Enhanced Kinematic Synthesis for Concept Generation with Generative and Sequential Models

Shrinath Deshpande

Mechanism Synthesis Pipeline

- Motion /Path /Function Generation Problem (Subjective)

Problem Setup (Requires problem understanding)

- Mathematically Precise Representation (Objective)

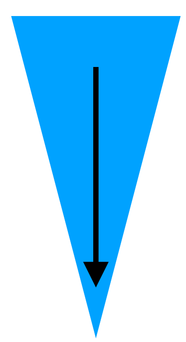
Problem Solving (Algorithmic, Nonlinear Mapping)

- Employ Numerical Solvers/ Optimizers

Problem Setup

Subjective Task

Problem Setup



Precise Problem

Why?

- Required by Solvers

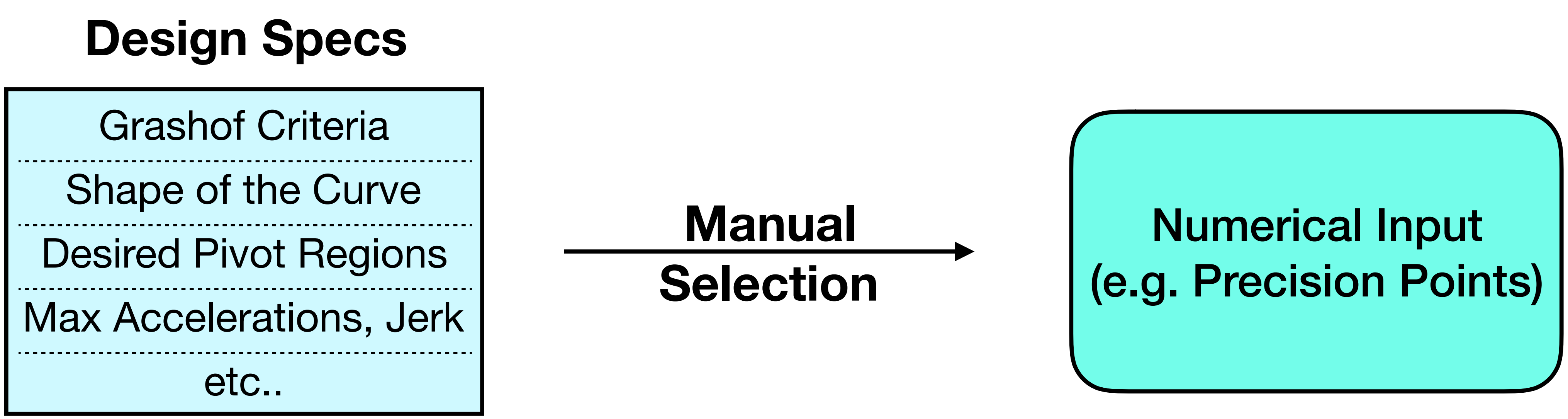
Cons

- Loss of Designer’s Intent (Information Loss)

- Defective Solutions

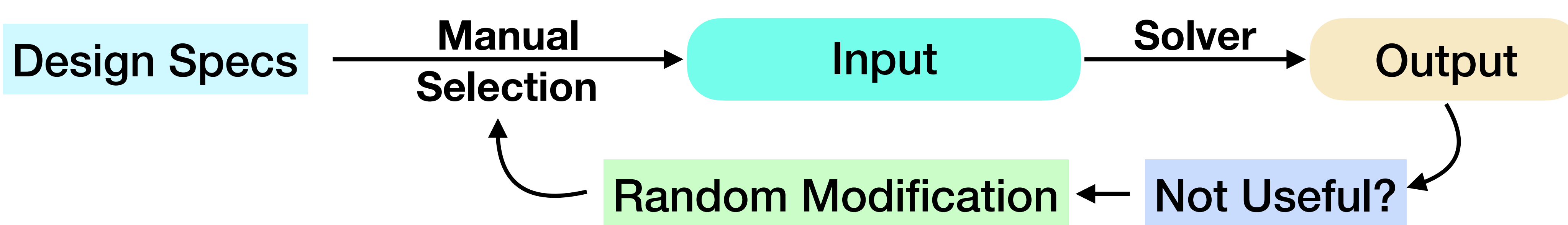
Problem Setup Goals

- Keep the designer's intent intact
  - Understand what aspects are important and Relax the less important constraints
- Keep it simple for solvers to operate
  - Numerical format



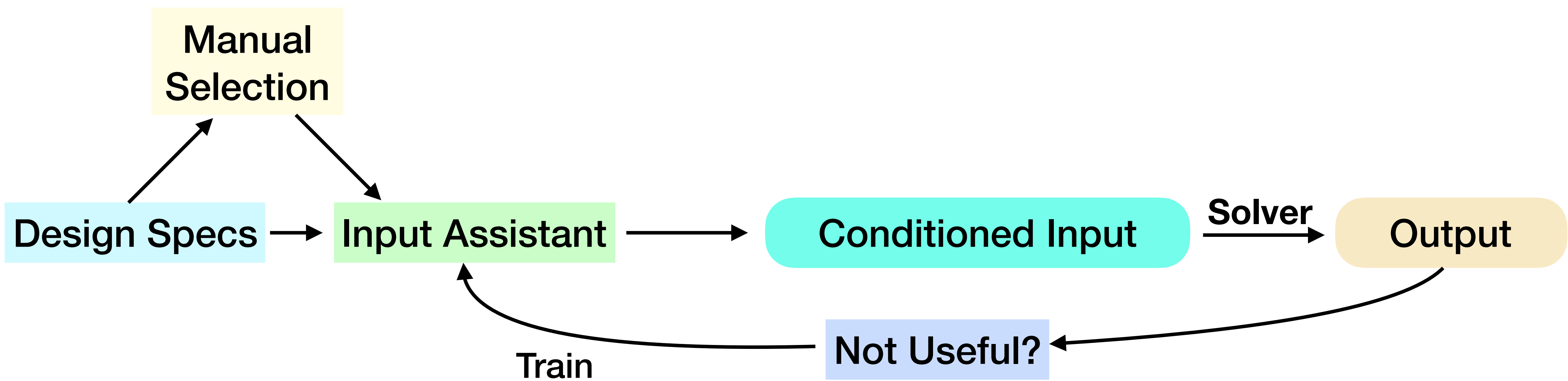
Difficulties in Setting Up the Problem

- Highly Nonlinear Mapping Between Numerical Input and Solver Results
  - Small Changes in precision poses can lead to very different coupler curves



Conditioned Input

- Exploit the nonlinear relationship between input and output
- Intelligently **modify** the Input to maximize the probability of usefulness of output
  - **Condition** the input to have some ‘learned’ properties
  - **Augment** the input with missing information/ free Choices



Conditional Precision Position Input

- X be the set of precision poses which results in useful output (e.g. set of 100 poses with dimension [100, 3])

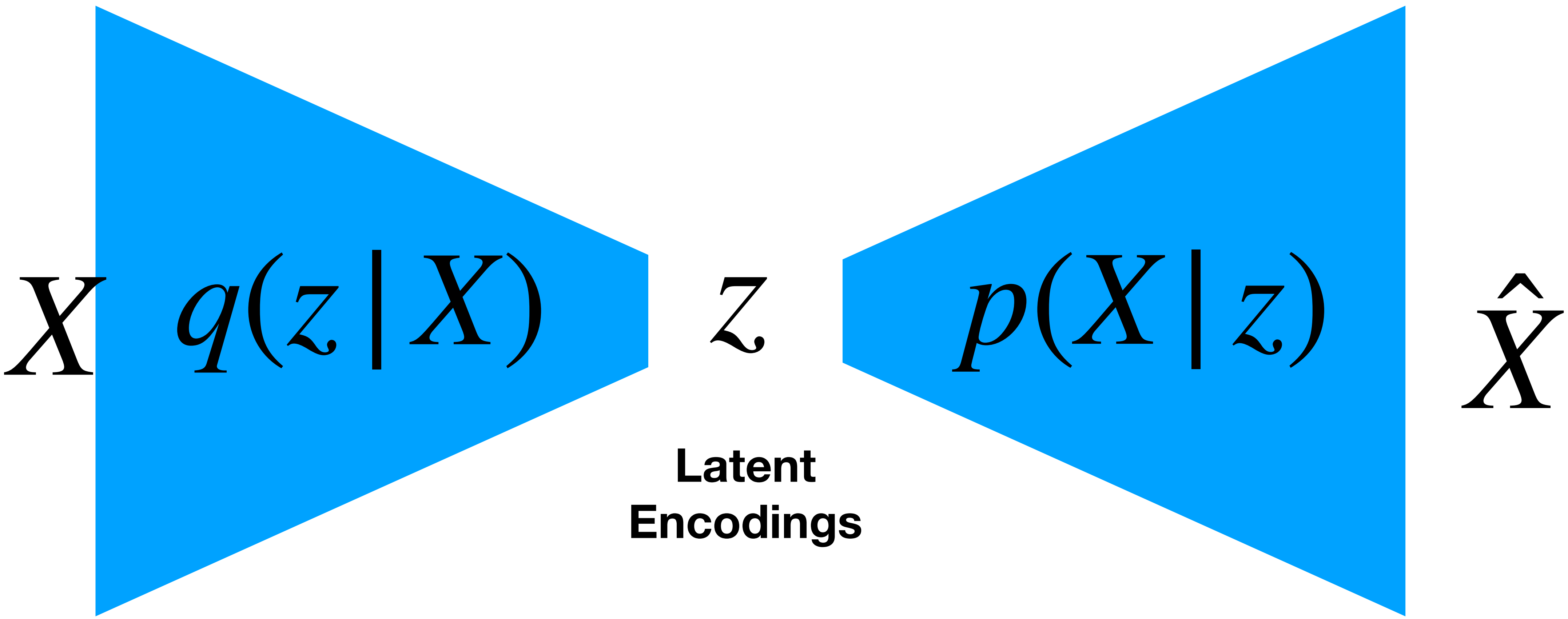
- Goal is to :
  1. approximate the model which generates the observed distribution of X.

$$X = G(z)$$

  2. Analytical approximation to the posterior probability of the unobserved variables z

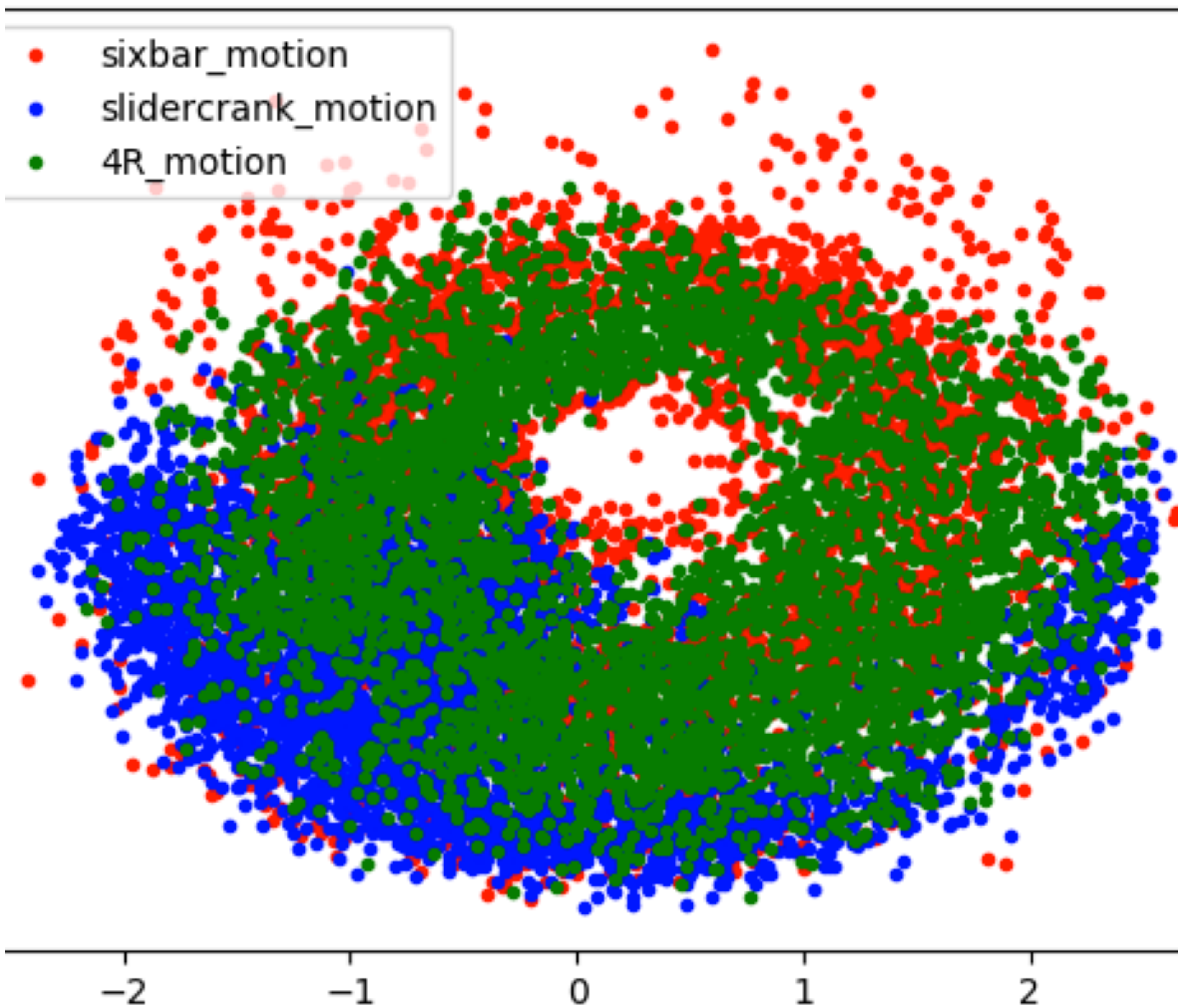
$$p(z \mid X) = \frac{p(X \mid z)p(z)}{p(X)} = F(X)$$

Variational Auto-Encoder



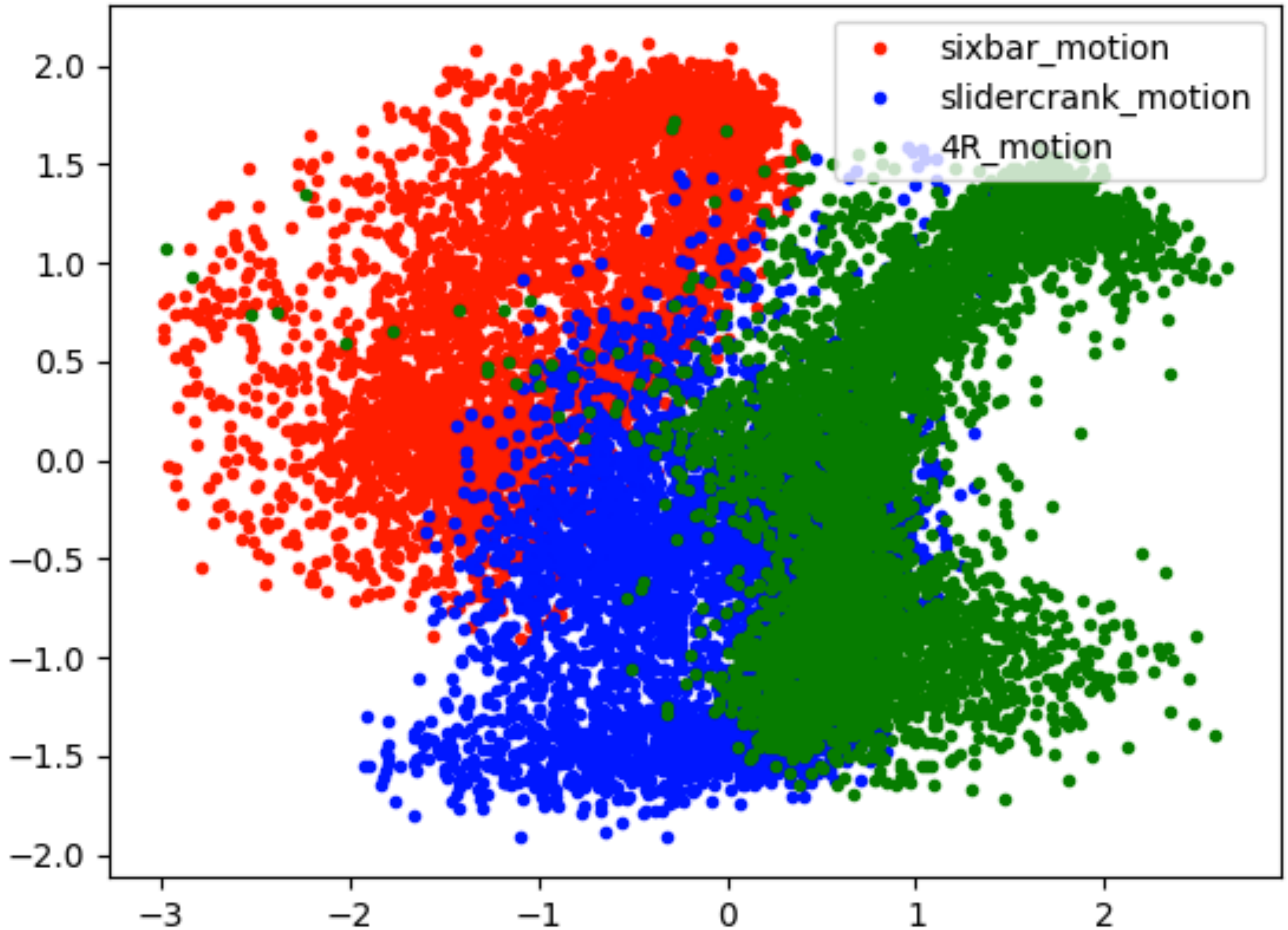
$$L = \underbrace{(X - \hat{X})^2}_{\textbf{Reconstruction Loss}} + \sum_j \underbrace{KL(q_j(z \mid X) \,||\, p(z))}_{\textbf{KL Divergence Loss}}$$

Latent Space For Coupler Path



- Latent Embeddings of coupler motions sampled four random Fourbar, Sixbar and Slider Crank linkages

Latent Space For Coupler Motion



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Distribution of Coupler Paths

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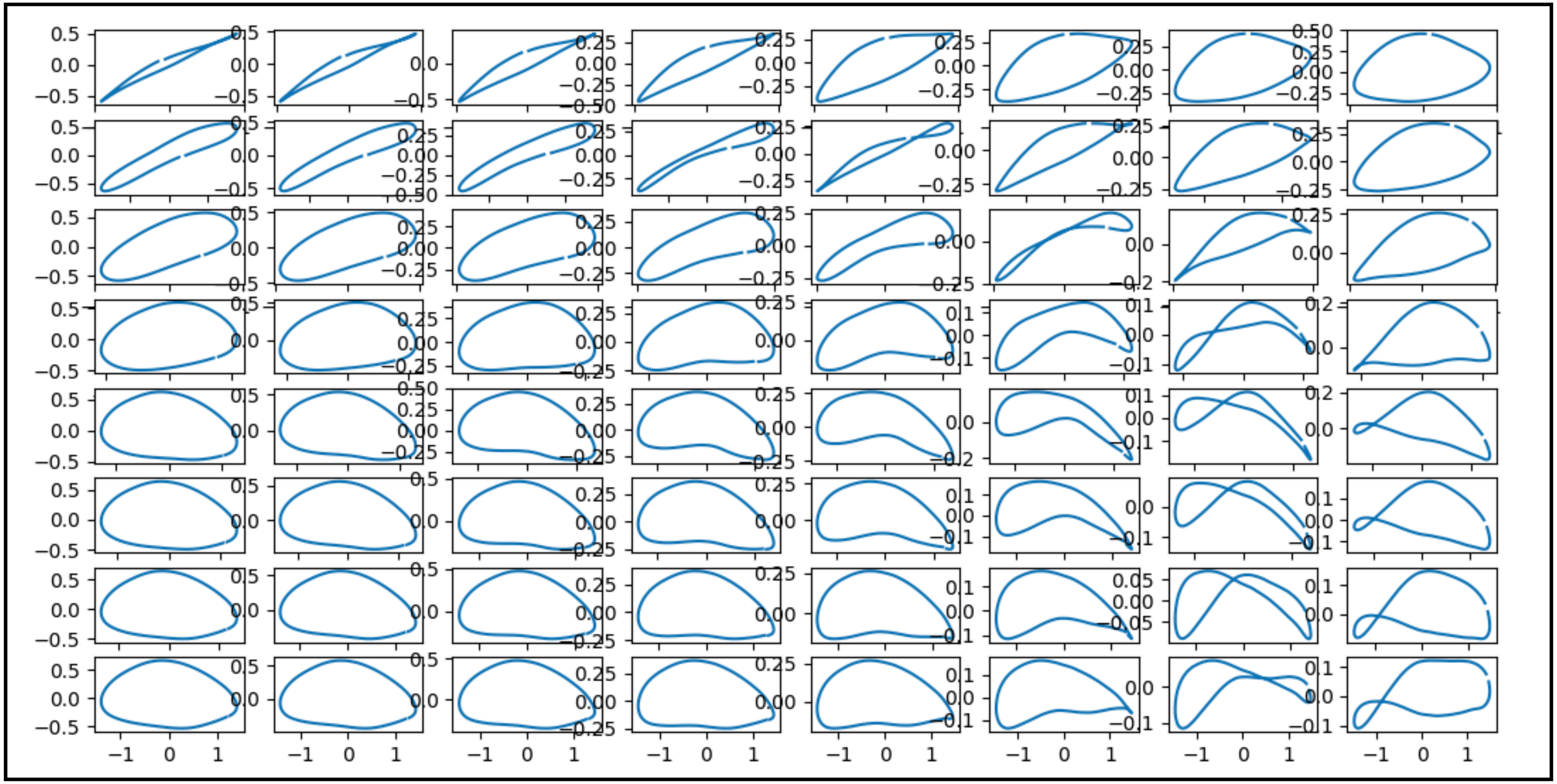

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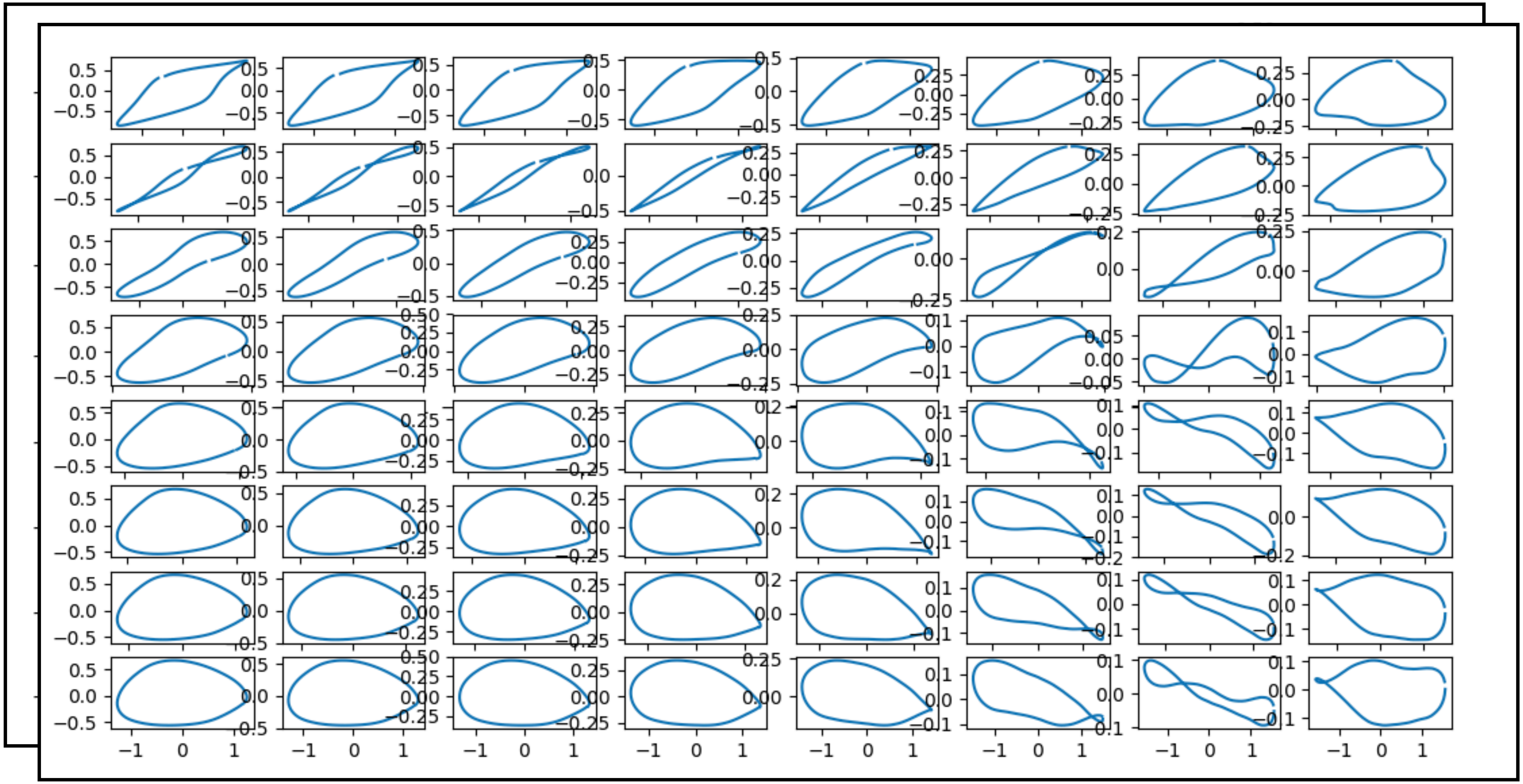

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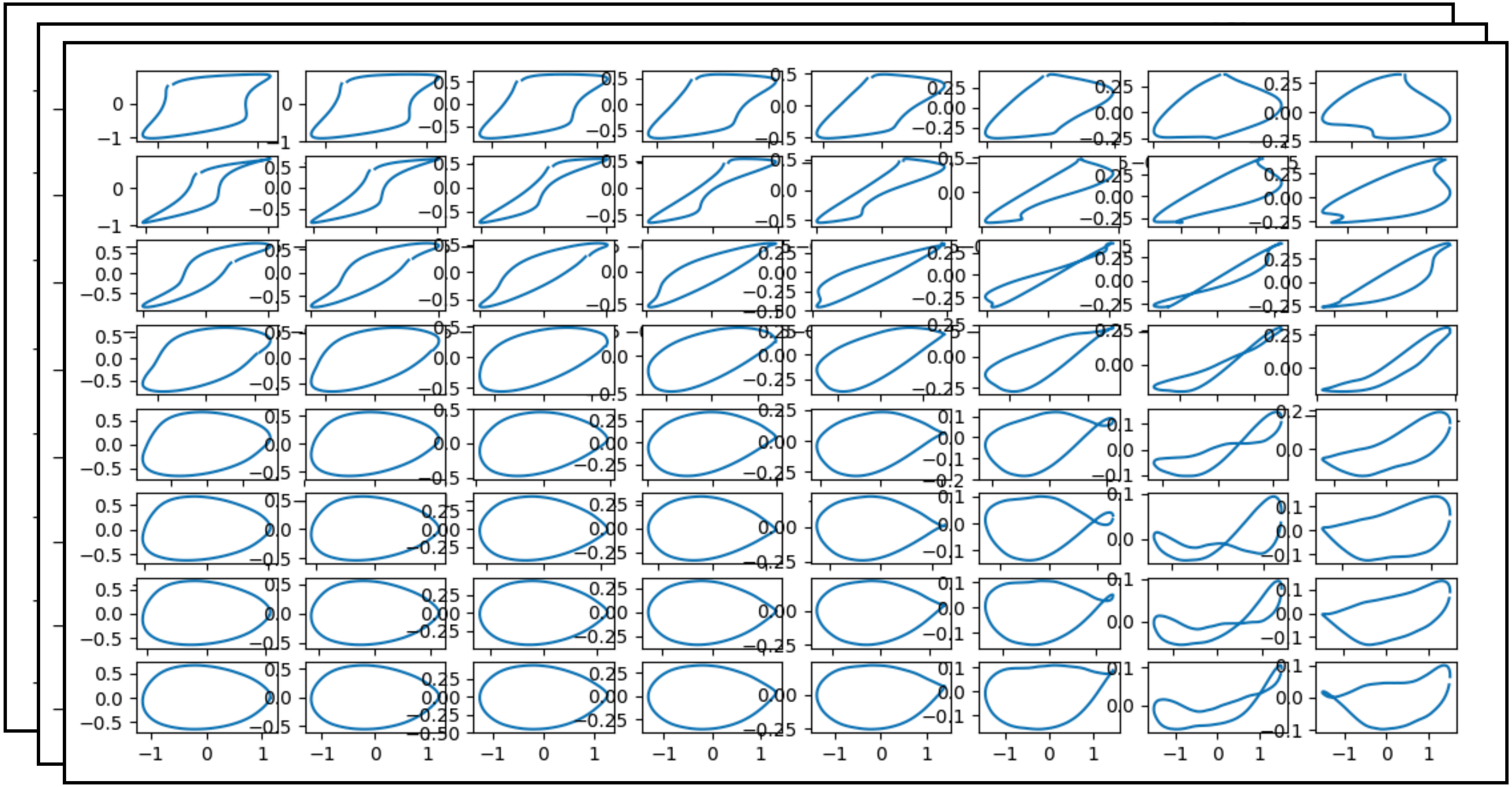

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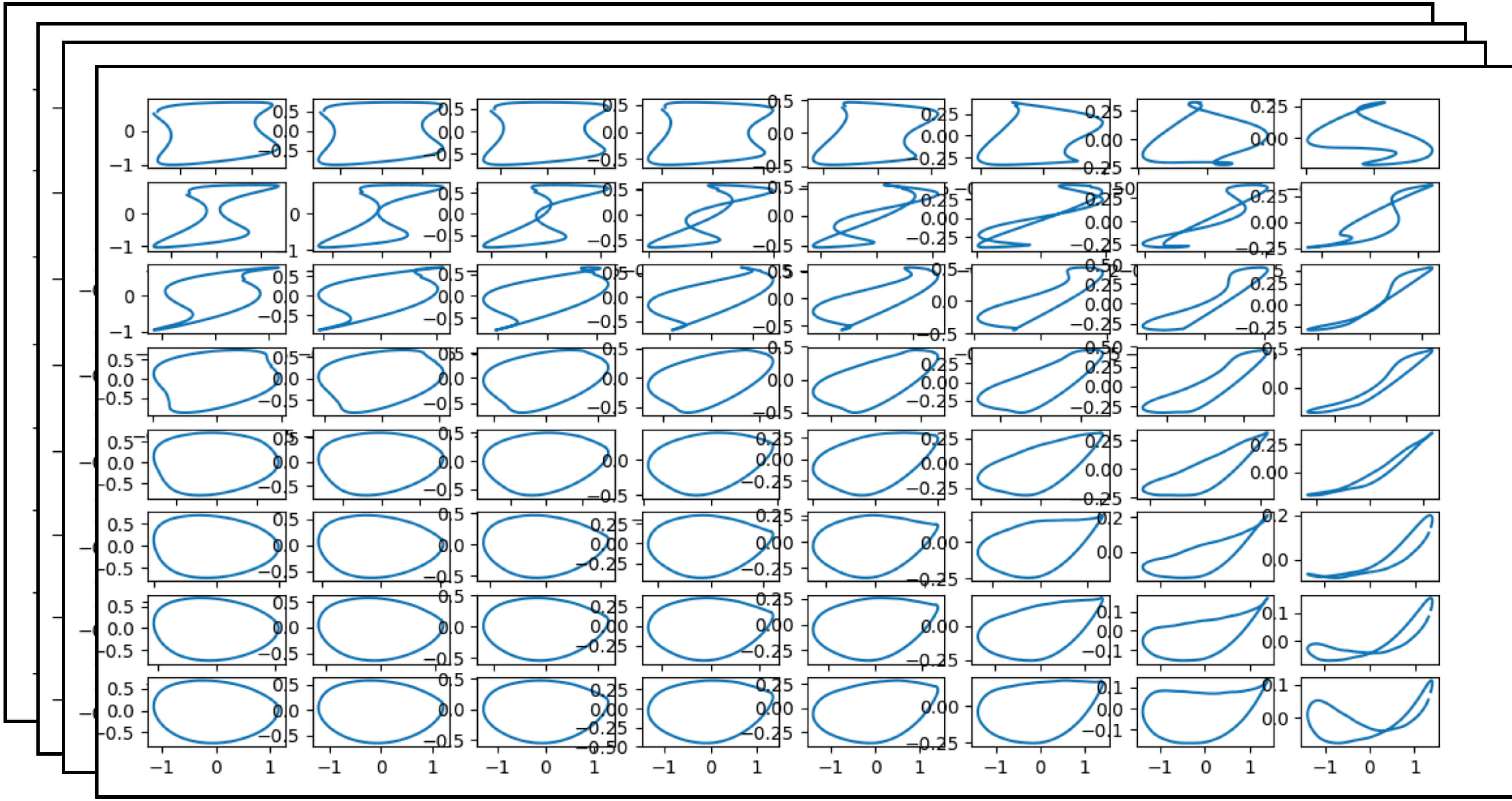

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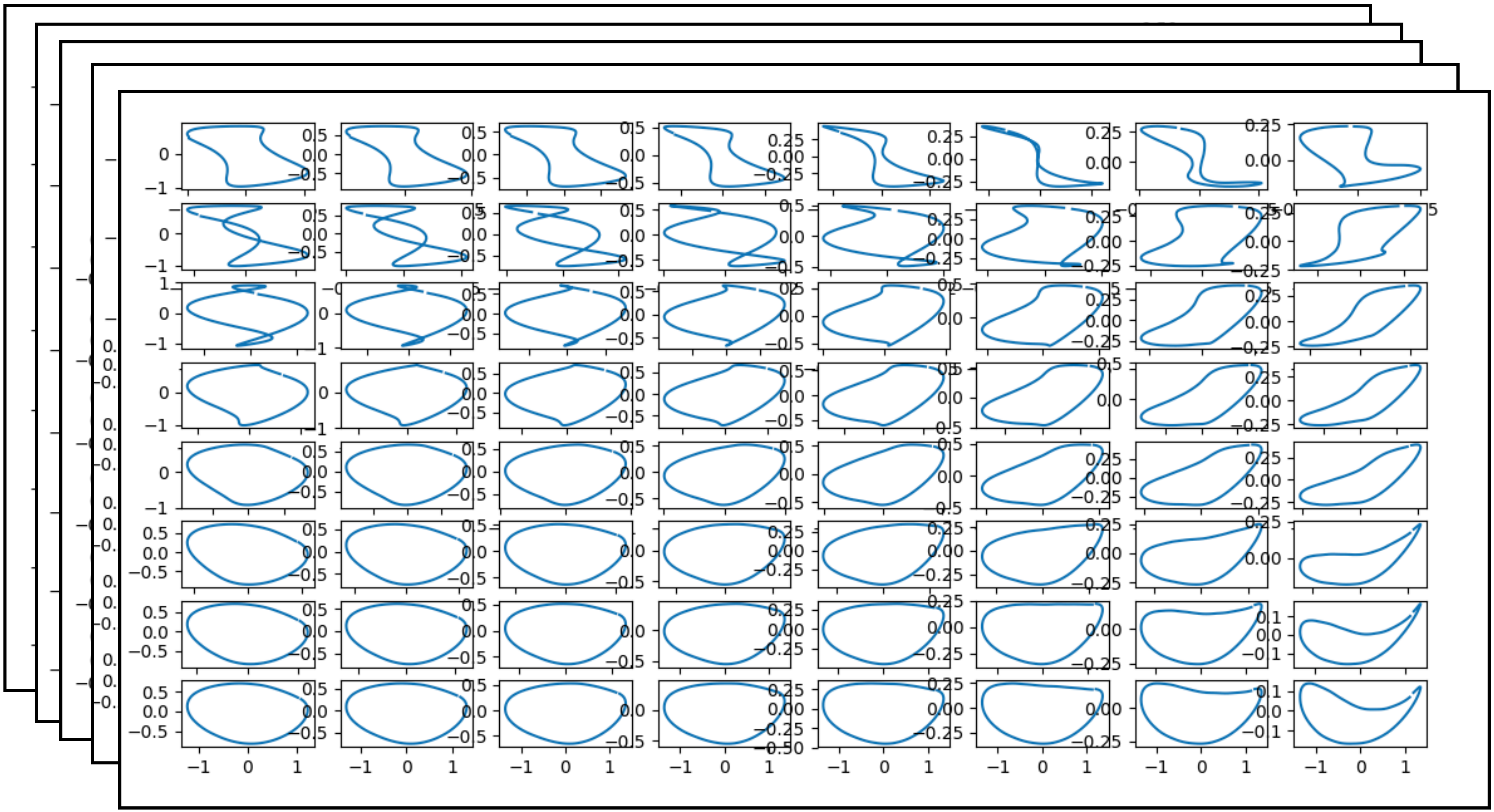

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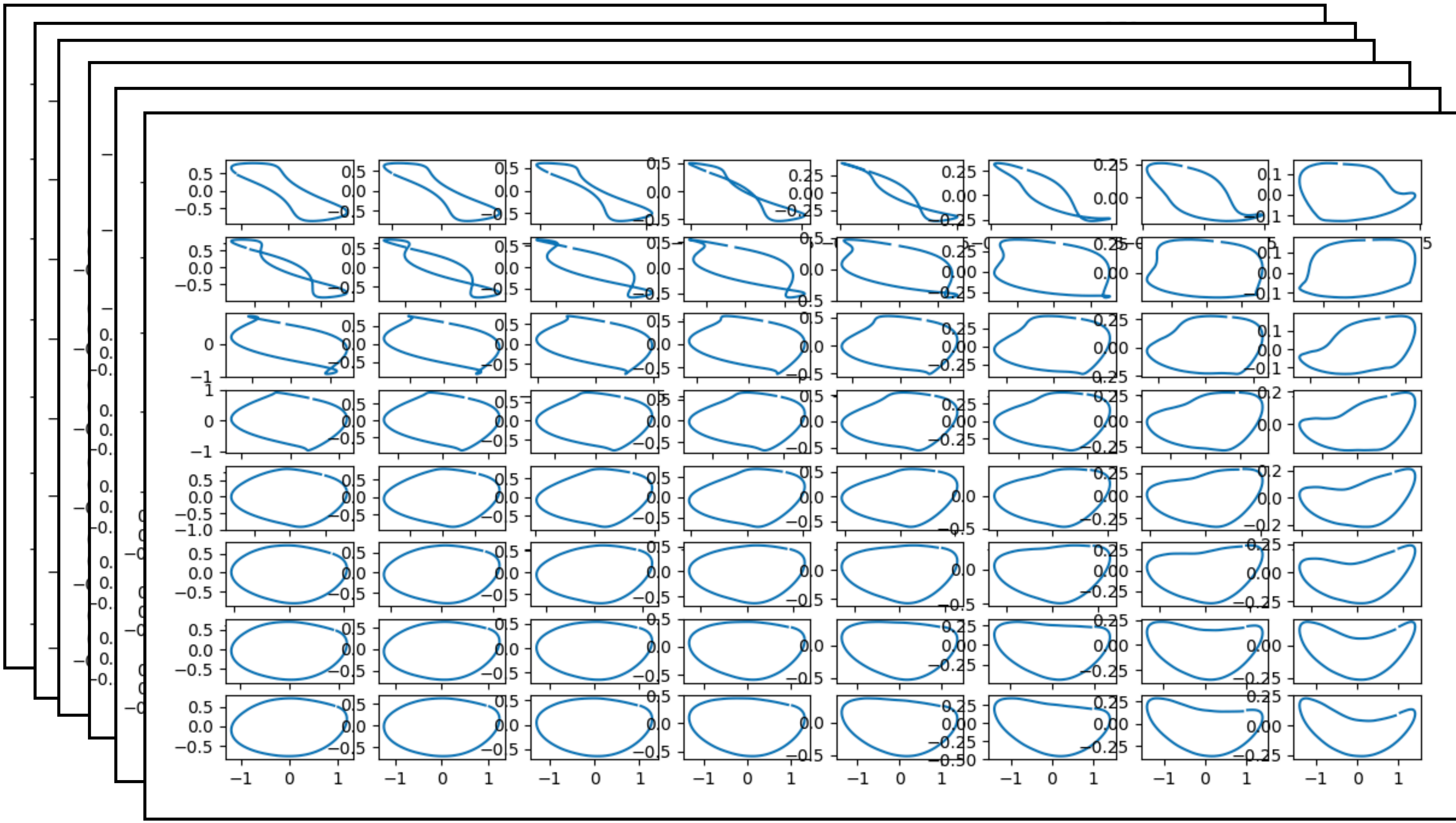

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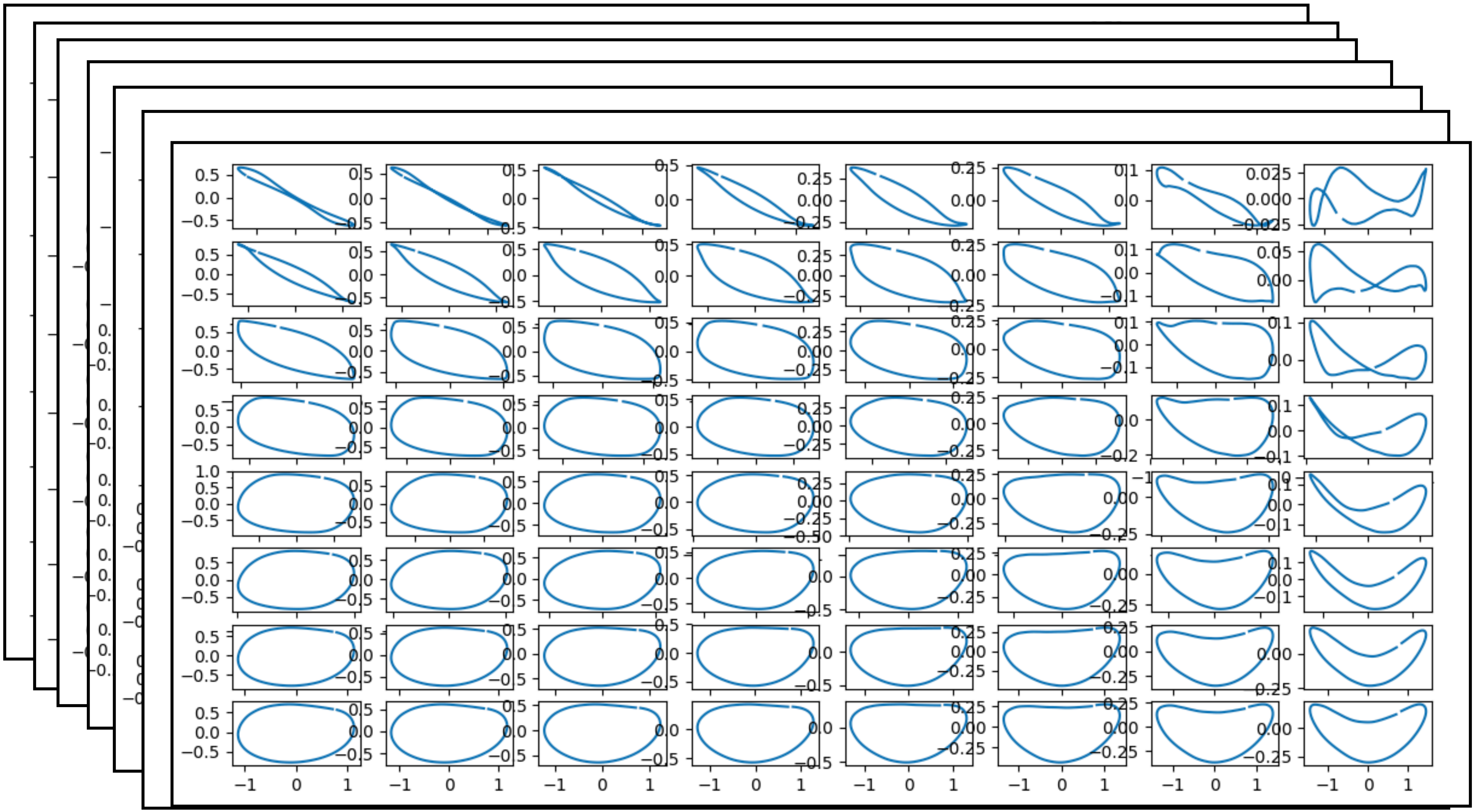

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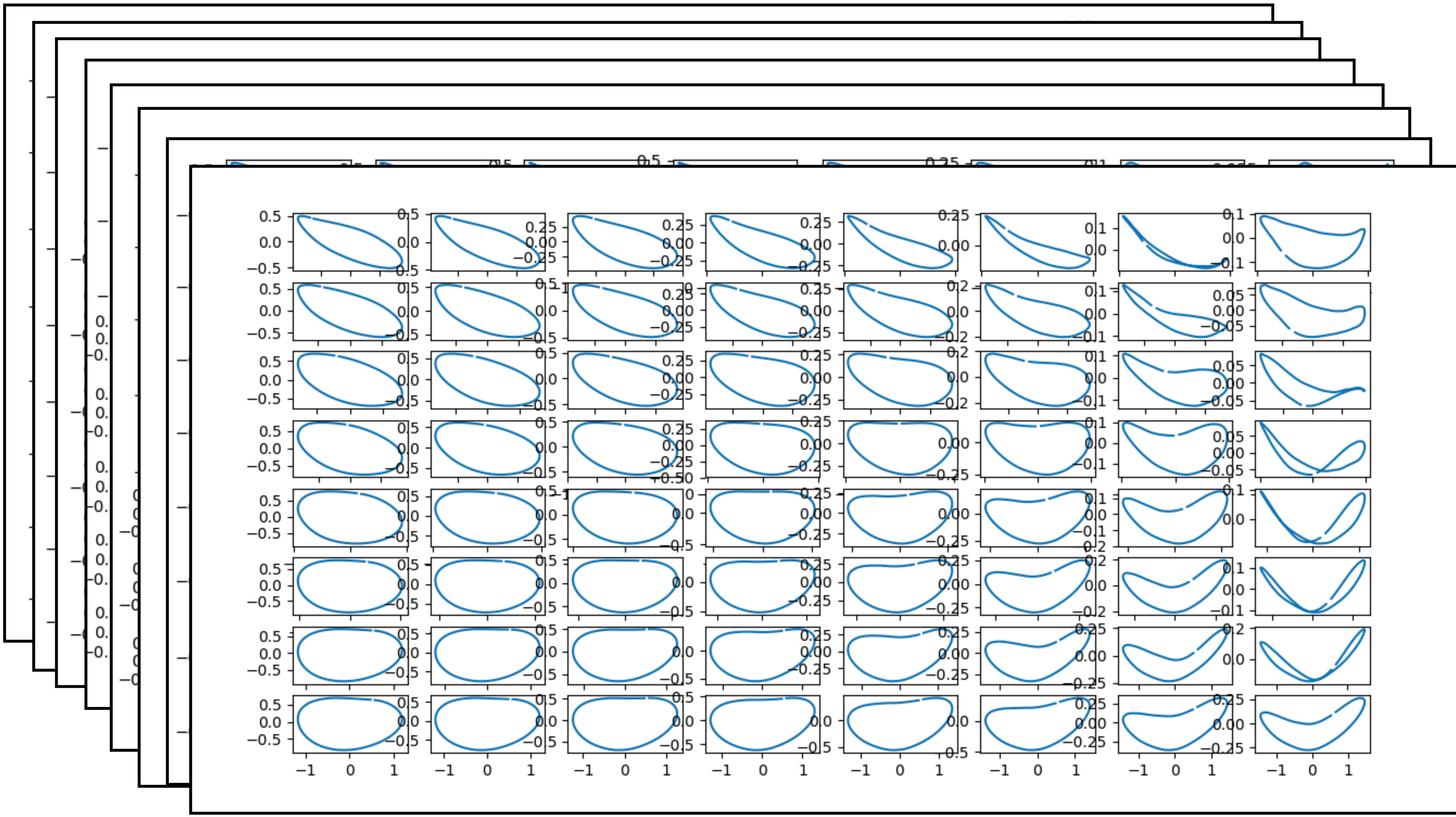


Variational Inference

$$p(z\,|\,x) = \frac{p(x\,|\,z)p(z)}{p(x)}$$

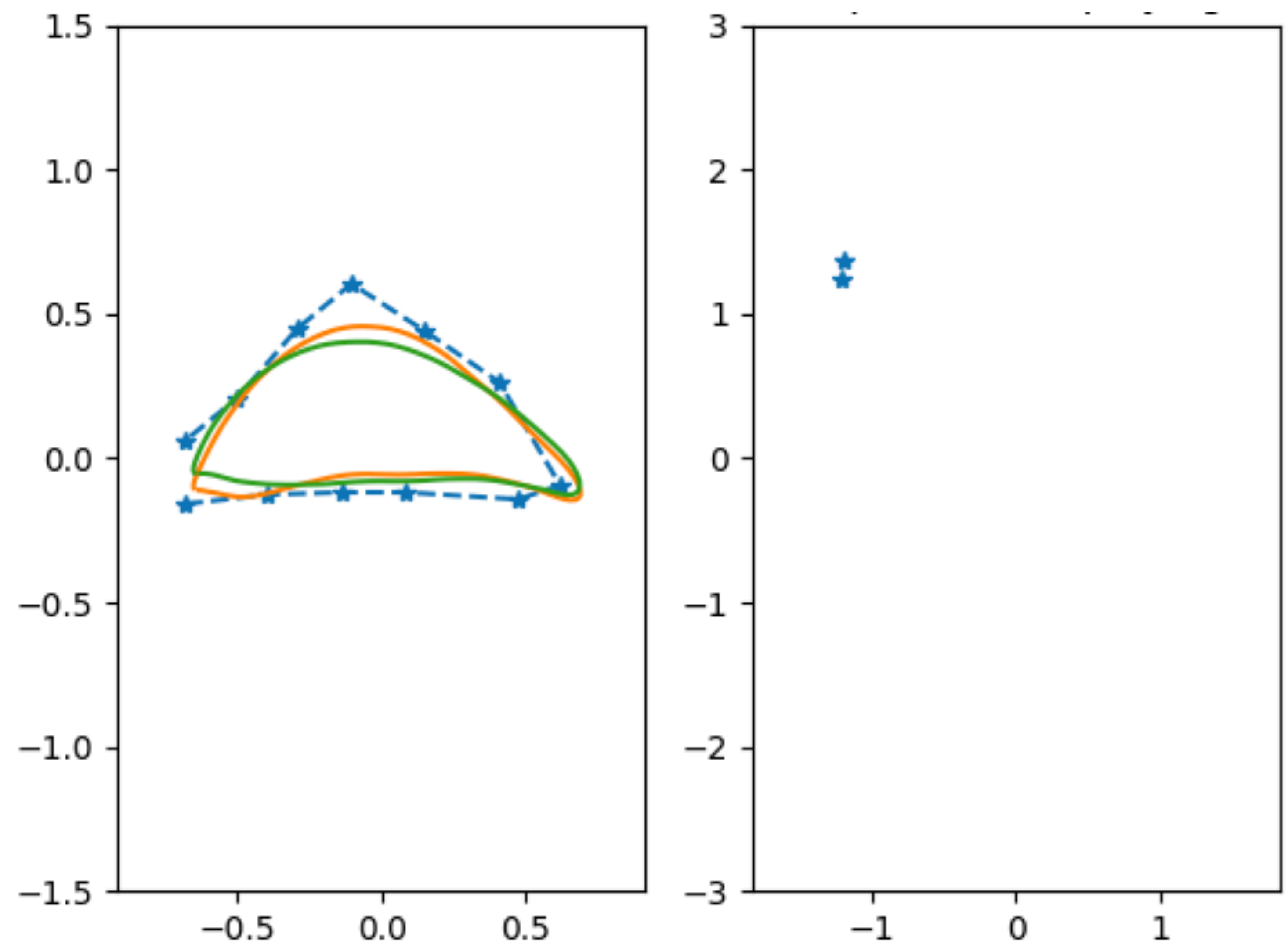
Encoder's Approximation

$$F(x) \approx p(z\,|\,x)$$

Decoder's Generation

$$\hat{x}_{samples} = G(z)$$

Coupler Paths **Latent Space**



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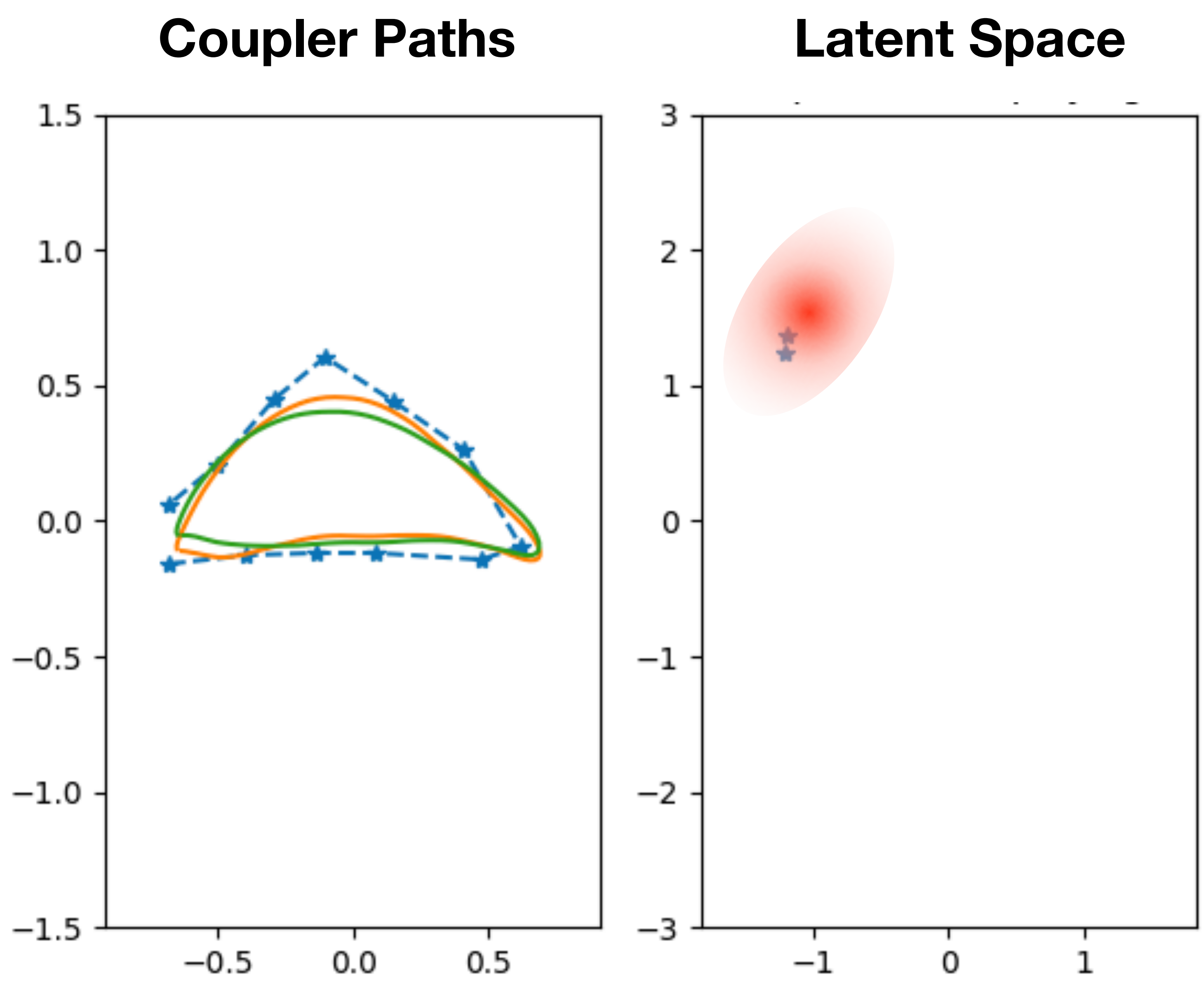

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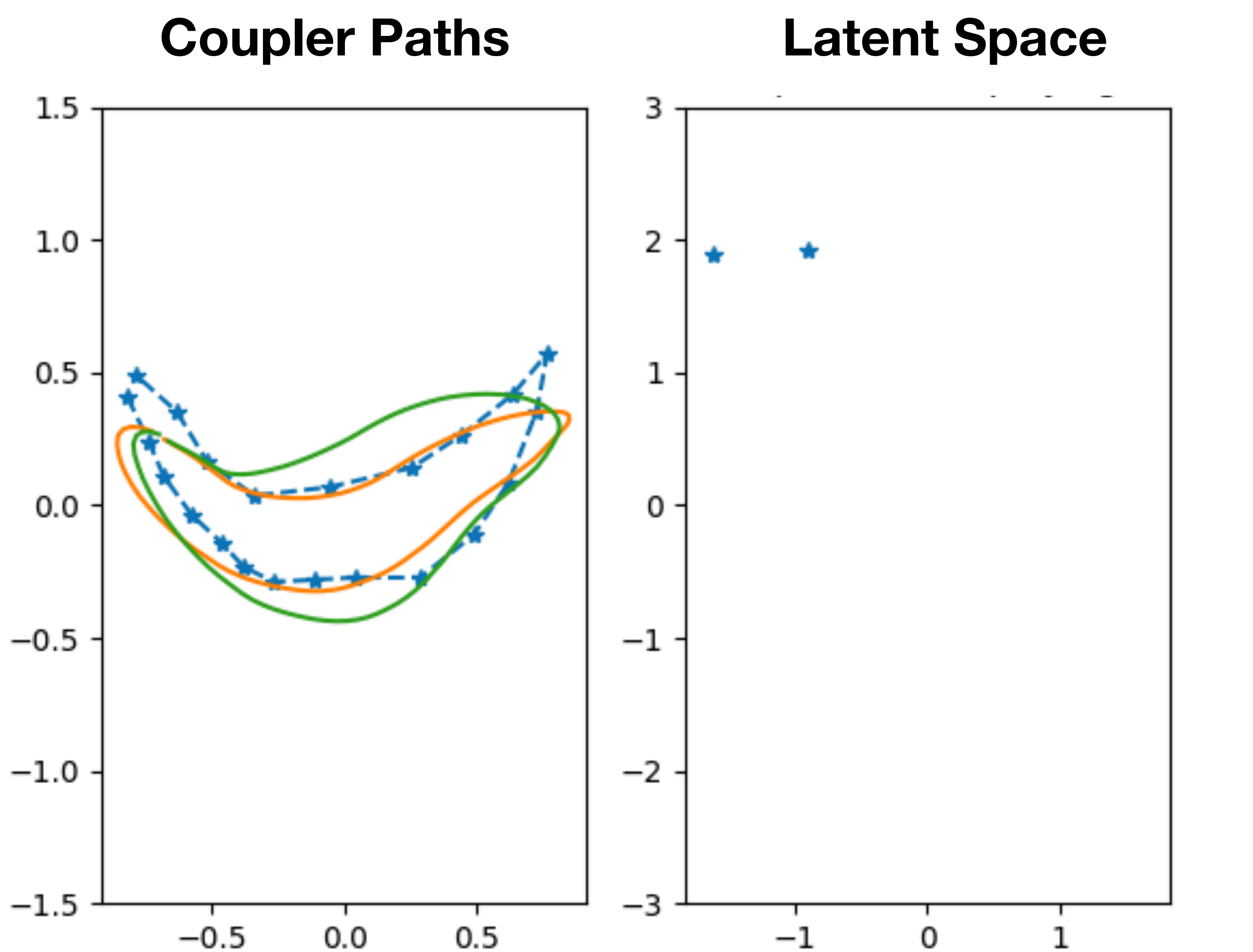

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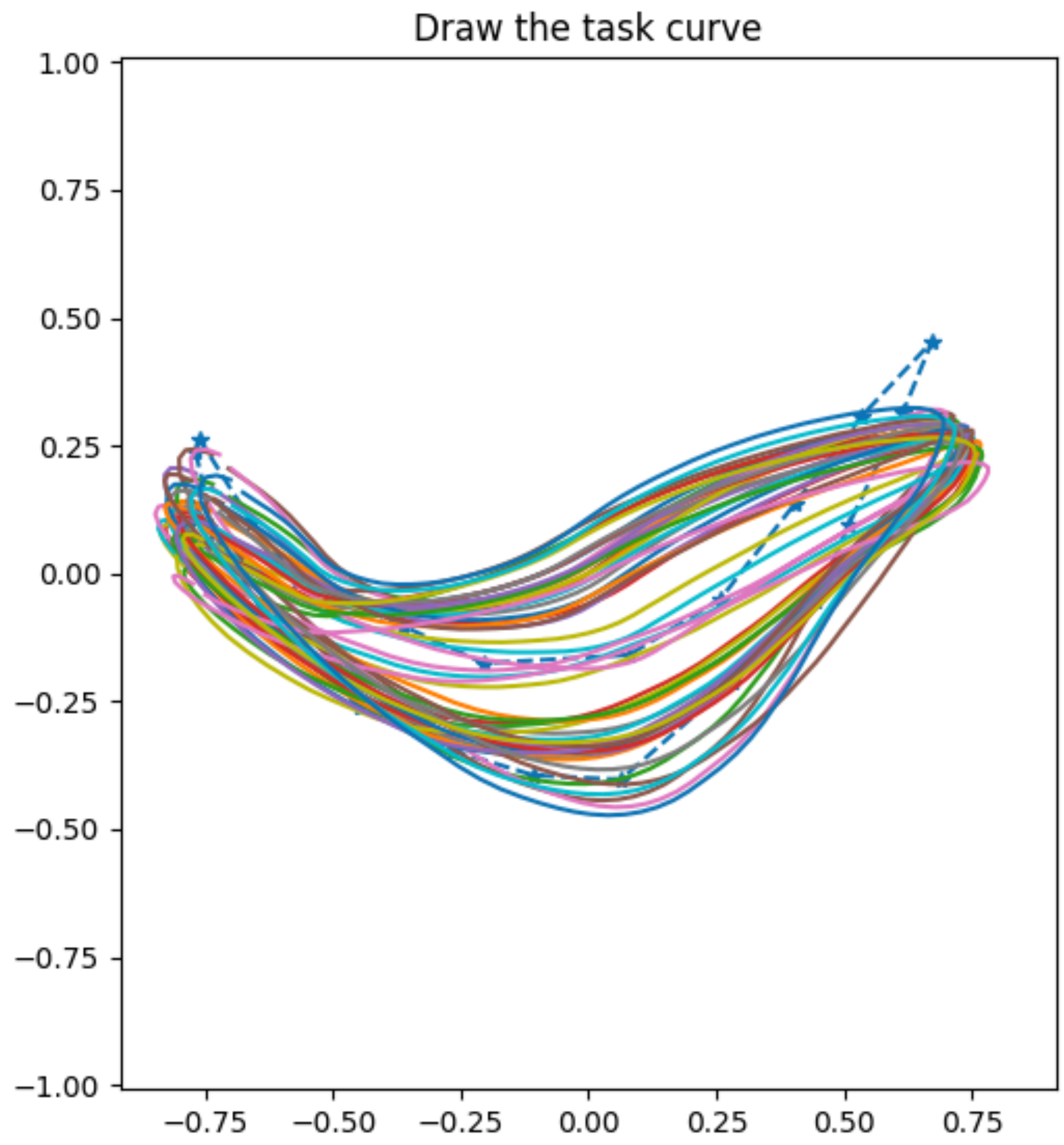

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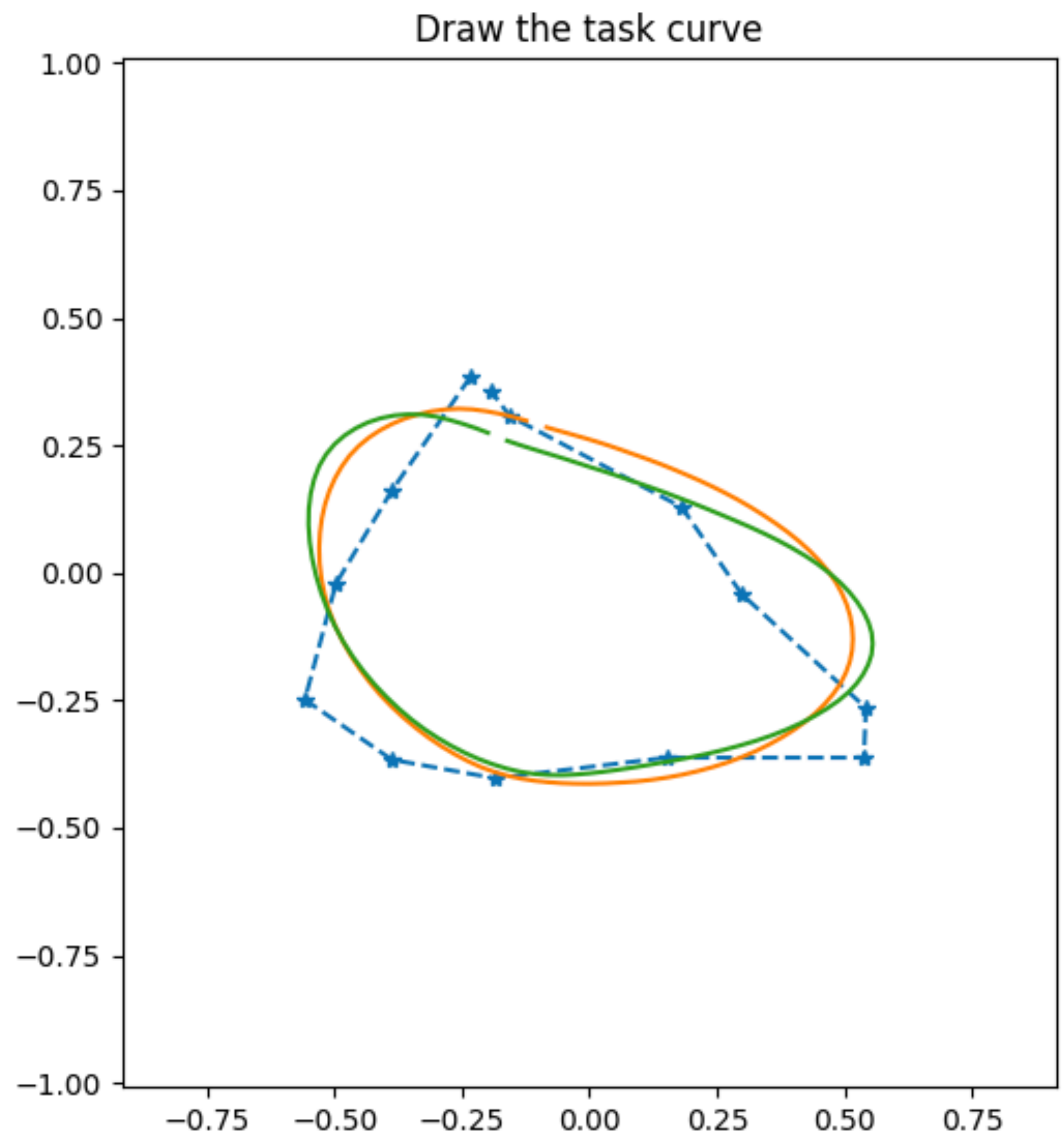

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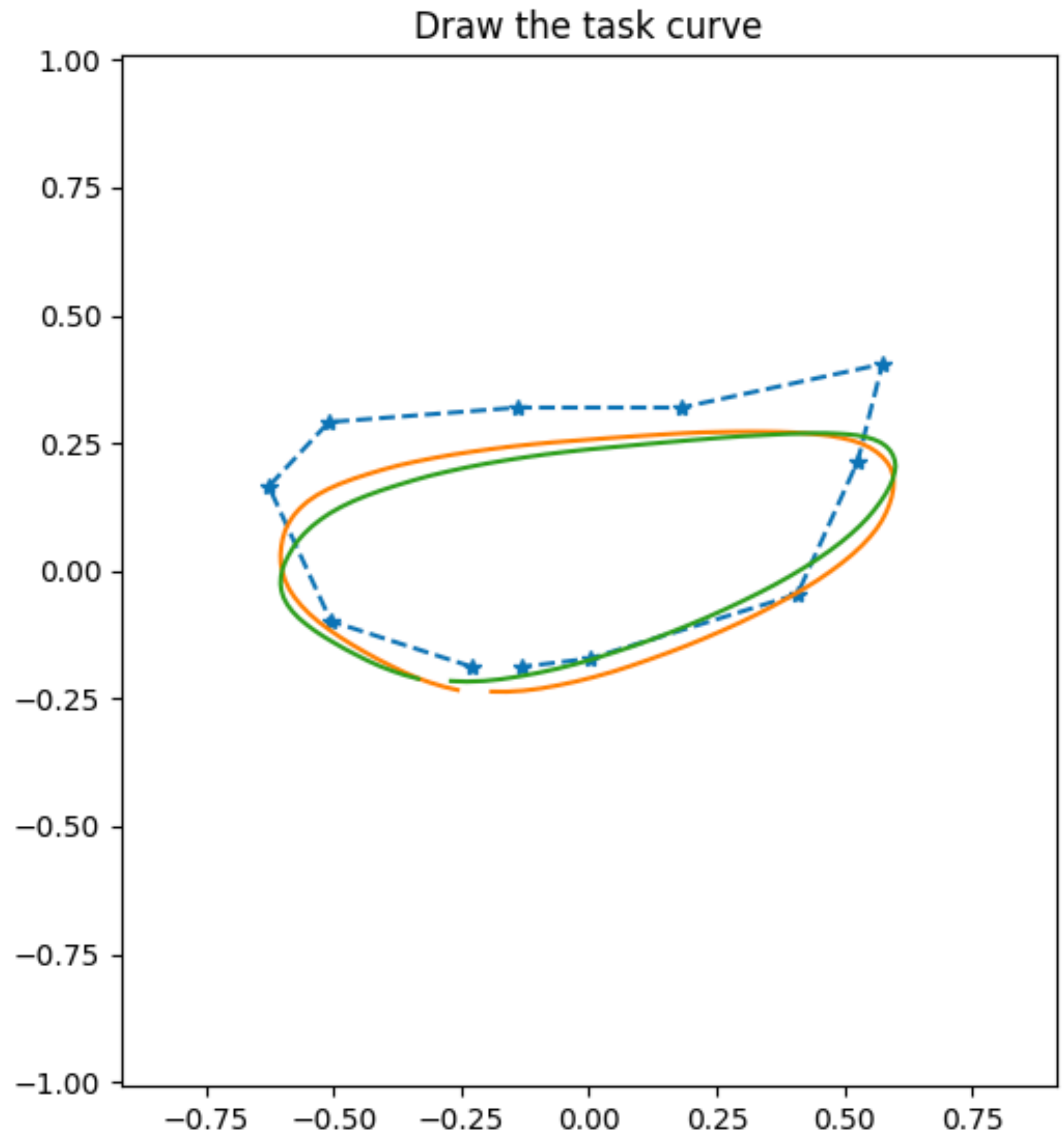

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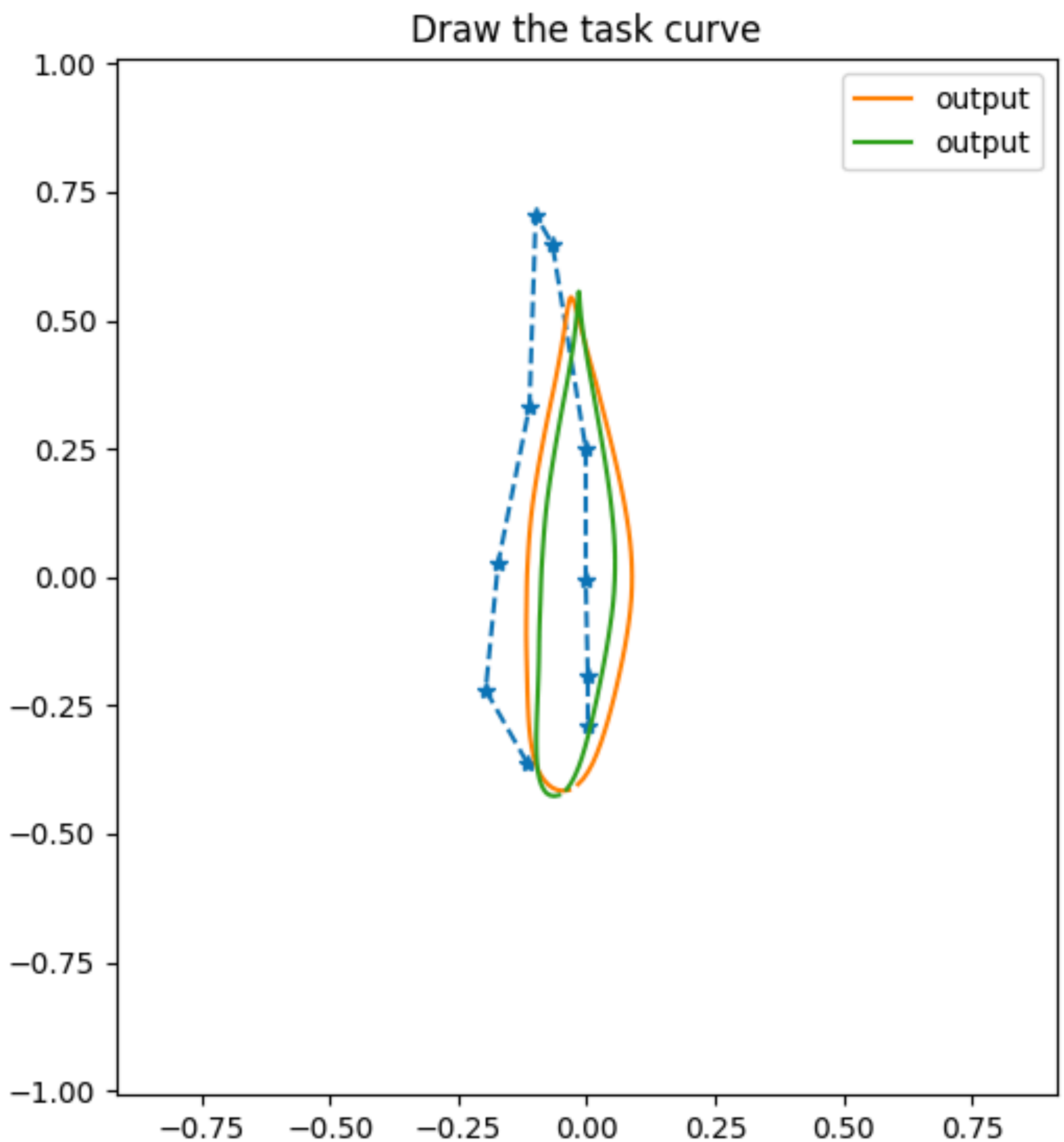

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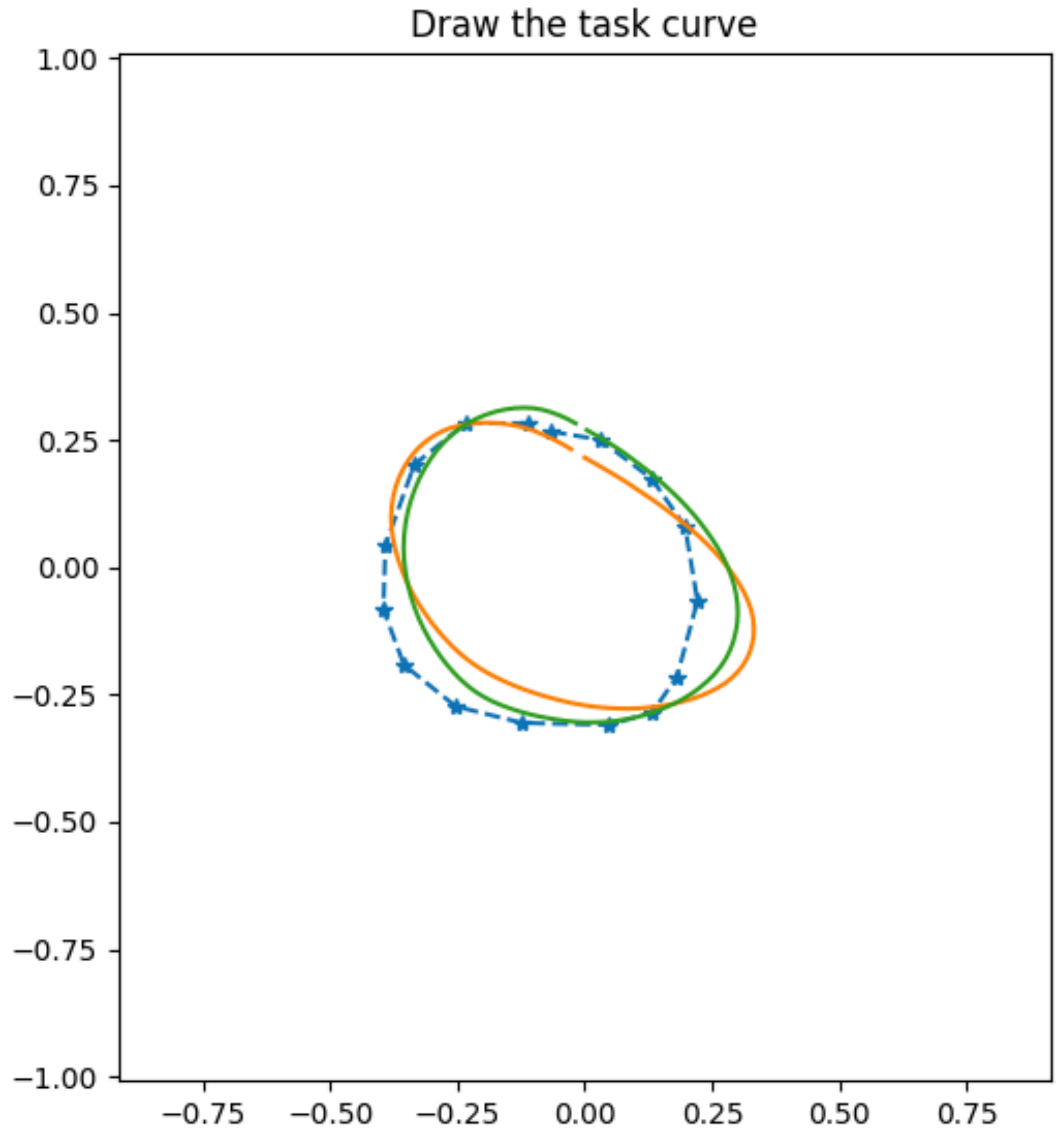

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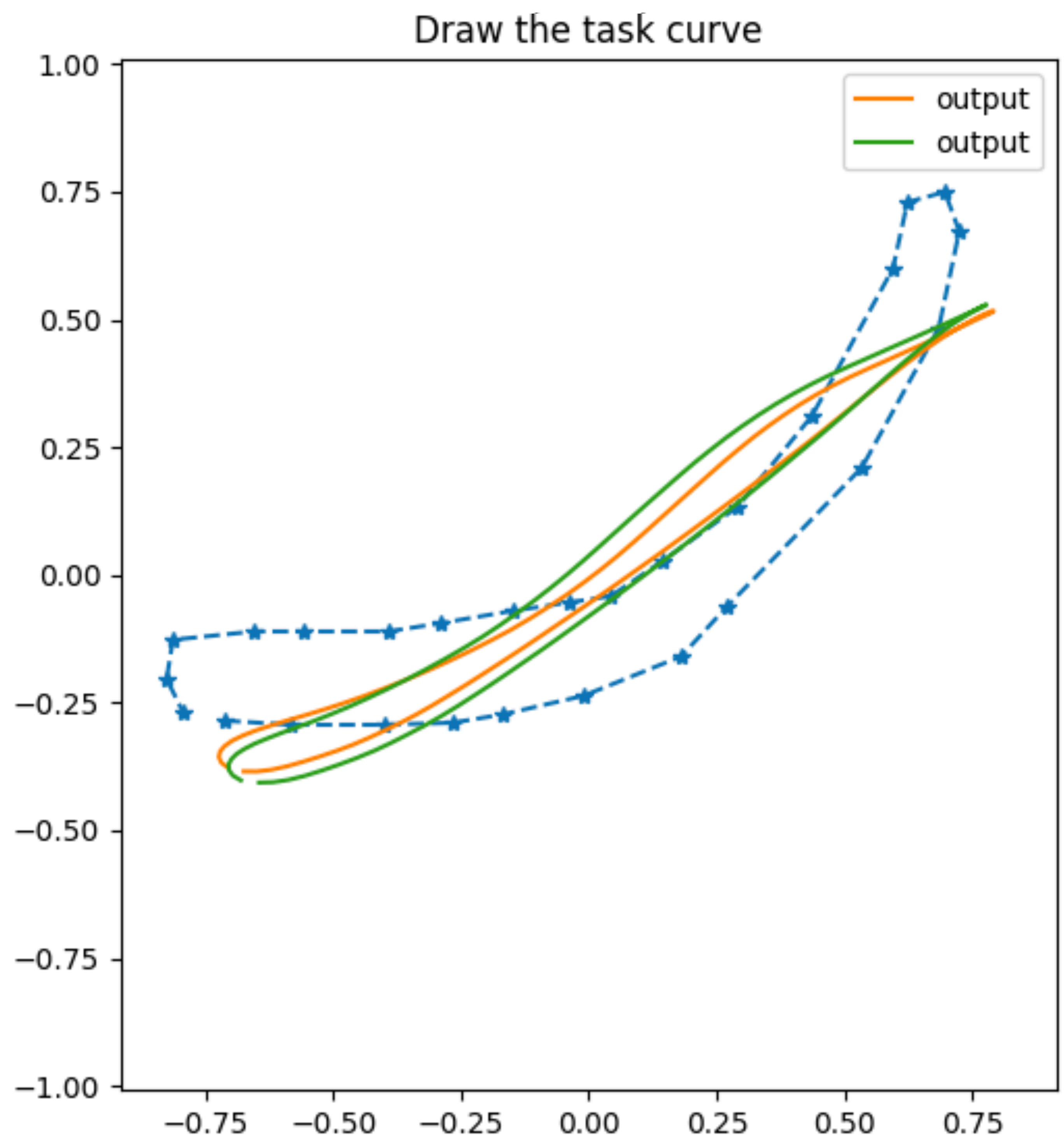

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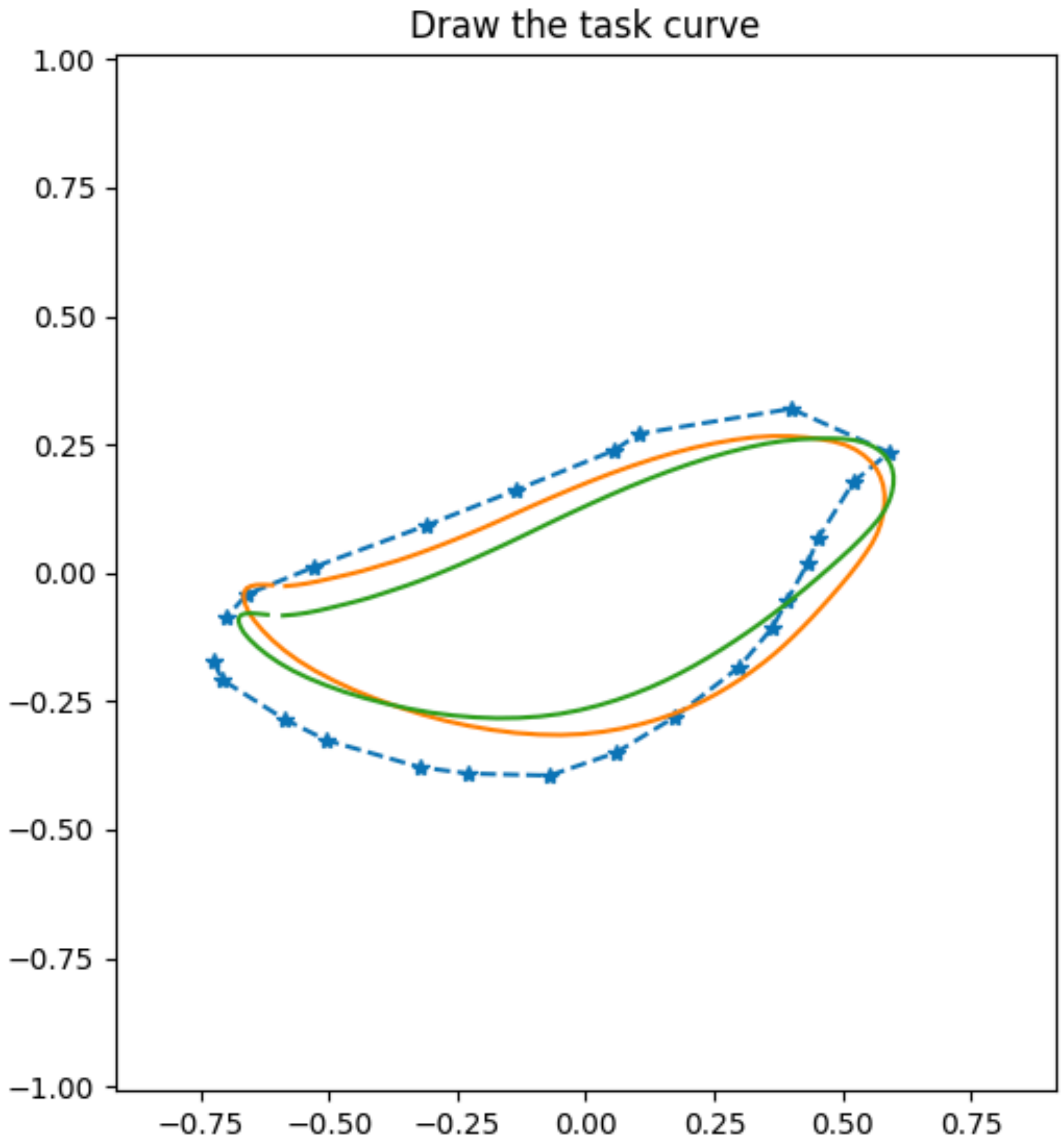

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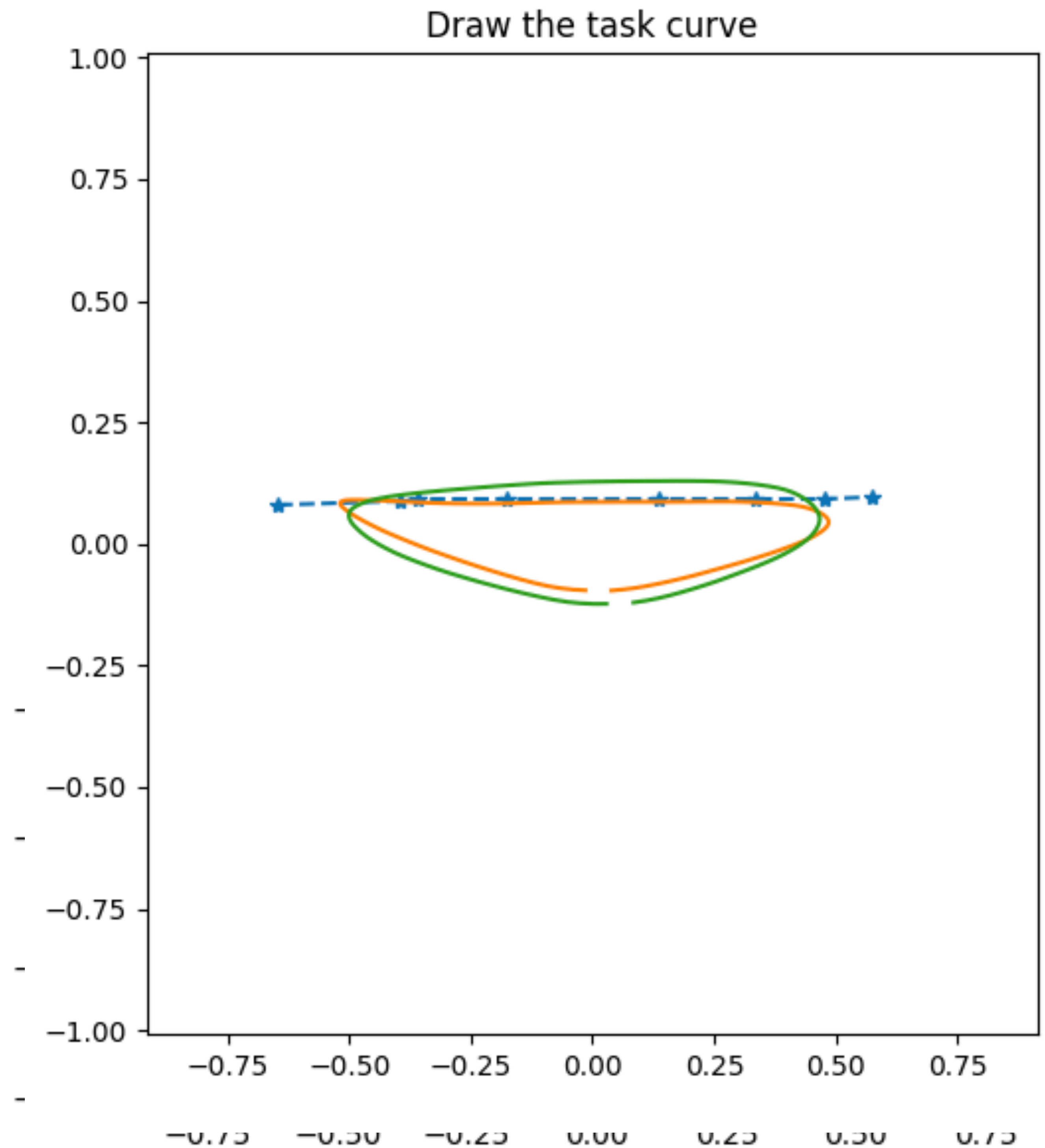

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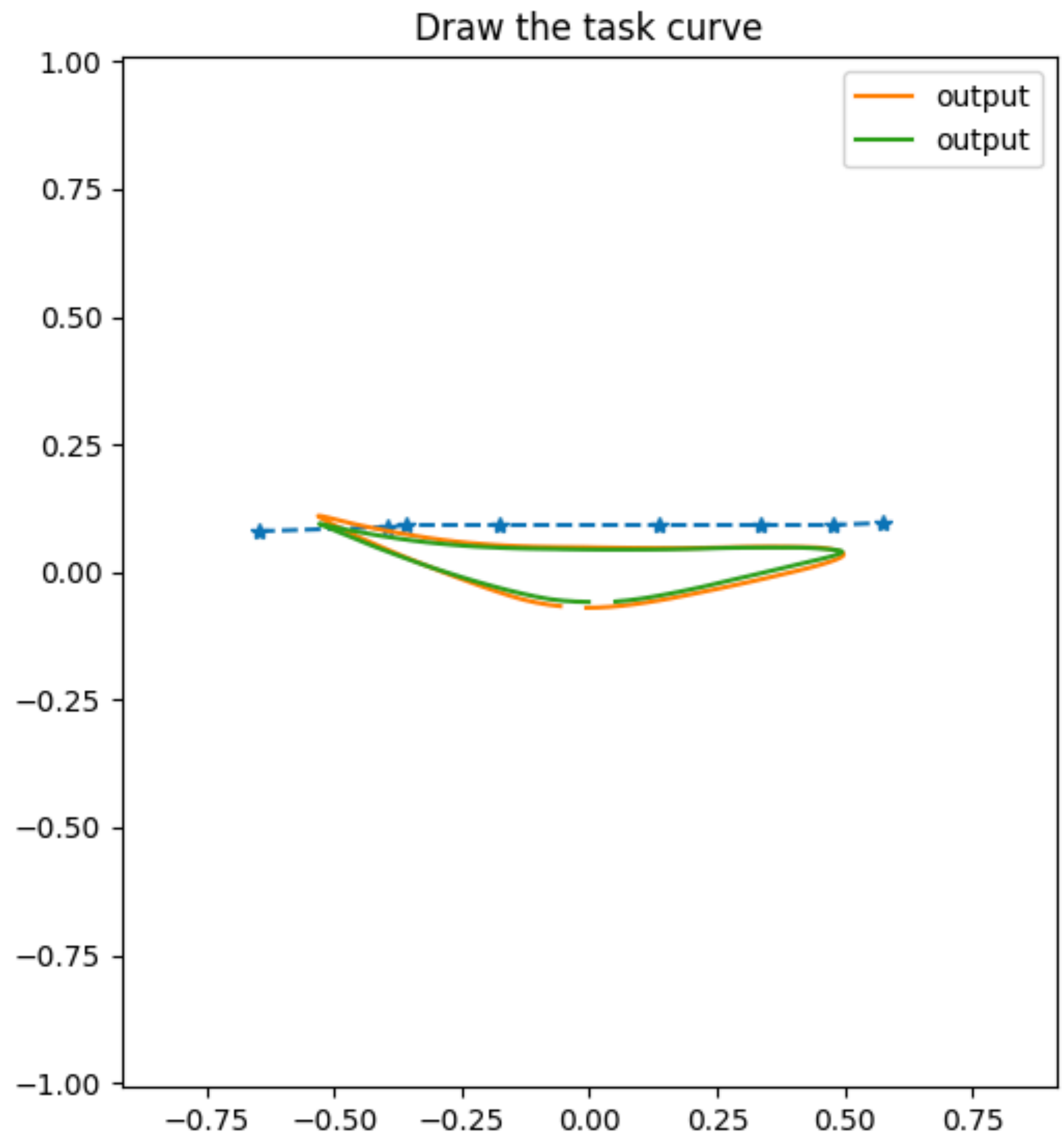

Input Augmentation: Orientation Prediction

- Given a path points, predict the orientation of the path points, with condition that path points are from unknown fourbar/sixbar/sixbar linkage.

$$\{\theta_i\}_i^N = Q(\{x_i, y_i\}_i^N)$$

- LSTM (Long Short Term Memory) Recurrent Neural Networks are used to approximate Q

Input Augmentation: Orientation Prediction

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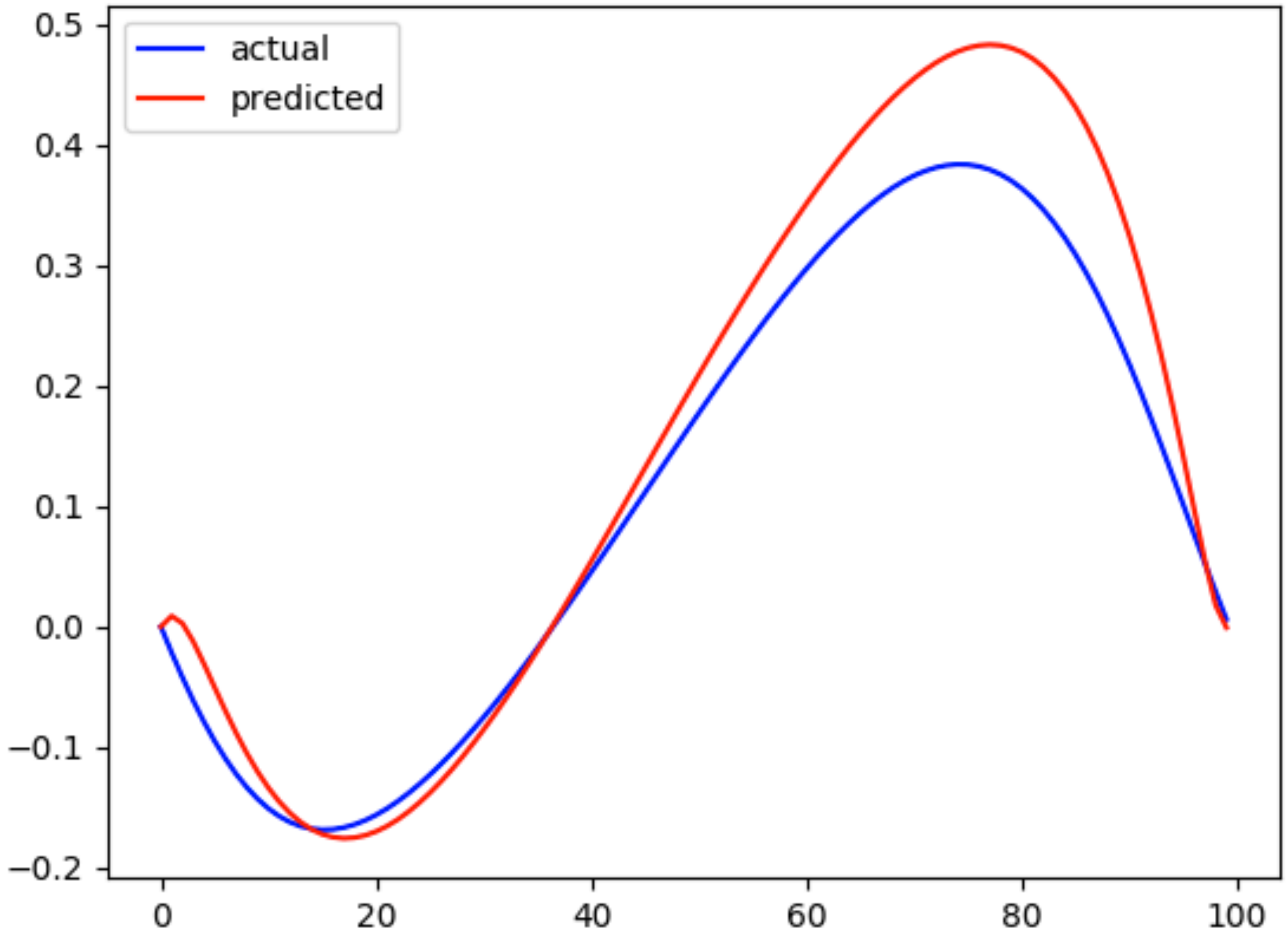

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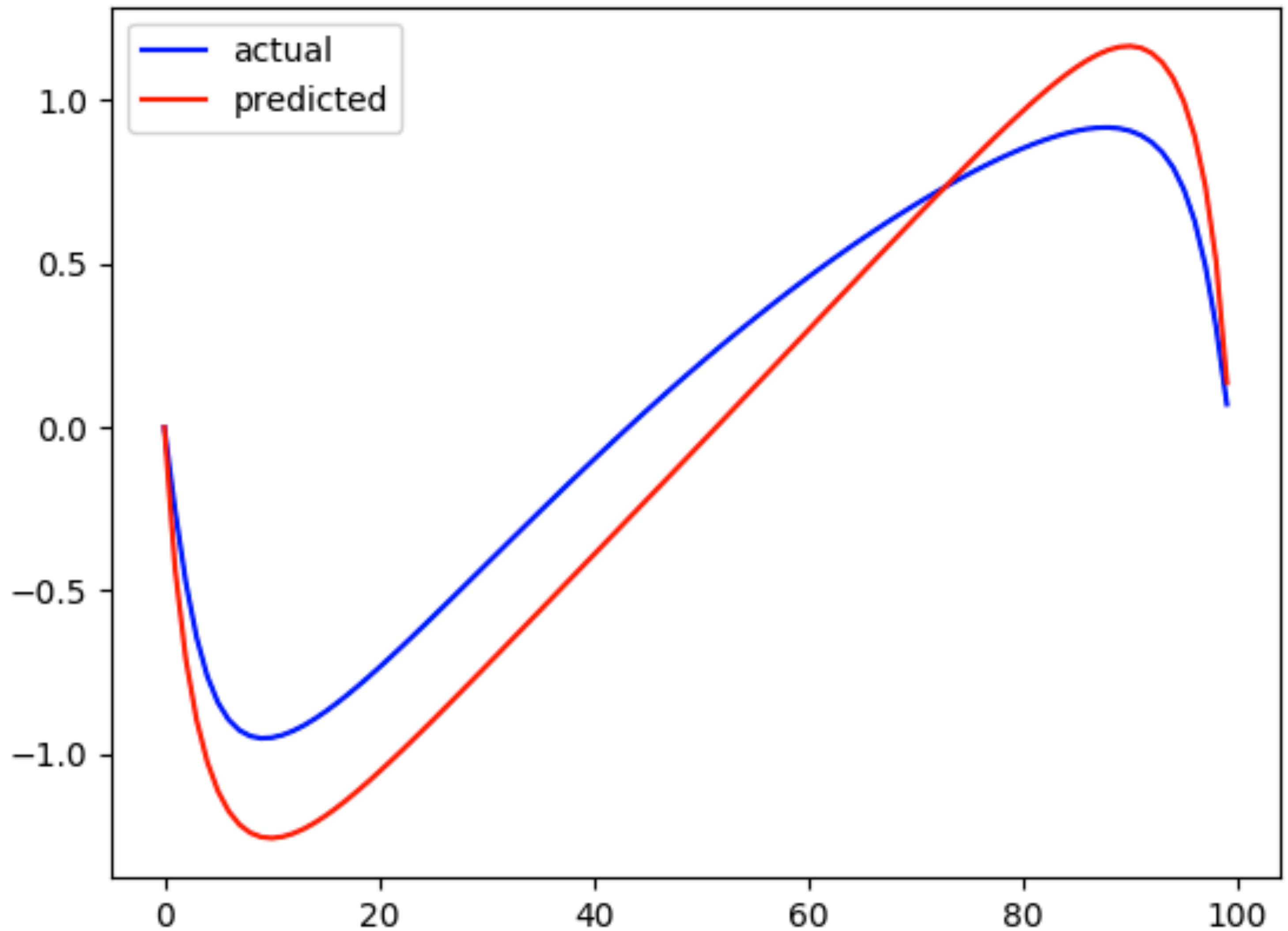

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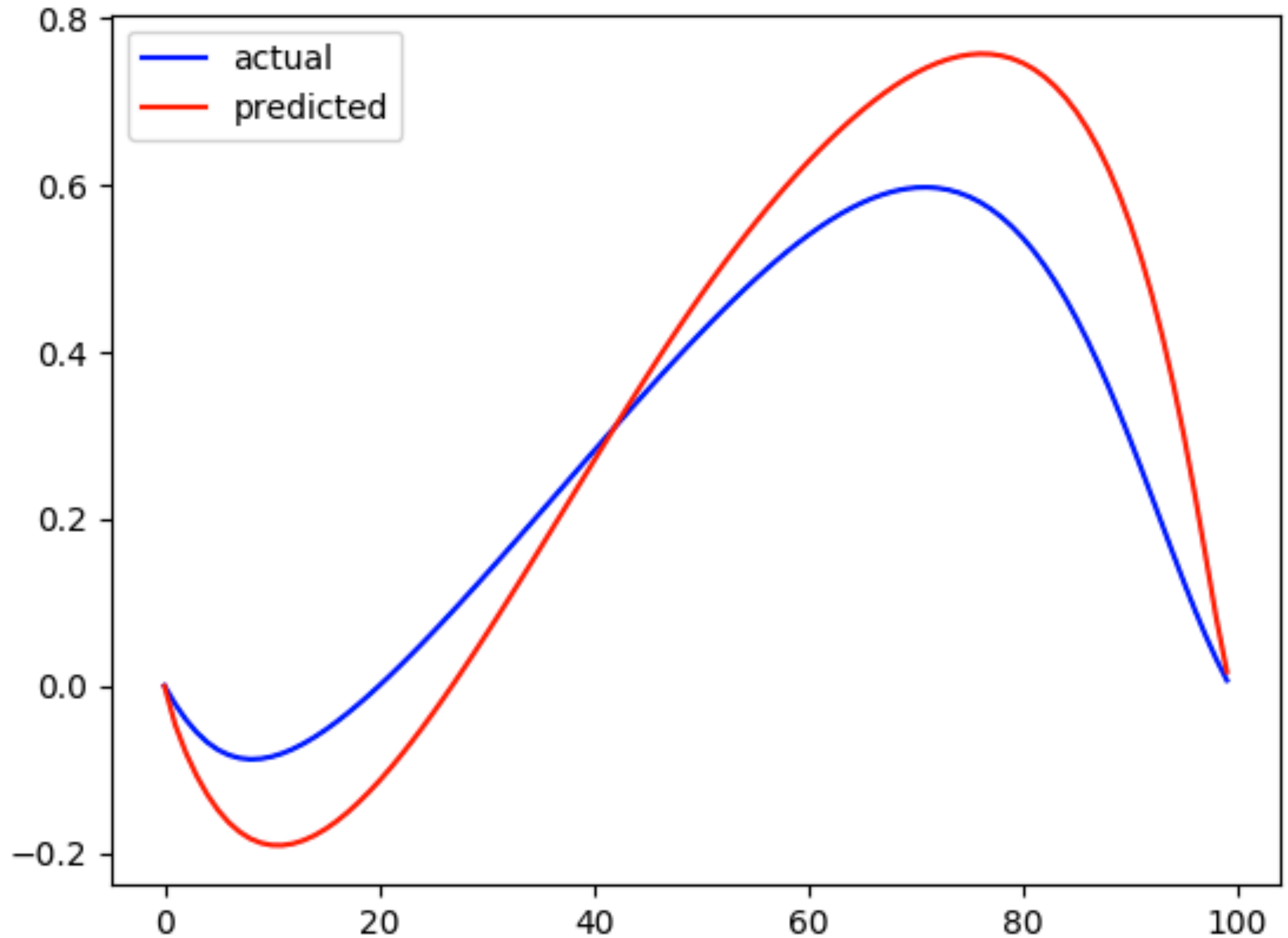

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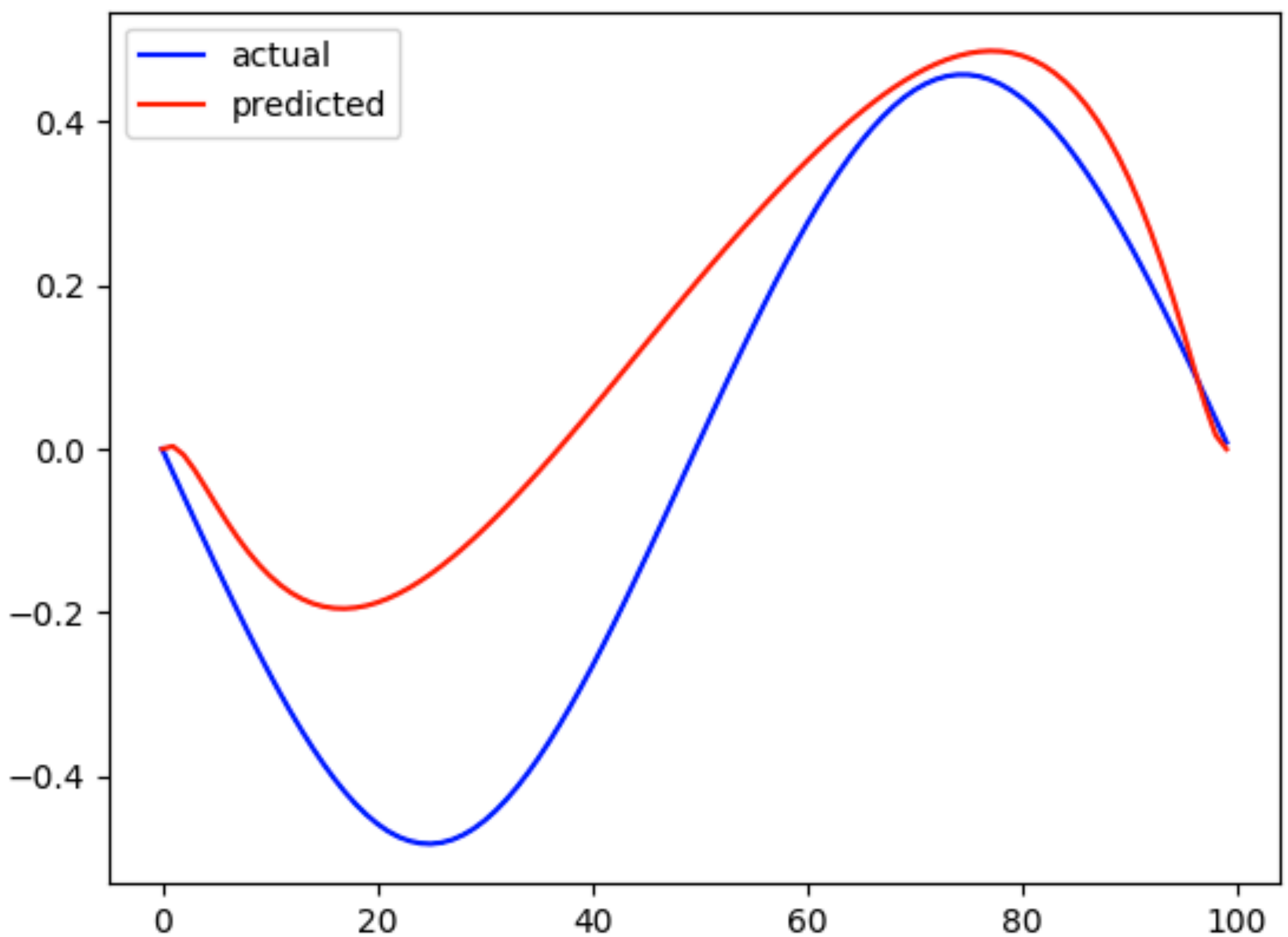

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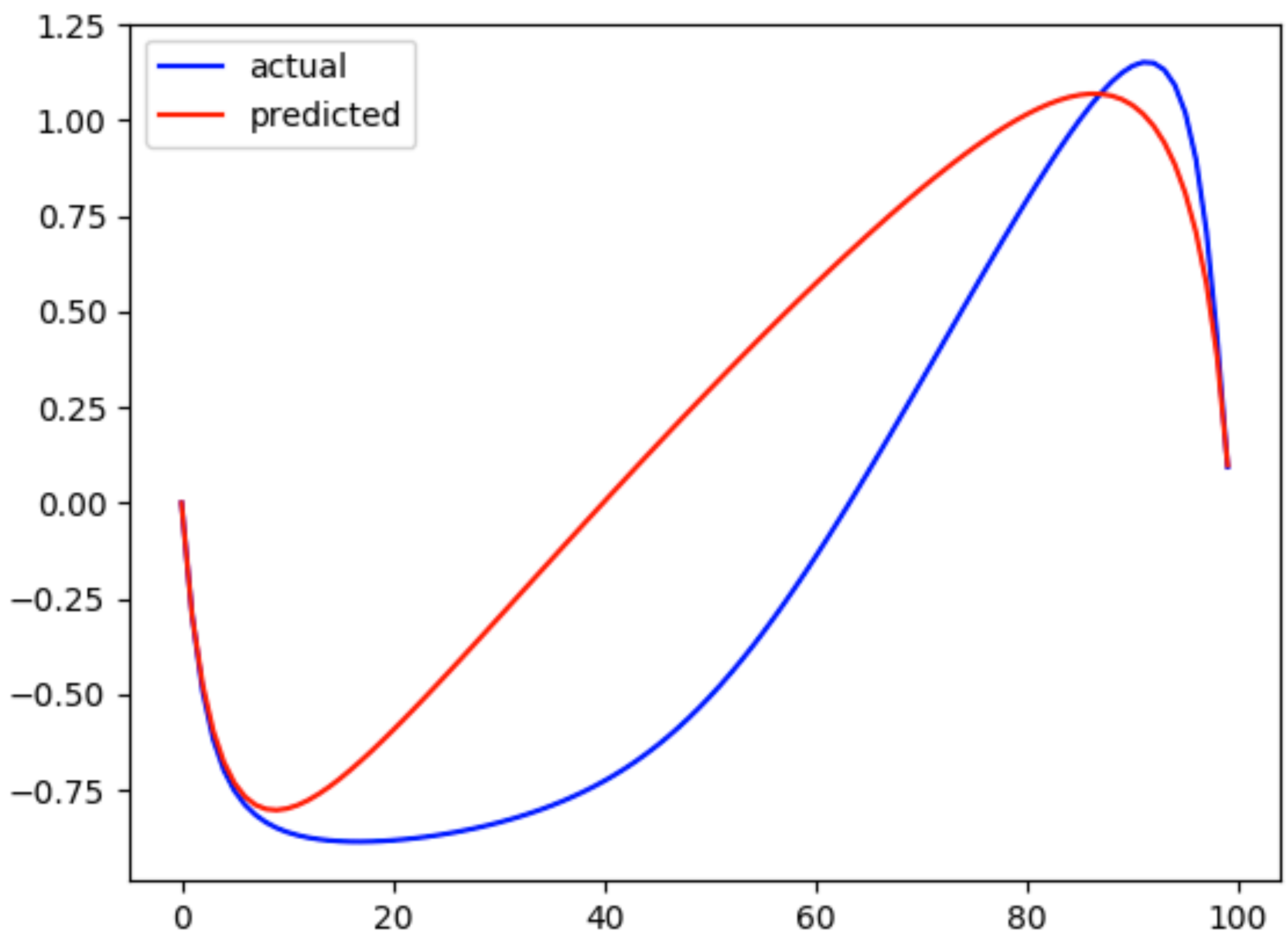


Intelligent Assistant

- Assist Human Designer to generate viable concepts by
  - Conditioning the input
  - Augmenting the input
  - Leveraging and managing uncertainty
  - Making Free Choices (e.g. in Synthesis of Sixbars)
  - Exploring Solutions and presenting it the right way to designer

Input Augmentation and Conditioning

- Manual Input of m points (m > 3)

$$X_{manual}\,.\,dim = [m,2]\ldots(m \geq 4)$$

- Cubic Spline is fitted to input

$$X = Bspline(X_{manual})\ldots X\,.\,dim = [100,2]$$

- Assistant-VAE is trained to convert previous input into closed coupler path

$$p(z\,|\,X) = F_{encoder}(x)$$

$$\hat{X} = G(z)\ldots z \sim p(z\,|\,X)$$

- Assistant-RNN is trained to predict the orientations for closed coupler path received

$$\theta = Q_{RNN}(\hat{X})$$

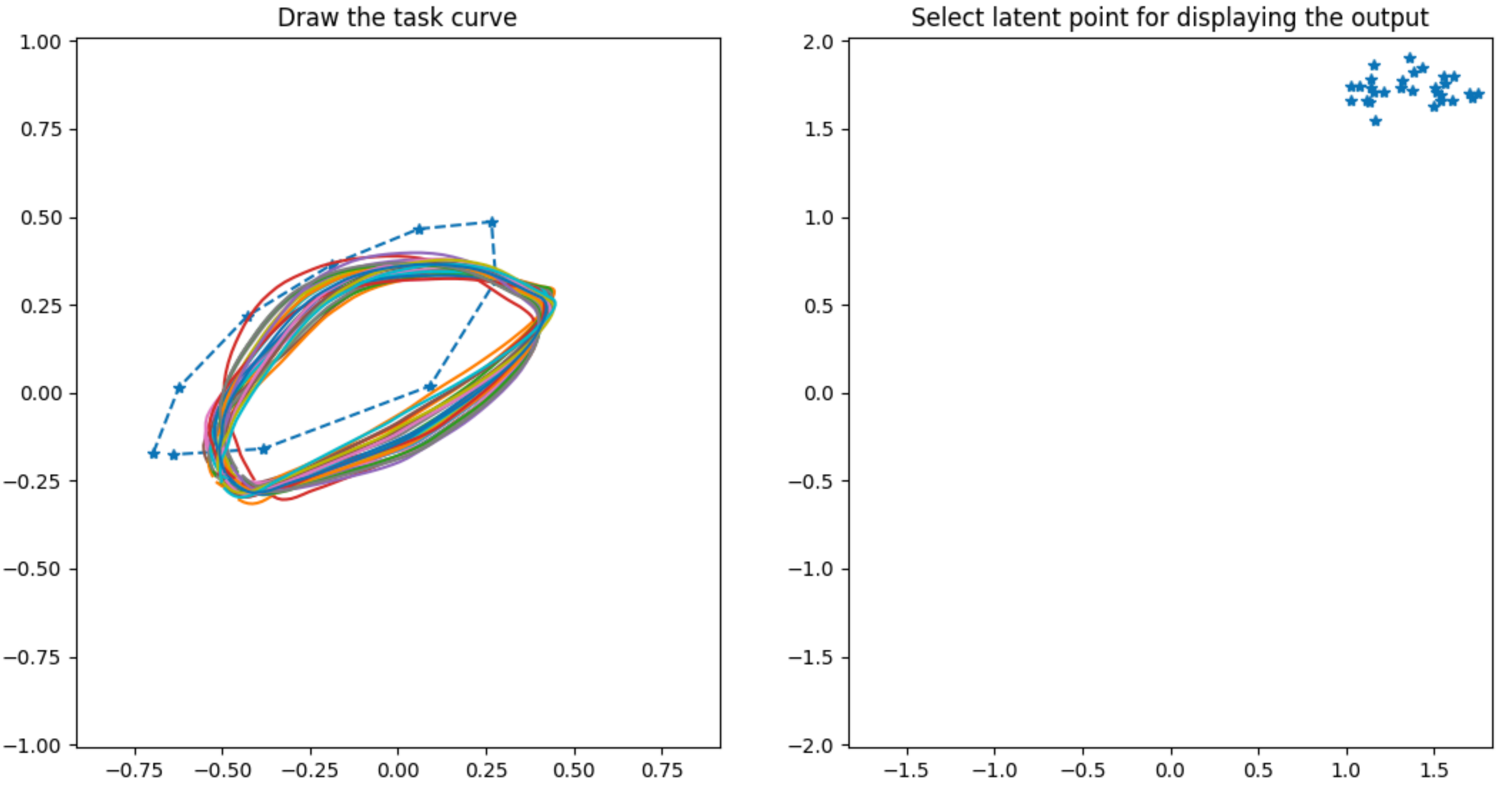
$$P = [\hat{X}, \theta]\ldots P\,.\,dim = [100,3]$$

- Assisted Input is fed to N-Pose Algebraic Fitting Algorithm

$$Solutions = \textbf{Algebraic Fitting}(P)$$

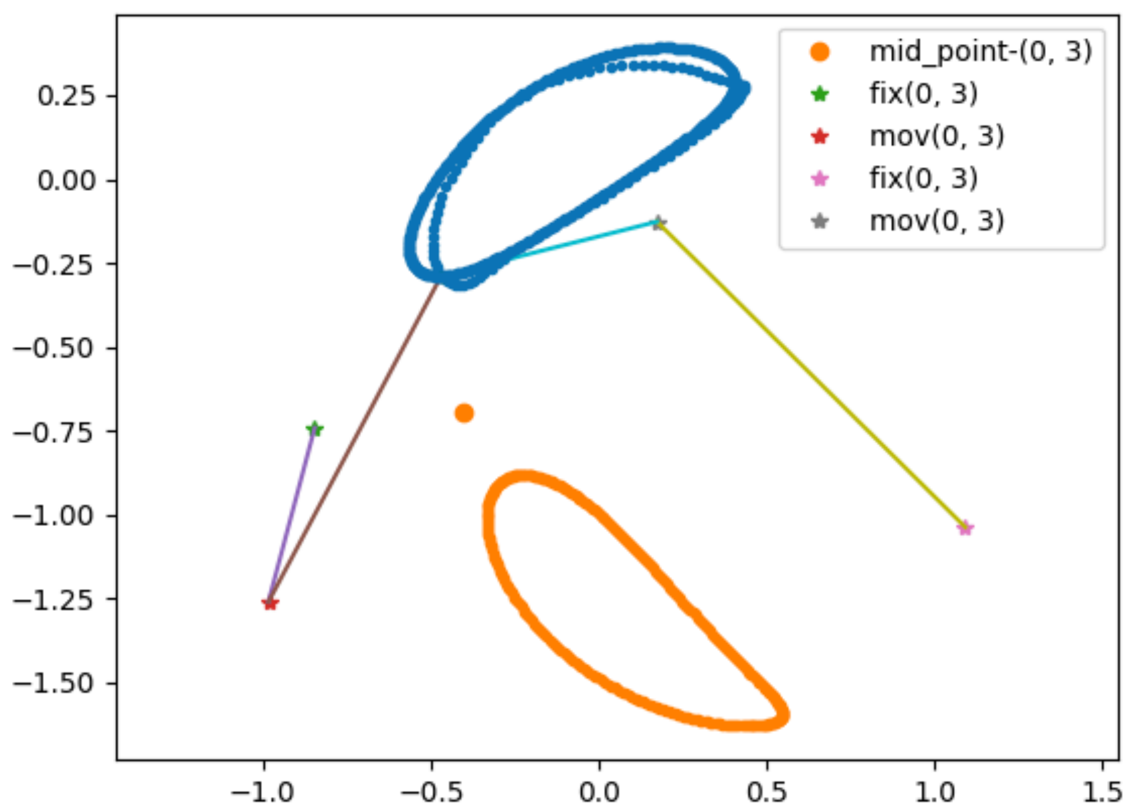
Input Augmentation and Conditioning Results

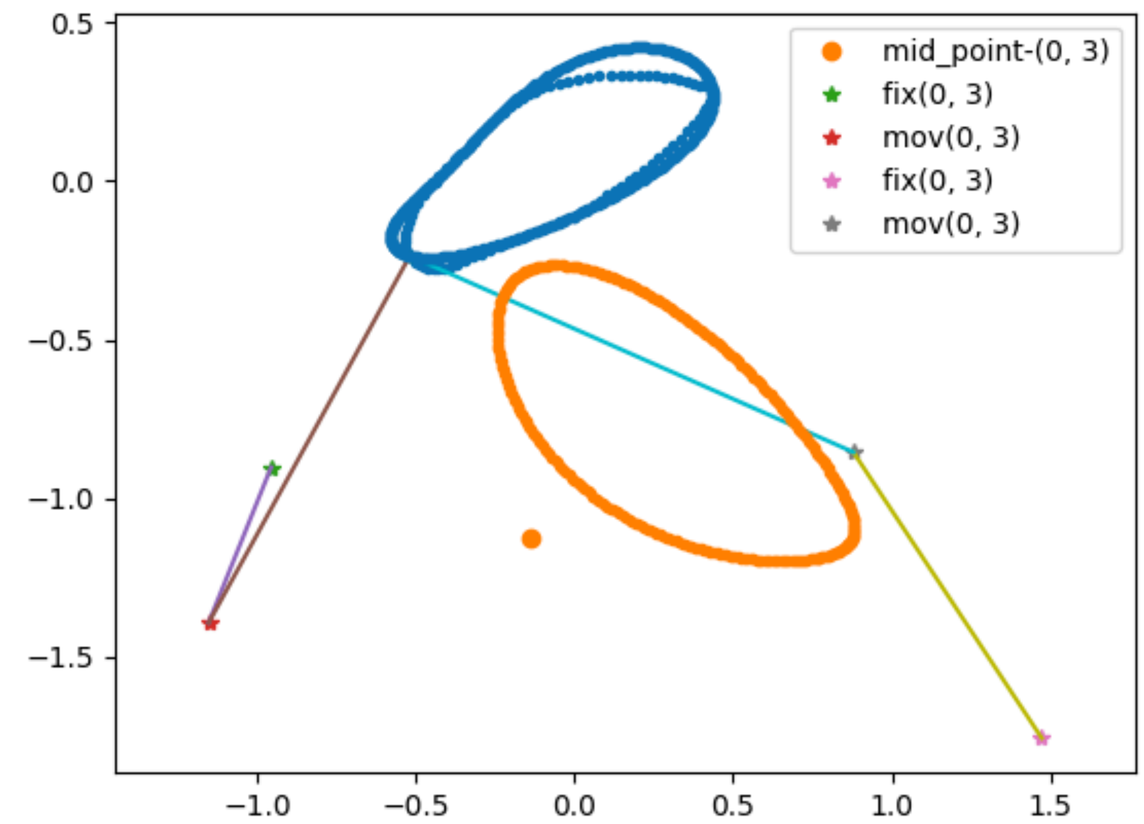
number of samples = 30



Input Augmentation and Conditioning Results

Concept 1

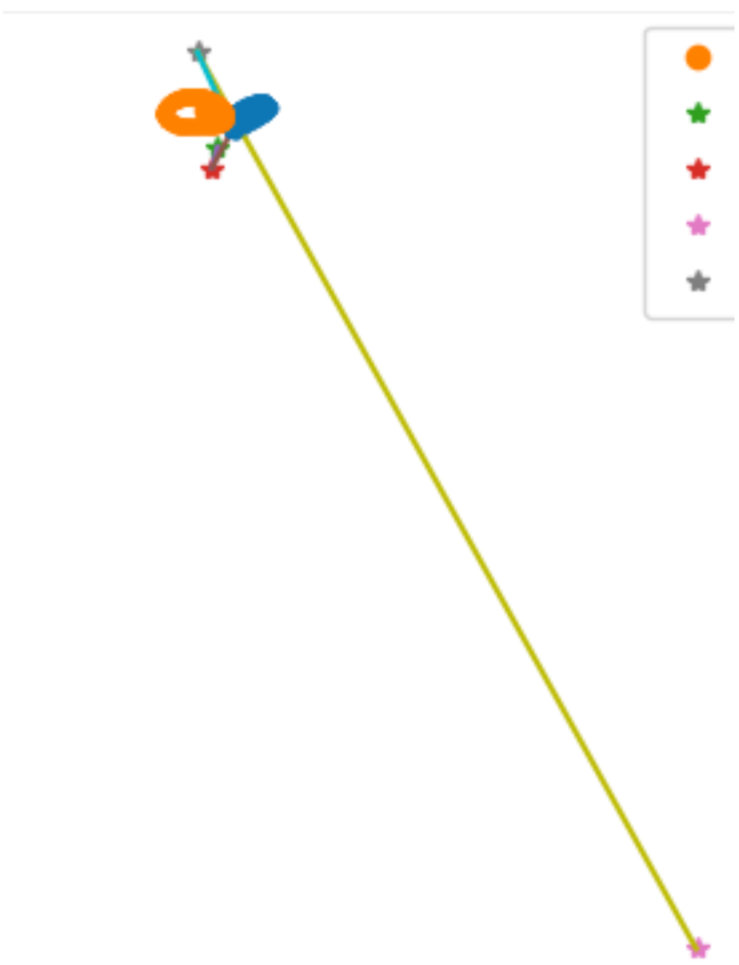


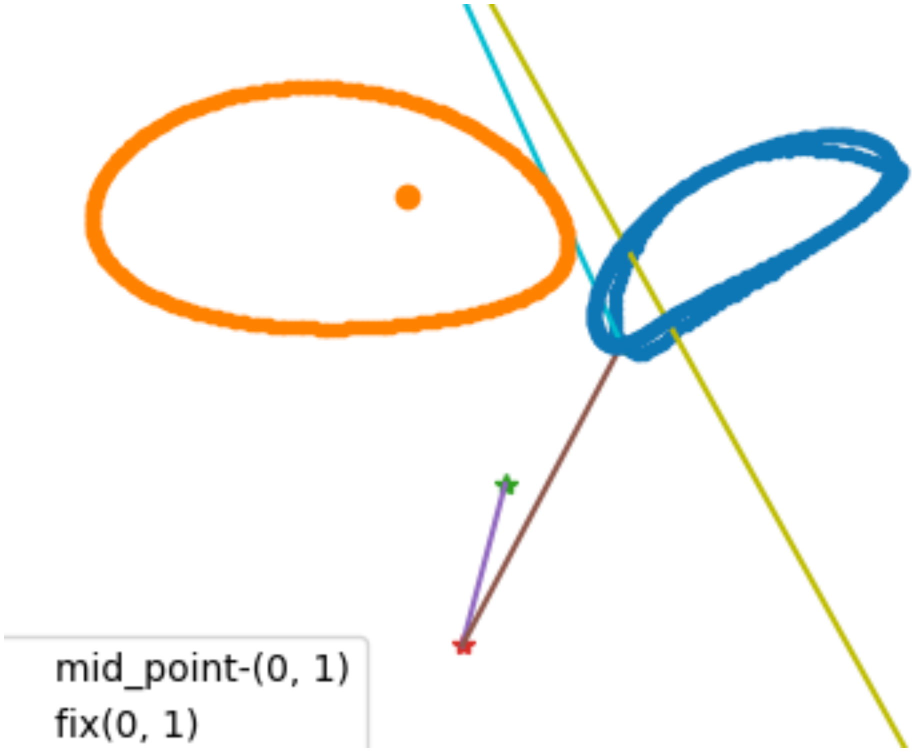


Similar Concepts, but very different link ratios

Input Augmentation and Conditioning Results

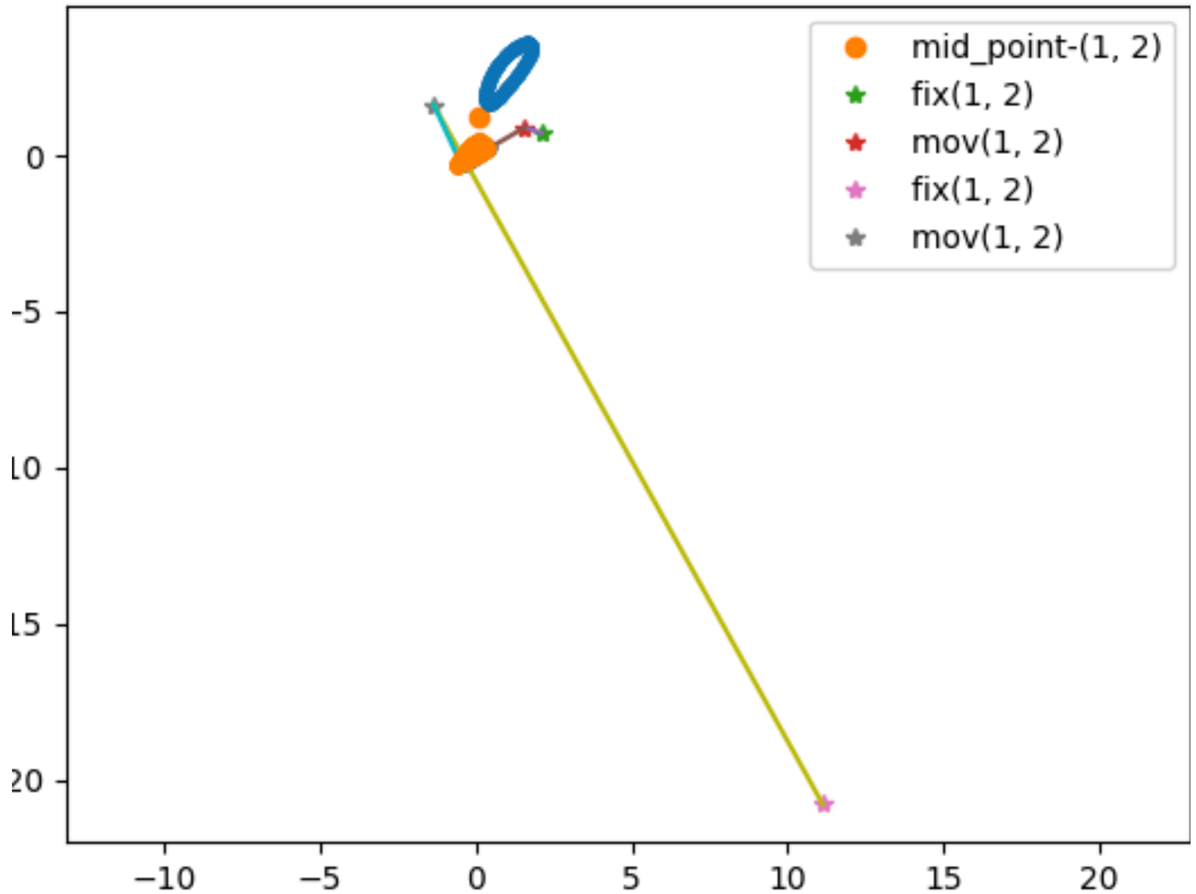
Concept 2

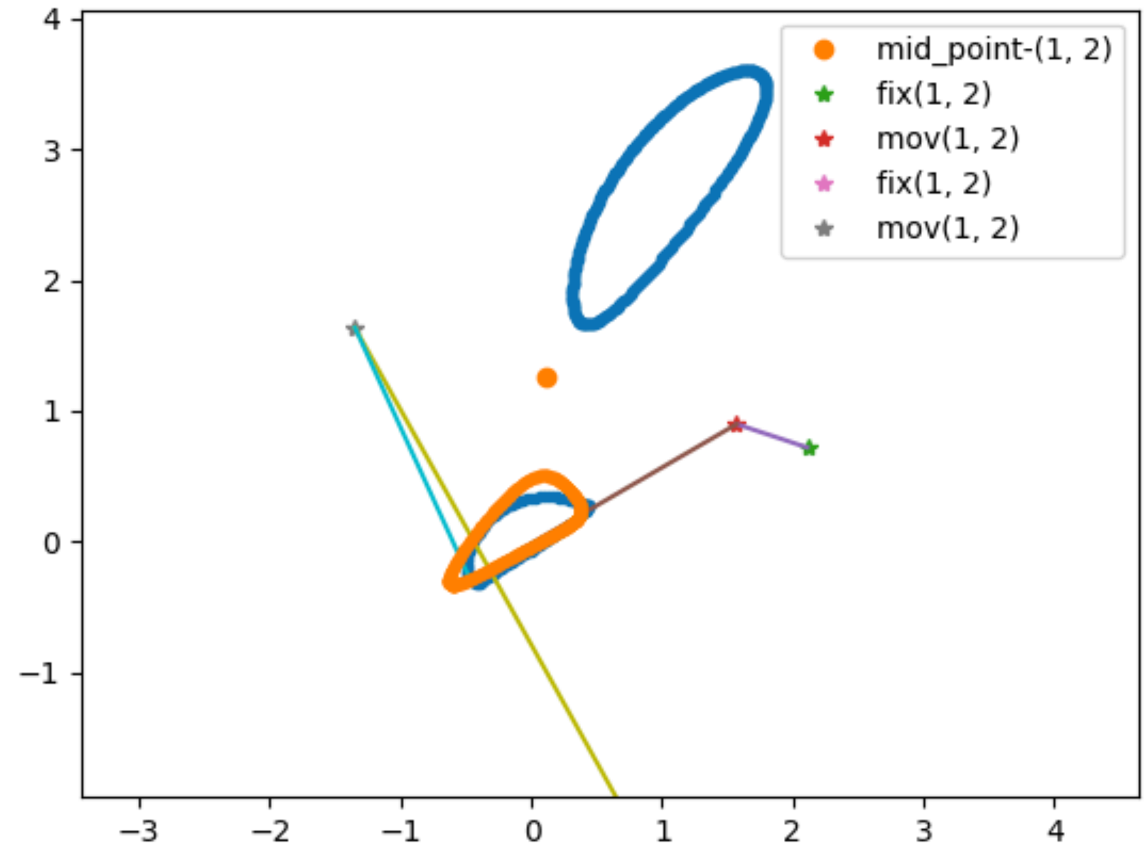




Input Augmentation and Conditioning Results

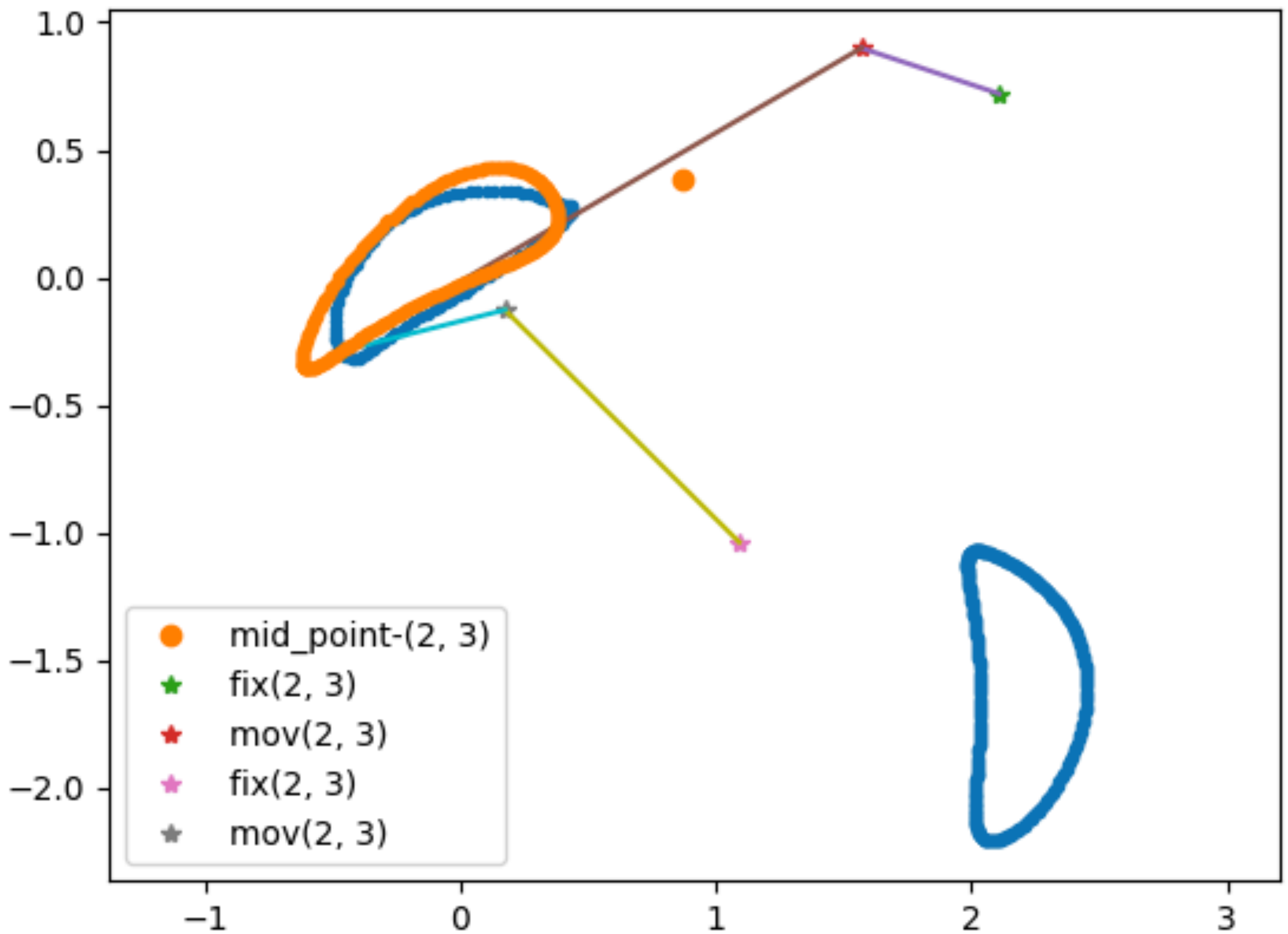
Concept 3





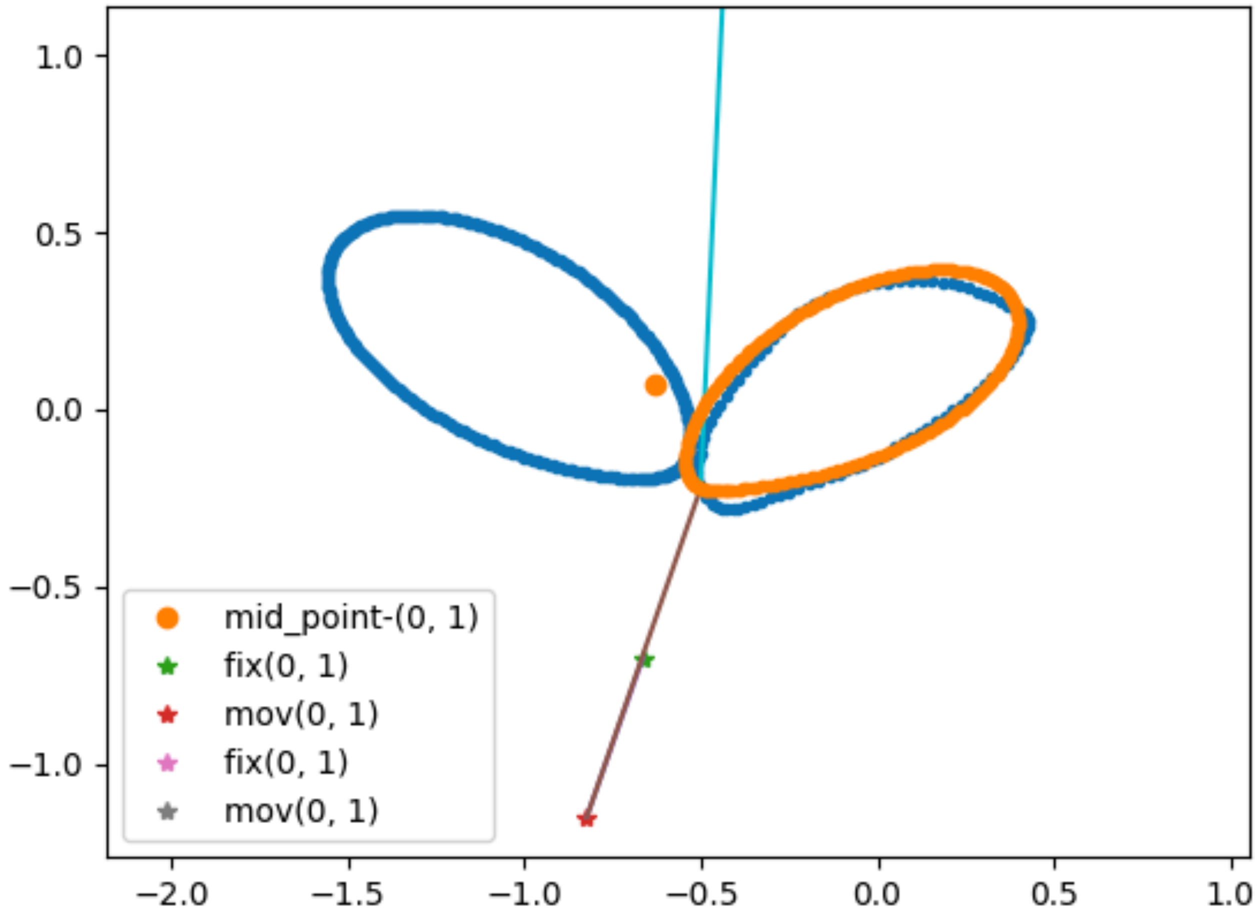
Input Augmentation and Conditioning Results

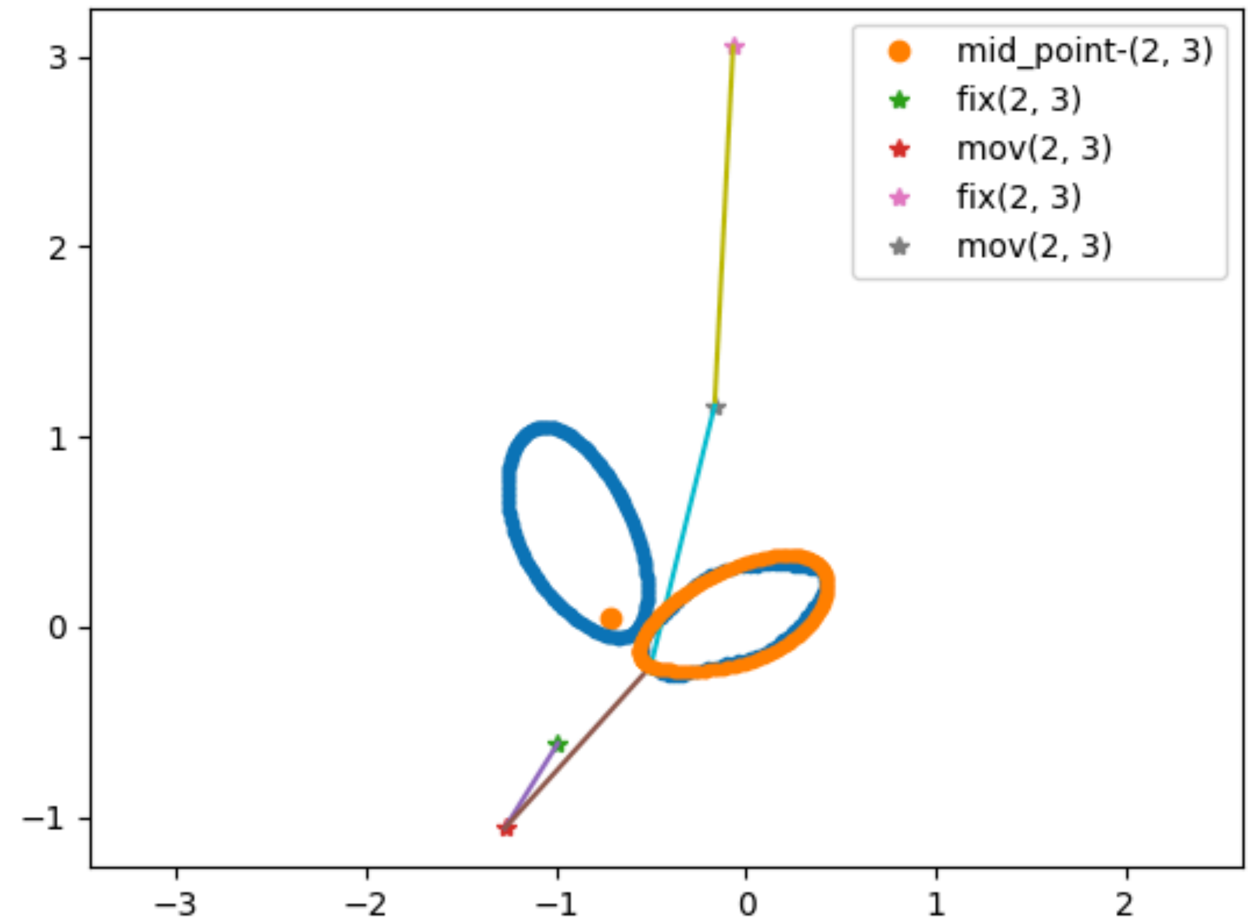
Concept 4



Input Augmentation and Conditioning Results

Concept 5





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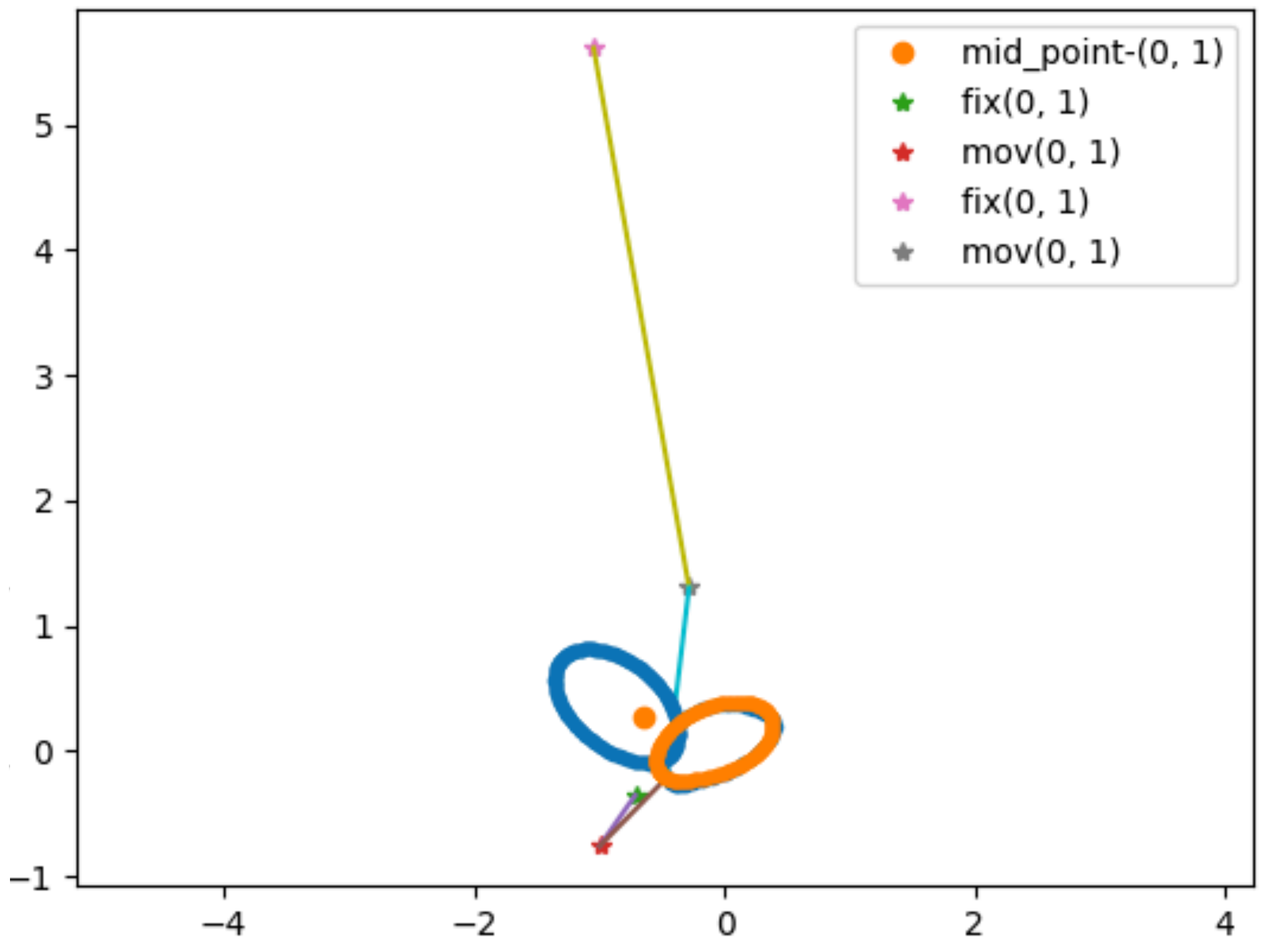
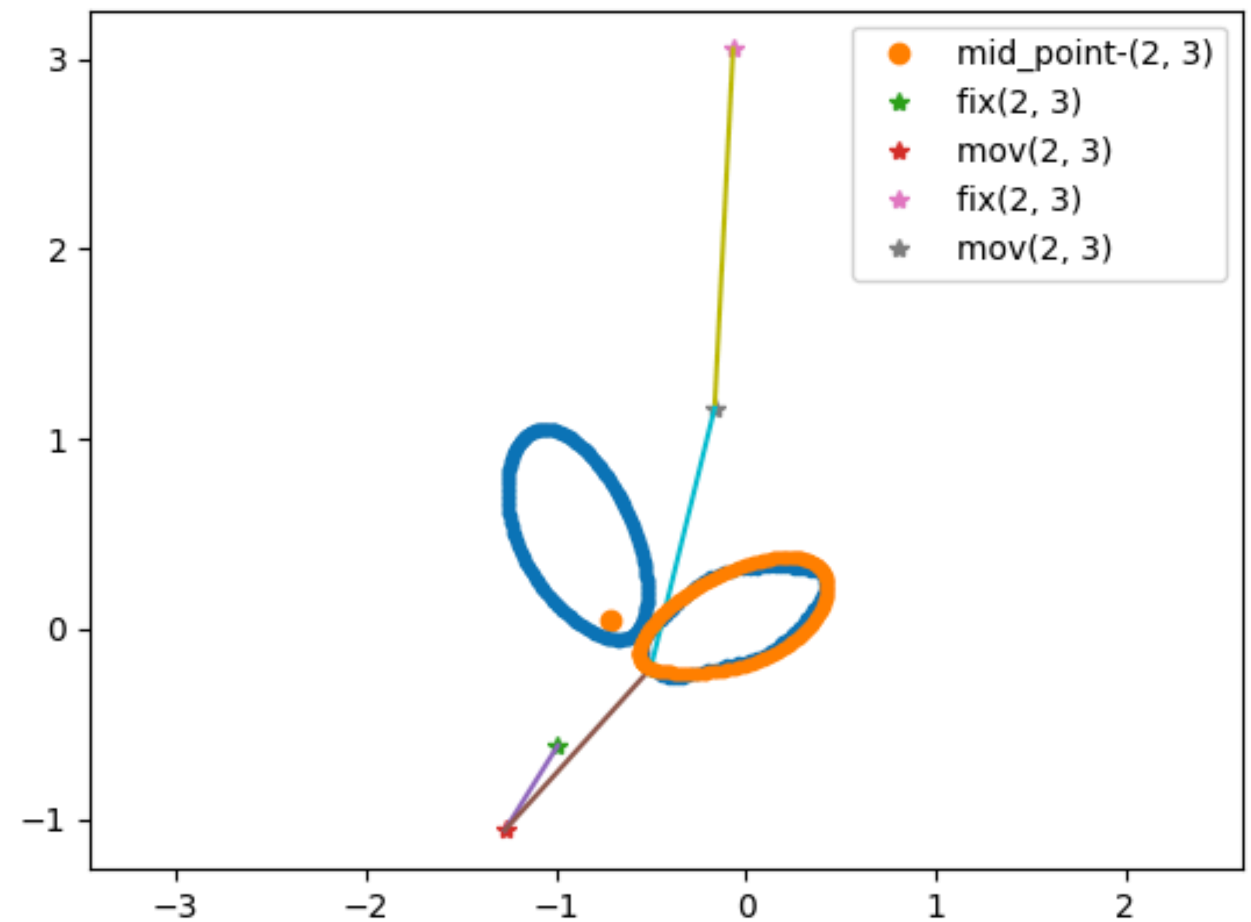
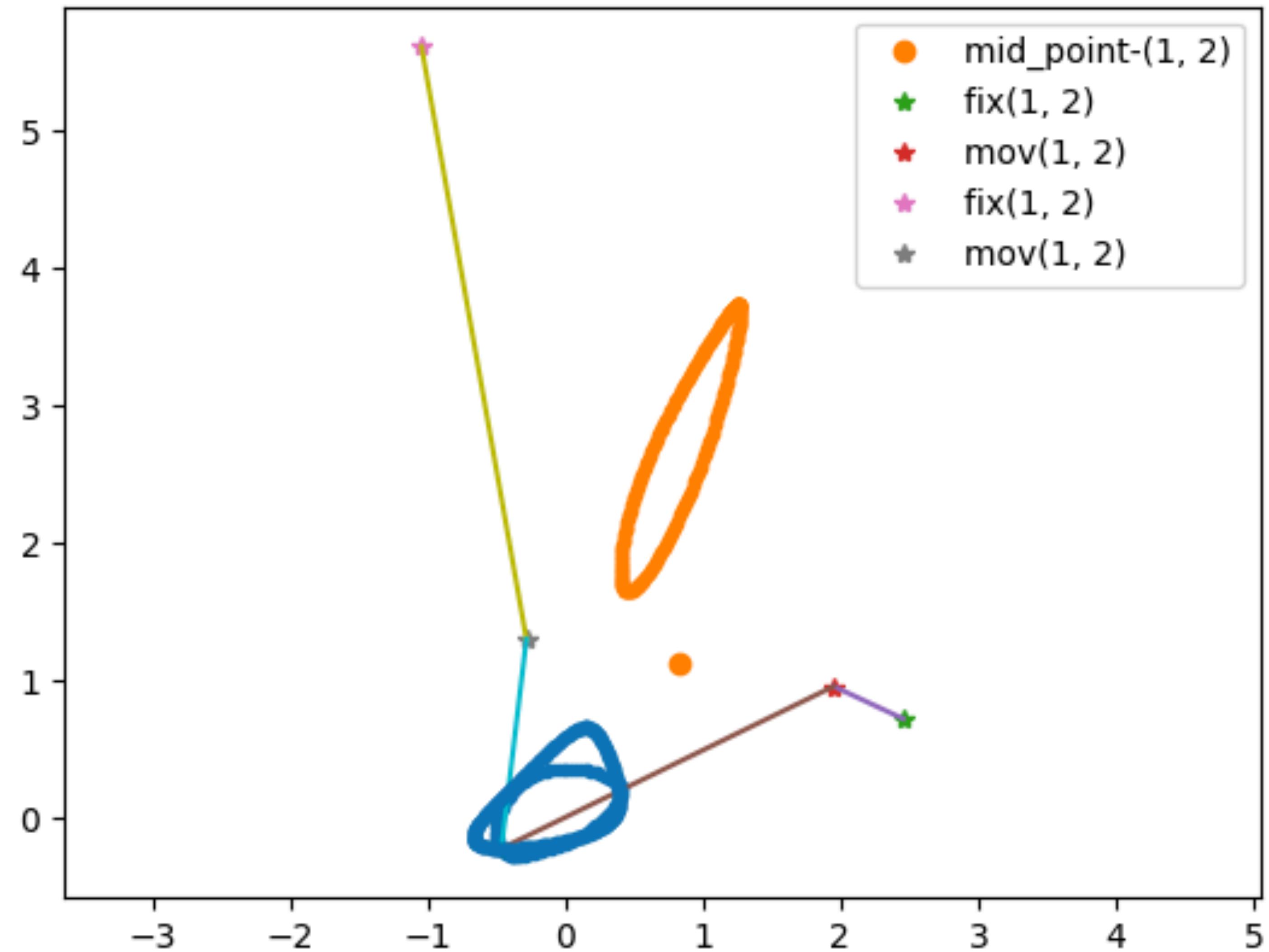




Input Augmentation and Conditioning Results

Concept 6



Input Augmentation and Conditioning Results

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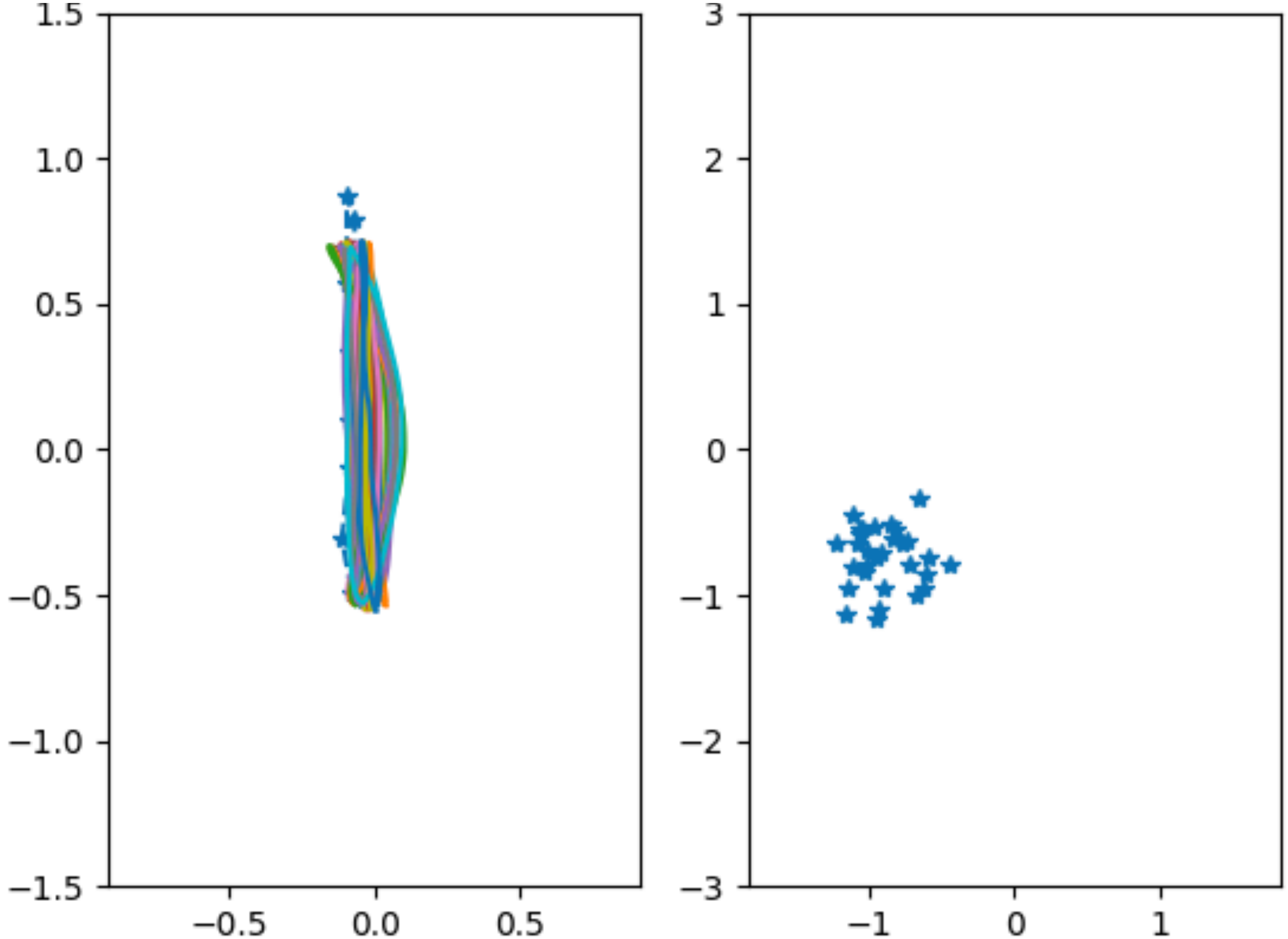

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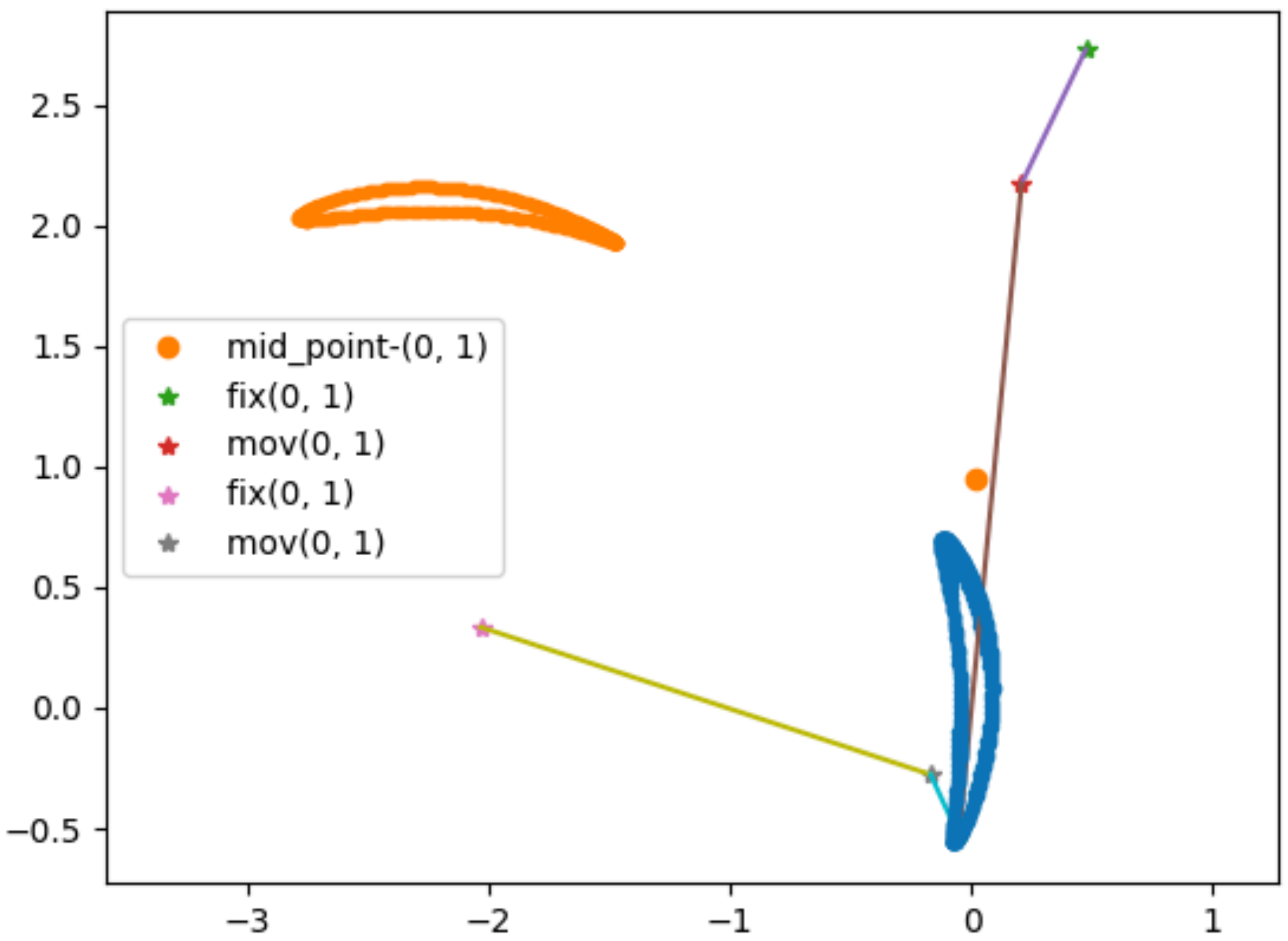
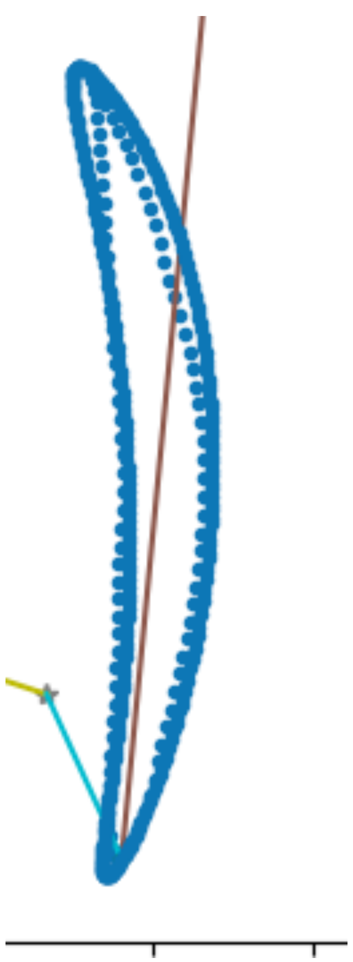


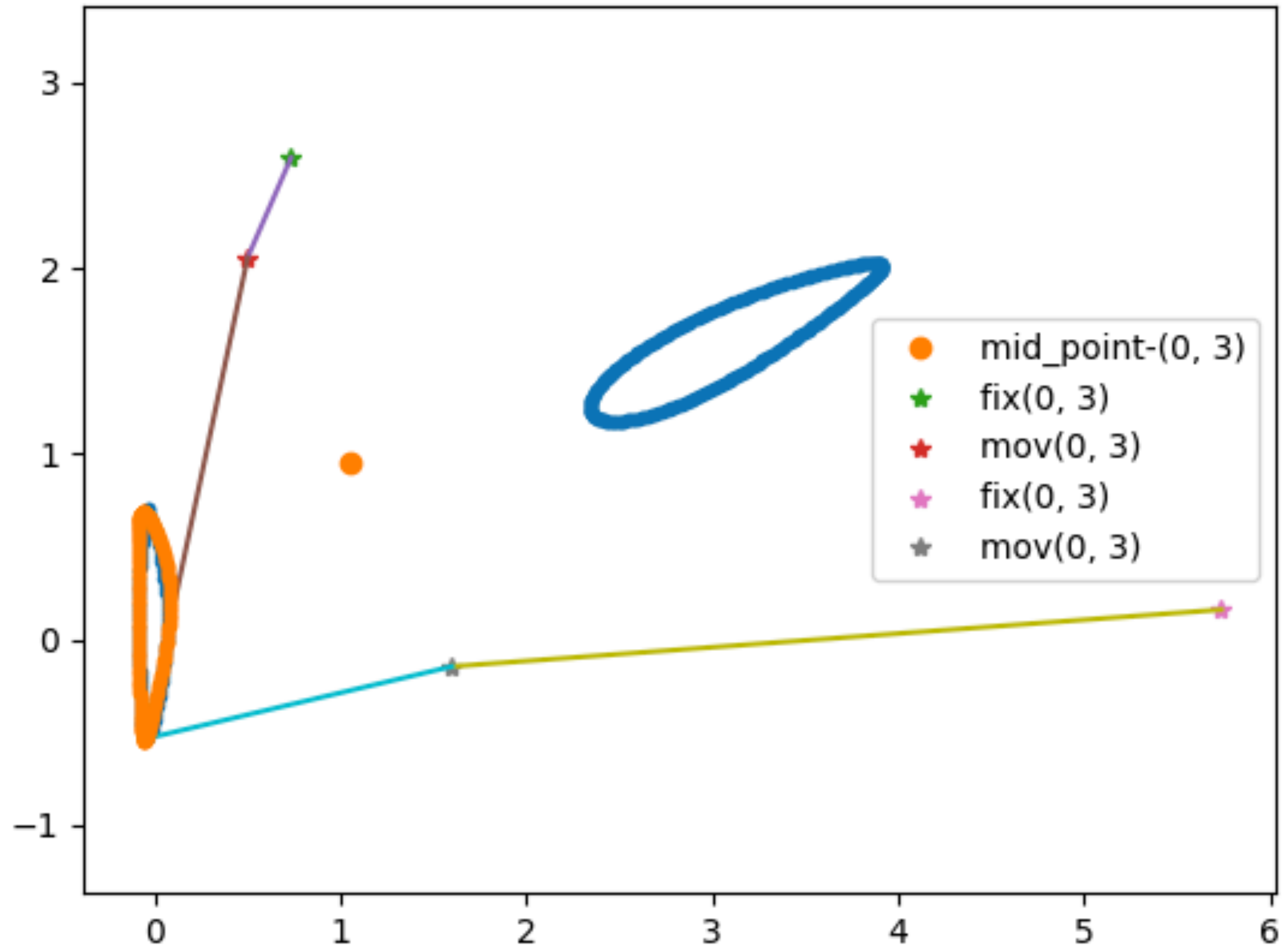


Input Augmentation and Conditioning Results

Concept 2

Input Augmentation and Conditioning Results

Concept 2



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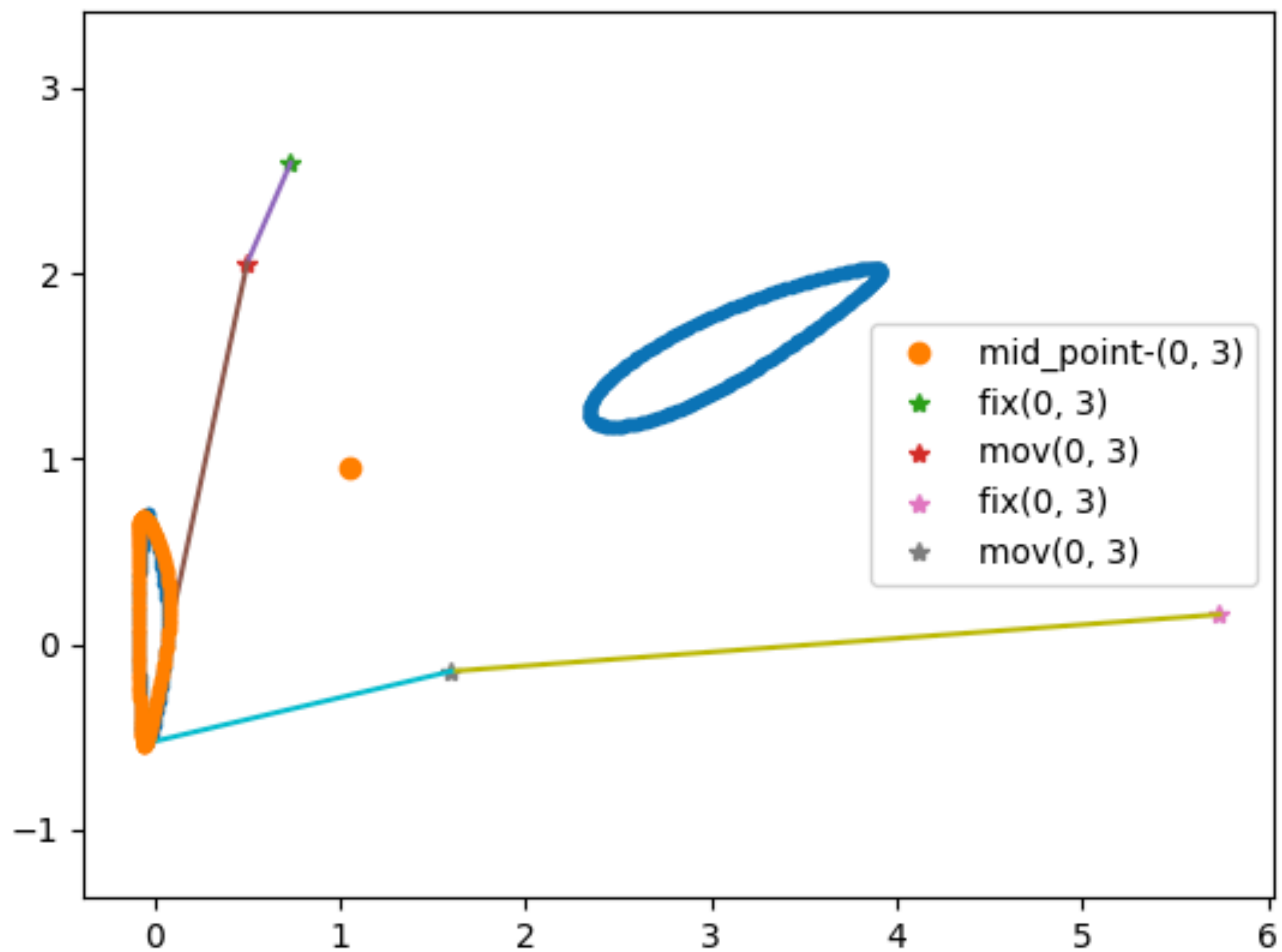

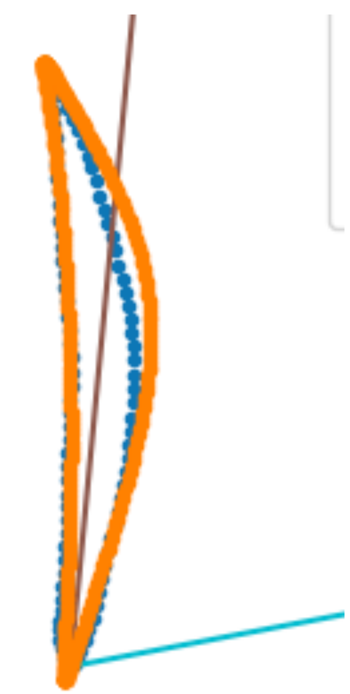

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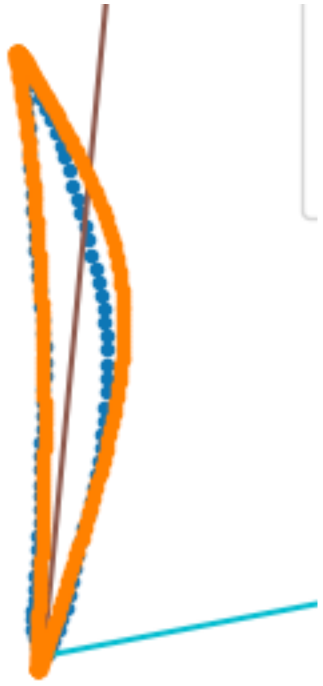

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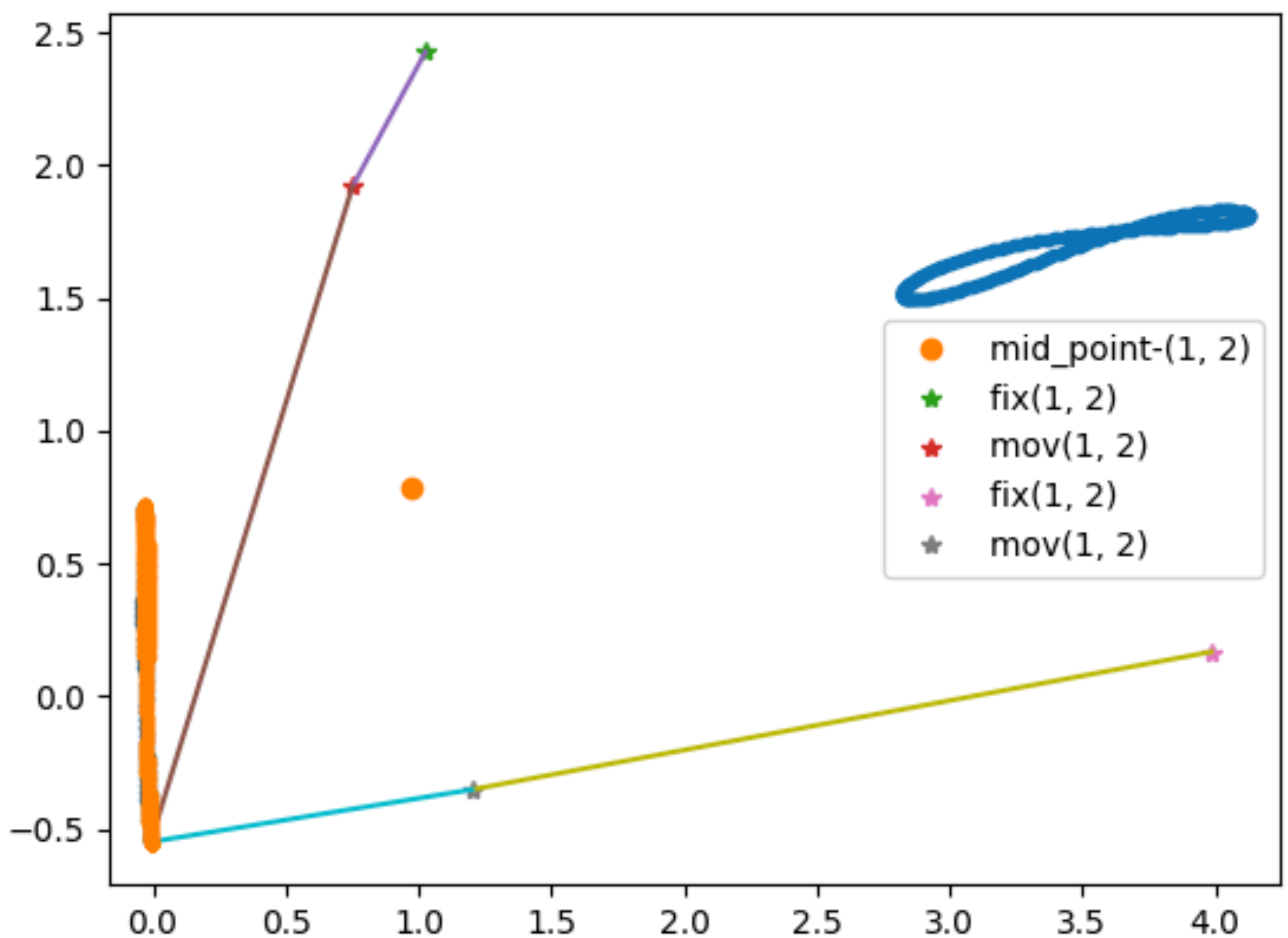

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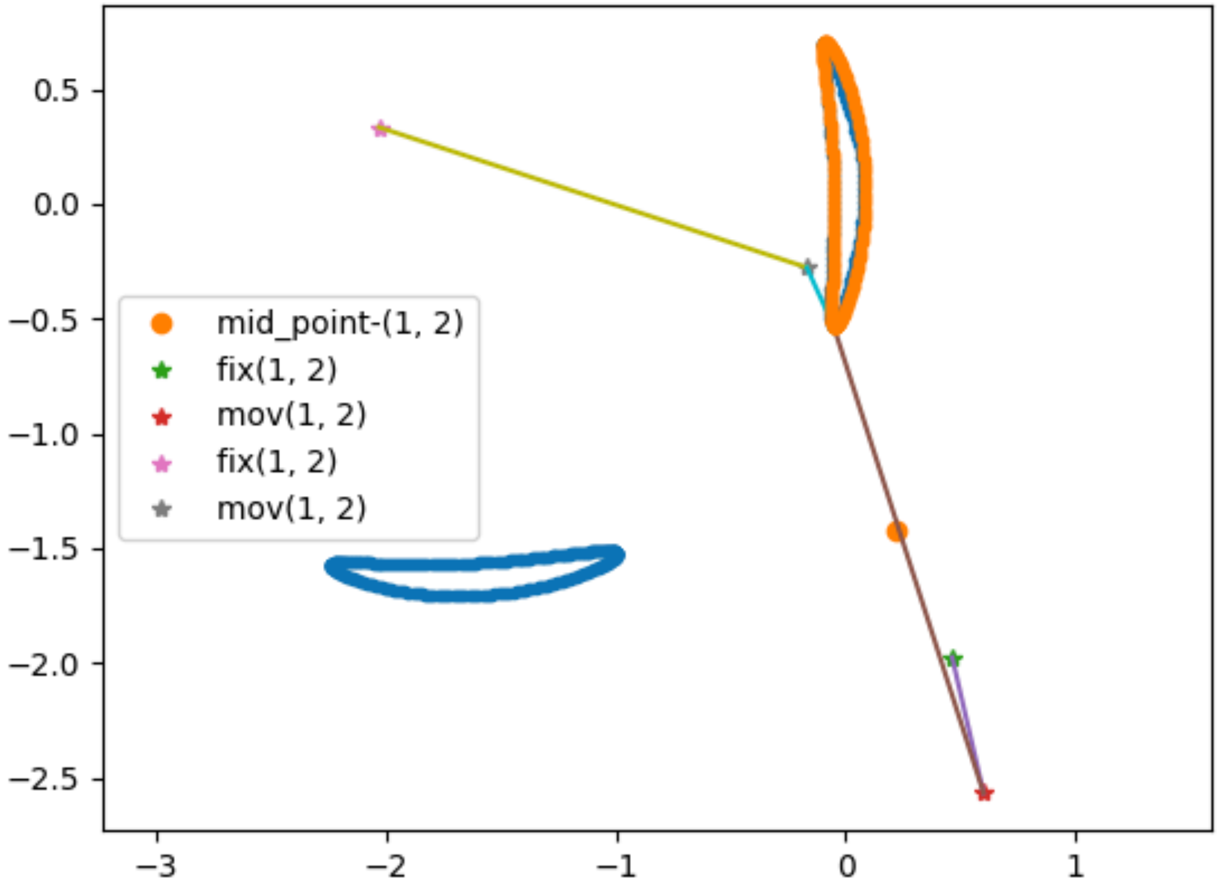

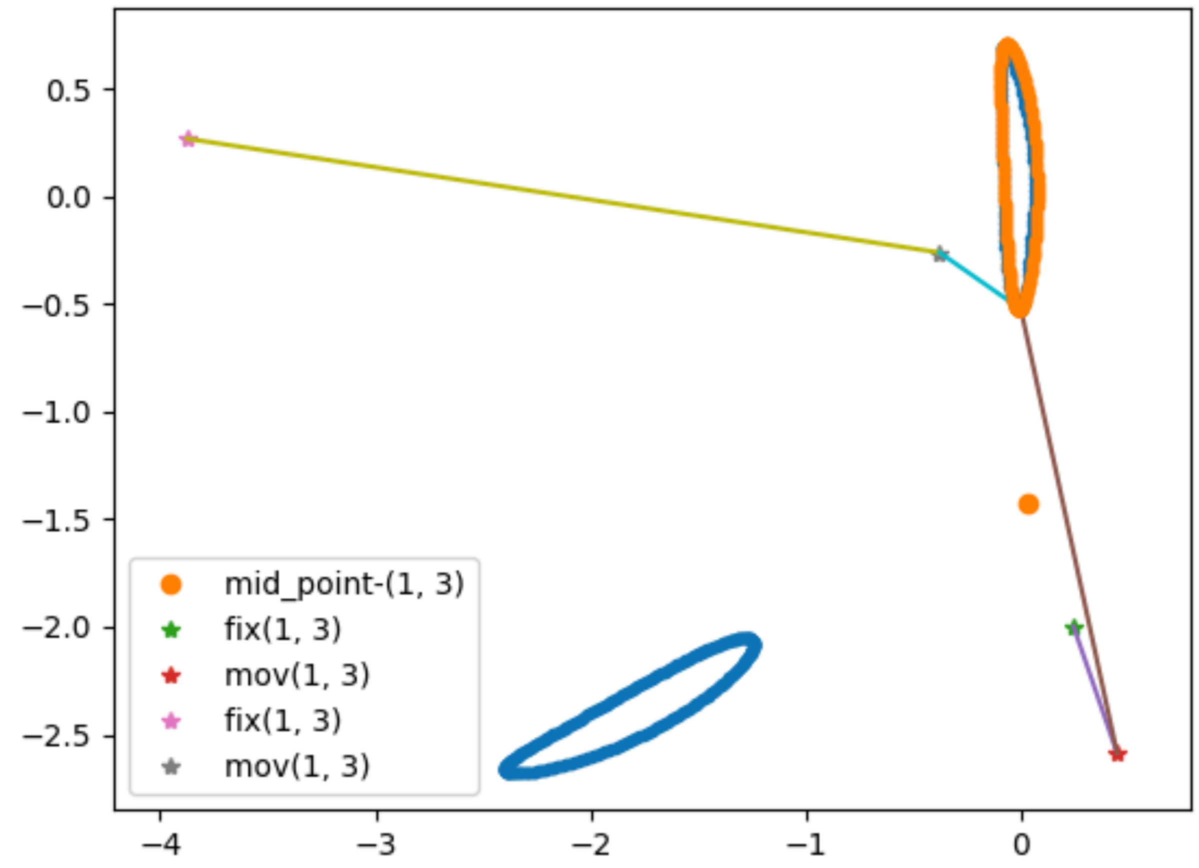

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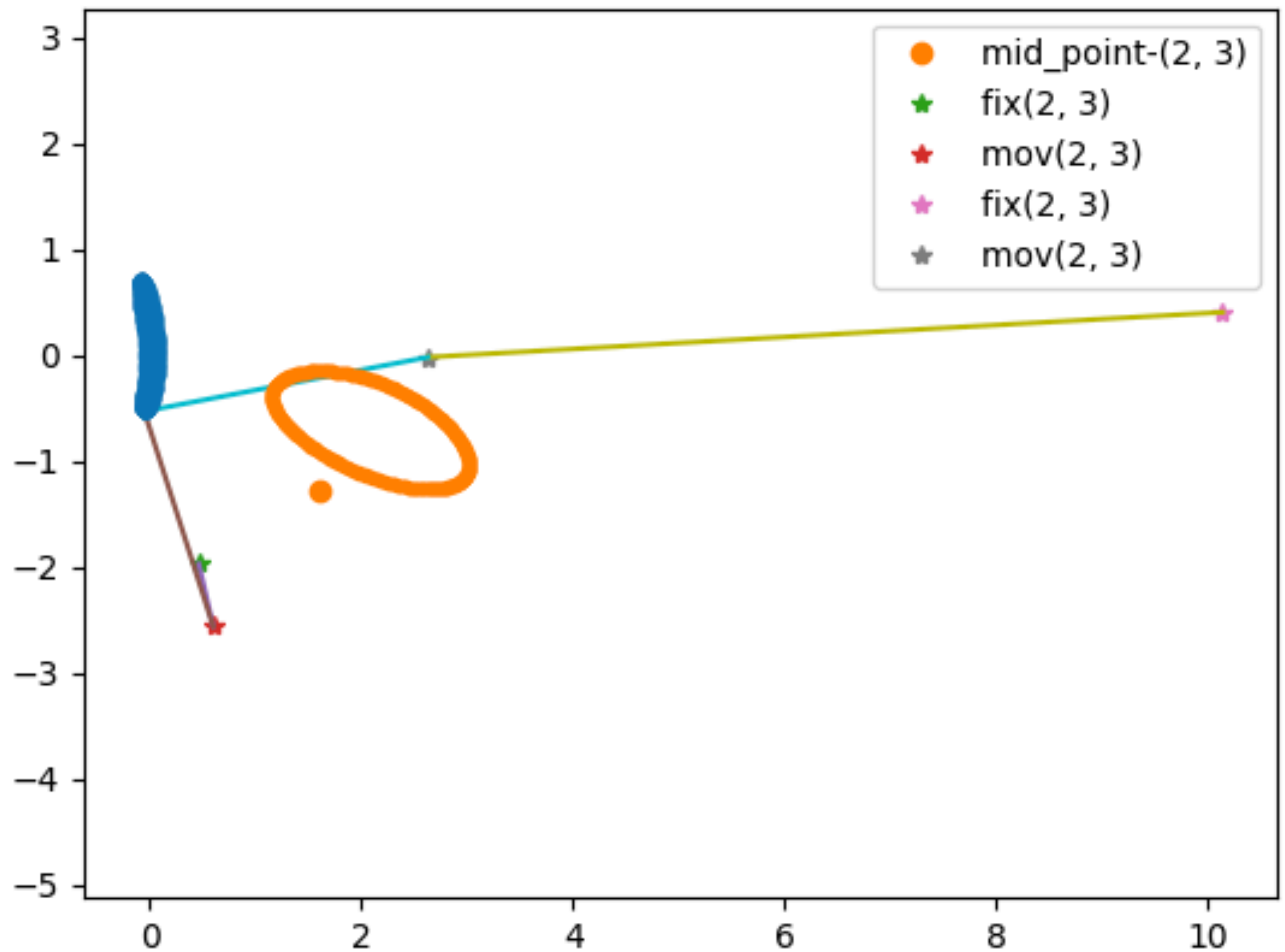
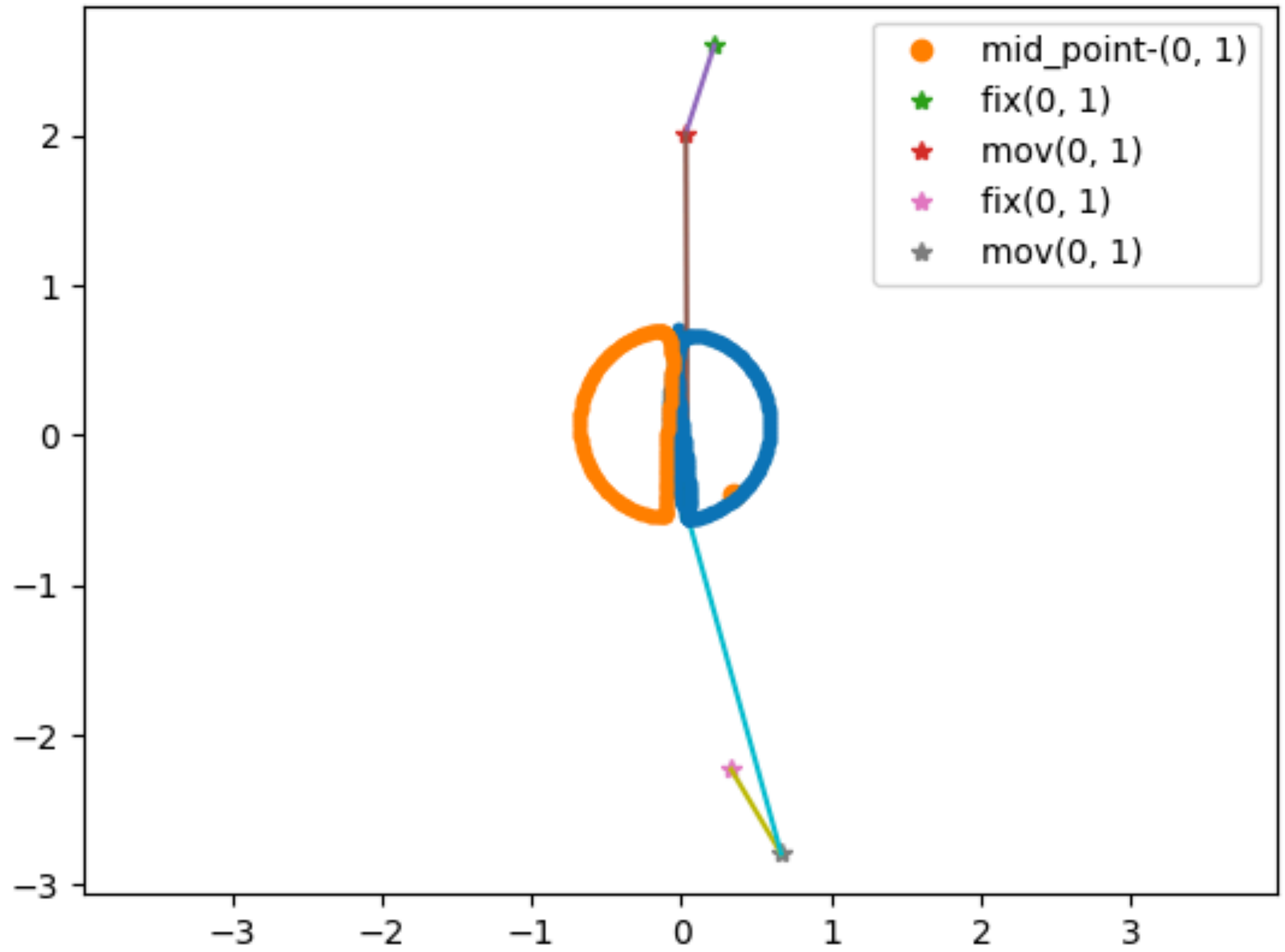


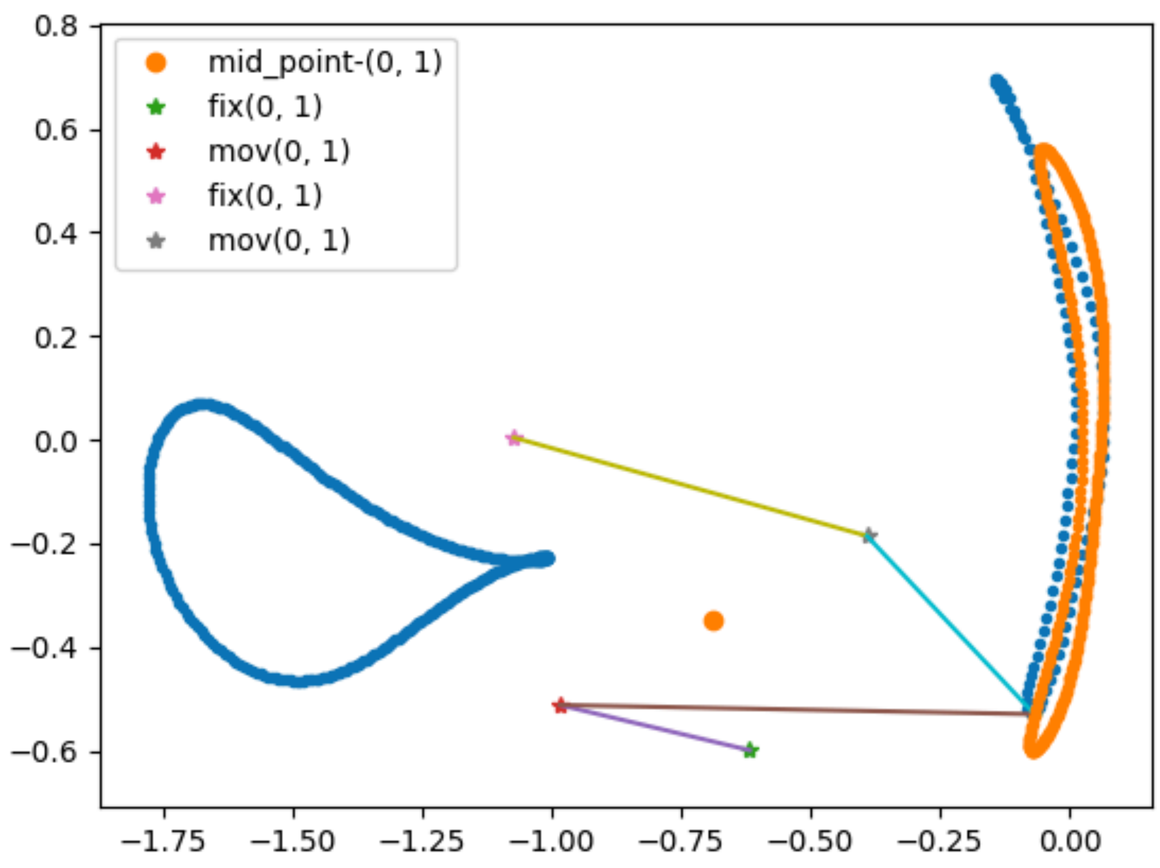
Input Augmentation and Conditioning Results

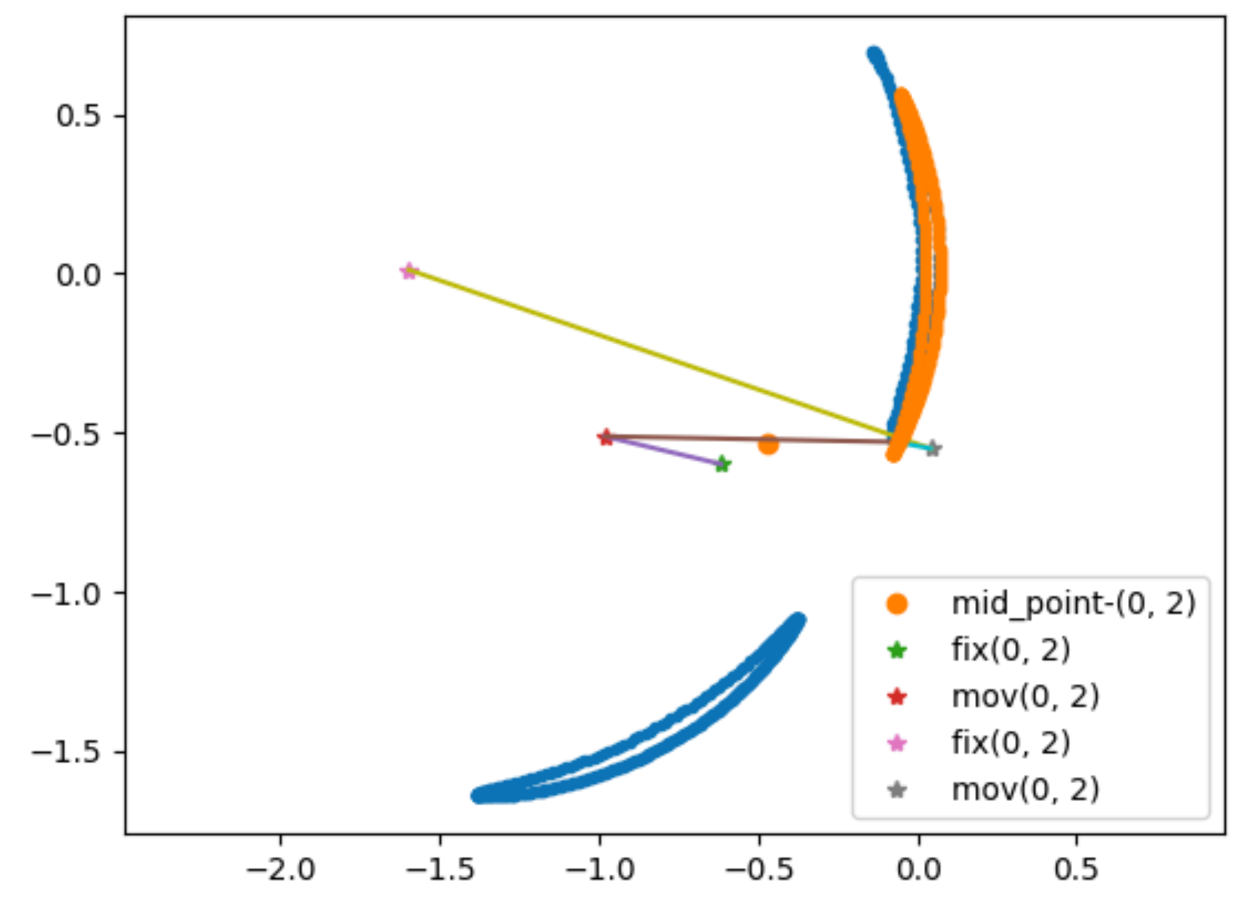
Concept 5



Input Augmentation and Conditioning Results

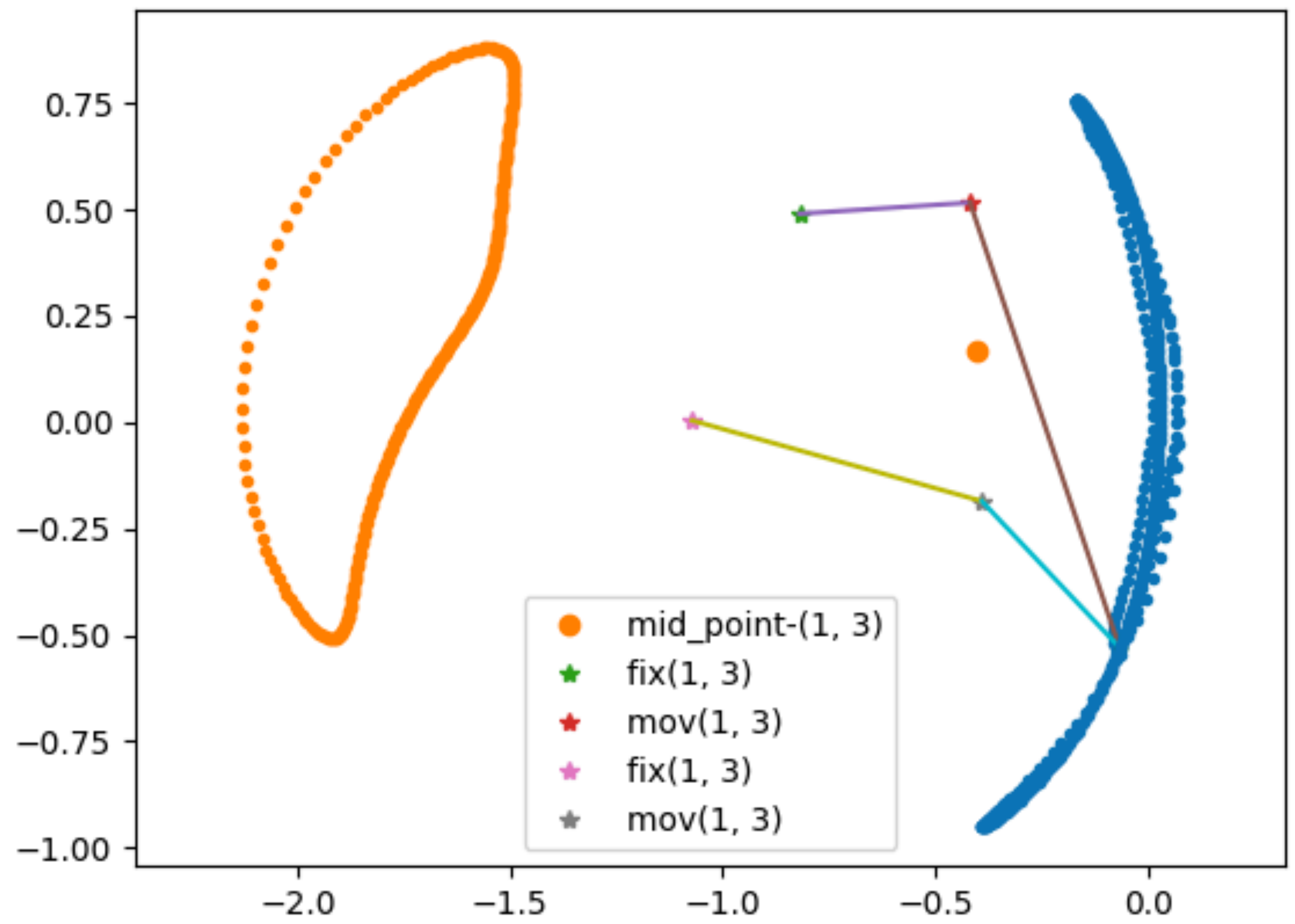
Concept 6





Input Augmentation and Conditioning Results

Concept 7



Conclusion

- Enhances Concept Generation efficacy of previously developed kinematic framework
- Greatly improves user's experience with input augmentation and conditioning
- Path synthesis problem was attempted for the approach validation, but the goal is to fill the gaps in problem setup
- Once a good problem is set, solvers can churn out meaningful solutions.

Conclusion

- Computations Aspects:
  - Solutions are computed in real-time
  - Entire Computation can be parallelize, and accelerated with GPU