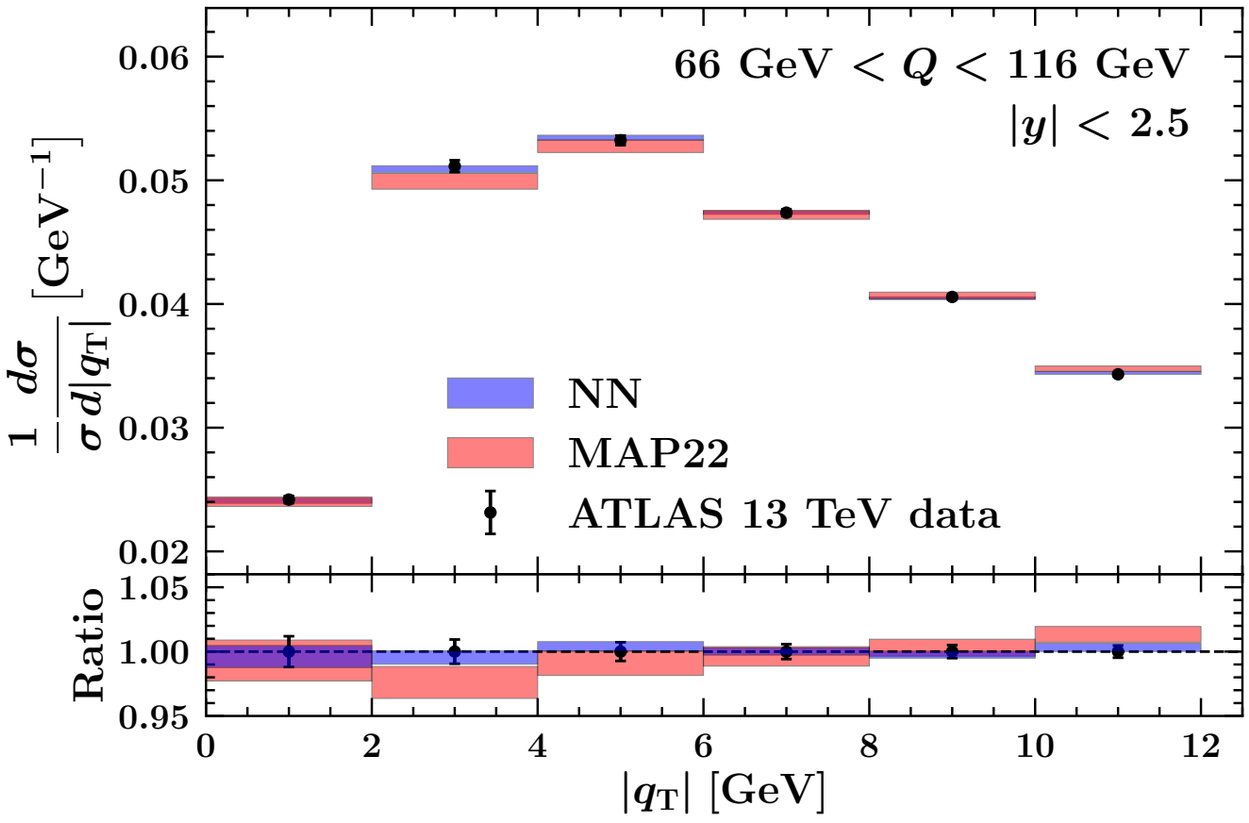

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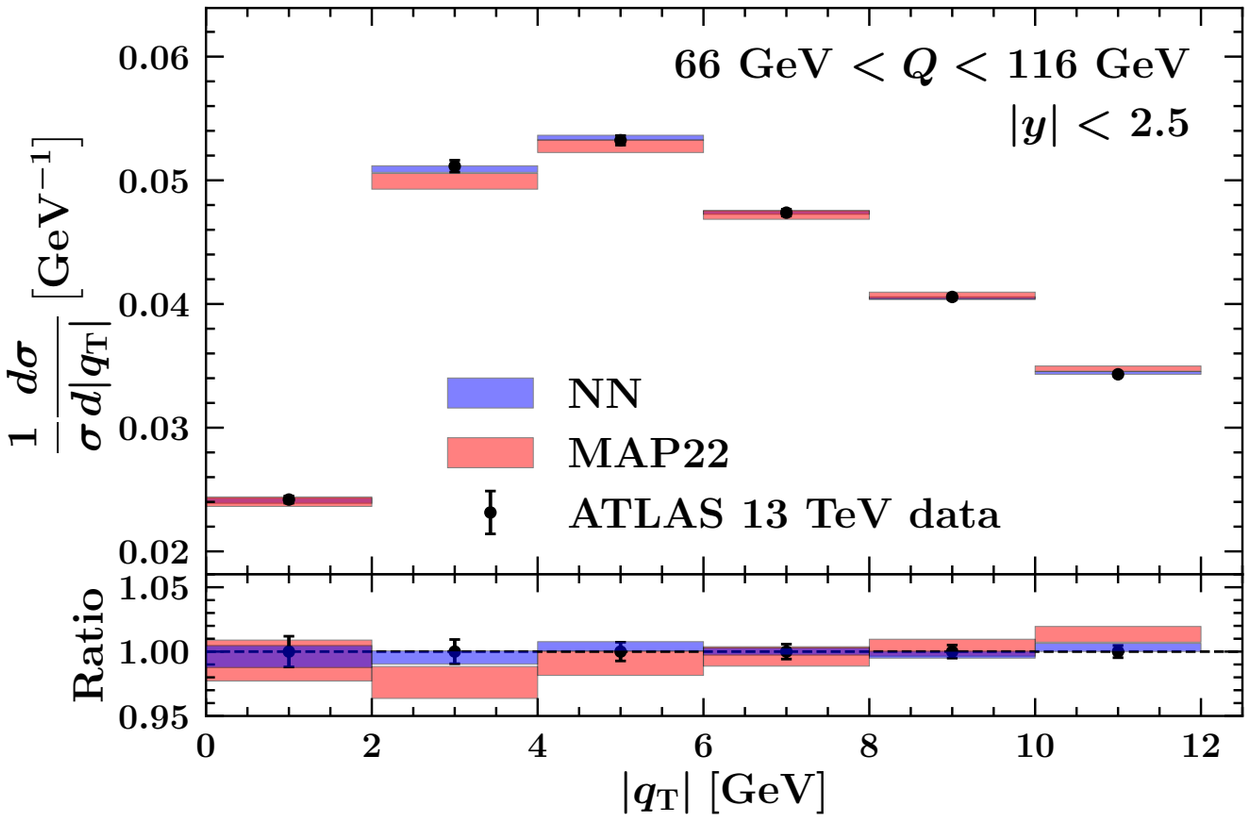

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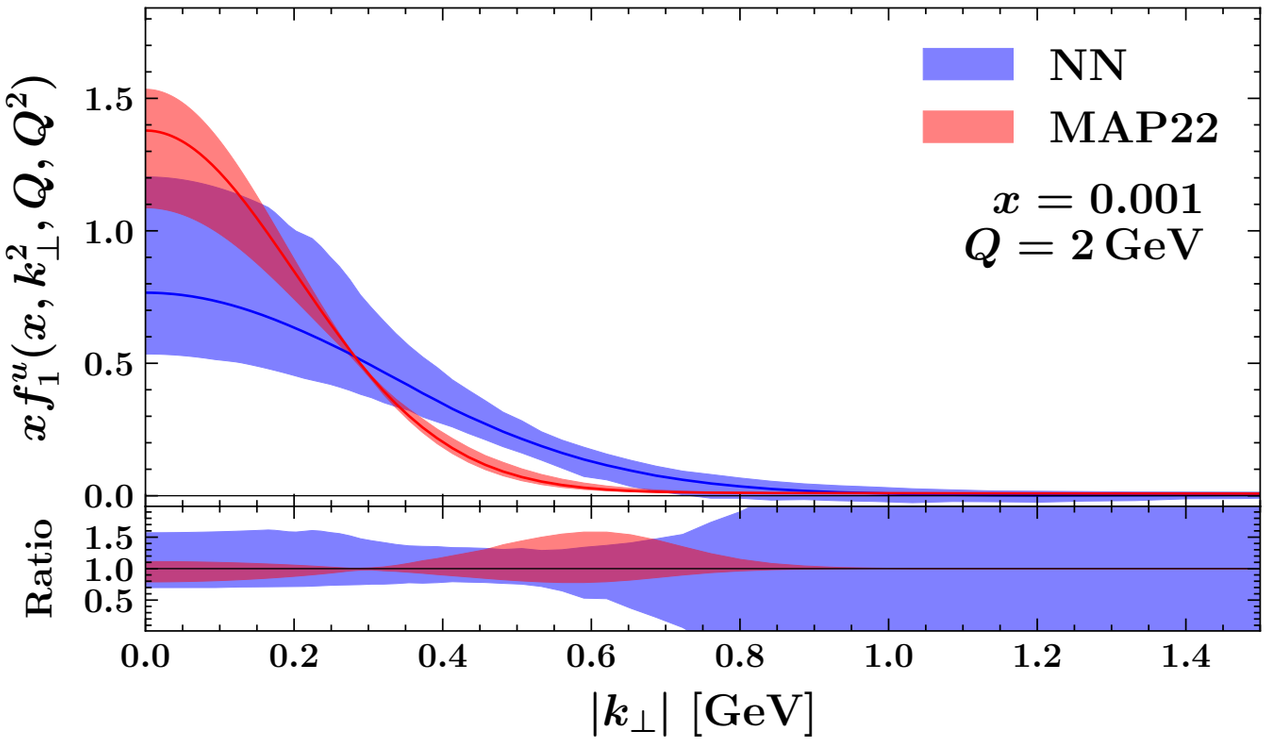
MAP22 relies more on systematic shifts ⇒ large error bands

Fit results

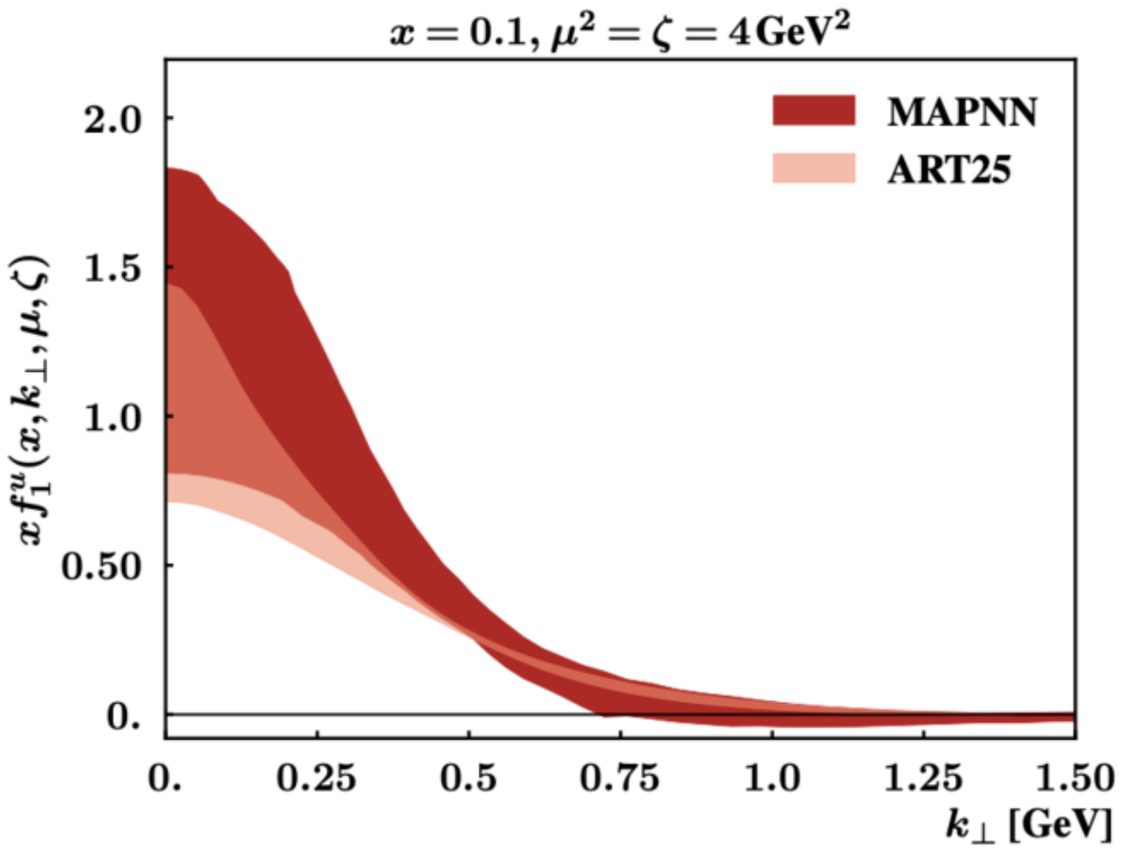
Extracted TMDs

MAP Collaboration, PRL 135 (2025)



more conservative estimates of uncertainties

NN fit has larger bands



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

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- 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)

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  → LHC (low-mass DY data)

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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)

Impact of SoLID pseudodata

Included dataset

$Q^2 > 1.4\ \mathrm{GeV}^2$

$x_B < 0.7$

$0.2 < z < 0.7$

$P_{hT} < P_{hT}^{\max}(z, Q)$

Final-state hadrons

π^+ π^-

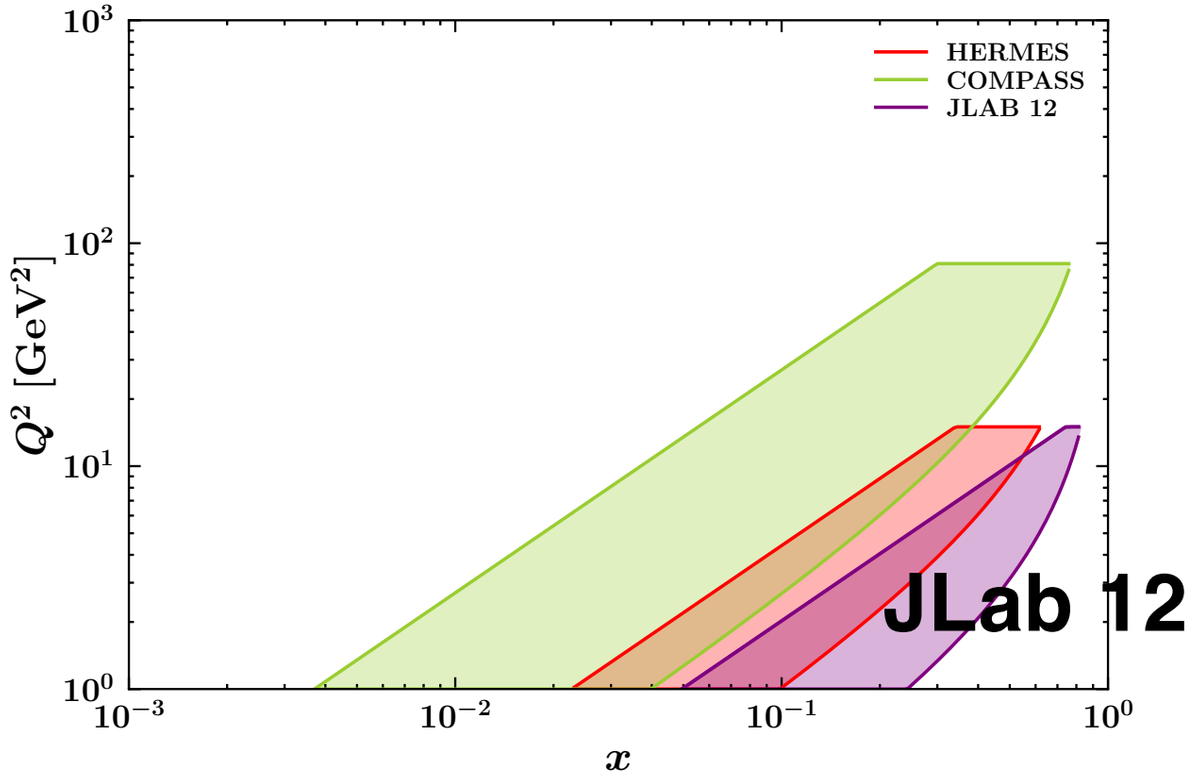
K^+ K^-

~ 2000 data points (MAP24)

+

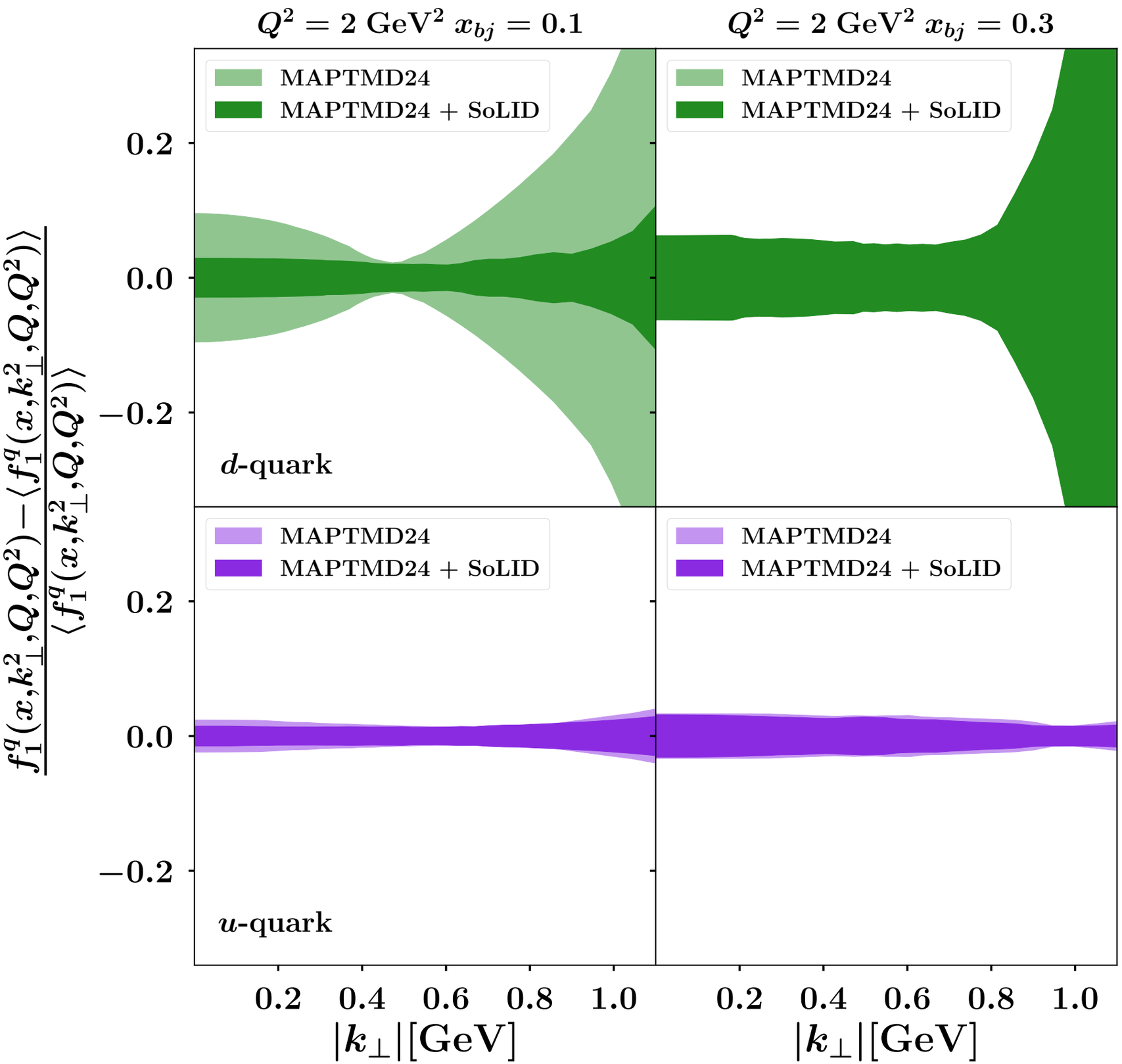
~ 1600 SoLID pseudodata

$\mathcal{O}(5\%)$ experimental errors



JLab 12

Final-state hadrons



π^+ π^-

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Uncertainty bands account for 68% CL

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- **Why SIDIS cross sections and not multiplicities?**

  → avoid theoretical mismatch between numerator and denominator

  → useful to study net power corrections

  Kinematic corrections
  Dynamic corrections ($F_{UU,L}(q_T)$)
  Light nuclear corrections