Artificial neural network modelling of GPDs

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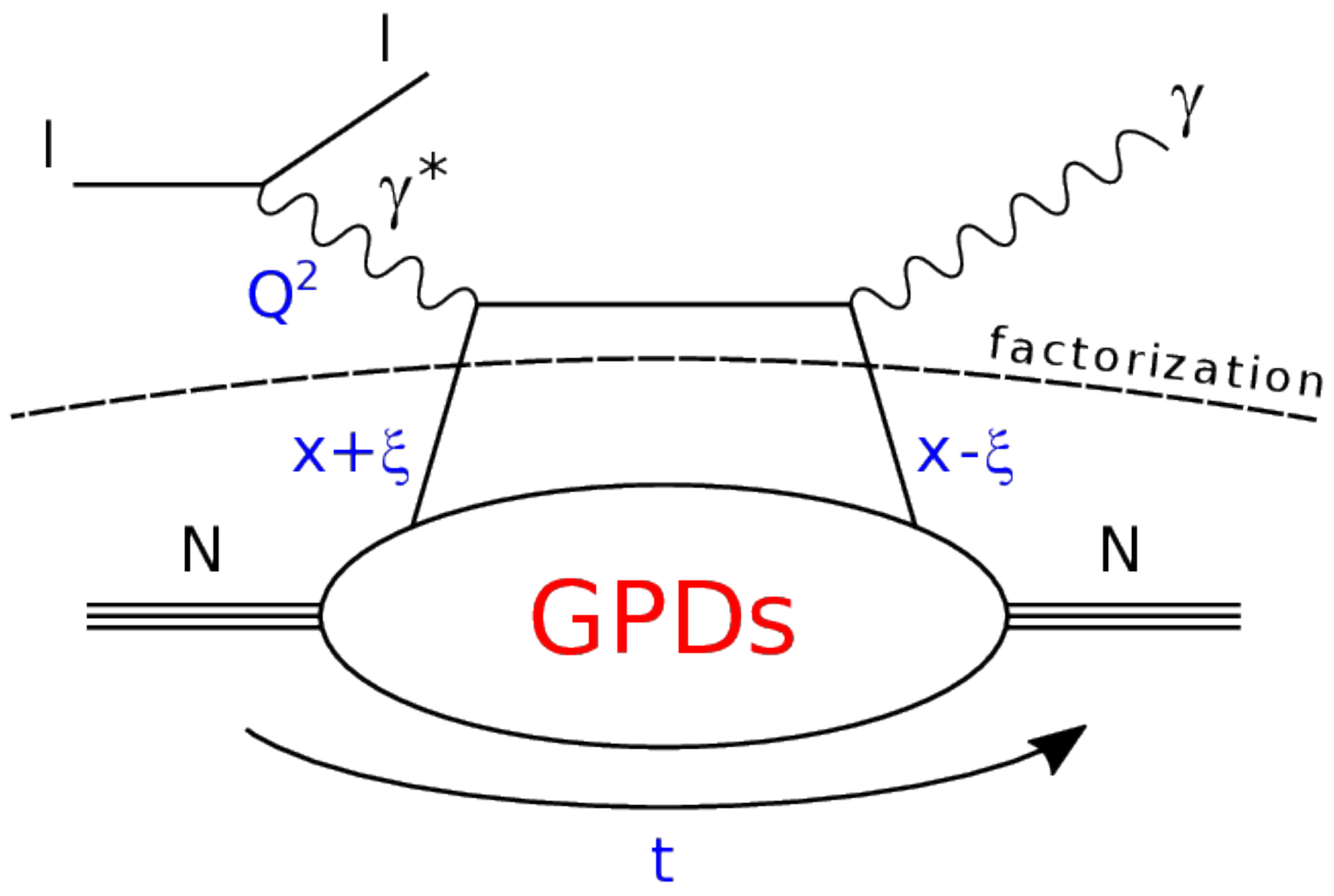
Deeply Virtual Compton Scattering (DVCS)



factorisation for $|t|/Q^2 \ll 1$

Chiral-even GPDs:
(helicity of parton conserved)

$H^{q,g}(x,\xi,t)$	$E^{q,g}(x,\xi,t)$	*for sum over parton helicities*
$\widetilde{H}^{q,g}(x,\xi,t)$	$\widetilde{E}^{q,g}(x,\xi,t)$	*for difference over parton helicities*
nucleon helicity conserved	*nucleon helicity changed*	

Reduction to PDF:

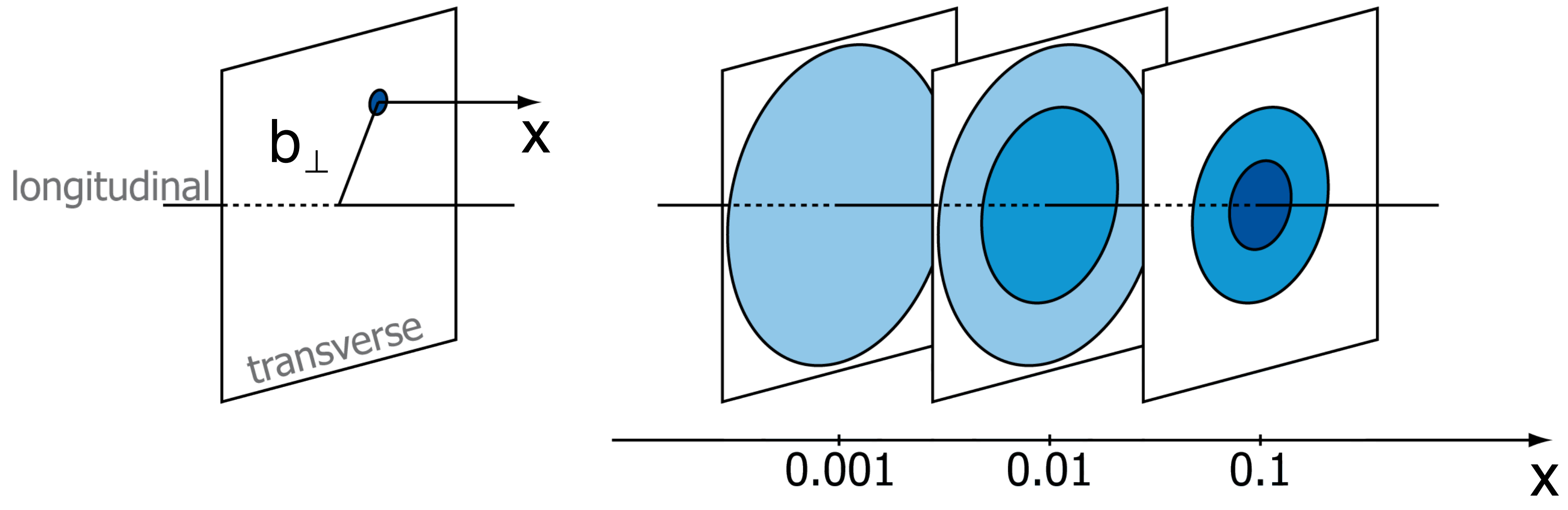
$$H(x, \xi = 0, t = 0) \equiv q(x)$$

Polynomiality - non-trivial consequence of Lorentz invariance:

$$\mathcal{A}_n(\xi, t) = \int_{-1}^{1} \mathrm{d}x x^n H(x, \xi, t) = \sum_{\substack{j=0 \\ \mathrm{even}}}^{n} \xi^j A_{n,j}(t) + \mathrm{mod}(n, 2) \xi^{n+1} A_{n,n+1}(t)$$

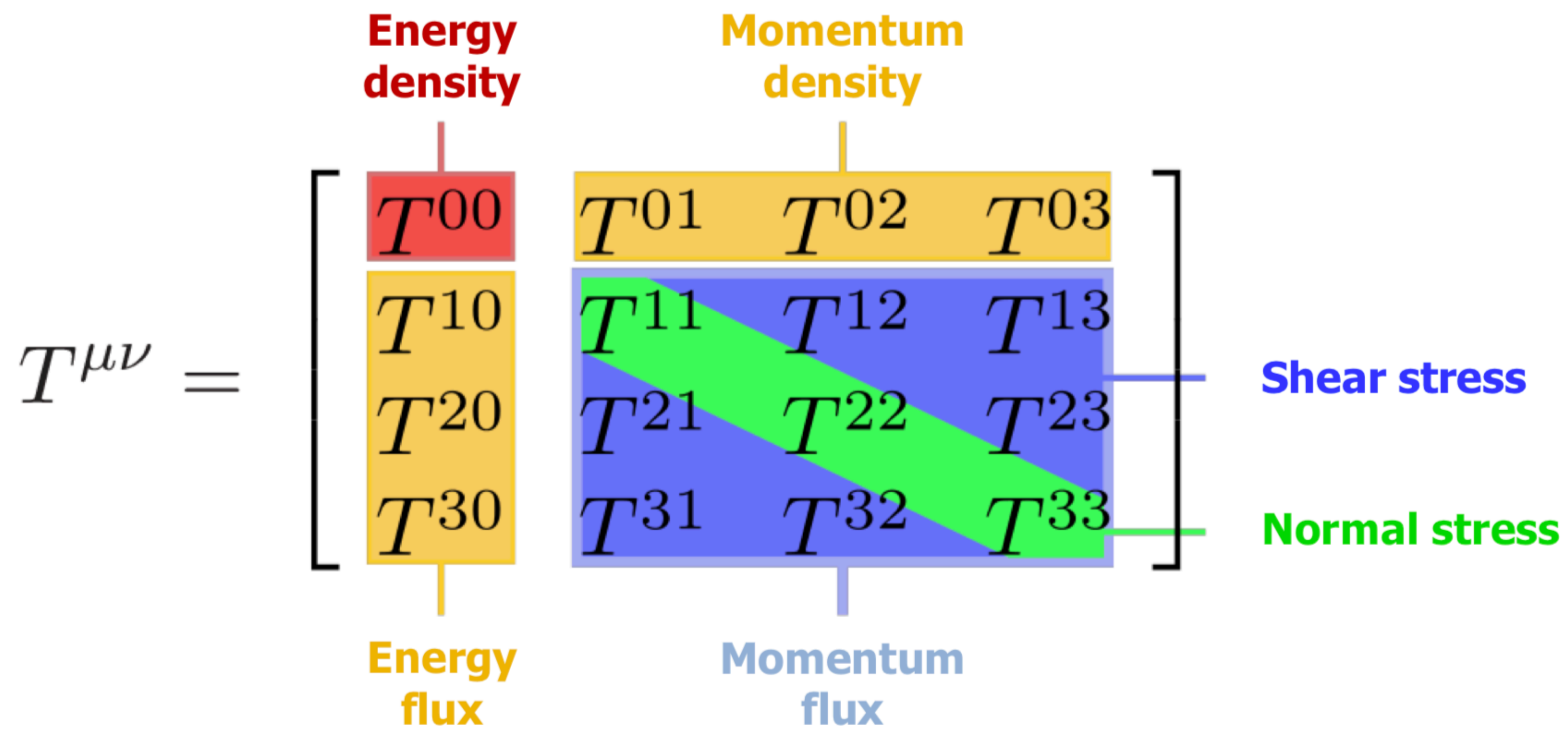
Positivity bounds - positivity of norm in Hilbert space, e.g.:

$$|H(x, \xi, t)| \leq \sqrt{q\left(\frac{x+\xi}{1+\xi}\right) q\left(\frac{x-\xi}{1-\xi}\right) \frac{1}{1-\xi^2}}$$



Nucleon tomography:

$$q(x, \mathbf{b}_\perp) = \int \frac{d^2\mathbf{\Delta}}{4\pi^2} e^{-i\mathbf{b}_\perp \cdot \mathbf{\Delta}} H^q(x, 0, t = -\mathbf{\Delta}^2)$$



Energy momentum tensor in terms of form factors (OAM and mechanical forces):

$$\langle p', s'|\widehat{T}^{\mu\nu}|p, s\rangle = \bar{u}(p', s')\Bigg[\frac{P^\mu P^\nu}{M} A(t) + \frac{\Delta^\mu \Delta^\nu - \eta^{\mu\nu}\Delta^2}{M} C(t) + M\eta^{\mu\nu}\bar{C}(t) + \frac{P^\mu i\sigma^{\nu\lambda}\Delta_\lambda}{4M}\left[A(t) + B(t) + D(t)\right] + \frac{P^\nu i\sigma^{\mu\lambda}\Delta_\lambda}{4M}\left[A(t) + B(t) - D(t)\right]\Bigg] u(p, s)$$

Motivation

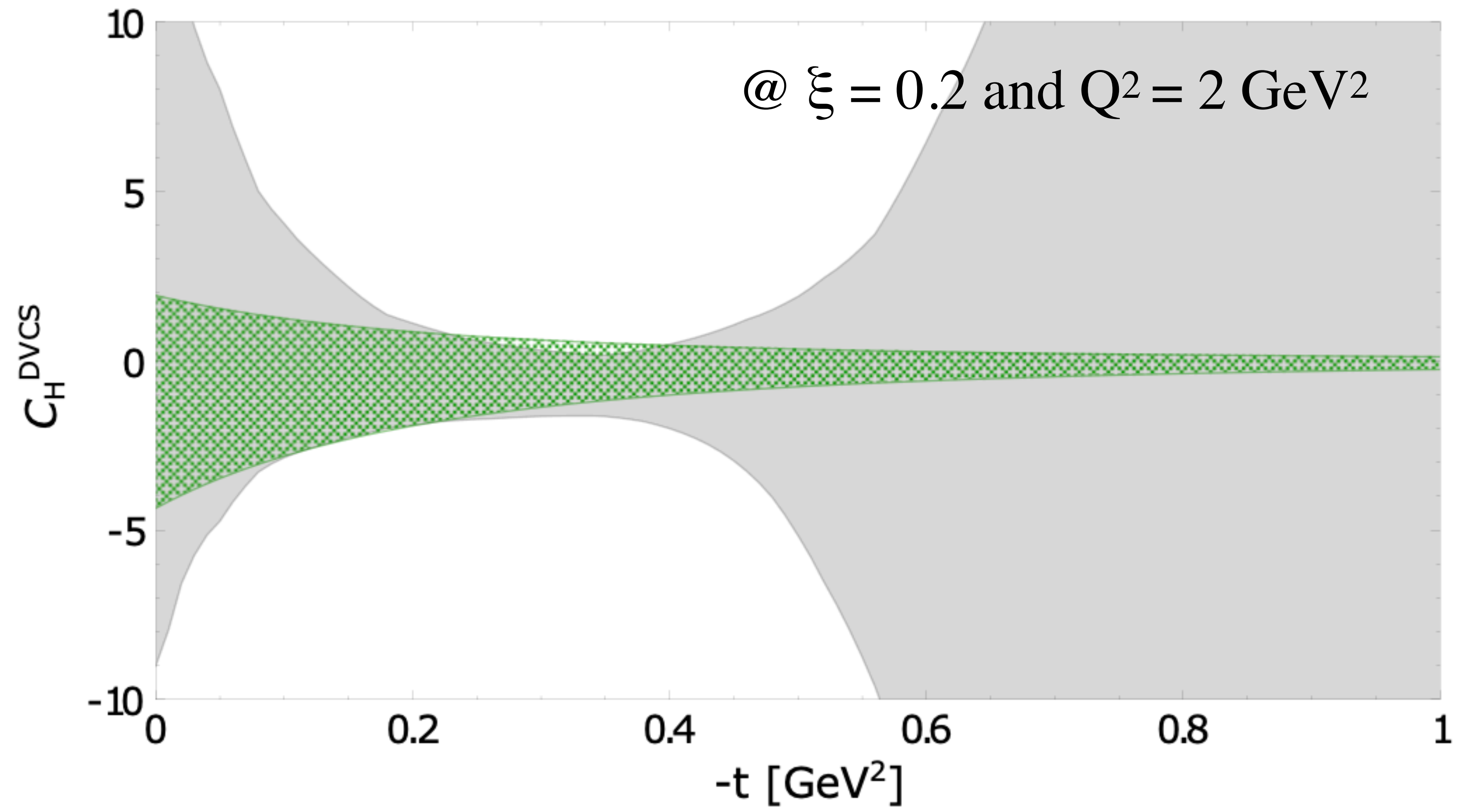
- Despite a substantial progress in both measurement and description of exclusive processes, and in lattice-QCD the problem of the model dependency of GPDs is still poorly addressed.

- Exceptions:
  - probing nucleon tomography at low-xB
  - extraction of D-term (see: *Nature 570 (2019) 7759, E1*, *EPJC 81 (2021) 4, 300 and below*)

ANN analysis

Model dependent extraction

$$d_1^{uds}(t, \mu_F^2) = d_1^{uds}(\mu_F^2)\left(1 - \frac{t}{\Lambda^2}\right)^{-\alpha} \qquad \alpha = 3 \qquad \Lambda = 0.8\ \mathrm{GeV}$$



- No GPD models that could be considered non-parametric → no tools to study model dependency of the extraction of GPDs, nucleon tomography and orbital angular momentum

Motivation

- This talk is based on: *EPJC 82 (2022) 3, 252*

Eur. Phys. J. C (2022) 82:252
https://doi.org/10.1140/epjc/s10052-022-10211-5

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Regular Article - Theoretical Physics

Artificial neural network modelling of generalised parton distributions

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- Modelling in (x, ξ)-space will be presented
- Then, modelling in (β, α)-space will be presented
- t-dependance neglected, but can be easily added

Polynomiality:

$$A_n(\xi) = \int_{-1}^{1} \mathrm{d}x x^n H(x,\xi) = \sum_{\substack{j=0 \\ \text{even}}}^{n} \xi^j A_{n,j} + \mathrm{mod}(n,2)\xi^{n+1} A_{n,n+1}$$

Let us express GPD by:

$$H^N(x,\xi) = \sum_{\substack{j=0 \\ \text{even}}}^{N} f_j(x)\xi^j$$

only even j as there is no odd power of ξ in polynomiality expansion

Support:

$$f_j(-1) = f_j(1) = 0$$

we want GPDs to vanish at |x| = 1

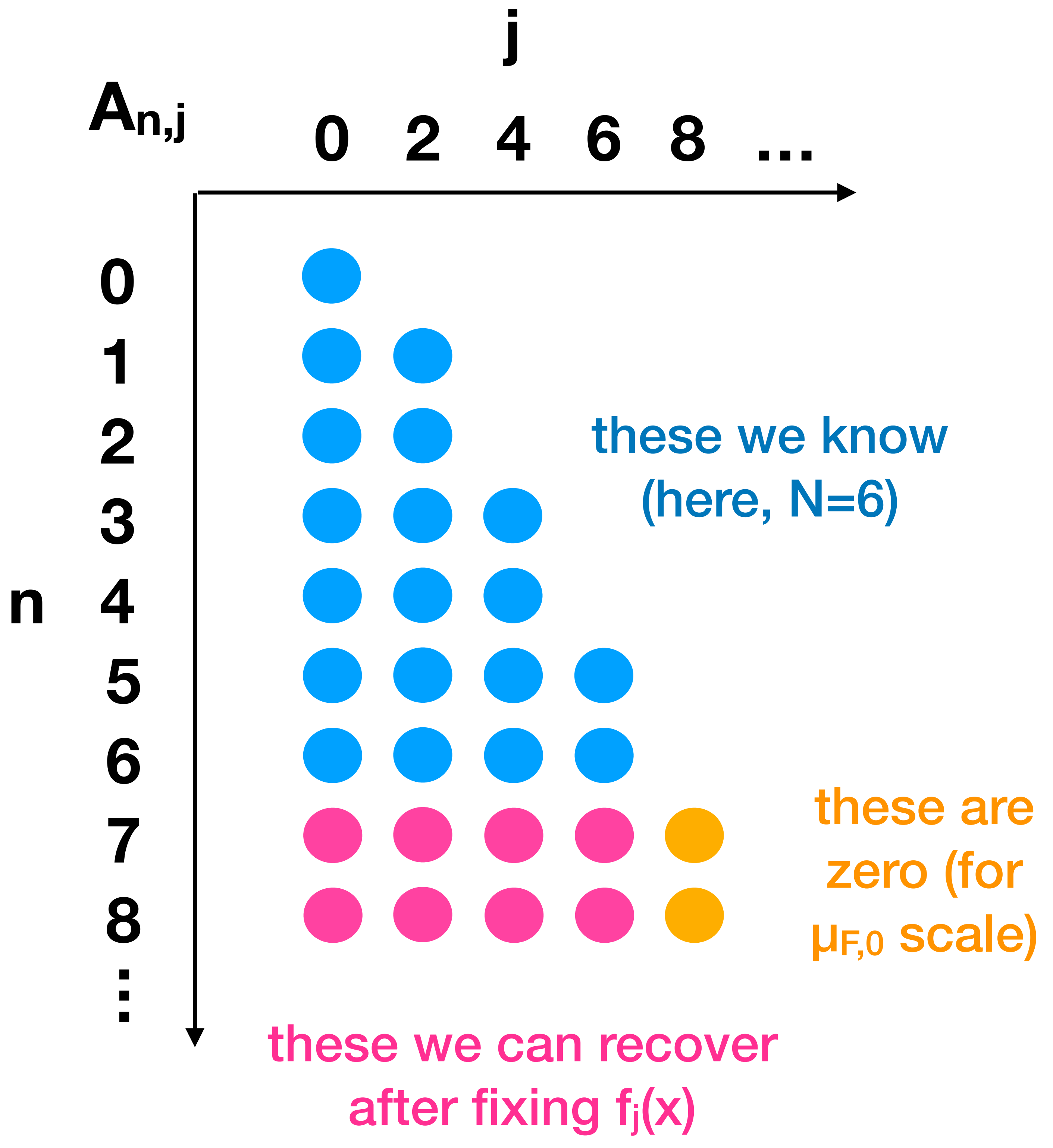
Mellin coefficients:

$$A_{n,j} = \int_{-1}^{1} \mathrm{d}x x^n f_j(x)$$

choice of $f_j(x)$ functional form is arbitrary

where e.g.:

$$A_{0,2} = \int_{-1}^{1} \mathrm{d}x f_0(x) = 0$$



Principles of modelling

Polynomial basis:

This basis leads to Dual Parameterisation → M. Polyakov, A. Shuvaev, hep-ph/0207153

Any attempt of describing GPDs by orthogonal polynomials will lead to this basis

$$f_j(x) = \sum_{i=0}^{N+2} w_{i,j} x^i$$

GPD will be expressed by sum of monomials $x^i \xi^j$

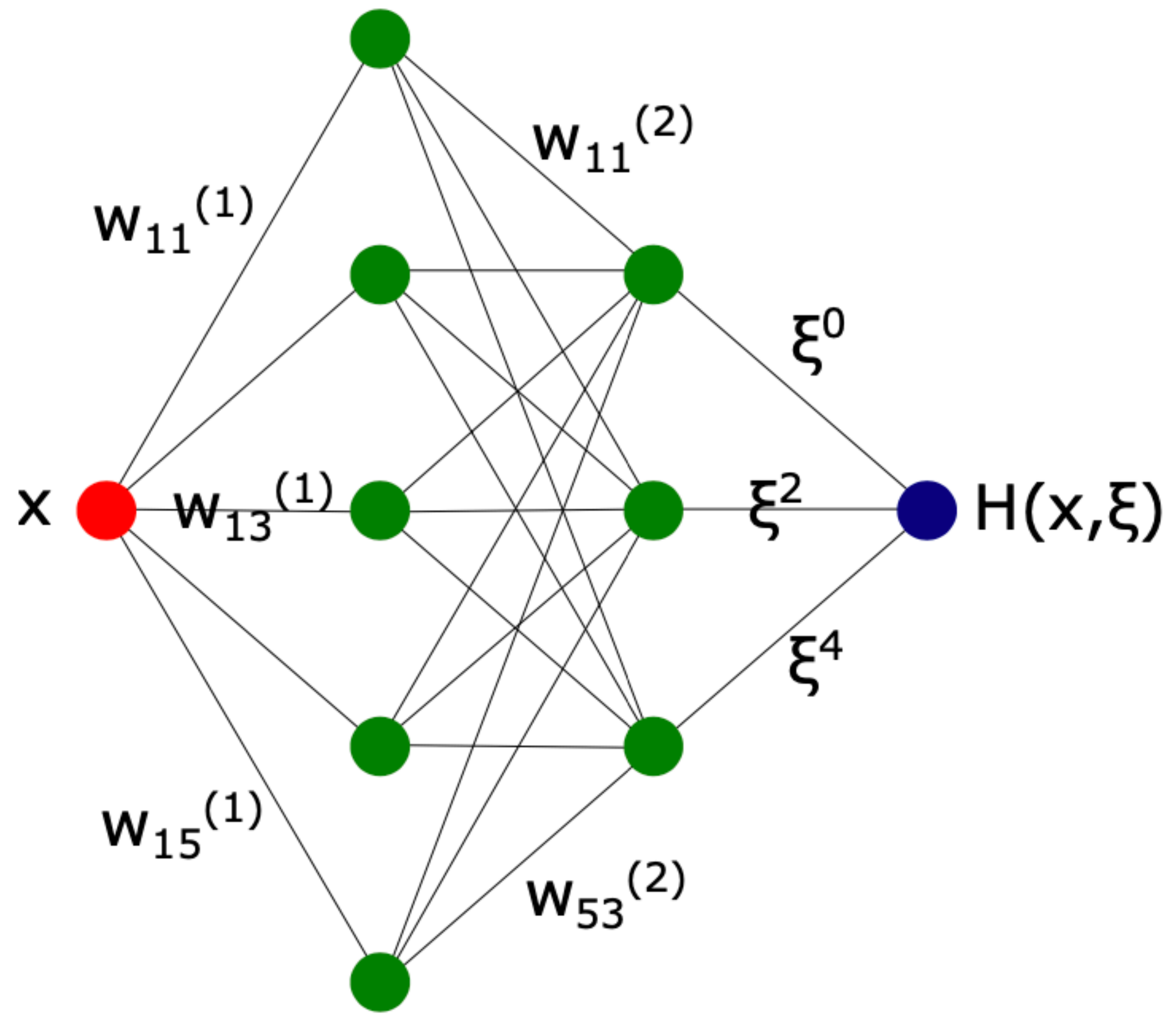
ANN basis:

New!

We can describe GPD by a single ANN

$$f_j(x) = \mathrm{ANN}_j(x)$$

GPD will be expressed by sum of ANNs multiplied by ξ^j



Demonstration of results

Test model (see e.g.: hep-ph/2110.06052):

$$H_\pi(x,\xi) = \Theta(x-|\xi|)\,\frac{30(1-x)^2(x^2-\xi^2)}{(1-\xi^2)^2} + \Theta(|\xi|-|x|)\,\frac{15(1-x)(\xi^2-x^2)(x+2x\xi+\xi^2)}{2\xi^3(1+\xi)^2}$$

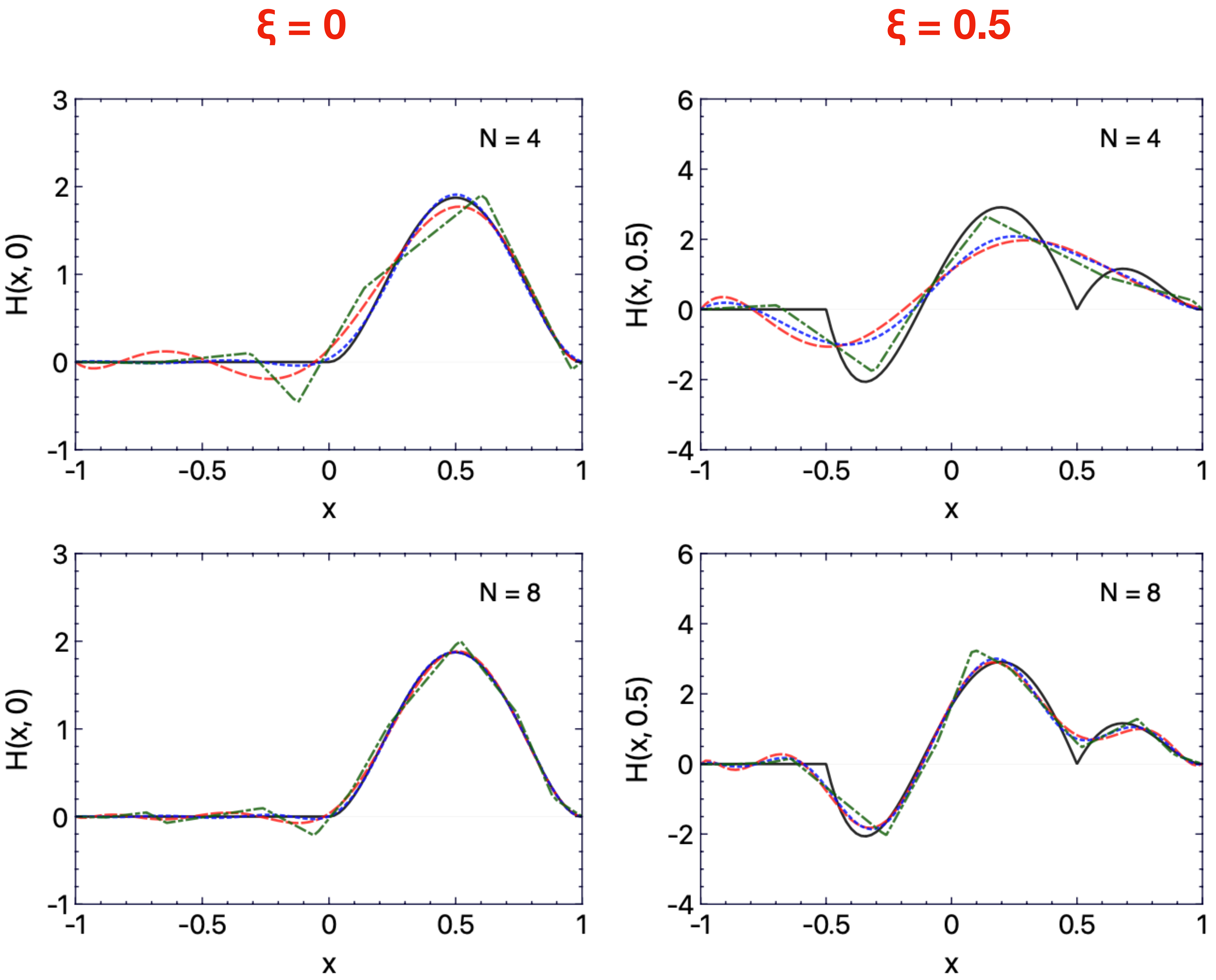
Polynomial basis

ANN basis - sigmoid

$$\varphi_k^{(2)}(\cdot) = \frac{1}{1+\exp(-(\cdot))}$$

ANN basis - ReLU

$$\varphi_k^{(2)}(\cdot) = (\cdot)\,\Theta(\cdot)$$



Note:

- *positivity not enforced here*
- *few extensions of this modelling possible, see the next slide*

Possible modifications

Basic:

$$H(x,\xi) = \sum_{\substack{j=0\\ \text{even}}}^{N} f_j(x)\xi^j$$

With explicit PDF:

$$H(x,\xi) = q(x) + \sum_{\substack{j=2\\ \text{even}}}^{N} f_j(x)\xi^j$$

Vanishing at x=xi:

$$H(x,\xi) = (x^2 - \xi^2)\sum_{\substack{j=0\\ \text{even}}}^{N} f_j(x)\xi^j$$

With D-term:

$$H(x,\xi) = D_{\text{term}}(x/\xi) + \sum_{\substack{j=0\\ \text{even}}}^{N} f_j(x)\xi^j$$

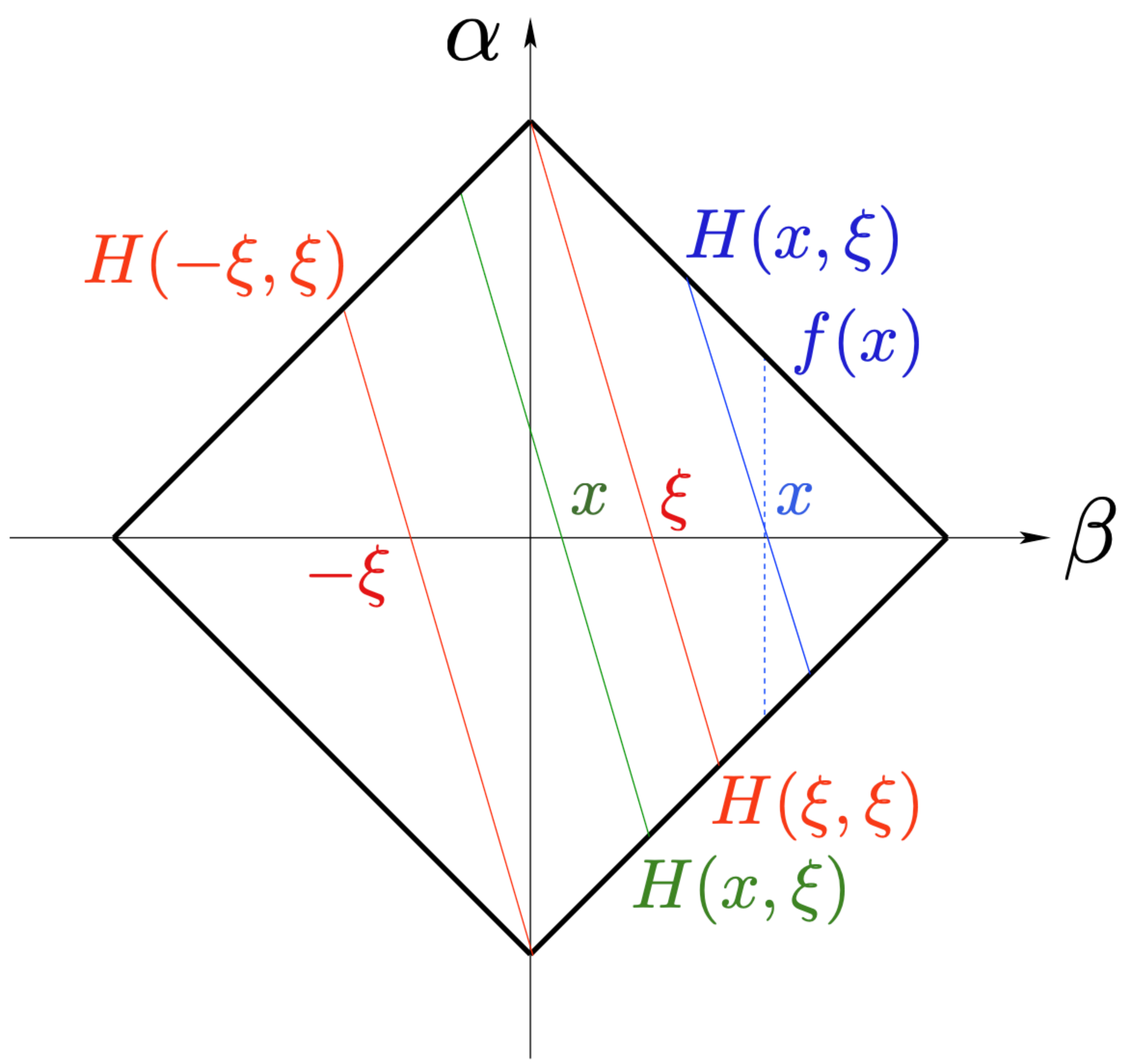
Double distribution:

$$H(x, \xi, t) = \int d\Omega \, F(\beta, \alpha, t)$$

where:

$$d\Omega = d\beta \, d\alpha \, \delta(x - \beta - \alpha\xi)$$

$$|\alpha| + |\beta| \leq 1$$



from PRD83, 076006, 2011

Principles of modelling

Double distribution:

$$(1-x^2)F_C(\beta,\alpha)+(x^2-\xi^2)F_S(\beta,\alpha)+\xi F_D(\beta,\alpha)$$

Classical term:

$$F_C(\beta,\alpha)=f(\beta)h_C(\beta,\alpha)\frac{1}{1-\beta^2}$$

$$f(\beta)=\mathrm{sgn}(\beta)q(|\beta|)$$

$$h_C(\beta,\alpha)=\frac{\mathrm{ANN}_C(|\beta|,\alpha)}{\int_{-1+|\beta|}^{1-|\beta|}\mathrm{d}\alpha\mathrm{ANN}_C(|\beta|,\alpha)}$$

Shadow term:

$$F_S(\beta,\alpha)=f(\beta)h_S(\beta,\alpha)$$

$$f(\beta)=\mathrm{sgn}(\beta)q(|\beta|)$$

$$h_S(\beta,\alpha)/N_S=\frac{\mathrm{ANN}_S(|\beta|,\alpha)}{\int_{-1+|\beta|}^{1-|\beta|}\mathrm{d}\alpha\mathrm{ANN}_S(|\beta|,\alpha)}-\frac{\mathrm{ANN}_{S'}(|\beta|,\alpha)}{\int_{-1+|\beta|}^{1-|\beta|}\mathrm{d}\alpha\mathrm{ANN}_{S'}(|\beta|,\alpha)}.$$

$$\mathrm{ANN}_{S'}(|\beta|,\alpha)\equiv\mathrm{ANN}_C(|\beta|,\alpha)$$

D-term:

$$F_D(\beta,\alpha)=\delta(\beta)D(\alpha)$$

$$D(\alpha)=(1-\alpha^2)\sum_{\substack{i=1\\ \mathrm{odd}}}d_iC_i^{3/2}(\alpha)$$

Modelling in (β, α)-space

V. Bertone et al.,
Phys. Rev. D 103 (2021) 11, 114019

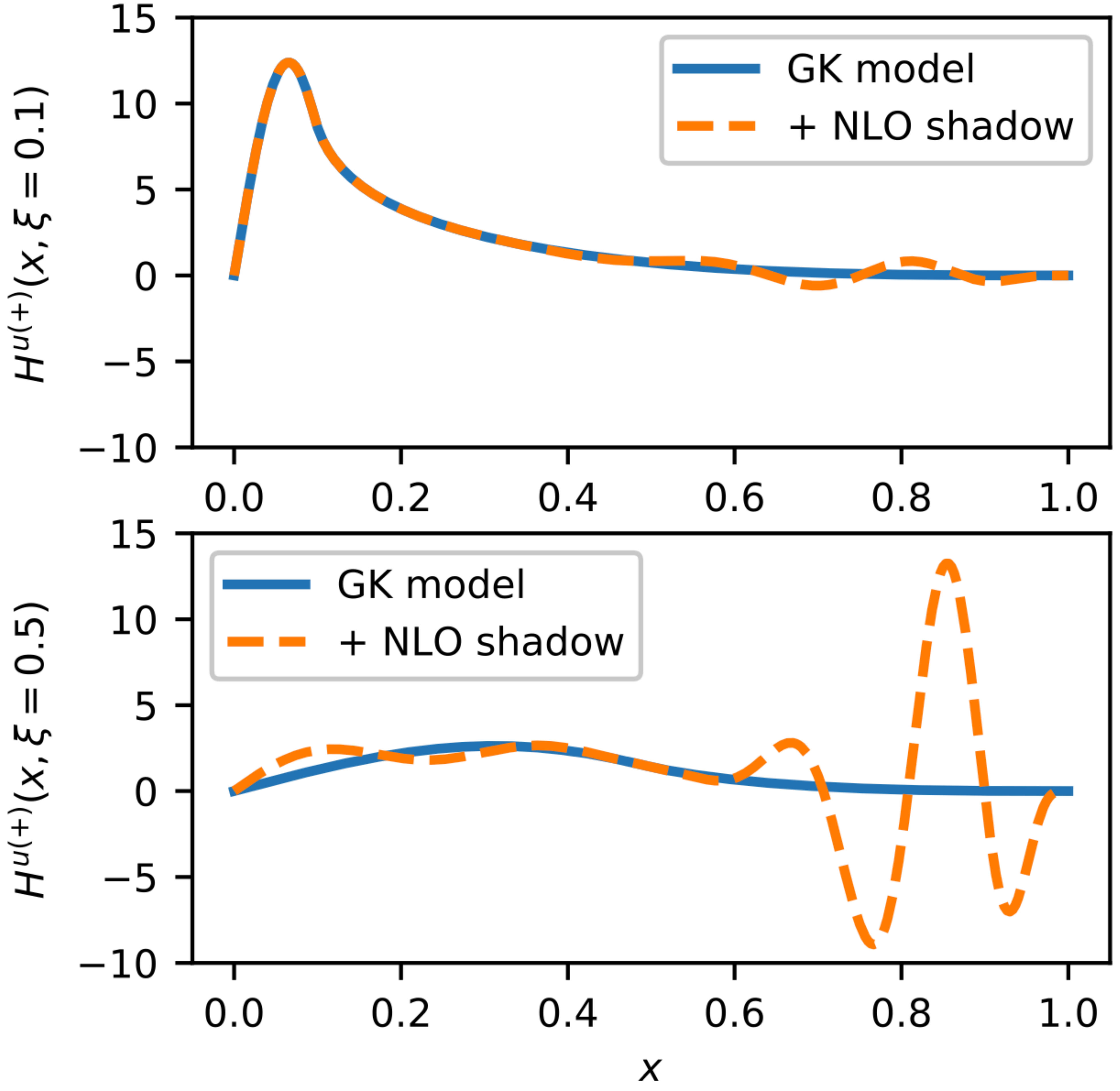
Shadow term is closely related to the so-called shadow GPDs

Shadow GPDs have considerable size and:

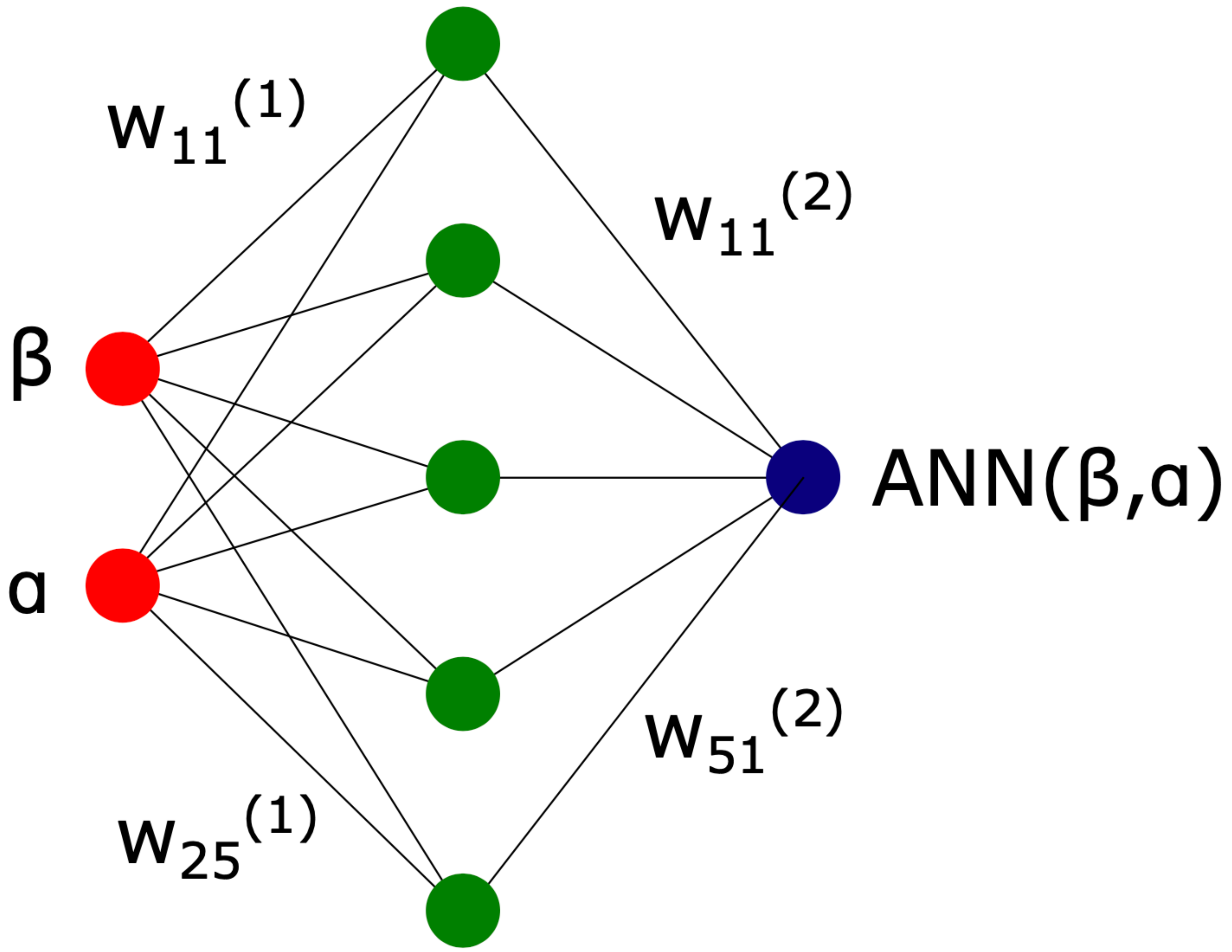
- at the initial scale do not contribute to both PDFs and CFFs
- at some other scale they contribute negligibly

making the deconvolution of CFFs ill-posed

We found such GPDs for both LO and NLO



Our ANNs:



Requirements:

symmetric w.r.t. α

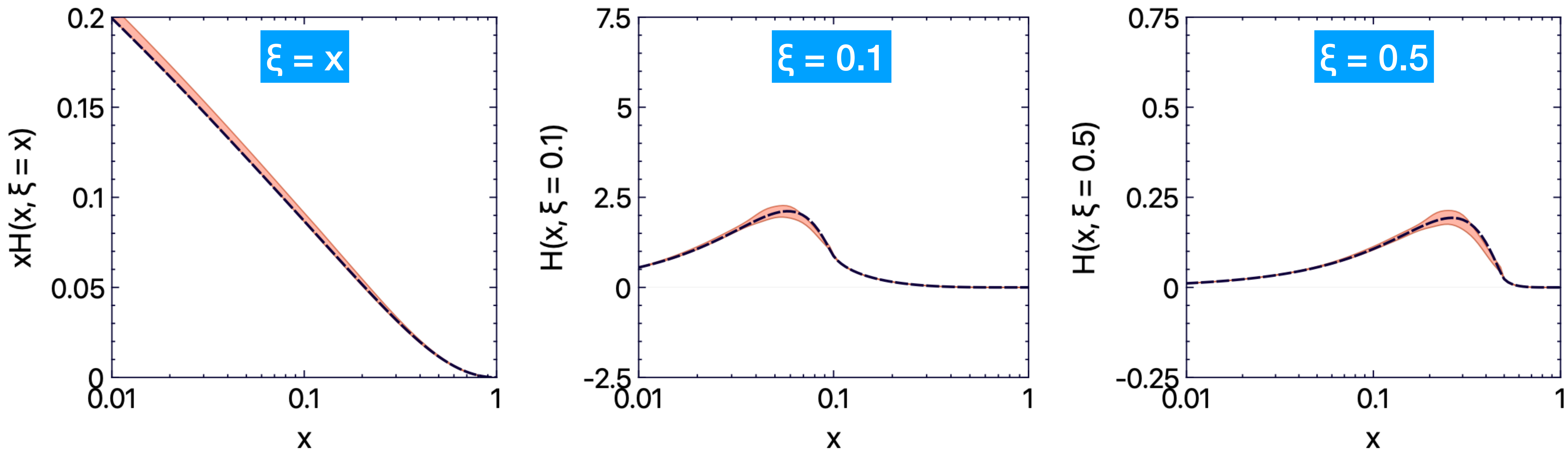
symmetric w.r.t. β

vanishes at $|\alpha| + |\beta| = 1$

Activation function:

$$\left(\varphi_i\left(w_i^\beta|\beta| + w_i^\alpha \alpha/(1-|\beta|) + b_i\right) - \varphi_i\left(w_i^\beta|\beta| + w_i^\alpha + b_i\right)\right) + (w^\alpha \to -w^\alpha)$$

Demonstration of results



Conditions:

- Input: 400 x ≠ ξ points generated with GK model
- Positivity not forced

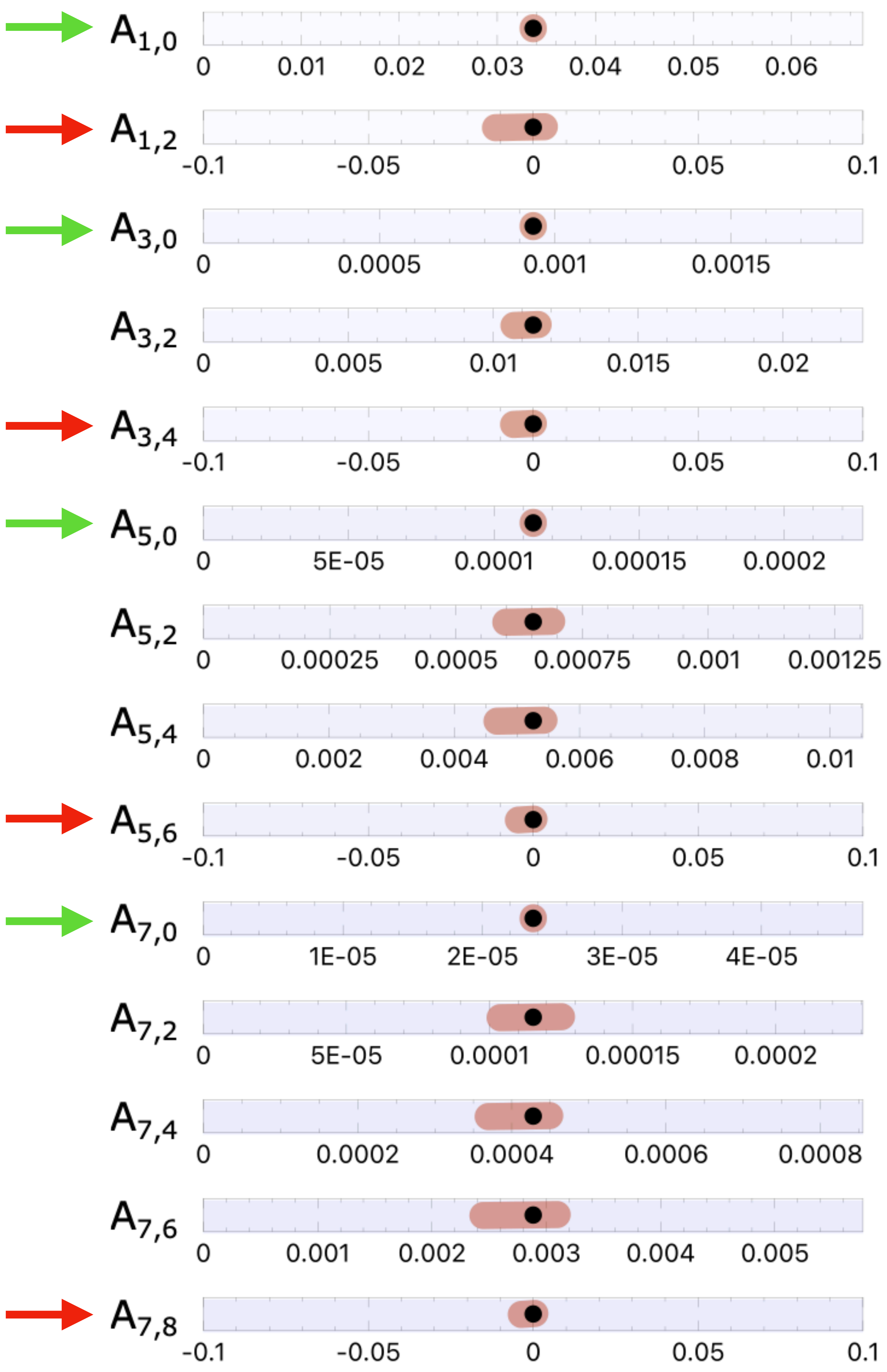
Technical detail of the analysis:

- Minimisation with genetic algorithm
- Replication for estimation of model uncertainties
- "Local" detection of outliers
- Dropout algorithm for regularisation

GK

ANN model 68% CL $F_C + F_S + F_D$

Demonstration of results



● **GK**

ANN model
68% CL
$F_C + F_S + F_D$

Mellin mom. coefficients:

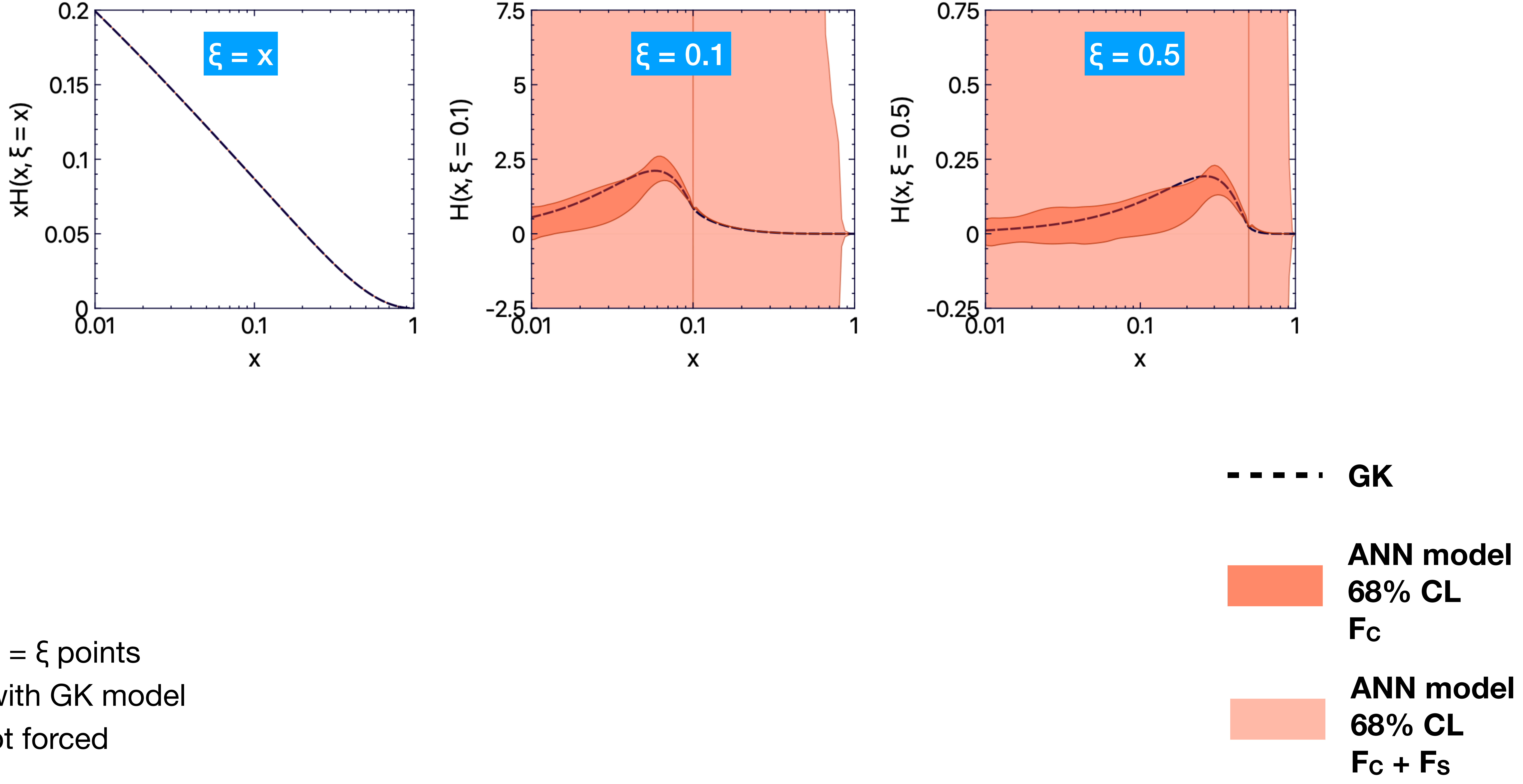
→ related to PDF

→ related to D-term

Conditions:

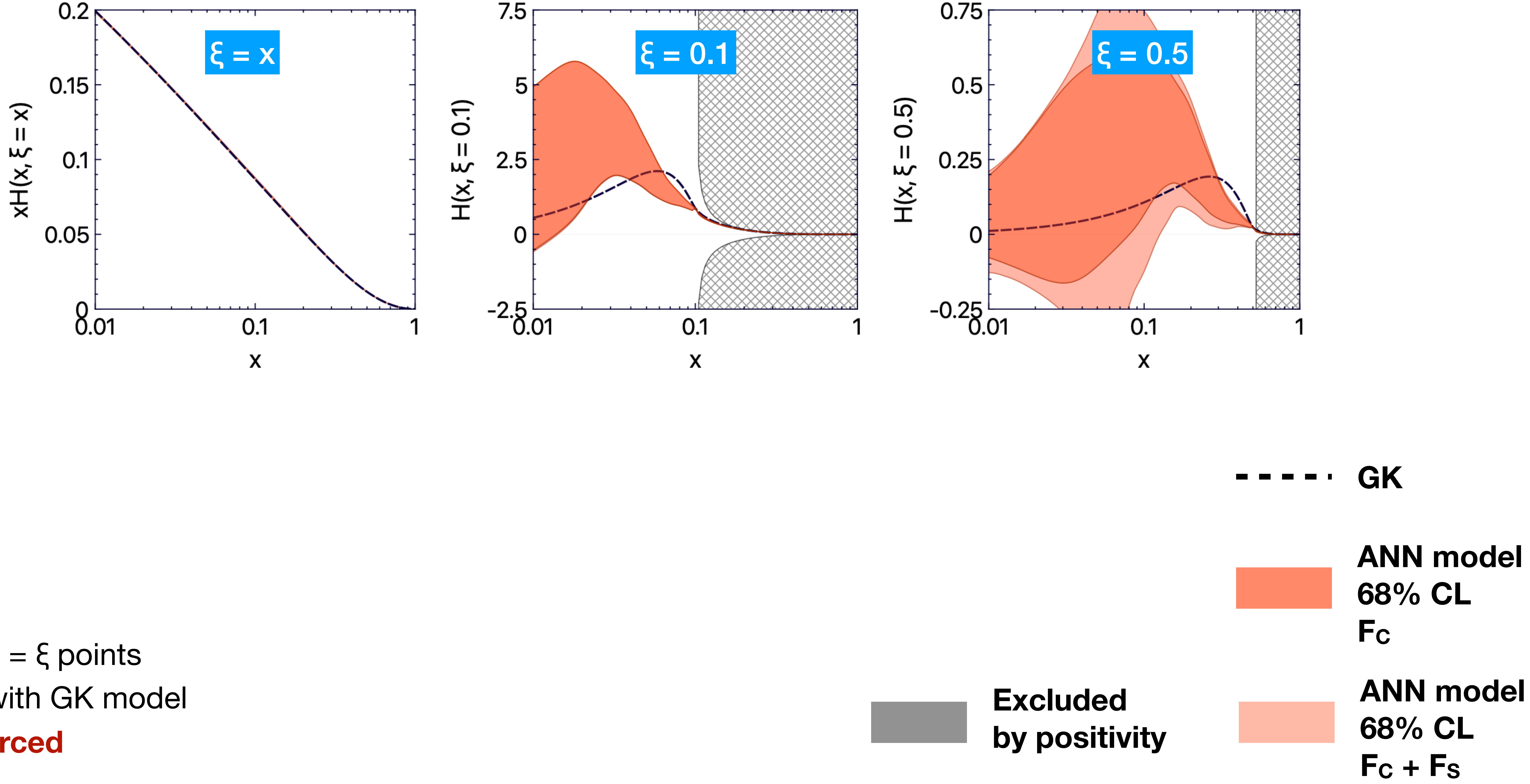
- Input: 400 x ≠ ξ points generated with GK model
- Positivity not forced

Demonstration of results



Conditions:

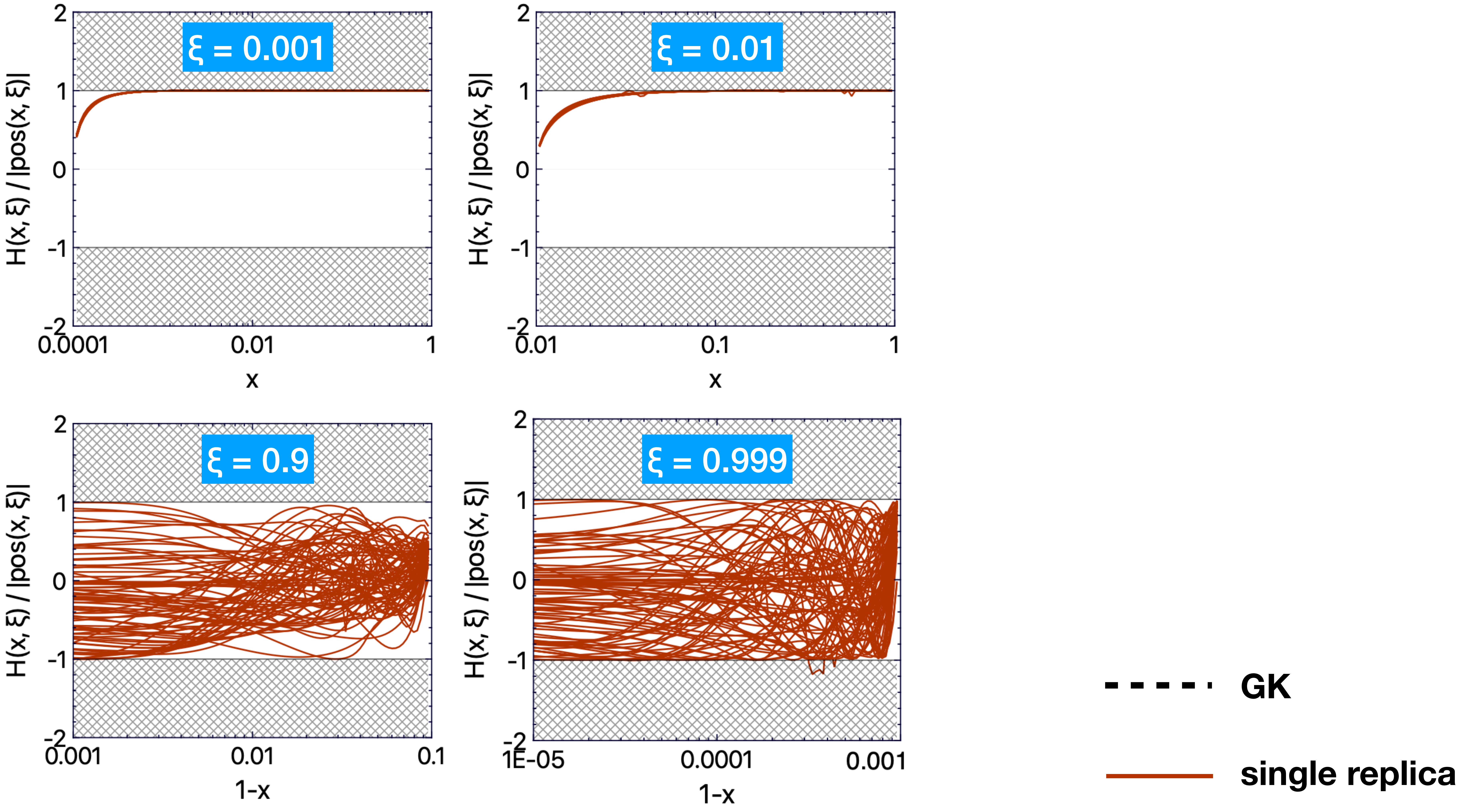
- Input: 200 x = ξ points generated with GK model
- Positivity not forced



Conditions:

- Input: 200 x = ξ points generated with GK model
- Positivity **forced**

Demonstration of results



Conditions:

- Input: 200 x = ξ points generated with GK model
- Positivity **forced**

PARTONS project

B. Berthou et al.,
Eur. Phys. J. C 78 (2018) 6, 478

- PARTONS - open-source framework to study GPDs
  → *http://partons.cea.fr*
- Come with number of available physics developments implemented
- Written in C++, also available via virtual machines (VirtualBox) and containers (Docker)
- Addition of new developments as easy as possible
- Developed to support effort of GPD community,
  can be used by both theorists and experimentalists
- v4 version of PARTONS is now available!

EpIC MC generator

E. C. Aschenauer et al.,
Eur. Phys. J. C 82 (2022) 9, 819

- Novel MC generator called EpIC released
  → *https://pawelsznajder.github.io/epic*

- EpIC is based on PARTONS

- EpIC is characterised by:
  - flexible architecture that utilises a modular programming paradigm
  - a variety of modelling options, including radiative corrections
  - multichannel capability (now: DVCS, TCS, DVπ^0P, diphoton)

- This is the new tool to be use in the precision era commenced by the new generation of experiments

- v1.1.0 version of EpIC is now available!

Summary

- For the first time, we propose modelling GPDs based on ANNs
  → new, nontrivial and timely analysis

- Our modelling fulfils all theory-driven constraints (including positivity)
  → subject not touched enough in the current literature

- Can easily accommodate lattice-QCD results
  → important to include new sources of GPD information

see Michael's talk on Tuesday

- These is the new tool to address the long-standing problem of model dependency of GPDs