

Theory and Phenomenology of Generalized Parton Distributions

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Outline

Introduction to GPDs

Local fits

Global fits (small x_B)

Global fits (all data)

Neural networks approach

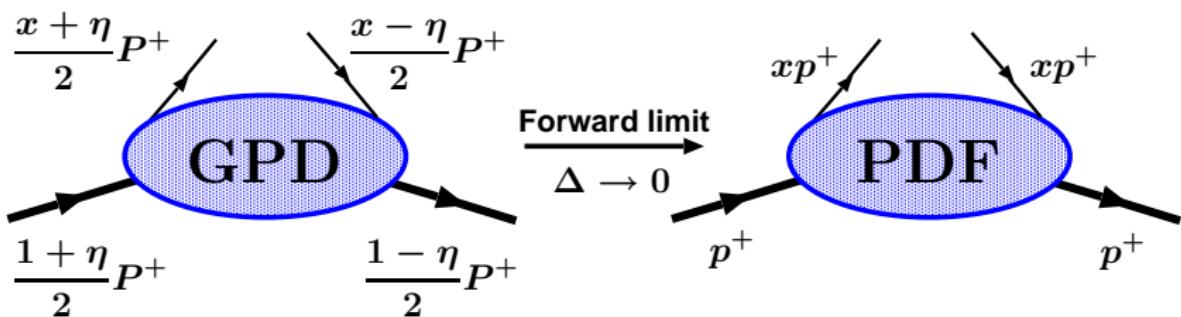
Looking ahead

Attractiveness of GPDs (1/3)

- 1. Well-defined within the QCD

[Müller '92, et al. '94, Ji, Radyushkin '96]

$$F^q(x, \eta, t = \Delta^2) = \int \frac{dz^-}{2\pi} e^{ixP^+z^-} \langle P_2 | \bar{q}(-z) \gamma^+ q(z) | P_1 \rangle \Big|_{z^+=0, z_\perp=0}$$



$$P = P_1 + P_2 ; \quad \Delta = P_2 - P_1 ; \quad \eta = -\frac{\Delta^+}{P^+} \text{ (skewedness)}$$

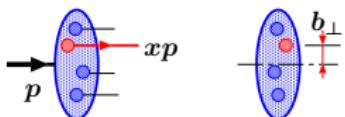
Attractiveness of GPDs (2/3)

- Decomposition into helicity conserving and non-conserving parts:

$$F^a = \frac{\bar{u}(P_2)\gamma^+ u(P_1)}{P^+} H^a + \frac{\bar{u}(P_2)i\sigma^{+\nu} u(P_1)\Delta_\nu}{2MP^+} E^a \quad a = q, g$$

- 2. Close contact to 3D quark-gluon hadron structure

$$\frac{1}{2} \int_{-1}^1 dx x \left[H^q(x, \eta, 0) + E^q(x, \eta, 0) \right] = J^q \quad [\text{Ji '97}]$$



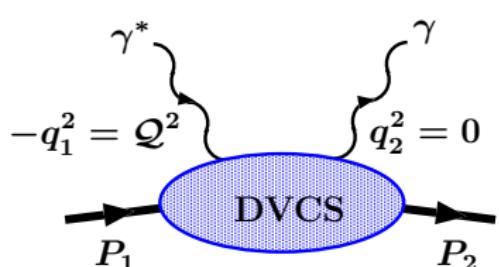
$$q(x, b_\perp) = \int \frac{d^2 \Delta_\perp}{(2\pi)^2} e^{ib_\perp \cdot \Delta_\perp} H^q(x, 0, -\Delta_\perp^2) \quad [\text{Burkardt '00}]$$

Attractiveness of GPDs (3/3)

- **3. Accessible to experiments**
- Deeply virtual Compton scattering (DVCS)

$$P = P_1 + P_2, \quad t = (P_2 - P_1)^2$$

$$q = (q_1 + q_2)/2$$



Generalized Bjorken limit:

$$-q^2 \simeq Q^2/2 \rightarrow \infty$$

$$\xi = \frac{-q^2}{2P \cdot q} = \frac{x_B}{2 - x_B} \rightarrow \text{const}$$

- We work at leading order accuracy where cross-section can be expressed in terms of **four Compton form factors** (CFFs)

$$\mathcal{F} \in \{\mathcal{H}(\xi, t, Q^2), \mathcal{E}(\xi, t, Q^2), \tilde{\mathcal{H}}(\xi, t, Q^2), \tilde{\mathcal{E}}(\xi, t, Q^2)\}$$

Factorization of DVCS \longrightarrow GPDs

- [Collins et al. '98]

$P = P_1 + P_2, \quad t = (P_2 - P_1)^2$
 $q = (q_1 + q_2)/2$

$-q^2 \simeq Q^2/2 \rightarrow \infty$
 $\xi = \frac{-q^2}{2P \cdot q} \rightarrow \text{const}$

- Compton form factor is a convolution:

$${}^a\mathcal{H}(\xi, t, Q^2) = \int dx \, C^a(x, \xi, Q^2/Q_0^2) \, H^a(x, \eta = \xi, t, Q_0^2)$$

$a=NS,S(\Sigma,G)$

Curse of dimensionality

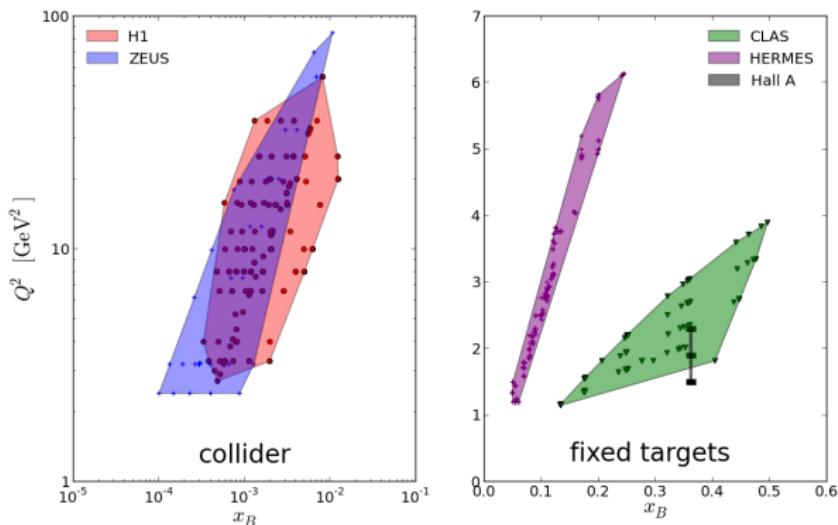
- *It is relatively easy to find a coin lying somewhere on 100 meter string. It is very difficult to find it on a football field.*

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 $\text{PDFs}(x)$, it is very difficult to perform truly model independent extraction of $\text{GPDs}(x, \xi, t)$
- Known GPD constraints don't decrease the dimensionality of the GPD domain space.
- As an intermediate step, one can attempt extraction of $\text{CFFs}(x_B, t)$
- (Dependence on additional variable, photon virtuality Q^2 , is in principle known — given by evolution equations.)

Fit types

Fit type	Data used	pQCD order	Target
1. Local fits	fixed target	LO	CFFs
2. Global fits	collider/fixed target	((N)N)LO	CFFs/GPDs
3. Neural nets	fixed target	LO	CFFs



Local fits to HERMES data

- Most complete set of asymmetries is measured in 12 bins:

$$d\sigma \propto |\mathcal{A}_{\text{BH}}|^2 + |\mathcal{A}_{\text{DVCS}}|^2(\mathcal{F}^2) + \mathcal{A}_{\text{Interference}}(\mathcal{F})$$

$$A_C \equiv \frac{d\sigma_{e^+} - d\sigma_{e^-}}{d\sigma_{e^+} + d\sigma_{e^-}} = \frac{\mathcal{A}_{\text{Interference}}(\mathcal{F})}{|\mathcal{A}_{\text{DVCS}}|^2(\mathcal{F}^2) + |\mathcal{A}_{\text{BH}}|^2}$$

$$A_C^{\cos(1\phi)} \propto \left[F_1 \Re \mathcal{H} - \frac{t}{4M_p^2} F_2 \Re \mathcal{E} + \frac{x_B}{2} (F_1 + F_2) \Re \tilde{\mathcal{H}} \right]$$

- ... and similarly for other observables → almost linear relation between observables and CFFs
- (up to $|\mathcal{A}_{\text{DVCS}}|^2$ contamination — taken into account)

Mapping

- Inverting these relations gives mapping from the set of observables ...

$$A_{\text{LU,I}}^{\sin(1\phi)}$$

$$A_{\text{C}}^{\cos(1\phi)}$$

$$A_{\text{C}}^{\cos(0\phi)}$$

$$A_{\text{UL,+}}^{\sin(1\phi)}$$

$$A_{\text{LL,+}}^{\cos(1\phi)}$$

$$A_{\text{LL,+}}^{\cos(0\phi)}$$

$$A_{\text{UT,I}}^{\sin(\varphi) \cos(1\phi)}$$

$$A_{\text{UT,I}}^{\cos(\varphi) \sin(1\phi)}$$

$$A_{\text{UT,DVCS}}^{\sin(\varphi) \cos(0\phi)}$$

$$A_{\text{UT,I}}^{\sin(\varphi) \cos(0\phi)}$$

$$A_{\text{LT,I}}^{\sin(\varphi) \sin(1\phi)}$$

$$A_{\text{LT,I}}^{\cos(\varphi) \cos(1\phi)}$$

$$A_{\text{LT,BH+DVCS}}^{\cos(\varphi) \cos(0\phi)}$$

$$A_{\text{LT,I}}^{\cos(\varphi) \cos(0\phi)}$$

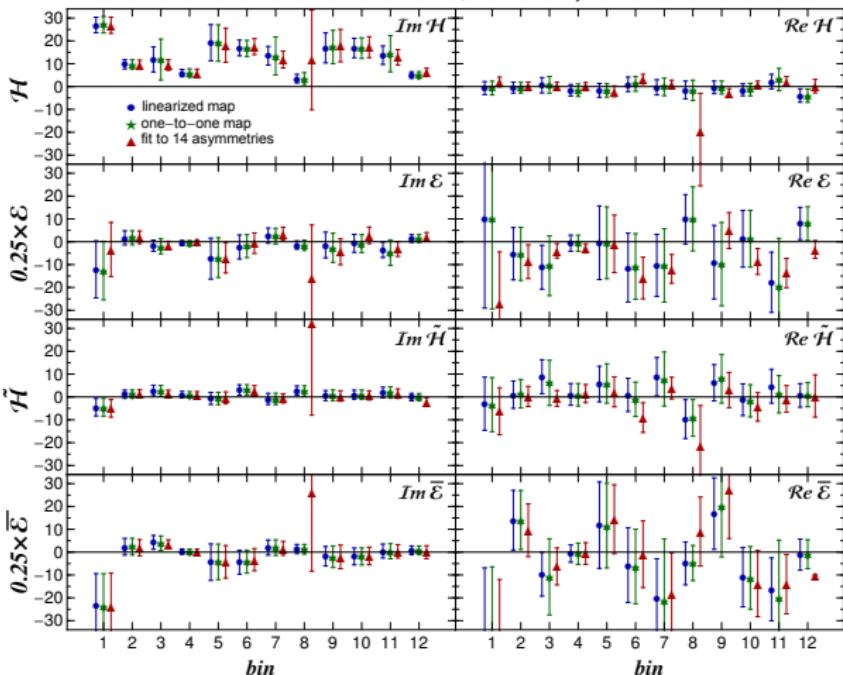
- ... to the set of eight real and imaginary parts of CFFs (sometimes called sub-CFFs or just CFFs) ...

$$\mathcal{F} = (\mathfrak{Im} \mathcal{H}, \mathfrak{Re} \mathcal{H}, \mathfrak{Im} \mathcal{E}, \mathfrak{Re} \mathcal{E}, \mathfrak{Im} \tilde{\mathcal{H}}, \mathfrak{Re} \tilde{\mathcal{H}}, \mathfrak{Im} \tilde{\mathcal{E}}, \mathfrak{Re} \tilde{\mathcal{E}})$$

- ... where error propagation is straightforward.

Mapping — results

- (Here compared also to standard local least-squares fit)



- Only $\text{Im } \mathcal{H}$, $\Re \mathcal{H}$ and $\text{Im } \tilde{\mathcal{H}}$ are reliably constrained.

Method of stepwise regression

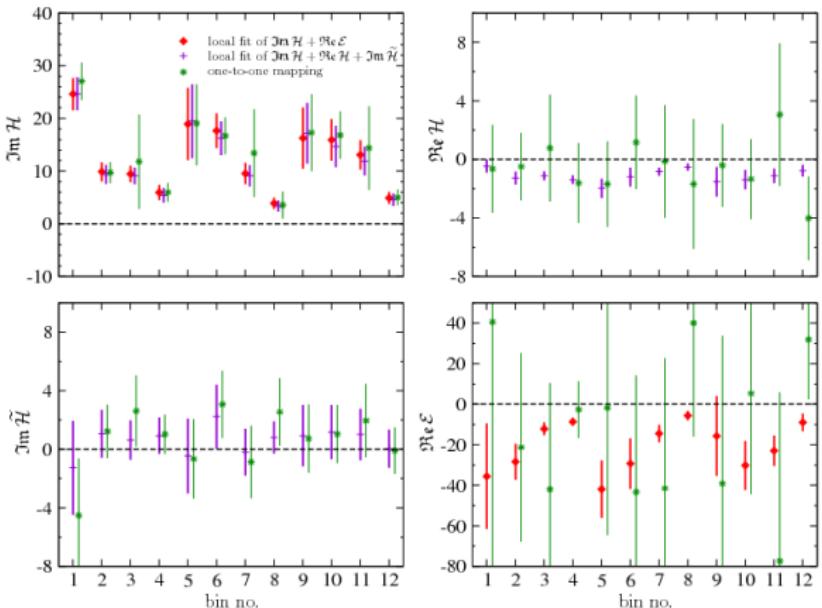
- Constraints from data are too weak to constrain simultaneously all eight $\{\text{Im } \mathcal{F}, \text{Re } \mathcal{F}\}$ CFFs
- Let us take smaller number of CFFs, choosing only those which are reliably extracted. **Stepwise regression** algorithm:
 - Starting from zero, add, one by one, CFFs that best improve description of data until improvement becomes statistically insignificant.

Method of stepwise regression

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- Let us take smaller number of CFFs, choosing only those which are reliably extracted. **Stepwise regression** algorithm:
 - Starting from zero, add, one by one, CFFs that best improve description of data until improvement becomes statistically insignificant.
- Algorithm stops after just 2 CFFs, and there are two equally good pairs of CFFs:
 1. $(\text{Im } \mathcal{H}, \text{Re } \mathcal{H})$ with $\chi^2/n_{\text{d.o.f.}} = 102.3/120$, and
 2. $(\text{Im } \mathcal{H}, \text{Re } \mathcal{E})$ with $\chi^2/n_{\text{d.o.f.}} = 103.0/120$.

Stepwise regression — results

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



Modelling GPDs in moment space

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

$$H_j^q(\eta, \dots) \equiv \frac{\Gamma(3/2)\Gamma(j+1)}{2^{j+1}\Gamma(j+3/2)} \int_{-1}^1 dx \eta^j C_j^{3/2}(x/\eta) H^q(\textcolor{red}{x}, \eta, \dots)$$

- They are analogous to Mellin moments in DIS: $x^j \rightarrow C_j^{3/2}(x)$
- $C_j^{3/2}(x)$ — Gegenbauer polynomials

Advantages of conformal moments

1. The evolution equations are most simple: There is **no mixing** among moments at LO, and in special (\overline{CS}) scheme not even at NLO
2. Powerful analytic methods of **complex j** plane are available (similar to complex angular momentum of Regge theory)
3. Stable and fast **computer code** for evolution and fitting
4. Moments are equal to matrix elements of **local** operators and are thus directly accessible on the **lattice**

I-PW model — only leading SO(3) partial wave

-

$$\mathbf{H}_j(\xi, t, \mu_0^2) = \begin{pmatrix} N'_\Sigma F_\Sigma(t) B(1+j-\alpha_\Sigma(0), 8) \\ N'_G F_G(t) B(1+j-\alpha_G(0), 6) \end{pmatrix}$$

$$\alpha_a(t) = \alpha_a(0) + 0.15t \quad F_a(t) = \frac{j+1-\alpha(0)}{j+1-\alpha(t)} \left(1 - \frac{t}{M_0^{a2}}\right)^{-p_a}$$

... corresponding in forward case to **PDFs** of form

$$\Sigma(x) = N'_\Sigma x^{-\alpha_\Sigma(0)} (1-x)^7; \quad G(x) = N'_G x^{-\alpha_G(0)} (1-x)^5$$

- $M_0^G = \sqrt{0.7}$ GeV is fixed by the J/ψ production data
- Free parameter (for DVCS): M_0^Σ

For small ξ (small x_{Bj}) valence quarks are less important $\Rightarrow \Sigma \approx \text{sea}$

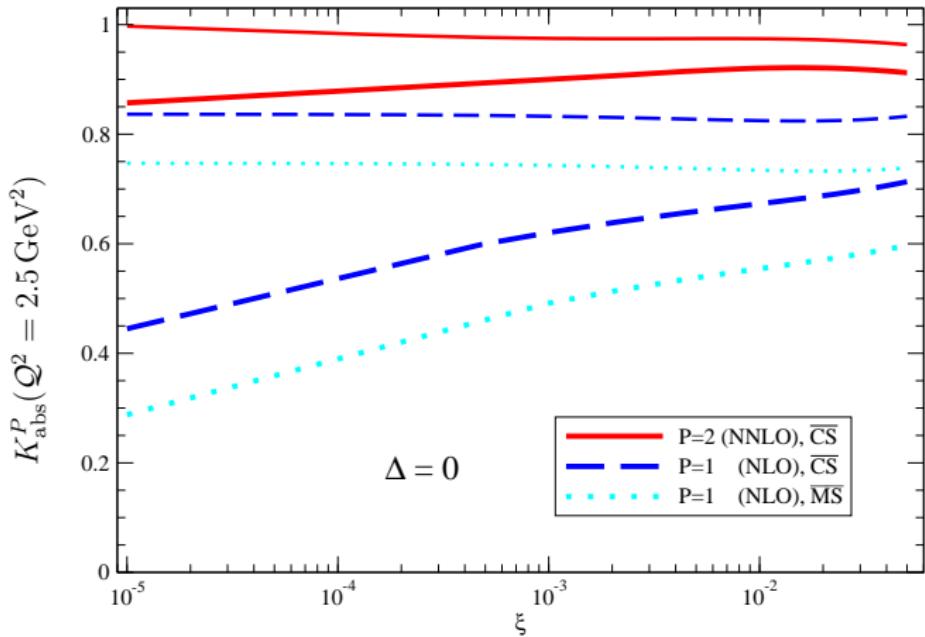
Inclusion of subleading PW — flexible models

$$\mathbf{H}_j(\eta, t) = \underbrace{\left(\begin{array}{c} N'_{\text{sea}} F_{\text{sea}}(t) B(1 + j - \alpha_{\text{sea}}(0), 8) \\ N'_G F_G(t) B(1 + j - \alpha_G(0), 6) \end{array} \right)}_{\text{skewness } r \approx 1.6 \text{ (too large)}} + \underbrace{\left(\begin{array}{c} s_{\text{sea}} \\ s_G \end{array} \right)}_{< 0} \left(\begin{array}{l} \text{subleading par-} \\ \text{tial waves, } \eta\text{-} \\ \text{dependence!} \end{array} \right)$$

negative skewness

- nl-PW — addition of second PW needed for good fits
- two new parameters: $s_{\text{sea}}^{(2)}$ and $s_G^{(2)}$
- nnl-PW — addition of third PW (doesn't improve fits much but makes possible positive gluon GPDs at small Q^2) — $s_{\text{sea}}^{(4)}$ and $s_G^{(4)}$

(N)NLO corrections

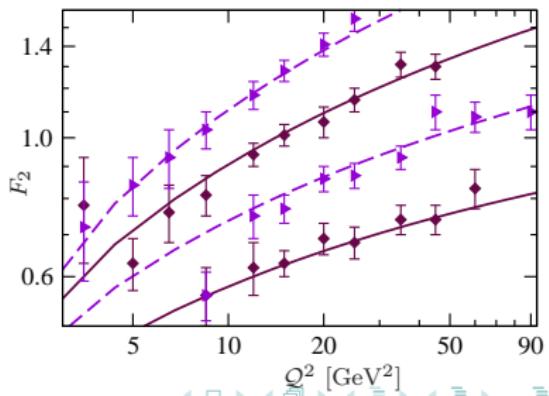
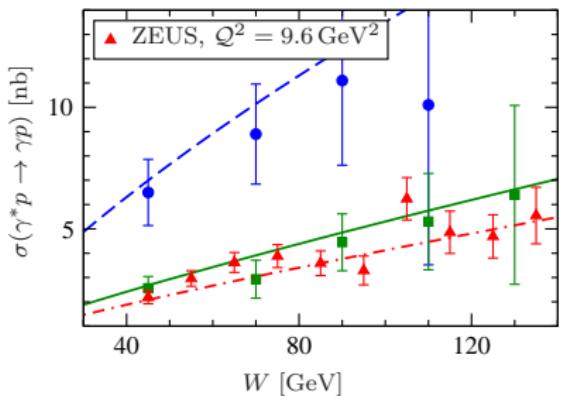
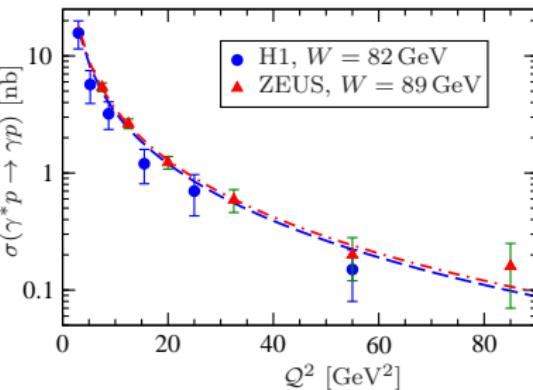
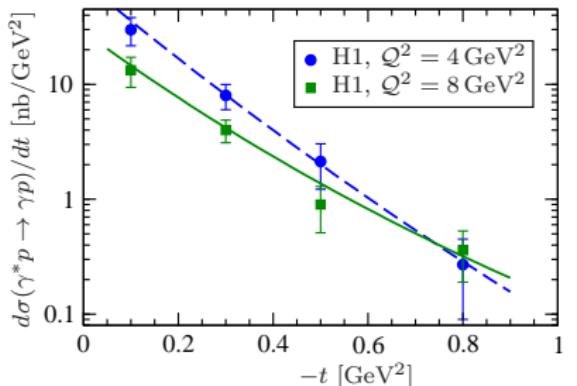


Thick lines:
 "hard" gluon
 $N_G = 0.4$
 $\alpha_G(0) = \alpha_\Sigma(0) + 0.05$

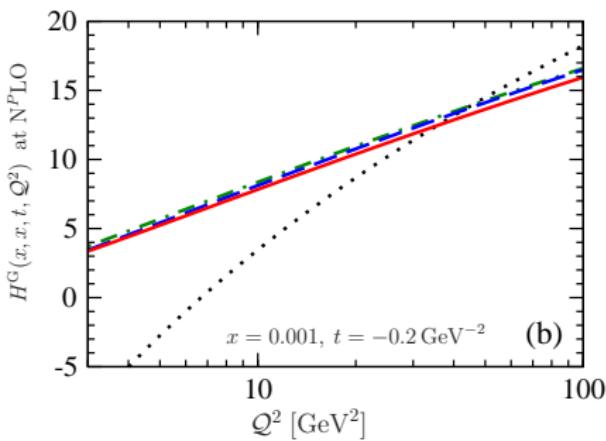
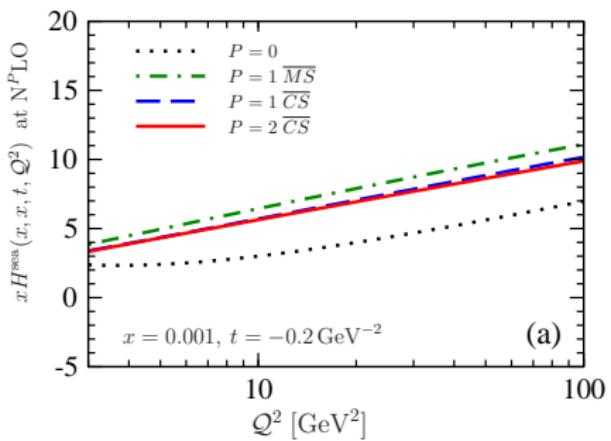
Thin lines:
 "soft" gluon
 $N_G = 0.3$
 $\alpha_G(0) = \alpha_\Sigma(0) - 0.02$

$$K_{\text{abs}}^P \equiv \left| \frac{\mathcal{H}^{(P)}}{\mathcal{H}^{(P-1)}} \right|$$

Example of fit result



Resulting small- x $H(x, x, t)$



- $P=0$: LO; $P=1$: NLO; $P=2$: NNLO
- The whole procedure is extended to meson production [Müller, Lautenschlager, Passek-Kumerički, Schäfer '13]

Extending global analysis to fixed target data

- **Hybrid models** at LO (1st just for *unpolarized* target)
- **Sea quarks and gluons** modelled like just described (conformal moments + SO(3) partial wave expansion + \mathcal{Q}^2 evolution).
- **Valence quarks** model (ignoring \mathcal{Q}^2 evolution):

$$\Im \mathcal{H}(\xi, t) = \pi \left[\frac{4}{9} H^{\mu_{\text{val}}}(\xi, \xi, t) + \frac{1}{9} H^{d_{\text{val}}}(\xi, \xi, t) + \frac{2}{9} H^{\text{sea}}(\xi, \xi, t) \right]$$

$$H(x, x, t) = n \, r \, 2^\alpha \left(\frac{2x}{1+x} \right)^{-\alpha(t)} \left(\frac{1-x}{1+x} \right)^b \frac{1}{\left(1 - \frac{1-x}{1+x} \frac{t}{M^2} \right)^p}.$$

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

$$\alpha^{\text{val}}(t) = 0.43 + 0.85 \, t/\text{GeV}^2 \quad (\rho, \omega)$$

- $\Re \mathcal{H}$ determined by dispersion relations

$$\Re \mathcal{H}(\xi, t) =$$

$$\frac{1}{\pi} \text{PV} \int_0^1 d\xi' \left(\frac{1}{\xi - \xi'} - \frac{1}{\xi + \xi'} \right) \Im \mathcal{H}(\xi', t) - \frac{\textcolor{red}{C}}{\left(1 - \frac{t}{M_C^2} \right)^2}$$

- Typical set of free parameters:

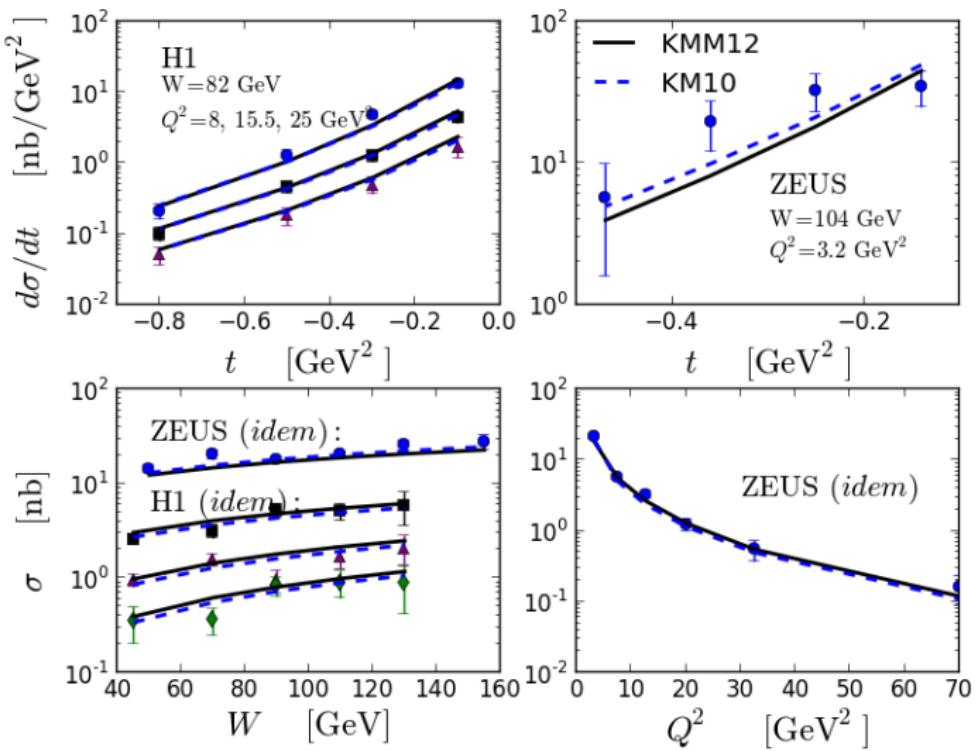
M_0^{sea} , $s_{\text{sea}}^{(2,4)}$, $s_G^{(2,4)}$	sea* quarks and gluons H
r^{val} , M^{val} , b^{val}	valence H
\tilde{r}^{val} , \tilde{M}^{val} , \tilde{b}^{val}	valence \tilde{H}
C , M_C	subtraction constant (H , E)
r_π , M_π	"pion pole" \tilde{E}

- Global fit to 175 data points turns out fine:

KM10 model: $\chi^2/d.o.f. = 135.9/160.$

* $s_{\text{sea},G}$ = strengths of subleading partial waves. LO evolution is included.

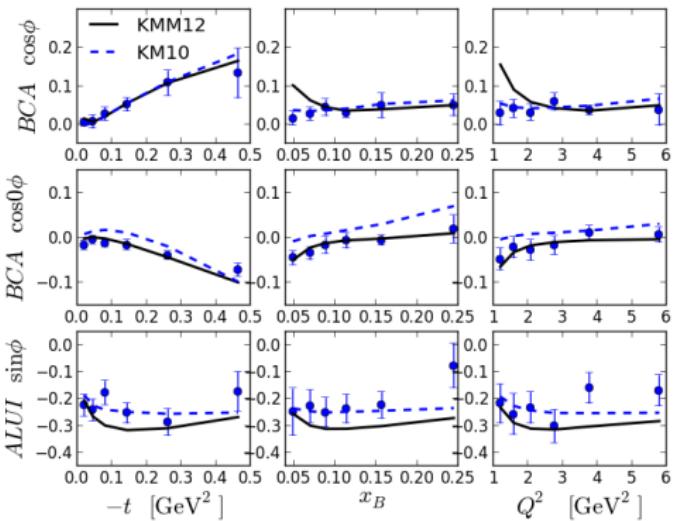
H1 (2007), ZEUS (2008)



HERMES (2008)

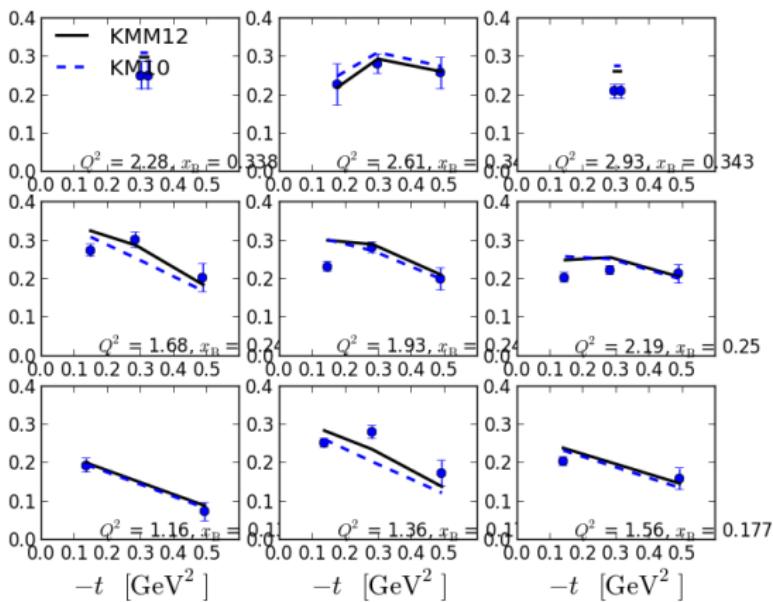
$$BCA \equiv \frac{d\sigma_{e^+} - d\sigma_{e^-}}{d\sigma_{e^+} + d\sigma_{e^-}} \sim A_C^{\cos 0\phi} + A_C^{\cos 1\phi} \cos \phi \sim \Re \mathcal{H}$$

$$BSA \equiv \frac{d\sigma_{e^\uparrow} - d\sigma_{e^\downarrow}}{d\sigma_{e^\uparrow} + d\sigma_{e^\downarrow}} \sim A_{LU}^{\sin 1\phi} \sin \phi \sim \Im \mathcal{H}$$



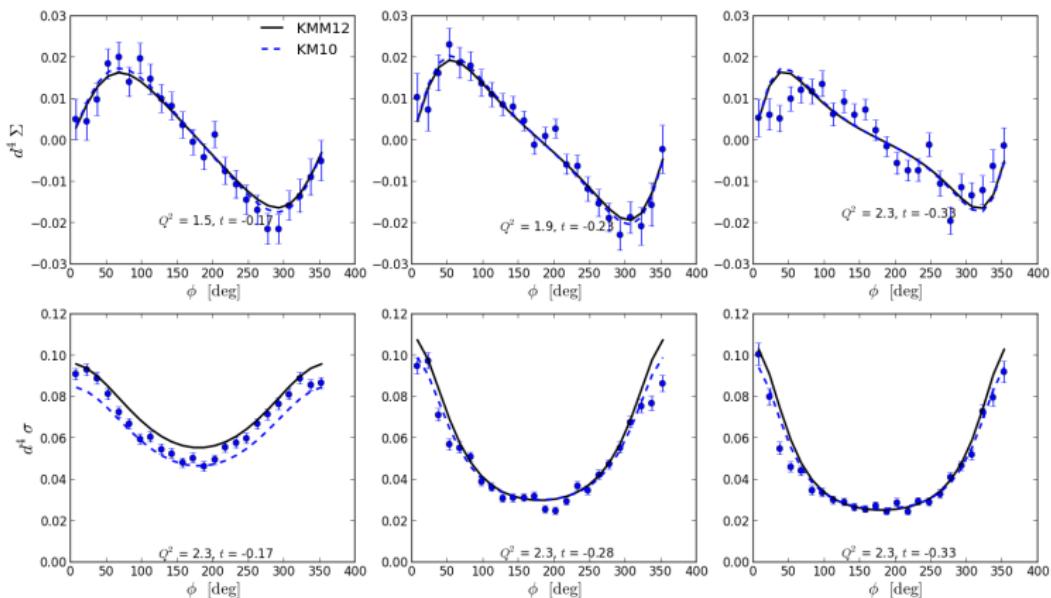
CLAS (2007)

- BSA. (Only data with $|t| \leq 0.3 \text{ GeV}^2$ used for fits.)



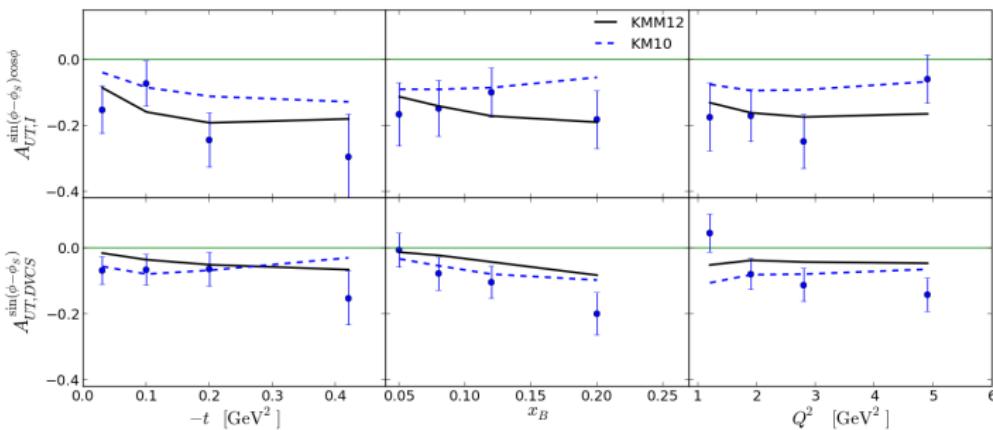
Hall A (2006)

- Fit to **unpolarized cross section** $d\sigma/(dx_B dQ^2 dt d\phi) \sim \Re \mathcal{H}$
- KM10 fit needs unusually large $\Re \mathcal{H}$.

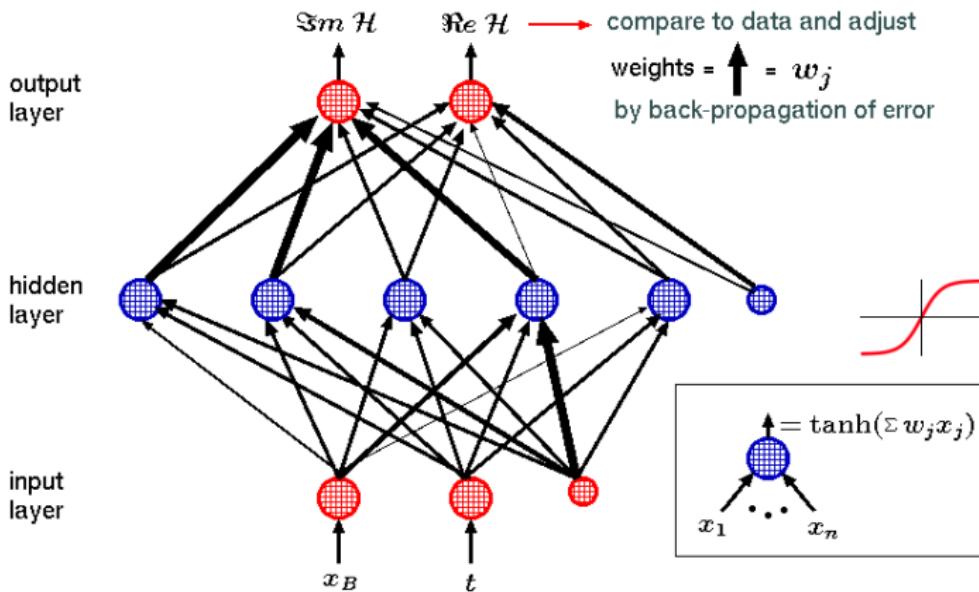


Including data with polarized target

- KMM12: $\chi^2/n_{\text{d.o.f.}} = 124.1/80$, strictly speaking not a good fit, but best what we have at the moment



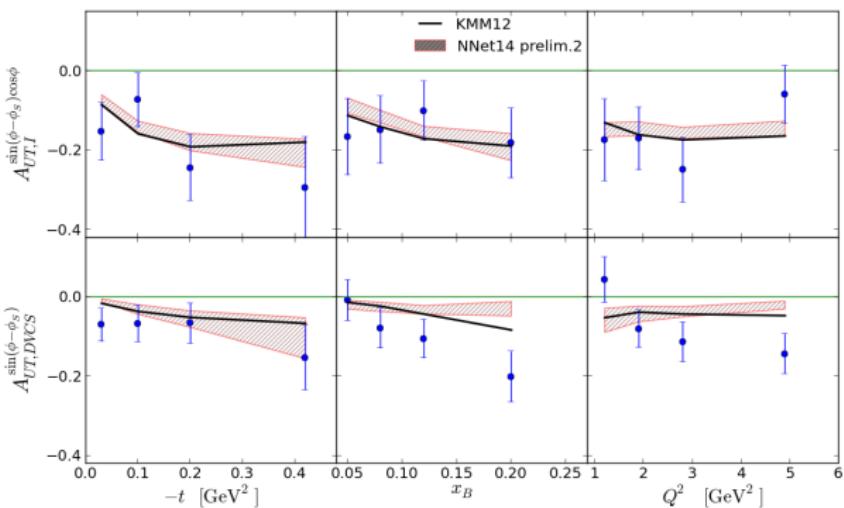
Multilayer perceptron



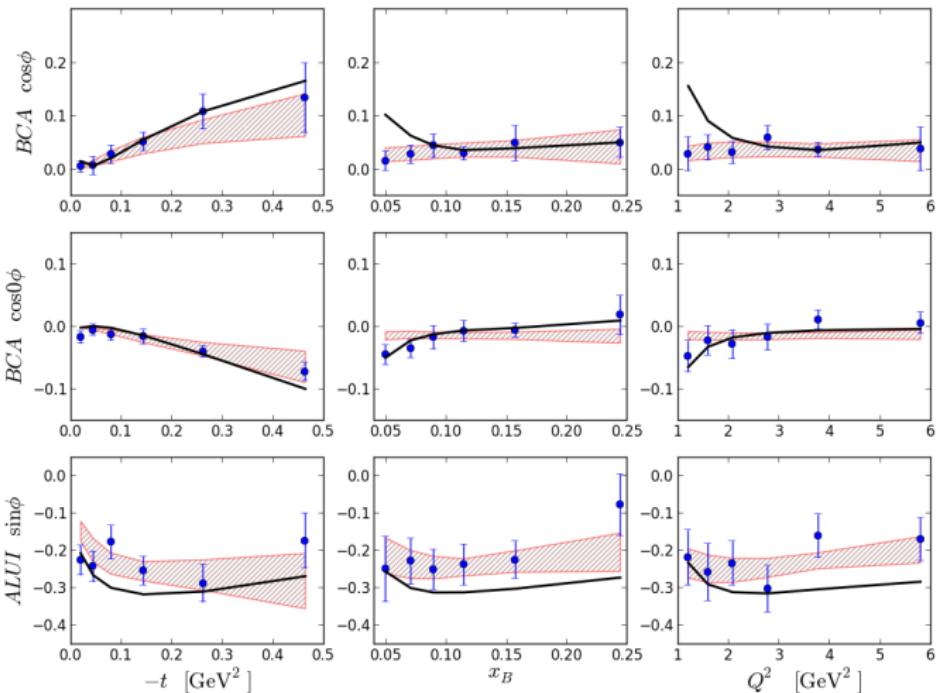
- Essentially a least-squares fit of a complicated many-parameter function. $f(x) = \tanh(\sum w_i \tanh(\sum w_j \dots))$
⇒ no theory bias

Preliminary neural Net HERMES fit

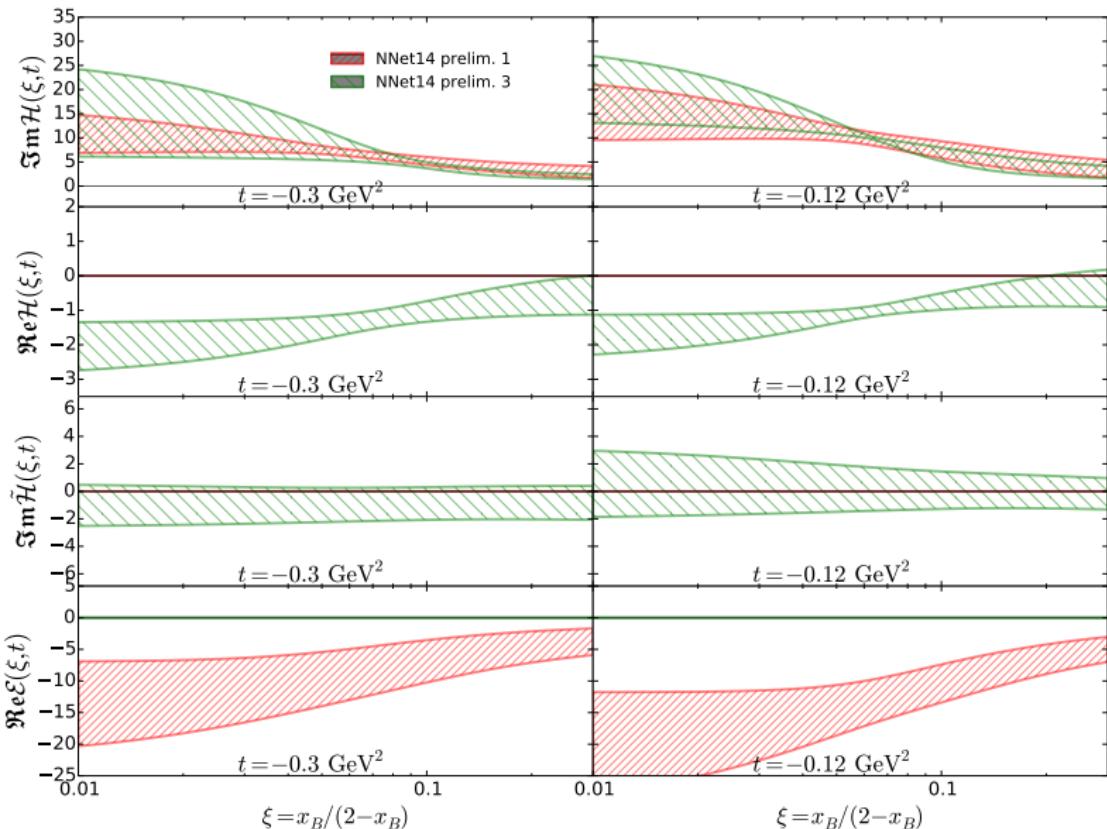
- Fit to all HERMES DVCS data with two types of neural nets
 - $(x_B, t) - (7 \text{ neurons}) - (\Im \mathcal{H}, \Re \mathcal{H}, \Im \tilde{\mathcal{H}})$: $\chi^2/n_{\text{pts}} = 135.4/144$
 - $(x_B, t) - (7 \text{ neurons}) - (\Im \mathcal{H}, \Re \mathcal{E})$: $\chi^2/n_{\text{pts}} = 120.2/144$



Neural Net HERMES fit - BSA/BCA

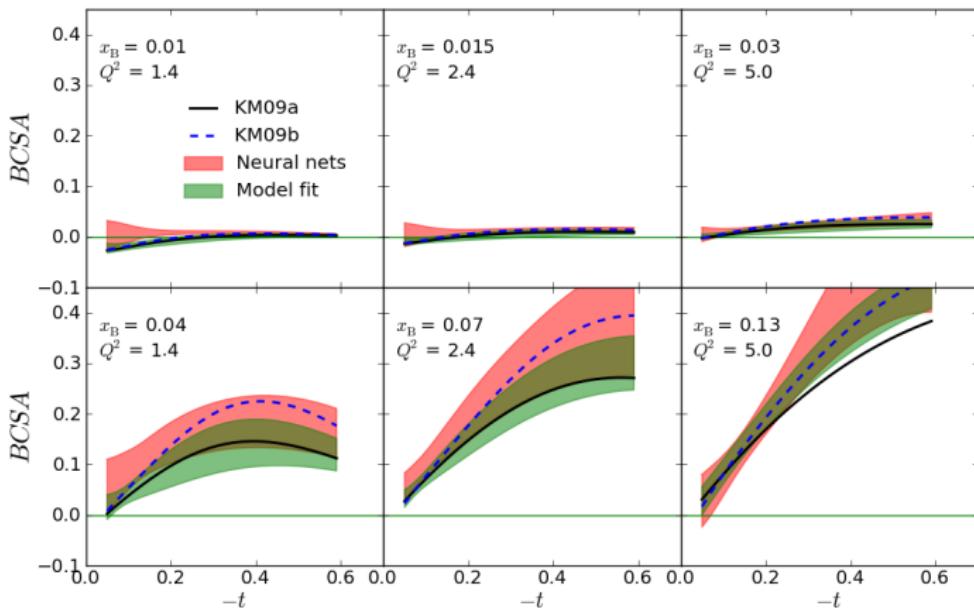


Neural Net HERMES fit - CFFs

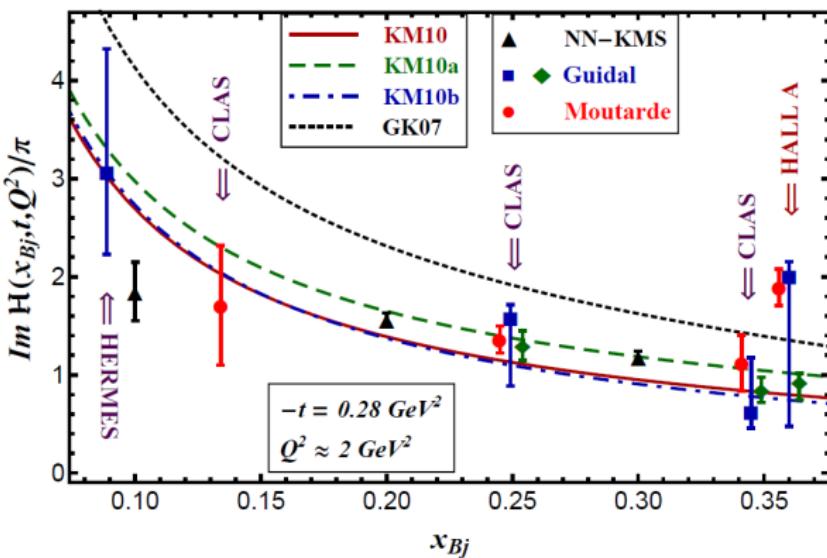


Prediction for COMPASS-II BCSA

$$BCSA = \frac{d\sigma_{\mu\downarrow+} - d\sigma_{\mu\uparrow-}}{d\sigma_{\mu\downarrow+} + d\sigma_{\mu\uparrow-}} \quad (E_\mu = 160 \text{ GeV})$$



Comparison to others



[Guidal '08, Guidal and Moutarde '09], seven CFF fit (blue squares), [Guidal '10] \mathcal{H} , $\tilde{\mathcal{H}}$ CFF fit (green diamonds), [Moutarde '09] H GPD fit (red circles). Also reasonable agreement with [Goloskokov and Kroll].

New directions

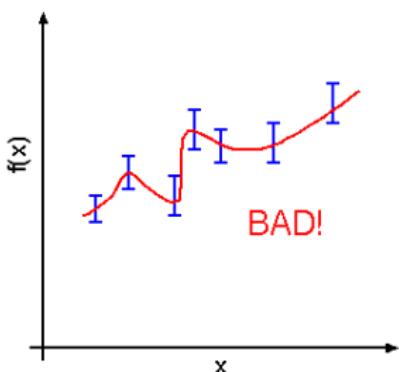
- Improved global LO fits with **all** unpolarized and polarized proton data.
- Adding deeply virtual **meson** production and going **NLO**
[Müller, Lautenschlager, Schäfer '13]
- Including higher twists
- Global neural network fits

Function fitting by a neural net

- **Theorem:** Given enough neurons, any smooth function $f(x_1, x_2, \dots)$ can be approximated to any desired accuracy. Single hidden layer is sufficient (but not always most efficient).

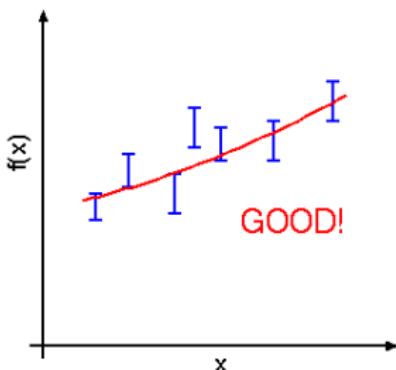
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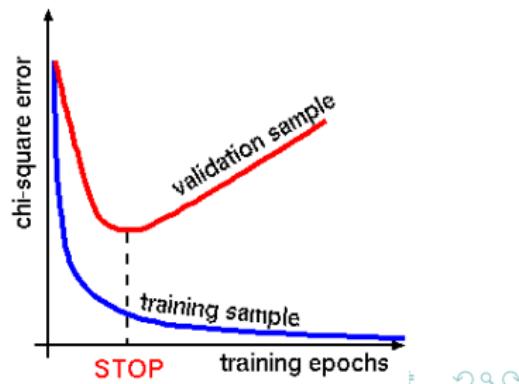
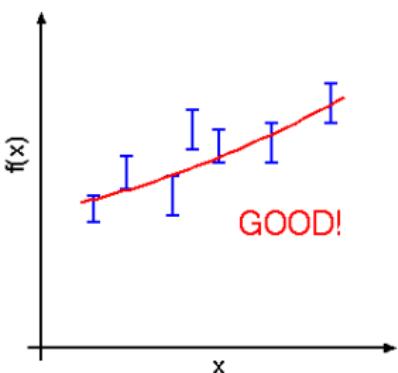
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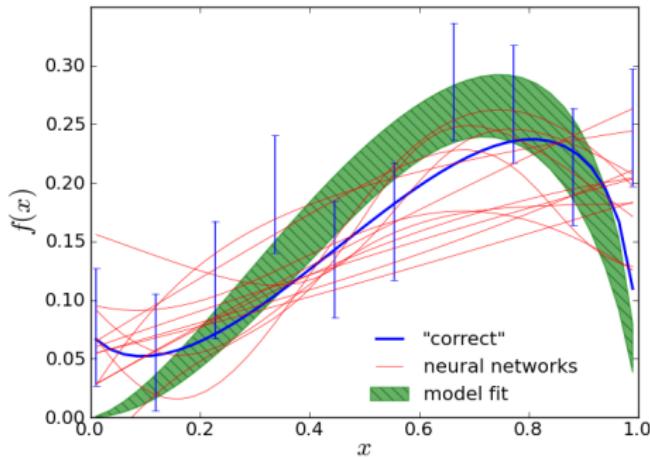
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- With simple training of neural nets to data there is a danger of **overfitting** (a.k.a. overtraining)
- **Solution:** Divide data (randomly) into two sets: *training sample* and *validation sample*. Stop training when error of validation sample starts increasing.



Toy fitting example

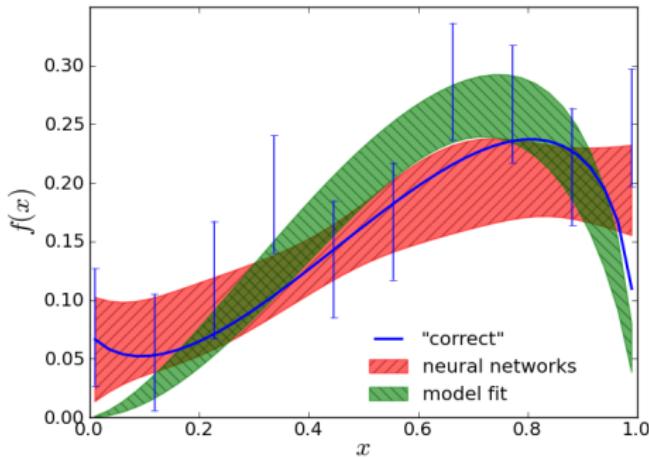
- Fit to data generated according to function (which we pretend not to know).



- Fit with
 - Standard Minuit fit with ansatz $f(x) = x^a(1 - x)^b$
 - Neural network fit

Toy fitting example

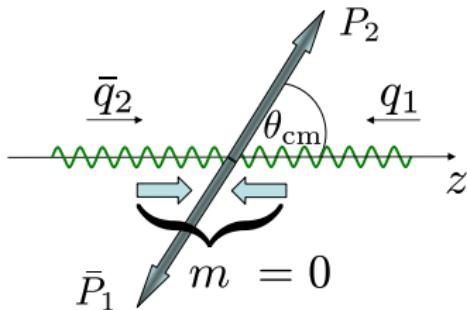
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Modelling conformal moments of GPDs (I)

- How to model η -dependence of GPD's $H_j(\eta, t)$?
- Idea: consider crossed t -channel process $\gamma^*\gamma \rightarrow p\bar{p}$

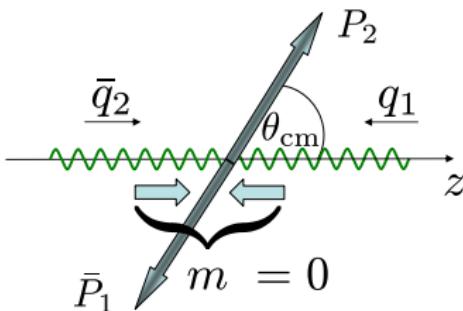


When crossing back
to DVCS channel we
have:

$$\cos \theta_{cm} \rightarrow -\frac{1}{\eta}$$

Modelling conformal moments of GPDs (I)

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When crossing back to DVCS channel we have:

$$\cos \theta_{\text{cm}} \rightarrow -\frac{1}{\eta}$$

- ... and dependence on θ_{cm} in t -channel is given by SO(3) partial wave decomposition of $\gamma^*\gamma$ scattering

$$\mathcal{H}(\eta, \dots) = \mathcal{H}^{(t)}(\cos \theta_{\text{cm}} = -\frac{1}{\eta}, \dots) = \sum_J (2J+1) f_J(\dots) d_{0,\nu}^J(\cos \theta)$$

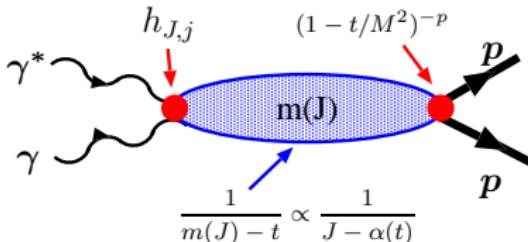
- $d_{0,\nu}^J$ — Wigner SO(3) functions (Legendre, Gegenbauer, ...)
 $\nu = 0, \pm 1$ — depending on hadron helicities

Modelling conformal moments of GPDs (II)

- OPE expansion of both \mathcal{H} and $\mathcal{H}^{(t)}$ leads to

$$H_j(\eta, t) = \eta^{j+1} H_j^{(t)}(\cos \theta = -\frac{1}{\eta}, s^{(t)} = t)$$

- and t -channel partial waves are modelled as:

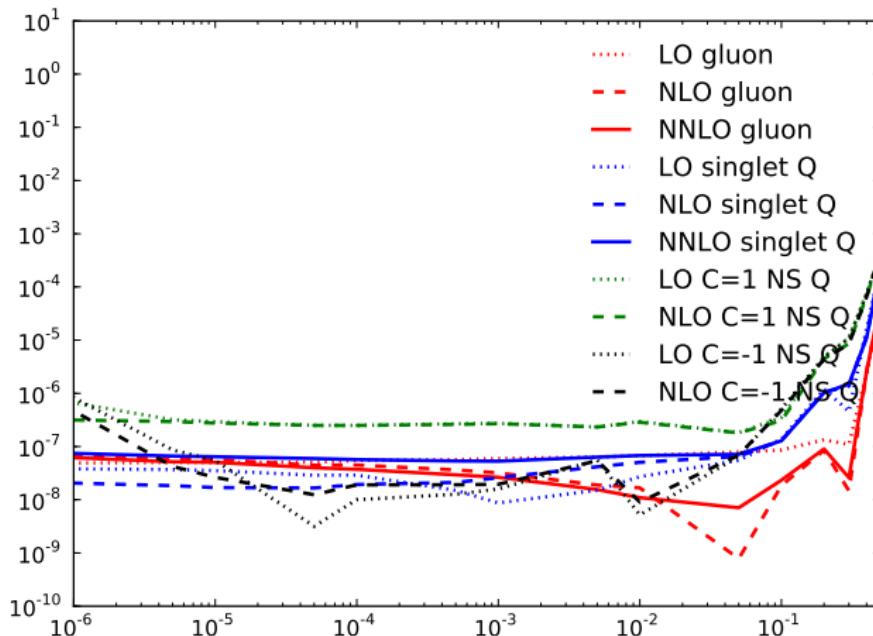


$$H_j(\eta, t) = \sum_J^{j+1} h_{J,j} \frac{1}{J - \alpha(t)} \frac{1}{\left(1 - \frac{t}{M^2(J)}\right)^p} \eta^{j+1-J} d_{0,\nu}^J$$

- Similar to “dual” parametrization [Polyakov, Shuvaev '02]

Checking the evolution code

- We checked agreement in the forward limit with QCD PEGASUS code for PDF evolution [Vogt '04]

GeParD vs. Pegasus @ 10000 GeV 2 

Dispersion-relation access to GPDs at LO

[Teryaev '05; K.K., Müller and Passek-K. '07, '08; Diehl and Ivanov '07]

- LO perturbative prediction is “handbag” amplitude

$$\mathcal{H}(\xi, t, Q^2) \stackrel{\text{LO}}{=} \int_{-1}^1 dx \left(\frac{1}{\xi - x - i\epsilon} - \frac{1}{\xi + x - i\epsilon} \right) H(x, \xi, t, Q^2)$$

- giving access to GPD on the “cross-over” line $\eta = x$

$$\frac{1}{\pi} \Im \mathcal{H}(\xi = x, t, Q^2) \stackrel{\text{LO}}{=} H(x, x, t, Q^2) - H(-x, x, t, Q^2)$$

- while dispersion relation connects it to $\Re \mathcal{H}$

$$\Re \mathcal{H}(\xi, t, Q^2) =$$

$$\frac{1}{\pi} \text{PV} \int_0^1 d\xi' \left(\frac{1}{\xi - \xi'} - \frac{1}{\xi + \xi'} \right) \Im \mathcal{H}(\xi', t, Q^2) + \mathcal{C}_{\mathcal{H}}(t, Q^2)$$

Fit results - LO

- For consistency, we don't take standard PDFs, but fit GPDs to DIS data. This determines N_{sea} , N_G , $\alpha_{\text{sea}}(0)$ and $\alpha_G(0)$, leaving only M_0^{sea} , s_{sea} and s_G for DVCS data
- χ^2 values:

model	α_s	$\chi^2/\text{d.o.f. DIS}$	$\chi^2/\text{d.o.f. DVCS}$	$\chi_t^2/\text{n.o.p.}$	$\chi_W^2/\text{n.o.p.}$	$\chi_Q^2/\text{n.o.p.}$
I, dipole	LO	49.7/82	280./100	181./56	63.6/29	36.2/16
I, exp.	LO	49.7/82	316./100	192./56	79./29	44.9/16
nl, dipole	LO	49.7/82	95.9/98	53.2/56	27./29	15.8/16
nl, exp.	LO	49.7/82	97.9/98	49.1/56	31.2/29	17.7/16
Σ , dipole	LO	49.7/82	101./98	57.7/56	27.4/29	16./16
Σ , exp.	LO	49.7/82	102./98	51./56	32.3/29	18.6/16
I, dipole	LO	321./182		189./56	51.1/29	27.9/16

- Parameter values:

model	α_s	N^{sea}	$\alpha^{\text{sea}}(0)$	$(M^{\text{sea}})^2$ [GeV 2]	s^{sea}	$\alpha^G(0)$	s^G	B^{sea} [GeV $^{-2}$]	b^{eff} [GeV $^{-2}$]	BCA
I, dipole	LO	0.152	1.158	0.062		1.247		33.	5.7	0.19
I, exp.	LO	0.152	1.158			1.247		29.	5.1	0.23
nl, dipole	LO	0.152	1.158	0.48	-0.15	1.247	-0.81	4.8	5.5	0.13
nl, exp.	LO	0.152	1.158		-0.18	1.247	-0.86	3.1	5.8	0.14
Σ , dipole	LO	0.152	1.158	0.42	-11.	1.247	-32.	5.4	5.5	0.14
Σ , exp.	LO	0.152	1.158		-13.	1.247	-34.	3.1	5.8	0.15

(boldface numbers = bad fits)

Fit results - NLO

- χ^2 values:

model	α_s	$\chi^2/\text{d.o.f}$ DIS	$\chi^2/\text{d.o.f}$ DVCS	$\chi_t^2/\text{n.o.p}$	$\chi_W^2/\text{n.o.p}$	$\chi_Q^2/\text{n.o.p}$
I	NLO($\overline{\text{MS}}$)	71.6/82	148./100	77.6/56	36.8/29	33.9/16
I	NLO($\overline{\text{CS}}$)	71.6/82	105./100	62.9/56	25.1/29	17./16
nl	NLO($\overline{\text{MS}}$)	71.6/82	102./98	60.2/56	23.9/29	17.5/16
nl	NLO($\overline{\text{CS}}$)	71.6/82	104./98	61.4/56	24.9/29	18.1/16
Σ	NLO($\overline{\text{MS}}$)	71.6/82	101./98	60./56	23.9/29	17.5/16
Σ	NLO($\overline{\text{CS}}$)	71.6/82	104./98	61.5/56	24.9/29	18.1/16

- Parameter values:

model	α_s	N^{sea}	$\alpha^{\text{sea}}(0)$	$(M^{\text{sea}})^2$	s^{sea}	$\alpha^G(0)$	s^G	B^{sea}	b^{eff}	BCA
I	NLO($\overline{\text{MS}}$)	0.168	1.128	0.71		1.099		3.5	5.0	0.10
I	NLO($\overline{\text{CS}}$)	0.168	1.128	0.57		1.099		4.2	5.7	0.09
nl	NLO($\overline{\text{MS}}$)	0.168	1.128	0.59	0.04	1.099	0.02	4.0	5.6	0.09
nl	NLO($\overline{\text{CS}}$)	0.168	1.128	0.58	-0.01	1.099	-0.01	4.1	5.6	0.09
Σ	NLO($\overline{\text{MS}}$)	0.168	1.128	0.60	3.10	1.099	1.10	4.0	5.7	0.09
Σ	NLO($\overline{\text{CS}}$)	0.168	1.128	0.58	-0.42	1.099	-0.58	4.1	5.6	0.09

(boldface numbers = bad fits)

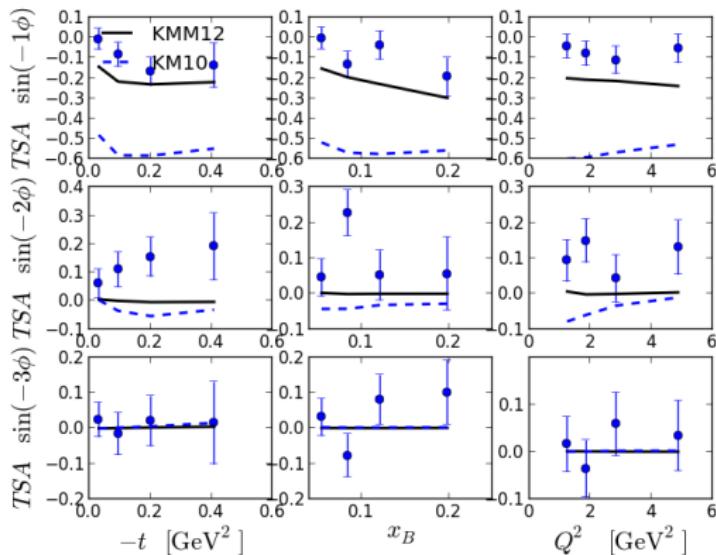
- $s^{\text{sea},G}$ small \rightarrow skewness ratio $r \sim 1.5$

Parameter values

KMM12	KM10
-----	-----
Mv = 0.951 +- 0.282	Mv = 4.00 +- 3.33
rv = 1.121 +- 0.099	rv = 0.62 +- 0.06
bv = 0.400 +- 0.000	bv = 0.40 +- 0.67
C = 1.003 +- 0.565	C = 8.78 +- 0.98
MC = 2.080 +- 3.754	MC = 0.97 +- 0.11
tMv = 3.523 +- 13.17	tMv = 0.88 +- 0.24
trv = 1.302 +- 0.206	trv = 7.76 +- 1.39
tbv = 0.400 +- 0.001	tbv = 2.05 +- 0.40
rpi = 3.837 +- 0.141	rpi = 3.54 +- 1.77
Mpi = 4.000 +- 0.036	Mpi = 0.73 +- 0.37
M02S = 0.462 +- 0.032	M02S = 0.51 +- 0.02
SECS = 0.313 +- 0.039	SECS = 0.28 +- 0.02
THIS = -0.138 +- 0.012	THIS = -0.13 +- 0.01
SECG = -2.771 +- 0.228	SECG = -2.79 +- 0.12
THIG = 0.945 +- 0.107	THIG = 0.90 +- 0.05

Polarized target (II)

- Surprisingly large $\sin(2\phi)$ harmonic of A_{UL} cannot be described within this leading twist framework



KM models are available at WWW

- Google for "gpd page" — get binary code for cross sections

```
% xs.exe
```

```
xs.exe ModelID Charge Polarization Ee Ep xB Q2 t phi
```

returns cross section (in nb) for scattering of lepton of energy Ee
on unpolarized proton of energy Ep. Charge=-1 is for electron.

ModelID is one of

- 0 debug, always returns 42,
- 1 KM09a - arXiv:0904.0458 fit without Hall A,
- 2 KM09b - arXiv:0904.0458 fit with Hall A,
- 3 KM10 - preliminary hybrid fit with LO sea evolution, from Trento presentation,
- 4 KM10a - preliminary hybrid fit with LO sea evolution, without Hall A data
- 5 KM10b - preliminary hybrid fit with LO sea evolution, with Hall A data

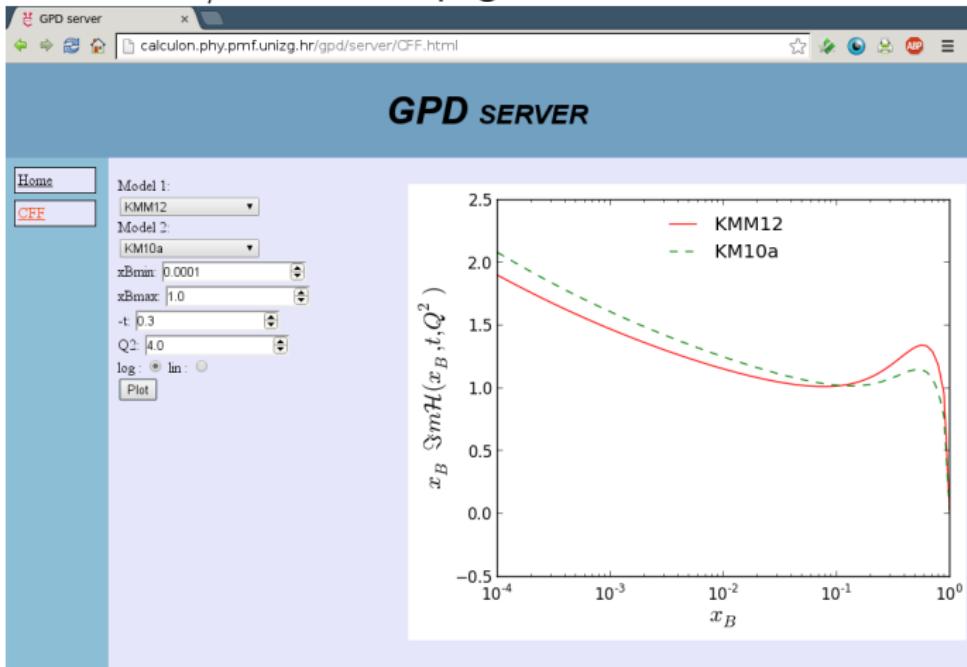
xB Q2 t phi -- usual kinematics (phi is in Trento convention)

```
% xs.exe 1 -1 1 27.6 0.938 0.111 3. -0.3 0
```

```
0.18584386497251
```

GPD page and server

- Durham-like CFF/GPD server page



- Do we need "Les Houches Accord" CFF/GPD interface?