Revealing proton structure with neural networks

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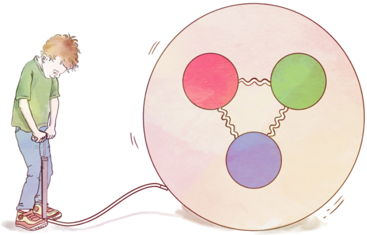
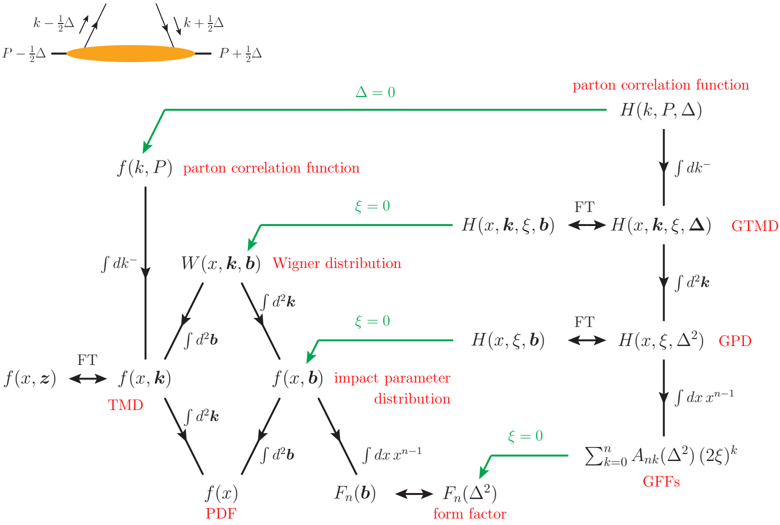


Outline

1. **Introduction: proton structure by GPDs**
2. **Quark pressure (using neural nets)**
3. **Flavor separation (using neural nets)**
4. **Summary**

Family tree of hadron structure functions

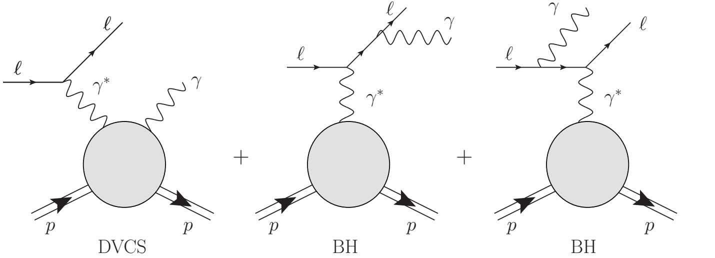


[Fig. by Markus Diehl]

($\xi \to \eta$ from now on)

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.

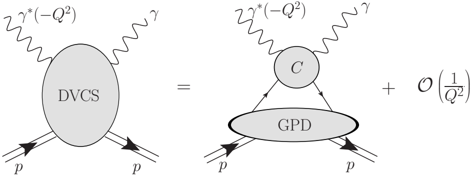
DVCS $\longrightarrow$ CFFs $\longrightarrow$ GPDs

- At leading order DVCS cross-section depends on four complex

Compton form factors (CFFs)

$$\mathcal{H}(\xi, t, Q^2), \quad \mathcal{E}(\xi, t, Q^2), \quad \widetilde{\mathcal{H}}(\xi, t, Q^2), \quad \widetilde{\mathcal{E}}(\xi, t, Q^2)$$

- [Collins et al. '98]



- CFFs are convolution:

$$^{a}\mathcal{H}(\xi, t, Q^2) = \int \mathrm{d}x \; C^a(x, \xi, \frac{Q^2}{Q_0^2}) \; H^a(x, \xi, t, Q_0^2)$$

$a{=}q, G$

- $H^a(x, \eta, t, Q_0^2)$ — Generalized parton distribution (GPD)

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

Three "classical" objectives of GPD studies

- Both meanings are valid:
  - "classical" = well known, venerable
  - "classical" = understandable from non-quantum viewpoint

❶ Ji's "sum rule"

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

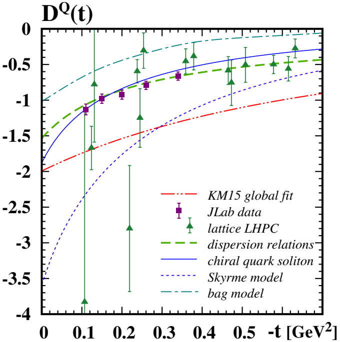
❷ 3D tomography

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

❸ Pressure distribution in the nucleon — directly related to subtraction constant $\Delta(t)$ of CFF dispersion relation — directly related to GPD "D-term" [Polyakov '03, Teryaev '05]

$$\Delta(t) = \mathfrak{Re}\,\mathcal{H}(\xi,t) - \frac{1}{\pi}\mathrm{P.V.}\int_0^1 dx \frac{2x}{\xi^2 - x^2}\,\mathfrak{Im}\,\mathcal{H}(x,t)$$

Extractions of D-term

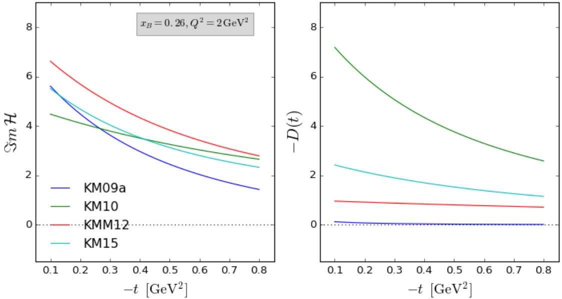


[Polyakov, Schweitzer '18]

- Several model and lattice QCD calculations
- But can we measure it?
- [Burkert, Elouadrhiri, Girod '18 (Nature)] use CLAS DVCS data to extract D-term with great precision!

Extractions of D-term in KM global fits

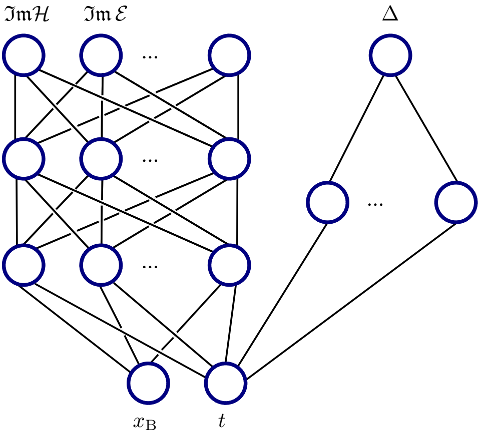
- In KM fits [K.K., D. Müller] systematic uncertainty due to model selection is unknown and for D-term seems very large:



- To fix this, we turn to neural nets method.

Neural nets fits

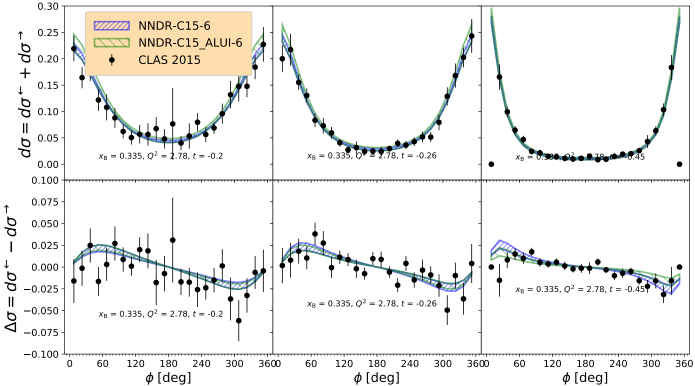
Fitting with neural networks



- Essentially a least-square fit of a complicated many-parameter function. $\Rightarrow$ no theory bias

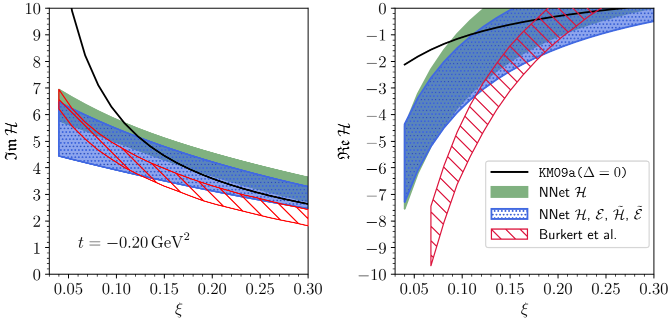
Study A: Neural net fit to CLAS 2015 data

- Description of CLAS 2015 $d\sigma$ and $\Delta\sigma$ measurements [Jo et al. '15] is good:



Resulting CFF $\mathcal{H}$

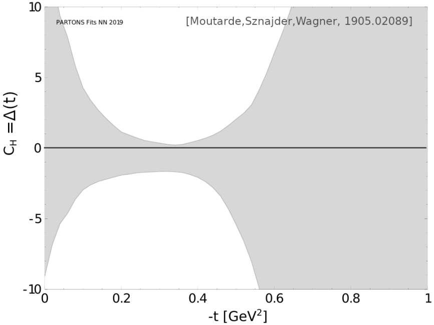
- $\mathfrak{Im}\,\mathcal{H}$ — good agreement with [Burkert et al., Nature '18]
- $\mathfrak{Re}\,\mathcal{H}$ — only qualitative agreement



- Resulting $\Delta(t) = 0.78 \pm 1.5$, with almost no dependence on t! So D-term (and pressure) are consistent with zero in this model-independent approach! [K.K., Nature '19]

Subtraction constant by PARTONS group

- Neural net fit to global DVCS data still results in a D-term consistent with zero ☹

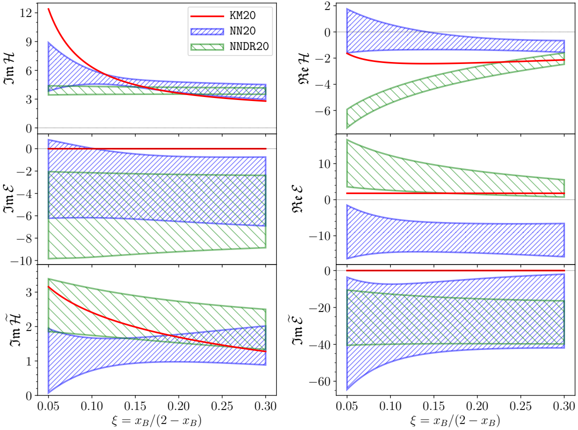


- [Moutarde, Sznajder, Wagner '19]

Flavor separation by neural nets

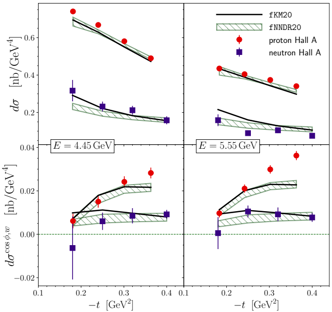
Study B: Neural net fit to JLab fixed target data

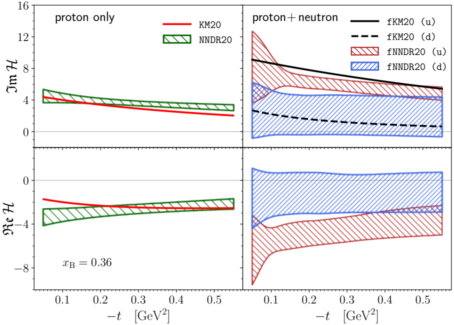
- [Čuić, K.K. and Schäfer '20]
- Extraction of 6 CFFs:



Flavor separation using neutron DVCS

- Including neutron DVCS data recently measured by Hall A at JLab [Benali et al. '20]





Summary

- Neural network method has a unique capability of extraction of Compton form factors (and, later, GPDs) with reliable uncertainties
- More experimental and phenomenological work is needed to determine pressure distribution in a nucleon in a reliable and model-independent way.
- proton and neutron DVCS data enable clear separation of u and d quark flavor contributions to leading CFF $\mathcal{H}$.

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The End