Artificial neural network modelling of generalised parton distributions

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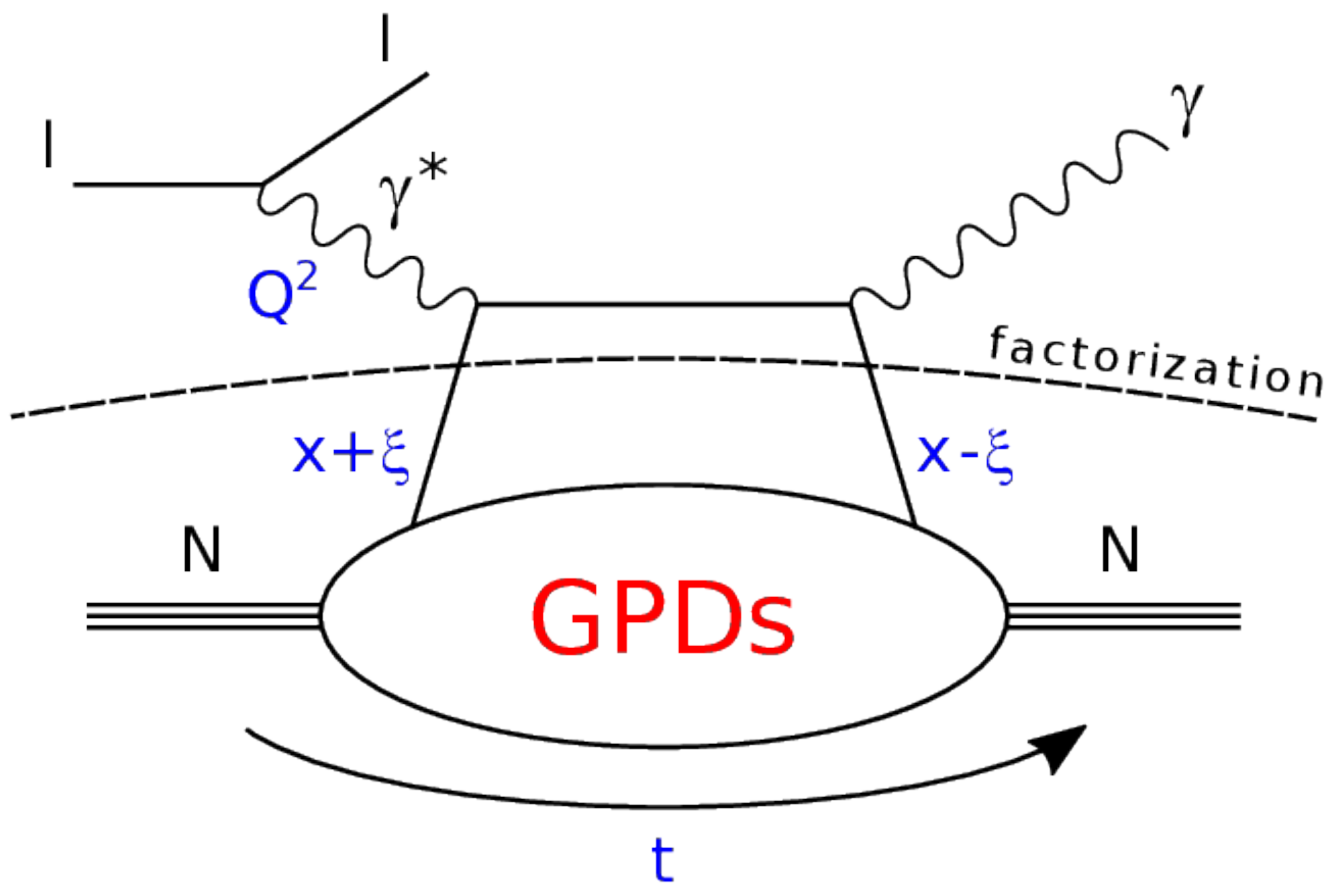
Deeply Virtual Compton Scattering (DVCS)



factorisation for |t|/Q² ≪ 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:

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

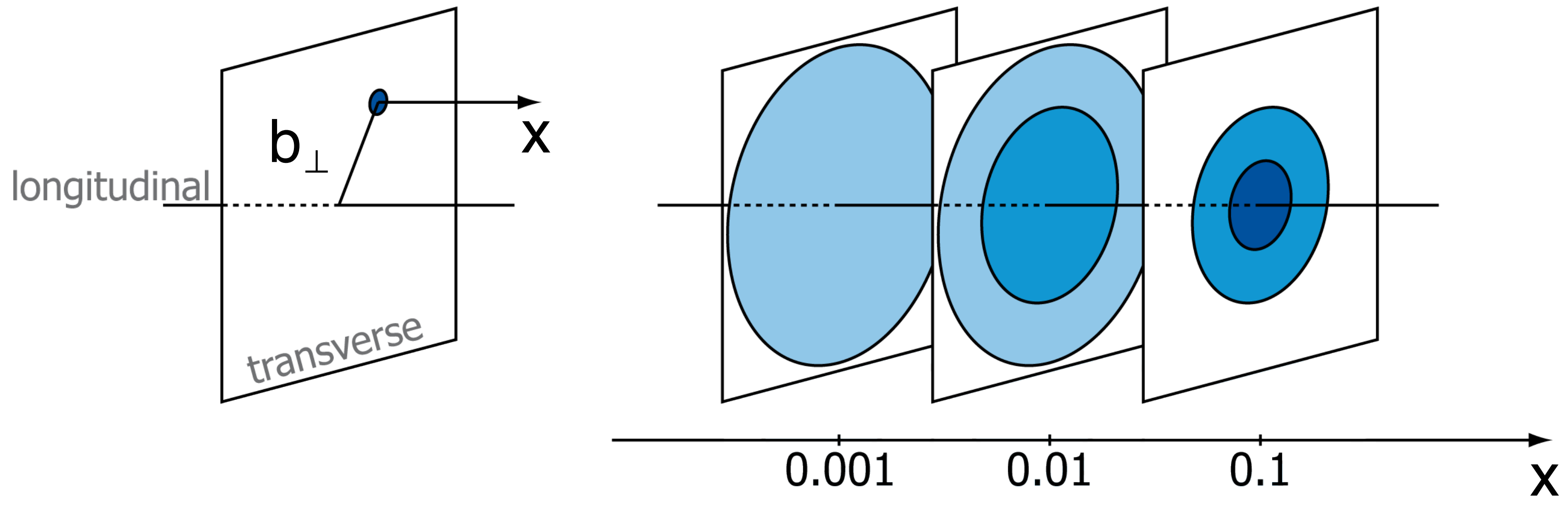
Polynomiality - non-trivial consequence of Lorentz invariance:

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

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

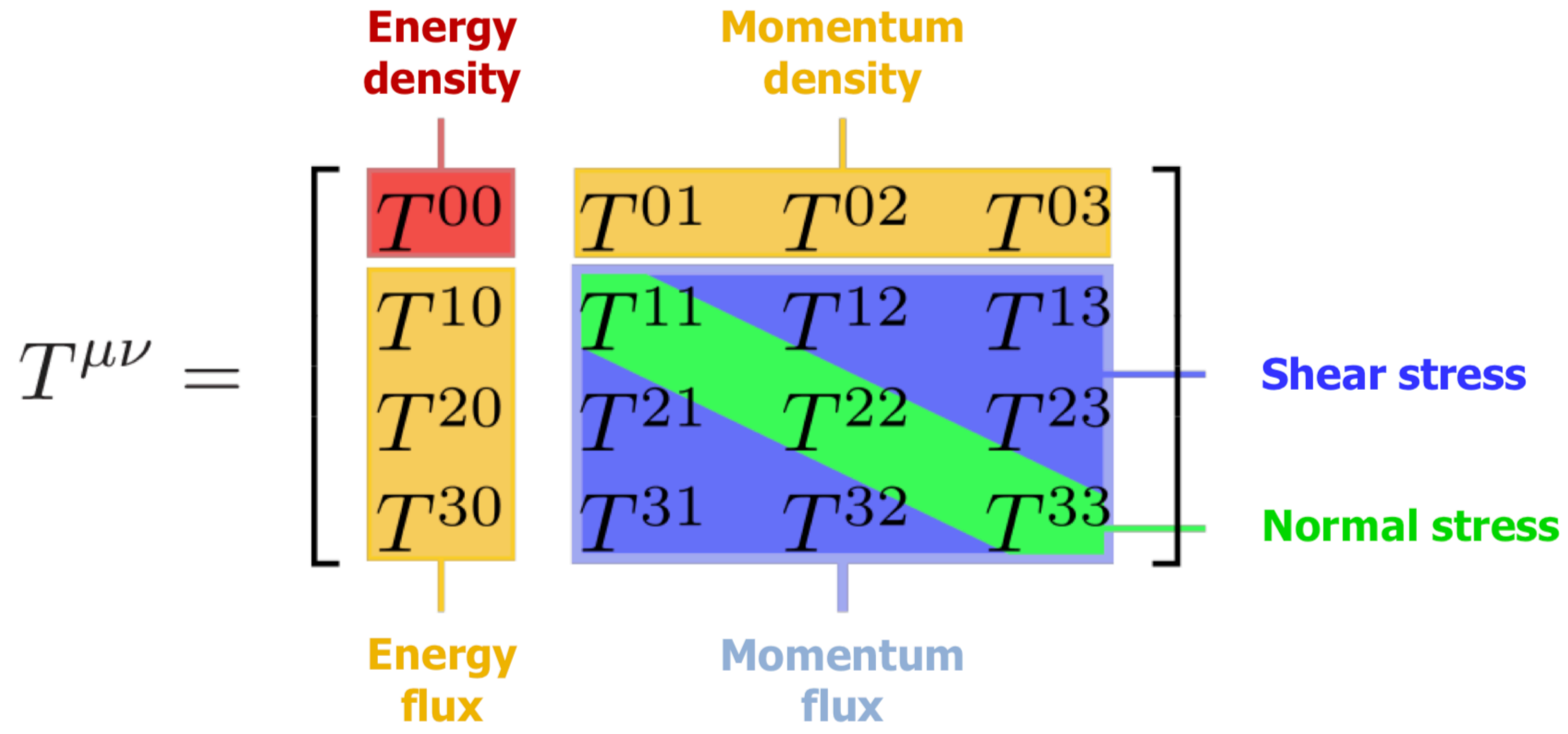
$$|H(x, \xi, t)| \leq \sqrt{q\left(\frac{x+\xi}{1+\xi}\right) q\left(\frac{x-\xi}{1-\xi}\right) \frac{1}{1-\xi^2}}$$

Introduction



Nucleon tomography:

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



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

- we witness a substantial progress in:
  - measurement and description of exclusive processes (see: *most of GPD-related contributions to this conference*)
  - understanding of fundamental problems, like the deconvolution of GPDs from data (see: *PRD 103 (2021) 11, 114019*, *V. Martínez-Fernández's poster*)
  - lattice-QCD (see: *EPJA 57 (2021) 2, 77*)

- however, problem of the model dependency of GPDs is still poorly addressed, except:
  - extraction of D-term (see: *Nature 570 (2019) 7759, E1*, *EPJC 81 (2021) 4, 300*)
  - probing nucleon tomography at low-xB (see: *J. V. Giarra's talk*)

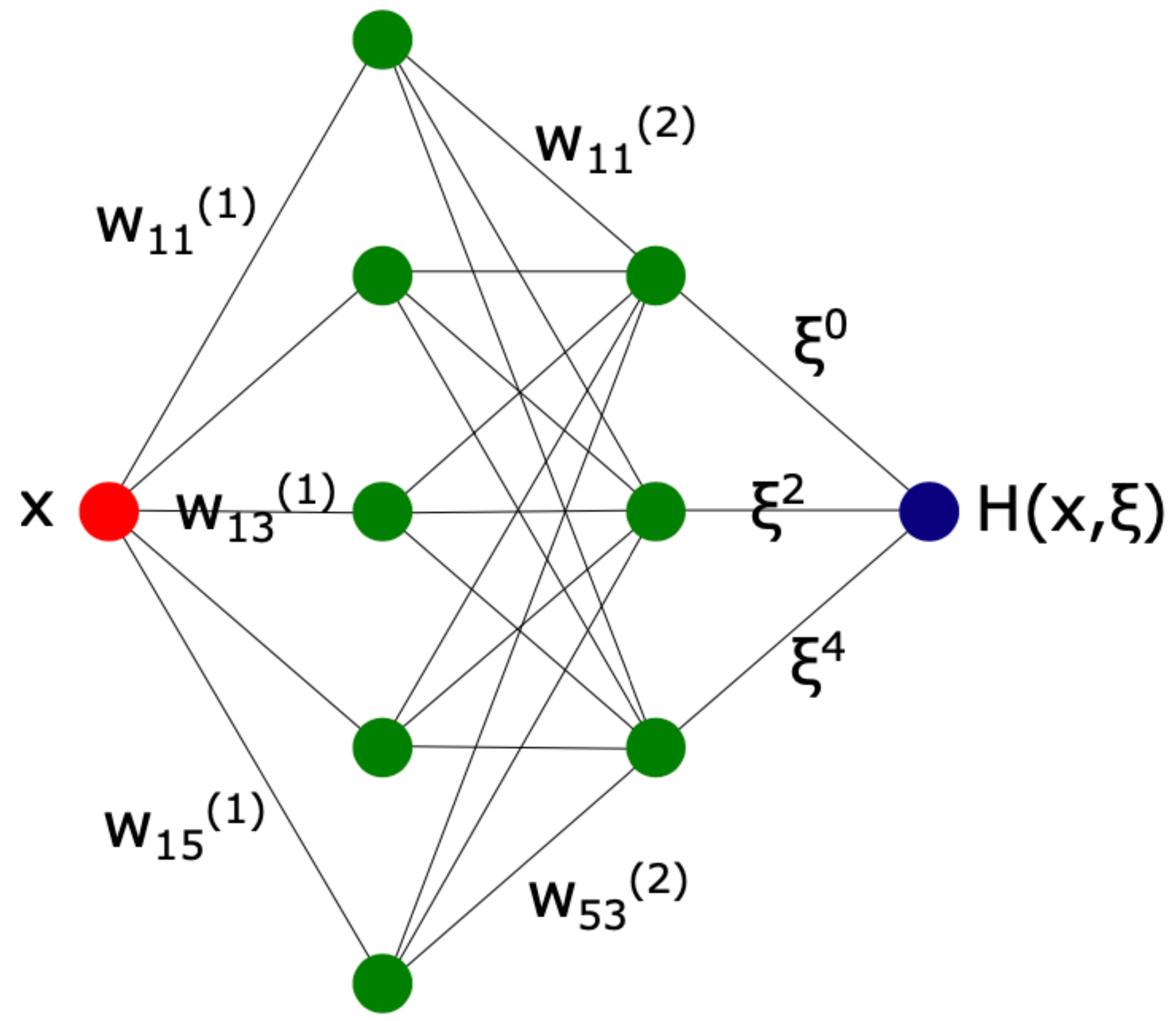
- no GPD models that could be considered non-parametric → no tools to study model dependency of the extraction of GPDs, nucleon tomography and orbital angular momentum (see: *this talk based on EPJC 82 (2022) 3, 252*)

Direct modelling in (x, ξ)-space

- Polynomiality:

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

suggests that true degrees of freedom of GPDs are $A_{n,j}$ coefficients



- This leads us to the moment problem
  → reconstruction of GPDs from their moments

- We address this problem with ANNs

- Drawback of this method:
  one can not keep PDF singularity for only x=0 and ξ=0

- See EPJC 82 (2022) 3, 252 and backup slides for more details

Principles of modelling

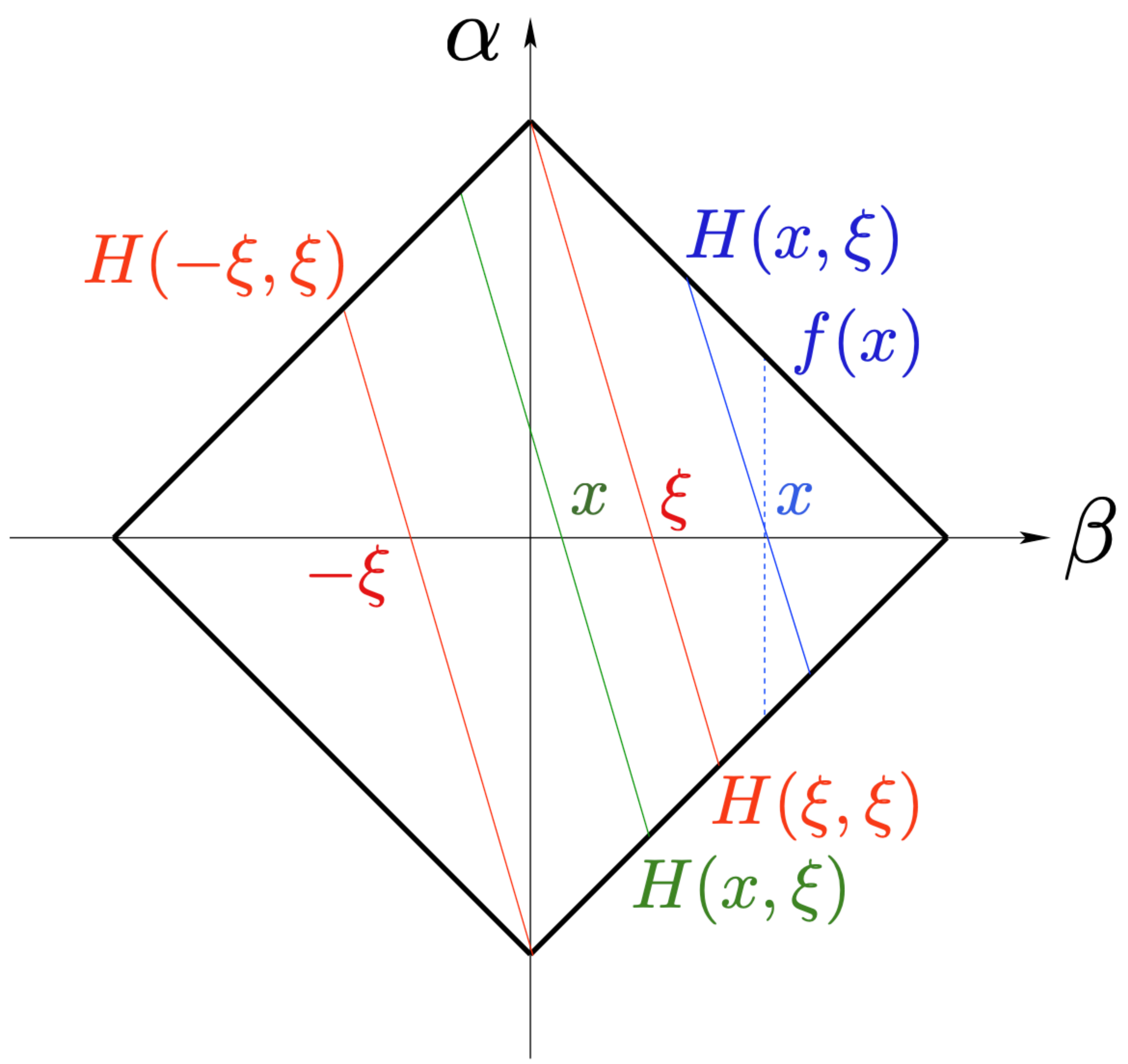
Double distribution:

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

where:

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

$$|\alpha| + |\beta| \le 1$$



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:

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

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

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

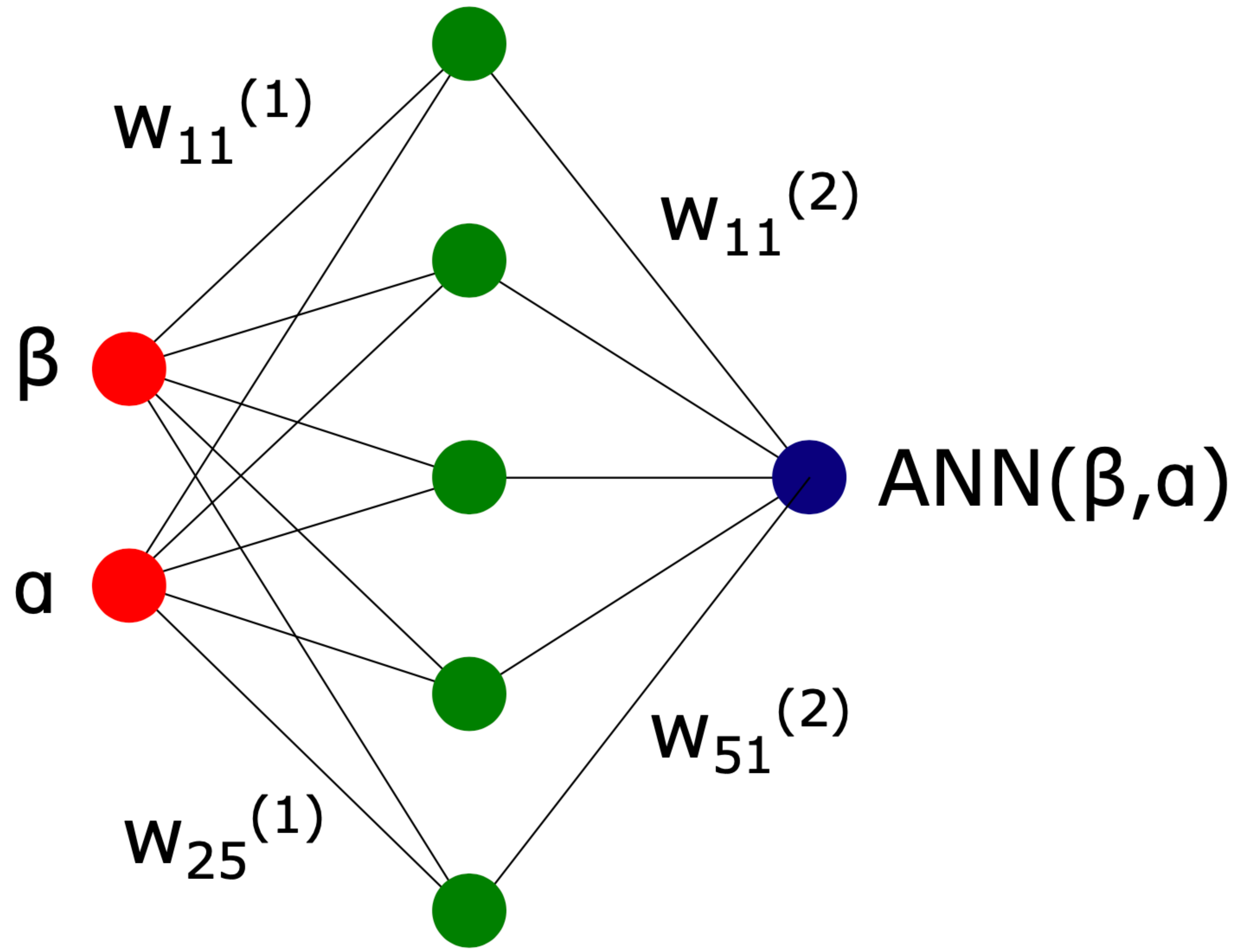
$$\mathrm{ANN}_{S'}(|\beta|,\alpha) \equiv \mathrm{ANN}_C(|\beta|,\alpha)$$

D-term:

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

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

Our ANNs:



Requirements:

symmetric w.r.t. α

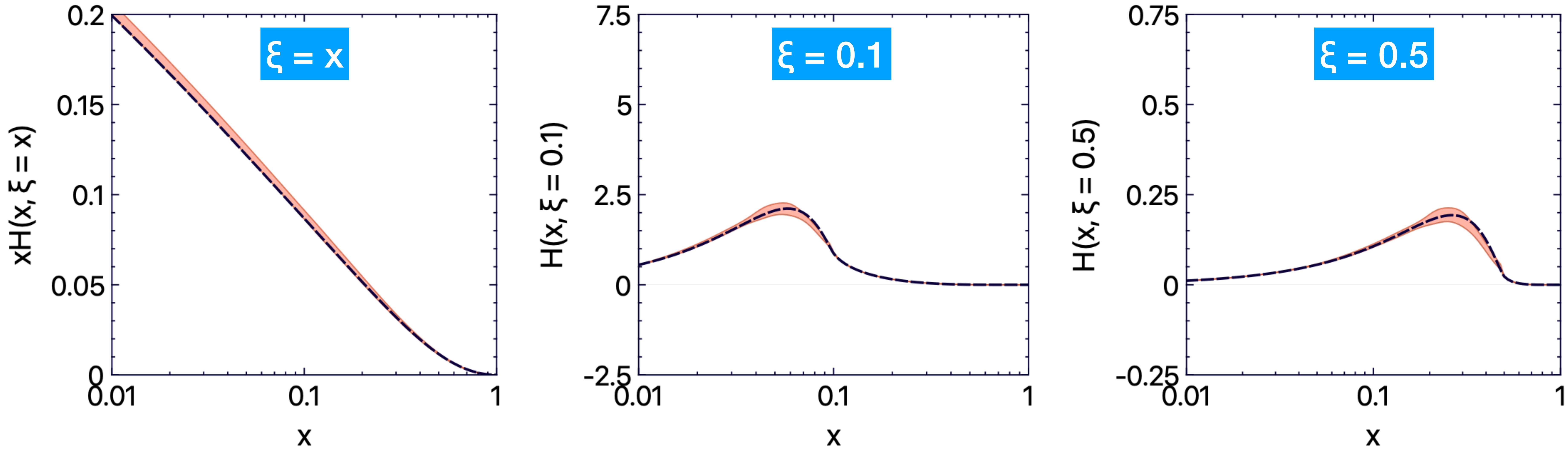
symmetric w.r.t. β

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

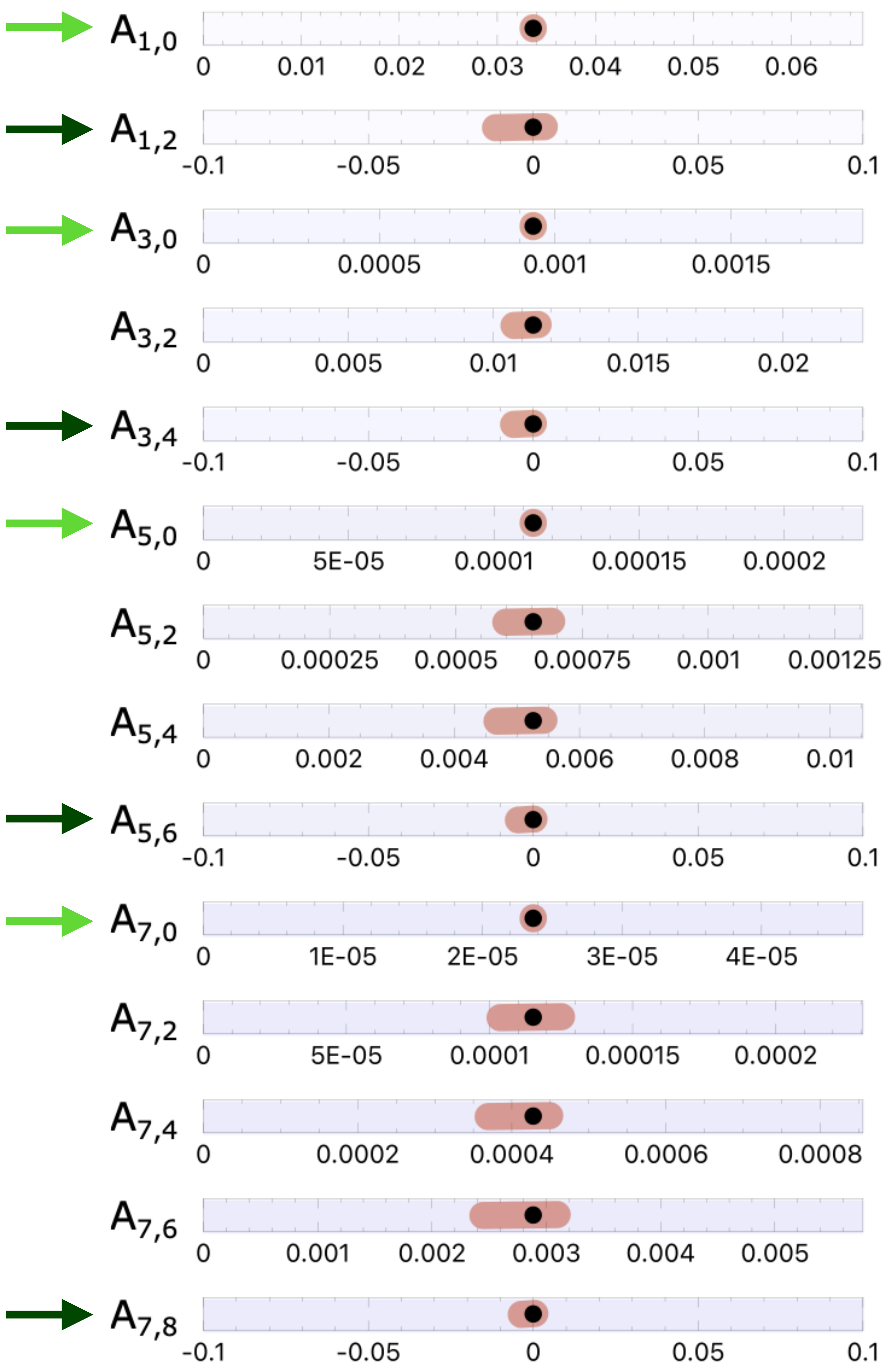
Technical detail of the analysis:

- 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:

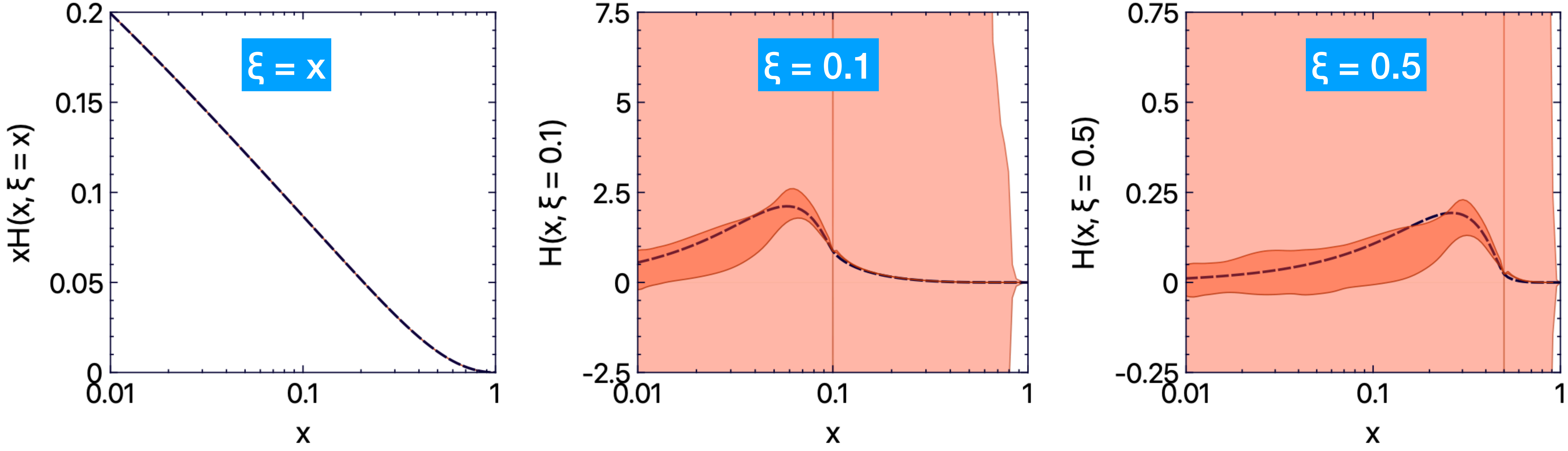
→ related to PDF

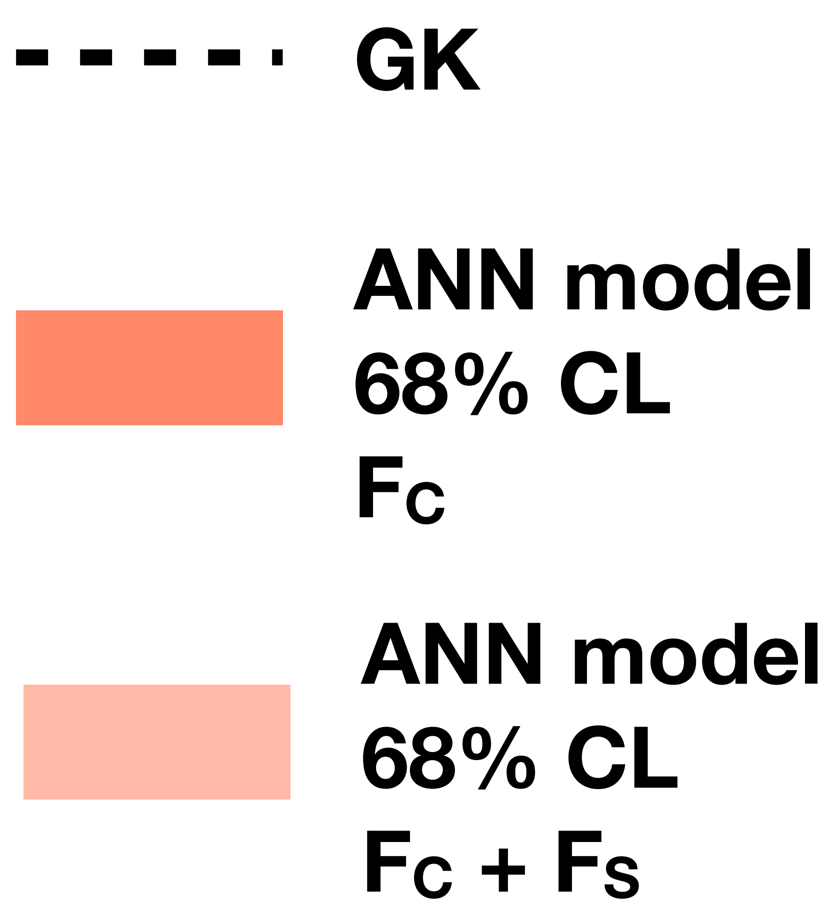
→ related to D-term

Conditions:

- Input: 400 $x \neq \xi$ points generated with GK model
- Positivity not forced

Demonstration of results

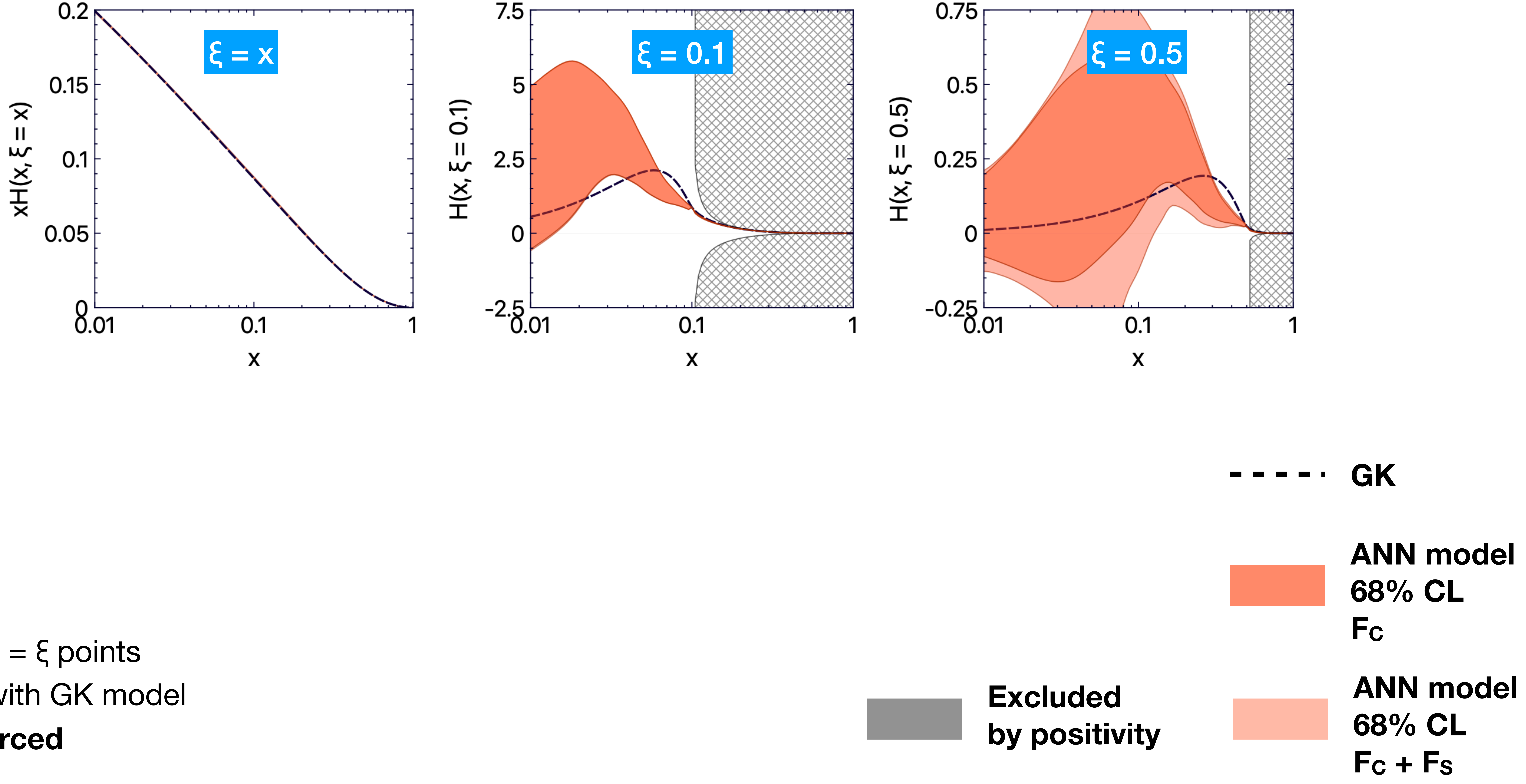




Conditions:

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

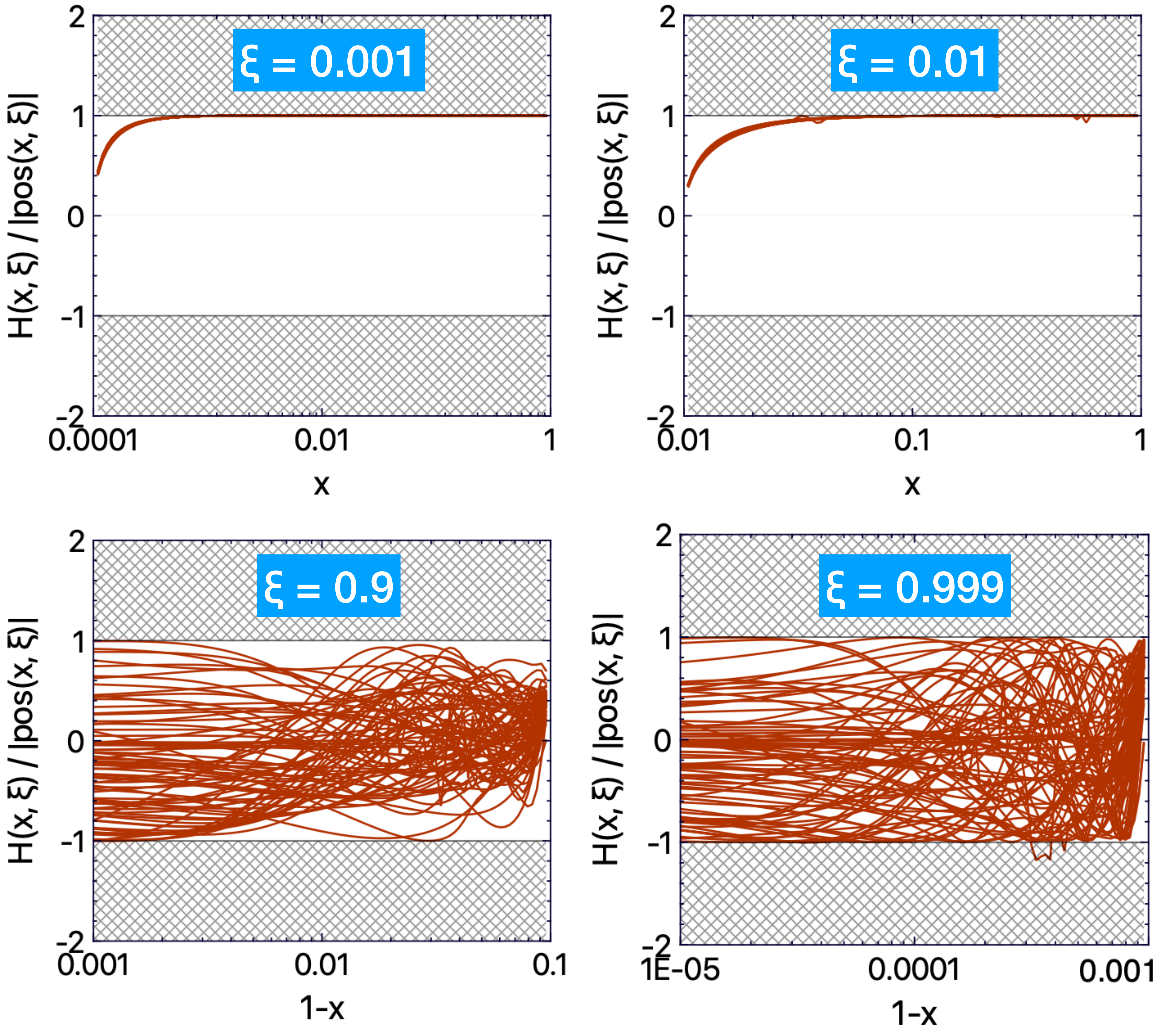
Demonstration of results



Conditions:

- Input: 200 $x = \xi$ points generated with GK model
- Positivity **forced**

Demonstration of results



Conditions:

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

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 additional sources of GPD information
- **These is the new tool to address the long-standing problem of model dependency of GPDs**

Principles of modelling

Backup

Polynomiality:

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

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

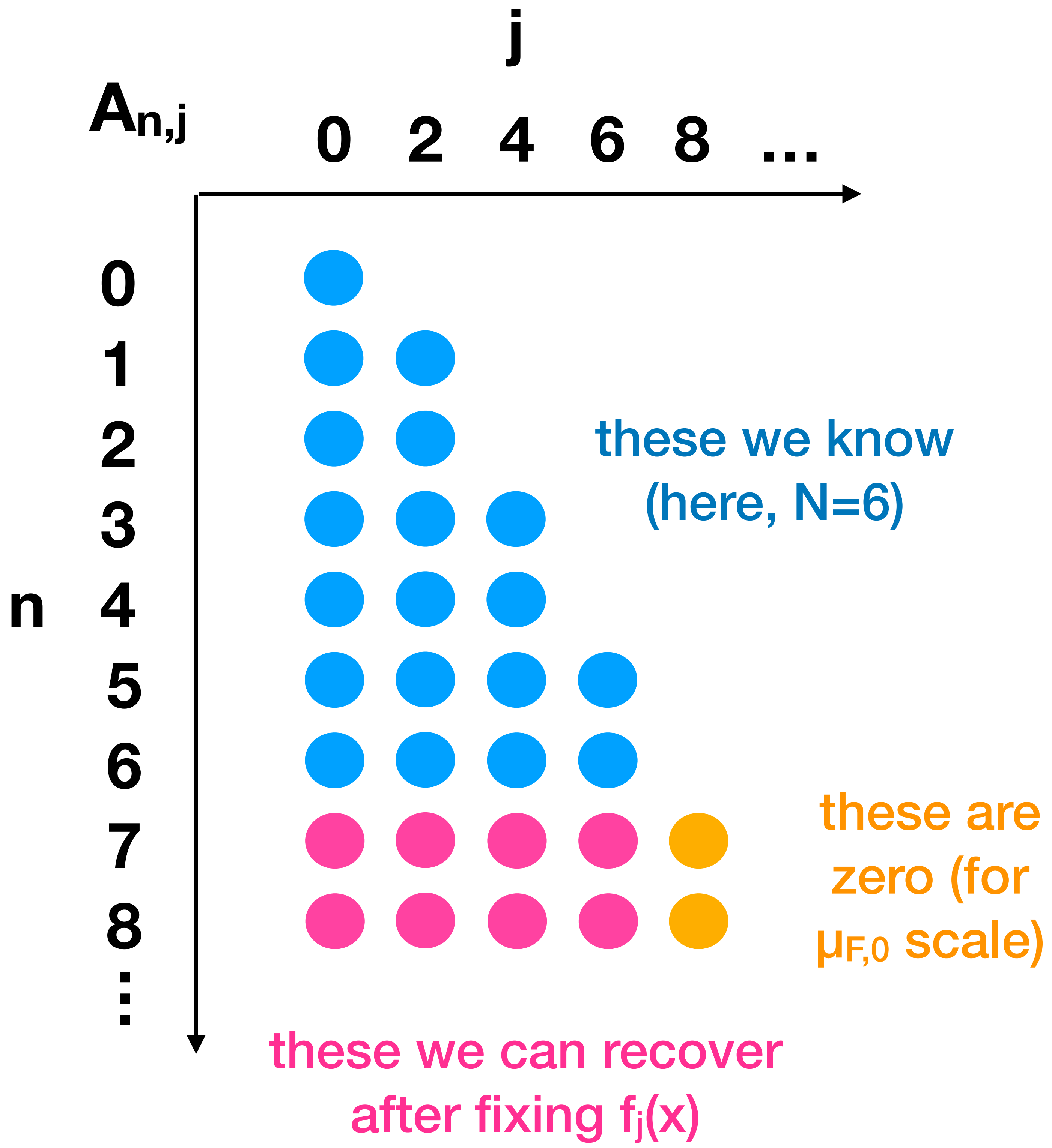
Mellin coefficients:

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

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

where e.g.:

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



Backup

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 $x^i \xi^j$

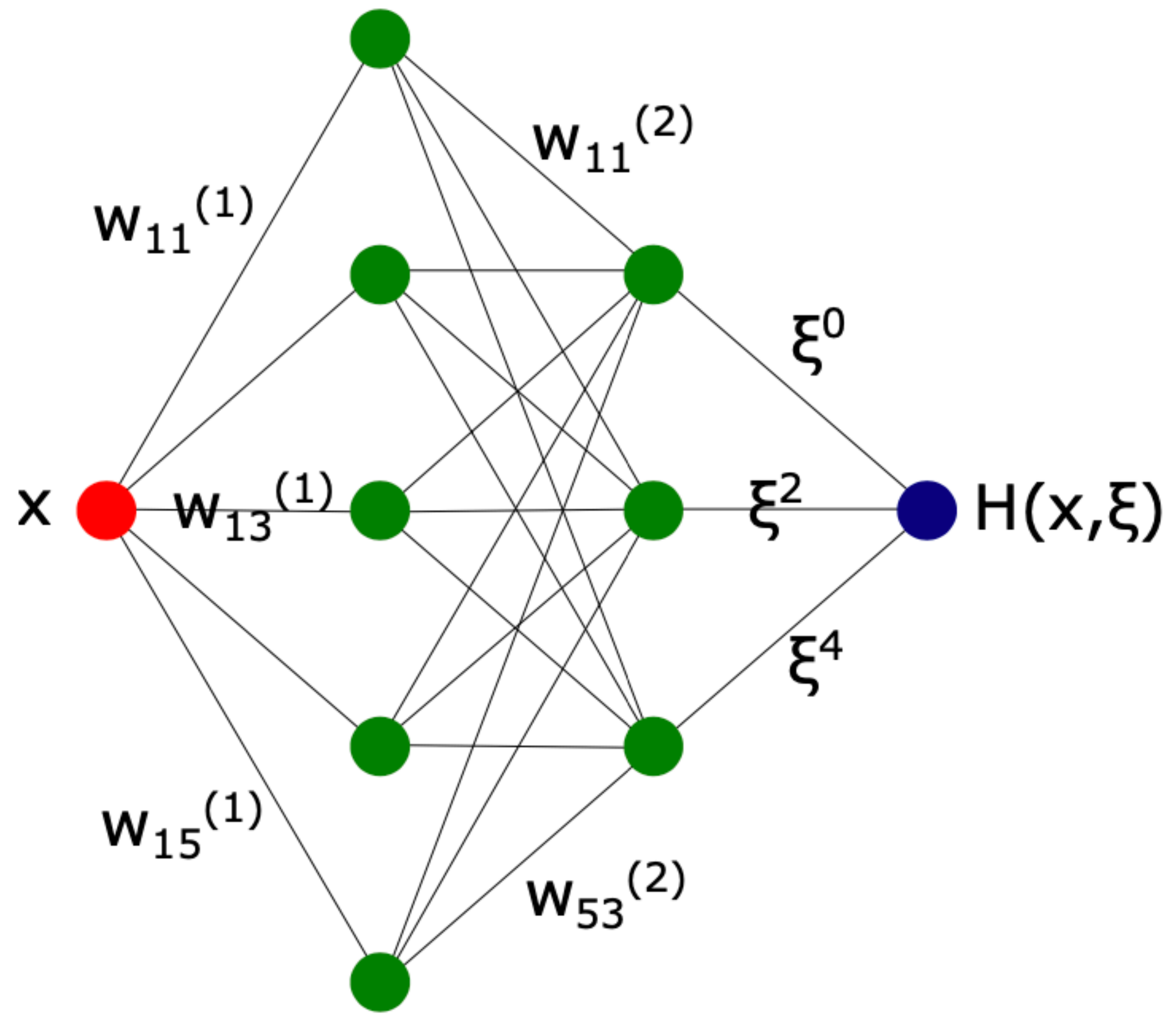
ANN basis:

New!

We can describe GPD by a single ANN

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

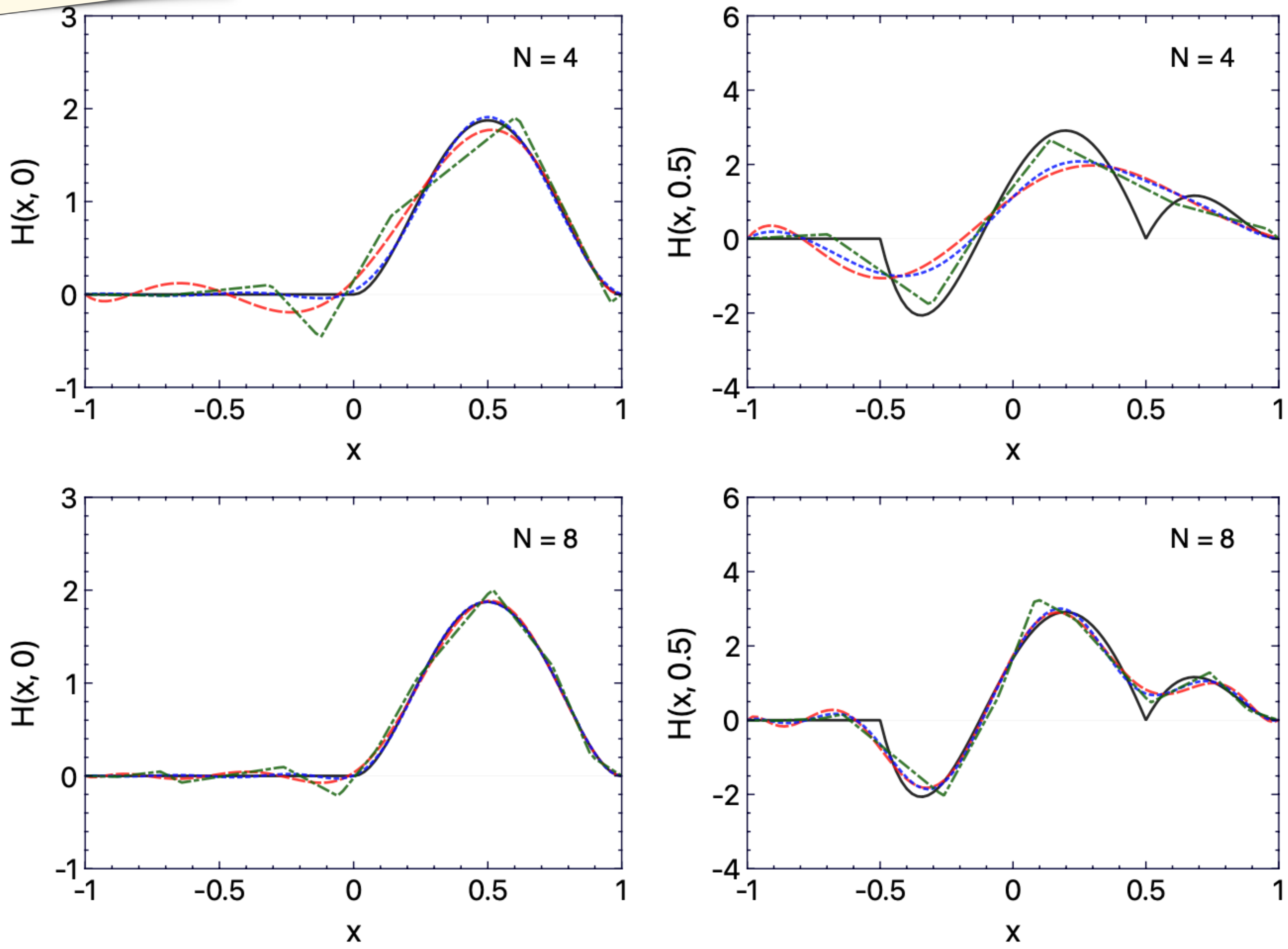
GPD will be expressed by sum of ANNs multiplied by ξ^j



Demonstration of results

Backup

ξ = 0 ξ = 0.5



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

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

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

Backup

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:

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