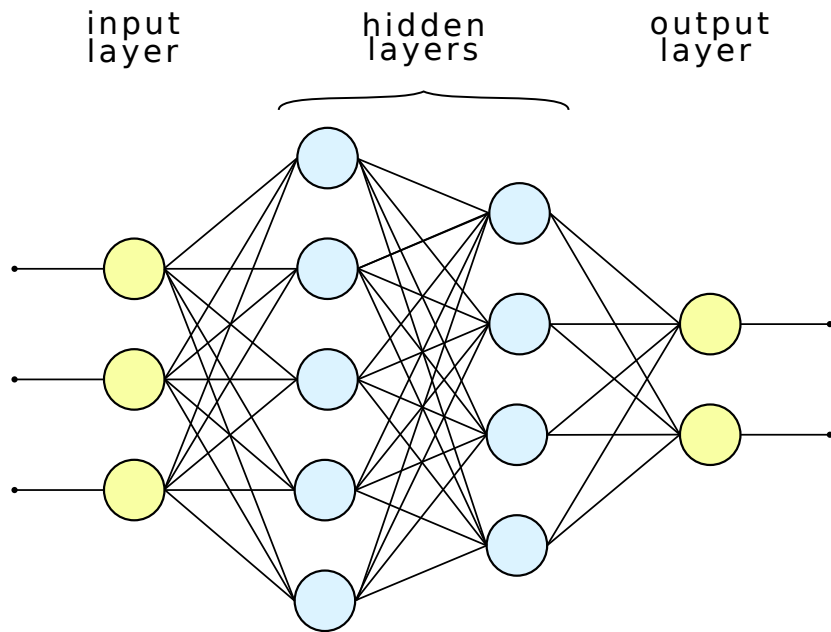


Proton mechanical properties from global fits to DVCS data

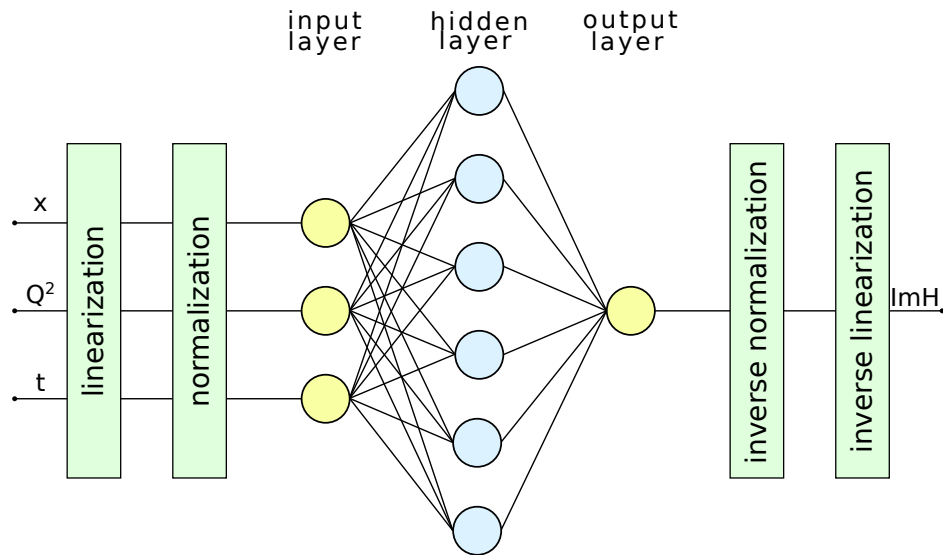
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Artificial neural networks (ANNs)

- 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
- Can be used for approximation of functions

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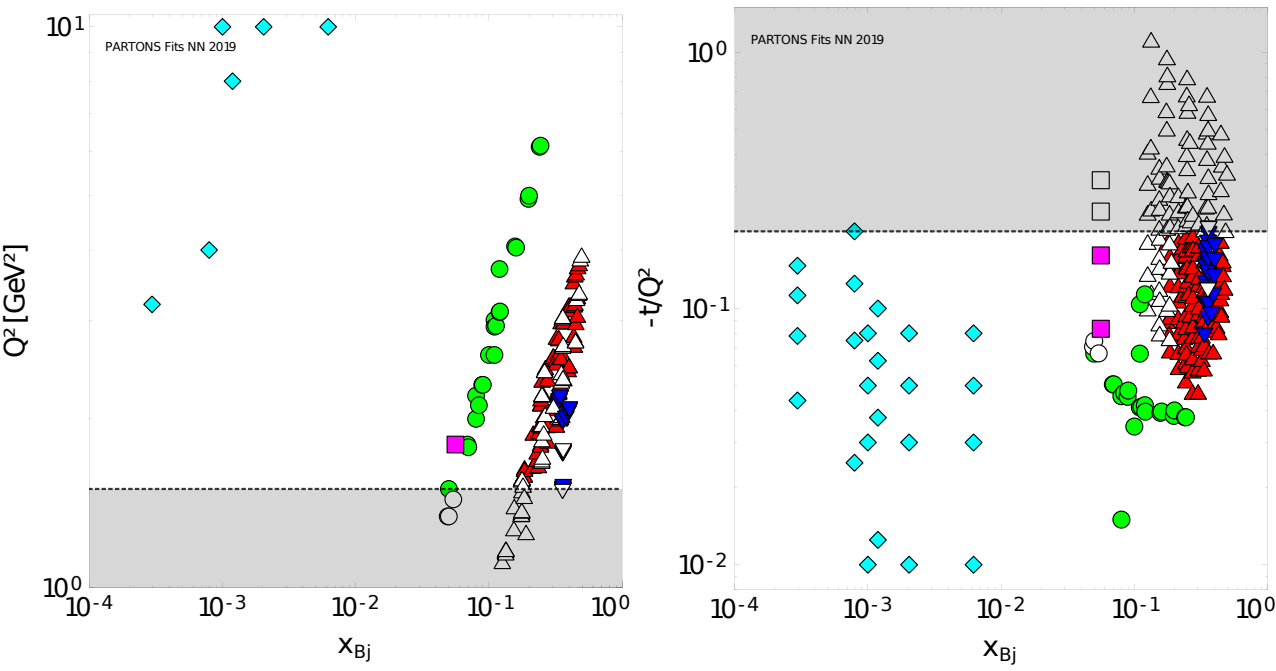


Features of our analysis:

- 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 of early stopping criterion
- Replica method to propagate experimental uncertainties

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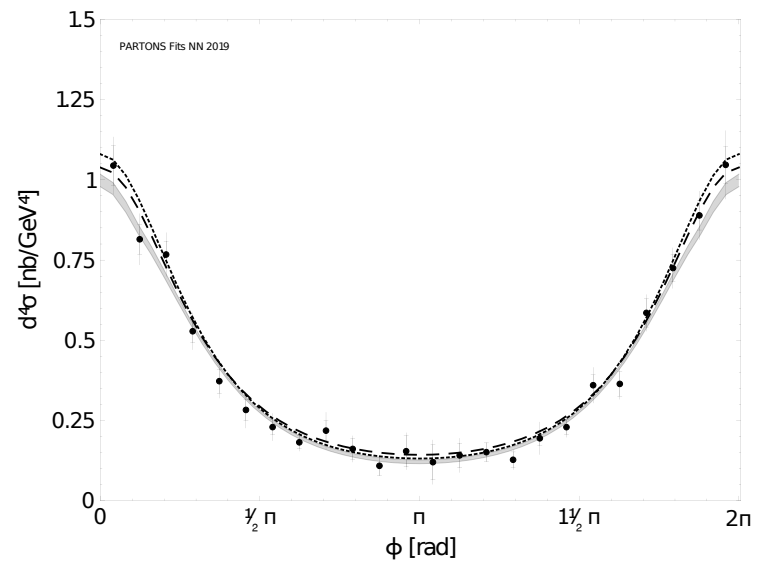
Coverage of phase-space:



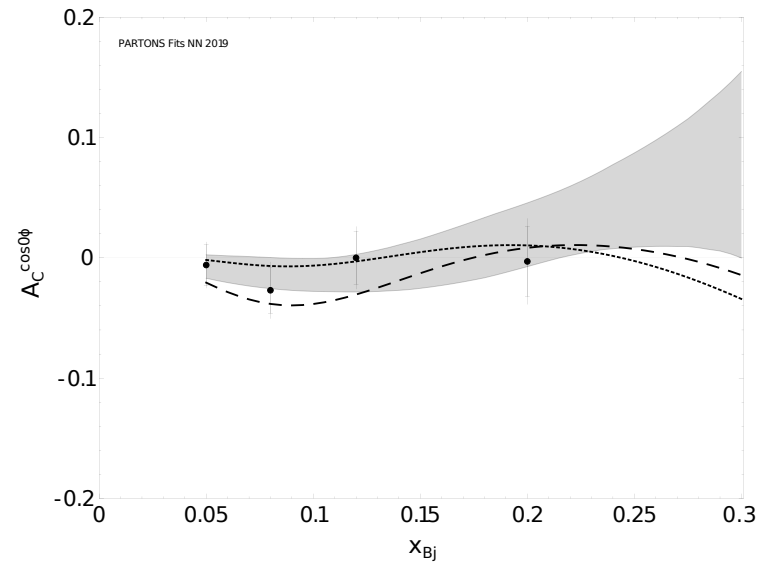
- ▼ HALL A
- HERMES
- ▲ CLAS
- ◆ H1 and ZEUS
- COMPASS

$-t/Q^2 < 0.2$ $Q^2 > 1.5 \text{ GeV}^2$

Fits: — — VGG
PARTONS NN 2019 GK



← CLAS



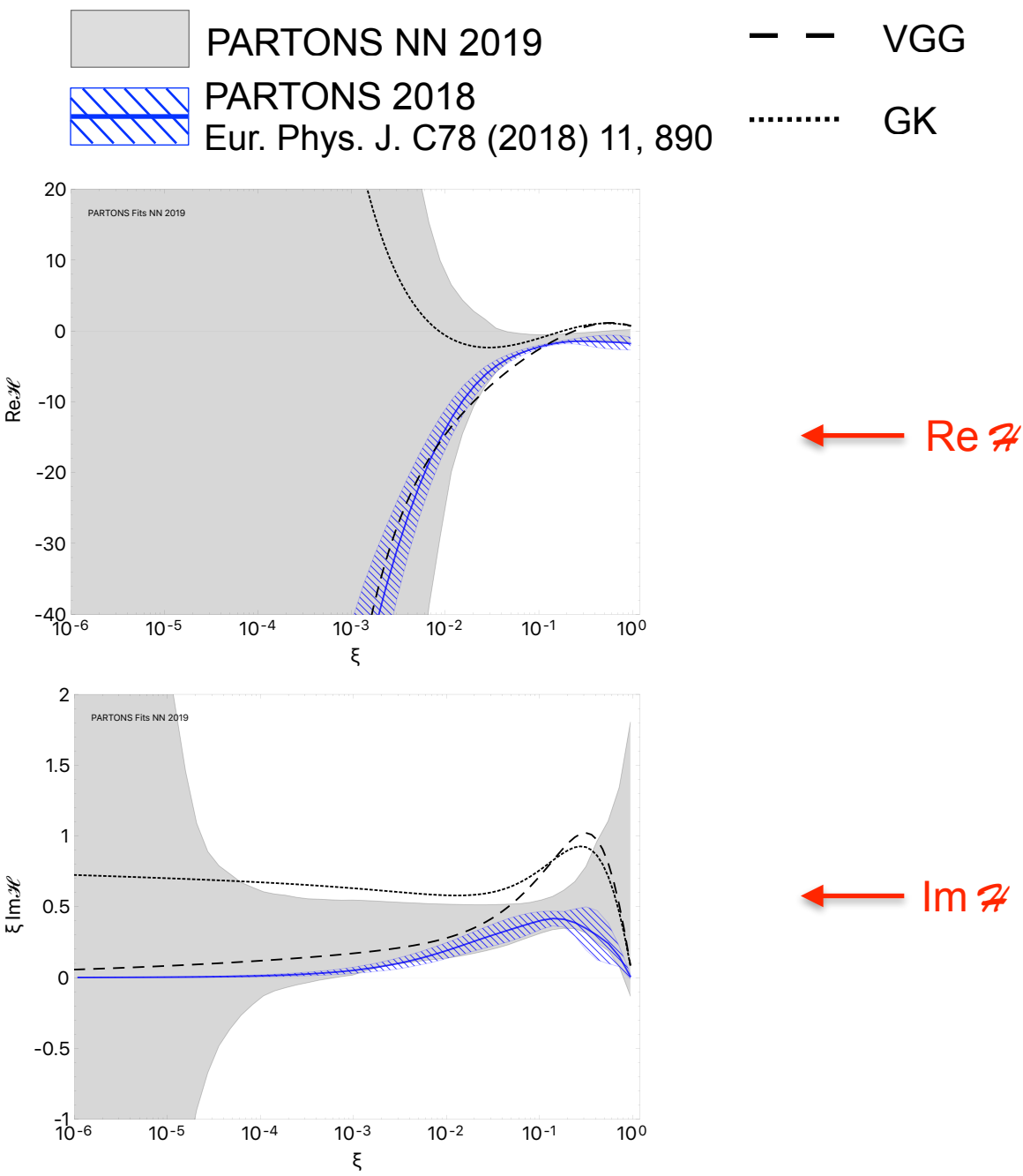
← HERMES

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Quality of fit:

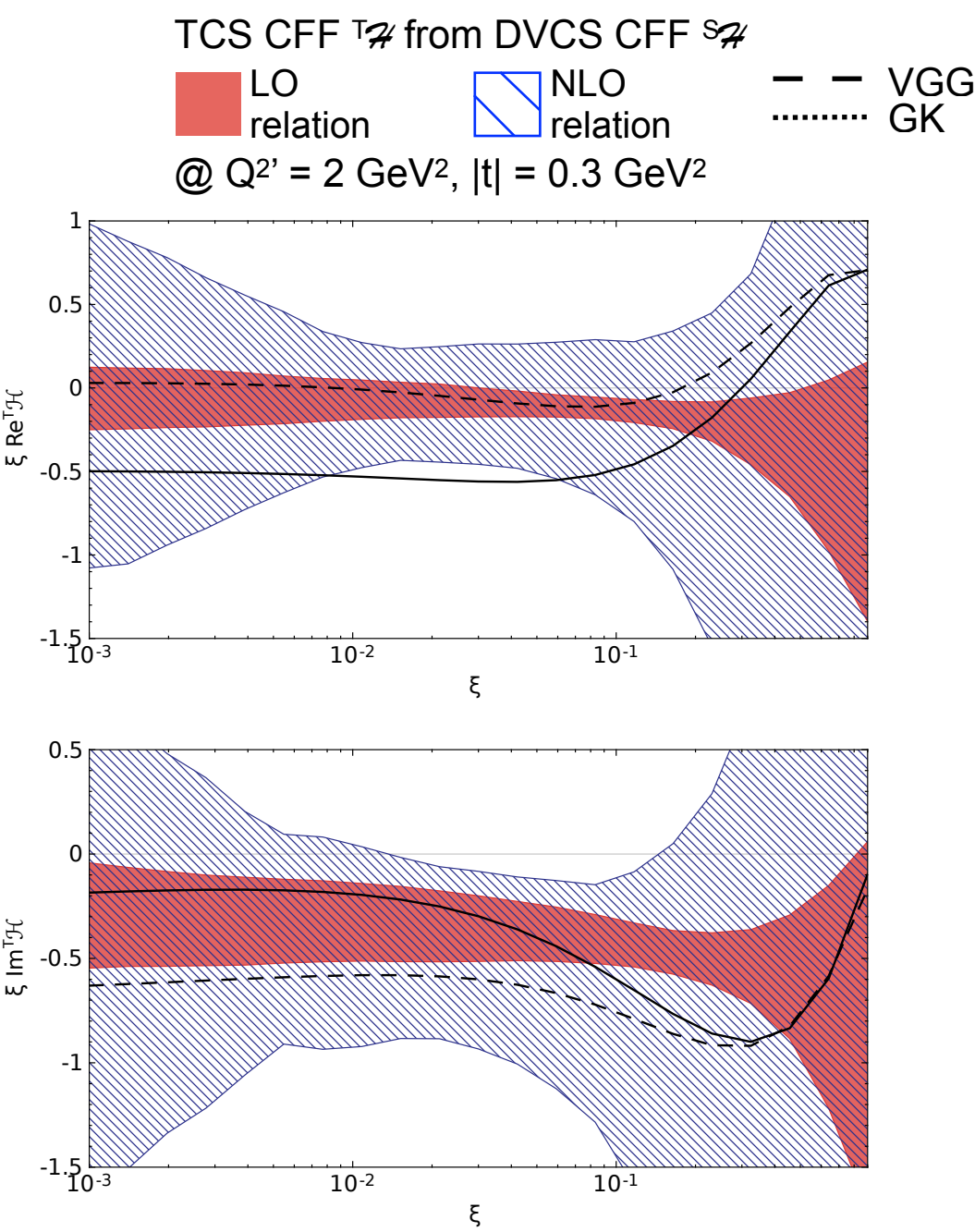
$\chi^2/nPoints = 2243.5/2624 \approx 0.85$

No.	Collab.	Year	χ^2	n	χ^2/n
1	HERMES	2001	10.7	10	1.07
2		2006	5.5	4	1.38
3		2008	18.5	18	1.03
4		2009	34.7	35	0.99
5		2010	40.7	18	2.26
6		2011	16.7	24	0.70
7		2012	22.4	35	0.64
8	CLAS	2001	—	0	—
9		2006	1.0	2	0.52
10		2008	376.4	283	1.33
11		2009	28.3	22	1.29
12		2015	306.6	311	0.99
13		2015	884.7	1333	0.66
14	Hall A	2015	231.8	228	1.02
15		2017	211.4	276	0.77
16	COMPASS	2018	3.0	2	1.50
17	ZEUS	2009	5.49	4	1.38
18	H1	2005	22.2	7	3.17
19		2009	23.4	12	1.95



O. Grocholski, H. Moutarde, B. Pire, P. S., J. Wagner
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see Jakub's talk from Temple meeting

	TCS	DVCS
LO:	$T_{\mathcal{H}} = S_{\mathcal{H}}^*$	
NLO:	$T_{\mathcal{H}} = S_{\mathcal{H}}^* - i\pi Q^2 \frac{\partial}{\partial Q^2} S_{\mathcal{H}}^*$	

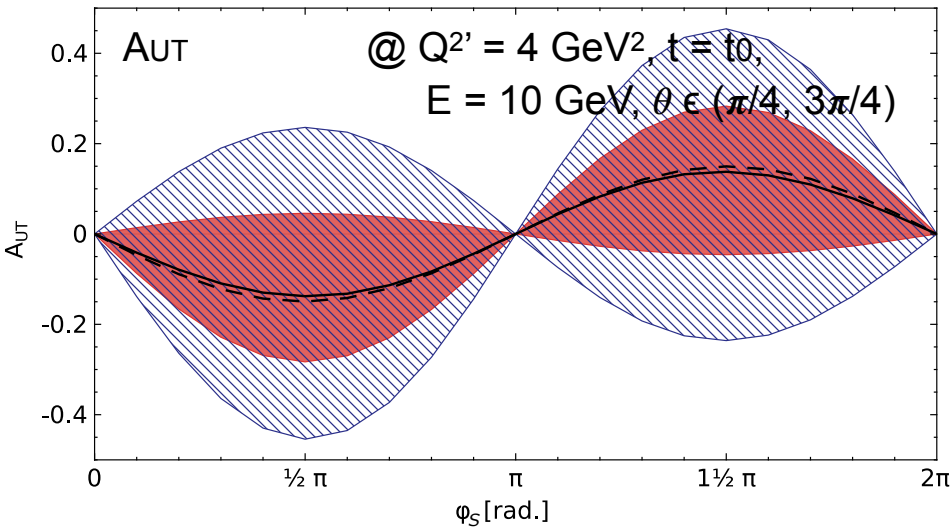
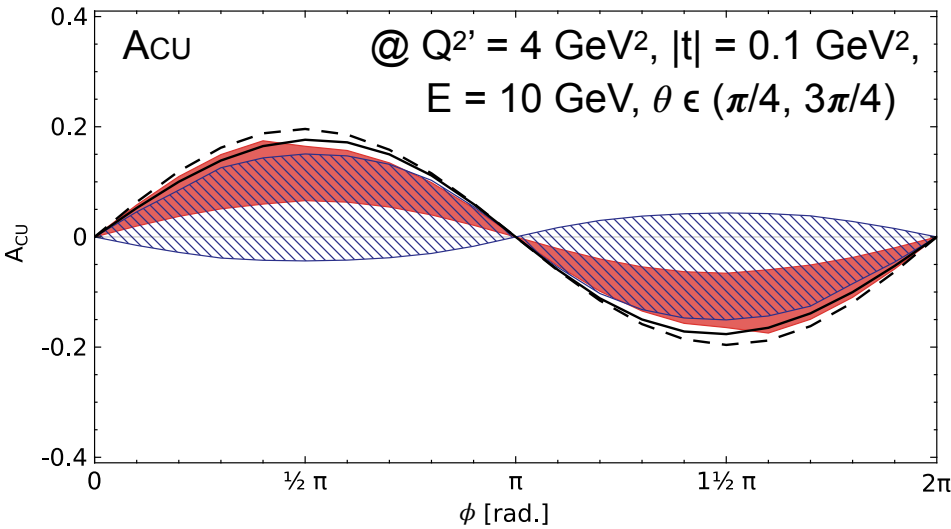


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	TCS	DVCS
LO:	$T\mathcal{H} = S\mathcal{H}^*$	
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TCS observables from DVCS CFFs

LO relation	NLO relation	VGG
		GK



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dispersion relation:

$$\text{SC}_H^{\text{DVCS}}(t, Q^2) = \text{Re} \mathcal{H}(\xi, t, Q^2) - \frac{1}{\pi} \text{p.v.} \int_0^1 d\xi' \text{Im} \mathcal{H}(\xi', t, Q^2) \left(\frac{1}{\xi - \xi'} - \frac{1}{\xi + \xi'} \right)$$

thanks to relation between SC and D-term:

$$\text{SC}_H^{\text{DVCS}}(t, Q^2) \stackrel{\text{LO}}{=} 4 \sum_q e_q^2 \sum_{\text{odd } n} d_n^q(t, \mu_F^2 \equiv Q^2)$$

relation to EMT form factor:

$$d_1^q(t, \mu_F^2) = 5C^q(t, \mu_F^2)$$

Modelling of subtraction constant:

- truncation to only d1

$$\text{SC}_H^{\text{DVCS}}(t, Q^2) = 4 \sum_q e_q^2 d_1^q(t, \mu_F^2 \equiv Q^2)$$

- symmetry of light quark contributions

$$d_1^u(t, \mu_F^2) = d_1^d(t, \mu_F^2) = d_1^s(t, \mu_F^2) \equiv d_1^{uds}(t, \mu_F^2)$$

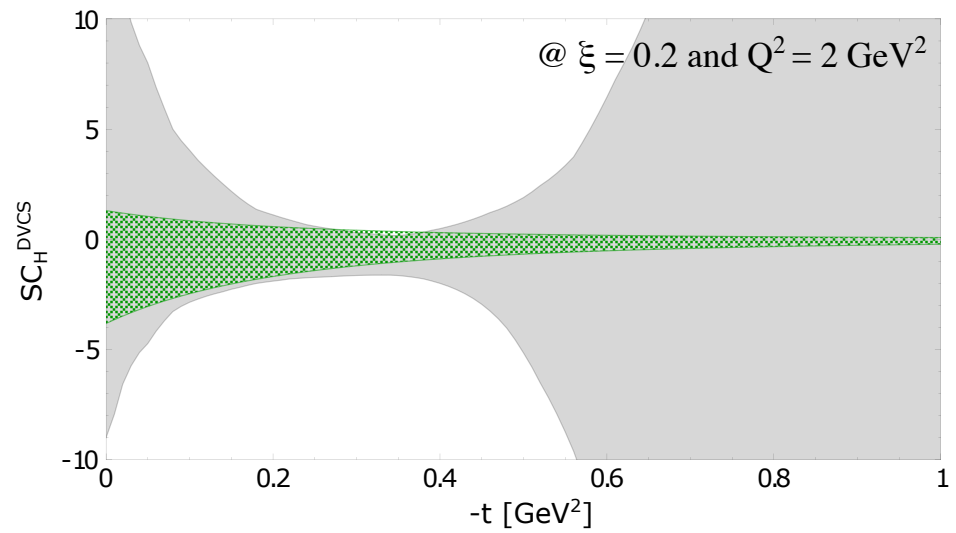
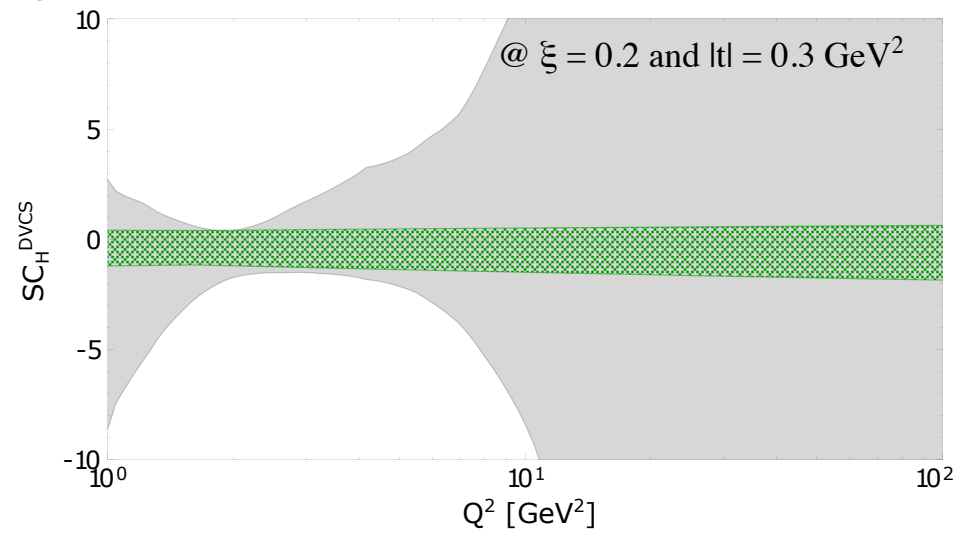
- radiative generation of gluon and charm contributions

$$d_1^G(t, \mu_{F,0}^2) = 0 \quad d_1^c(t, m_c^2) = 0 \quad \mu_{F,0}^2 = 0.1 \text{ GeV}^2$$

- tripole Ansatz for t-dependence

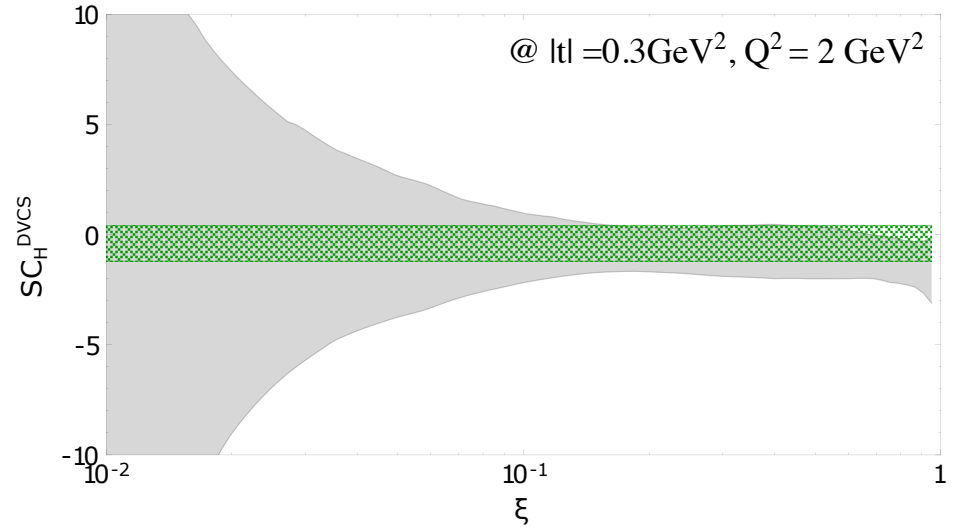
$$d_1^{uds}(t, \mu_F^2) = d_1^{uds}(\mu_F^2) \left(1 - \frac{t}{\Lambda^2} \right)^{-\alpha} \quad \begin{aligned} \alpha &= 3 \\ \Lambda &= 0.8 \text{ GeV} \end{aligned}$$

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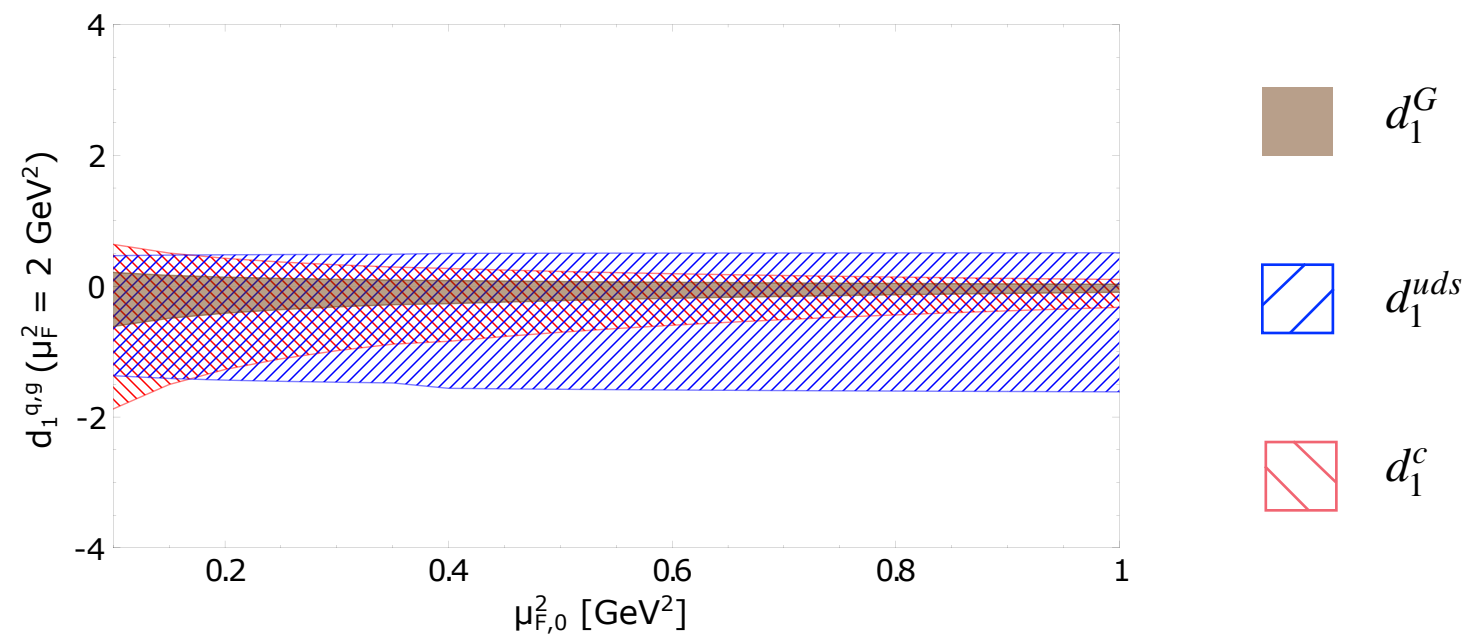


Parameter	Value
$d_1^{uds}(\mu_F^2)$	-0.45 ± 0.92
$d_1^c(\mu_F^2)$	-0.0020 ± 0.0041
$d_1^G(\mu_F^2)$	-0.6 ± 1.3

@ $\mu_F^2 = 2$ GeV²



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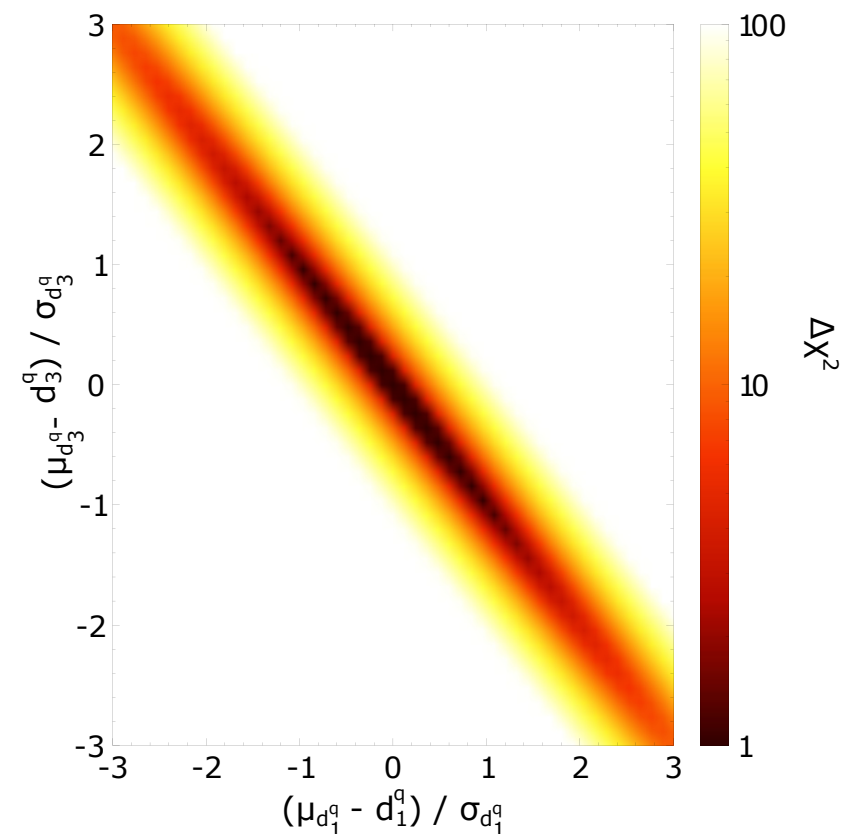
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Results when a pair of parameters is extracted at the same time

No.	Fitted parameters	Value	Allowed range	
			min	max
1	$d_1^{uds}(\mu_F^2)$	-0.8 ± 1.3		
	$d_1^G(\mu_F^2)$	2 ± 11		
2	$d_1^{uds}(\mu_F^2)$	0.8 ± 6.3		
	$d_3^{uds}(\mu_F^2)$	-1.6 ± 7.0		
3	$d_1^{uds}(\mu_F^2)$	-0.7 ± 1.4		
	Λ/GeV	1.4 ± 0.71	0	2
4	$d_1^{uds}(\mu_F^2)$	-0.5 ± 1.1		
	α	2.3 ± 3.2	0	10

@ $\mu_F^2 = 2 \text{ GeV}^2$

Correlation between d_1^{uds} and d_3^{uds}



Neural network parameterization of CFFs

→ powerful tool to study GPDs

→ model independent

→ many applications:

→ analysis of TCS:

data driven prediction, multichannel analysis, GPD universality test

→ extraction of subtraction constant:

interpretation too model dependent, large uncertainties → need for more precise data and extended kinematic range covered, what we can learn at EIC?

→ fast generation of DVCS cross sections

→ ...