QCD Evolution 20205 - Jefferson Lab

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First Neural Network extraction of unpolarized TMDs

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Map Collaboration

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based on arXiv:2502.04166

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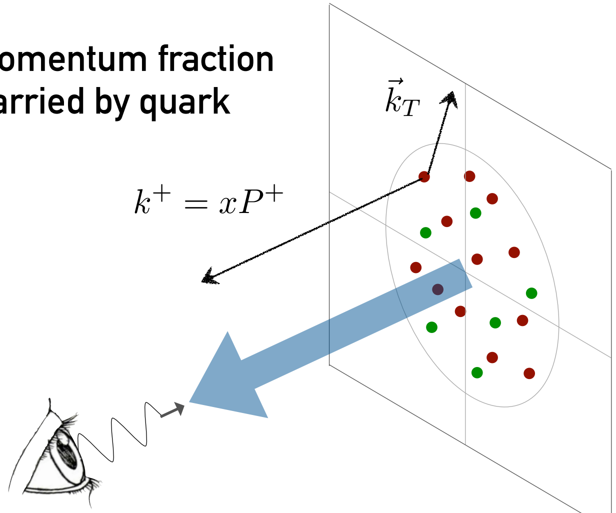
TMDs: 3D maps

in momentum space

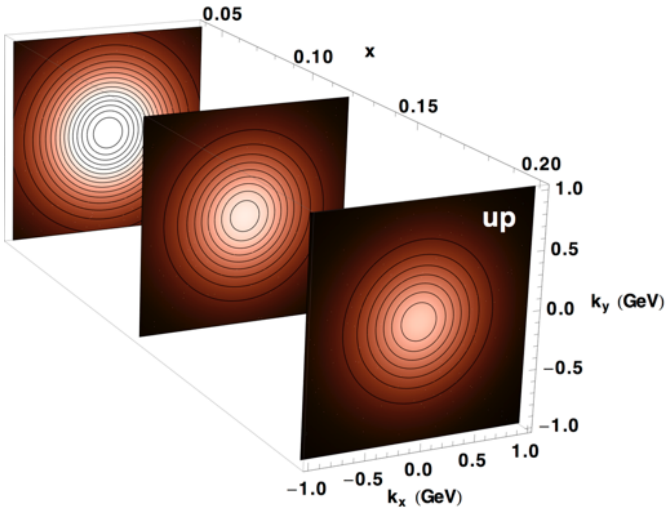
x: momentum fraction carried by quark



Transverse Momentum Distributions

TMDs

$$f^q(x, \mathbf{k_T})$$



Transverse Momentum Distributions

the distribution of quarks sharply depends on the orientation of their spins

this work

Leading Quark TMDPDFs

Nucleon Spin   Quark Spin

Nucleon Polarization	Quark Polarization: Un-Polarized (U)	Quark Polarization: Longitudinally Polarized (L)	Quark Polarization: Transversely Polarized (T)
U	f_1 = Unpolarized		$h_1^\perp$ = Boer-Mulders
L		g_1 = Helicity	$h_{1L}^\perp$ = Worm-gear
T	$f_{1T}^\perp$ = Sivers	$g_{1T}^\perp$ = Worm-gear	h_1 = Transversity $h_{1T}^\perp$ = Pretzelosity

from the TMD handbook
arXiv:2304.03302

TMDs — *unpolarized quark TMD PDF*

factorizes as hard and longitudinal non-perturbative

matching to the collinear region

$b_T \ll 1/\Lambda_{QCD}$

$$
\begin{aligned}
F_{f/P}(x, \mathbf{b}_T; \mu, \zeta) \quad &= \quad \sum_j C_{f/j}(x, b_*; \mu_b, \zeta_F) \otimes f_{j/P}(x, \mu_b) \\
&\times \quad \exp\left\{ K(b_*; \mu_b) \ln \frac{\sqrt{\zeta_F}}{\mu_b} + \int_{\mu_b}^{\mu} \frac{d\mu'}{\mu'} \left[\gamma_F - \gamma_K \ln \frac{\sqrt{\zeta_F}}{\mu'} \right] \right\} \\
&\times \quad \exp\left\{ g_{j/P}(x, b_T) + g_K(b_T) \ln \frac{\sqrt{\zeta_F}}{\sqrt{\zeta_{F,0}}} \right\}
\end{aligned}
$$

CS and RGE evolution

non-perturbative transverse content

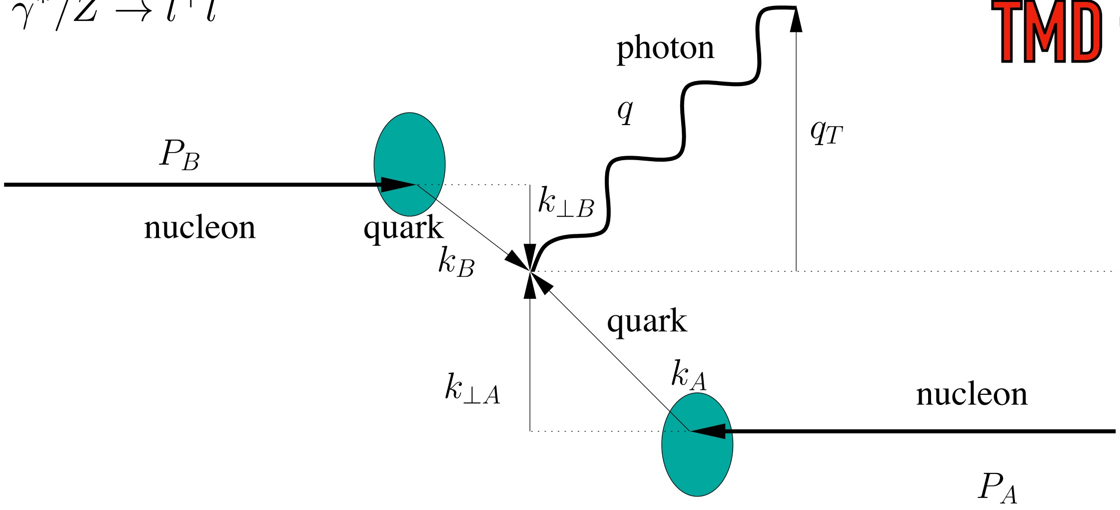
parametrized and fitted to data

Drell-Yan

$$N(P_A) + N(P_B) \to \gamma^*/Z \to l^+l^-$$

for $q_T \ll Q$

TMD factorization



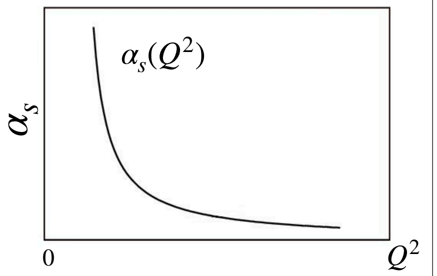
$$\left(\frac{d\sigma}{dq_T}\right)_{\text{res.}} \propto H(Q,\mu) \int \frac{d^2\mathbf{b}}{4\pi} e^{i\mathbf{b}\cdot\mathbf{q}_T} x_1 f_1^q(x_1,\mathbf{b};\mu,\zeta_1) x_2 f_1^{\bar{q}}(x_2,\mathbf{b};\mu,\zeta_2)$$

b* prescription

integration up to infinity

$$\frac{d\sigma}{dq_T} \propto \int \frac{d^2\mathbf{b}}{4\pi} e^{i\mathbf{b}\cdot\mathbf{q}_T} f_1^q(x_1,\mathbf{b}) f_1^{\bar{q}}(x_2,\mathbf{b})$$

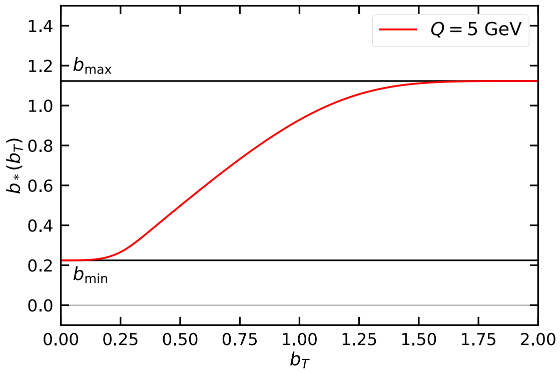
cross section



when b_T becomes large

$$\alpha_s(\mu_b) = \alpha\left(\frac{2e^{-\gamma_E}}{b}\right) \gg 1$$

invalidates perturbative calculations $\Rightarrow b_{\max}$



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

$$b_{\min} = 2e^{-\gamma_E}/Q$$

necessary to introduce a prescription

$$b_*(b) = b_{\max}\left(\frac{1-\exp\left(-\frac{b^4}{b_{\max}^4}\right)}{1-\exp\left(-\frac{b^4}{b_{\min}^4}\right)}\right)^{\frac{1}{4}}$$

b* prescription and definition of f_{NP}

perturbative

$$f(x,b;\mu,\zeta) = \left[\frac{f(x,b;\mu,\zeta)}{f(x,b_*(b);\mu,\zeta)}\right] \boxed{f(x,b_*(b);\mu,\zeta)}$$

non perturbative

$$\boxed{f_{\mathrm{NP}}(x,b,\zeta)}$$

$\longrightarrow$ fit to data

Non perturbative function depends on the choice of b*-prescription

Motivation

What would we like to accomplish?

goal: **fit for the first time TMDs with NN**

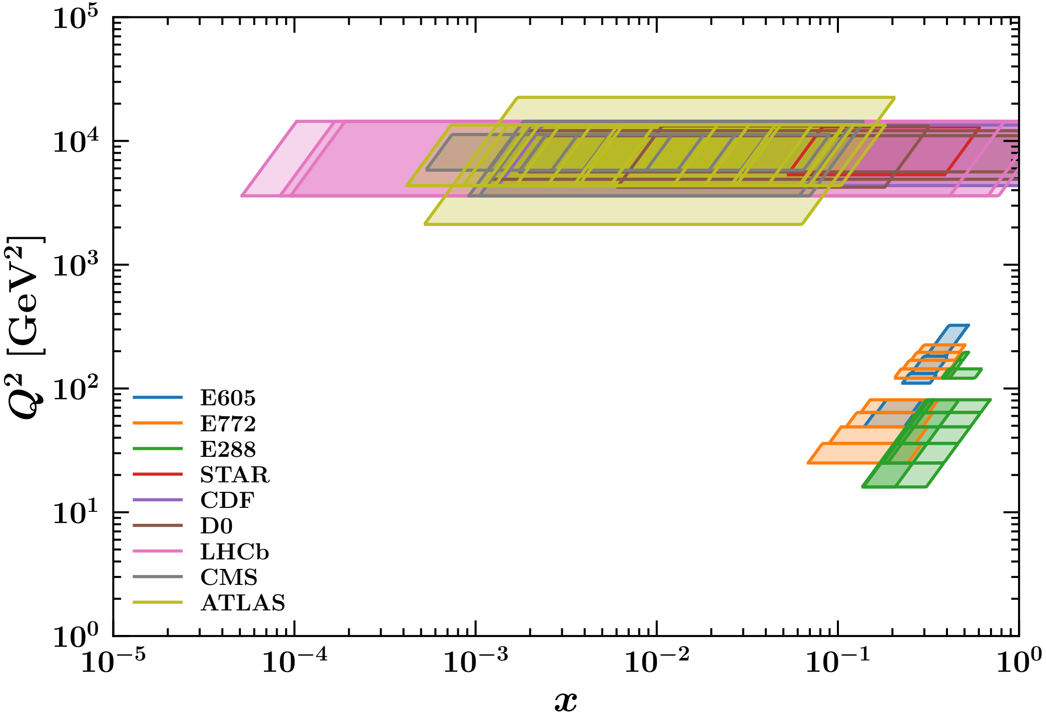
proof of concept

- do NN offer an advantage in fitting (real) data?
- we want to **test the methodology**

→ with **closure tests**

Data kinematical coverage

high and low energy Drell-Yan data



TMD region

$$q_T/Q < 0.2$$

total number of data: 482

included all available DY data with the exception of PHENIX (2 data points)

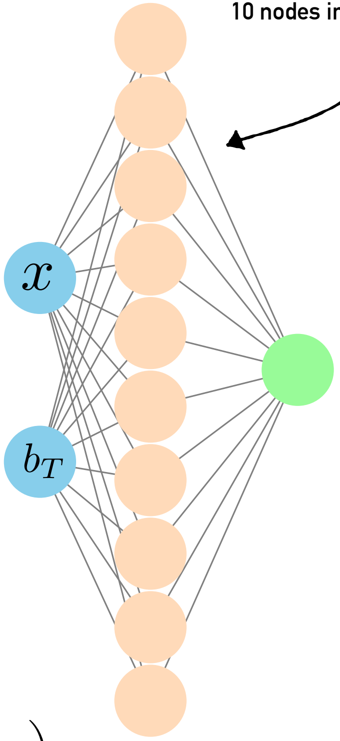
Parametrization

of the non-perturbative part of $f_1(x, k_T)$

MAP Collaboration
arXiv:2502.04166

Neural Network

10 nodes in a single hidden layer



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

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

41+1 parameters

parametrization

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

- physically required constraints

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

with activation function

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

Parameterization

"analytic", "with a functional form"

of the non-perturbative part of TMDs

TMD PDF

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

Gaussians

weighted Gaussian

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

NP evolution

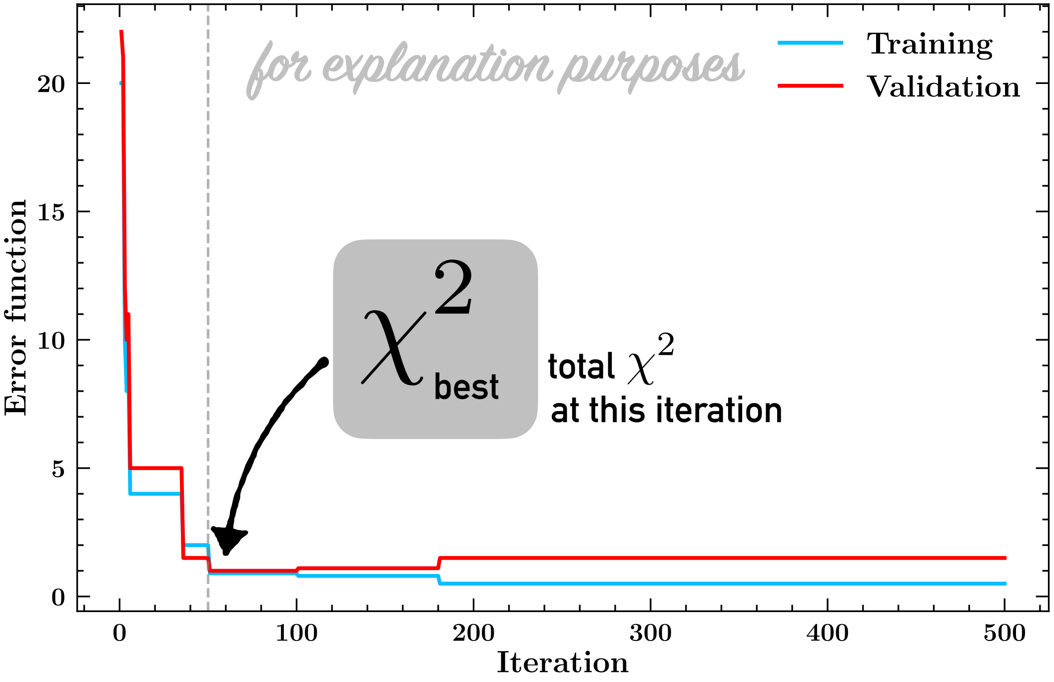
$$g_K(b_T^2) = -g_2^2 \frac{b_T^2}{4}$$

MAP22

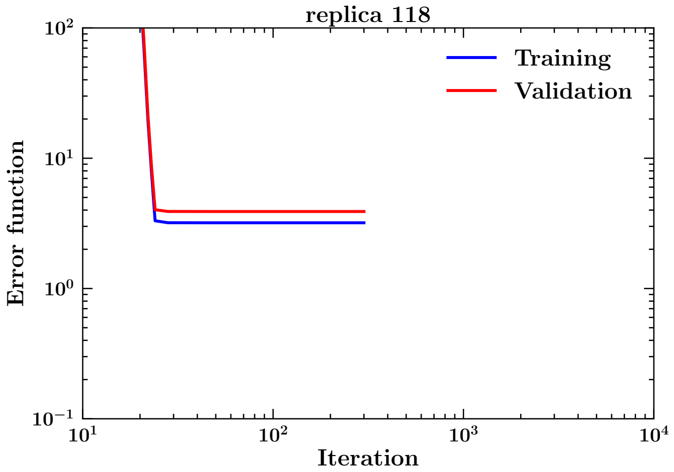
12 parameters

avoid overfitting

split data into training and validation set



χ^2_{best} total χ^2 at this iteration



random splitting

50% – 50%

dataset by dataset

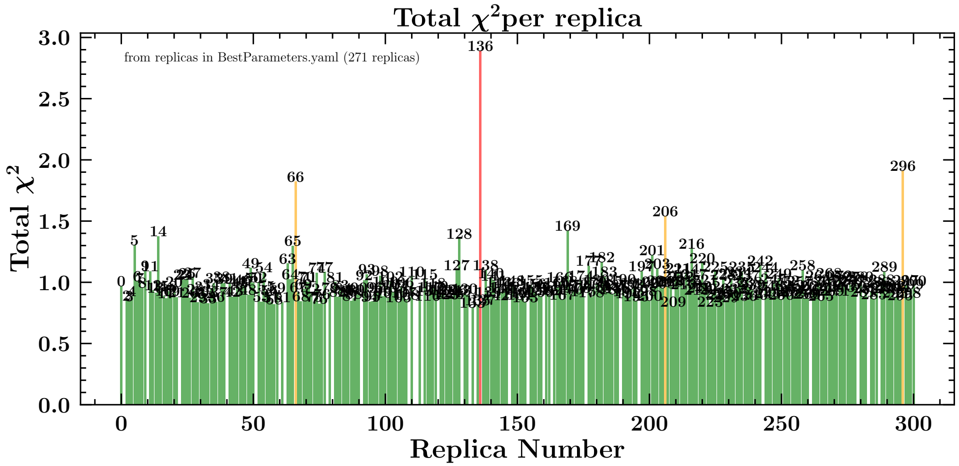
Monte Carlo replicas

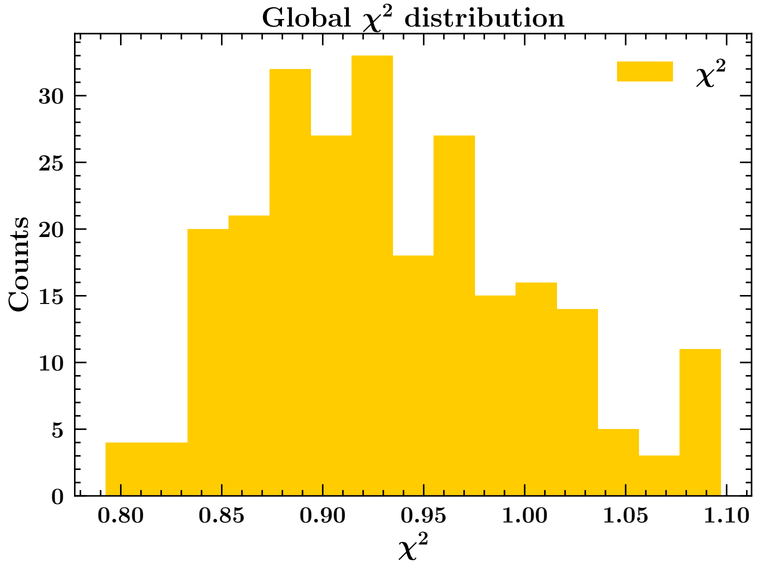
each replica is an independent fit

$\chi_0^2 = 0.97$

a fit runs in ~15 mins

nearly all replicas get to the end of the fit



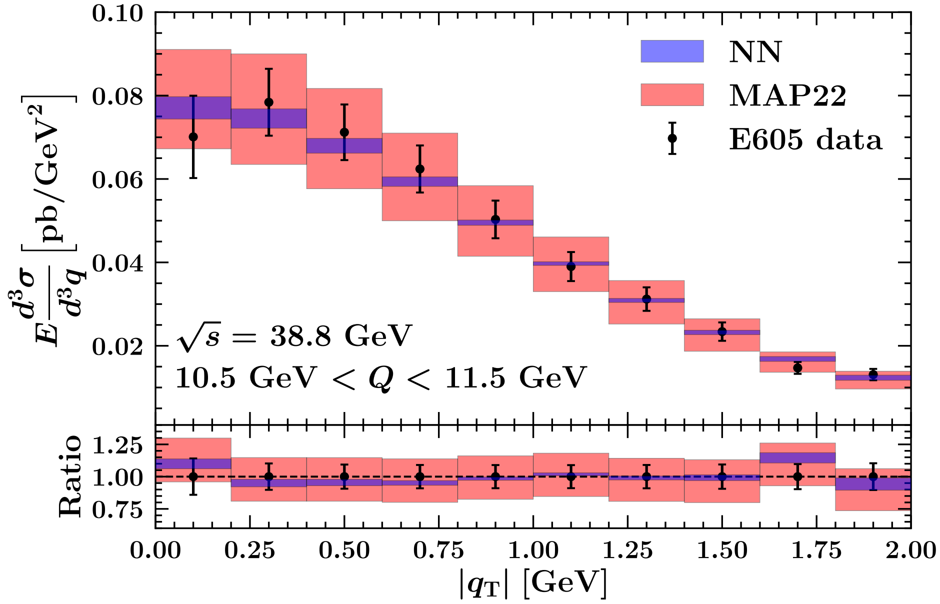


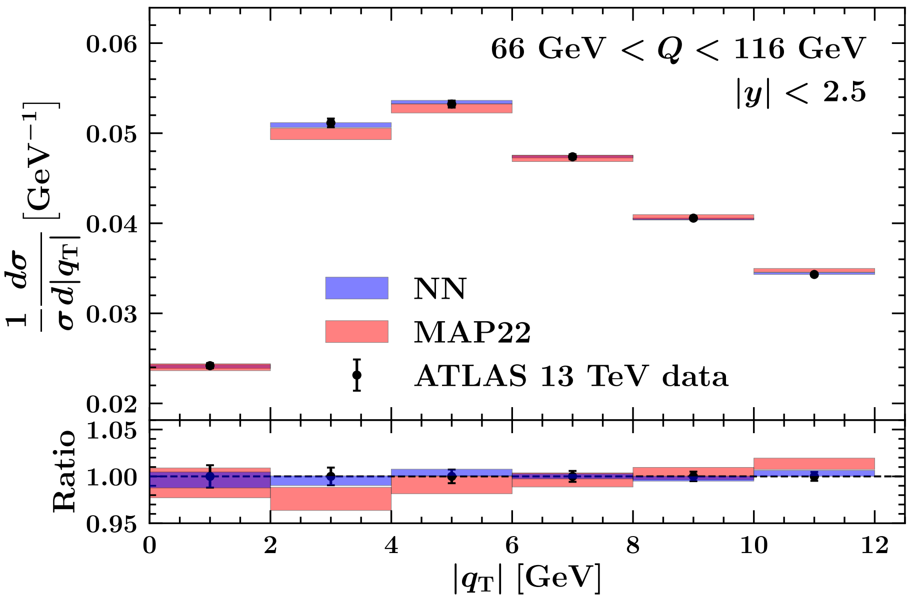
Comparison with data

logarithmic accuracy: N3LL

$\chi^2 = 0.97$

great description of data





Comparison with data

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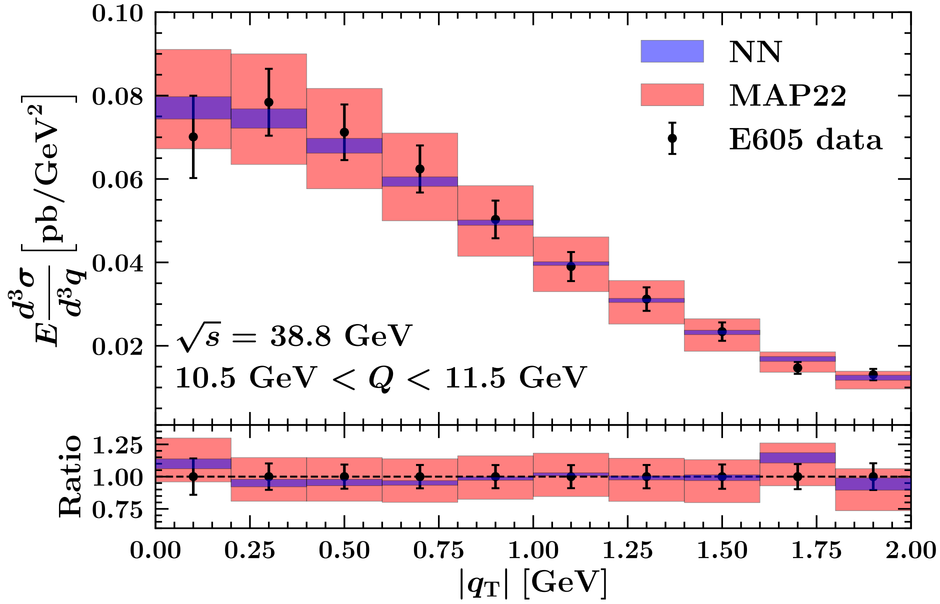

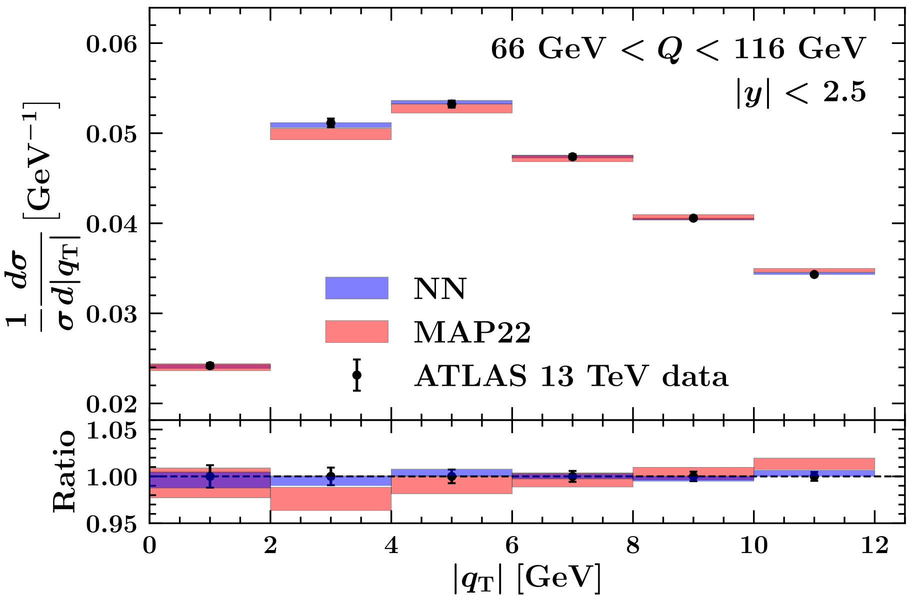

why are NN bands so much smaller than MAP22's?

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Shifted predictions

& decomposition of the χ^2

experimental data

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

uncorrelated

correlated

$$\chi^2 = \underbrace{\sum_{i=1}^{n} \left(\frac{m_i - \bar{t}_i}{s_i} \right)^2}_{\text{uncorrelated contribution}} + \underbrace{\sum_{\alpha=1}^{k} \lambda_\alpha^2}_{\text{penalty term}}$$

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

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

shifted prediction

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

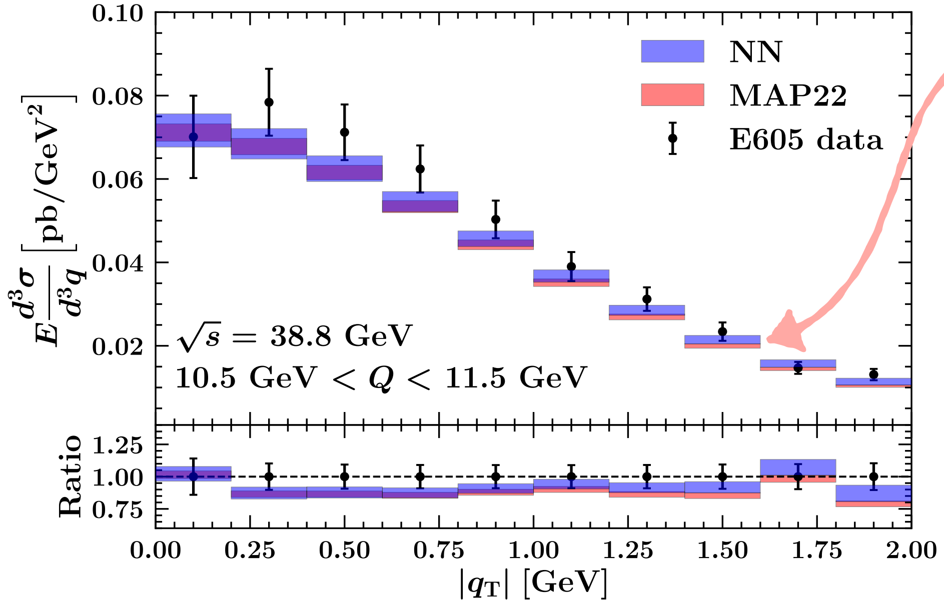
Comparison with data

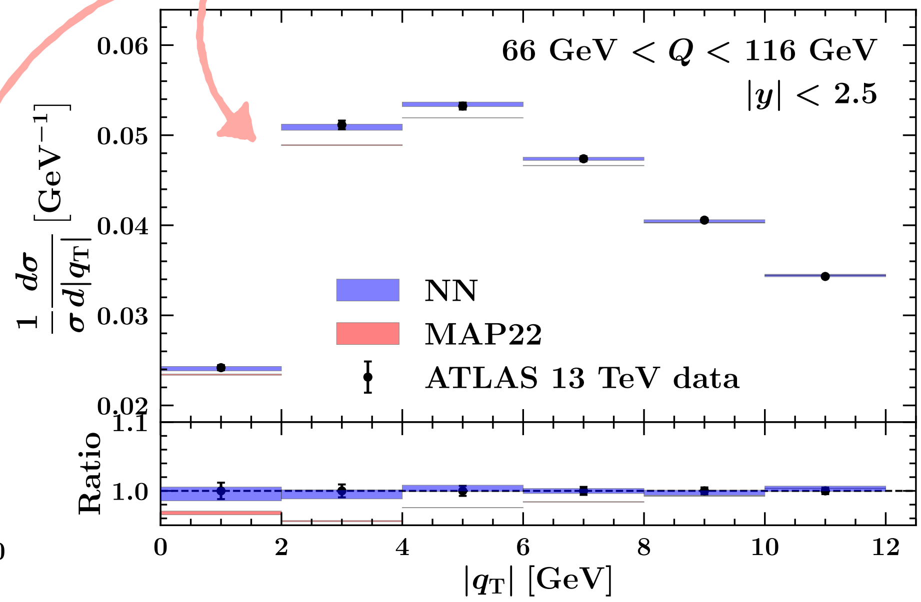
without including systematic shifts

significant reduction
of the bands for MAP22

$\chi^2 = 0.97$

$\chi^2 = 1.28$



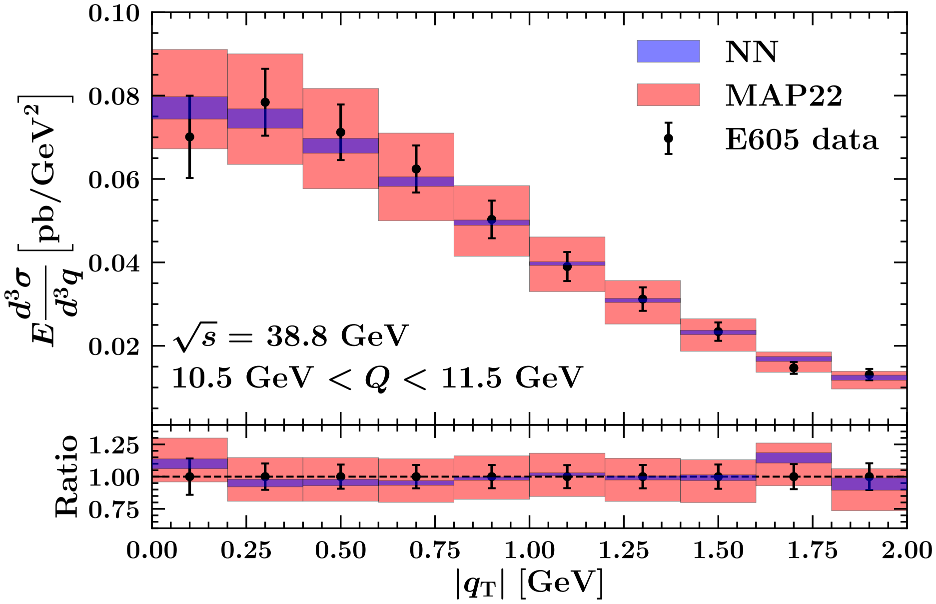


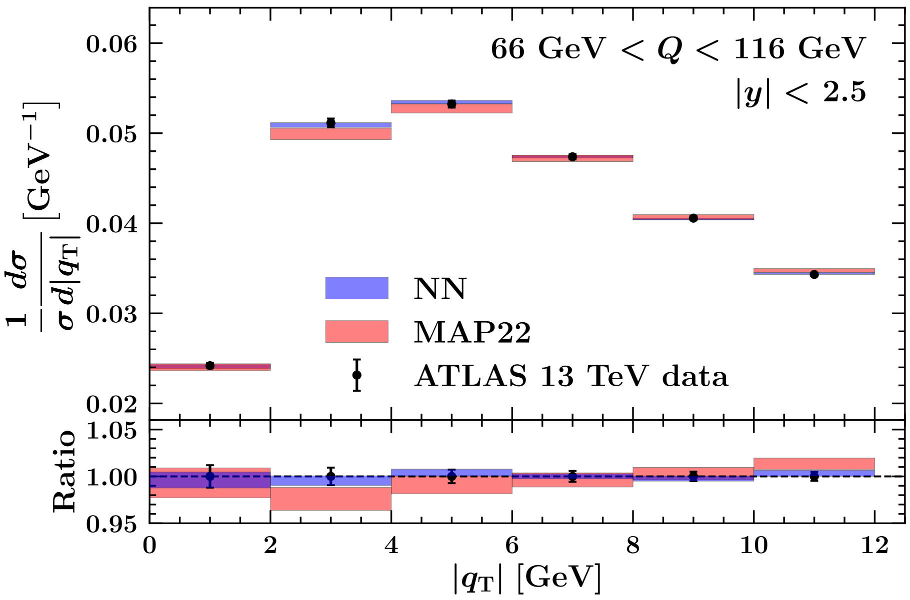
… just to compare again

N3LL

$\chi^2 = 0.97$

$\chi^2 = 1.28$





Description of data

numerical breakdown

$$\chi^2 = \underbrace{\sum_{i=1}^{n}\left(\frac{m_i - \bar{t}_i}{s_i}\right)^2}_{\text{uncorrelated contribution}} + \underbrace{\sum_{\alpha=1}^{k}\lambda_\alpha^2}_{\text{penalty term}}$$

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)

great improvement

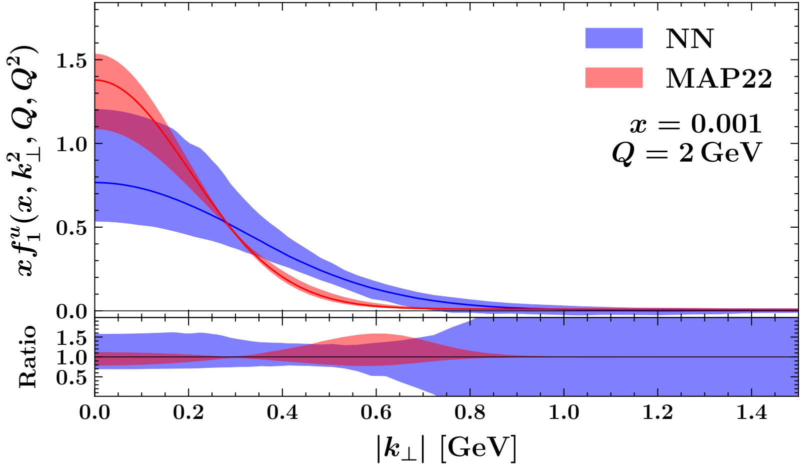
rule of thumb: it's best when it's small

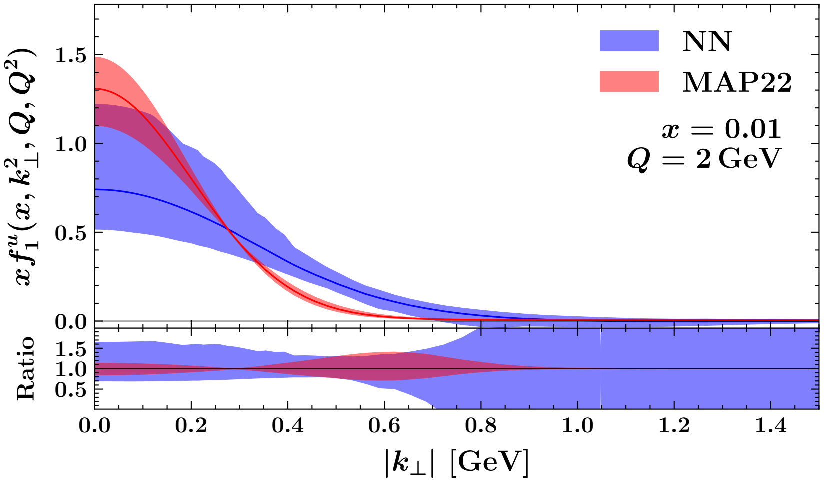
MAP22 relies more on the shifts with respect to the NN fit

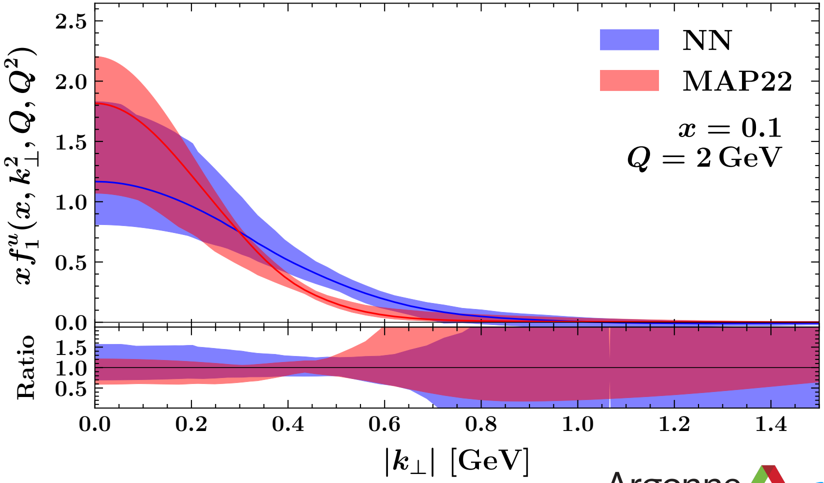
NN TMDs

extraction of $f_1(x, k_T)$ from DY data

MAP Collaboration
arXiv:2502.04166







NN fit has larger bands

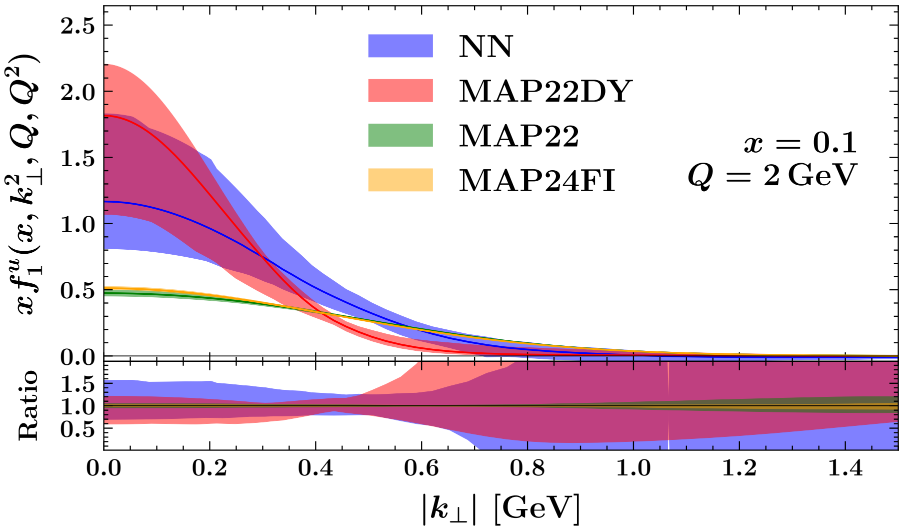
more reliable estimation uncertainties

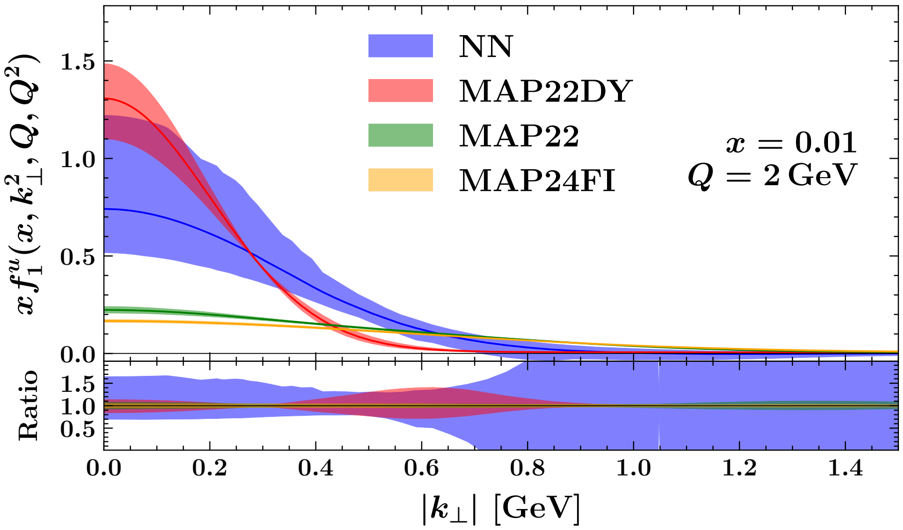
TMDs

comparison with other MAP fits

MAP22 and MAP24
full global fits, including SIDIS data

- narrower uncertainty bands
- wider TMDs

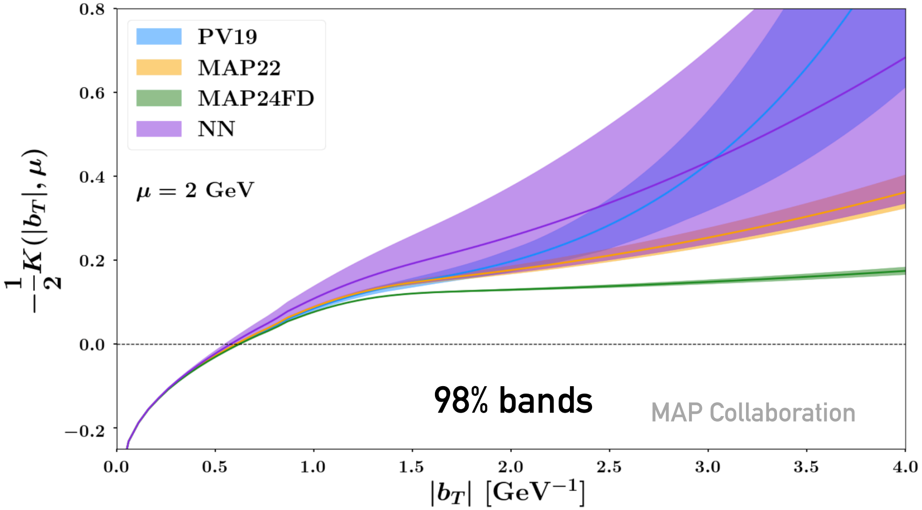


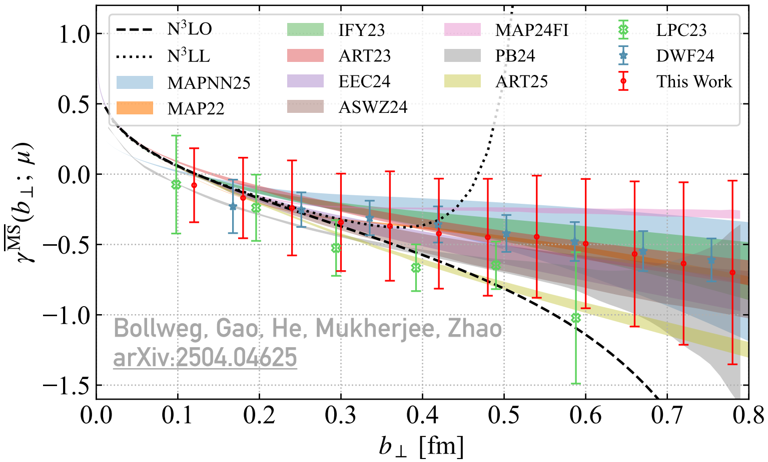


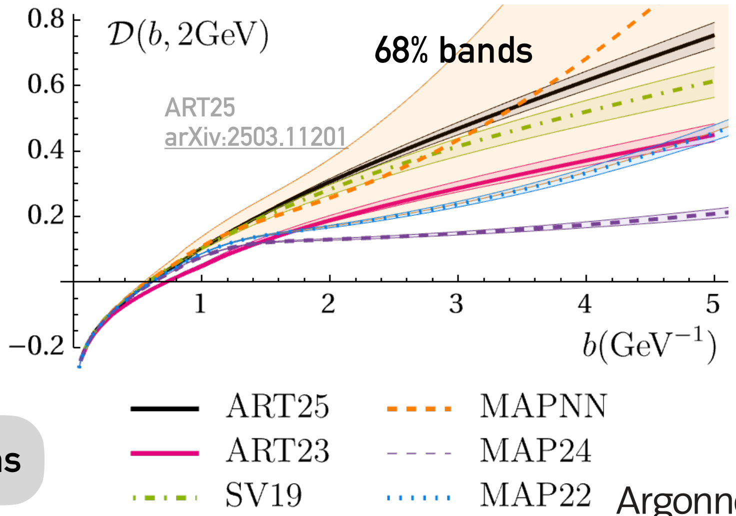
Collins-Soper kernel

“strong” universality

process independent,
insensitive to the types of external hadrons involved,
not dependent on polarization, on the flavors of the quarks, and on the scale Q



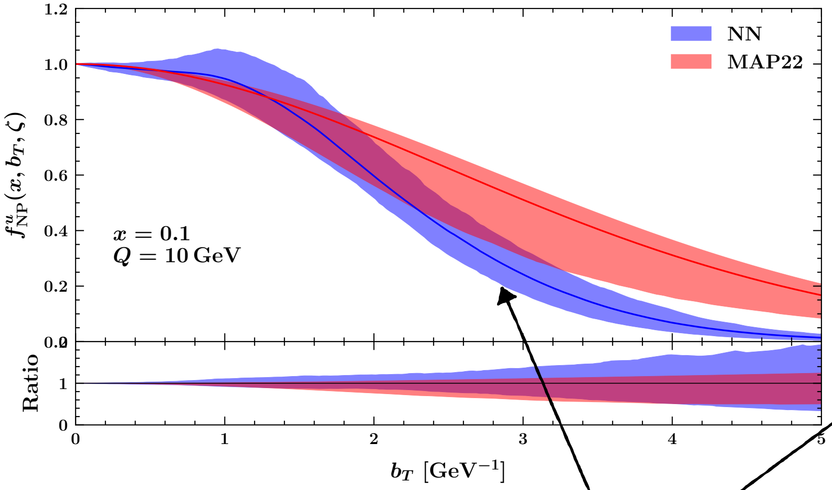


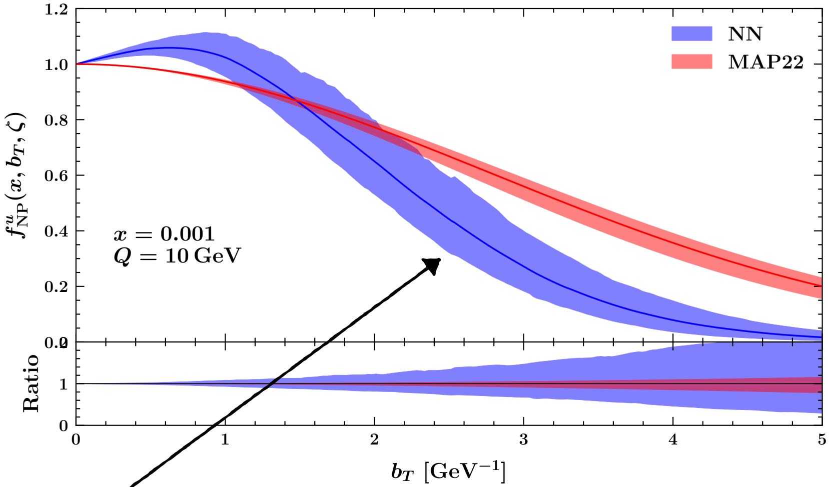


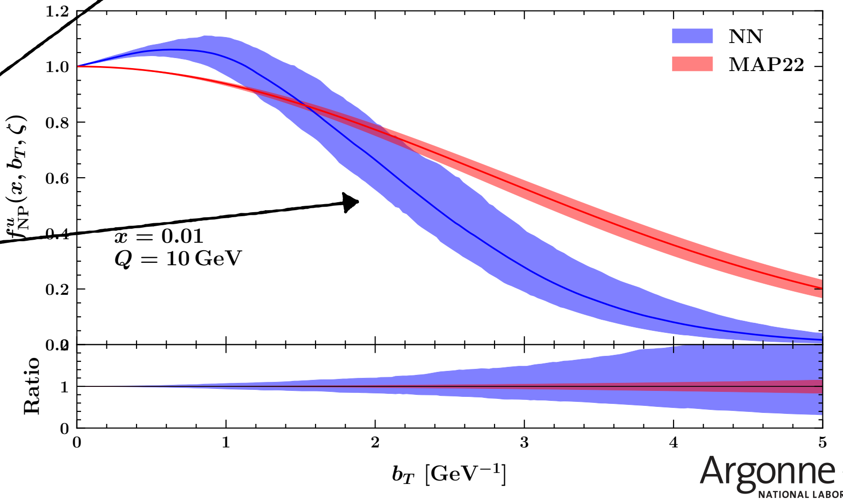
good agreement between the extractions

fNP

comparison with MAP22 only DY



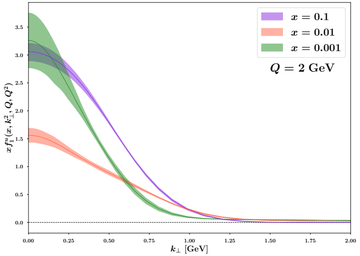




NN falls sharply with bT

Closure tests *only Drell-Yan data*

to validate the methodology



closure test – level 0

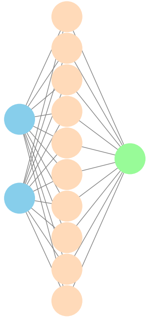
$$g_1 = 0.304$$
$$g_2 = 0.028$$

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

Generate **pseudodata** based on a model that we know

- central value: computed with **DWS** parameters
- uncertainties: real DY data

fit with NN



can we recover the DWS result?

yes!

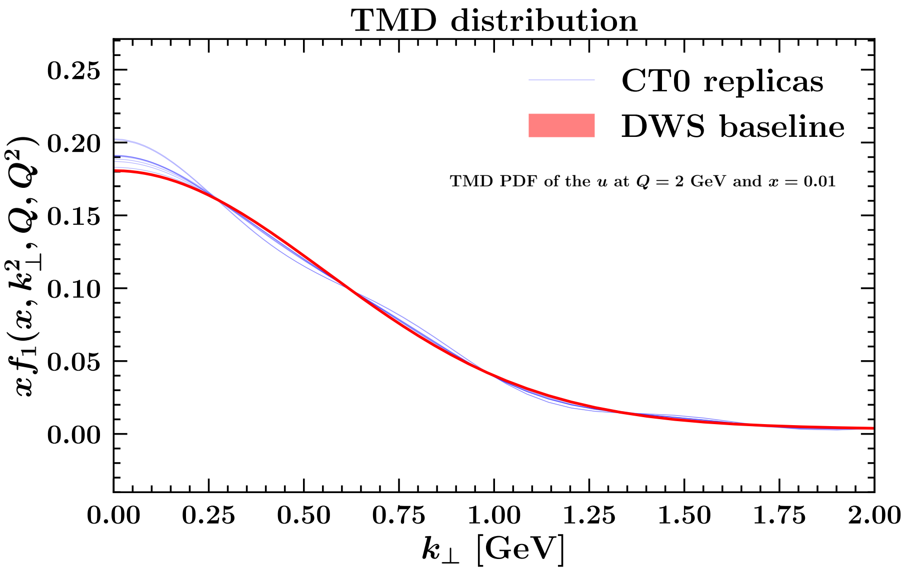
and for MAP22?

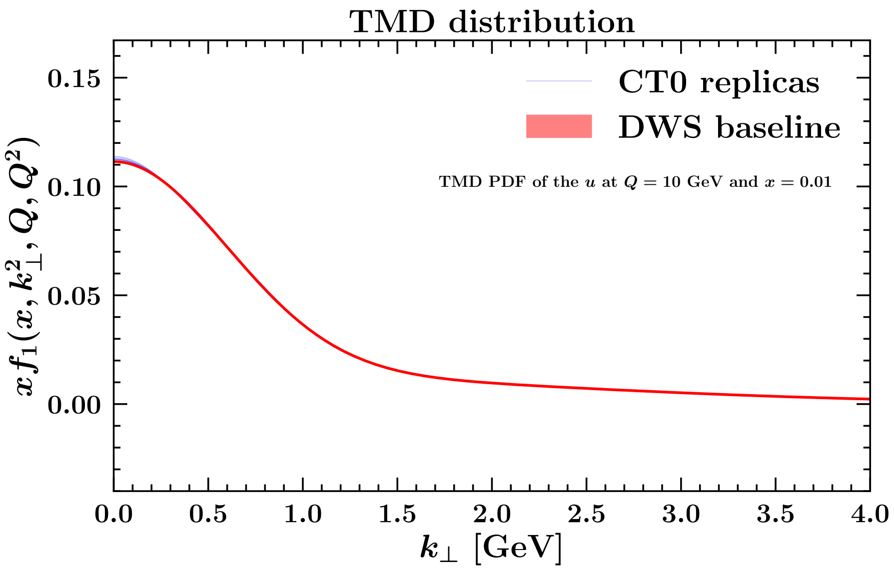
…work in progress

Closure tests

closure test – level 0

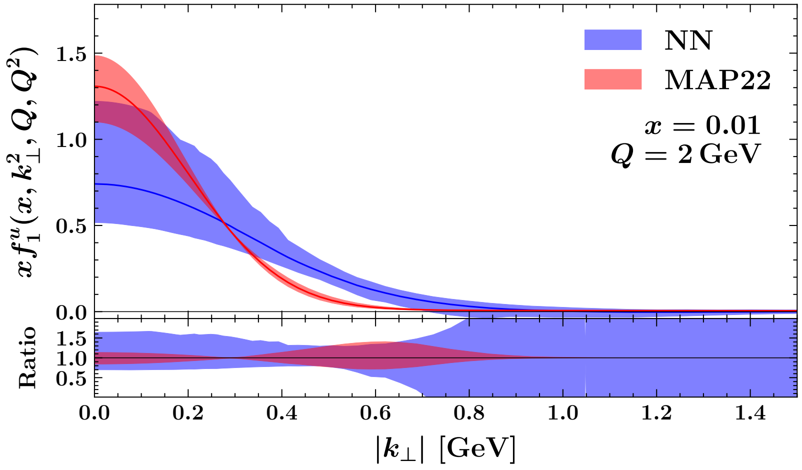
$$f_{\rm NP}^{\rm DWS}(b_T,\zeta) = \exp\left[-\frac{1}{2}\left(g_1 + g_2 \ln\left(\frac{\zeta}{2Q_0^2}\right)\right) b_T^2\right]$$





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

Conclusions



- **first Neural Networks extraction**

  of the unpolarized quark TMD PDFs in the proton

at N3LL ⊥ **Drell-Yan** data, 482 points

great description of data

$\chi^2 = 0.97$

more reliable uncertainties

OROS

the genesis of a new fitting framework

MAP Collaboration

ὄρος

— more flexible, modular and versatile

- suited for fitting all kinds distributions, PDFs, TMDs, GPDs
- very fast
- written in C++ but with a python wrapper

to do next:

- Study b* prescription - is there an impact on the extracted TMDs?
- Perform closure tests - validate the use of NN
- perform NN TMD fit for DY + SIDIS

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TMD

every TMD has the same general structure

many subtleties involved in TMD analyses

b* prescription, ζ-prescription, logarithmic accuracy

matching to the collinear region

collinear PDFs

$$f_1^q(x, b; \mu, \zeta) = \sum_j \left(C_j \otimes f^j\right)(x, b_*; \mu_b) e^{R(b_*;\mu_b,\mu)} f_{\rm NP}(x, b)$$

double scale dependence

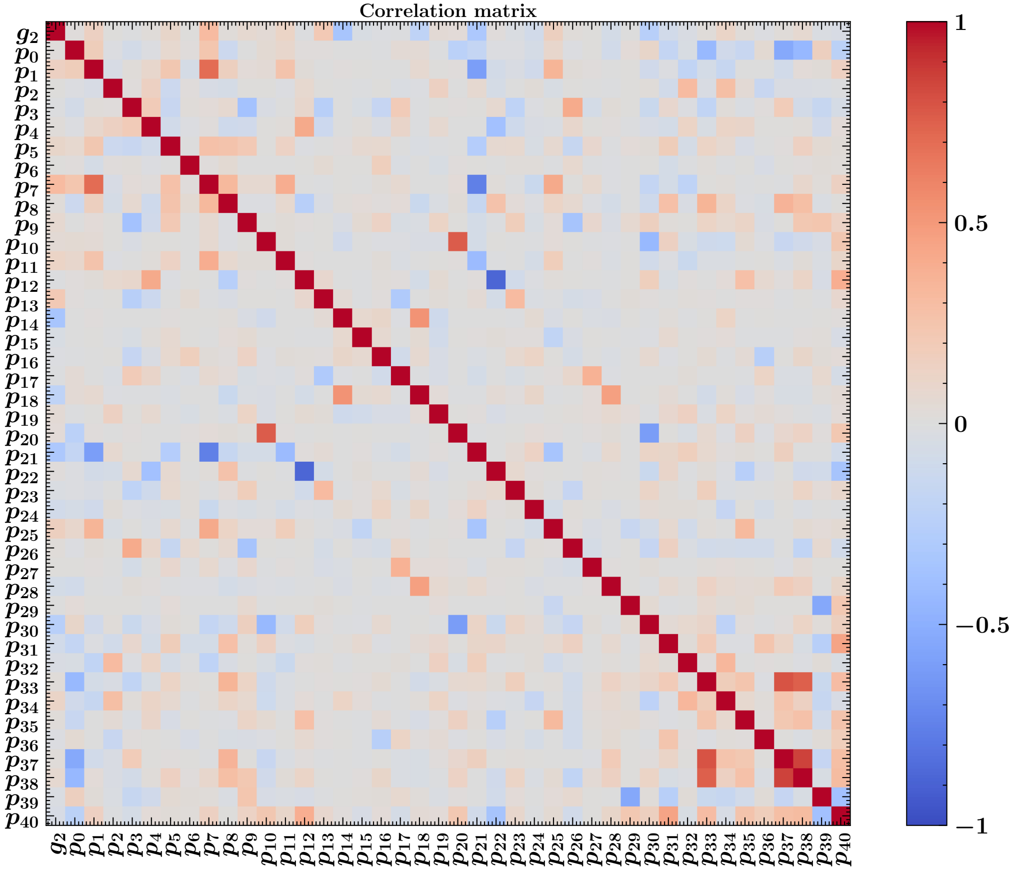
perturbative evolution

non perturbative transverse content

parametrized and fitted to data

correlation matrix

41 parameters



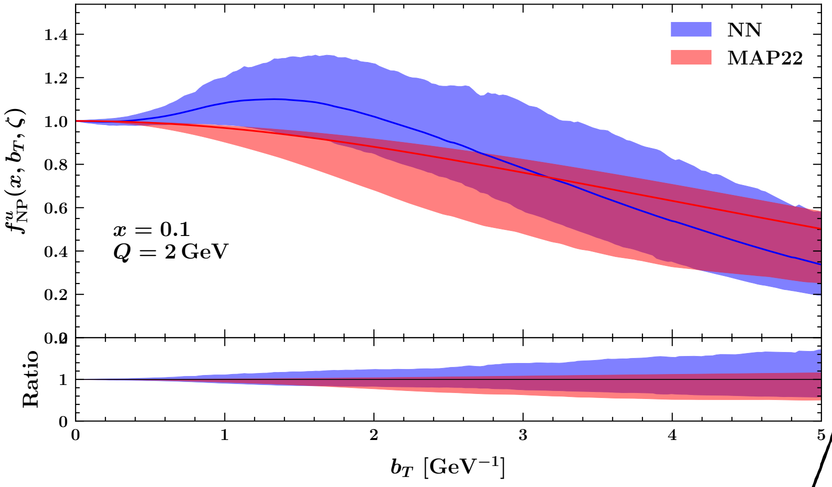
Closure tests

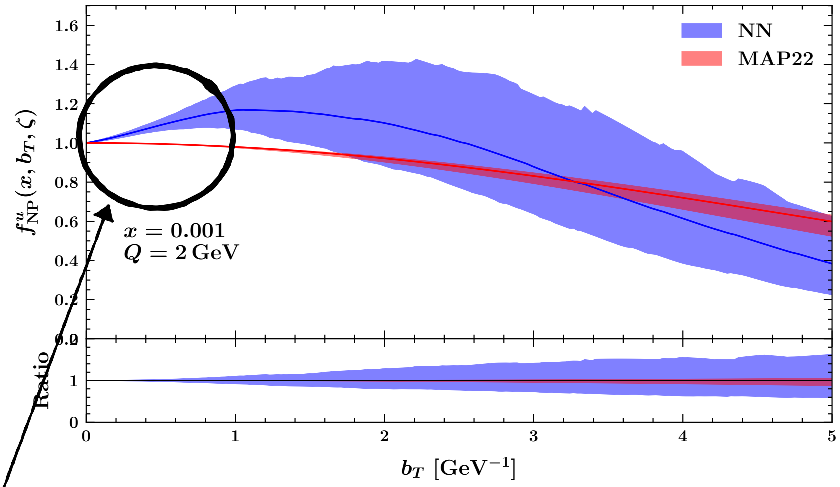
to validate the methodology

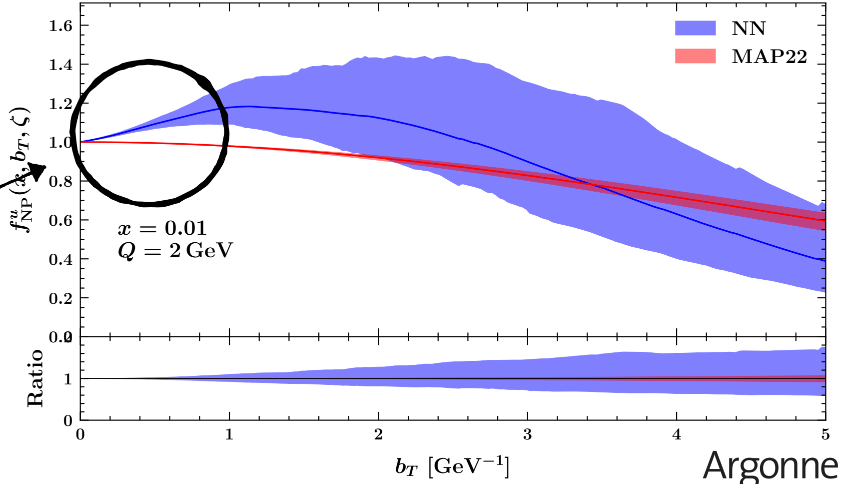
- **Level 0**
  - central pseudo-data is given by **central predictions** of the known model
  - **no Monte Carlo noise** is added on top of the central data — each replica is fitting the same set of data
- **Level 1**
  - central pseudo-data is shifted by some noise η drawn from the experimental covariance matrix
  - no MC noise is added — each replica fits a subset of the same shifted data
- **Level 2**
  - central pseudo-data is shifted by level 1 noise η
  - MC noise is added on top of the level 1 shift

fNP

comparison with MAP22 only DY







NN has a bump at very small bT
it reaches 1 from above