Impact of a positron beam at JLab on an unbiased determination of DVCS Compton Form Factors

Paweł Sznajder
National Centre for Nuclear Research, Poland

with collaboration of H. Dutrieux, V. Bertone, H. Moutarde

NATIONAL CENTRE FOR NUCLEAR RESEARCH ŚWIERK

QCD GDR / STRONG 2020 Joint Workshop, Jun 1th, 2021

Outline

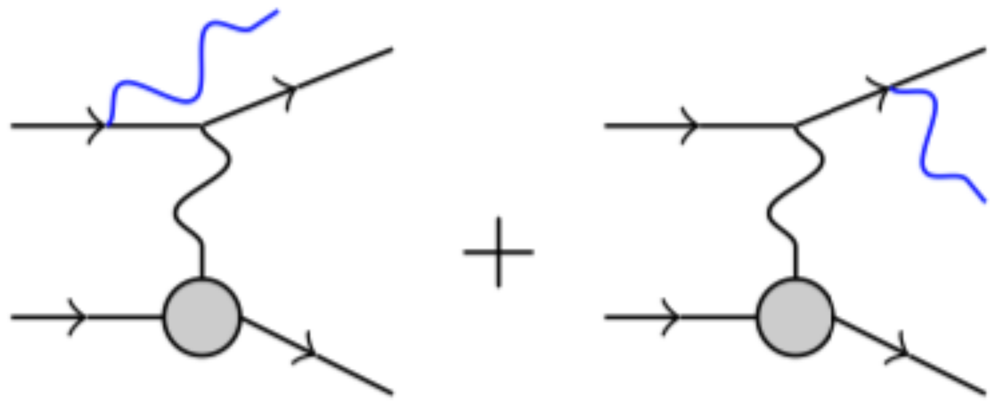
- Introduction
- Fits with neural networks
- Re-weighting methods
- Impact of JLab positron programme
- Summary

DVCS Compton Form Factors

Cross-section for single photon production $(l + N \to l + N + \gamma)$:

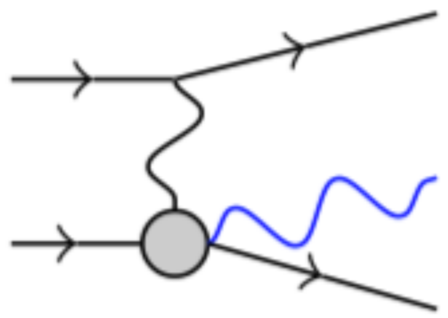
$$\sigma \propto |\mathscr{A}|^2 = |\mathscr{A}_{BH} + \mathscr{A}_{DVCS}|^2 = |\mathscr{A}_{BH}|^2 + |\mathscr{A}_{DVCS}|^2 + \mathscr{I}$$

Bethe-Heitler process



calculable within QED

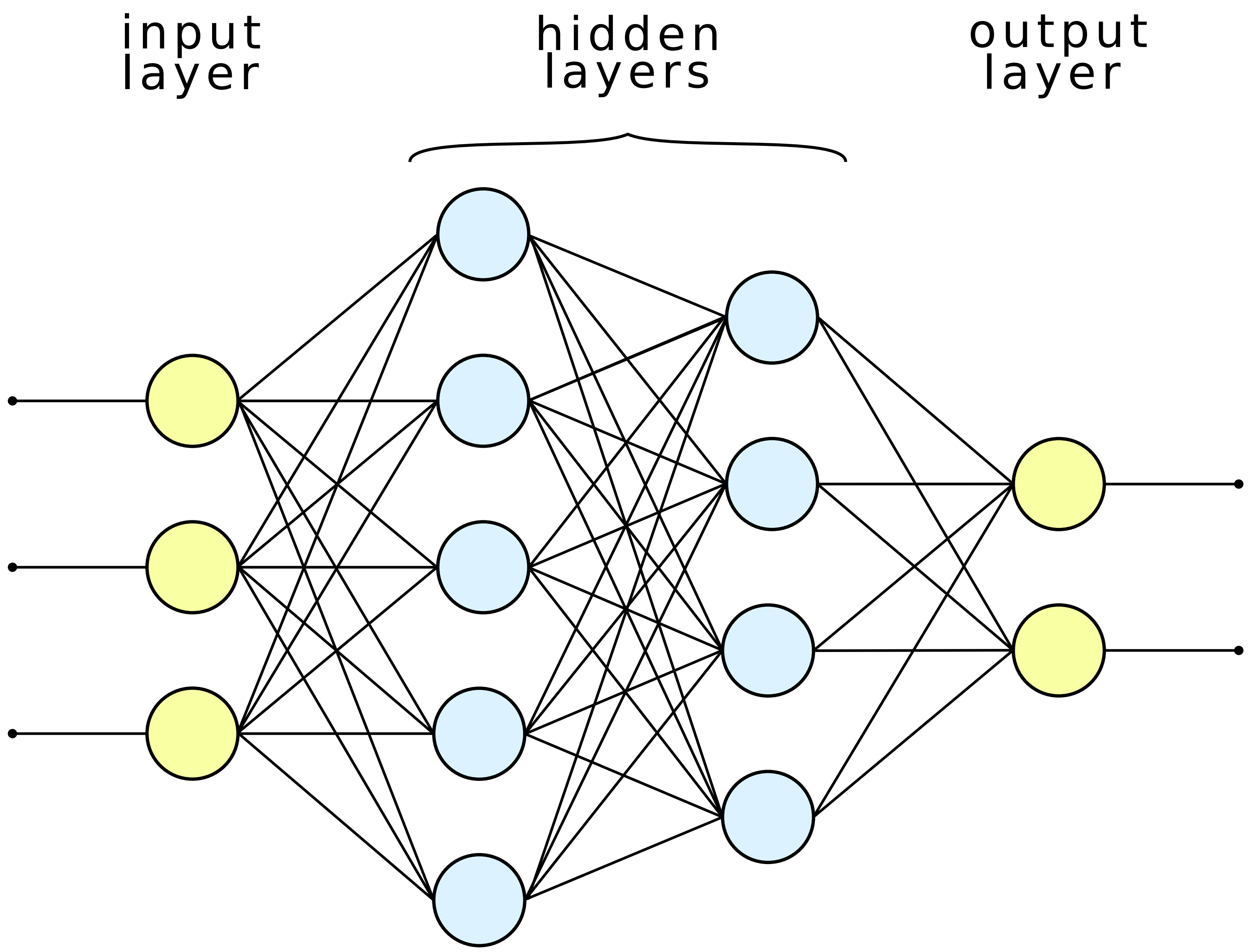
DVCS



parametrised by CFFs

CFF - the most basic GPD-sensitive observables
- analogy with connection between structure functions and PDFs

Neural Networks

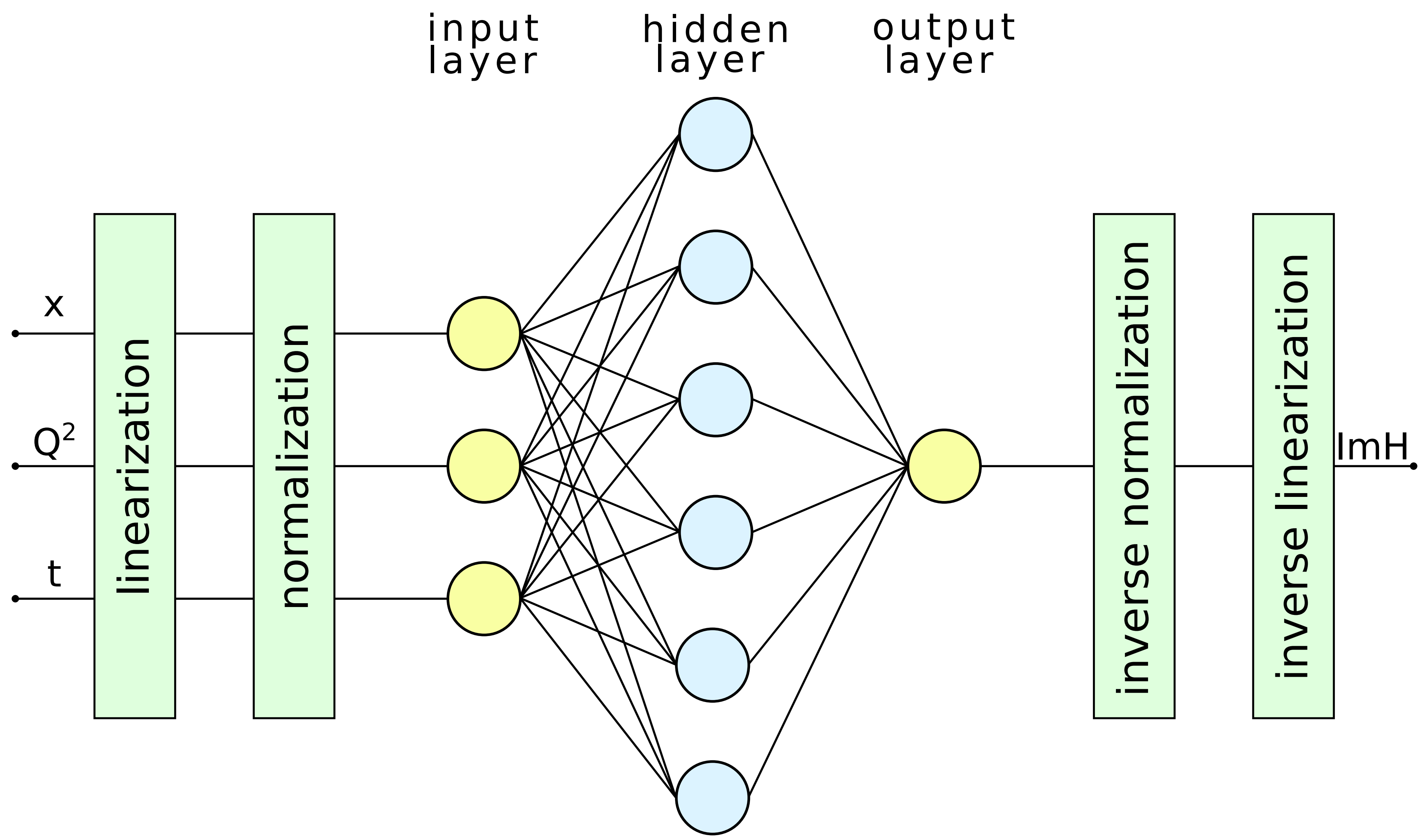


Artificial neural networks (ANNs)

- Data processing technique inspired by Nature
- Network made out of simple but highly connected elements → connectionists system
- Many variations, but most popular deep feed-forward ANNs
  - data processed layer by layer
    input layer → hidden layers→ output layer
  - generalisation capability given by consecutive hidden layers
    output of *i-1* layer is more refined than that of *i* layer
- Information containers

Neural Networks

H. Moutarde, PS, J. Wagner,
Eur. Phys. J. C 79 (2019) 7, 614



DVCS cross-section can be parametrised by Compton Form Factors (CFFs)

We extract those CFFs from world proton data

Features of analysis:

- Independent network for each CFF and Re/Im parts
- Functions of x_B, Q^2 and t
- Network size determined using benchmark sample
- No power-behaviour pre-factors
- Trained with genetic algorithm
- Regularisation method based on early stopping criterion
- Replica method for propagation of experimental uncertainties

DVCS data

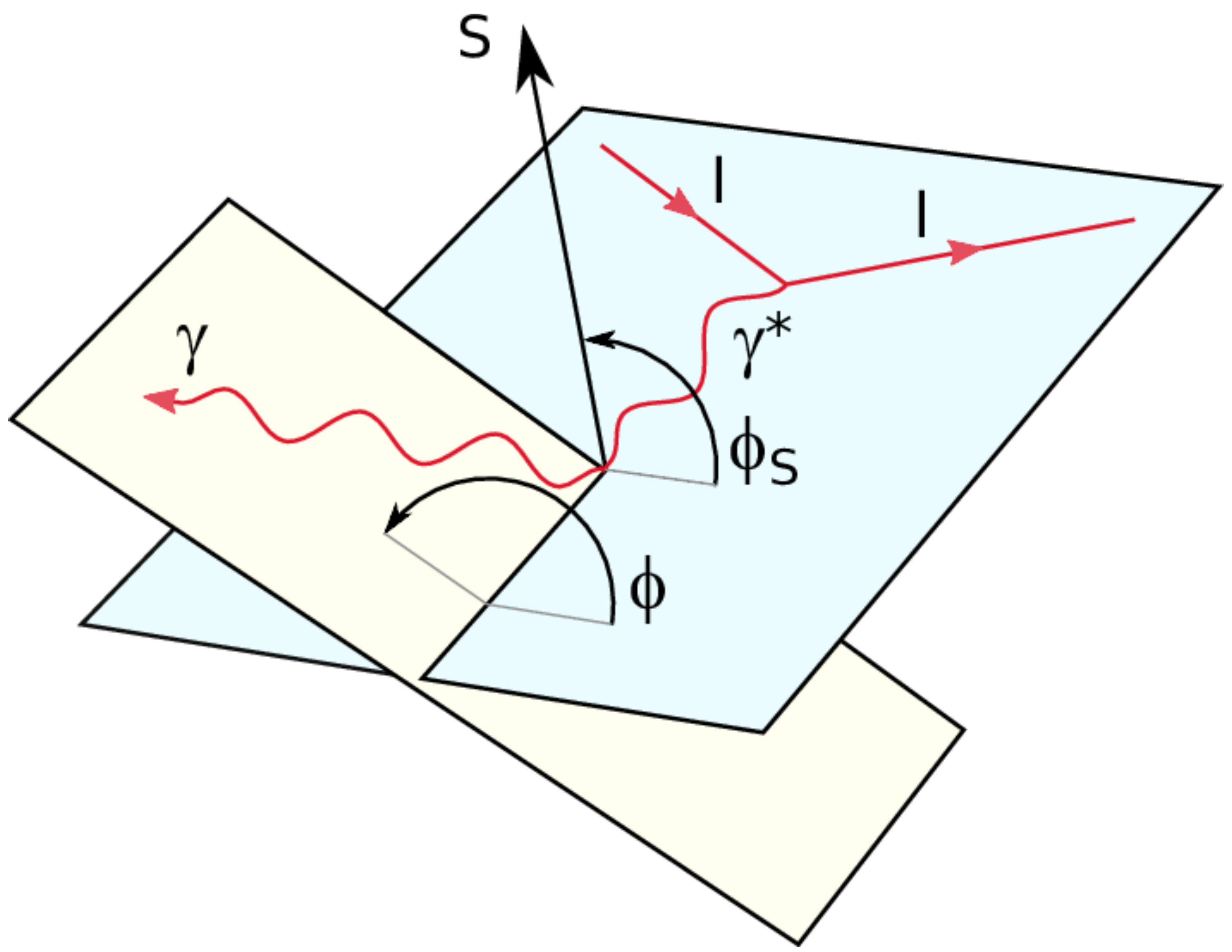
H. Moutarde, PS, J. Wagner,
Eur. Phys. J. C 79 (2019) 7, 614

Kinematic cuts
used in presented analyses:

$$Q^2 > 1.5\ \mathrm{GeV}^2$$

$$-t/Q^2 < 0.2$$

Angles:



No.	Collab.	Year	Observable		Kinematic dependence	No. of points used / all
1	HERMES	2001	A_{LU}^{+}		ϕ	10 / 10
2		2006	$A_{C}^{\cos i\phi}$	$i=1$	t	4 / 4
3		2008	$A_{C}^{\cos i\phi}$	$i=0,1$	x_{Bj}	18 / 24
			$A_{UT,\mathrm{DVCS}}^{\sin(\phi-\phi_S)\cos i\phi}$	$i=0$		
			$A_{UT,\mathrm{I}}^{\sin(\phi-\phi_S)\cos i\phi}$	$i=0,1$		
			$A_{UT,\mathrm{I}}^{\cos(\phi-\phi_S)\sin i\phi}$	$i=1$		
4		2009	$A_{LU,\mathrm{I}}^{\sin i\phi}$	$i=1,2$	x_{Bj}	35 / 42
			$A_{LU,\mathrm{DVCS}}^{\sin i\phi}$	$i=1$		
			$A_{C}^{\cos i\phi}$	$i=0,1,2,3$		
5		2010	$A_{UL}^{+,\sin i\phi}$	$i=1,2,3$	x_{Bj}	18 / 24
			$A_{LL}^{+,\cos i\phi}$	$i=0,1,2$		
6		2011	$A_{LT,\mathrm{DVCS}}^{\cos(\phi-\phi_S)\cos i\phi}$	$i=0,1$	x_{Bj}	24 / 32
			$A_{LT,\mathrm{DVCS}}^{\sin(\phi-\phi_S)\sin i\phi}$	$i=1$		
			$A_{LT,\mathrm{I}}^{\cos(\phi-\phi_S)\cos i\phi}$	$i=0,1,2$		
			$A_{LT,\mathrm{I}}^{\sin(\phi-\phi_S)\sin i\phi}$	$i=1,2$		
7		2012	$A_{LU,\mathrm{I}}^{\sin i\phi}$	$i=1,2$	x_{Bj}	35 / 42
			$A_{LU,\mathrm{DVCS}}^{\sin i\phi}$	$i=1$		
			$A_{C}^{\cos i\phi}$	$i=0,1,2,3$		
8	CLAS	2001	$A_{LU}^{-,\sin i\phi}$	$i=1,2$	—	0 / 2
9		2006	$A_{UL}^{-,\sin i\phi}$	$i=1,2$	—	2 / 2
10		2008	A_{LU}^{-}		ϕ	283 / 737
11		2009	A_{LU}^{-}		ϕ	22 / 33
12		2015	A_{LU}^{-}, A_{UL}^{-}, A_{LL}^{-}		ϕ	311 / 497
13		2015	$d^4\sigma_{UU}^{-}$		ϕ	1333 / 1933
14	Hall A	2015	$\Delta d^4\sigma_{LU}^{-}$		ϕ	228 / 228
15		2017	$\Delta d^4\sigma_{LU}^{-}$		ϕ	276 / 358
16	COMPASS	2018	$d^3\sigma_{UU}^{\pm}$		t	2 / 4
17	ZEUS	2009	$d^3\sigma_{UU}^{+}$		t	4 / 4
18	H1	2005	$d^3\sigma_{UU}^{+}$		t	7 / 8
19		2009	$d^3\sigma_{UU}^{\pm}$		t	12 / 12
					SUM:	2624 / 3996

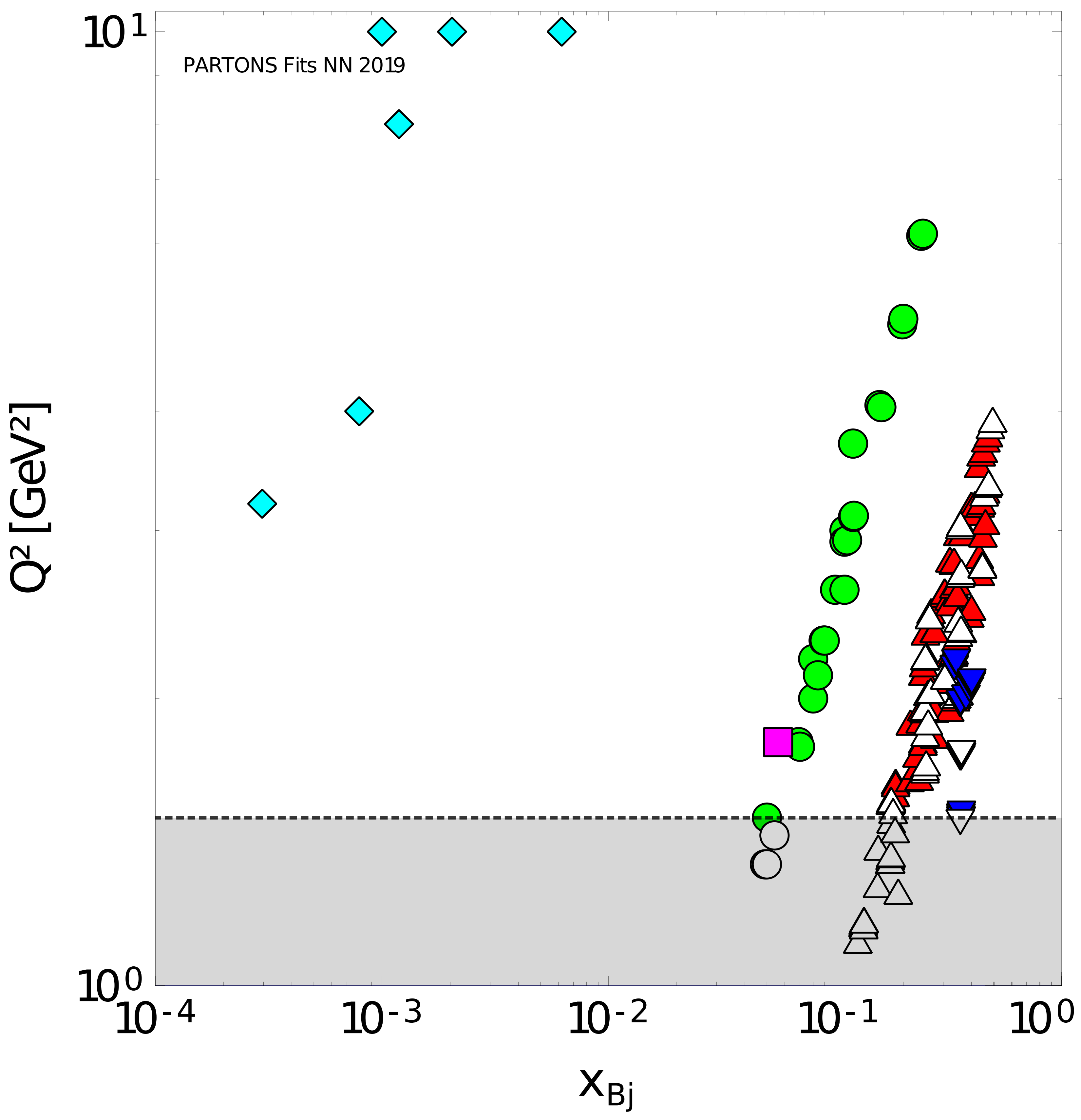
H. Moutarde, PS, J. Wagner,
Eur. Phys. J. C 79 (2019) 7, 614

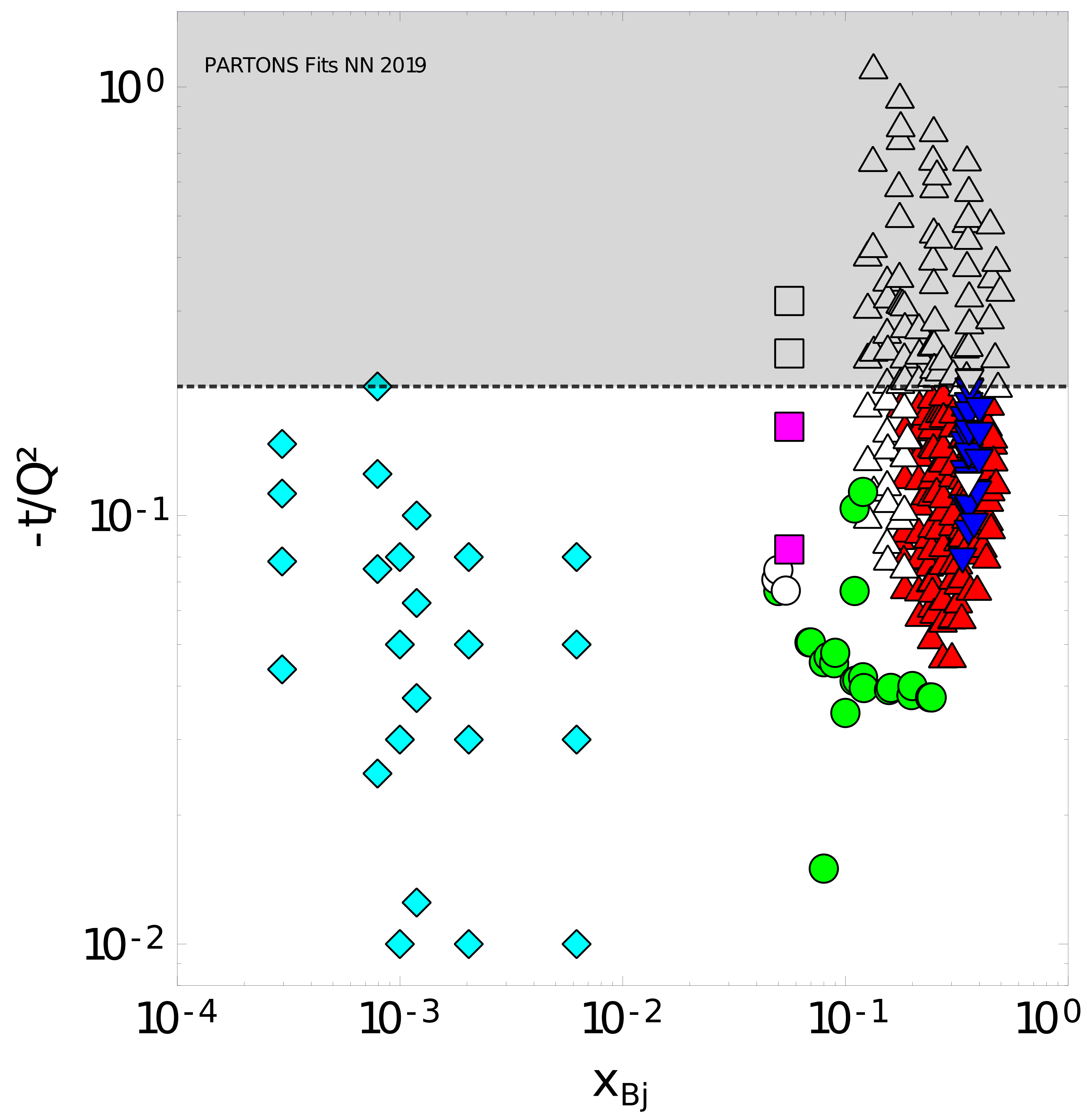
Kinematic cuts
used in our recent analyses:

$$Q^2 > 1.5\ \mathrm{GeV}^2$$

$$-t/Q^2 < 0.2$$

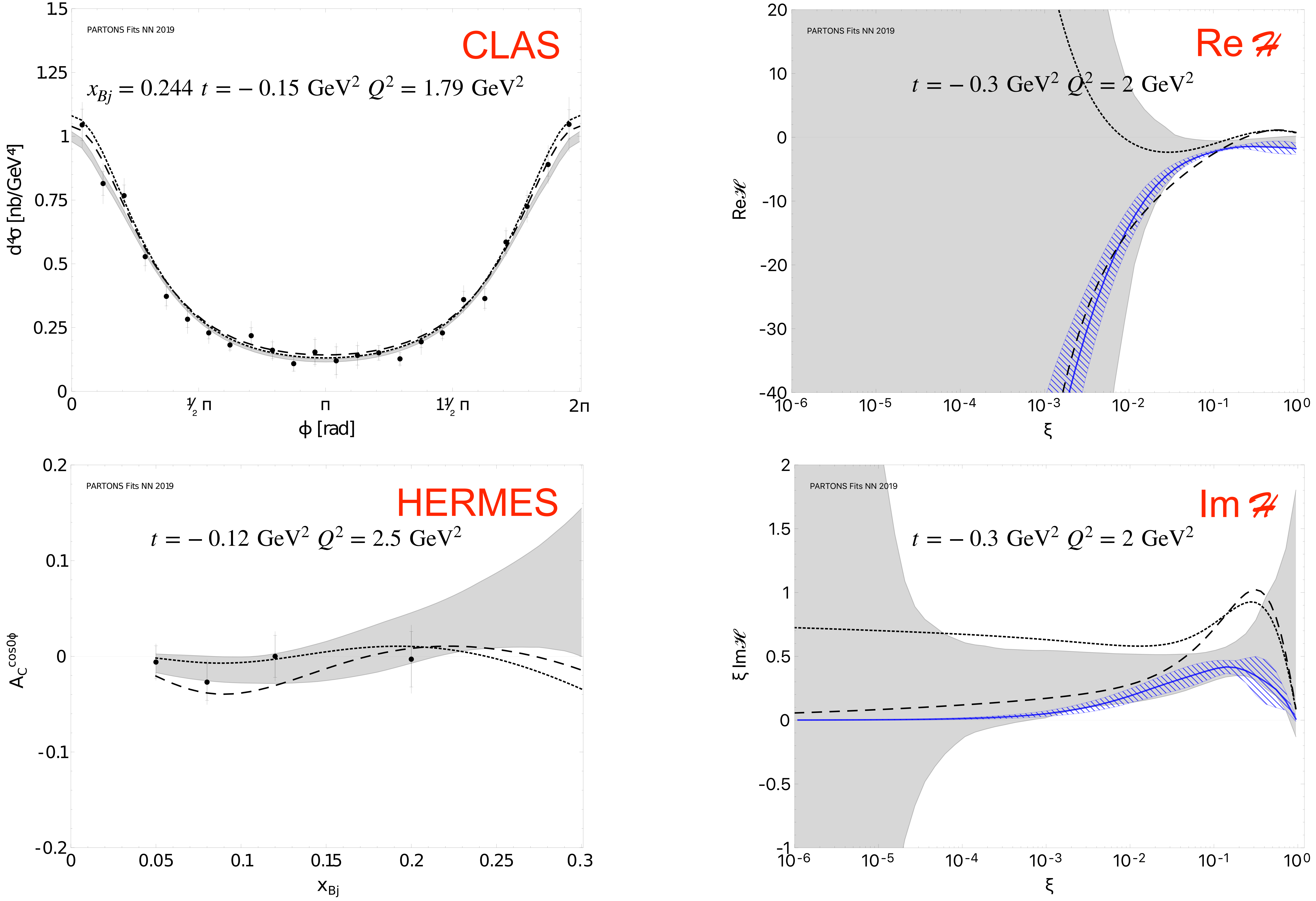
- ▼ HALL A
- ▲ CLAS
- ● HERMES
- ■ COMPASS
- ◆ H1 and ZEUS

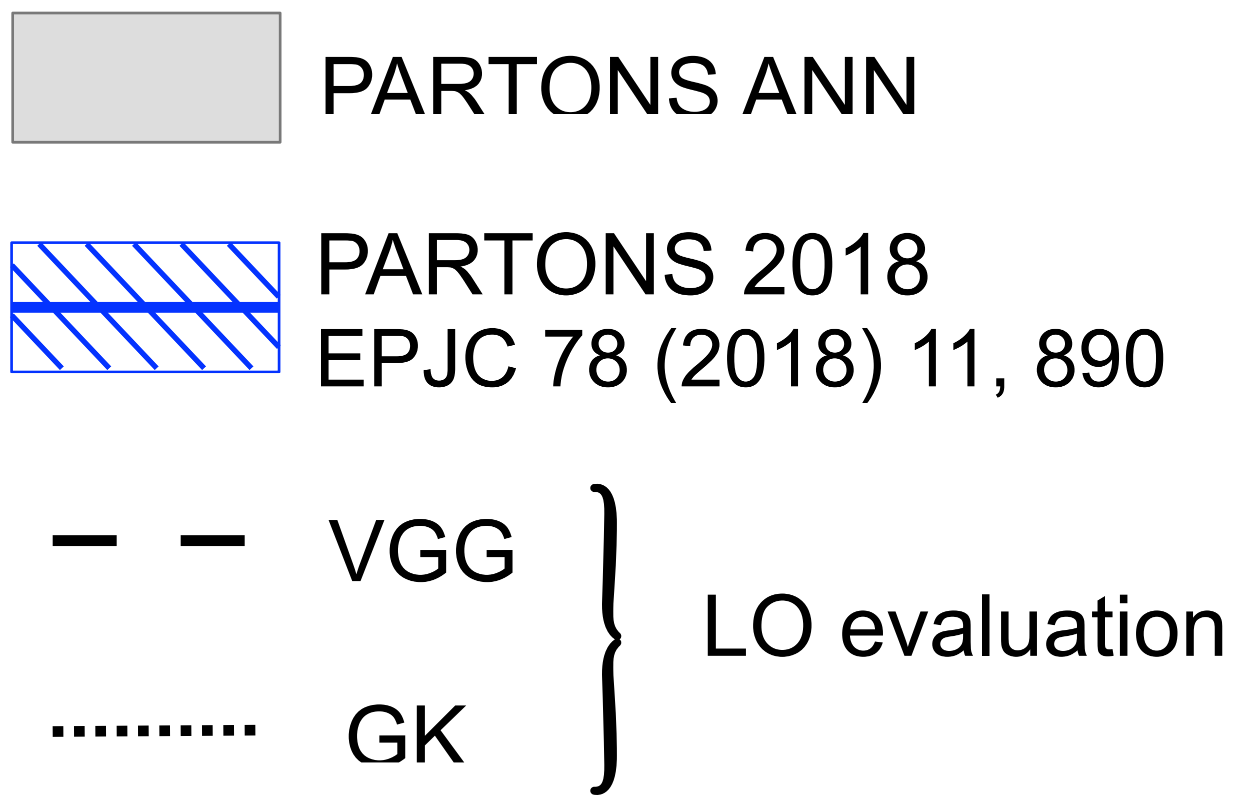




Neural Networks

H. Moutarde, PS, J. Wagner,
Eur. Phys. J. C 79 (2019) 7, 614





$$\xi \approx x_{Bj}/(2 - x_{Bj})$$

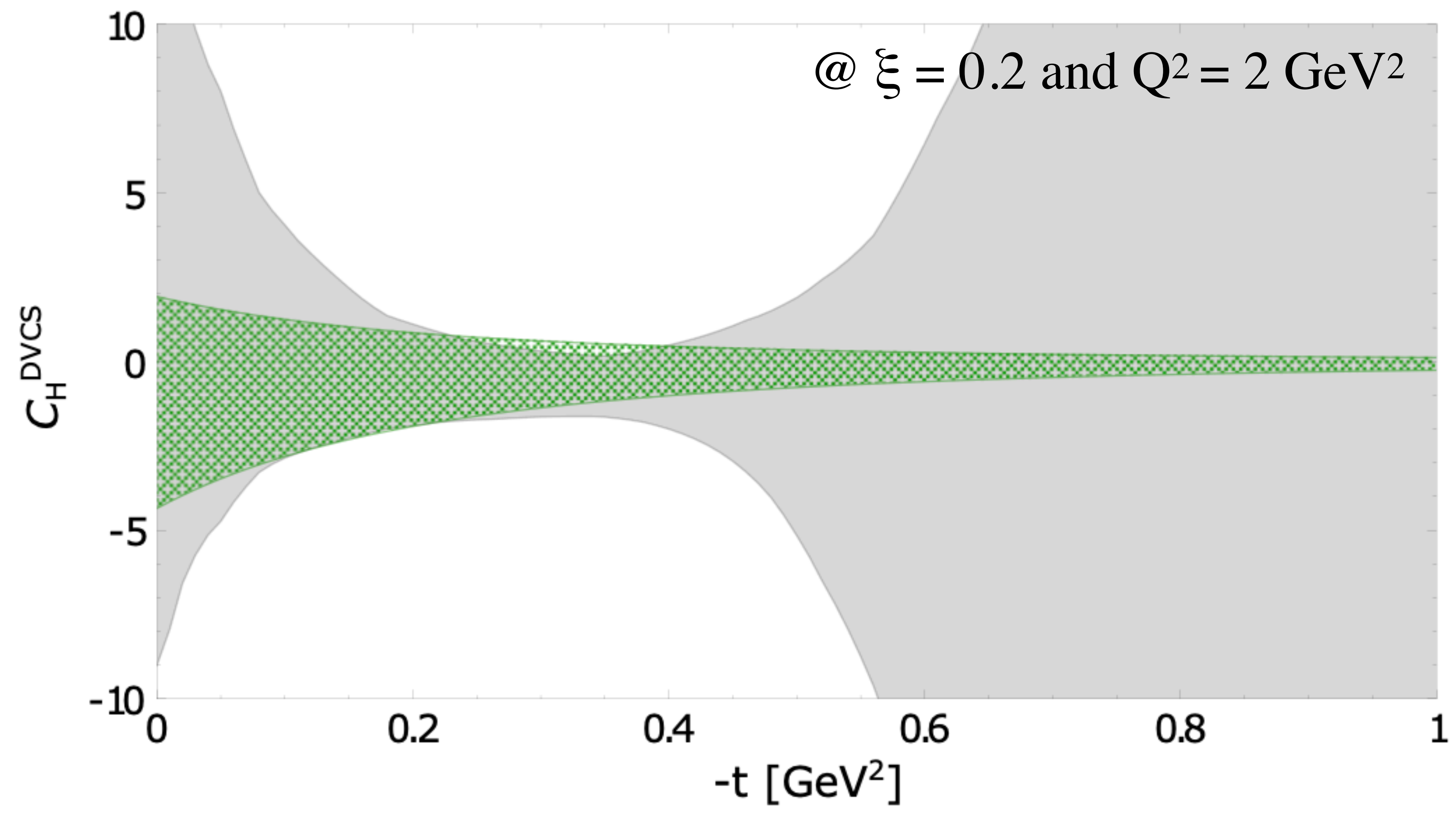
Subtraction constant

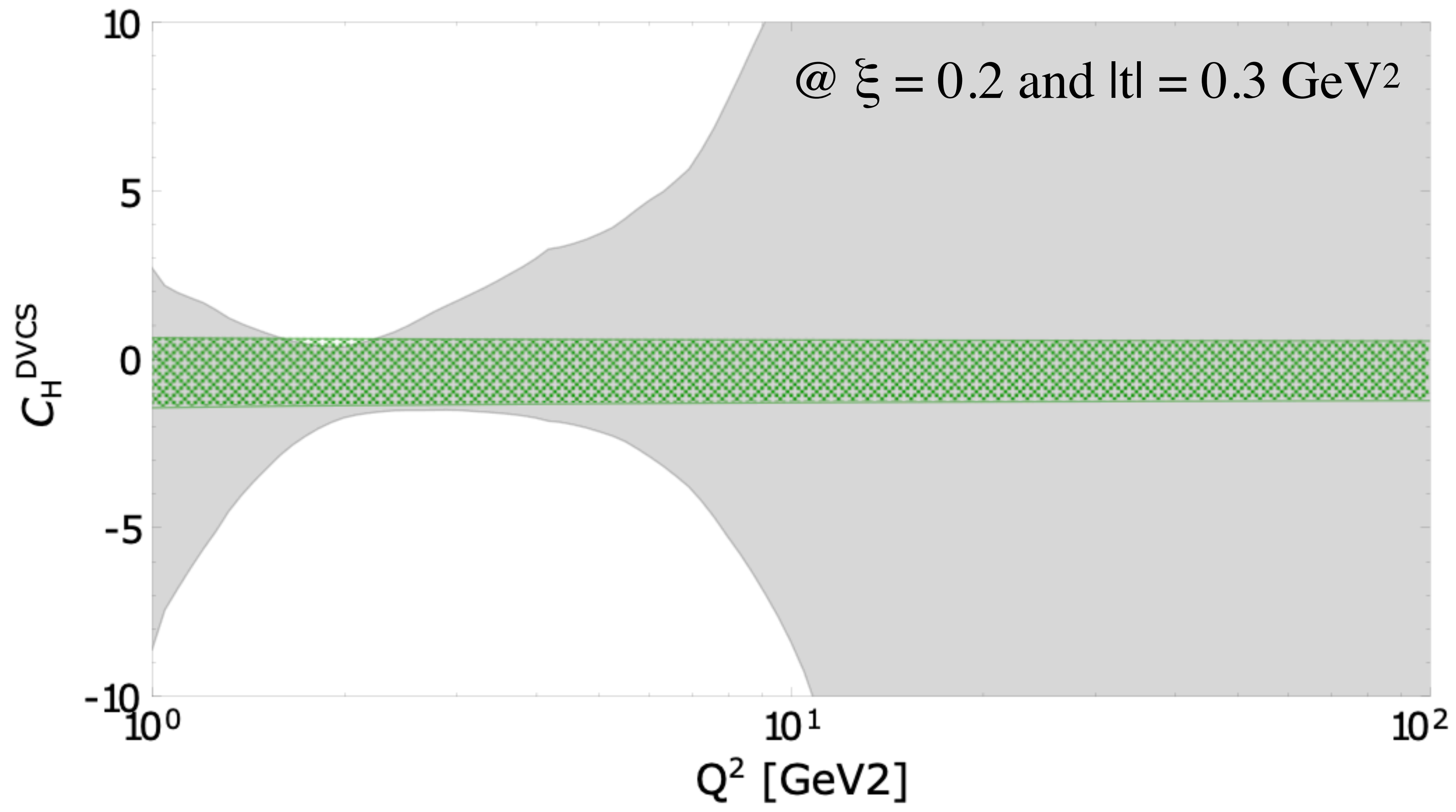
H. Dutrieux et al.,
Eur. Phys. J. C 81 (2021), 300

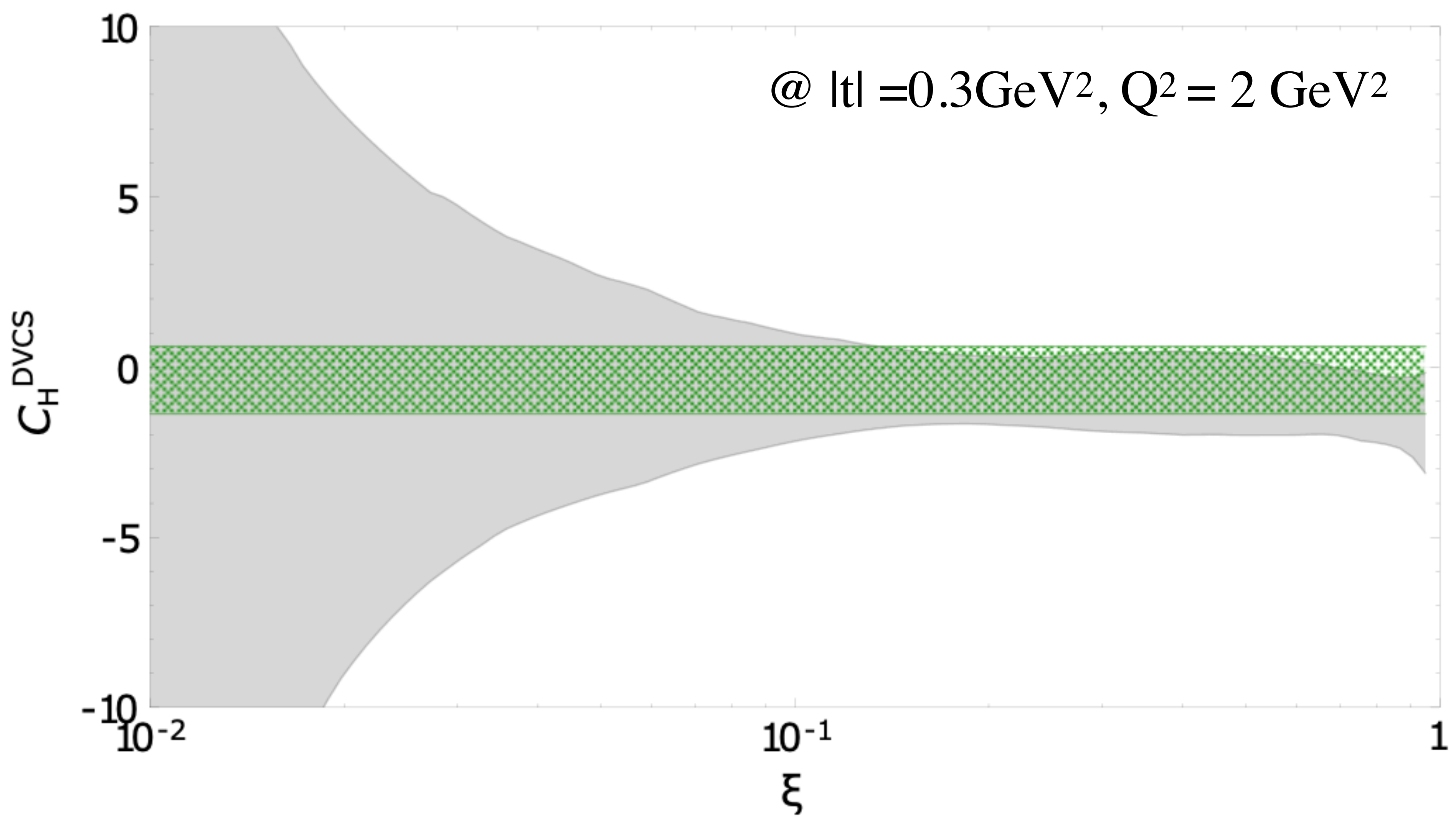
- Subtraction constant:

  ANN analysis

  Model dependent extraction







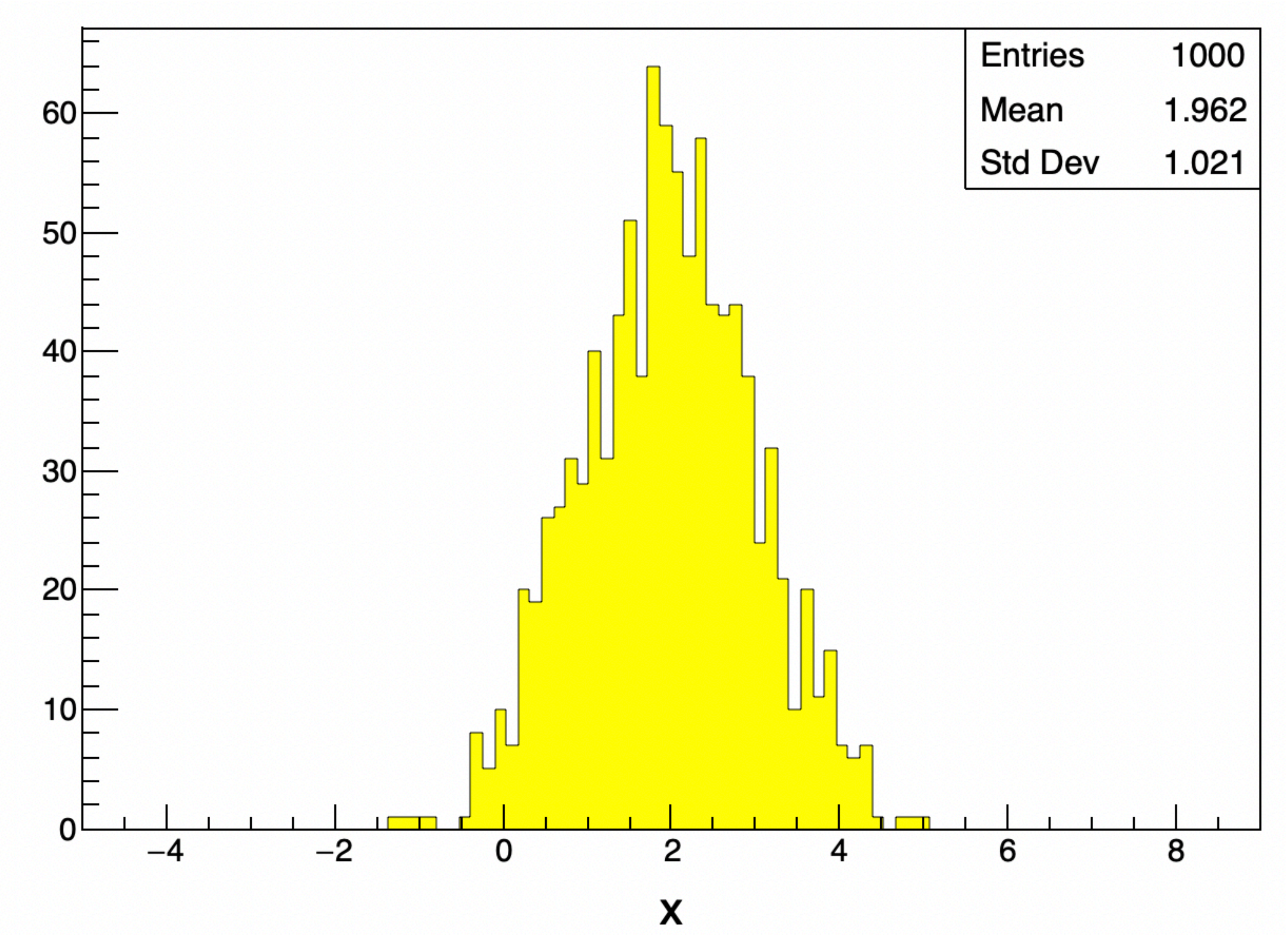
Simple case:

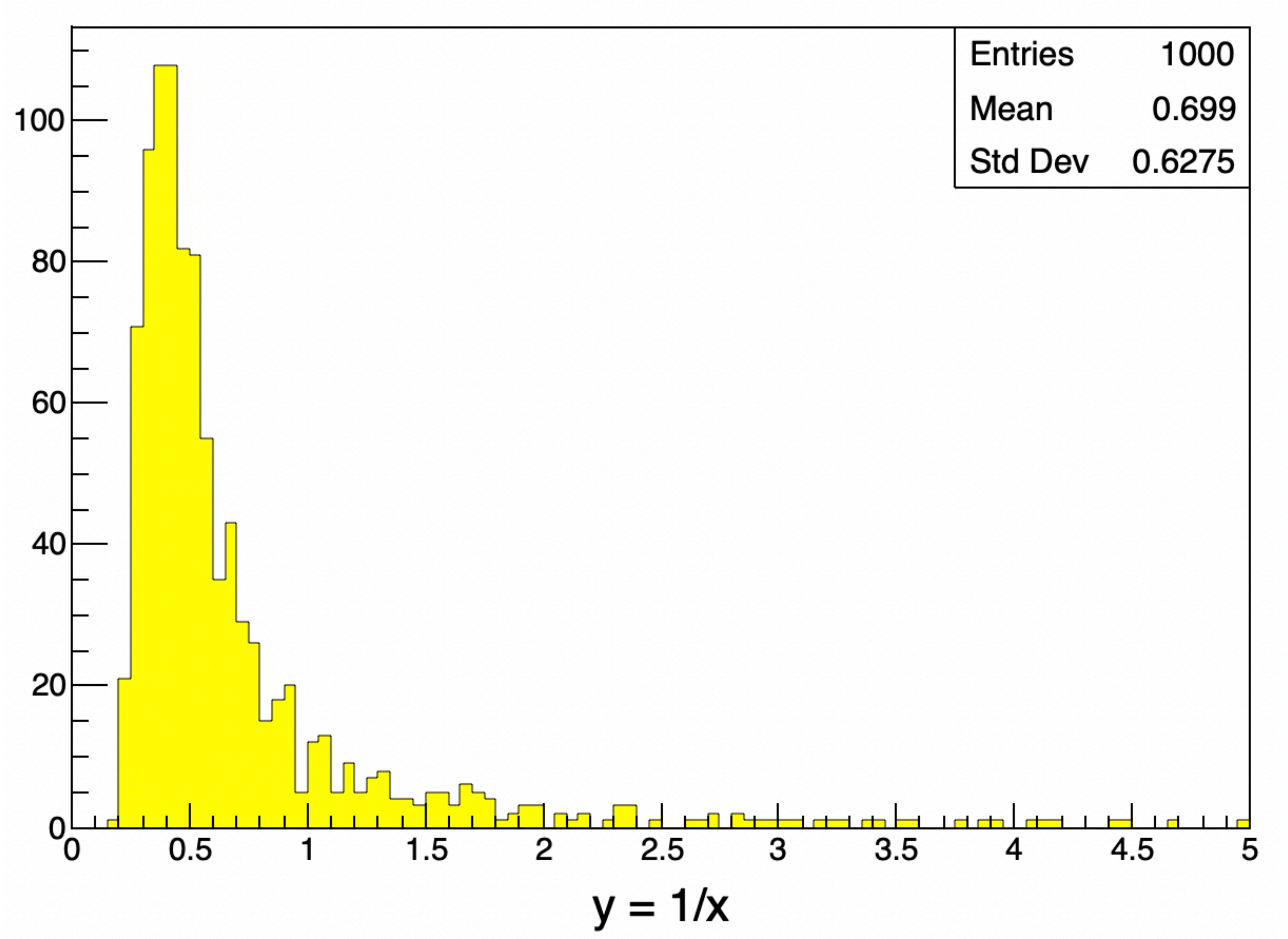
we know $\langle x \rangle = 2 \pm 1$
what's $\langle y \rangle$ if $y = f(x) = 1/x$?

Result:

$\langle y \rangle_{\text{replica}} = 0.628$

$\langle y \rangle_{\text{Taylor1st}} = f(\langle x \rangle) = 0.5$
$\langle y \rangle_{\text{Taylor2nd}} = f(\langle x \rangle) + 0.5\, \sigma_x^2\, f''(\langle x \rangle) = 0.625$





Neural Networks

H. Dutrieux et al.,
arXiv:2105.09245 [hep-ph]

Question:
what's the impact of foreseen measurements at JLab with e-/e+ beams?

To answer this question we could either:
repeat fits with foreseen data **or**
re-weight existing parameterisations of CFFs

H. Dutrieux et al., arXiv:2105.09245 [hep-ph]

Experimental conditions:

$E = 10.6$ GeV

$\mathscr{L} = 0.6 \times 10^{35}\,\mathrm{cm}^{-2}\mathrm{s}^{-1}$

80 days of data taking

Observable:

Expected cross-sections evaluated with result of parametric fit (Eur.Phys.J.C 78 (2018) 11, 890)

$$A_{\mathrm{C}}(x_{\mathrm{B}}, t, Q^2, \phi) = \frac{\mathrm{d}^4\sigma^+ - \mathrm{d}^4\sigma^-}{\mathrm{d}^4\sigma^+ + \mathrm{d}^4\sigma^-}$$

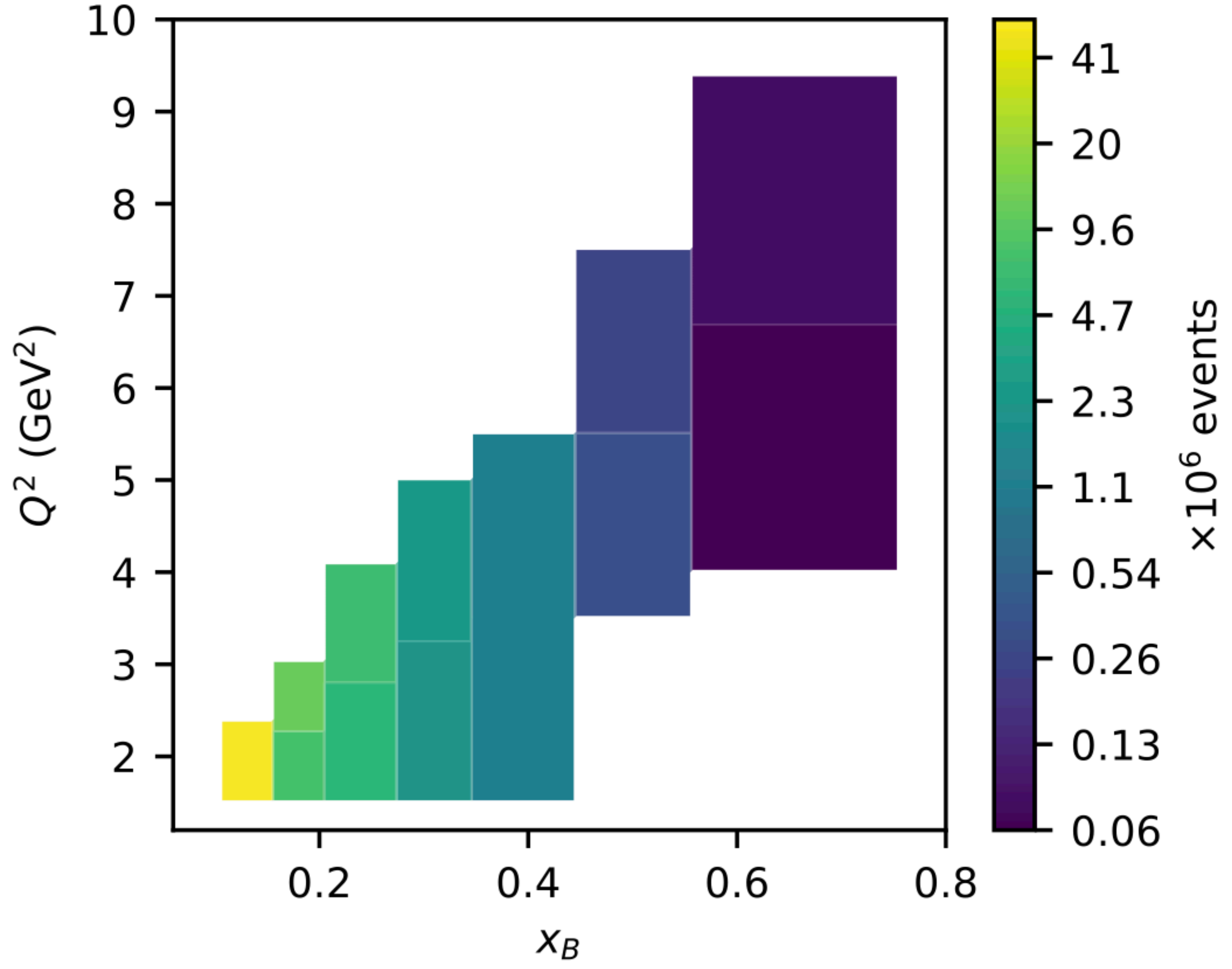
$$A_C^{\cos\phi} \propto \mathrm{Re}\left[F_1\mathcal{H} + \xi\,(F_1 + F_2)\,\widetilde{\mathcal{H}} - \frac{t}{4M^2}F_2\mathcal{E}\right]$$

$$\Delta A_{C,i} = \sqrt{\frac{1 - \langle A_{C,i}\rangle^2}{N_i}} \oplus 0.03\,\langle A_{C,i}\rangle$$

3% systematic unc. added in quadrature

Binning:

13 bins in (xB, Q2), divided into 6 bins in t and 24 bins in phi



H. Dutrieux et al.,
arXiv:2105.09245 [hep-ph]

Bases on Bayes theorem:

$$\omega_k = \frac{1}{Z}\chi_k^{n-1}\exp(-\chi_k^2/2)$$

$$\chi_k^2 = (y - y_k)\Sigma^{-1}(y - y_k)^T$$

weight

normalisation factor

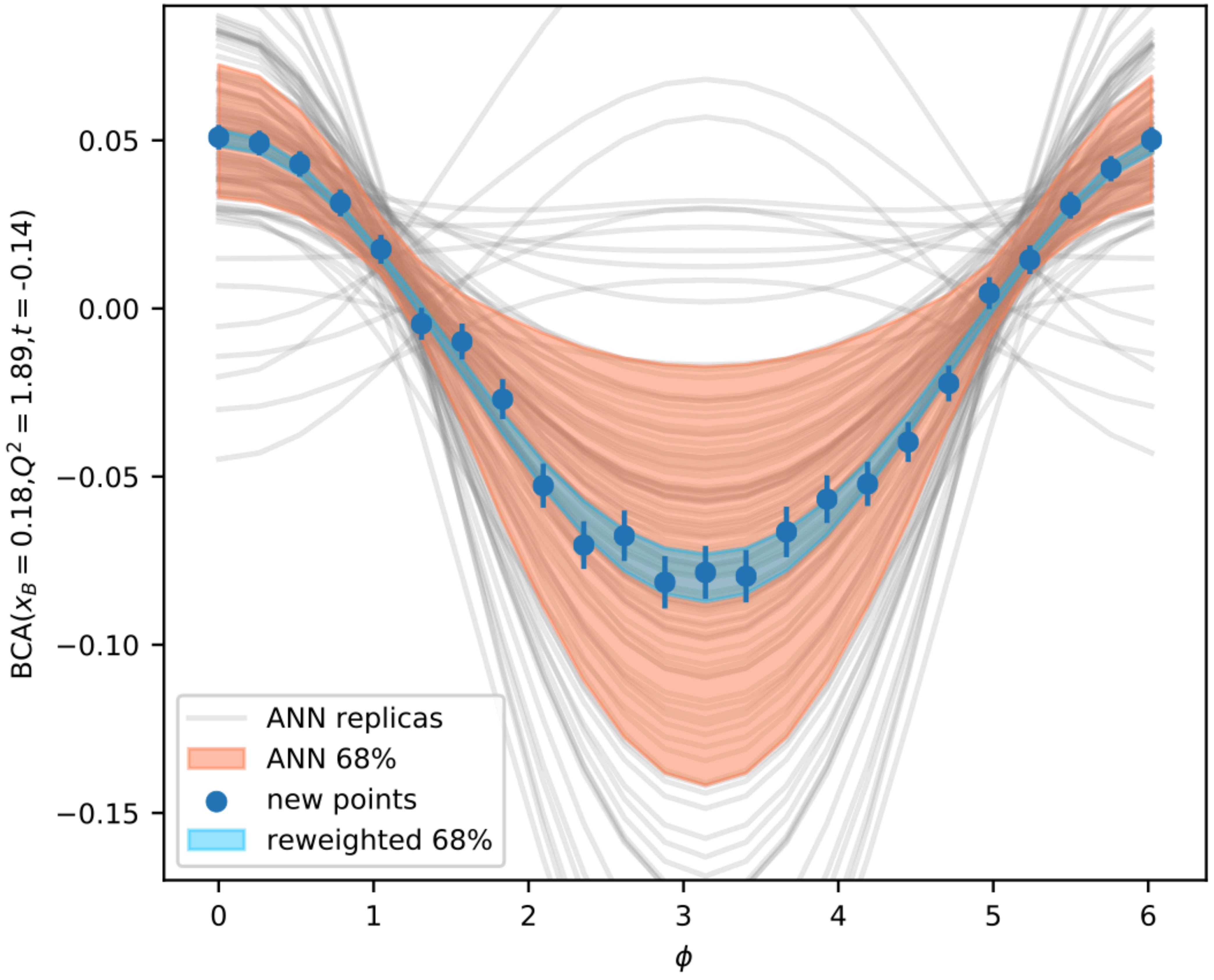
new dataset

covariance matrix

k-th replica

H. Dutrieux et al., arXiv:2105.09245 [hep-ph]

“Local” reweighing

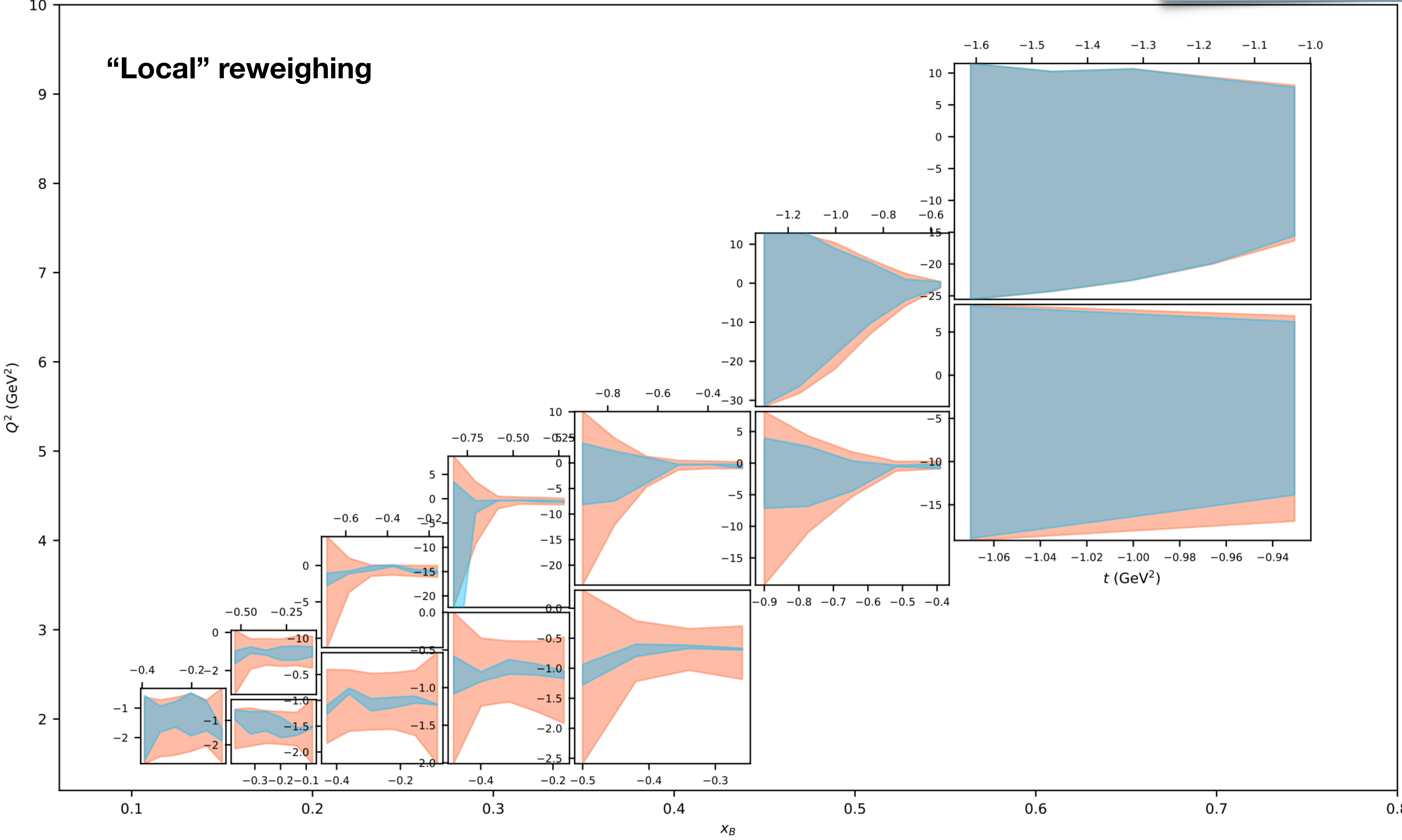


$$N_{\text{eff}} = \exp\left(- \sum_{k=1}^{N_{\text{rep}}} \omega_k \log(\omega_k) \right)$$

here $N_{\text{eff}} = 8$

Neural Networks

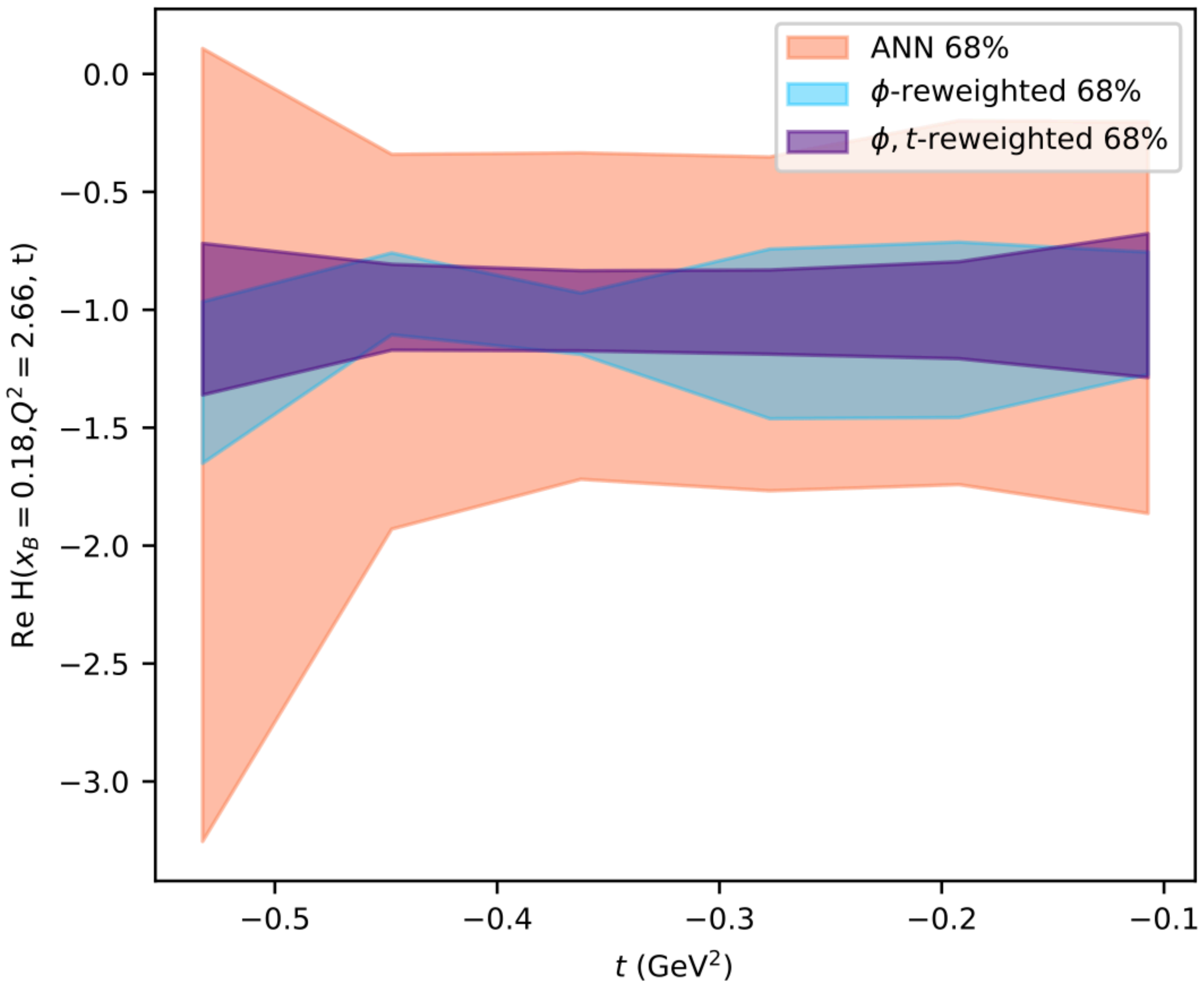
H. Dutrieux et al., arXiv:2105.09245 [hep-ph]



Neural Networks

towards “global” reweighing

H. Dutrieux et al., arXiv:2105.09245 [hep-ph]



Conclusions

- Positron programme at JLab will have a major effect on our understanding of ReH
- This will influence the whole GPD phenomenology

- Re-weighting is a convenient tool to check the foreseen impact of new experiments, check also EICC White Paper (arXiv: 2102.09222 [nucl-ex])

- However (limiting factor), the number of replicas must be large, in particular if:

  new data are precise
  new data probe unknown kinematic region

  + the curse of multidimensionality,