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Transverse Momentum Distributions Phenomenology With NN

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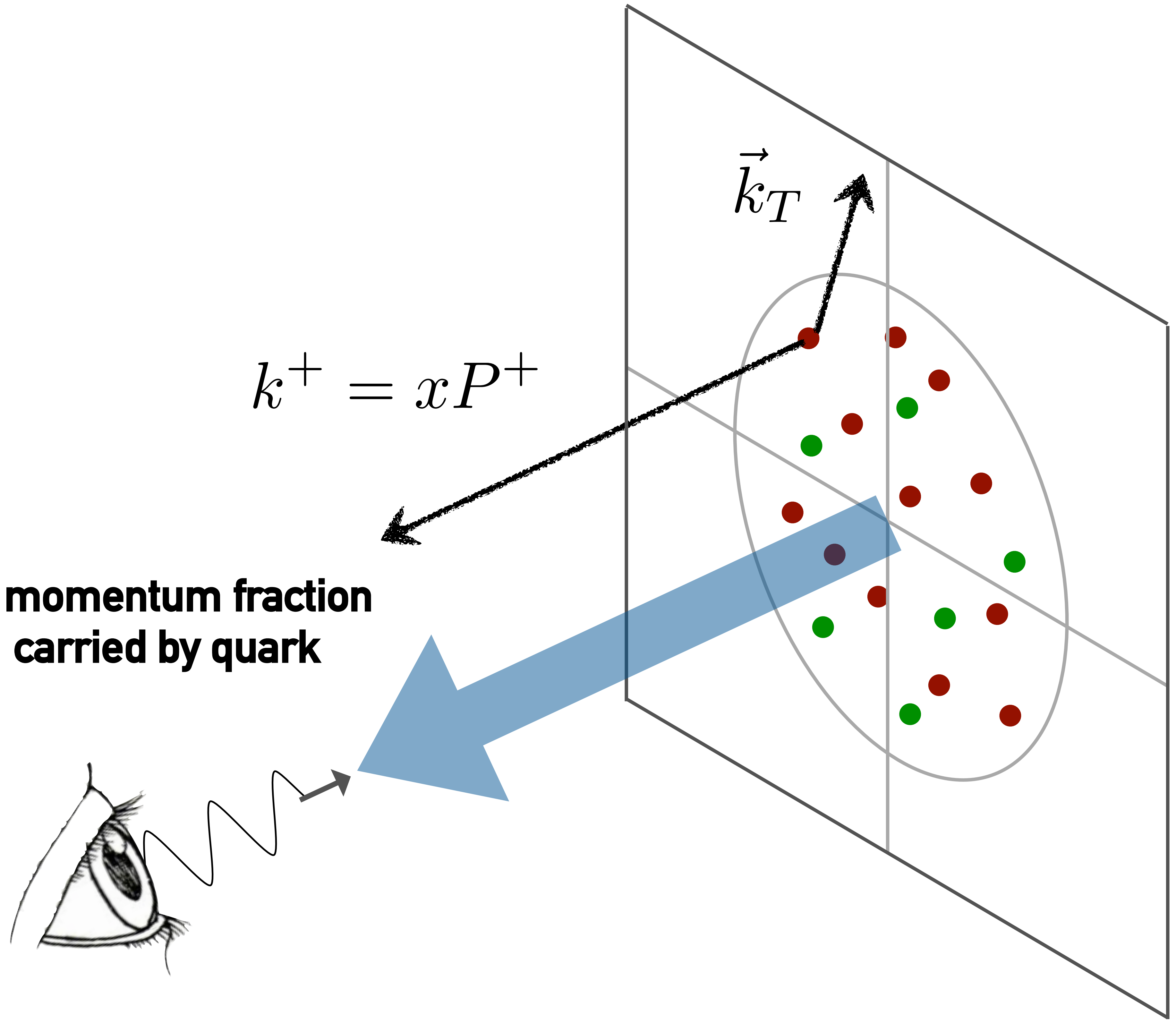
HAS QCD
HADRONIC STRUCTURE AND QUANTUM CHROMODYNAMICS

TMDs: 3D maps

in momentum space



x: momentum fraction carried by quark

Transverse Momentum Distributions

TMDs

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

$$\int d^2\mathbf{k}_T$$

collinear

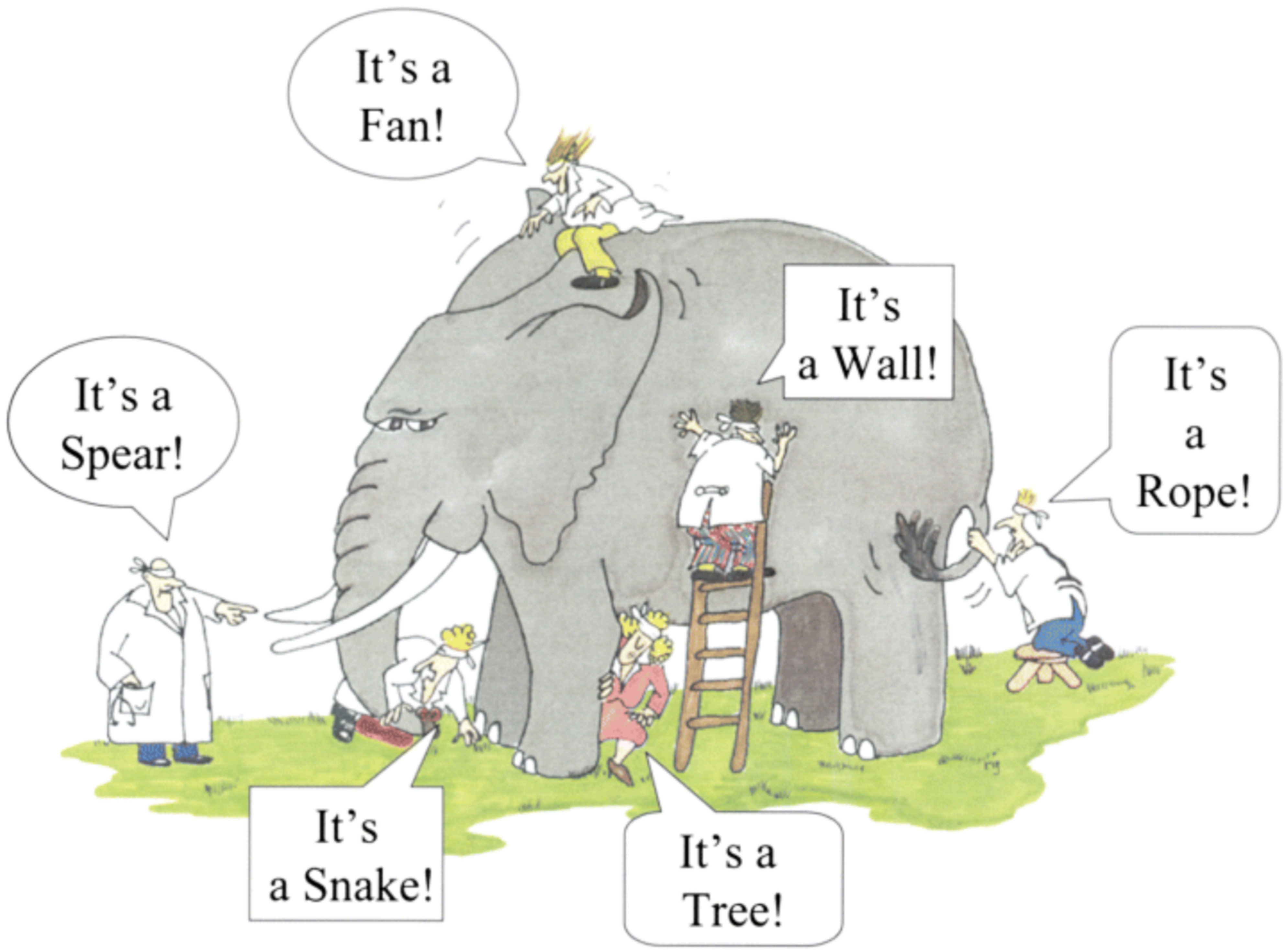
Parton Distribution Functions

1D maps

PDFs

Nucleon tomography

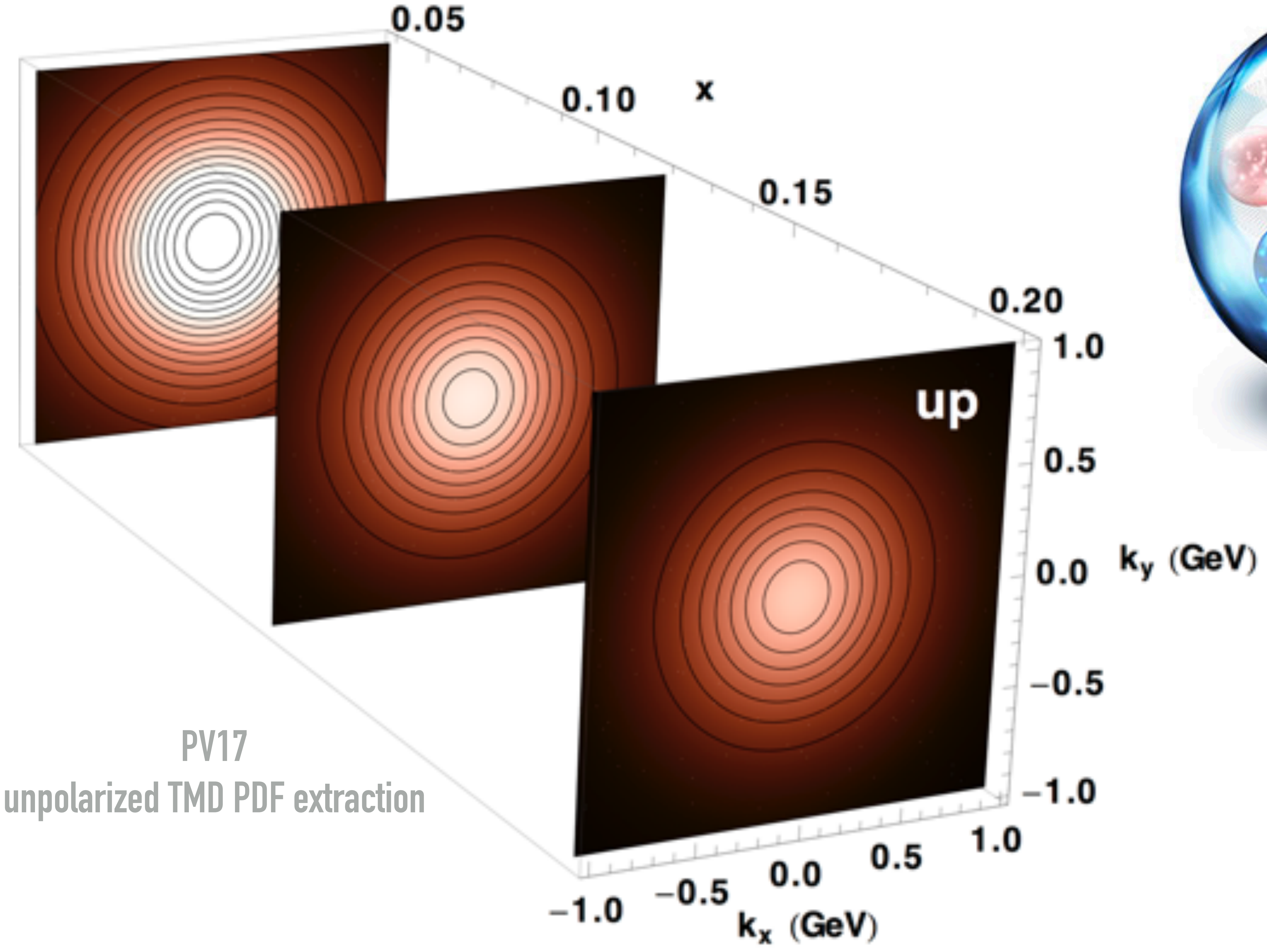
Mapping the proton



...what you see depends on how you look!

TMDs: 3D maps

in momentum space



PV17
unpolarized TMD PDF extraction

Transverse Momentum Distributions

TMDs

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

$$\int d^2\mathbf{k}_T$$

collinear

Parton Distribution Functions

PDFs

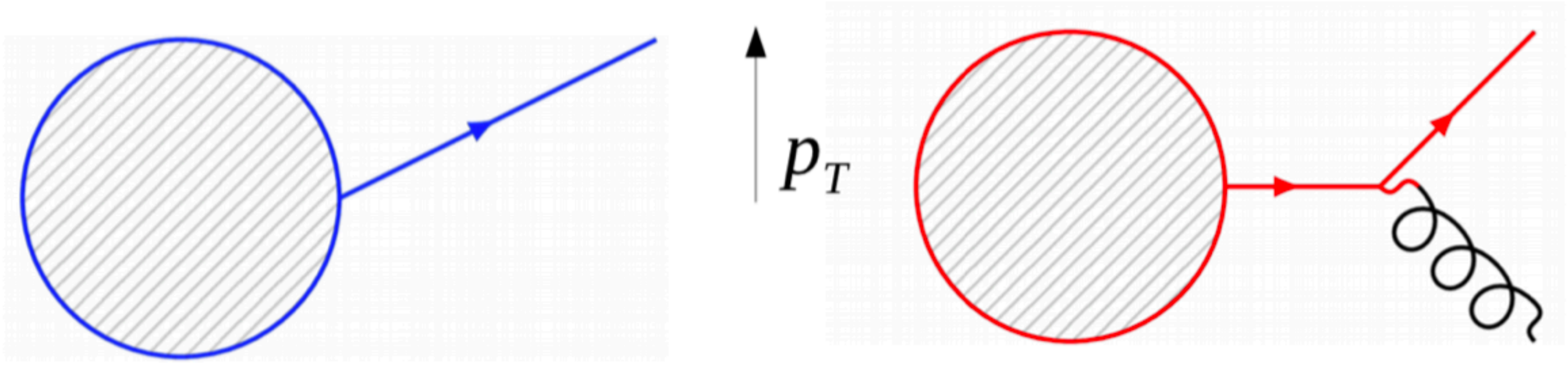
slide credit: Fulvio Piacenza

Complications!

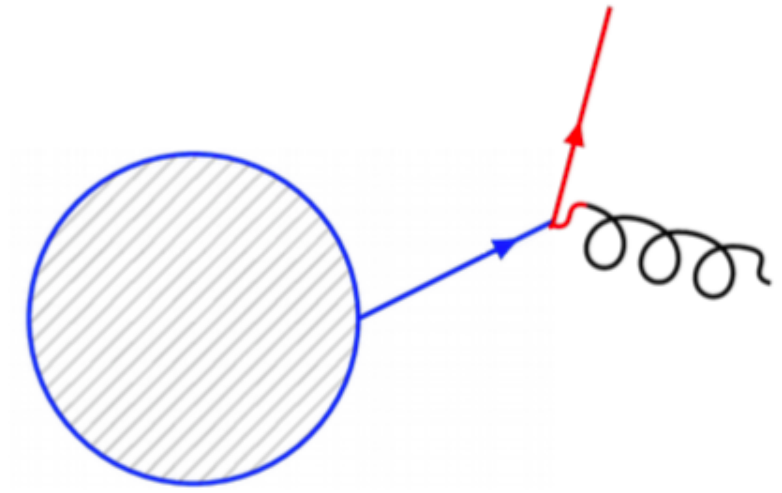
Transverse momentum can be …

intrinsic

perturbative



what we measure is:



TMD PDFs

unpolarized Transverse Momentum Dependent Parton Distribution Functions

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

TMD PDFs

unpolarized Transverse Momentum Dependent Parton Distribution Functions

collinear PDFs

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TMD PDFs

unpolarized Transverse Momentum Dependent Parton Distribution Functions

matching to the collinear region

collinear PDFs

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

perturbative expansion in $\alpha_s(\mu)$

perturbative evolution

TMD PDFs

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perturbative expansion in $\alpha_s(\mu)$

perturbative evolution

$$L = \ln \frac{Q^2}{\mu_b^2}$$

resummation of large logarithms

TMD PDFs

unpolarized Transverse Momentum Dependent Parton Distribution Functions

matching to the collinear region

collinear PDFs

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

perturbative expansion in $\alpha_s(\mu)$

perturbative evolution

non perturbative transverse content

$$L = \ln \frac{Q^2}{\mu_b^2}$$

resummation of large logarithms

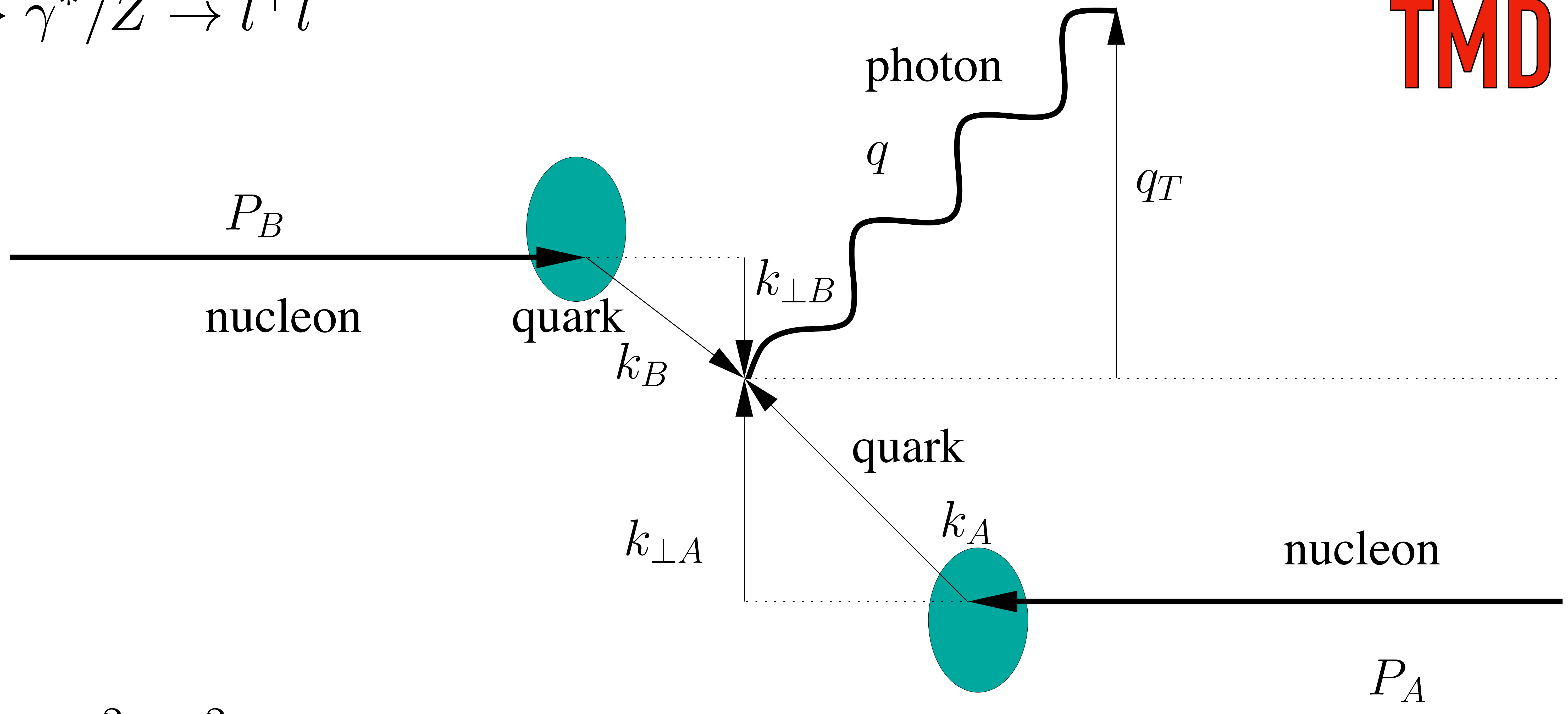
parametrized and fitted to data

Drell-Yan

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

for $q_T \ll Q$

TMD factorization



$$F_{UU}^1(x_A, x_B, \boldsymbol{q}_T^2, Q^2)$$

$$= \sum_a \mathcal{H}_{UU}^{1a}(Q^2, \mu^2) \int d^2\boldsymbol{k}_{\perp A}\, d^2\boldsymbol{k}_{\perp B}\, f_1^a(x_A, \boldsymbol{k}_{\perp A}^2; \mu^2)\, f_1^{\bar{a}}(x_B, \boldsymbol{k}_{\perp B}^2; \mu^2)\, \delta^{(2)}(\boldsymbol{k}_{\perp A} - \boldsymbol{q}_T + \boldsymbol{k}_{\perp B})$$

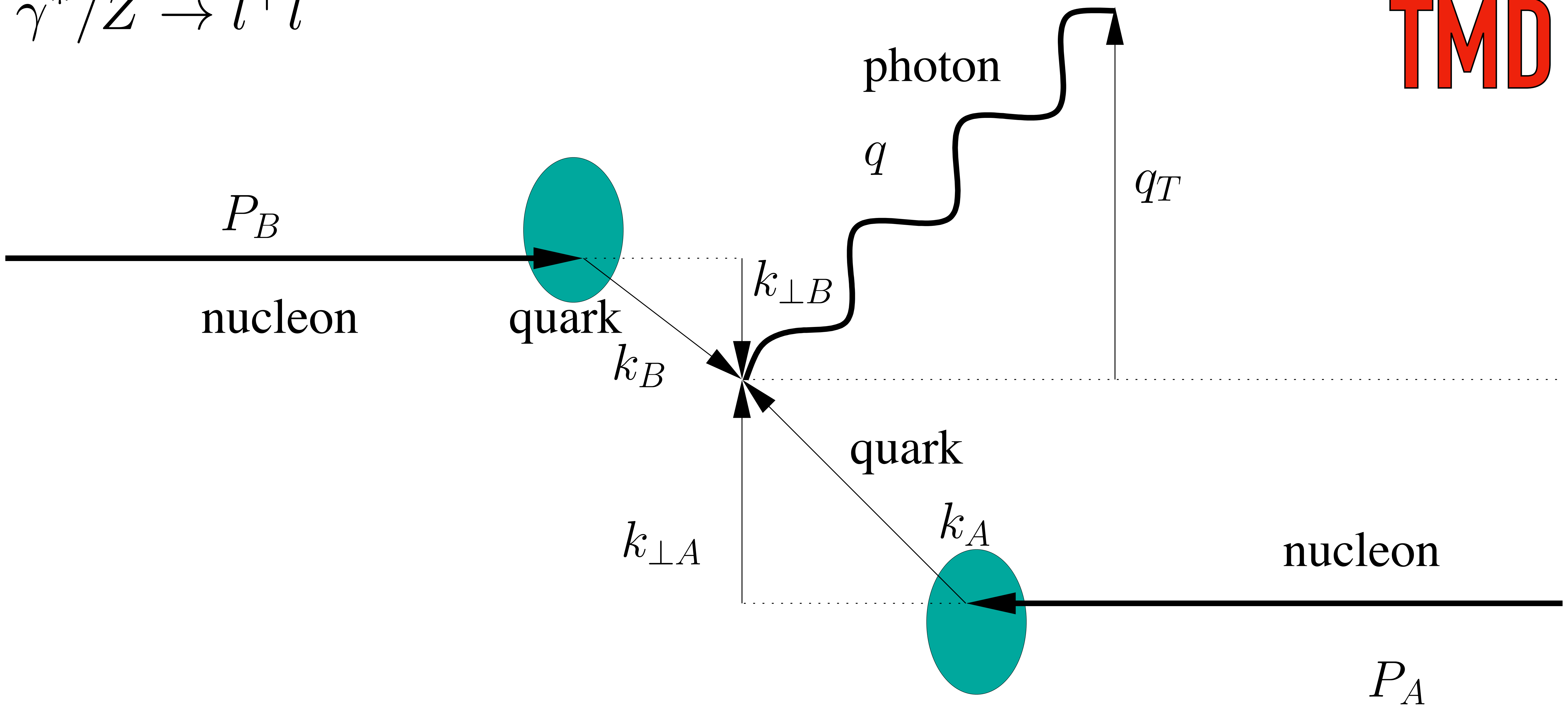
$$+ Y_{UU}^1(Q^2, \boldsymbol{q}_T^2) + \mathcal{O}(M^2/Q^2)$$

Drell-Yan

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

for $q_T \ll Q$

TMD factorization



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

large b_T

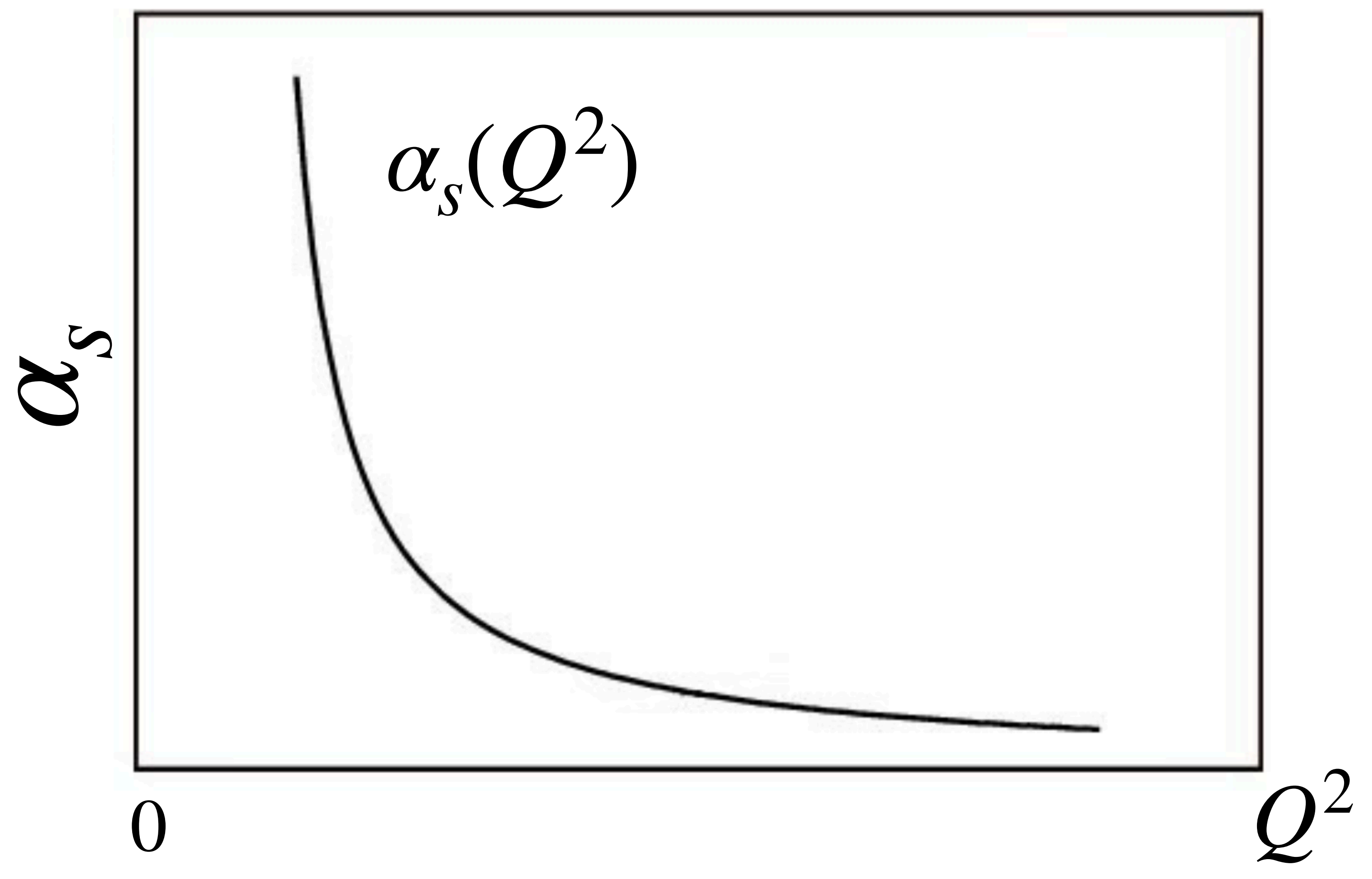
integration up to infinity

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

cross section

when b_T becomes large

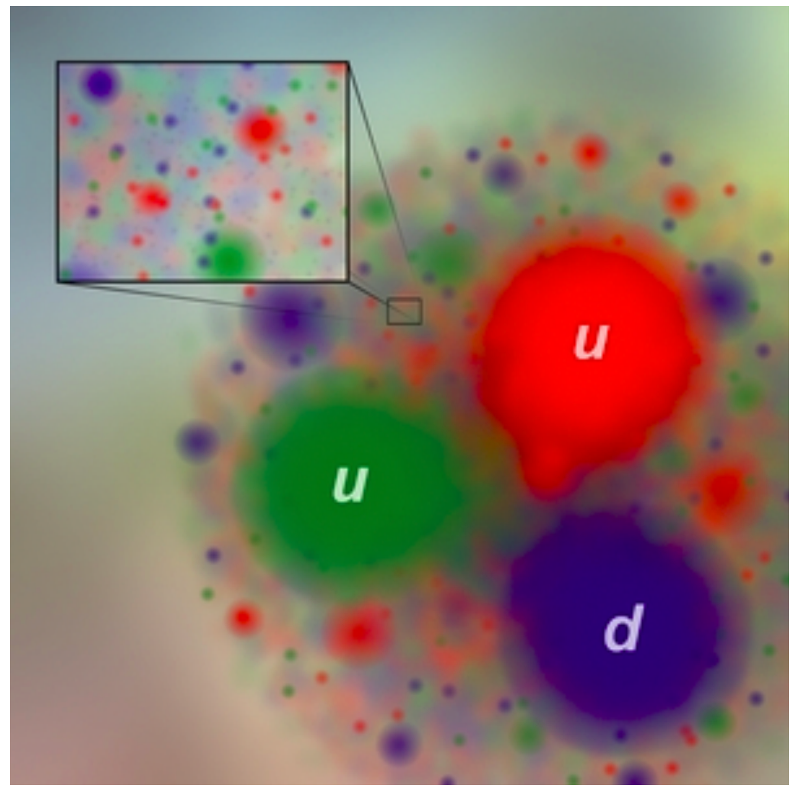
$$\alpha_s(\mu_b) = \alpha\left(\frac{2e^{-\gamma_E}}{b}\right) \gg 1$$

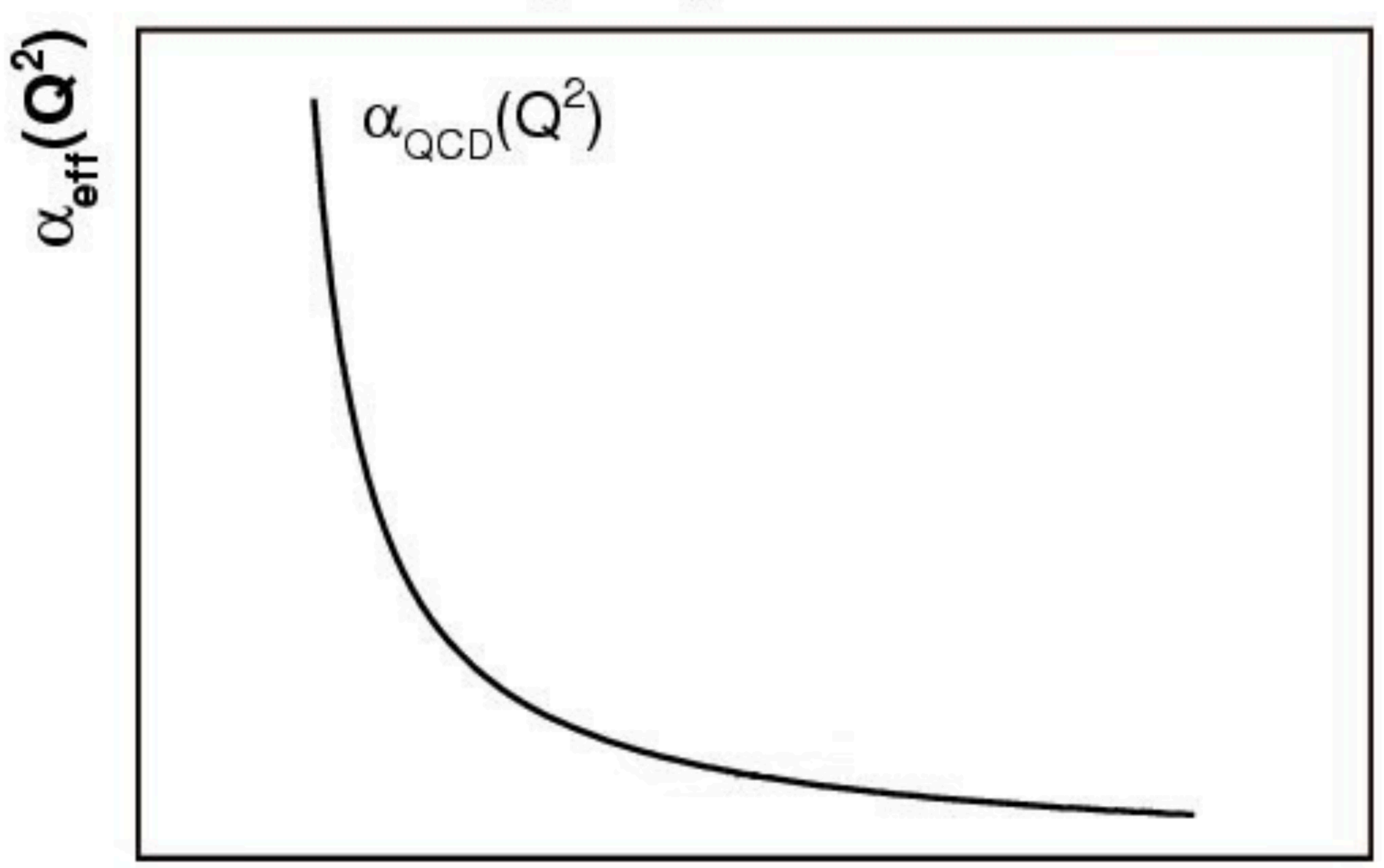


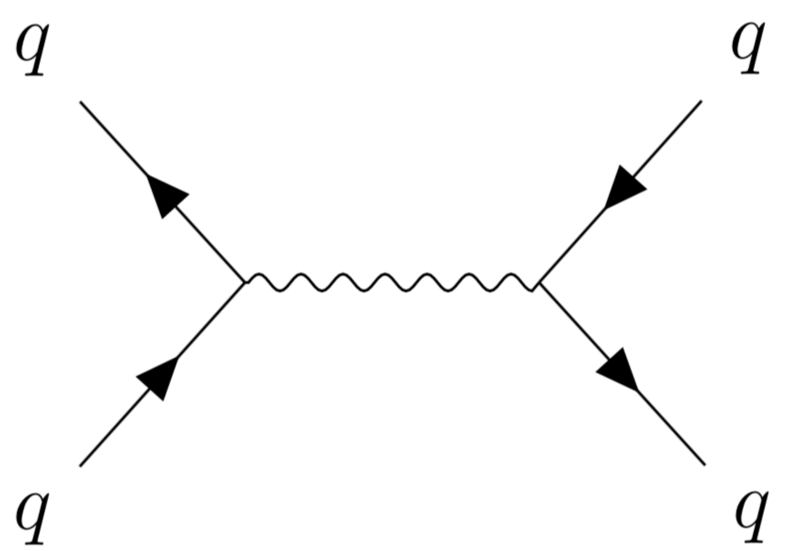
invalidates perturbative calculations

necessary to introduce a prescription

QCD running constant α_s







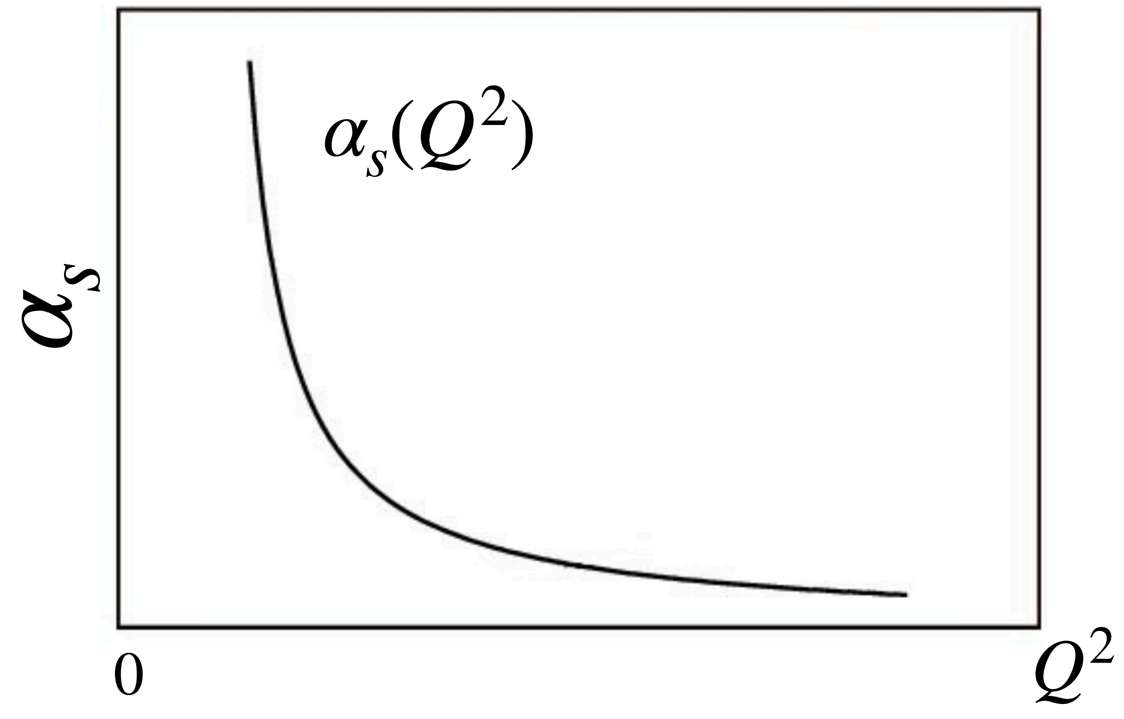
probing small distance scales

high Q^2

non perturbative region → quark confinement

perturbative region → asymptotic freedom

b* prescription



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

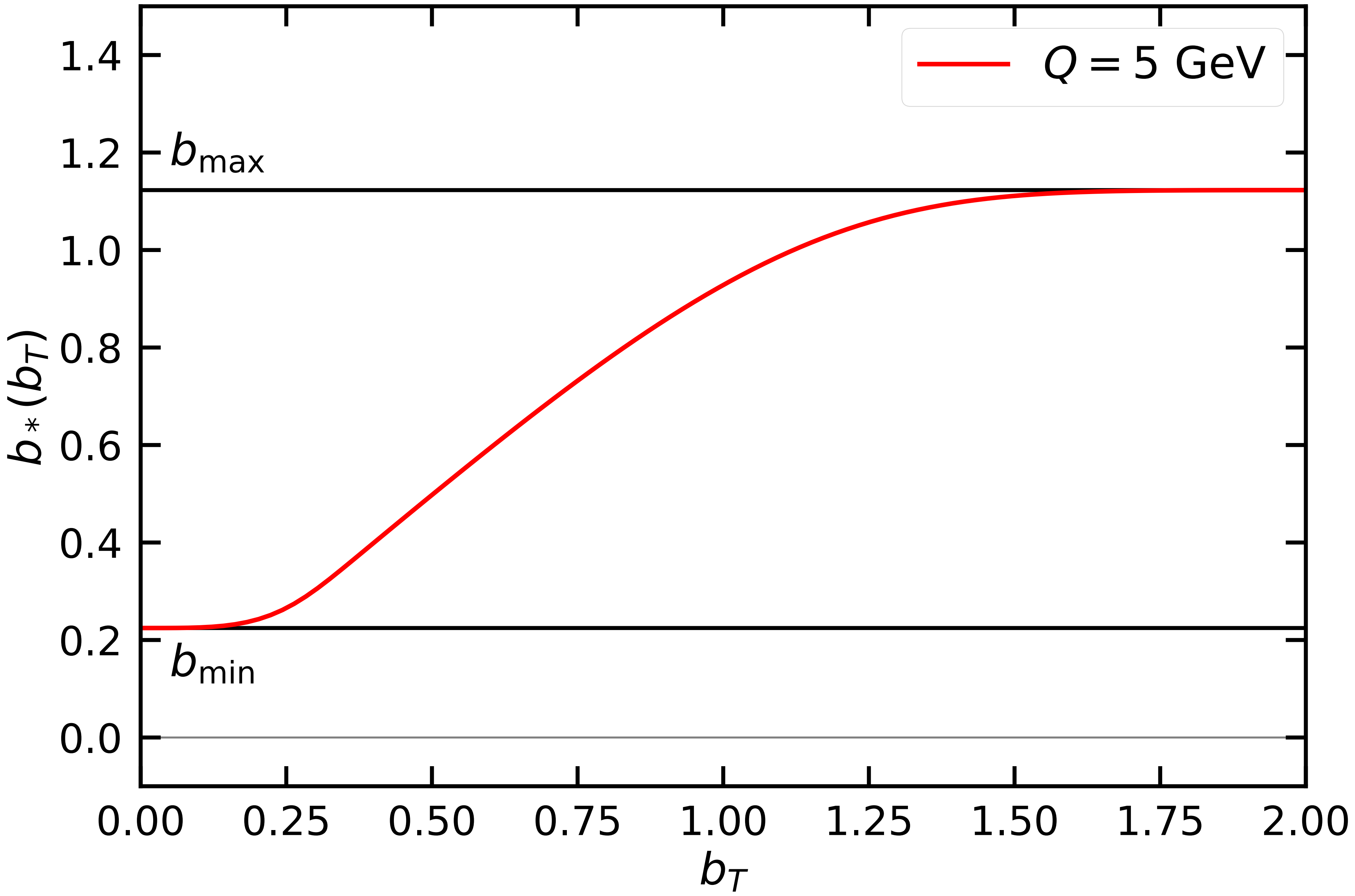
when b_T becomes large

$\longrightarrow$ $\alpha_s(\mu_b) = \alpha\left(\frac{2e^{-\gamma_E}}{b}\right) \gg 1$ $\longrightarrow$ invalidates perturbative calculations $\Rightarrow b_{\max}$

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

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

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



b* prescription and definition of $f_{\rm NP}$

perturbative

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

non perturbative

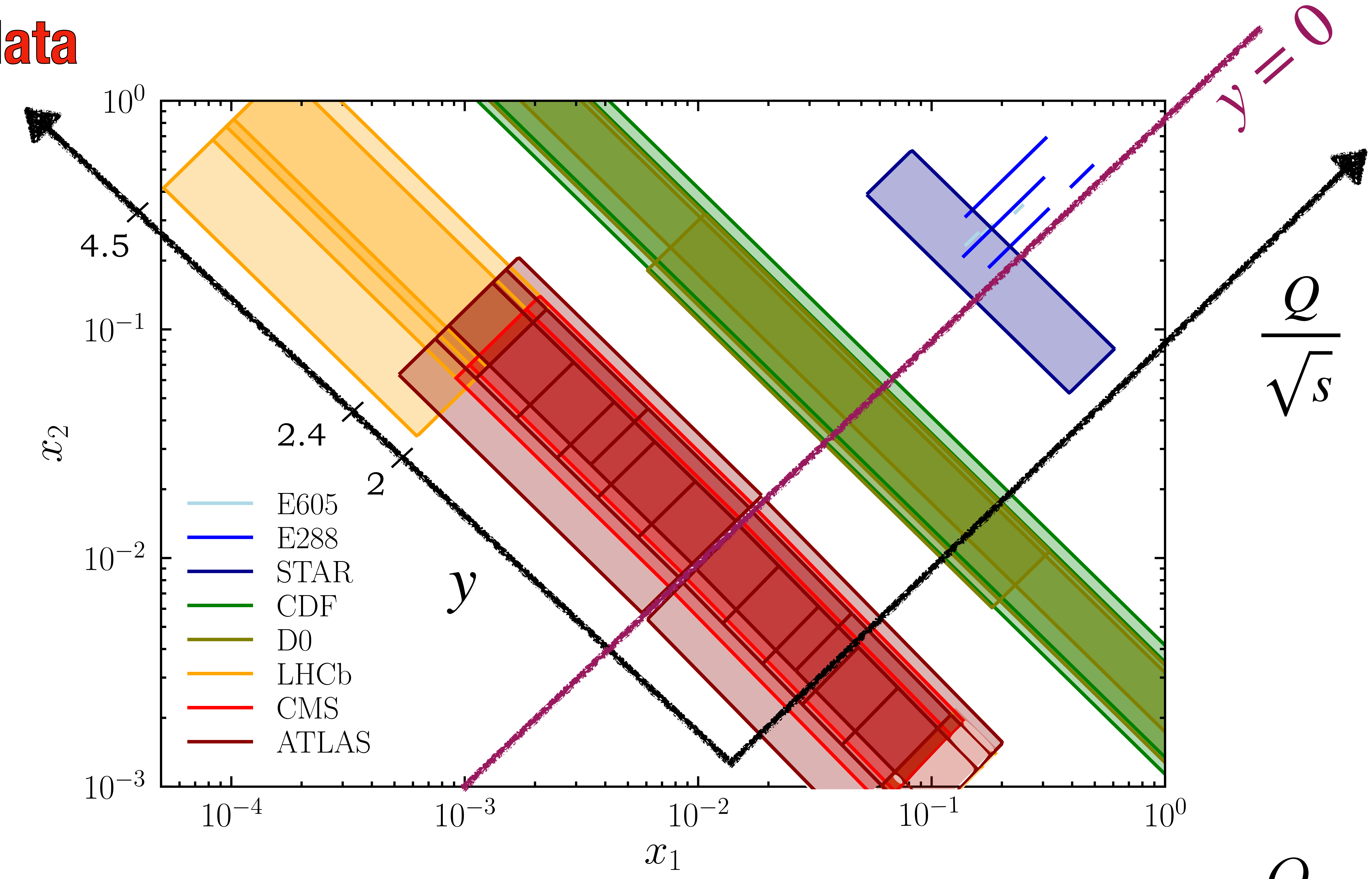
$$f_{\rm NP}(x,b,\zeta)$$

fit to data

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

x, Q, y coverage

only Drell-Yan data



$$x_{1,2} = \frac{Q}{\sqrt{s}} e^{\pm y}$$

Integrations

In order to compare theory with data

✻ experiments measure the cross section σ

integration over the range in momentum transfer	integration over the range in rapidity	integration over bins in transverse momentum q_T

$$\sigma = \int_{Q_{\min}}^{Q_{\max}} dQ \int_{y_{\min}}^{y_{\max}} dy \int_{q_{T,\min}}^{q_{T,\max}} dq_T \left[\frac{d\sigma}{dQ\,dy\,dq_T} \right]$$

numerical integration

Ogata quadrature

analytic integration

see PV19 paper

Parameterization

"analytic", "with a functional form"

of the non-perturbative part of TMDs

TMD PDF

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

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

Parameterization

of the non-perturbative part of TMDs

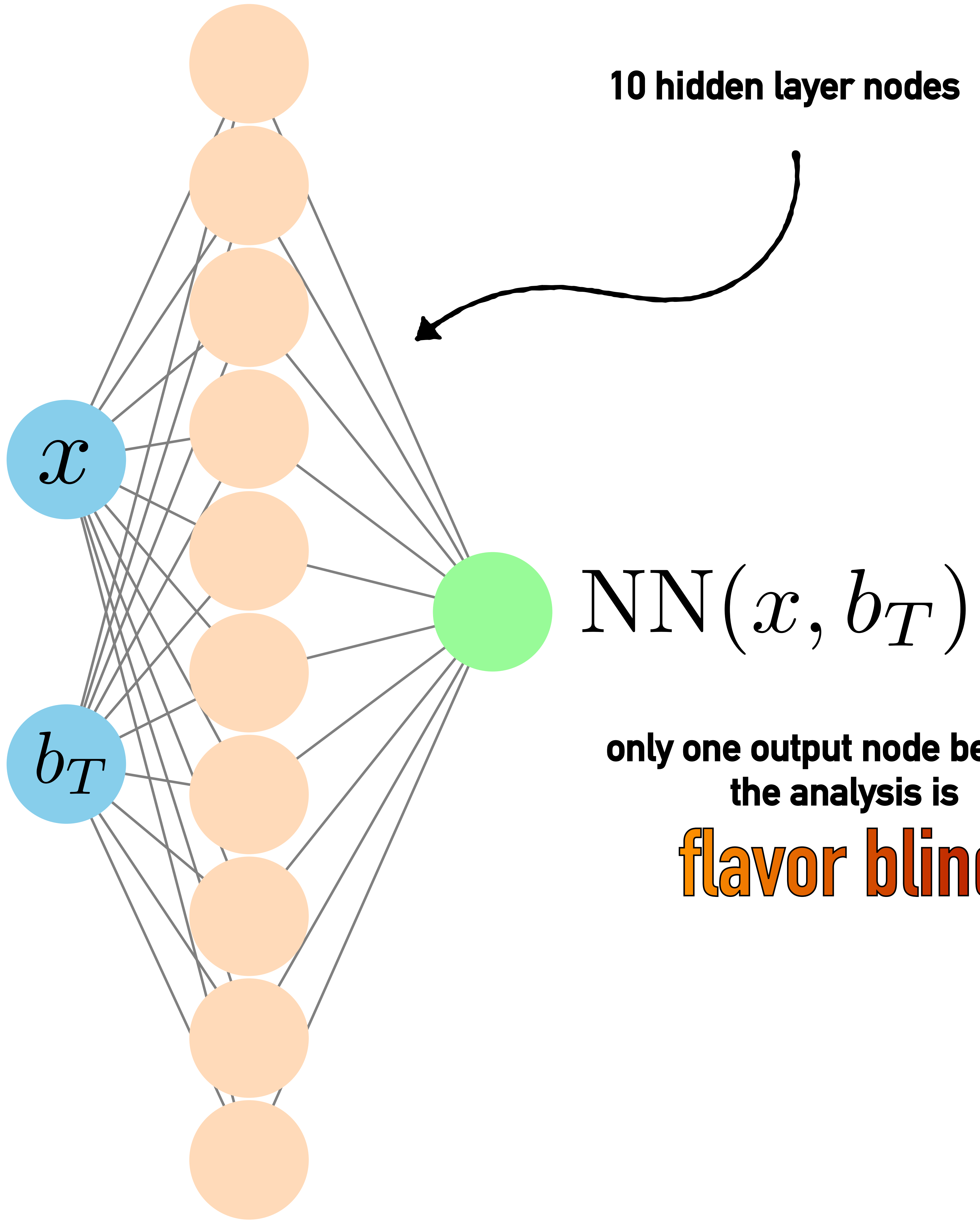
proof of concept

$$f_{NP}(x, b_T) = e^{NNAD(x,b_T)} e^{S_{NP}}$$

formula implemented in NangaParbat

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

Neural Network



only one output node because the analysis is **flavor blind**

Motivation

What do we want to do? What do we want to prove?

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

- are NN really a more general parameterization with respect to the “analytic classics”?

  e.g. ‘analytic functional forms’, like sums of Gaussian and weighted Gaussians

- we want to/have to **test methodology**

  → with **closure tests**

https://docs.nnpdf.science/tutorials/closuretest.html

Closure tests

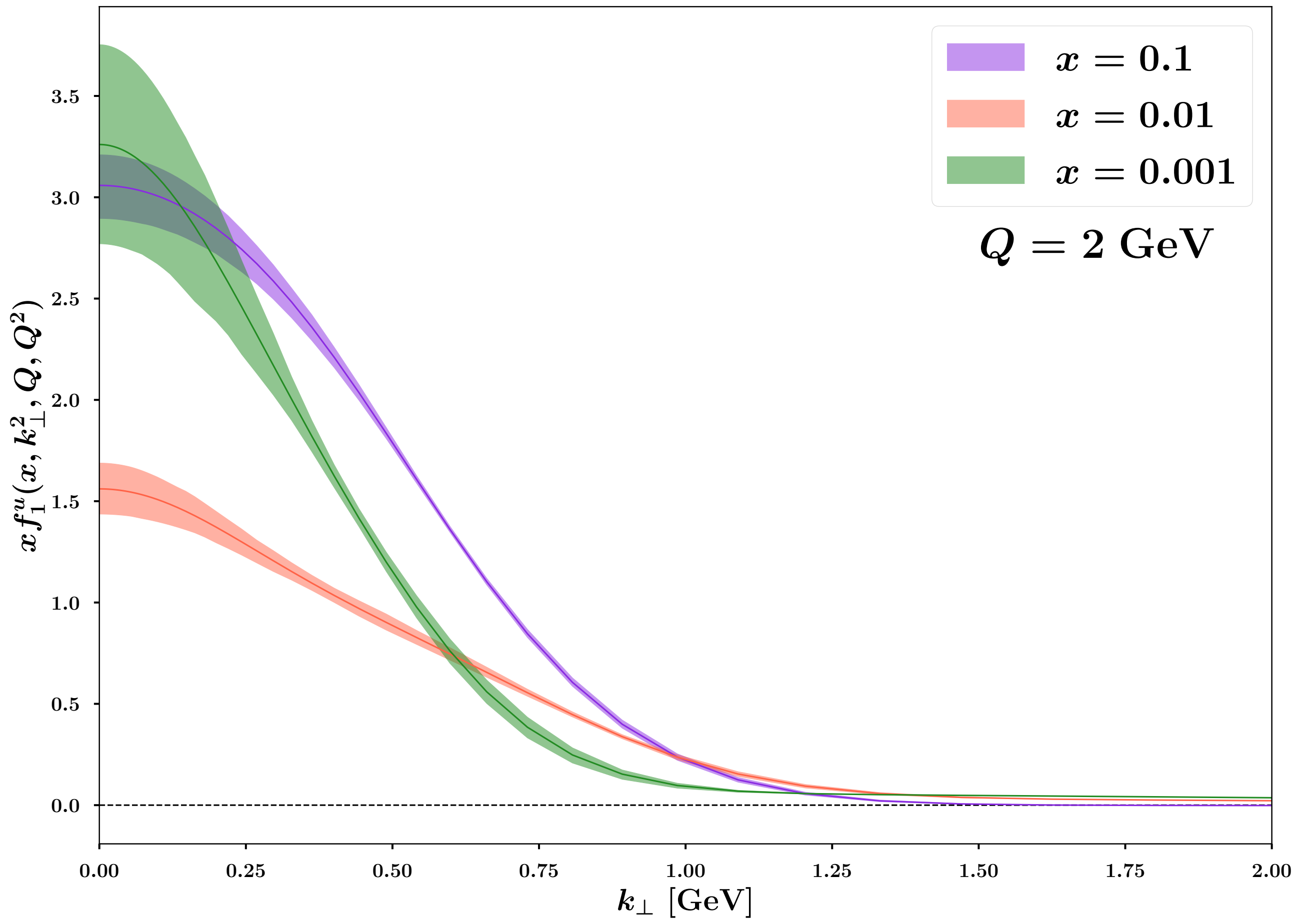
to validate the methodology

- **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

Closure tests *only Drell-Yan data*

to validate the methodology

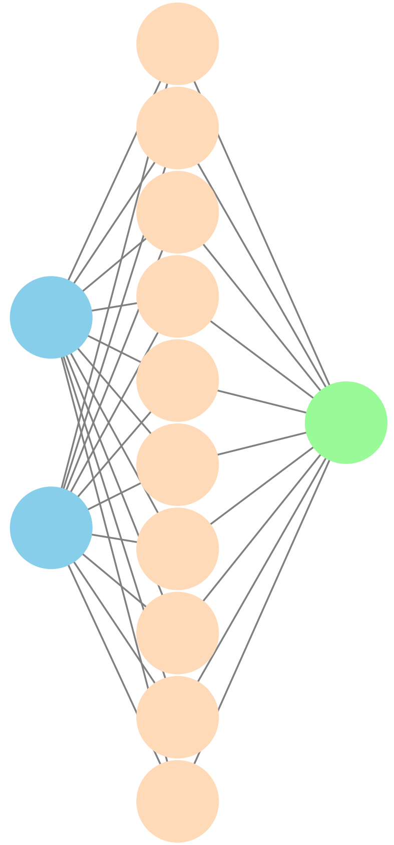
closure test of level 0



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

- central value: **MAP22**
- uncertainties: real DY data

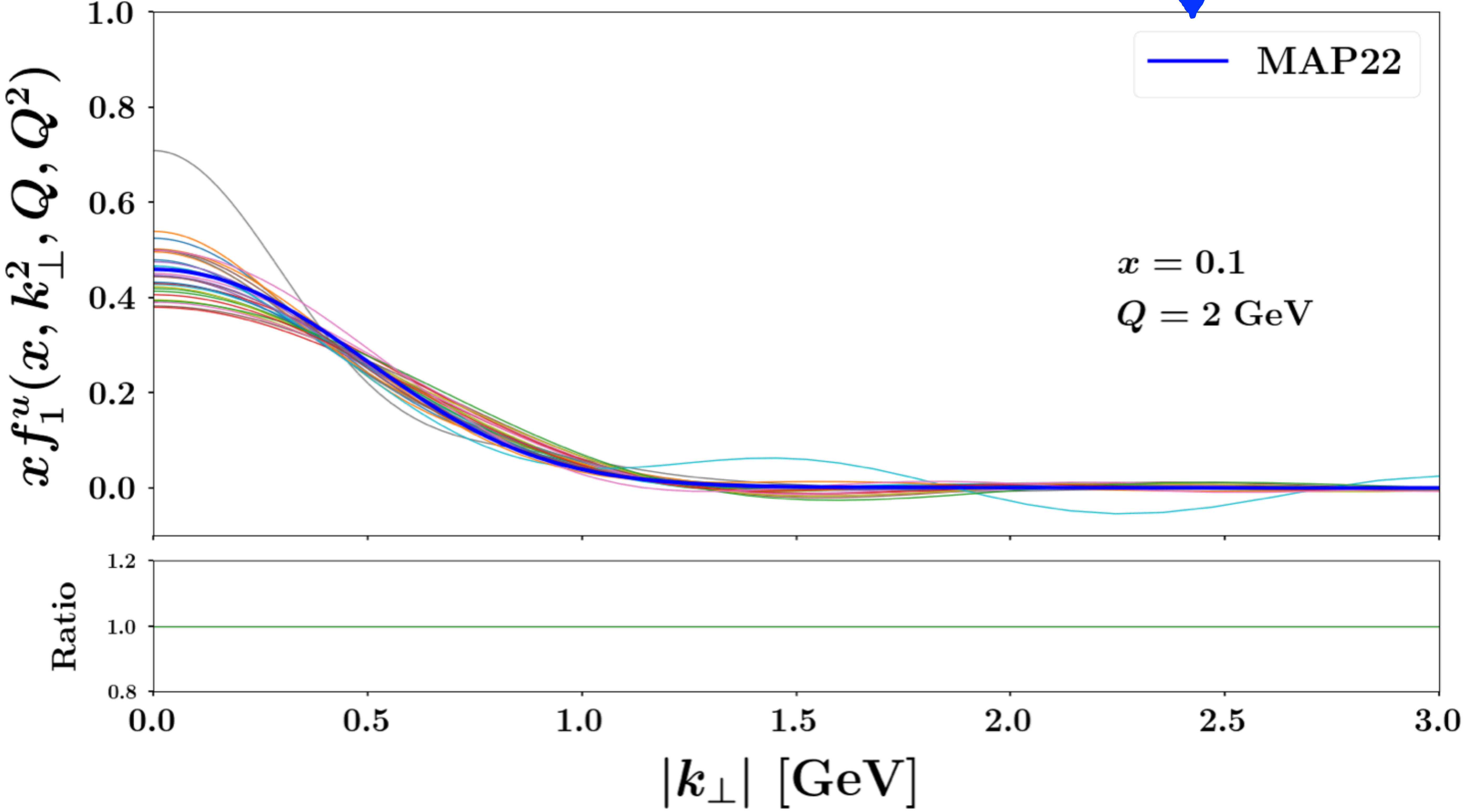
fit with NN



can we recover the MAP22 result?

Closure test - level 0

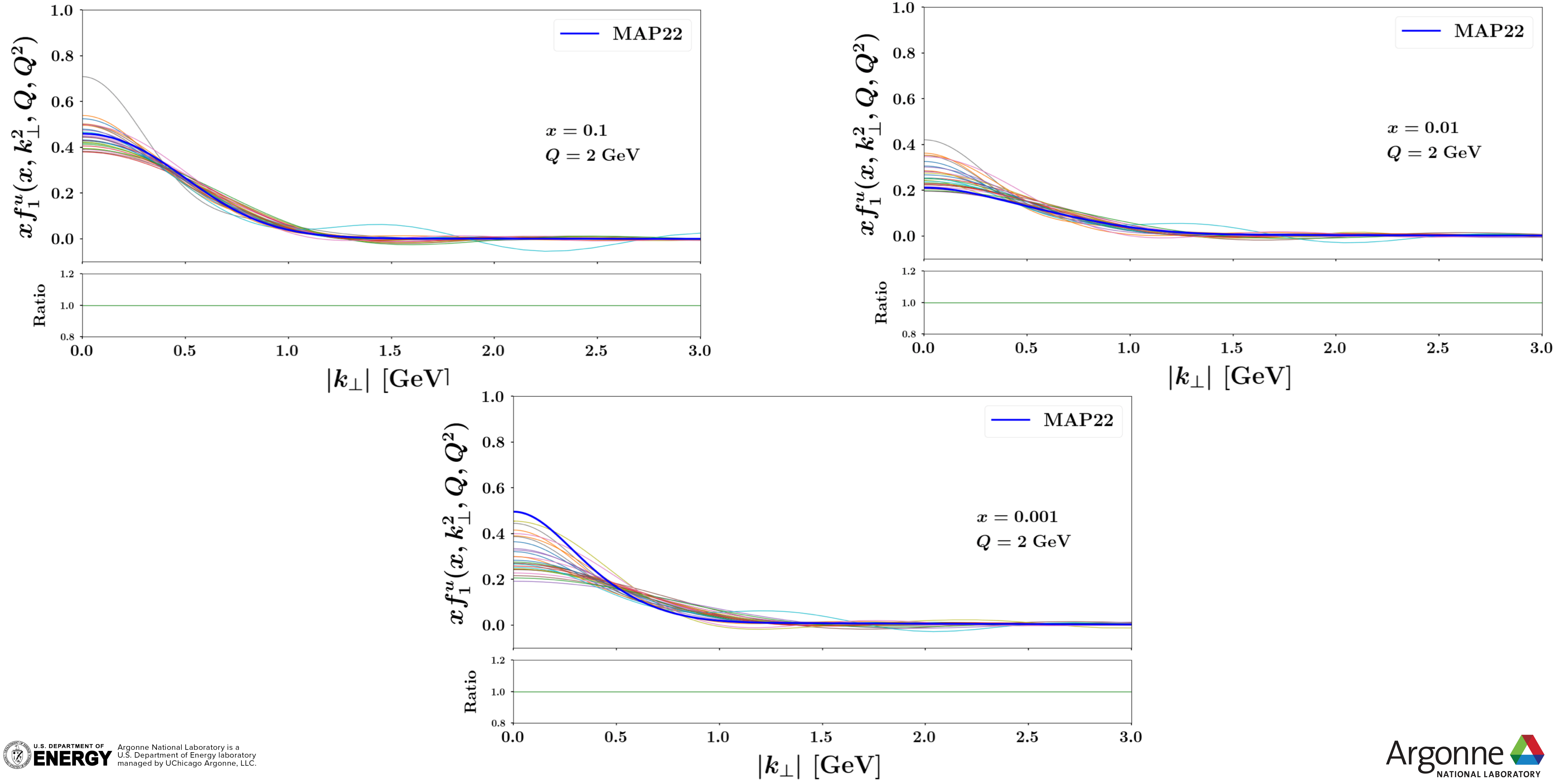
comparison with central replica of MAP22



replicas here come from variating the random seed for the initial values of the parameters

$\chi^2 \sim 10^{-5}$

Closure test - level 0

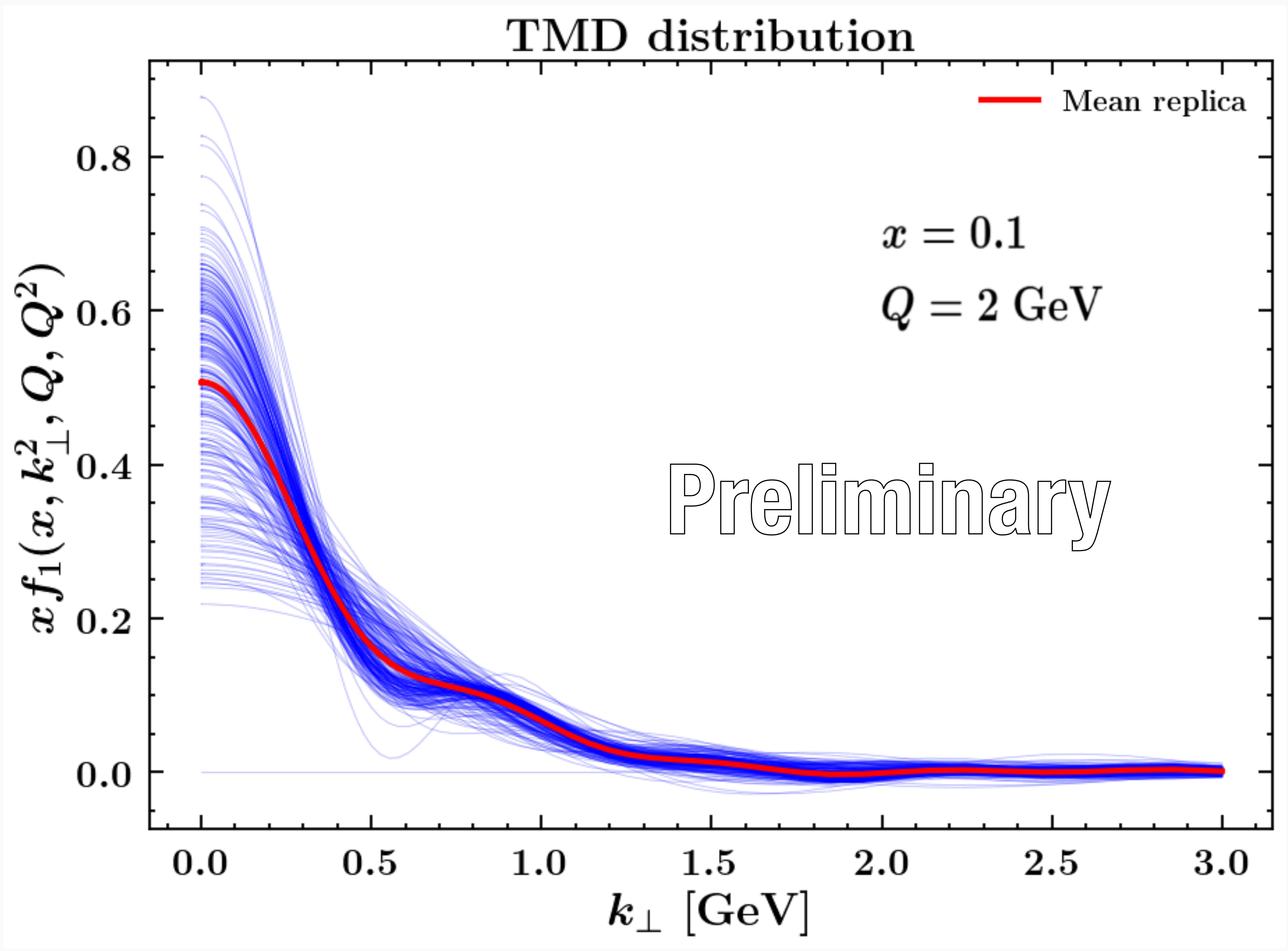


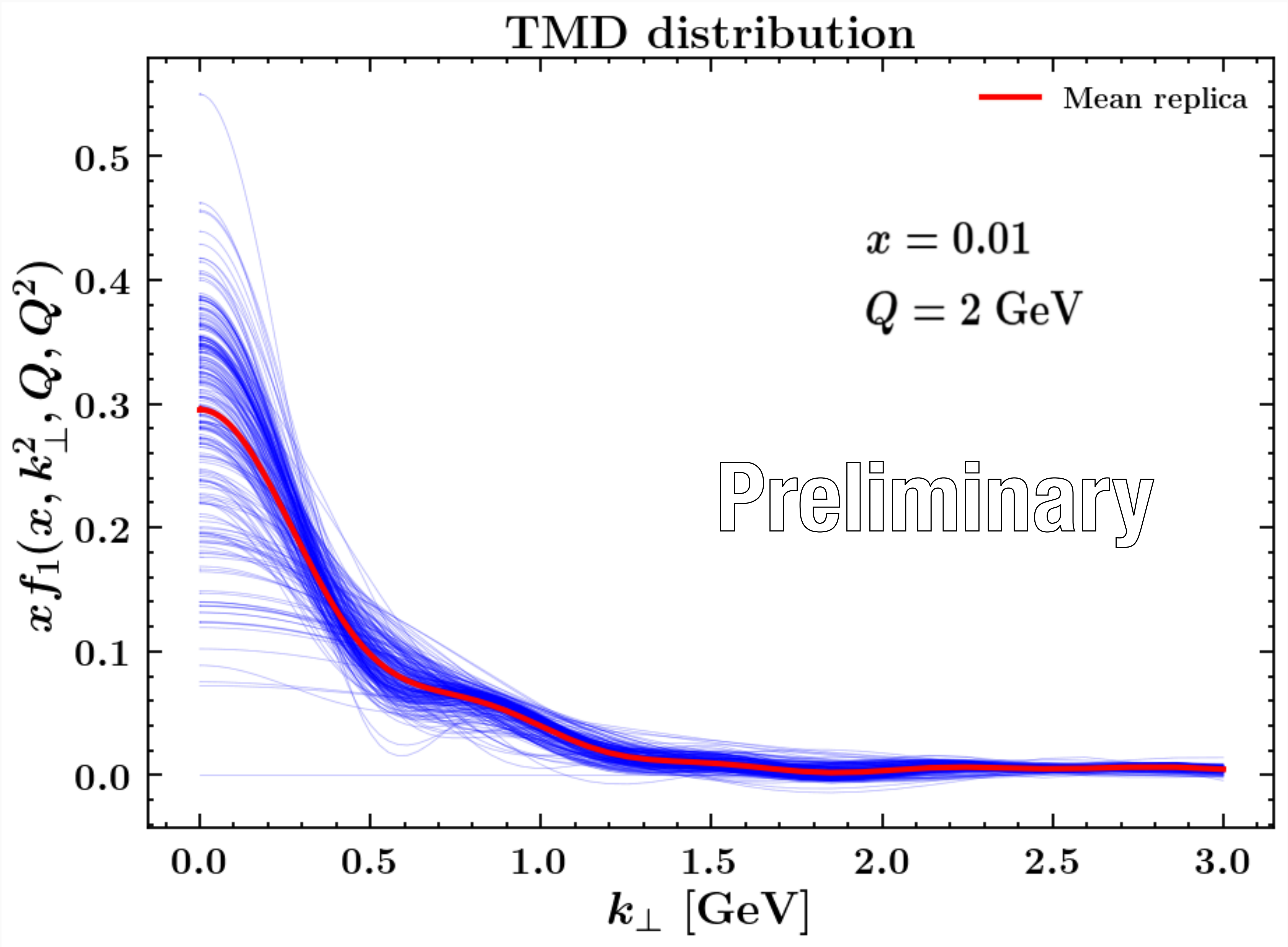
Results of NN TMD fit

Caveat: very preliminary results!

χ^2 = 1.02

5 nodes (hidden layer)



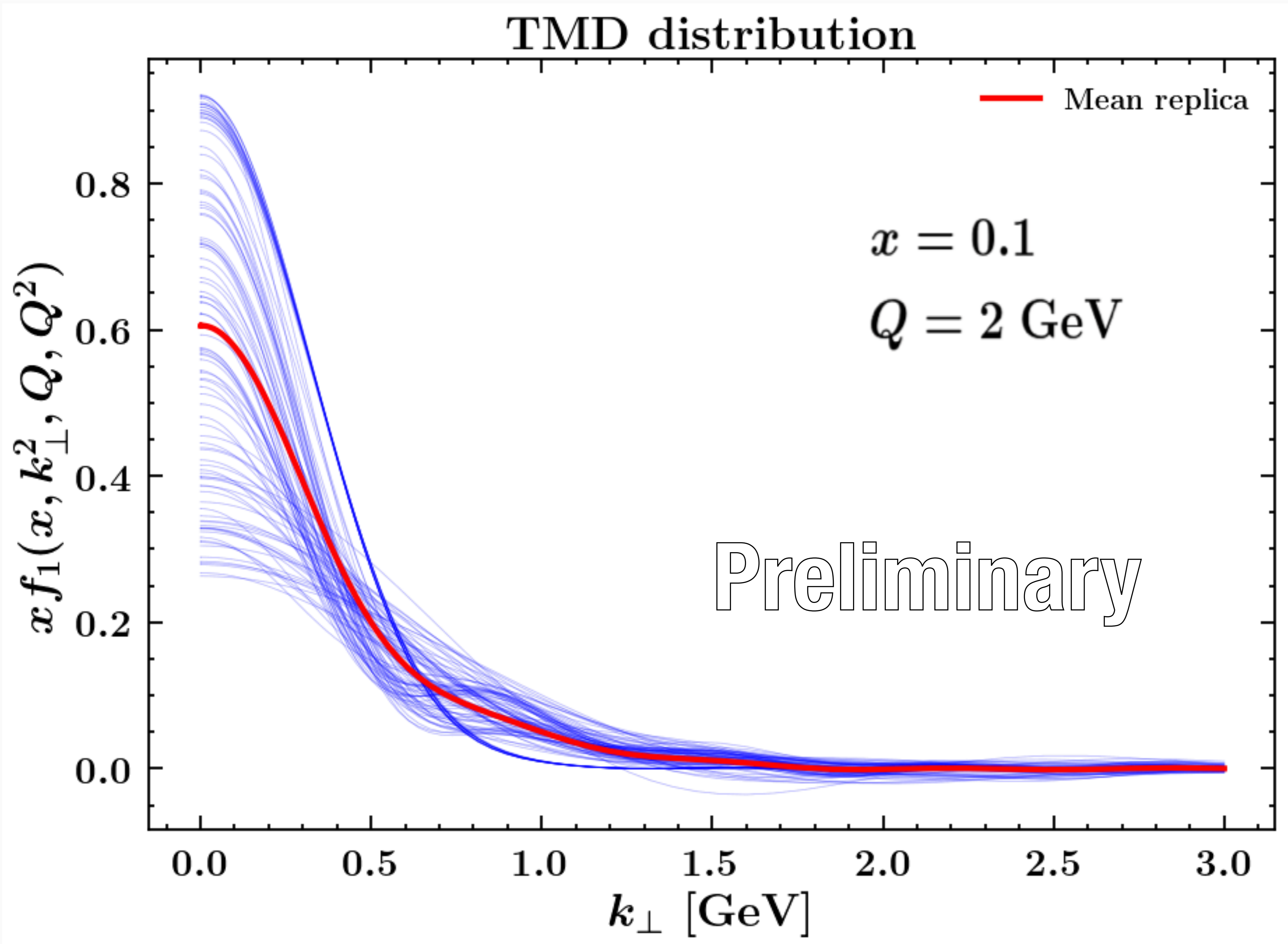


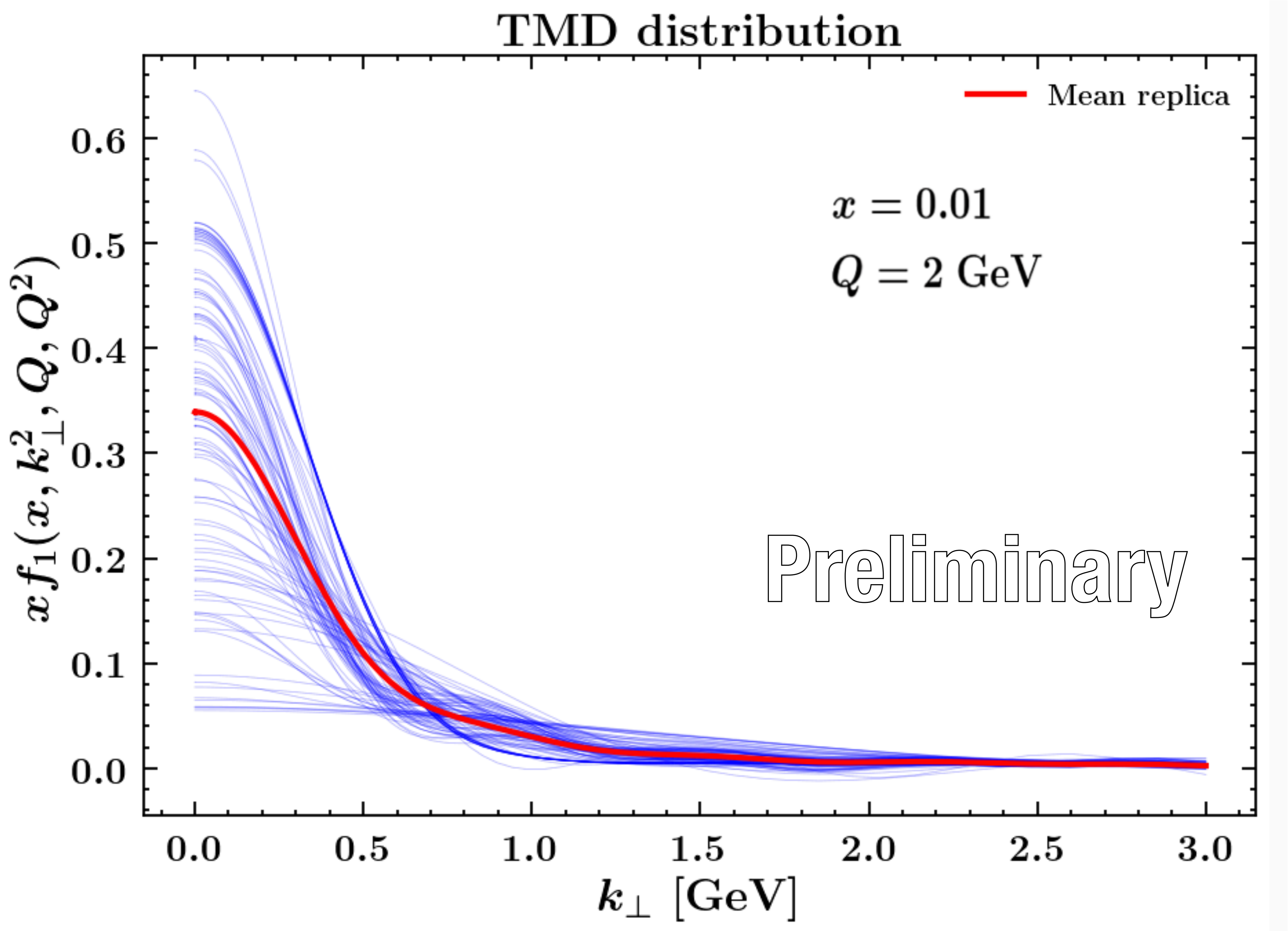
Results of NN TMD fit

Caveat: very preliminary results!

$\chi^2 = 0{,}97$

10 nodes (hidden layer)





Conclusions

Neural Networks opened up a new realm of possibilities for fits

- **preliminary results** on Drell-Yan data
- **closure tests**

to do

- Study b* prescriptions - do they have an impact on the TMDs?
- Perform all stages of closure tests - validate the use of NN
- … keep trying to use NN in TMD fits