Progress towards a machine learning extraction of GPDs from data

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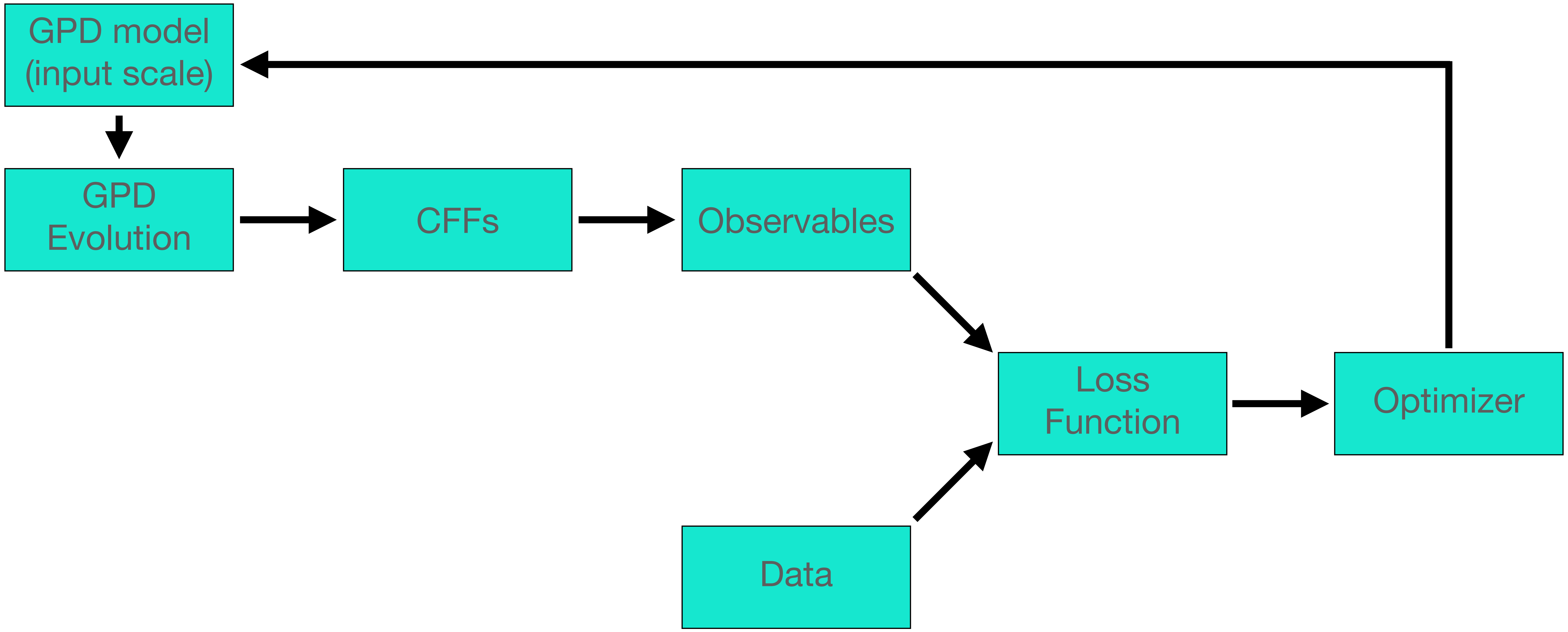
Introduction

- The goal:
  - Perform a global analysis of CFFs and GPDs from available data using machine learning
  - How do we get there?
    - Develop the machinery initially using parametric model:
      - Perform closure test using data generated from an existing model ✓
      - Fit to existing data (work in progress)
    - Replace parametric model with neural network (NN) model:
      - Repeat closure tests with the NNs (work in progress)
      - Fit to existing data

The machinery



- All pieces are backward differentiable to facilitate machine learning

The machinery

- GPD model:
  - Utilize double distributions to guarantee polynomiality

$$H^f(x,\xi,t;\mu_0^2) = \int_\Omega d\beta d\alpha\, \delta(x-\beta-\xi\alpha)\left[H^f_{DD}(\beta,\alpha,t;\mu_0^2) + \xi\delta(\beta)D^f(\alpha,t;\mu_0^2)\right]$$

$$E^f(x,\xi,t;\mu_0^2) = \int_\Omega d\beta d\alpha\, \delta(x-\beta-\xi\alpha)\left[E^f_{DD}(\beta,\alpha,t;\mu_0^2) - \xi\delta(\beta)D^f(\alpha,t;\mu_0^2)\right]$$

$$\tilde{H}^f(x,\xi,t;\mu_0^2) = \int_\Omega d\beta d\alpha\, \delta(x-\beta-\xi\alpha)\left[\tilde{H}^f_{DD}(\beta,\alpha,t;\mu_0^2)\right]$$

$$\tilde{E}^f(x,\xi,t;\mu_0^2) = \int_\Omega d\beta d\alpha\, \delta(x-\beta-\xi\alpha)\left[\tilde{E}^f_{DD}(\beta,\alpha,t;\mu_0^2)\right]$$

  - For H and $\tilde{H}$, use existing parton distribution functions for the forward limit

- Loss function:
  - Typical chi squared function

$$\sum\left(\frac{\text{data} - \text{theory}}{\text{uncertainty}}\right)^2$$

- Optimizer:
  - Use PyTorch Adam algorithm
    - Stochastic Gradient Descent

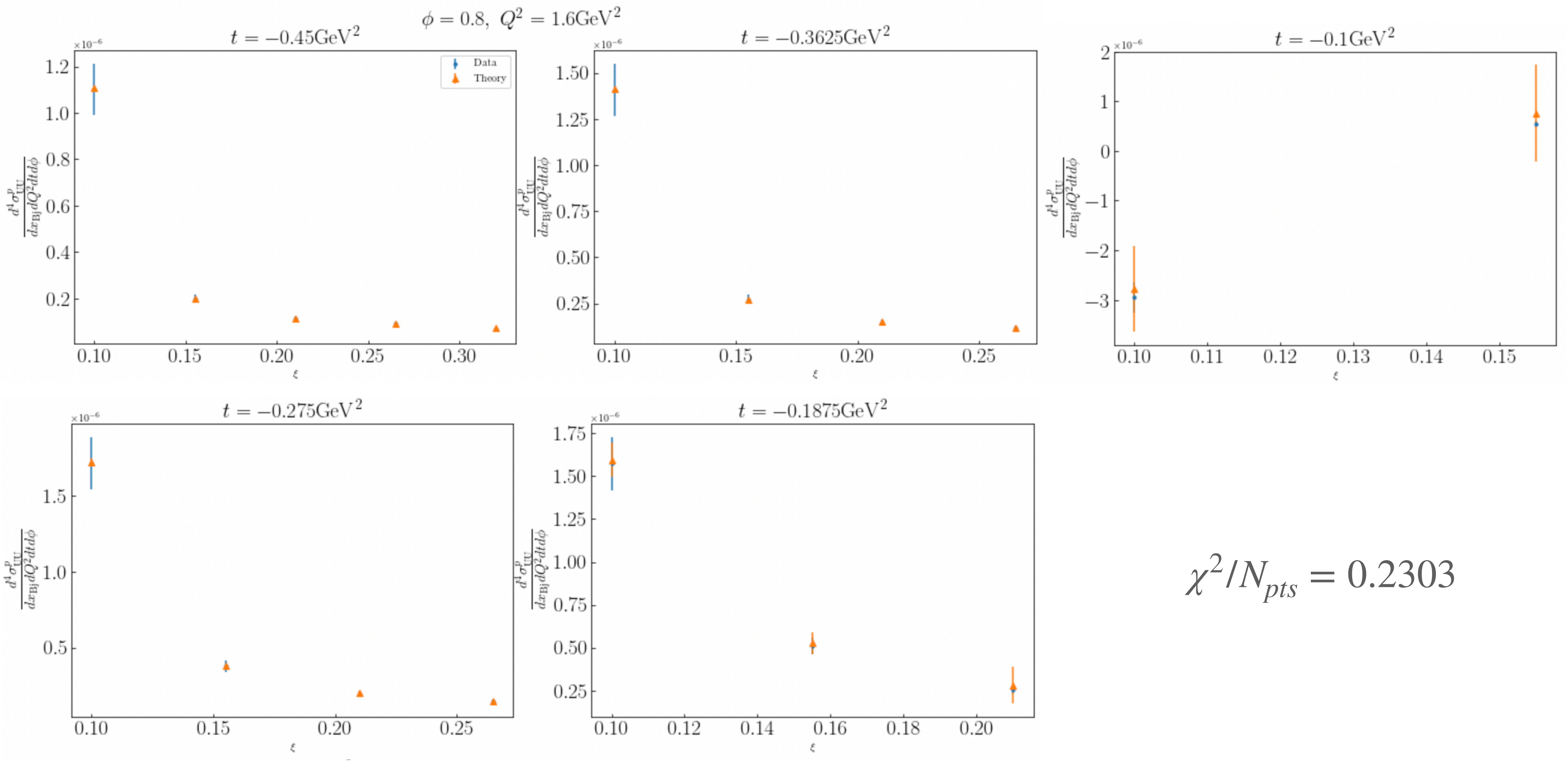
Closure test

- Generated pseudodata for various DVCS observables from model GPDs:
  - GPD model:
    - Double distributions:
      - Use GK model (Kroll, Moutarde, Sabatie, Eur. Phys. J. C (2013) 73:2278)
    - D term:
      - Use first three terms of a Gegenbauer series (Goeke, Polyakov, Vanderhaeghan, Prog. Part. Nucl. Phys. 47, 401 (2001)
  - Assume 10% uncertainty for all data points
- Fitted parameters (31 in total):
  - Fit uv and dv double distribution parameters:
    - For H and $\tilde{H}$, keep pdf parameters fixed and only fit profile function parameters
  - Fit the coefficients in the D term for u and d

Closure test

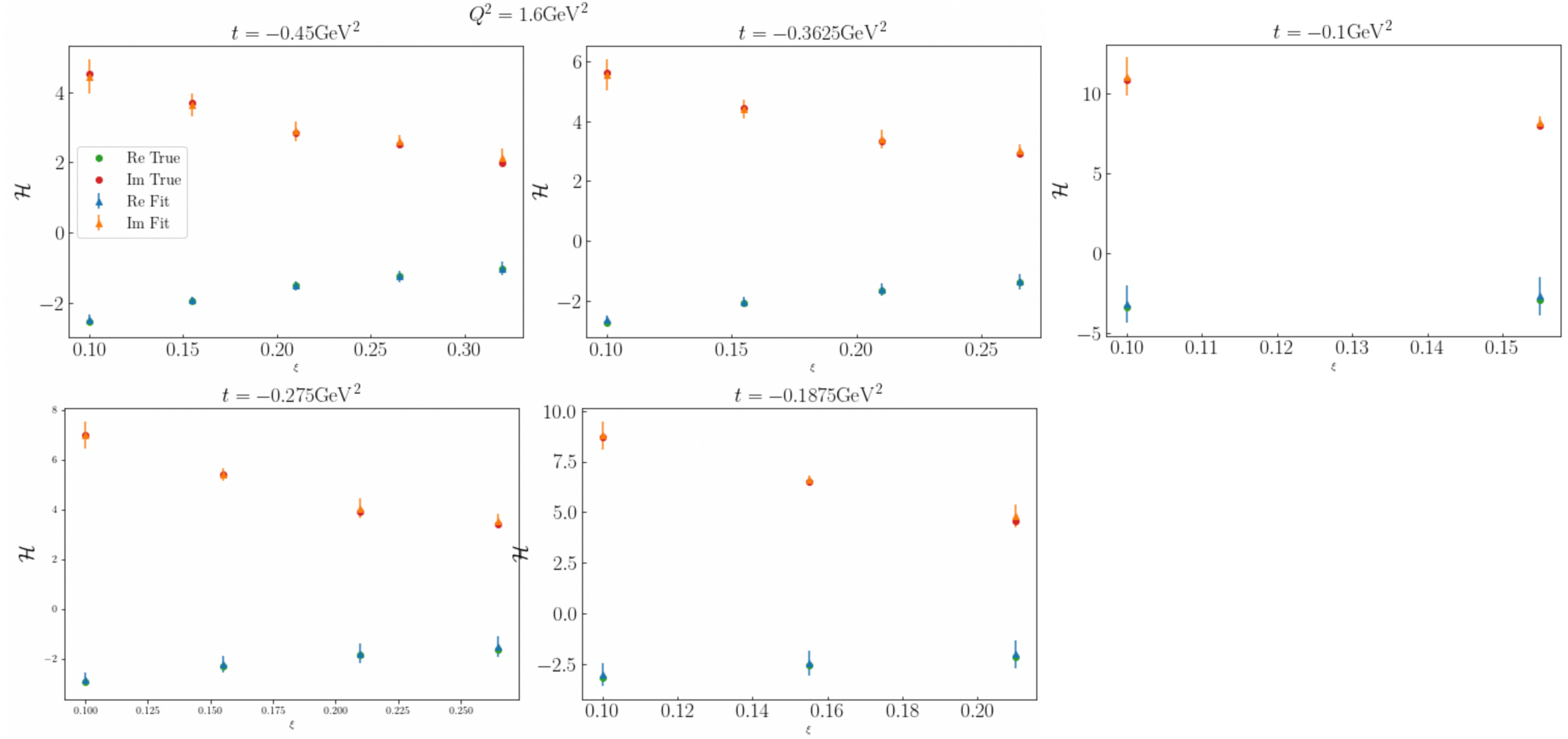
- Monte Carlo fit:
  - Conduct multiple fits (called replicas):
    - For each replica:
      - Starting parameters are randomly sampled
      - Data values sampled from Gaussian distribution
  - Calculate average and standard deviation of all replicas

Closure test results

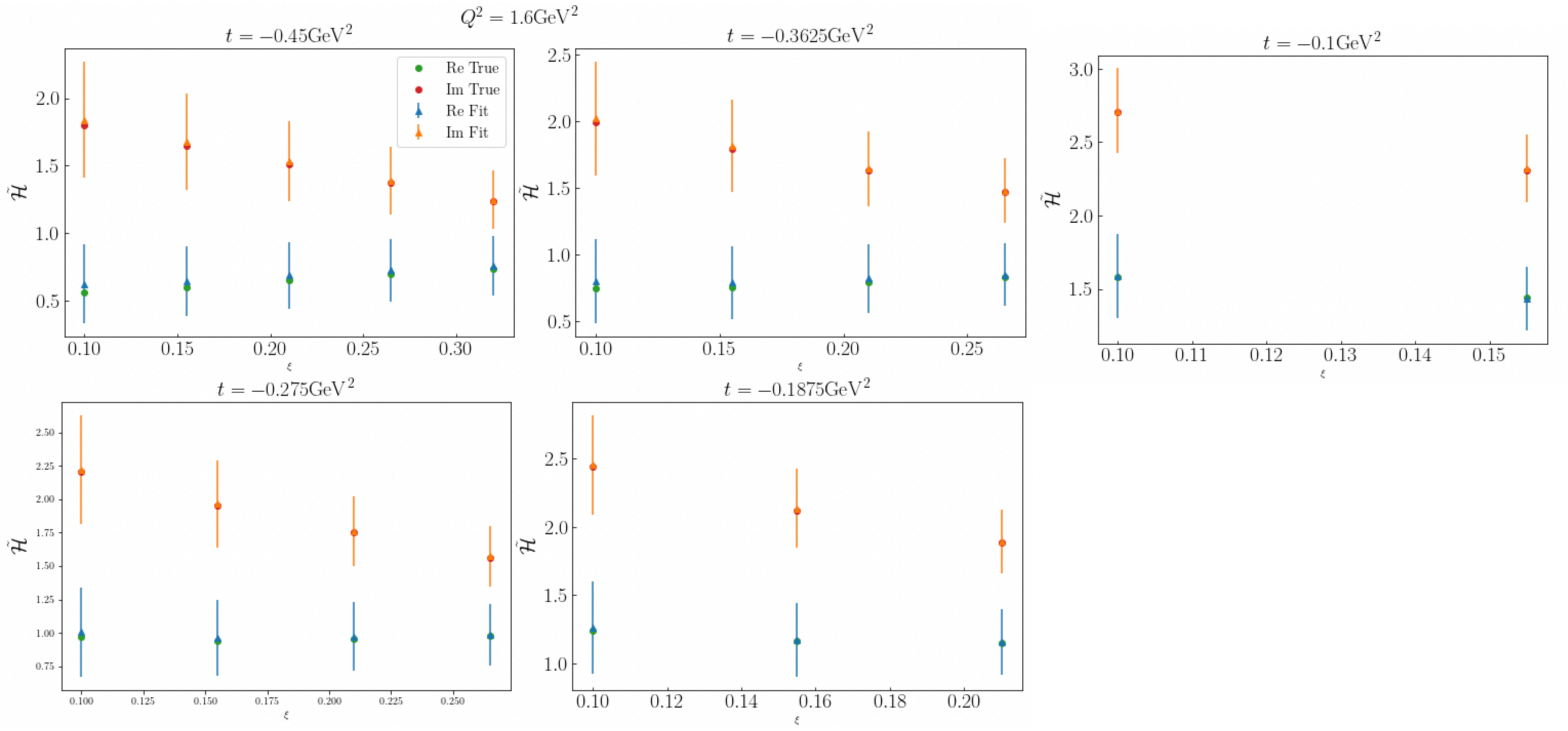


$\chi^2/N_{pts} = 0.2303$

Closure test results



Closure test results



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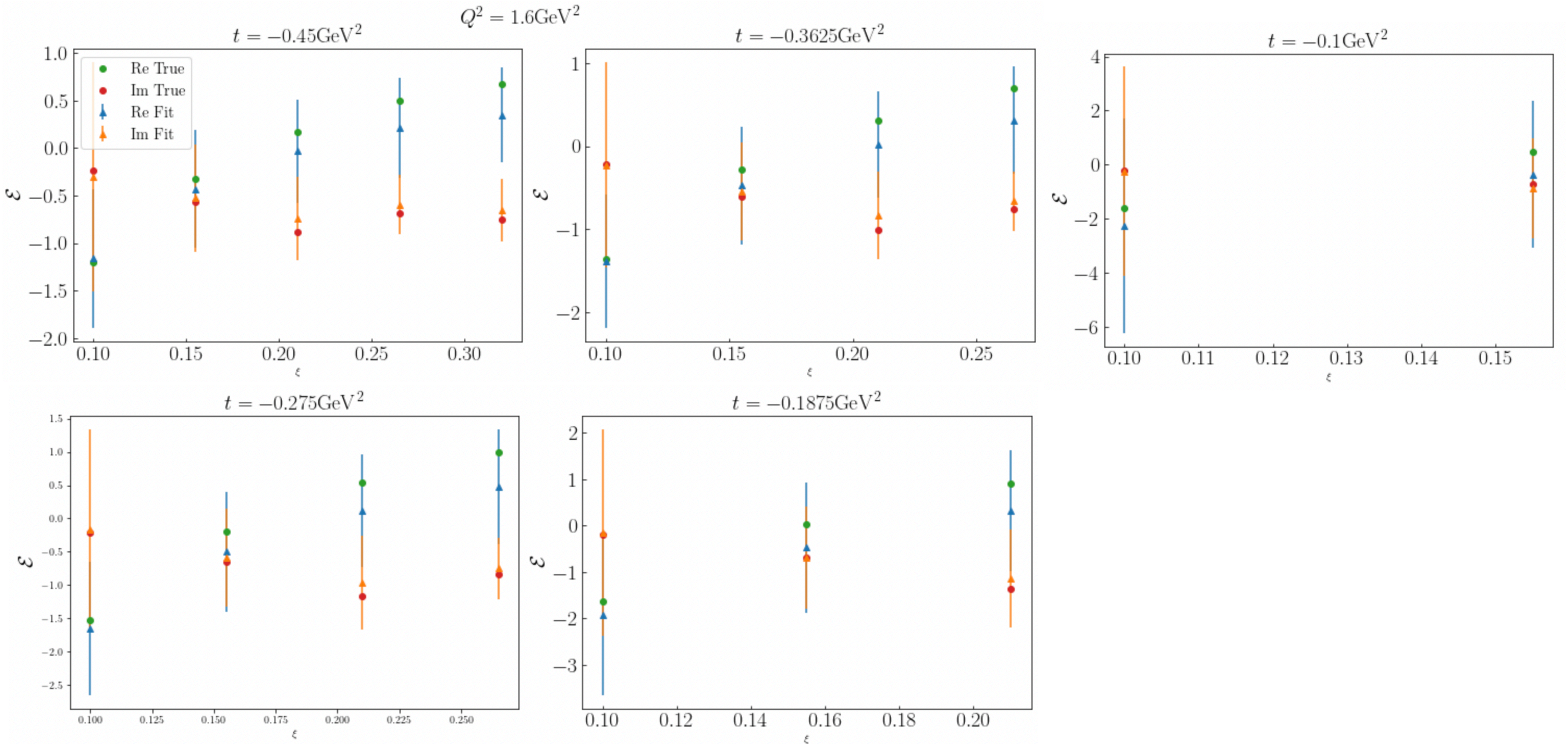

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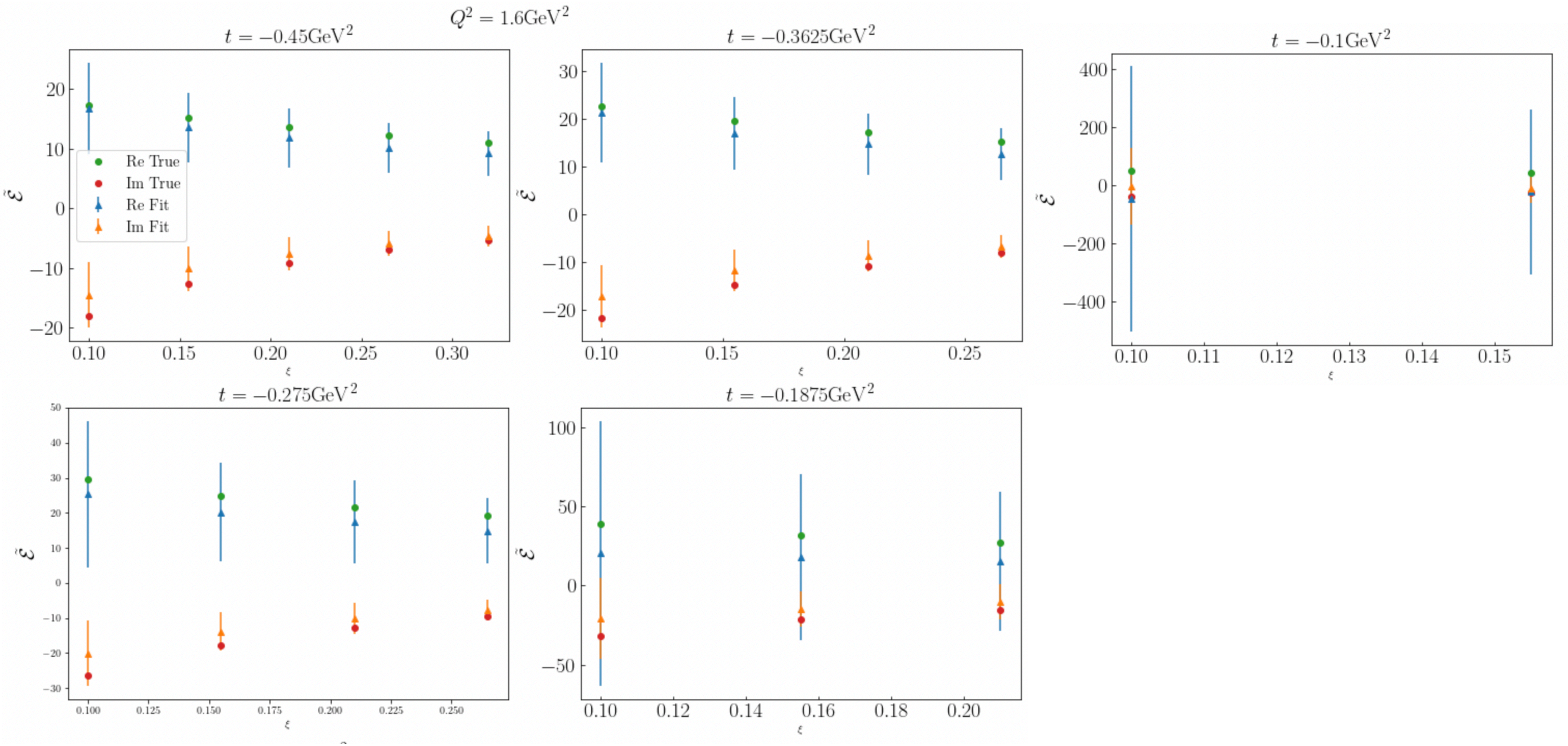

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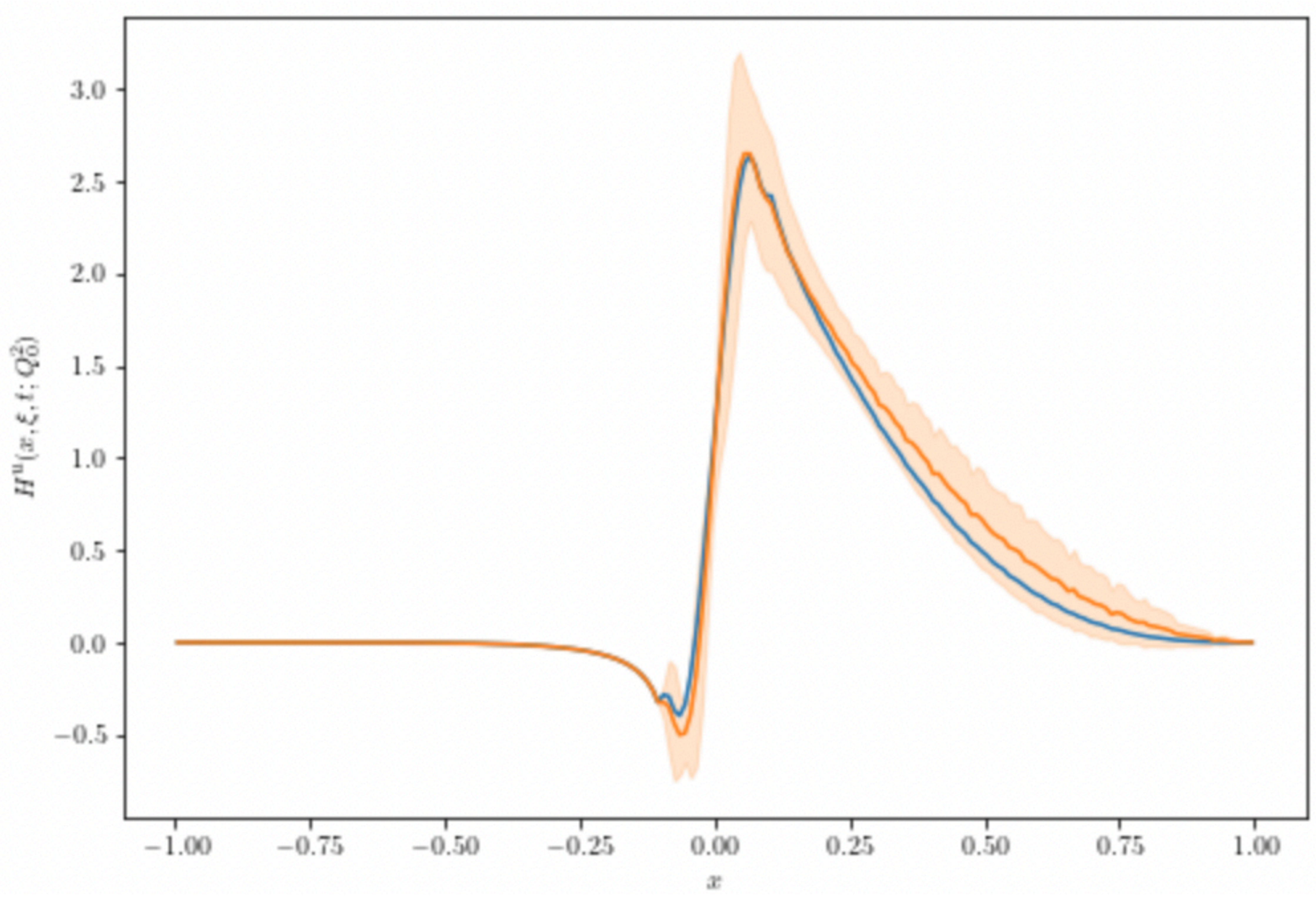

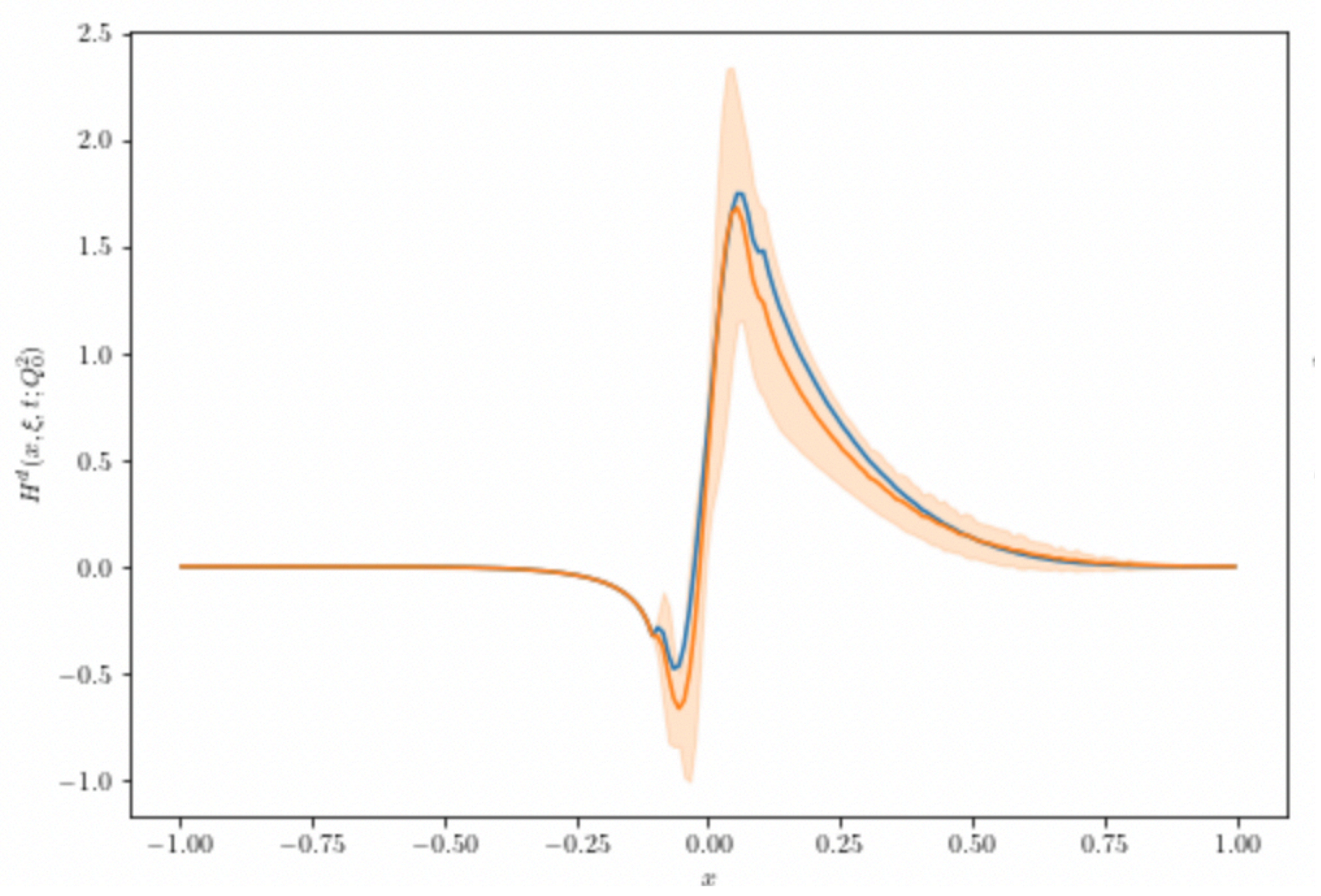

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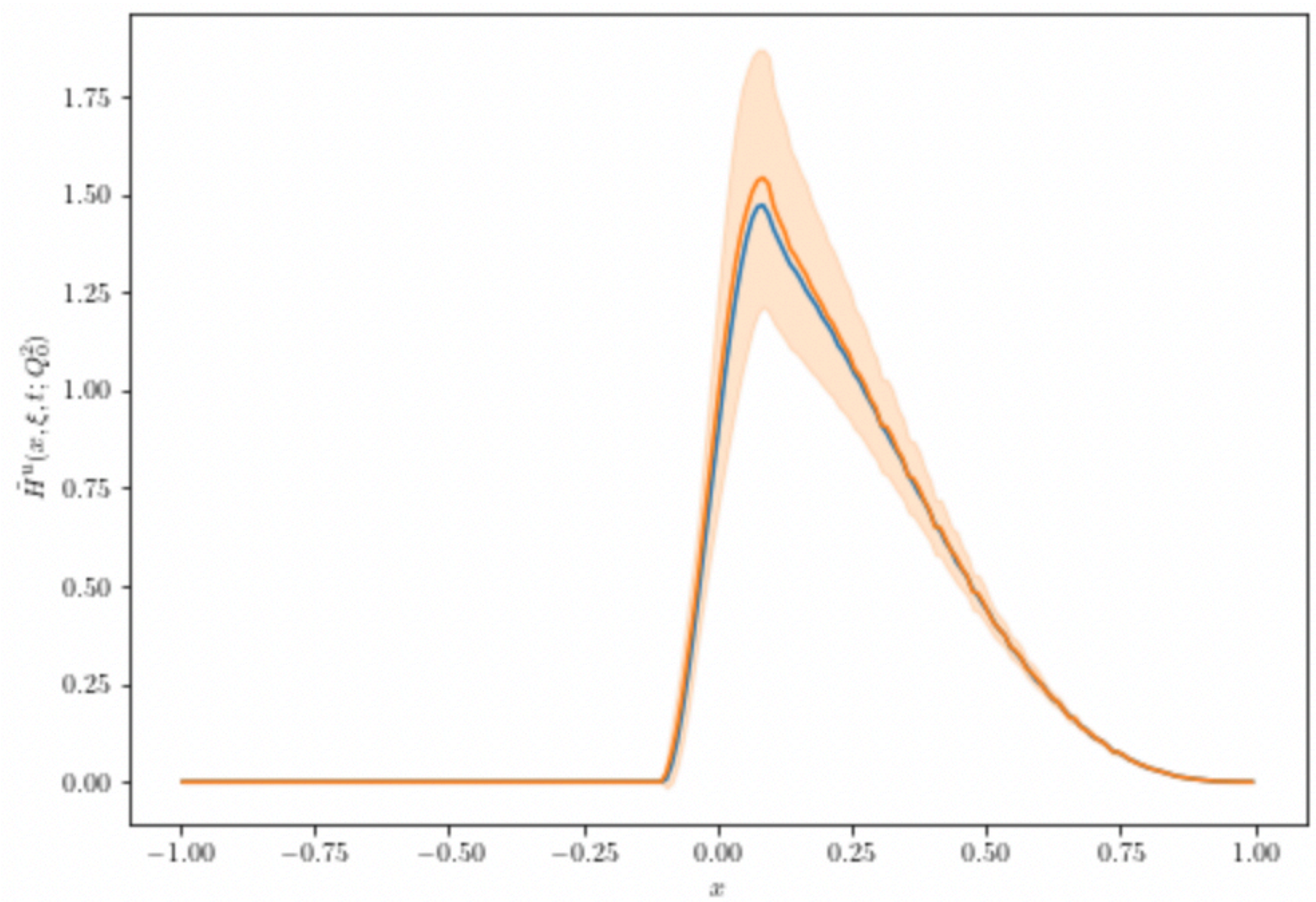

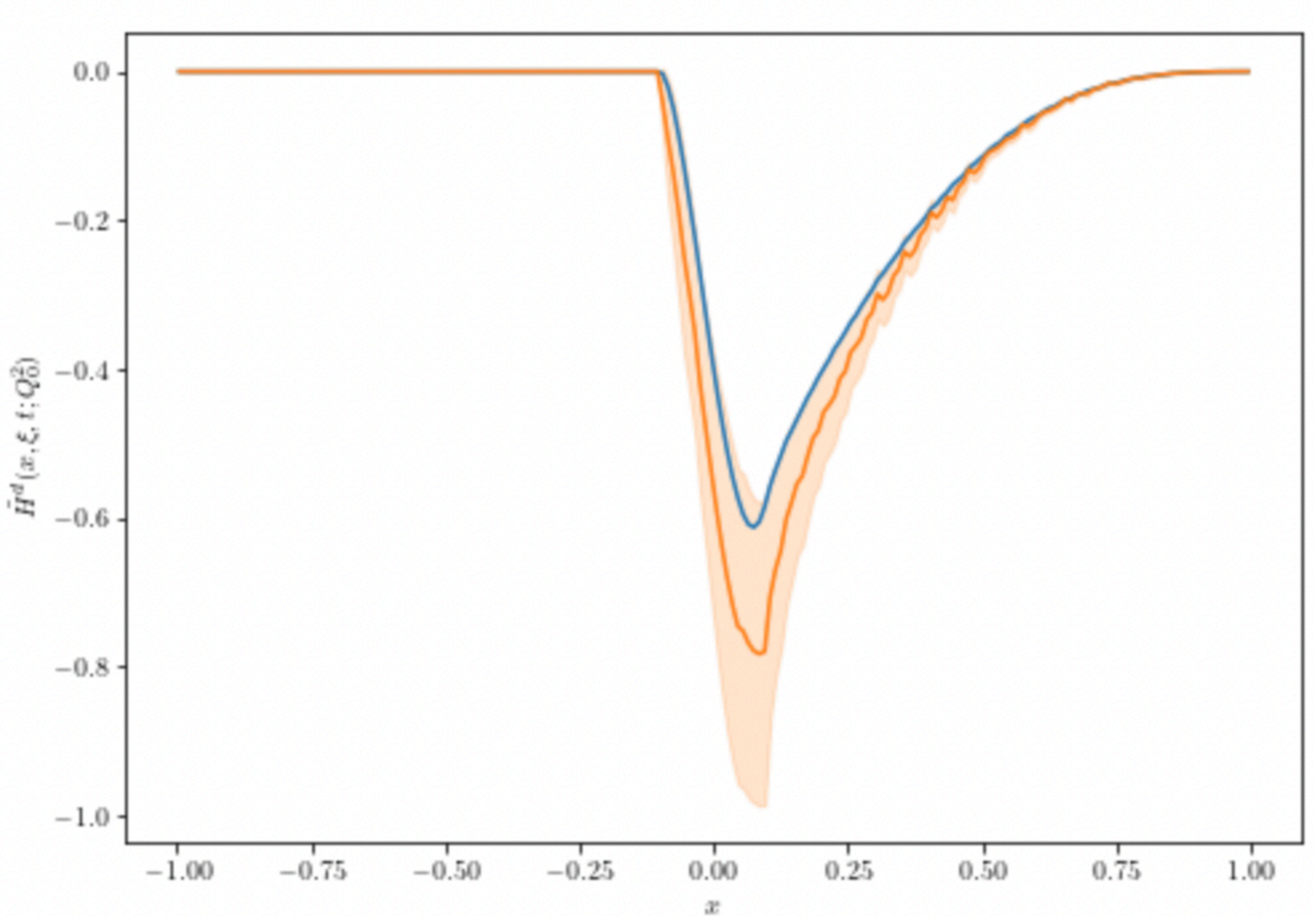

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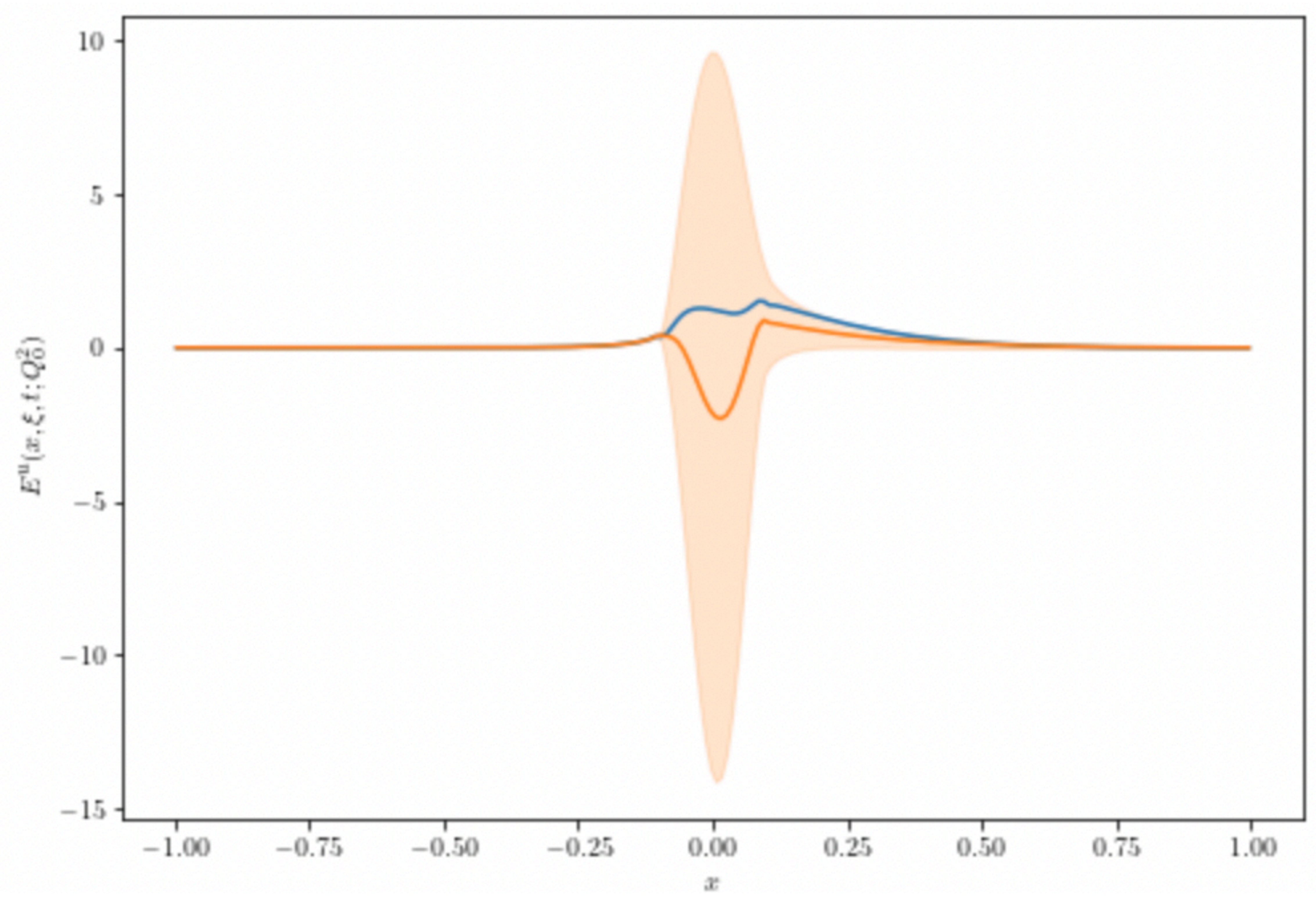

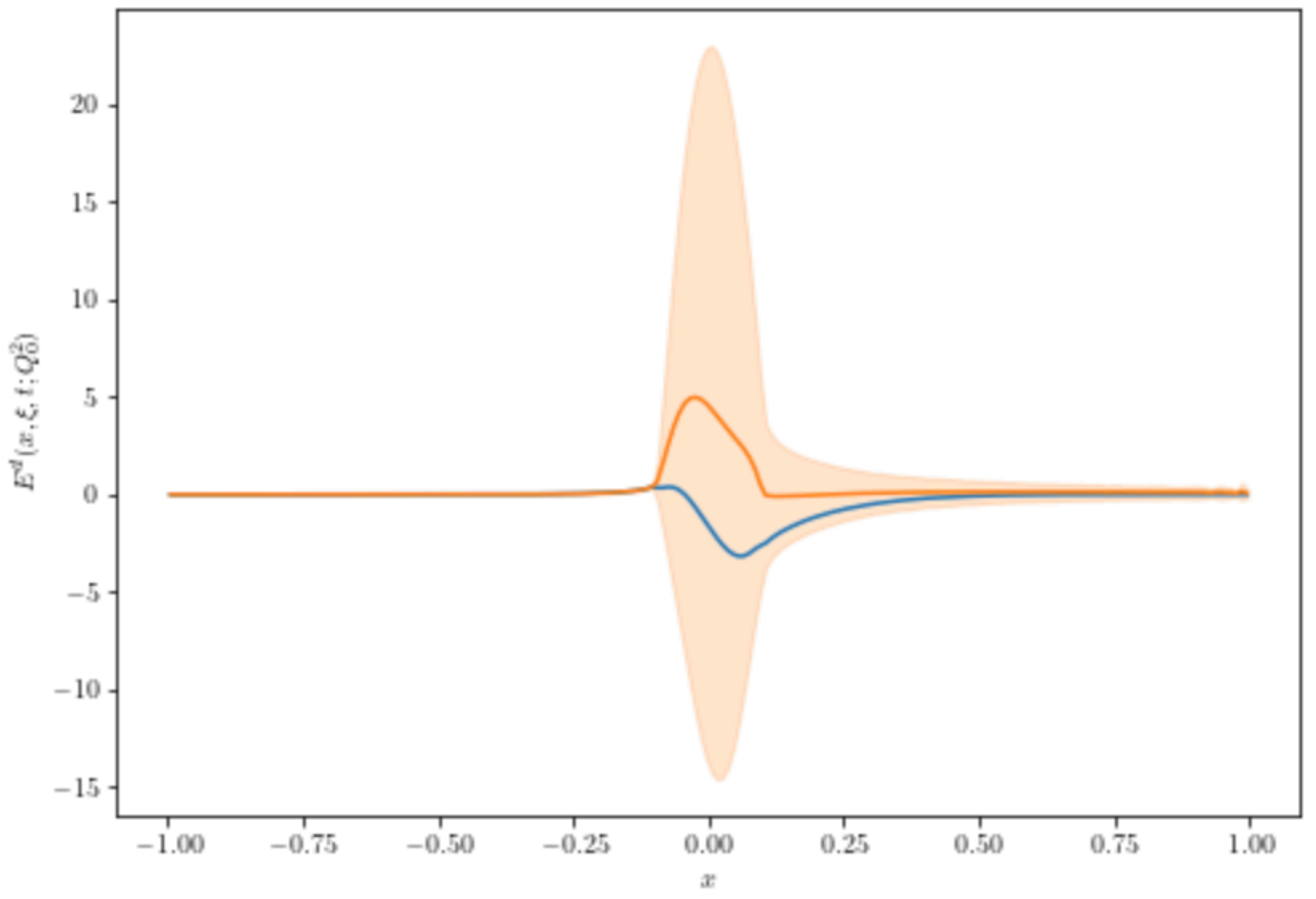

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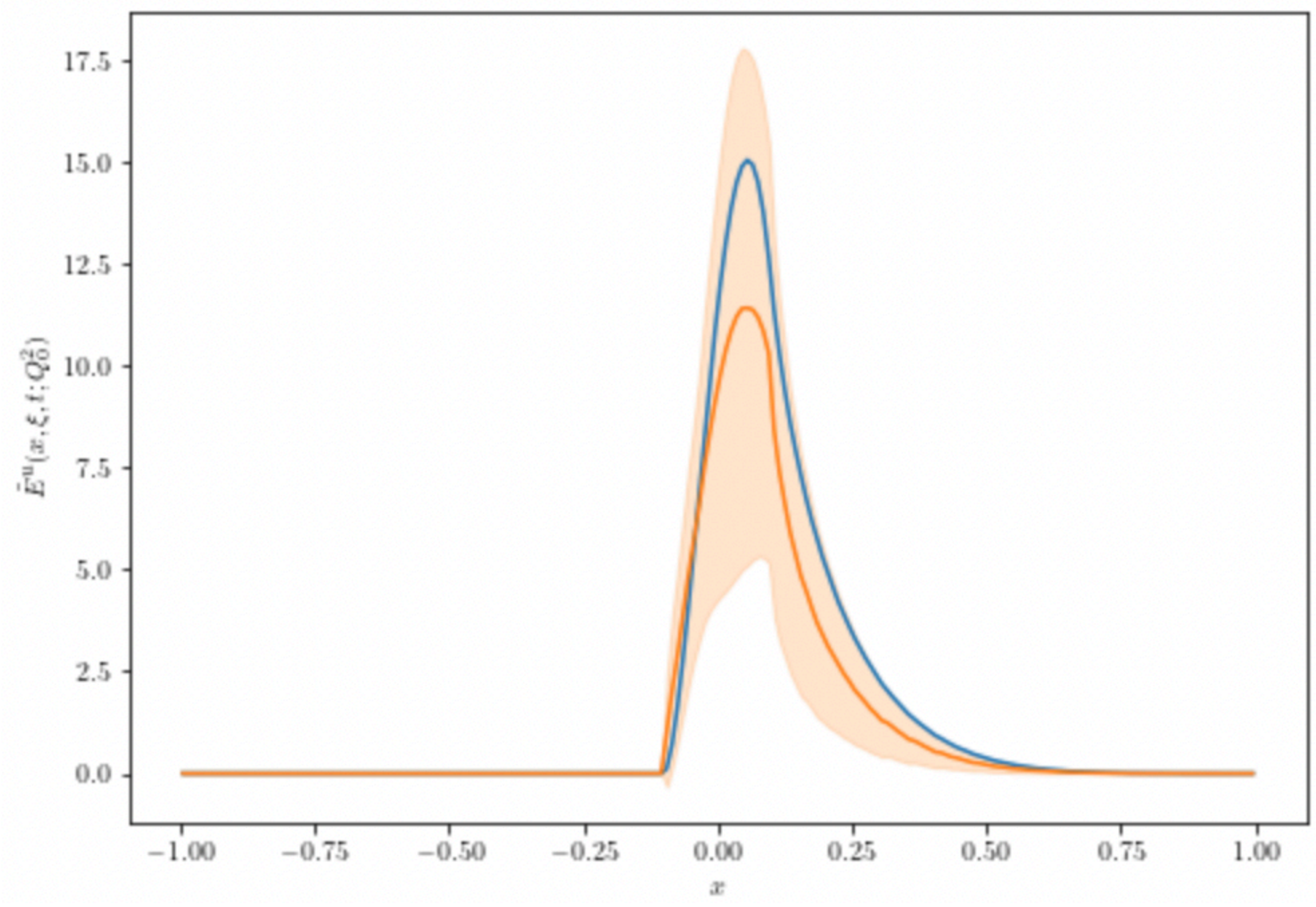
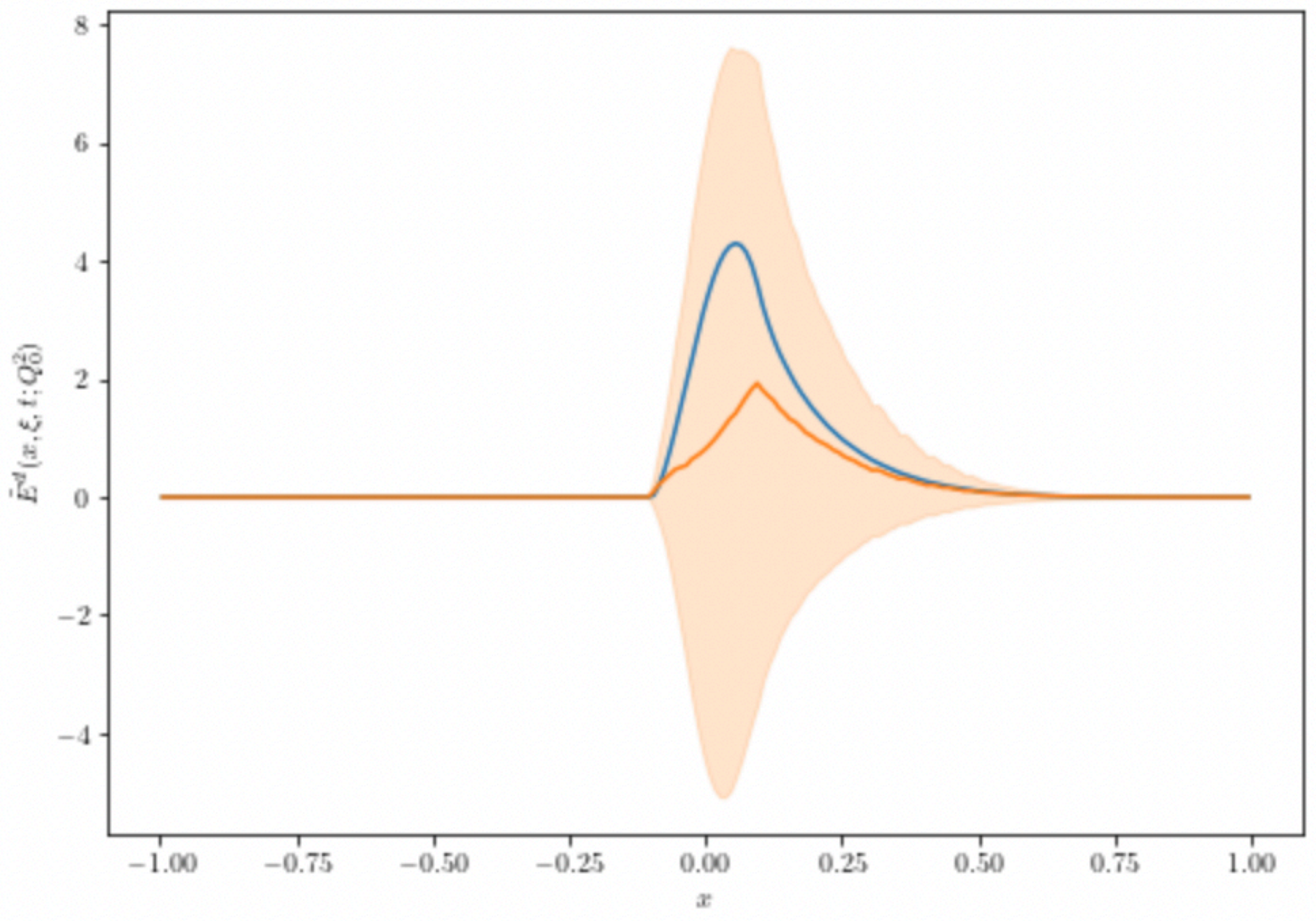
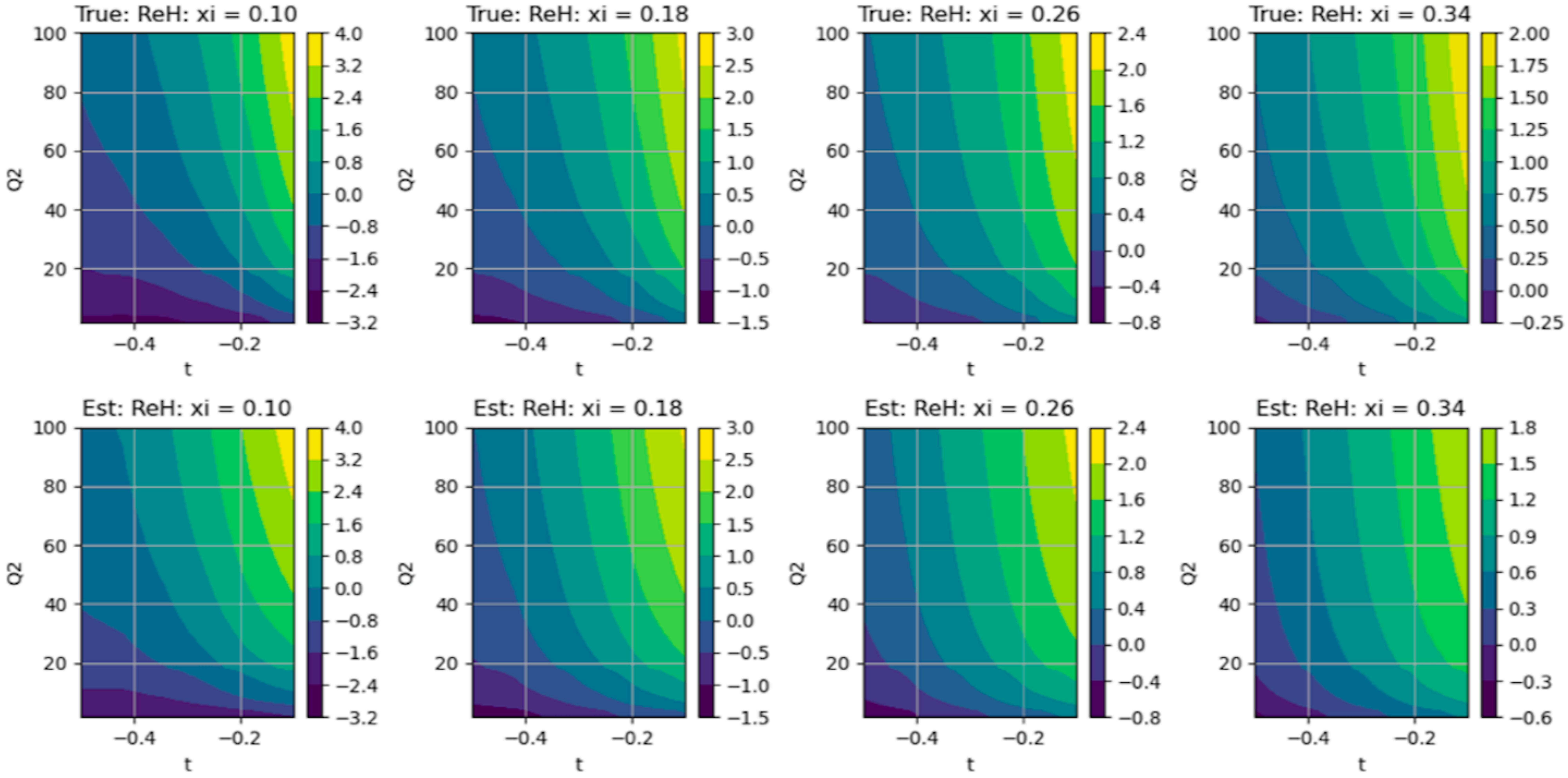




Neural network fit (work in progress)

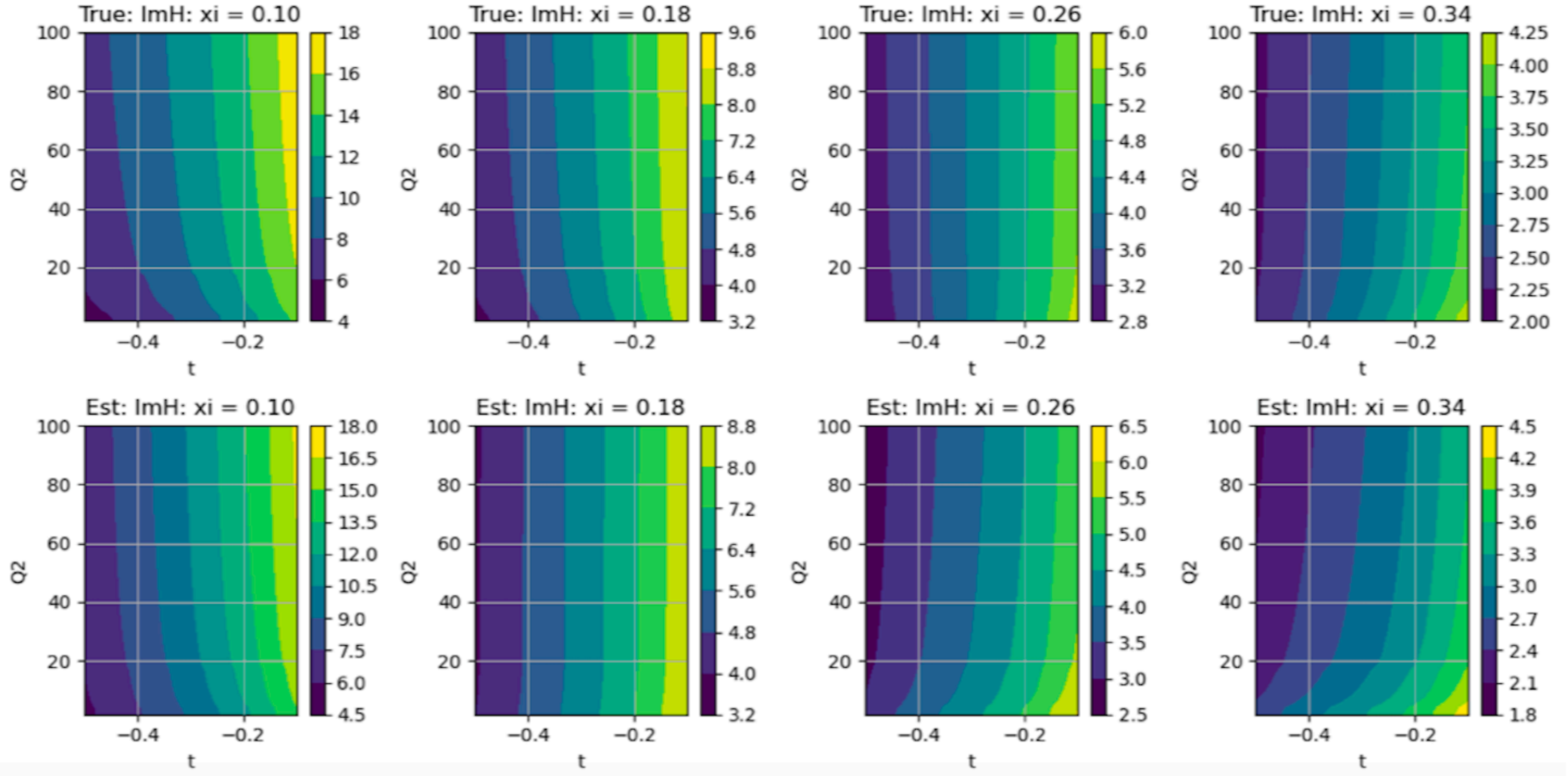
- Started with just trying to fit NN model for H GPD to H CFF pseudodata
  - Used GK model with one modification to generate the pseudodata:
    - Set the parameters of the profile functions to be the same for all flavors
  - NN model:
    - Keep the pdf portion from the GK model
    - NN models a flavor symmetric profile function

Neural network fit (work in progress)



Preliminary

Neural network fit (work in progress)



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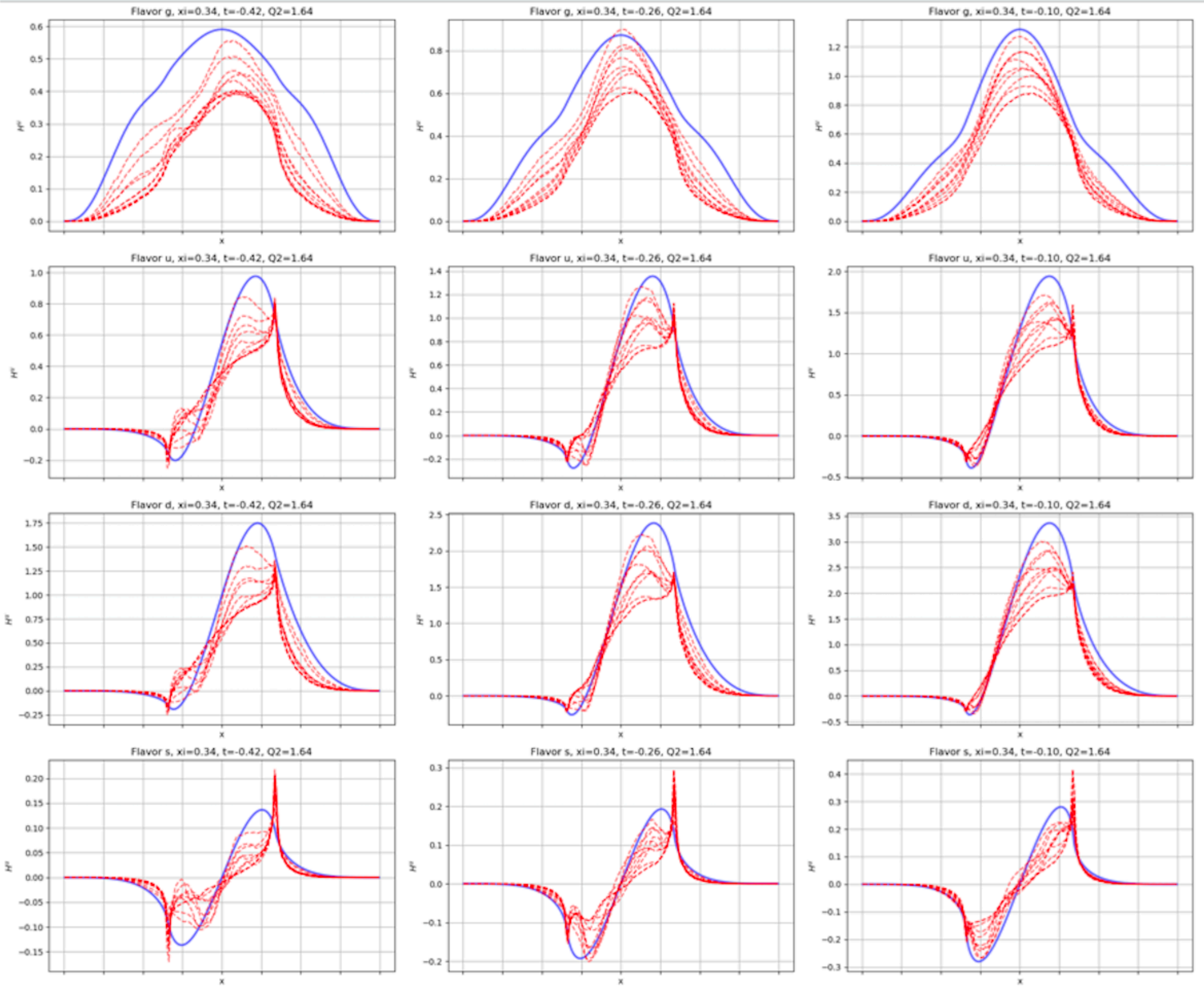

Conclusion and Next Steps

- Summary:
  - Successful closure tests of fitting machinery with parametric model of the GPDs
  - Begun testing with NN model of the GPD. Currently troubleshooting an issue of spikes at x=xi.
- Next Steps:
  - Parametric model:
    - Conduct an analysis with real data
  - NN model:
    - Resolve the current issue
    - Use NN to further explore the impact of evolution and data uncertainty on shadow GPDs
    - Expand tests to allow variation between flavors, and include the other twist 2 GPDs and fit to observable level rather than CFFs