Introduction to Generalized Parton Distributions

Krešimir Kumerički

Physics Department University of Zagreb, Croatia



QCD-N'16 4th Workshop on the QCD Structure of the Nucleon Getxo, Spain, 11–15 July 2016

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへで





Fitting to DVCS data 000000000

Neural networks

Conclusion 000

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 \tilde{F}^g).



Fitting to DVCS data

Neural networks

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Conclusion

Some properties of GPDs

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

$$F^{a} = \frac{\bar{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\bar{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q,g$$
$$\tilde{F}^{a} = \frac{\bar{u}(P_{2})\gamma^{+}\gamma_{5}u(P_{1})}{P^{+}}\tilde{H}^{a} + \frac{\bar{u}(P_{2})\gamma_{5}u(P_{1})\Delta^{+}}{2MP^{+}}\tilde{E}^{a} \qquad a = q,g$$

Fitting to DVCS data

Neural networks

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Conclusion

Some properties of GPDs

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

$$F^{a} = \frac{\bar{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\bar{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q,g$$
$$\tilde{F}^{a} = \frac{\bar{u}(P_{2})\gamma^{+}\gamma_{5}u(P_{1})}{P^{+}}\tilde{H}^{a} + \frac{\bar{u}(P_{2})\gamma_{5}u(P_{1})\Delta^{+}}{2MP^{+}}\tilde{E}^{a} \qquad a = q,g$$

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

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

Fitting to DVCS data

Neural networks

Conclusion

Some properties of GPDs

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

$$F^{a} = \frac{\bar{u}(P_{2})\gamma^{+}u(P_{1})}{P^{+}}H^{a} + \frac{\bar{u}(P_{2})i\sigma^{+\nu}u(P_{1})\Delta_{\nu}}{2MP^{+}}E^{a} \qquad a = q,g$$
$$\tilde{F}^{a} = \frac{\bar{u}(P_{2})\gamma^{+}\gamma_{5}u(P_{1})}{P^{+}}\tilde{H}^{a} + \frac{\bar{u}(P_{2})\gamma_{5}u(P_{1})\Delta^{+}}{2MP^{+}}\tilde{E}^{a} \qquad a = q,g$$

• "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]

• Distribution of partons in transversal space

$$\rho(x, \vec{b}_{\perp}) = \int \frac{d^2 \vec{\Delta}_{\perp}}{(2\pi)^2} e^{-i\vec{b}_{\perp} \cdot \vec{\Delta}_{\perp}} H(x, 0, -\vec{\Delta}_{\perp}^2) \qquad \text{[Burkardt '00]}$$

Fitting to DVCS data

Neural networks

イロト イポト イラト イラト

Conclusion 000

Access to GPDs via DVCS

- 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.

Fitting to DVCS data

Neural networks

Conclusion 000

DVCS cross section

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

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

• 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)

Fitting to DVCS data

Neural networks

Conclusion 000

Factorization of DVCS \longrightarrow GPDs

• [Collins et al. '98]



• Compton form factor is a convolution:

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

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

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

Fitting to DVCS data

Neural networks

Conclusion 000

(N)NLO corrections





Coming soon: COMPASS, JLab12, ... EIC

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

Fitting to DVCS data

Neural networks

Conclusion 000

з.

Experimental coverage (2/2)

Collab	Voor	Observables		Kinematics		No. of points		
Collab.	Tear	Observables	x _B	$Q^2 [\text{GeV}^2]$	t [GeV ²]	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	$A_{III}^{\sin \phi}$	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	$\begin{array}{l} A_{\rm C}^{\cos(0,1)\phi}, \ A_{\rm UT,DVCS}^{\sin(\phi-\phi_S)}, \\ A_{{\rm UT,I}}^{\sin(\phi-\phi_S)\cos(0,1)\phi}, \\ A_{{\rm UT,I}}^{\cos(\phi-\phi_S)\sin\phi} \end{array}$	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	$\begin{array}{l} A_{\mathrm{LU,I}}^{\sin(1,2)\phi}, A_{\mathrm{LU,DVCS}}^{\sin\phi}, \\ A_{\mathrm{C}}^{\cos(0,1,2,3)\phi} \end{array}$	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	$egin{aligned} & A_{\mathrm{UL}}^{\sin(1,2,3)\phi}, \ & A_{\mathrm{LL}}^{\cos(0,1,2)\phi} \end{aligned}$	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	$\begin{array}{l} A_{\mathrm{LT},\mathrm{I}}^{\cos(\phi-\phi_{\mathrm{S}})\cos(0,1,2)\phi},\\ A_{\mathrm{LT},\mathrm{I}}^{\sin(\phi-\phi_{\mathrm{S}})\sin(1,2)\phi},\\ A_{\mathrm{LT},\mathrm{I}}^{\cos(\phi-\phi_{\mathrm{S}})\cos(0,1)\phi},\\ A_{\mathrm{LT},\mathrm{BH+DVCS}}^{\cos(\phi-\phi_{\mathrm{S}})\sin\phi},\\ A_{\mathrm{LT},\mathrm{BH+DVCS}}^{\sin(\phi-\phi_{\mathrm{S}})\sin\phi}, \end{array}$	0.03–0.35	1–10	<0.7	12+12+12 12+12 12+12 12	4+4+4 4+4 4	
HERMES	2012	$A_{\mathrm{LU,I}}^{\sin(1,2)\phi}$, $A_{\mathrm{LU,DVCS}}^{\sin\phi}$, $A_{\mathrm{COS}}^{\cos(0,1,2,3)\phi}$	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	

Fitting to DVCS data

Neural networks

イロト 不得 トイヨト イヨト

Conclusion 000

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 [Goloskokov, Kroll]
- Wide-angle Compton scattering (WACS)
 - 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, ... (see Trento

workshop October 2016)

Fitting to DVCS data •••••• Neural networks

▲□▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

Conclusion 000

Extraction of GPDs/CFFs by fits to DVCS data

 In contrast to *PDFs*(x), it is very difficult to perform truly model-independent extraction of *GPDs*(x, η, t)

- In contrast to *PDFs(x)*, it is very difficult to perform truly model-independent extraction of *GPDs(x, η, t)*
- When the dimensionality of domain space increases, the available data becomes sparse very fast. ("Curse of dimensionality")

▲日▼ ▲□▼ ▲ □▼ ▲ □▼ ■ ● ● ● ●

- In contrast to *PDFs(x)*, it is very difficult to perform truly model-independent extraction of *GPDs(x, η, t)*
- When the dimensionality of domain space increases, the available data becomes sparse very fast. ("Curse of dimensionality")
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

- In contrast to *PDFs(x)*, it is very difficult to perform truly model-independent extraction of *GPDs(x, η, t)*
- When the dimensionality of domain space increases, the available data becomes sparse very fast. ("Curse of dimensionality")
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.
- As an intermediate step, one can attempt extraction of *CFFs*(x_B, t).

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

- In contrast to *PDFs(x)*, it is very difficult to perform truly model-independent extraction of *GPDs(x, η, t)*
- When the dimensionality of domain space increases, the available data becomes sparse very fast. ("Curse of dimensionality")
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.
- As an intermediate step, one can attempt extraction of *CFFs*(x_B, t).
- Instead of functions CFFs(x_B, t) one can extract CFFs as numbers for fixed x_B and t — local fits (hope of a model-independent procedure)

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

- In contrast to *PDFs(x)*, it is very difficult to perform truly model-independent extraction of *GPDs(x, η, t)*
- When the dimensionality of domain space increases, the available data becomes sparse very fast. ("Curse of dimensionality")
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.
- As an intermediate step, one can attempt extraction of *CFFs*(x_B, t).
- Instead of functions CFFs(x_B, t) one can extract CFFs as numbers for fixed x_B and t — local fits (hope of a model-independent procedure)
- (Dependence on additional variable, photon virtuality Q², is in principle known — given by evolution equations.)

Fitting to DVCS data

Neural networks

Conclusion 000

Local fits — some results

 [K.K., Müller, Murray '13]: using HERMES set of 10+ observables measured at same 12 kinematical points and extracting 8 leading "CFFs"



Most CFFs are not reliably constrained.

Krešimir Kumerički: Introduction to GPDs

Fitting to DVCS data

Neural networks

Conclusion 000

Reducing the number of CFFs

- Scenario 1: Fit of $\mathfrak{Im} \mathcal{H}$, $\mathfrak{Re} \mathcal{H}$ and $\mathfrak{Im} \widetilde{\mathcal{H}}$. $\chi^2/n_{\mathrm{d.o.f.}} = 148.8/144$. (In good agreement with local fit of [Guidal '10])
- Scenario 2: Fit of $\Im \mathfrak{m} \mathcal{H}$ and $\mathfrak{Re} \mathcal{E}$. $\chi^2/n_{\rm d.o.f.} = 134.2/144$.



Fitting to DVCS data

Neural networks

Conclusion 000

Hybrid GPD models for global fits

- Sea quarks and gluons modelled using SO(3) partial wave expansion in conformal GPD moment space + Q² evolution.
- Valence quarks model CFFs directly (ignoring Q^2 evolution):

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

- $\mathfrak{Re}\,\mathcal{H}$ determined by dispersion relations
- 15 free parameters in total for H, \tilde{H} , E, \tilde{E} .

Fitting to DVCS data $0000 \bullet 0000$

Neural networks

Conclusion 000

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 ₂	{85}	{85}	{85}	{85}	{85}		{85}	{85}
$\sigma_{ m DVCS}$	(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 publicly available (google for "gpd page")
- Other approach: recursive fit [Goldstein, Gonzalez, Liuti '11] focuses on fixed-target data

Fitting to DVCS data

Neural networks

Conclusion 000

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.



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

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

Fitting to DVCS data

Neural networks

Conclusion 000

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 ϕ -space)

(日)、(四)、(三)、(三)、

э

Fitting to DVCS data

Neural networks

Conclusion 000

2006 vs 2015 Hall A cross-sections



• Improvement of global $\chi^2/d.o.f. 123.5/80 \rightarrow 240./275$

Fitting to DVCS data

Neural networks

▲ 🗇 🕨 🔺

Conclusion 000

э

2007 CLAS beam spin asymmetry



- Only data with $|t| \leq 0.3 \, {
m GeV}^2$ used for fits.



 Essentially a least-squares fit of a complicated many-parameter function. f(x) = tanh(∑ w_i tanh(∑ w_j ···))
 ⇒ no theory bias

メロト メポト メヨト メヨト

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: Introduction to GPDs



Fitting to DVCS data

Neural networks

Conclusion 000

Neural net HERMES fit — CFFs



Fitting to DVCS data

Neural networks

Conclusion •00

CFFs from various fits







• Sivers effect for valence quarks ([GK] model)



- See also [Dupré, Guidal, Vanderhaeghen '16]
- Tomography is still very much model-dependent; e.g. some extrapolation from H(x, x, t) to H(x, 0, t) is needed.



Fitting to DVCS data

Neural networks

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

Conclusion

Summary

- 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 JLab data relieve some old tensions
- Neural networks are very promising method for GPD/CFF extraction



Fitting to DVCS data

Neural networks

▲日 ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ▲ □ ▶ ● ○ ○ ○

Conclusion

Summary

- 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 JLab data relieve some old tensions
- Neural networks are very promising method for GPD/CFF extraction

The End