# Nucleon GPDs from DVCS

#### Krešimir Kumerički

Physics Department University of Zagreb, Croatia



ECT\* Workshop Probing Transverse Nucleon Structure at High Momentum Transfer Trento, Italy, 18–22 April 2016

◆□▶ ◆□▶ ◆三▶ ◆三▶ ○○ のへで

Extraction from da

JLab 2015 0000000 Some Older Data

・ロト ・ 同ト ・ ヨト ・ ヨト ・ ヨ

Neural networks

## Parton distribution functions

• Deep-inelastic scattering,  $-q_1^2 o \infty, \; x_{BJ} \equiv rac{-q_1^2}{2 \rho \cdot q_1} o {
m const}$ 



Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

## Parton distribution functions

• Deep-inelastic scattering,  $-q_1^2 o \infty, \; x_{BJ} \equiv rac{-q_1^2}{2 \rho \cdot q_1} o {
m const}$ 



Extraction from dat

JLab 2015 0000000 Some Older Data

Neural networks

#### Parton distribution functions

• Deep-inelastic scattering,  $-q_1^2 \to \infty, \ x_{BJ} \equiv rac{-q_1^2}{2 \rho \cdot q_1} \to {
m const}$ 



Extraction from dat 000000 JLab 2015

Some Older Data

Neural networks

#### Electromagnetic form factors





3

 $q_1$ 

D

Extraction from data

p'

JLab 2015

Some Older Data

Neural networks

# Electromagnetic form factors

• Transversal density

$$q(b_{\perp}) = [2$$
-dim F.T.]  $\otimes$   $F_1(t = q_1^2)$ 





・ロト ・ 同ト ・ ヨト ・ ヨト

э



 $q_1$ 

Extraction from data

JLab 2015 0000000 Some Older Data

**(**)

Neural networks

-



• Transversal density

$$q(b_\perp) = [ ext{2-dim F.T.}] \otimes F_1(t=q_1^2)$$





 $q_1$ 

Extraction from data

JLab 2015

Some Older Data

**(**)

Neural networks

# Electromagnetic form factors

• Transversal density

$$q(b_{\perp}) = [ ext{2-dim F.T.}] \otimes F_1(t=q_1^2)$$





 $q_1$ 

Extraction from data

JLab 2015

Some Older Data

<ロト < 同ト < ヨト < ヨト

Neural networks

# Electromagnetic form factors

Transversal density

$$q(b_{\perp}) = [ ext{2-dim F.T.}] \otimes F_1(t=q_1^2)$$



[Burkardt '00, Ralston, Pire '02]

Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

## Definition of GPDs

• In QCD GPDs are defined as [Müller '92, et al. '94, Ji, Radyushkin '96]

$$F^{q}(x,\eta,t) = \int \frac{dz^{-}}{2\pi} e^{ixP^{+}z^{-}} \langle P_{2}|\bar{q}(-z)\gamma^{+}q(z)|P_{1}\rangle\Big|_{z^{+}=0,z_{\perp}=0}$$
$$\widetilde{F}^{q}(x,\eta,t) = \int \frac{dz^{-}}{2\pi} e^{ixP^{+}z^{-}} \langle P_{2}|\bar{q}(-z)\gamma^{+}\gamma_{5}q(z)|P_{1}\rangle\Big|_{z^{+}=0,z_{\perp}=0}$$

(and similarly for gluons  $F^g$  and  $F^g$ ).



Extraction from dat

JLab 2015 0000000 Some Older Data

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Neural networks

#### Some properties of GPDs

• Decomposing into spin-non-flip and spin-flip part:

$$F^{a} = \frac{\overline{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\overline{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q,g$$

Extraction from dat

JLab 2015 0000000 Some Older Data

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Neural networks

## Some properties of GPDs

• Decomposing into spin-non-flip and spin-flip part:

$$F^{a} = \frac{\overline{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\overline{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q, g$$

• Forward limit  $(\Delta \rightarrow 0)$ :  $\Rightarrow$  GPD  $\rightarrow$  PDF

$$F^{q}(x,0,0) = H^{q}(x,0,0) = \theta(x)q(x) - \theta(-x)\overline{q}(-x)$$

Extraction from dat

JLab 2015 0000000 Some Older Data

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Neural networks

## Some properties of GPDs

• Decomposing into spin-non-flip and spin-flip part:

$$F^a=rac{ar{u}(P_2)\gamma^+u(P_1)}{P^+}H^a+rac{ar{u}(P_2)i\sigma^{+
u}u(P_1)\Delta_
u}{2MP^+}E^a \qquad a=q,g$$

• Forward limit ( $\Delta \rightarrow 0$ ):  $\Rightarrow$  GPD  $\rightarrow$  PDF

$$F^{q}(x,0,0) = H^{q}(x,0,0) = \theta(x)q(x) - \theta(-x)\bar{q}(-x)$$

• Sum rules:

$$\int_{-1}^{1} dx \begin{cases} H^{q}(x,\eta,t) \\ E^{q}(x,\eta,t) \end{cases} = \begin{cases} F_{1}^{q}(t) & \text{Dirac} \\ F_{2}^{q}(t) & \text{Pauli} \end{cases}$$

Extraction from dat

JLab 2015 0000000 Some Older Data

Neural networks

## Some properties of GPDs

• Decomposing into spin-non-flip and spin-flip part:

$$F^{a} = \frac{\overline{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\overline{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q,g$$

• Forward limit ( $\Delta \rightarrow 0$ ):  $\Rightarrow$  GPD  $\rightarrow$  PDF

$$F^{q}(x,0,0) = H^{q}(x,0,0) = \theta(x)q(x) - \theta(-x)\bar{q}(-x)$$

• Sum rules:

$$\int_{-1}^{1} dx \begin{cases} H^{q}(x,\eta,t) \\ E^{q}(x,\eta,t) \end{cases} = \begin{cases} F_{1}^{q}(t) & \text{Dirac} \\ F_{2}^{q}(t) & \text{Pauli} \end{cases}$$

• "Ji's sum rule" (related to proton spin problem)

$$J^{q} = \frac{1}{2} \int_{-1}^{1} dx x \Big[ H^{q}(x,\eta,t) + E^{q}(x,\eta,t) \Big]_{t \to 0}$$
 [Ji '96]



- Access to GPDs: Deeply virtual Compton scattering (DVCS)
   "gold plated" process of exclusive physics
- DVCS is measured via leptoproduction of a photon



• Interference with Bethe-Heitler process gives unique access to both real and imaginary part of DVCS amplitude.

Extraction from dat

JLab 2015 0000000 Some Older Data

Neural networks

#### DVCS cross section

$$d\sigma \propto |\mathcal{T}|^2 = |\mathcal{T}_{\mathrm{BH}}|^2 + |\mathcal{T}_{\mathrm{DVCS}}|^2 + \mathcal{I} \; .$$

$$\mathcal{I} \propto \frac{-e_{\ell}}{\mathcal{P}_{1}(\phi)\mathcal{P}_{2}(\phi)} \left\{ c_{0}^{\mathcal{I}} + \sum_{n=1}^{3} \left[ c_{n}^{\mathcal{I}} \cos(n\phi) + s_{n}^{\mathcal{I}} \sin(n\phi) \right] \right\},$$
  
$$\mathcal{T}_{\text{DVCS}}|^{2} \propto \left\{ c_{0}^{\text{DVCS}} + \sum_{n=1}^{2} \left[ c_{n}^{\text{DVCS}} \cos(n\phi) + s_{n}^{\text{DVCS}} \sin(n\phi) \right] \right\},$$

 Choosing polarizations (and charges) we focus on particular harmonics:

$$c_{1, ext{unpol.}}^\mathcal{I} \propto \left[ F_1 \, \mathfrak{Re} \, \mathcal{H} - rac{t}{4M_
ho^2} F_2 \, \mathfrak{Re} \, \mathcal{E} + rac{x_ ext{B}}{2-x_ ext{B}} (F_1+F_2) \, \mathfrak{Re} \, \widetilde{\mathcal{H}} 
ight]$$

[Belitsky, Müller et. al '01–'14] •  $\mathcal{H}(x_{\mathrm{B}}, t, \mathcal{Q}^{2}), \ldots$  four Compton form factors (CFFs)

Extraction from da 000000

JLab 2015 0000000 Some Older Data 00000

Neural networks

## Factorization of DVCS $\longrightarrow$ GPDs

• [Collins et al. '98]



• Compton form factor is a convolution:

$${}^{a}\mathcal{H}(x_{\mathrm{B}}, t, \mathcal{Q}^{2}) = \int \mathrm{d}x \ C^{a}(x, \frac{x_{\mathrm{B}}}{2 - x_{\mathrm{B}}}, \frac{\mathcal{Q}^{2}}{\mathcal{Q}_{0}^{2}}) \ H^{a}(x, \frac{x_{\mathrm{B}}}{2 - x_{\mathrm{B}}}, t, \mathcal{Q}_{0}^{2})$$

$${}^{a=q,G}$$

$$H^{a}(x, \eta, t, \mathcal{Q}_{0}^{2}) - \text{Generalized parton distribution (GPD)}$$

Extraction from da

JLab 2015

Some Older Data 00000 Neural networks

# (N)NLO corrections





• Coming soon: COMPASS, JLab12, ... EIC

Krešimir Kumerički: Nucleon GPDs from DVCS

Extraction from dat

JLab 2015

Some Older Data 00000 Neural networks

æ

## Experimental coverage (2/2)

Collab Vear	Voor	Observables		Kinematics		No. of points		
Conab.	rear	Obscivabics	$x_{\rm B}$	$Q^2  [\text{GeV}^2]$	t  [GeV <sup>2</sup> ]	total	indep.	
HERMES	2001	$A_{LU}^{\sin \phi}$	0.11	2.6	0.27	1	1	
CLAS	2001	$A_{LU}^{\sin \phi}$	0.19	1.25	0.19	1	1	
CLAS	2006	$A_{UL}^{\sin \phi}$	0.2-0.4	1.82	0.15-0.44	6	3	
HERMES	2006	$A_{C}^{\cos \phi}$	0.08-0.12	2.0-3.7	0.03-0.42	4	4	
Hall A	2006	$\sigma(\phi), \Delta\sigma(\phi)$	0.36	1.5-2.3	0.17-0.33	$4 \times 24 + 12 \times 24$	$_{4\times24+12\times24}$	
CLAS	2007	$A_{LU}(\phi)$	0.11-0.58	1.0-4.8	0.09-1.8	62×12	62×12	
HERMES	2008	$\begin{array}{l} A_{\rm C}^{\cos(0,1)\phi}, \ A_{\rm UT,DVCS}^{\sin(\phi-\phi_{\rm S})}, \\ A_{\rm UT,I}^{\sin(\phi-\phi_{\rm S})\cos(0,1)\phi}, \\ A_{\rm UT,I}^{\cos(\phi-\phi_{\rm S})\sin\phi}, \end{array}$	0.03–0.35	1–10	<0.7	12+12+12 12+12 12	$\overset{4+4+4}{\overset{4+4}{_4}}$	
CLAS	2008	$A_{LU}(\phi)$	0.12-0.48	1.0-2.8	0.1-0.8	66	33	
HERMES	2009	$A_{LU,I}^{\sin(1,2)\phi}, A_{LU,DVCS}^{\sin\phi}, A_{C}^{\cos(0,1,2,3)\phi}$	0.05-0.24	1.2-5.75	<0.7	18+18+18 18+18+ <i>18</i> +18	6+6+6 6+6+ <i>6</i> +6	
HERMES	2010	$A_{\rm UL}^{\sin(1,2,3)\phi}, \ A_{\rm LL}^{\cos(0,1,2)\phi}$	0.03–0.35	1–10	<0.7	12+12+ <i>12</i> 12+ <i>12</i> +12	4+4+4 4+4+4	
HERMES	2011	$\begin{array}{l} A_{\mathrm{LT,I}}^{\cos(\phi-\phi_S)\cos(0,1,2)\phi},\\ A_{\mathrm{LT,I}}^{\sin(\phi-\phi_S)\sin(1,2)\phi},\\ A_{\mathrm{LT,I}}^{\sin(\phi-\phi_S)\cos(0,1)\phi},\\ A_{\mathrm{LT,BH+DVCS}}^{\cos(\phi-\phi_S)\sin\phi},\\ A_{\mathrm{LT,BH+DVCS}}^{\sin(\phi-\phi_S)\sin\phi} \end{array}$	0.03–0.35	1–10	<0.7	12+12+12 12+12 12+12 12	4+4+4 4+4 4+4 4	
HERMES	2012	$A_{LU,I}^{\sin(1,2)\phi}$ , $A_{LU,DVCS}^{\sin\phi}$ , $A_{C}^{\cos(0,1,2,3)\phi}$	0.03-0.35	1–10	<0.7	18+ <i>18</i> + <i>18</i> 18+18+ <i>18</i> + <i>18</i>	6+ <i>6</i> + <i>6</i> 6+6+ <i>6</i> + <i>6</i>	
CLAS	2015	$A_{LU}(\phi), A_{UL}(\phi), A_{LL}(\phi)$	0.17-0.47	1.3-3.5	0.1-1.4	166 + 166 + 166	166 + 166 + 166	
CLAS	2015	$\sigma(\phi), \Delta\sigma(\phi)$	0.1-0.58	1-4.6	0.09-0.52	2640+2640	2640+2640	
Hall A	2015	$\sigma(\phi), \Delta\sigma(\phi)$	0.33-0.40	1.5-2.6	0.17-0.37	480+600	240+360	

Extraction from dat 000000

JLab 2015 0000000 Some Older Data

Neural networks

## Alternative processes for GPD access

• Deeply virtual meson production (DVMP)  $\gamma^* p \rightarrow Mp$ .



- Theory more "dirty" than for DVCS (second "soft" function appears: meson distribution amplitude)
- Different mesons enable access to different flavours of GPDs

[P. Kroll's talk?]

- Wide-angle Compton scattering (WACS) [Tommorrow's talks]
  - WACS: proton momentum transfer *t* is large (unlike DVCS, where photon virtuality is large:  $Q^2 \gg t!$ )
  - data reasonably described by GPD models [Diehl, Kroll, '13]
- double DVCS  $\gamma^* p \rightarrow \gamma^* p$ , timelike DVCS, ...

Extraction from data •00000 JLab 2015

Some Older Data

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Neural networks

## Curse of dimensionality

• It is relatively easy to find a coin lying somewhere on 100 meter string. It is very difficult to find it on a football field.

Extraction from data •00000 JLab 2015 0000000 Some Older Data

Neural networks

## Curse of dimensionality

- It is relatively easy to find a coin lying somewhere on 100 meter string. It is very difficult to find it on a football field.
- When the dimensionality increases, the volume of the space increases so fast that the available data becomes sparse.
- Analogously, in contrast to *PDFs(x)*, it is very difficult to perform truly model independent extraction of *GPDs(x, η, t)*
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.
- As an intermediate step, one can attempt extraction of *CFFs*(x<sub>B</sub>, t)
- (Dependence on additional variable, photon virtuality Q<sup>2</sup>, is in principle known — given by evolution equations.)

# Modelling sea quark and gluon GPDs

- Instead of considering momentum fraction dependence H(x,...)
- ... it is convenient to make a transform into complementary space of conformal moments *j*:

$$H_{j}^{q}(\eta,...) \equiv \frac{\Gamma(3/2)\Gamma(j+1)}{2^{j+1}\Gamma(j+3/2)} \int_{-1}^{1} \mathrm{d}x \ \eta^{j} \ C_{j}^{3/2}(x/\eta) \ H^{q}(x,\eta,...)$$

- They are analogous to Mellin moments in DIS:  $x^j \rightarrow C_i^{3/2}(x)$
- $C_i^{3/2}(x)$  Gegenbauer polynomials
- At LO easy multiplicative evolution (pQCD series behaviour and evolution of CFFs studied also to NNLO)

Extraction from data

JLab 2015 0000000 Some Older Data

Neural networks

# SO(3) partial wave expansion

• To model  $\eta$ -dependence of GPD's  $H_j(\eta, t)$  consider crossed t-channel process  $\gamma^*\gamma \to p\bar{p}$  and perform SO(3) partial wave expansion:



$$H_{j}(\eta, t) = \sum_{J=J_{\min}}^{j+1} h_{J,j} \frac{1}{J-\alpha(t)} \frac{1}{\left(1-\frac{t}{M^{2}}\right)^{p}} \eta^{j+1-J} d_{0,\nu}^{J}(\frac{1}{\eta})$$

- $d_{0,\nu}^J$  Wigner SO(3) functions (Legendre, Gegenbauer,...)  $\nu = 0, \pm 1$  — depending on hadron helicities
- Similar to "dual" parametrization [Polyakov, Shuvaev '02]
- We take leading waves  $J = j + 1, j 1, \cdots$  and expand for small  $\eta$ .

Extraction from data

JLab 2015 0000000 Some Older Data

Neural networks

# Modelling valence quark GPDs

- Hybrid models at LO
- Sea quarks and gluons modelled like just described (conformal moments + SO(3) partial wave expansion + Q<sup>2</sup> evolution).
- Valence quarks model (ignoring  $Q^2$  evolution):

$$\Im \mathfrak{M} \mathcal{H}(\xi, t) = \pi \left[ \frac{4}{9} H^{u_{\text{val}}}(\xi, \xi, t) + \frac{1}{9} H^{d_{\text{val}}}(\xi, \xi, t) + \frac{2}{9} H^{\text{sea}}(\xi, \xi, t) \right]$$
$$H(x, x, t) = n r 2^{\alpha} \left( \frac{2x}{1+x} \right)^{-\alpha(t)} \left( \frac{1-x}{1+x} \right)^{b} \frac{1}{\left( 1 - \frac{1-x}{1+x} \frac{t}{M^{2}} \right)^{p}}.$$

• Fixed: *n* (from PDFs),  $\alpha(t)$  (eff. Regge), *p* (counting rules)

$$\alpha^{
m val}(t) = 0.43 + 0.85 t/{
m GeV}^2$$
 ( $ho, \omega$ )

Intro to GPDs and DVCS	Extraction from data	JLab 2015	Some Older Data	Neural networks
0000000000	000000	0000000	00000	000000000

•  $\mathfrak{Re} \mathcal{H}$  determined by dispersion relations

$$\mathfrak{Re} \, \mathcal{H}(\xi, t) = \frac{1}{\pi} \mathrm{PV} \int_0^1 d\xi' \left( \frac{1}{\xi - \xi'} - \frac{1}{\xi + \xi'} \right) \mathfrak{Im} \, \mathcal{H}(\xi', t) - \frac{C}{\left( 1 - \frac{t}{M_C^2} \right)^2}$$

Typical set of free parameters:

 $\begin{array}{ll} M_0^{\rm sea}, \, s_{\rm sea}^{(2,4)}, \, s_{\rm G}^{(2,4)} & {\rm sea \ quarks \ and \ gluons \ H} \\ r^{\rm val}, \, M^{\rm val}, \, b^{\rm val} & {\rm valence \ H} \\ \tilde{r}^{\rm val}, \, \tilde{M}^{\rm val}, \, \tilde{b}^{\rm val} & {\rm valence \ \widetilde{H}} \\ C, \, M_C & {\rm subtraction \ constant \ (H, \ E)} \\ r_{\pi}, \, M_{\pi} & {\rm "pion \ pole" \ \widetilde{E}} \end{array}$ 

Krešimir Kumerički: Nucleon GPDs from DVCS

イロト 不得 とくほと くほと

Intro to GPDs and DVCS 00000000000	Extraction from data 00000●		JLab 2015 0000000		Some Older Data 00000			Neural networ	
Model	KM09a	KM09b	KM10	KM10a	KM10b	KMS11	KMM12	KM15	
free params.	{3}+(3)+5	{3}+(3)+6	$\{3\}+15$	$\{3\}+10$	$\{3\}+15$	NNet	$\{3\}+15$	{3}+15	
$\chi^2$ /d.o.f.	32.0/31	33.4/34	135.7/160	129.2/149	115.5/126	13.8/36	123.5/80	240./275	
F <sub>2</sub>	{85}	{85}	{85}	{85}	{85}		{85}	{85}	
$\sigma_{\rm DVCS}$	(45)	(45)	51	51	45		11	11	
$d\sigma_{ m DVCS}/dt$	(56)	(56)	56	56	56		24	24	
$A_{LU}^{\sin\phi}$	12+12	12 + 12	12	16	12 + 12		4	13	
$A_{LU,I}^{\sin\phi}$			18	18		18	6	6	
$A_C^{\cos 0\phi}$							6	6	
$A_C^{\cos\phi}$	12	12	18	18	12	18	6	6	
$\Delta \sigma^{\sin \phi, w}$			12				12	63	
$\sigma^{\cos 0\phi,w}$			4				4	58	
$\sigma^{\cos\phi,w}$			4				4	58	
$\sigma^{\cos\phi,w}/\sigma^{\cos0\phi,w}$		4			4				
$A_{UL}^{\sin \phi}$							10	17	
$A_{LL}^{\cos 0\phi}$							4	14	
$A_{LL}^{\cos \phi}$								10	
$A_{UT,I}^{\sin(\phi-\phi_S)\cos\phi}$							4	4	

#### • [K.K., Müller, et al. '09-'15]

• These models are available at WWW (google for "gpd page")

Krešimir Kumerički: Nucleon GPDs from DVCS

Extraction from dat

JLab 2015 •000000 Some Older Data

Neural networks

## 2015 CLAS cross-sections (1/2)

• Restriction to kinematics where leading-order framework should be valid:  $-t/Q^2 < 0.25$  with  $Q^2 > 1.5 \,\mathrm{GeV^2}$ , means using 48 out of measured 110  $x_{\mathrm{B}}-Q^2-t$  bins.



•  $\chi^2/\text{npts} = 1032.0/1014$  for  $d\sigma$ 

and 936,1/1012 for  $\Delta\sigma$ 

Extraction from dat

JLab 2015 000000 Some Older Data

Neural networks

# $\phi$ -space vs. harmonics (1/2)

- $\phi\text{-space}$  figures and perfect  $\chi^2$  are not revealing the whole story
- Instead to  $\sigma(\phi)$  it is favourable to work with harmonics like

$$\sigma^{\sin n\phi, w} \equiv rac{1}{\pi} \int_{-\pi}^{\pi} dw \, \sin(n\phi) \, \sigma(\phi) \; ,$$

with specialy weighted Fourier integral measure

$$egin{aligned} & {dm w} \equiv rac{2\pi \mathcal{P}_1(\phi)\mathcal{P}_2(\phi)}{\int_{-\pi}^{\pi} d\phi\,\mathcal{P}_1(\phi)\mathcal{P}_2(\phi)} d\phi \ , \end{aligned}$$

thus cancelling strongly oscillating factors  $1/(\mathcal{P}_1(\phi)\mathcal{P}_2(\phi))$  in Bethe-Heitler and interference terms in  $d\sigma$ . Series of such weighted harmonic terms converges then faster with increasing *n* than normal Fourier series.

Extraction from dat

JLab 2015

Some Older Data

Neural networks

# $\phi$ -space vs. harmonics (2/2)

- How many harmonics to extract?
- One approach:
  - 1. Fit harmonic expansion

 $\sigma(\phi) = c_0 + c_1 \cos \phi + \dots + s_1 \sin \phi + \dots$ 

to randomly chosen subset of data in a bin, and calculate  $\chi^2$  error for description of the rest of data (so called cross-validation procedure)

- 2. Increase the number of harmonics until  $\chi^2/{\rm d.o.f}$  starts to fall
- Highest extractable harmonics in 2015 cross-section data:

	CLAS			Hall A			
	sine	cosine		sine	cosine		
$\Delta \sigma^w$	$0.9\pm0.4$	$0.1\pm0.3$		$1.1\pm0.3$	$0.1\pm0.3$		
$d\sigma^w$	$0.3\pm0.6$	$0.7\pm0.7$		$0.6\pm0.8$	$1.5\pm0.7$		

• (So  $\Delta \sigma^w = s_1 \sin \phi$  and  $d\sigma^w = c_0 + c_1 \cos \phi$  is enough.)

Extraction from da

JLab 2015

Some Older Data

Neural networks

э

## 2015 CLAS cross-sections (2/2)





•  $\chi^2/\text{npts} = \frac{62.2}{48}$ for  $d\sigma^{\cos\phi,w}$ 

(O.K. but not so perfect as in  $\phi$ -space)

(日)、(四)、(三)、(三)、

Extraction from da

JLab 2015

Some Older Data

Neural networks

#### 2006 vs 2015 Hall A cross-sections





 $Q^2 = 2.6702, x_8 = 0.337185$ 

KM15 prelim.

CLAS 2015

-- KMM12

 $Q_{-}^{2} = 2.36222, z_{\infty} = 0.254504$ 

= 3.31407, y<sub>1</sub> = 0.442331

-t [GeV<sup>2</sup>]

F

02 03 0.4 0.5 0.600 0.1 0.2 0.3 0.4 0.5 0.6

0.0 0.4

 $A_{LU}^{\sin\phi}$ 

0.2

0.4

 $A_{UL}^{\sin\phi}$ 

q1 = 2.36222. 3p = 0.254504

 $Q^2 = 3.31407, \mu_B = 0.442331$ 

-t [GeV<sup>2</sup>]

 $Q_{\perp}^2 = 2.6702, x_{\rm B} = 0.337185$ 

- - KMM12

0.1 0.2 0.3 0.4 0.5 0.60.0 0.1 0.2 0.3 0.4 0.5 0.6

CLAS 2015

KM15 prelim.

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@



JLab 2015



Krešimir Kumerički: Nucleon GPDs from DVCS

A D > A P > A D > A D >

3

Extraction from da

JLab 2015

Some Older Data •0000

メロト メポト メヨト メヨト

Neural networks

э

H1 (2007), ZEUS (2008)



Extraction from da

JLab 2015 0000000 Some Older Data

(日)

Neural networks

э

# **HERMES** (2012)



Extraction from da

JLab 2015

Some Older Data

Neural networks

ъ

э

## CLAS (2007)



• Only data with  $|t| \le 0.3 \, {\rm GeV}^2$  used for fits.

 co GPDs and DVCS
 Extraction from data
 JLab 2015
 Some Older Data
 Neural

 0000000
 000000
 000000
 000000
 000000

Transversally polarized target — HERMES (2008)



Krešimir Kumerički: Nucleon GPDs from DVCS

(日)

3.5 3

Extraction from da

JLab 2015 0000000 Some Older Data

< ロ > < 同 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ >

Neural networks

э

## Longitudinally polarized target — HERMES (2010)

 Surprisingly large sin(2φ) harmonic of A<sub>UL</sub> cannot be described within this leading twist framework





Essentially a least-squares fit of a complicated many-parameter function. f(x) = tanh(∑ w<sub>i</sub> tanh(∑ w<sub>j</sub> ··· )) ⇒ no theory bias

<ロト < 同ト < ヨト < ヨト

Extraction from da

JLab 2015 0000000 Some Older Data 00000

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Neural networks

## Function fitting by a neural net

Theorem: Given enough neurons, any smooth function f(x<sub>1</sub>, x<sub>2</sub>, ···) can be approximated to any desired accuracy.
 Single hidden layer is sufficient (but not always most efficient).

Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

# Function fitting by a neural net

- Theorem: Given enough neurons, any smooth function f(x<sub>1</sub>, x<sub>2</sub>, ···) can be approximated to any desired accuracy.
   Single hidden layer is sufficient (but not always most efficient).
- With simple training of neural nets to data there is a danger of overfitting (a.k.a. overtraining)



Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

# Function fitting by a neural net

- Theorem: Given enough neurons, any smooth function f(x<sub>1</sub>, x<sub>2</sub>, ···) can be approximated to any desired accuracy.
   Single hidden layer is sufficient (but not always most efficient).
- With simple training of neural nets to data there is a danger of overfitting (a.k.a. overtraining)



Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

# Function fitting by a neural net

- Theorem: Given enough neurons, any smooth function f(x<sub>1</sub>, x<sub>2</sub>, ···) can be approximated to any desired accuracy.
   Single hidden layer is sufficient (but not always most efficient).
- With simple training of neural nets to data there is a danger of overfitting (a.k.a. overtraining)
- Solution: Divide data (randomly) into two sets: *training* sample and *validation sample*. Stop training when error of validation sample starts increasing.



Krešimir Kumerički: Nucleon GPDs from DVCS

Extraction from da

JLab 2015 0000000 Some Older Data

3 N 3

Neural networks

## Example of a training with crossvalidation



Extraction from da 000000 JLab 2015 0000000 Some Older Data

・ロト ・ 同 ト ・ ヨ ト ・ ヨ ・ クタ(や

Neural networks

#### Fitting by a set of neural networks

ΤΙΙ

Extraction from da 000000 JLab 2015 0000000 Some Older Data

・ロト ・ 同 ト ・ ヨ ト ・ ヨ ・ クタ(や

Neural networks

#### Fitting by a set of neural networks

ή Ι Ι

Extraction from da 000000 JLab 2015 0000000 Some Older Data

・ロト ・ 同 ト ・ ヨ ト ・ ヨ ・ クタ(や

Neural networks

#### Fitting by a set of neural networks



Extraction from da<sup>.</sup> 000000 JLab 2015 0000000 Some Older Data

・ロト ・ 同 ト ・ ヨ ト ・ ヨ ・ クタ(や

Neural networks

### Fitting by a set of neural networks



Extraction from da 000000 JLab 2015 0000000 Some Older Data

▲ロ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● の Q @

Neural networks

## Fitting by a set of neural networks



Extraction from da 000000 JLab 2015 0000000 Some Older Data 00000

Neural networks

= nac

## Fitting by a set of neural networks





Neural networks

・ロト ・ 同 ト ・ ヨ ト ・ ヨ ・ クタ()



- Training networks on Monte Carlo replicated data preserves experimental uncertainties and their correlations [Giele et al. '01]
- Already successfully applied to PDF fitting by [NNPDF] group. Has even larger potential in GPD fitting with GPDs being less-known functions of more variables.

Extraction from da

JLab 2015 0000000 Some Older Data

Neural networks

## Preliminary neural Net HERMES fit

- Fit to all HERMES DVCS data with two types of neural nets
  - $(x_B, t) (7 \text{ neurons}) (\Im \mathfrak{m} \mathcal{H}, \mathfrak{Re} \mathcal{H}, \Im \mathfrak{m} \tilde{\mathcal{H}})$ :  $\chi^2/n_{\text{pts}} = 135.4/144$
  - $(x_B, t) (7 \text{ neurons}) (\Im \mathfrak{m} \mathcal{H}, \mathfrak{Re} \mathcal{E}): \chi^2 / n_{pts} = 120.2/144$



Krešimir Kumerički : Nucleon GPDs from DVCS

Extraction from da

JLab 2015 0000000 Some Older Data 00000 Neural networks

## Neural Net HERMES fit - BSA/BCA



Extraction from dat 000000

JLab 2015

Some Older Data 00000 Neural networks

#### Neural Net HERMES fit - CFFs



Extraction from dat

JLab 2015

Some Older Data

Neural networks

#### Comparison of various approaches





- Global fits of all proton DVCS data using flexible hybrid models are in healthy shape
- Data clearly restrict H(x, x, t), and to some extent  $\tilde{H}$ , but any information about E is very model-dependent
- New 2015 data relieve some old tensions
- Neural networks are very promising method for GPD/CFF extraction



- Global fits of all proton DVCS data using flexible hybrid models are in healthy shape
- Data clearly restrict H(x, x, t), and to some extent  $\tilde{H}$ , but any information about E is very model-dependent
- New 2015 data relieve some old tensions
- Neural networks are very promising method for GPD/CFF extraction

#### The End