First Results on Deeply Virtual Exclusive Experiments from the EXCLAIM Collaboration

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EXCLAIM (Exclusives with Artificial Intelligence and Machine Learning)

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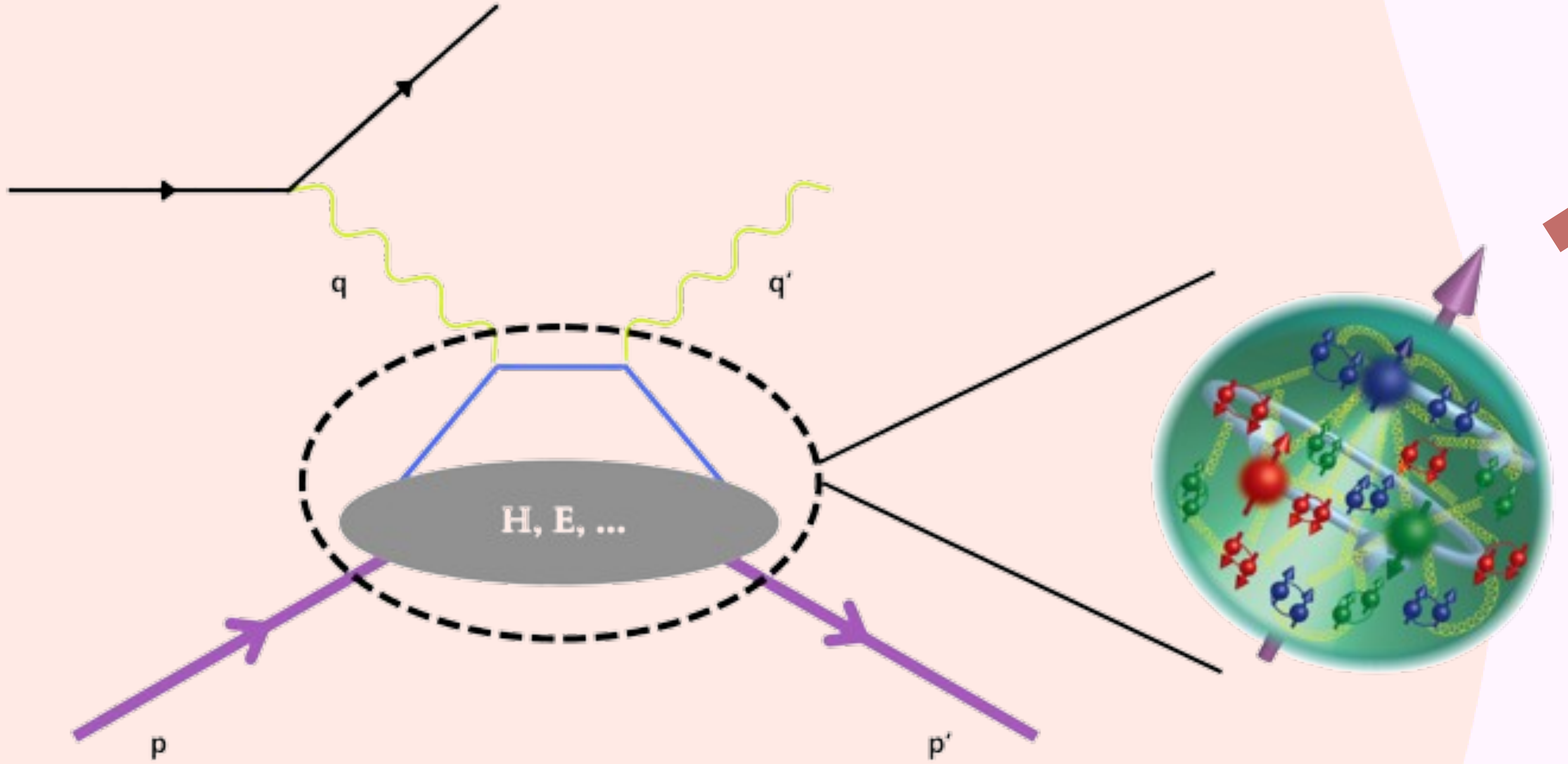
- **Phenomenology/Theory**: Simonetta Liuti, Gary Goldstein, Dennis Sivers, Matt Sievert, MČ, Saraswati Pandey, Joshua Bautista, Adil Khawaja, Zaki Panjsheeri, Carter Gustin, Andrew Dotson, Kiara Ruffin

Nucleon structure

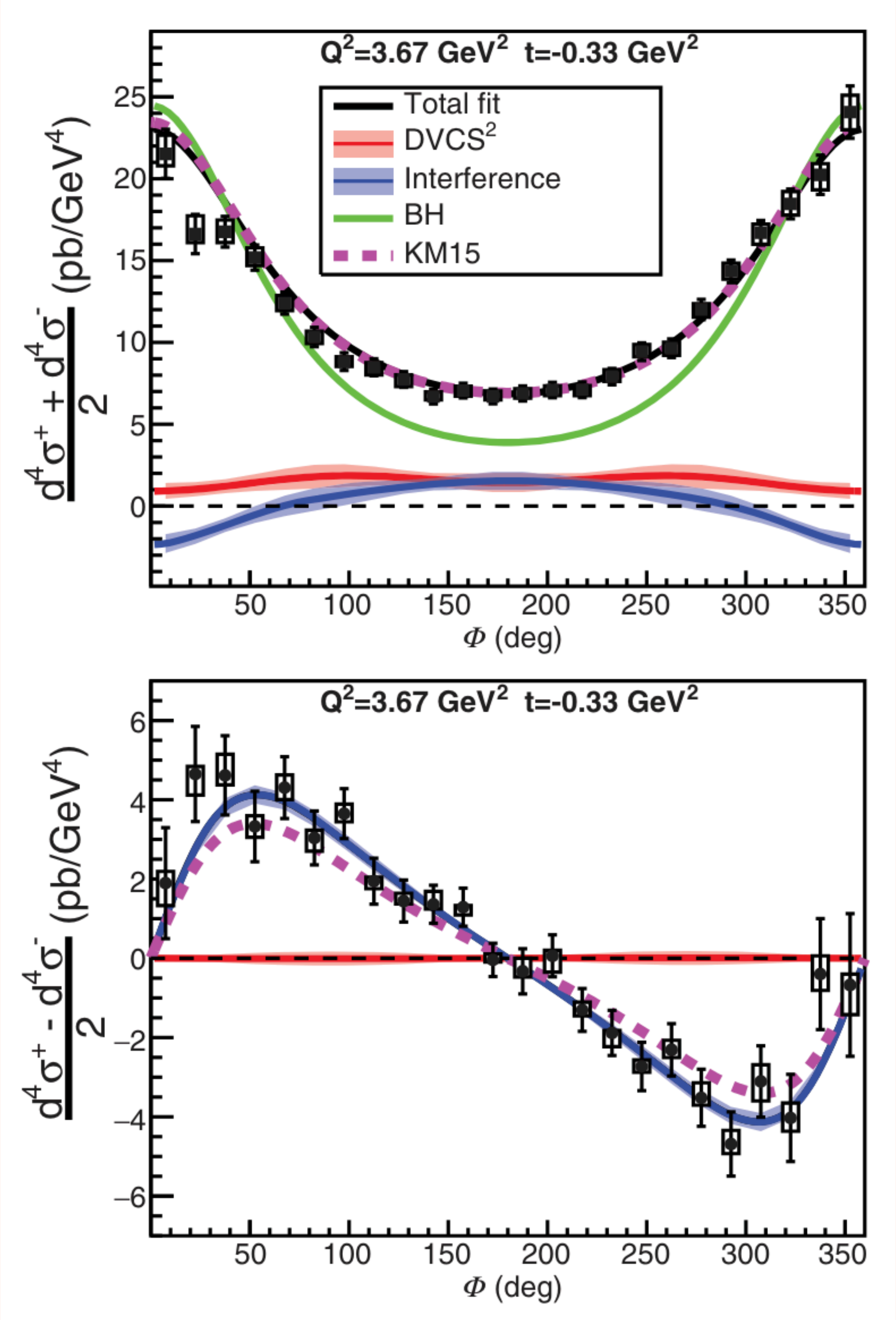


$$\frac{d^5\sigma_{DVCS}}{dx_B\,dy\,dt\,d\phi\,d\varphi} \propto 4\,(1-x_B)\left(|\,\mathcal{H}\,|^2 + |\,\widetilde{\mathcal{H}}\,|^2\right) + \dots$$

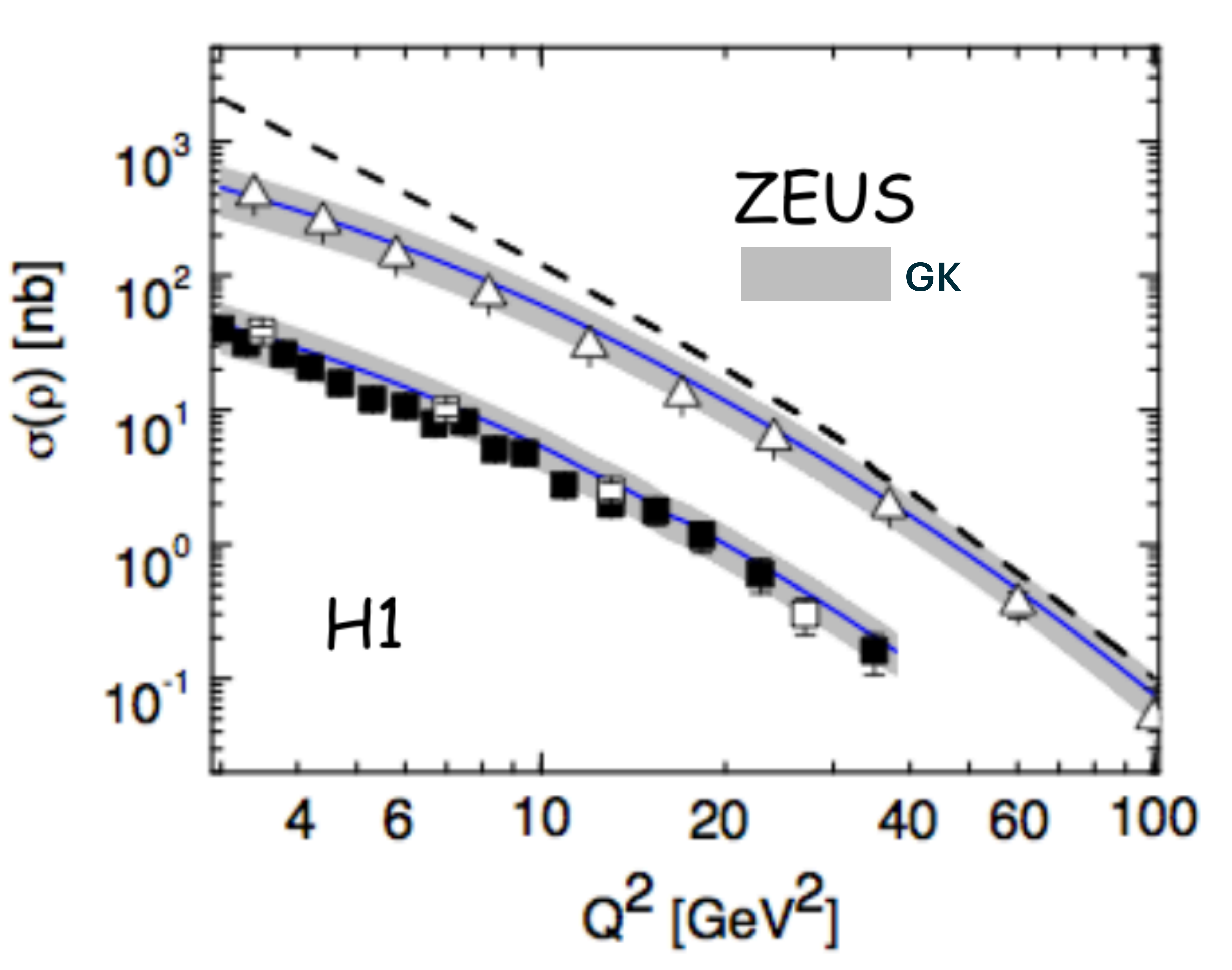
$$\mathcal{H}^A\left(\xi,\Delta^2,Q^2\right) = \int_{-1}^{1}\frac{dx}{2\xi}\,\underbrace{{}^{A}T\left(x,\xi\,|\,\alpha_s\left(\mu_R\right),\left\{\frac{Q^2}{\mu^2}\right\}\right)}_{\text{hard scale}}\underbrace{H^A\left(x,\xi,\Delta^2,\mu_F^2\right)}_{\text{soft scale}}$$

Inverse problem: observables → GPDs inside convolution
→ ill-posed problem!

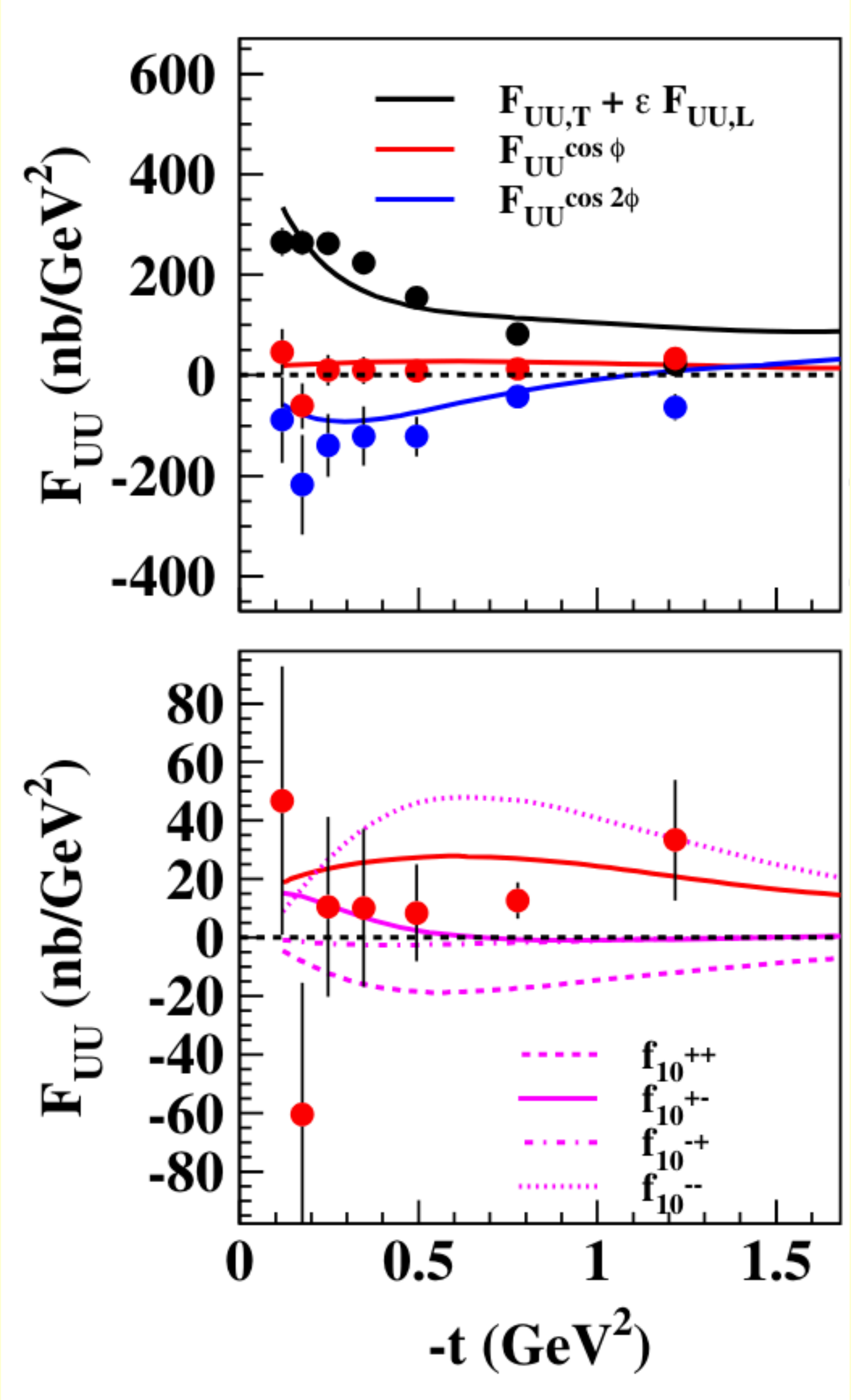
GPD models



Kumerički-Muller model

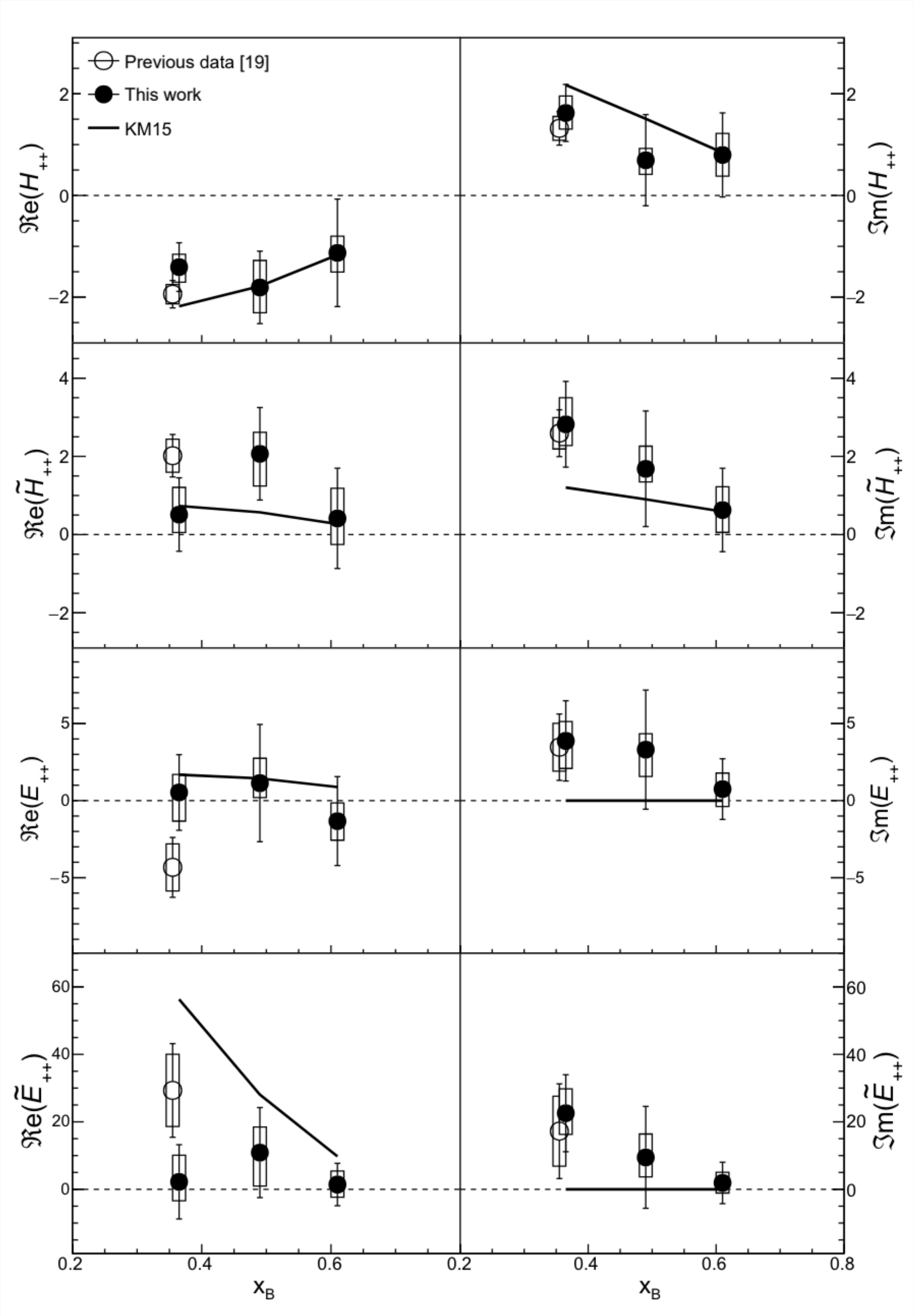


Goloskokov-Kroll model

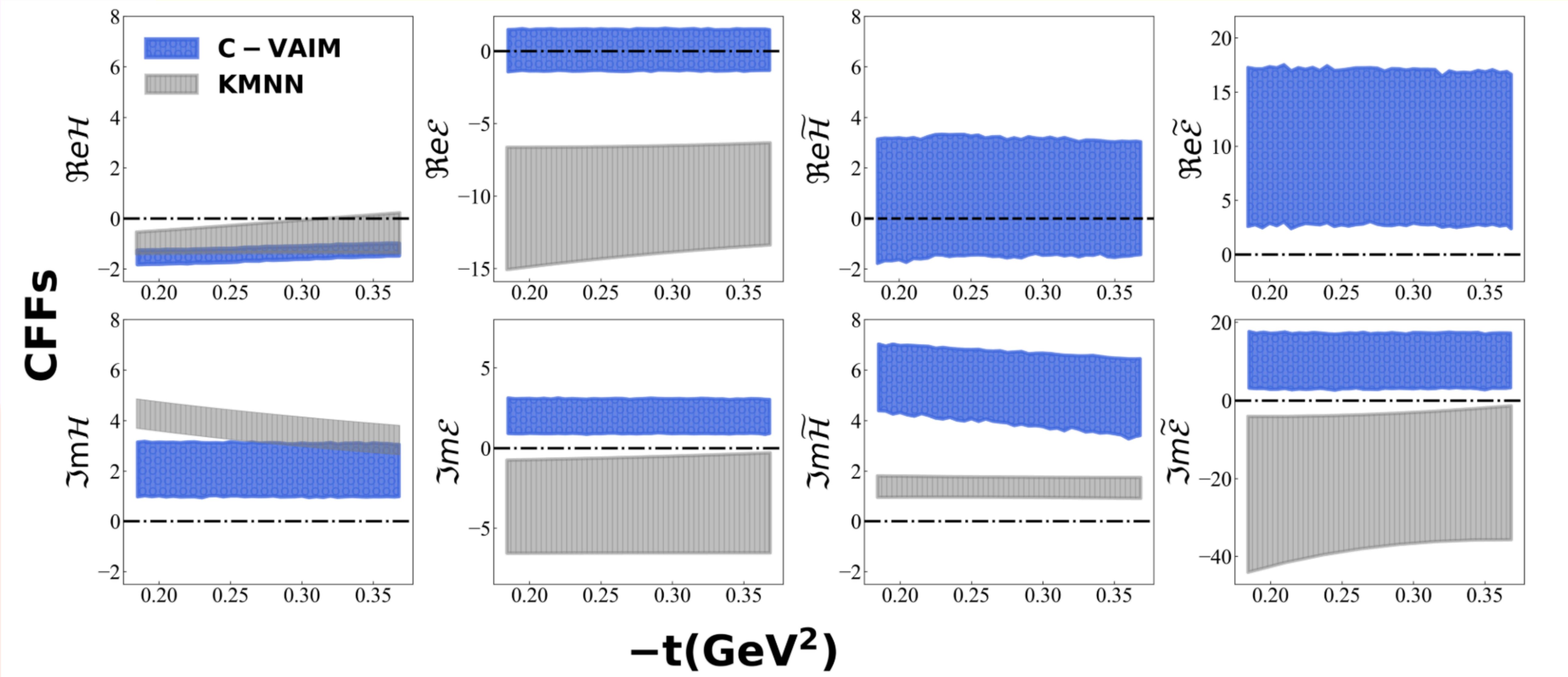


Goldstein-Gonzales-Liuti

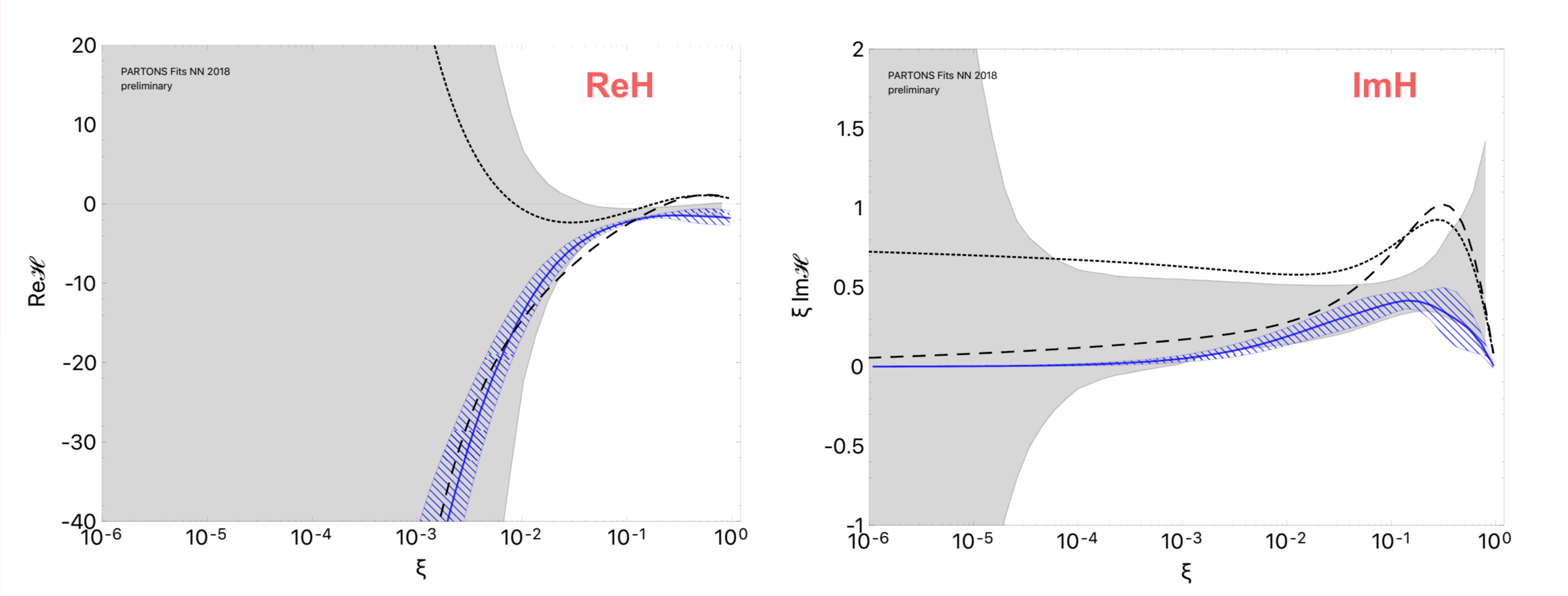
CFF extraction



Hessian based approach, Hall A



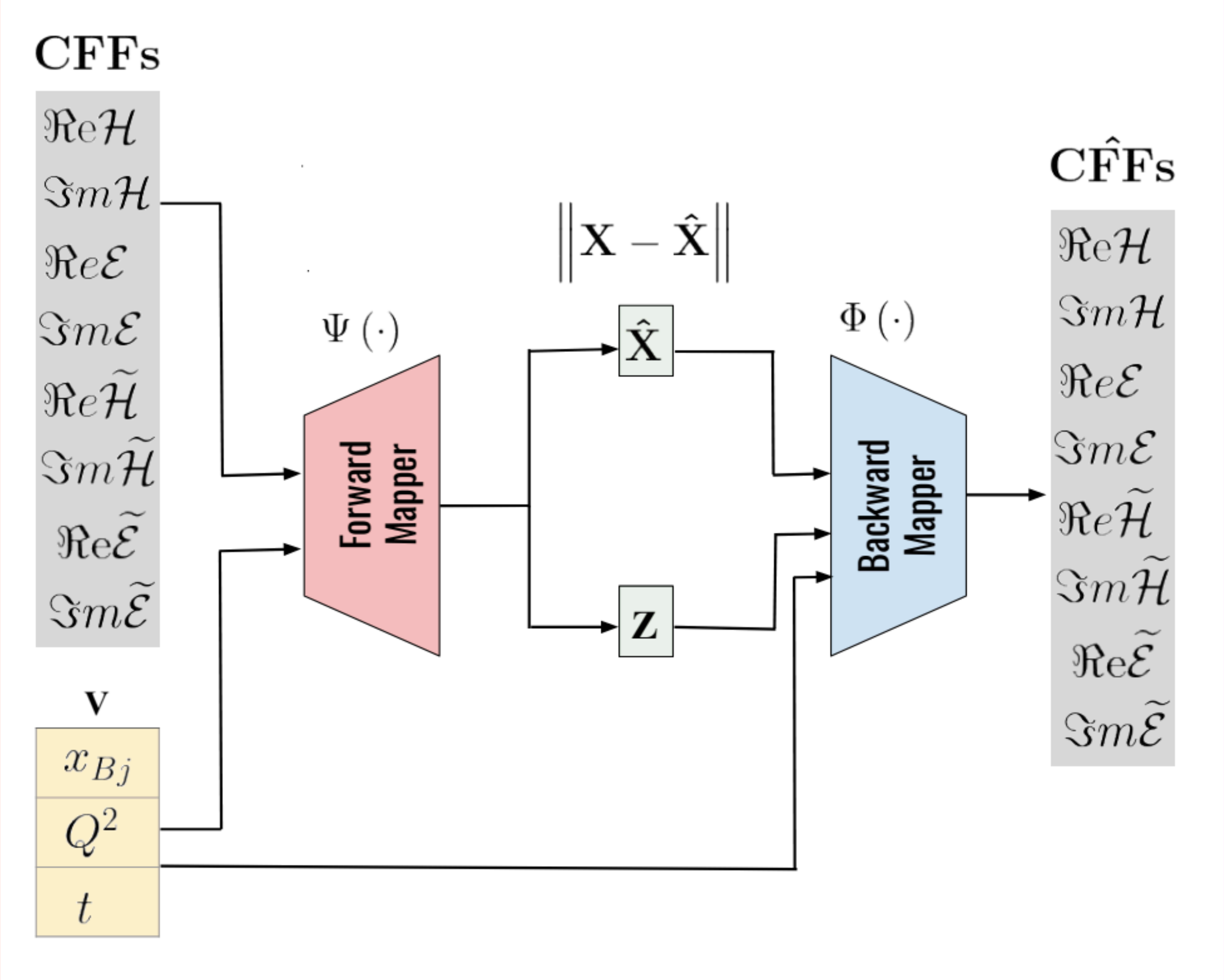
ML calculations, Kumerički vs VAIM



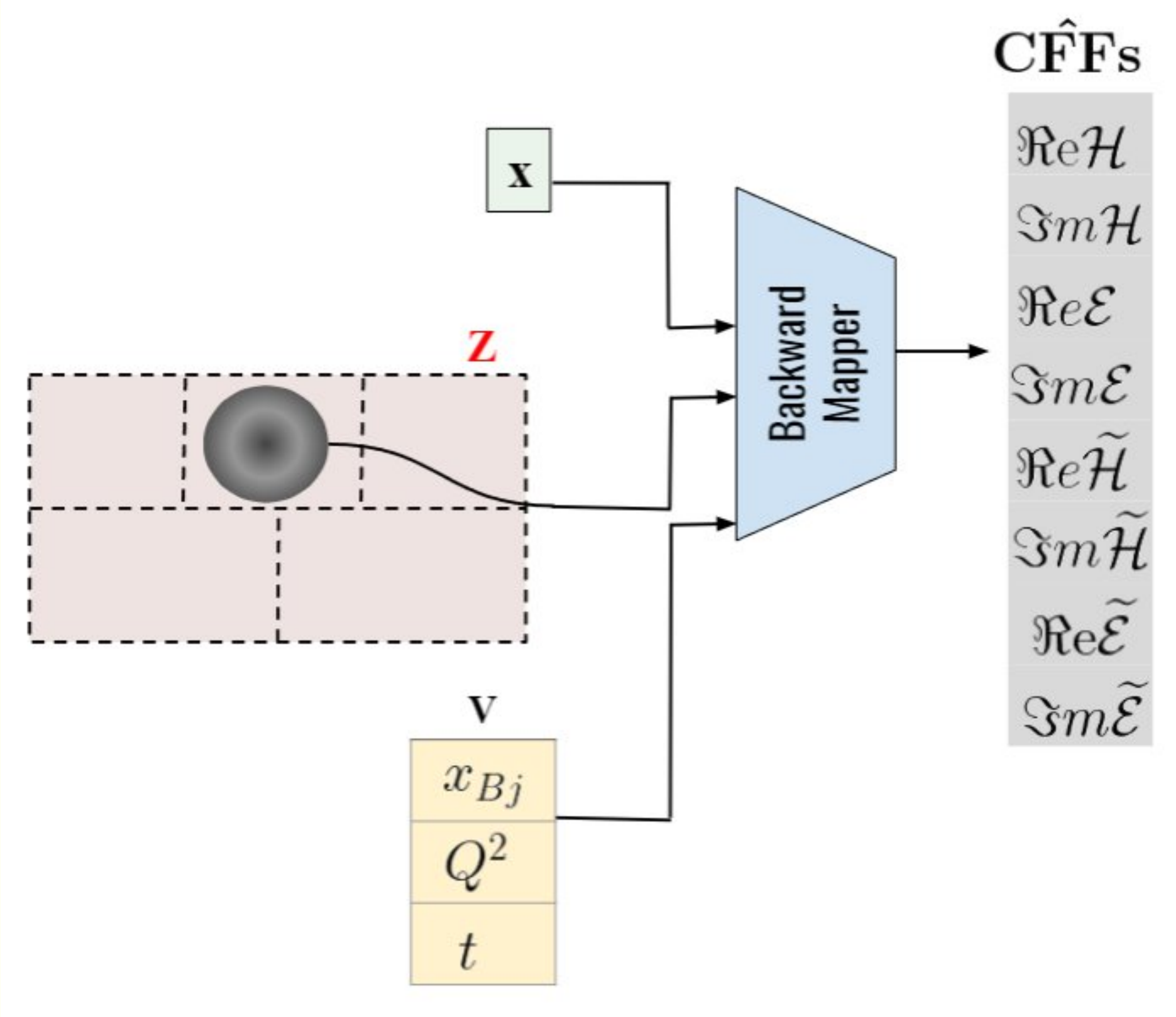
Partons 2018

Can we benchmark our results?

VAIM (Variational Autoencoder Inverse Mapper)



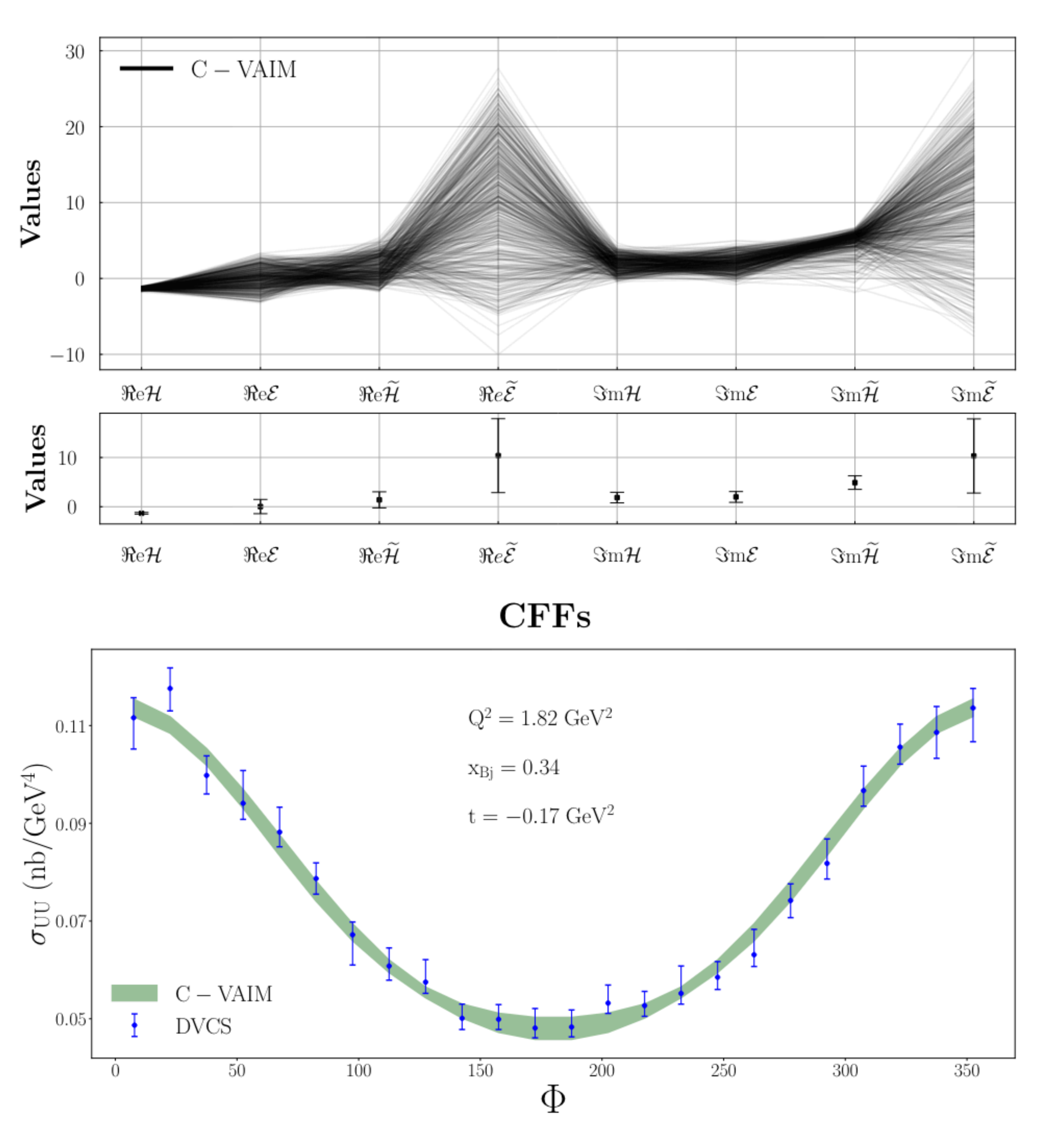
C-VAIM architecture to extract CFFs



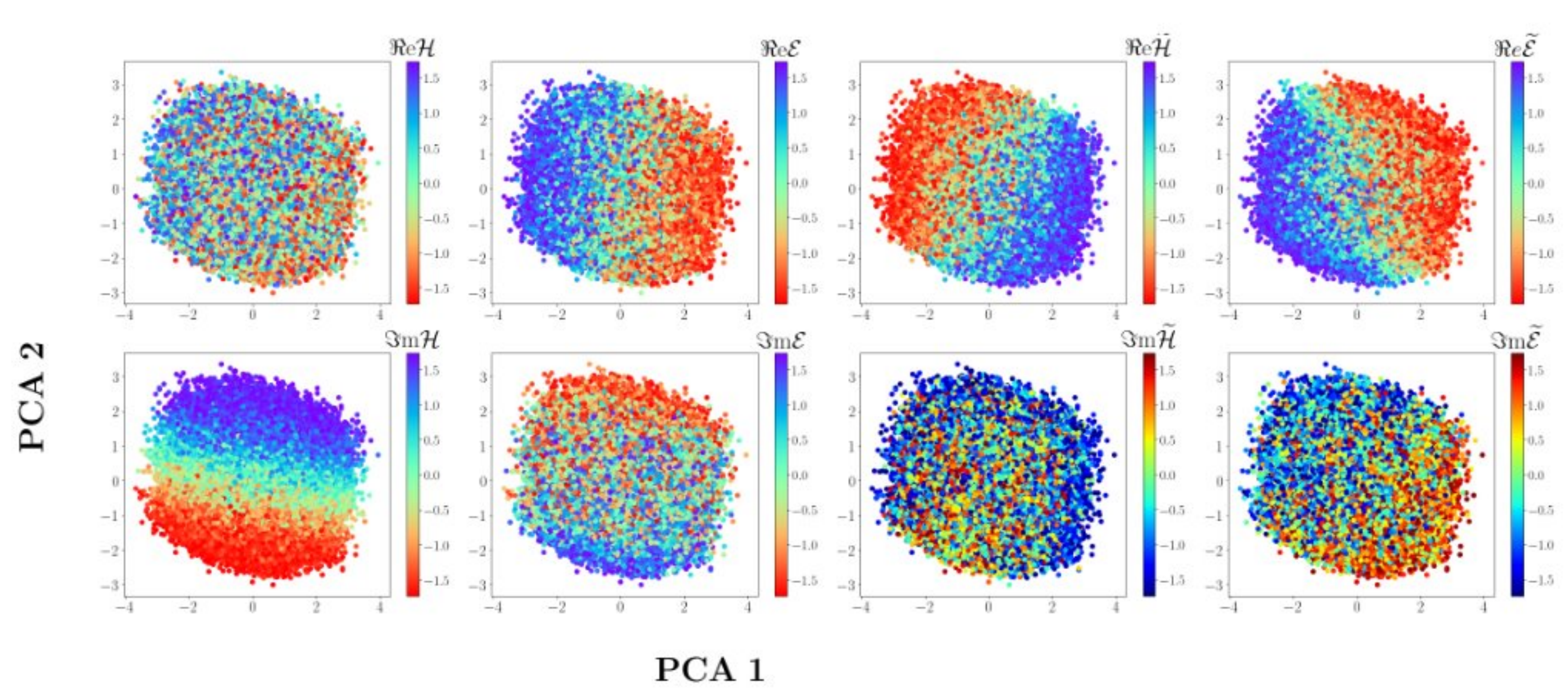
Decoder after VAIM is trained

[arXiv:2405.05826]

CFF results



Latent space



We are not losing information on $\Re e\mathscr{H}$, we are losing sign information for $\Im m\mathscr{H}$, we cannot extract $\Im m\tilde{\mathscr{E}}$, etc…

Symbolic regression (PySR)

Data table

t	Q^2	ϕ
-0.1	2	0
-0.2	4	20
⋮	⋮	⋮

Attempted expression

$y + ax^2 + bx + c$

Goodness

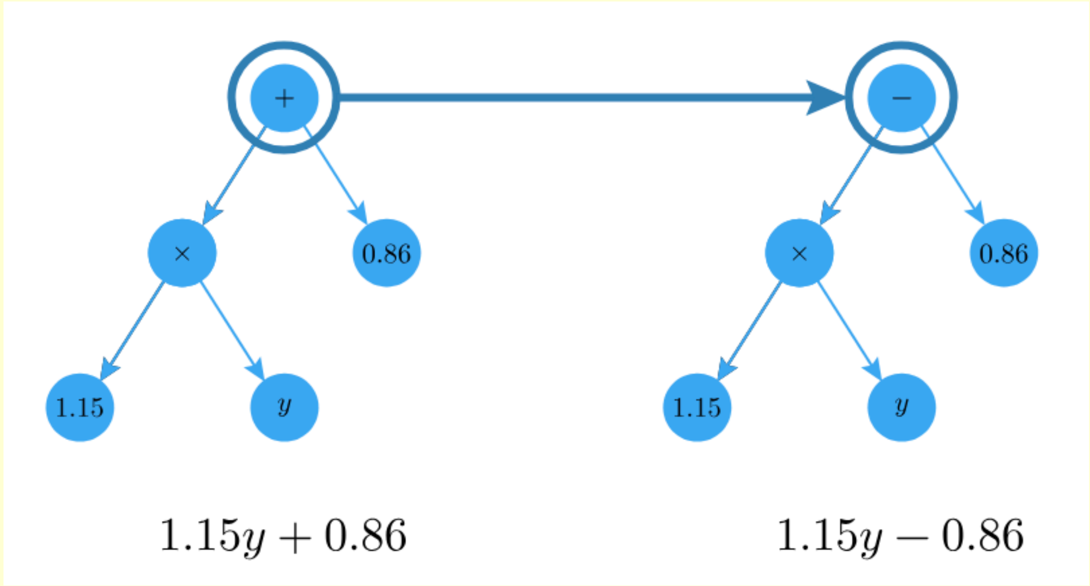
Fitness metric

e.g. squared error

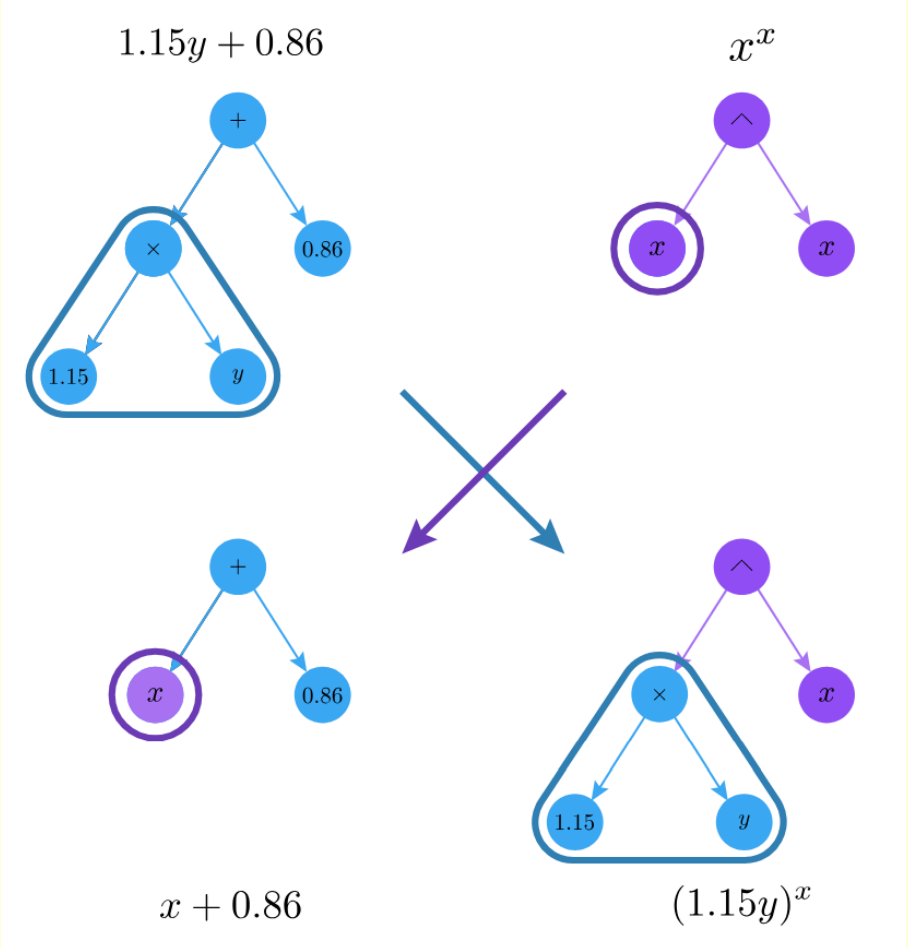
Form metric

e.g. #terms

Symbolic modification



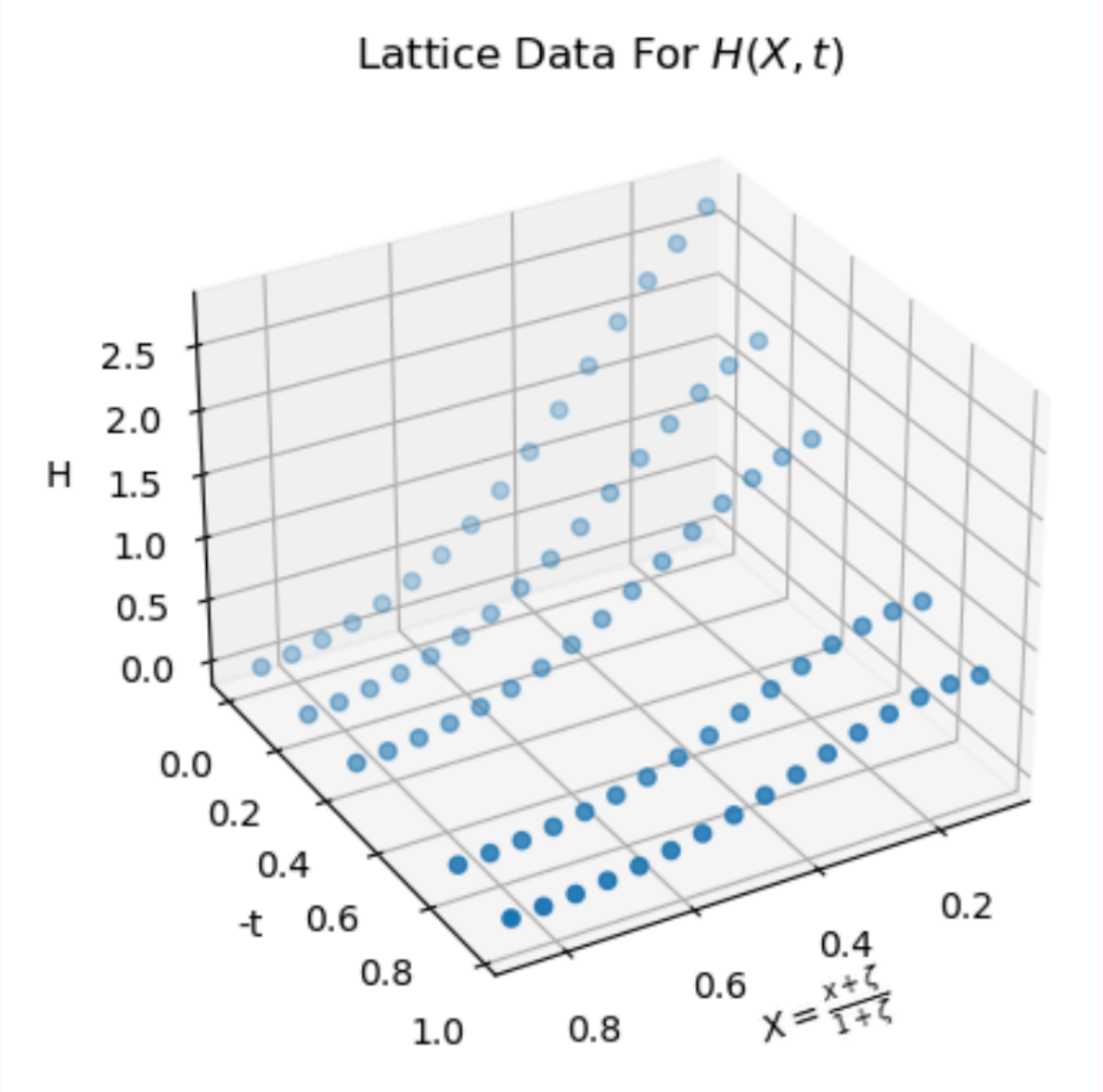
Mutation



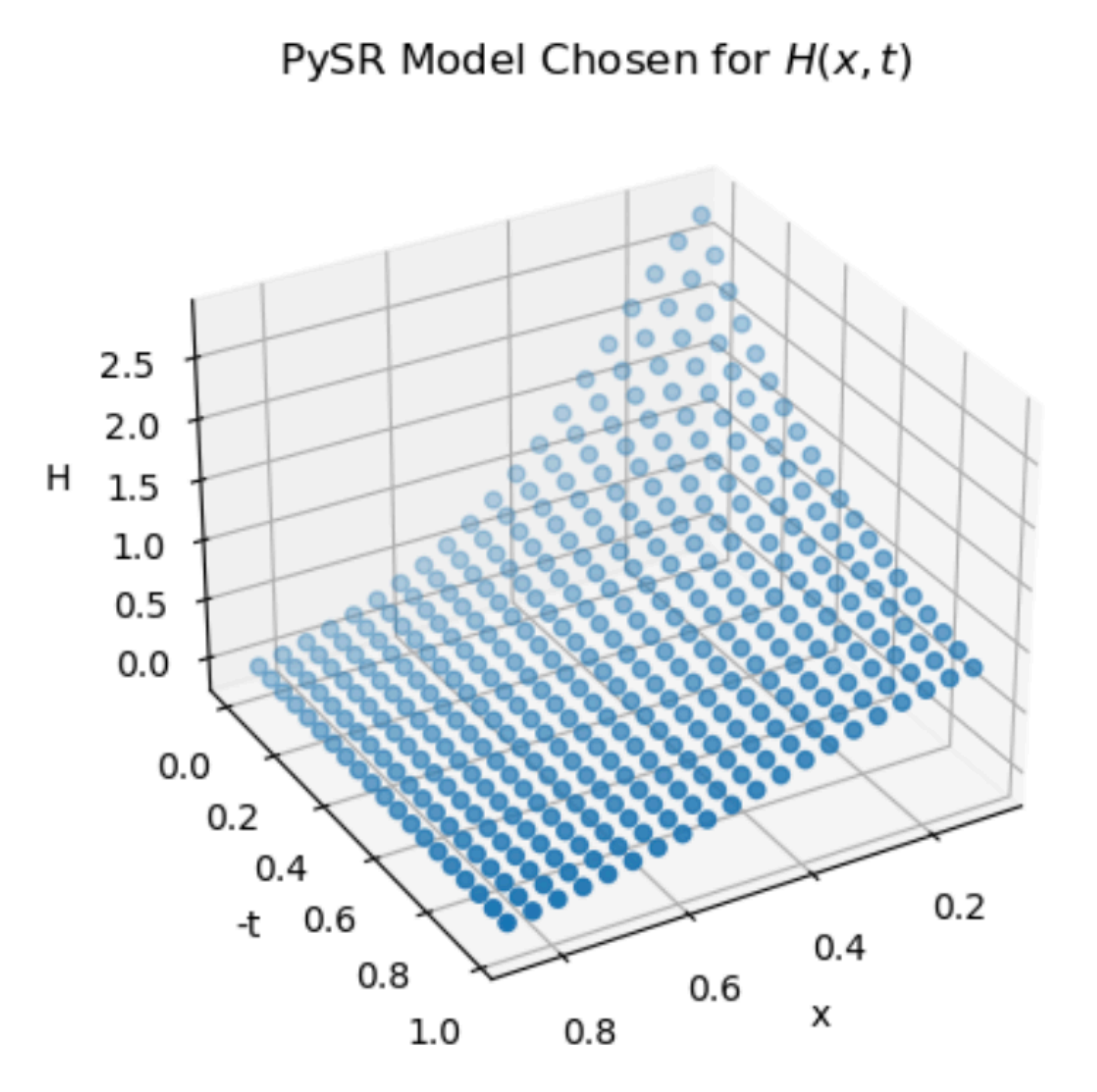
Crossover

Good? — No / Yes — Done

Symbolic regression on lattice data



Huey-Wen Lin

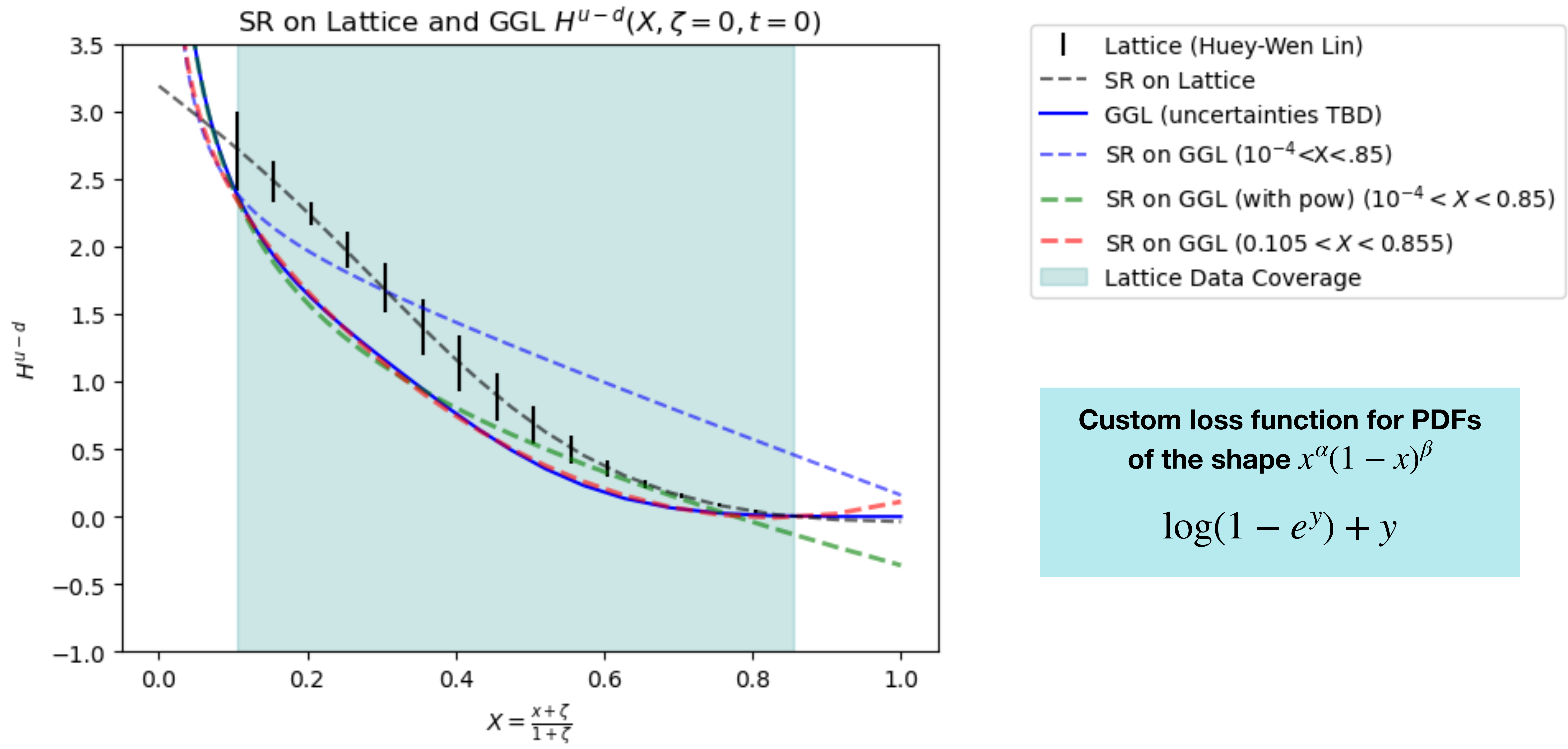


$$H^{SR}(X,t) = \frac{0.847517 - X}{\left(2X^2 + 0.458866\right)\left(-t + 0.549654\right)}$$

Factorization of X and t!

Figures by Andrew Dotson

SR on GGL

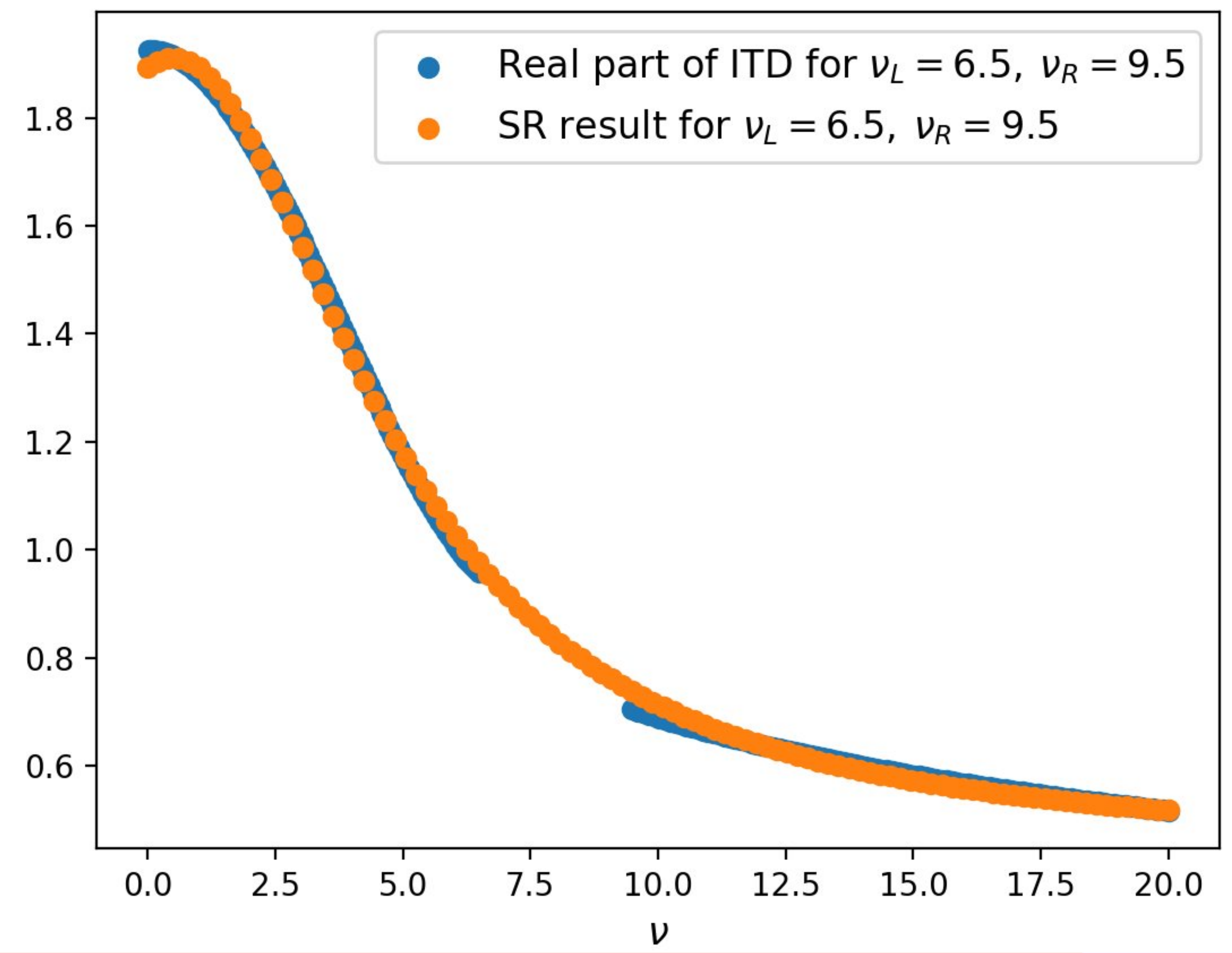


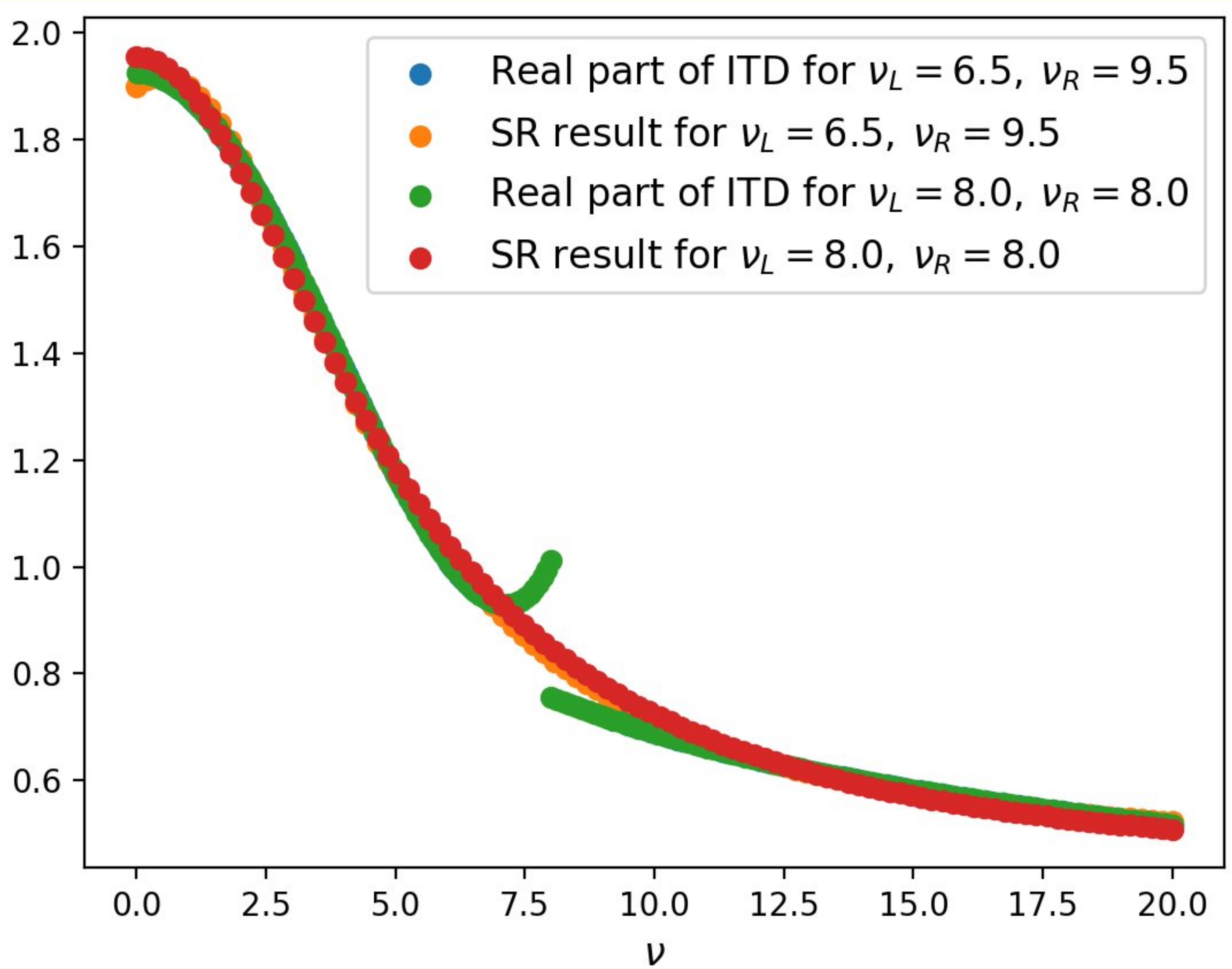
Custom loss function for PDFs of the shape $x^{\alpha}(1-x)^{\beta}$

$$\log(1-e^{y}) + y$$

Figure by Andrew Dotson

Ioffe time distribution matching





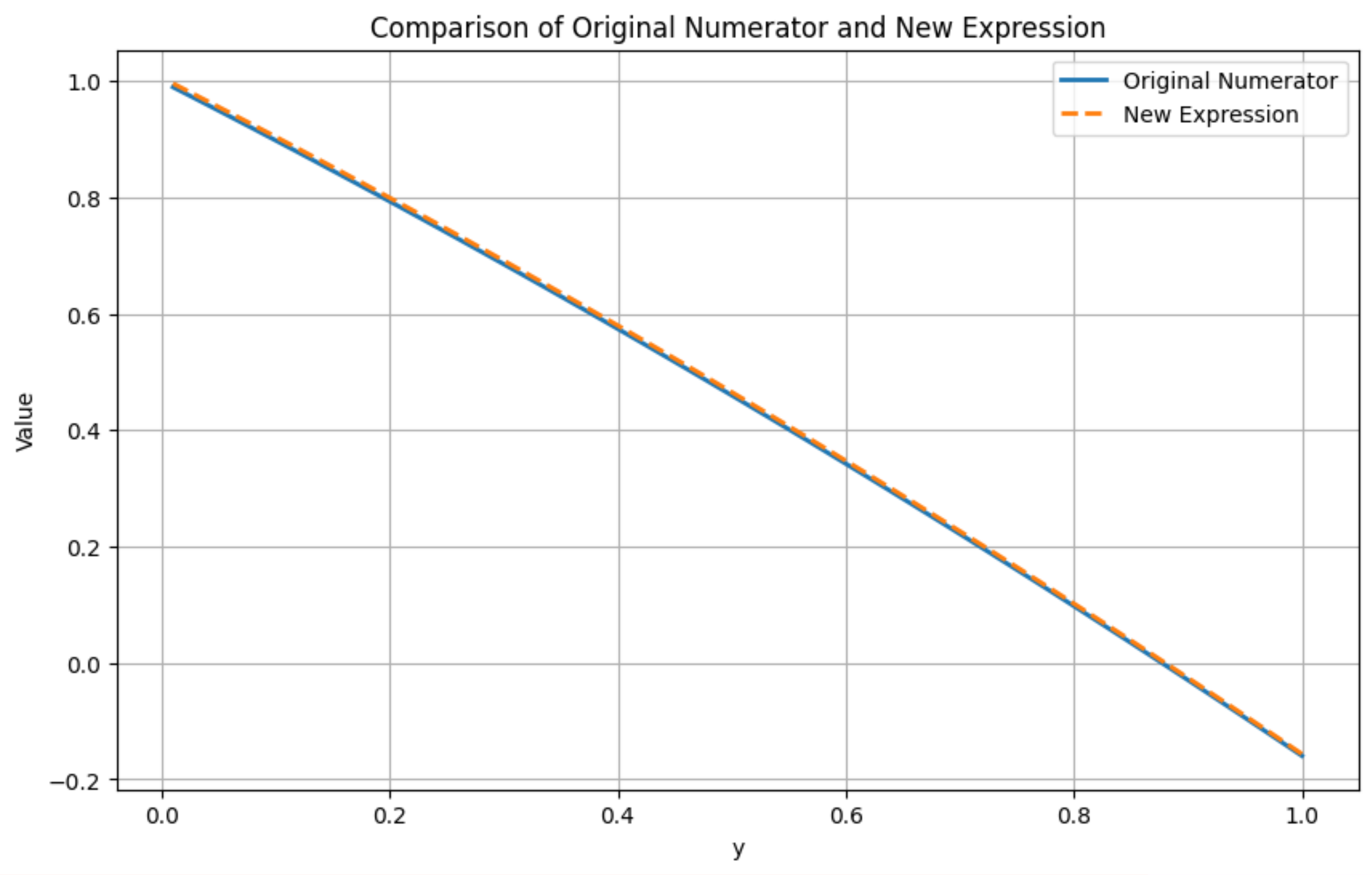
PySR result:

$$\Re\mathrm{e}\mathscr{M}(\nu) = \alpha + \frac{\beta}{\nu^2 - \nu + \gamma}$$

$$\alpha = 0.443\ , \beta = 29.89\ , \gamma = 20.6$$

Figures by Zaki Panjsheeri

Symbolic approximation - simplifying analytic expressions



$$\epsilon = \frac{1 - y - \frac{1}{4}y^2\gamma^2}{1 - y + \frac{1}{2}y^2 + \frac{1}{4}y^2\gamma^2}$$

$$\epsilon_{simplified} = \frac{1.006 - y - 0.20 \times \gamma \times y^2}{y^2 \times \left(0.25 \times \gamma + 0.45\right) - y + 0.99}$$

Figure by Anusha Singireddy

Likelihood analysis

Extracting CFFs from unpolarized DVCS data

$$\sigma_{UU}^{DVCS} = f(\mathfrak{Re}\mathcal{H}, \mathfrak{Re}\mathcal{E}, \mathfrak{Re}\widetilde{\mathcal{H}}, \mathfrak{Re}\widetilde{\mathcal{E}}, \mathfrak{Im}\mathcal{H}, \mathfrak{Im}\mathcal{E}, \mathfrak{Im}\widetilde{\mathcal{H}}, \mathfrak{Im}\widetilde{\mathcal{E}}, Q^2, t, \xi, E_b)$$

no angle dependence

$$\sigma_{UU}^{BH} = f(\xi, Q^2, t, \boxed{\phi}, E_b)$$

no CFF dependence

$$\sigma_{UU}^{INT} = f(\mathfrak{Re}\mathcal{H}, \mathfrak{Re}\mathcal{E}, \mathfrak{Re}\widetilde{\mathcal{H}}, \xi, Q^2, t, \boxed{\phi}, E_b)$$

angle and 3 CFF dependence

$$[\sigma_{UU}^{TOT}(\phi_A) - \sigma_{UU}^{BH}(\phi_A)] - [\sigma_{UU}^{TOT}(\phi_B) - \sigma_{UU}^{BH}(\phi_B)] = \sigma_{UU}^{INT}(\phi_A) - \sigma_{UU}^{INT}(\phi_B)$$

We can extract 3 CFFs!

Single point likelihood

$$\mathcal{L}\left(\text{row}_A, \text{row}_B, 3\text{CFFs}\right) = \text{Gaussian}\left(x = \sigma_{\text{obsA}} - \sigma_{\text{obsB}}, \mu = \sigma_{\text{model}}\left(\phi_A, 3\text{CFFs}\right) - \sigma_{\text{model}}\left(\phi_B, 3\text{CFFs}\right), \sigma_{\text{err}}^2 = \sigma_{\text{errA}}^2 + \sigma_{\text{errB}}^2\right)$$

Total likelihood

$$\mathcal{L}_{\text{TOT}}(3\text{CFFs}) = \Pi_{A,B}\mathcal{L}\left(\text{row}_A, \text{row}_B, 3\text{CFFs}\right)$$

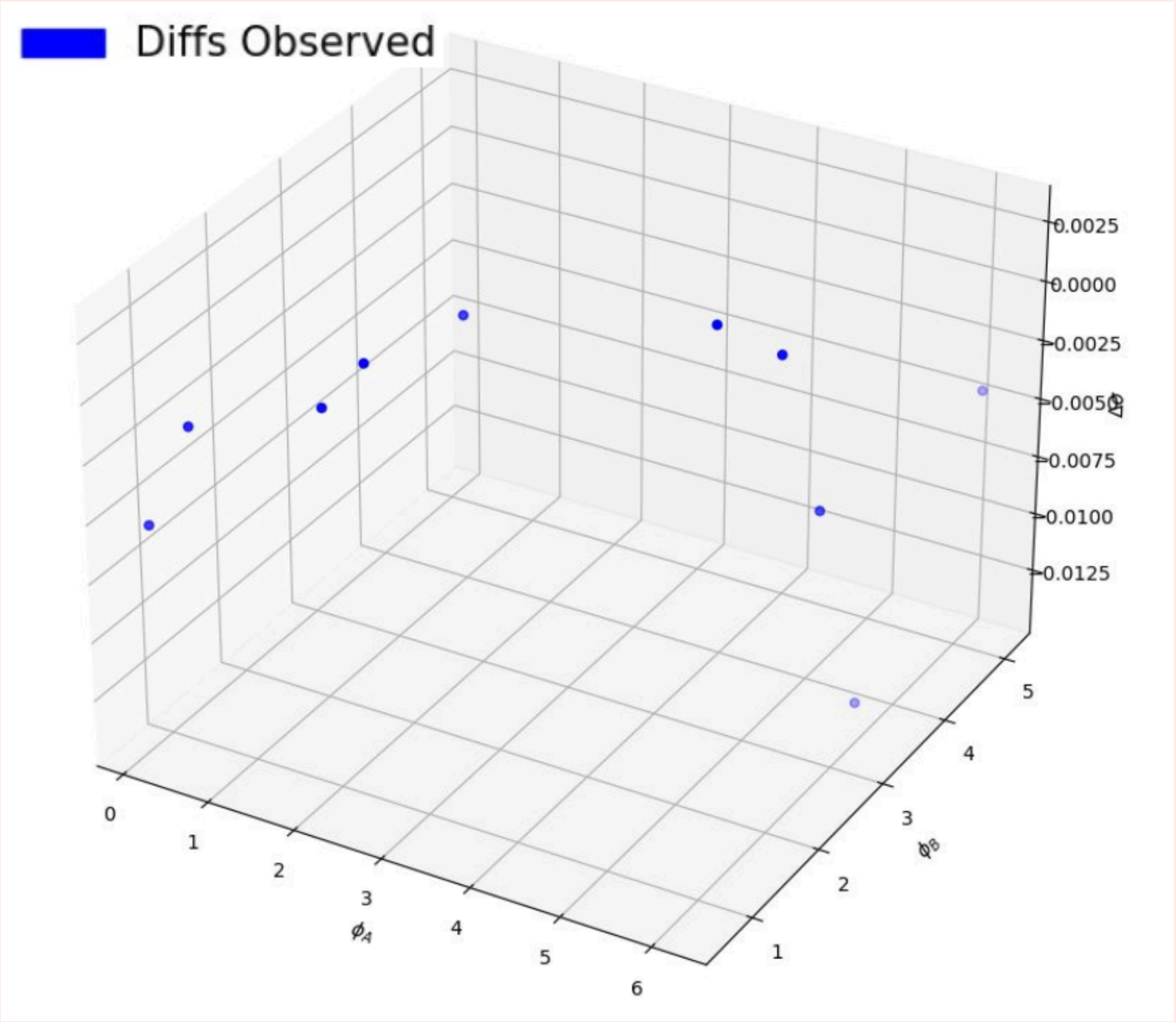
Maximum likelihood result

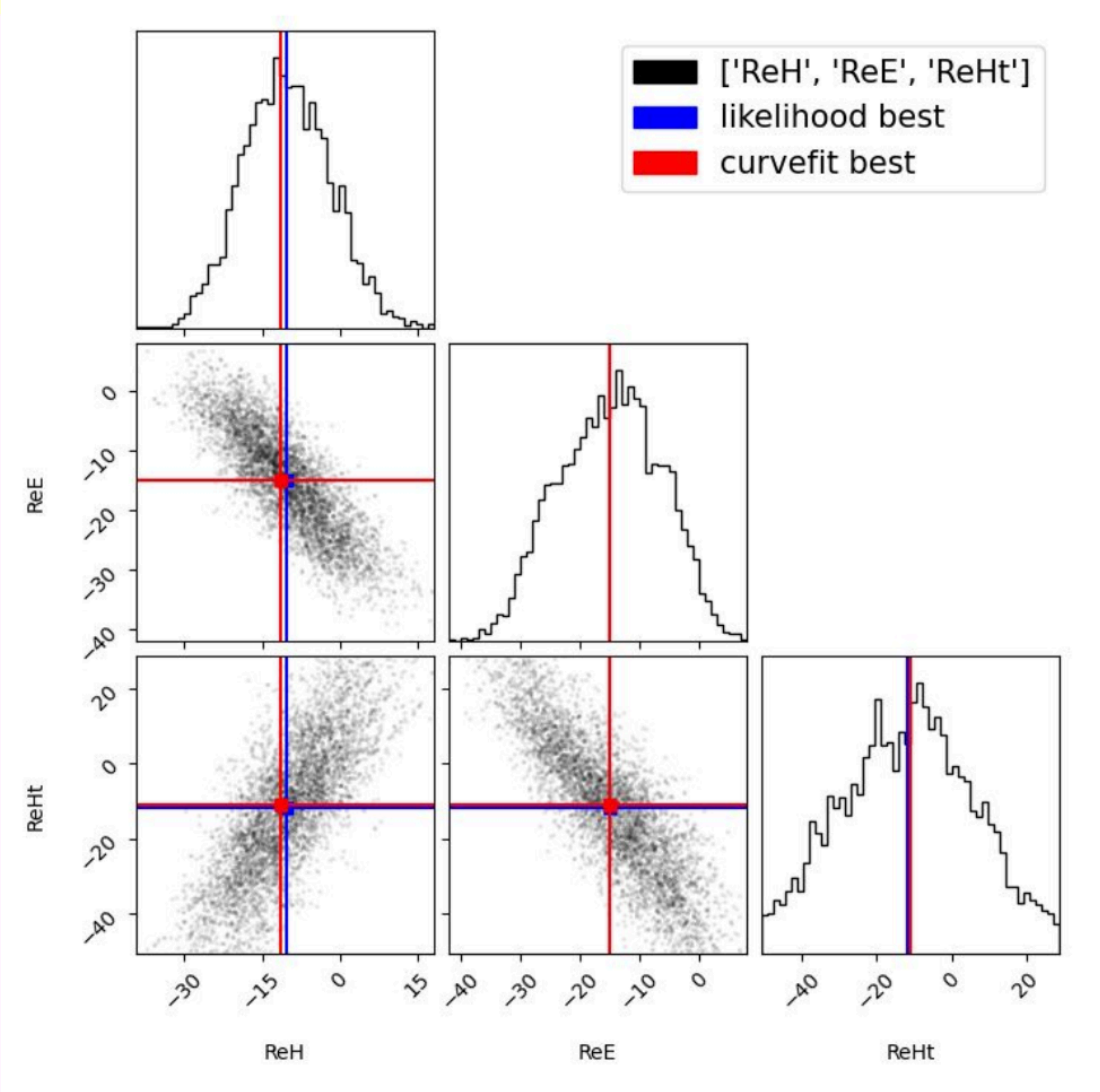
$E_b = 4.487,\ x_B = 0.483,\ Q^2 = 2.710,\ t = -0.3906$

$\mathfrak{Re}\mathscr{H} = -11.40,\ \mathfrak{Re}\mathscr{E} = -15.09,\ \mathfrak{Re}\widetilde{\mathscr{H}} = -10.90$

Best curve fit

$\mathfrak{Re}\mathscr{H} = -11.42,\ \mathfrak{Re}\mathscr{E} = -15.06,\ \mathfrak{Re}\widetilde{\mathscr{H}} = -10.99$





Figures by Doug Adams

Conclusion

- **Can we use likelihood analysis to see what information is available in data?**
  - **Does DVCS factorize, does data see GPDs, does data contain physics?**
- **Can we benchmark as a community?**
  - **Combine ML methods and physics to understand uncertainties**
- **Can we interpolate between kinematic regions?**
  - **Are models reliable outside of regions where there is no data?**
- **Can we understand the latent space in order to constrain GPDs better?**
- **Can symbolic regression and approximation extract formulas from the data?**