

Data-driven learning of the manifolds of a robotic manipulator

Thesis Committee Meeting Presentation

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Human level dexterity is still a challenge



Many possibilities for dexterity and manipulation.



YES BUT

High numbers of control variables
→ difficult to control. (OpenAI et al., 2019)

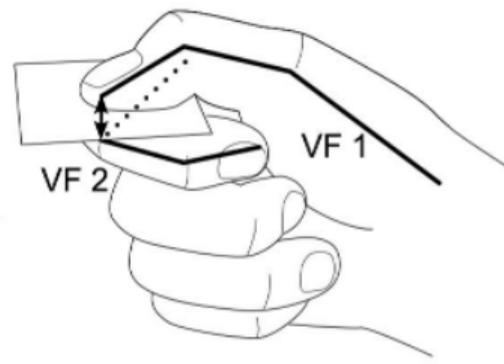
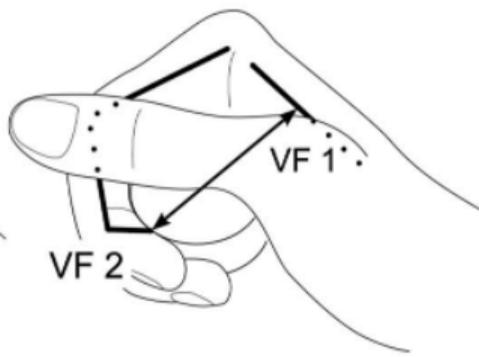
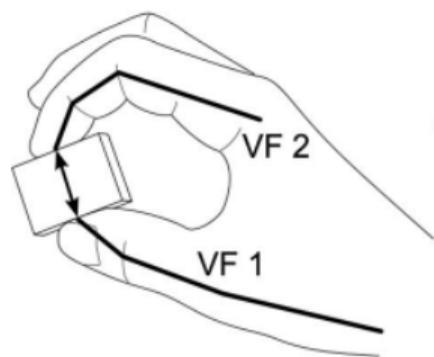
Inspiration from human dexterity

At Human level

- ▶ Broad range of motions
- ▶ Lot of actuators
- ▶ Muscles co-activation (synergies)



Robotic manipulators



(Feix et al., 2016)

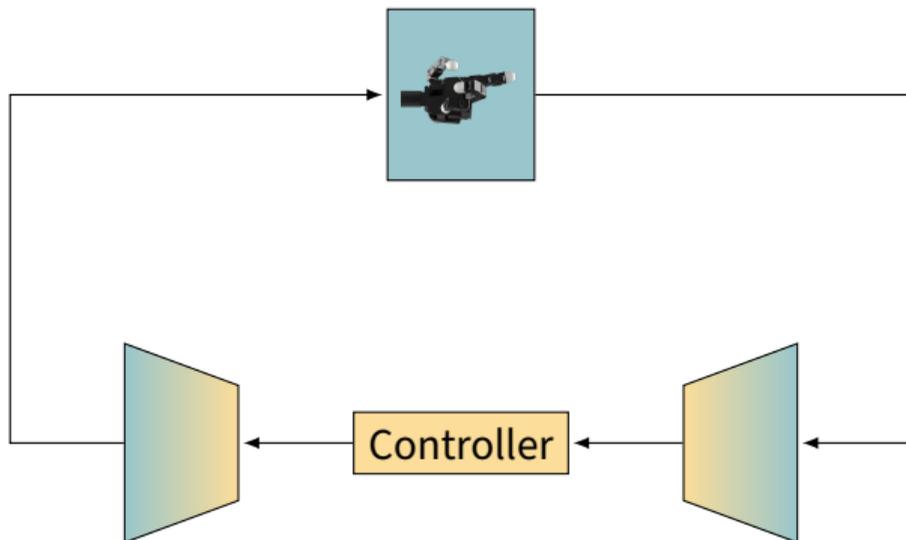
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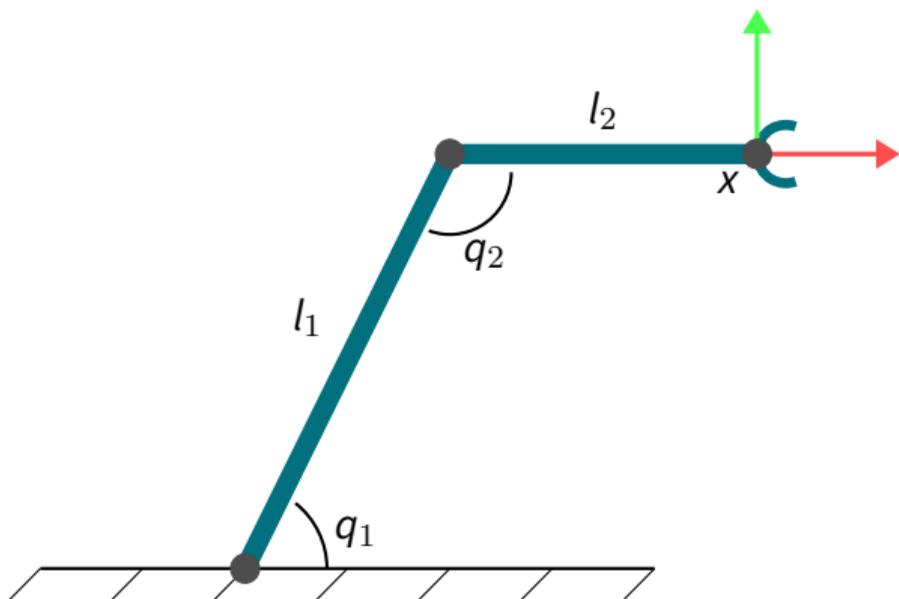
Robotic manipulators



adapted from (Alnajjar et al., 2015)

Can we learn a low dimensional representation for robotic manipulators ?

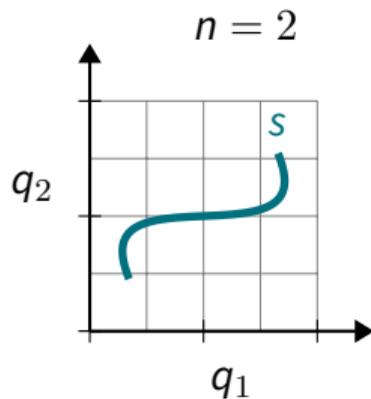
Describing the robotic manipulator



- ▶ q_1, q_2 : Joint angles
- ▶ x : End-effector position
- ▶ $x = f(q)$
- ▶ Jacobian $J(q) = \nabla_q f$

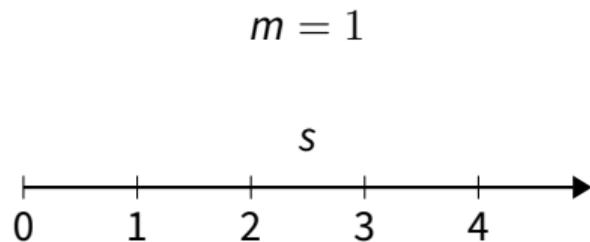
The manipulator's representation can be simplified

Joint coordinates $q \in \mathcal{R}^n$



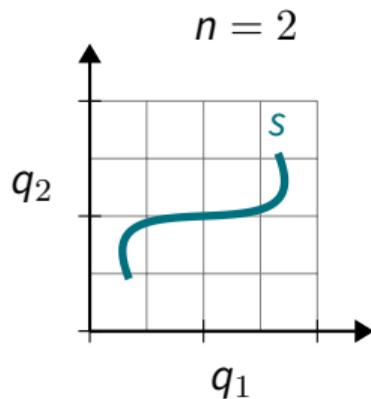
?

Reduced coordinates $s \in \mathcal{R}^m$



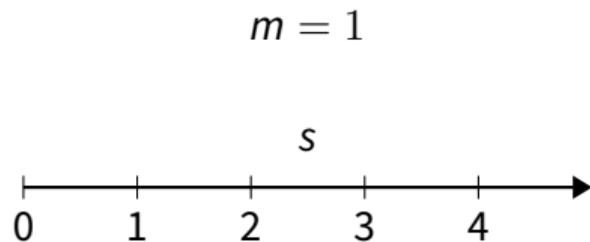
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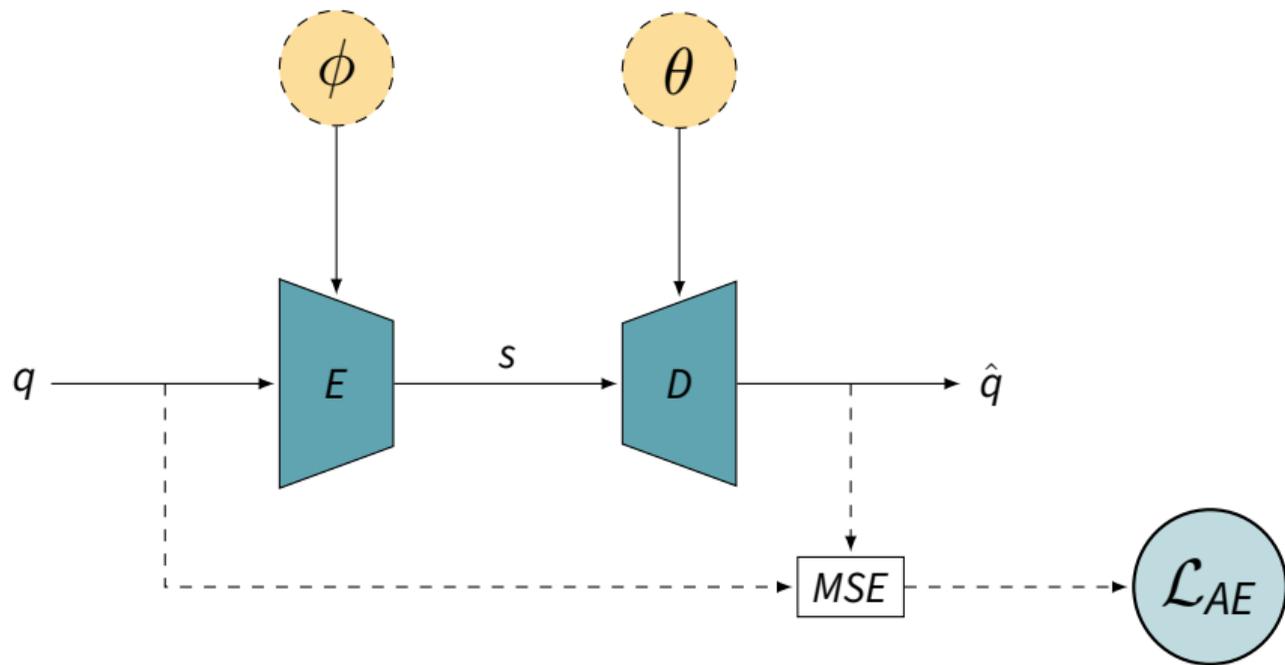
$D(s)$
←
 $n > m$

Reduced coordinates $s \in \mathcal{R}^m$

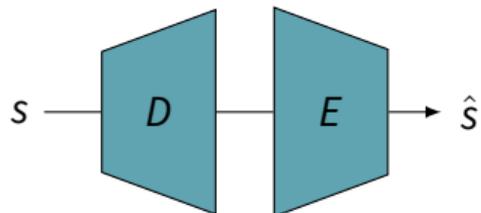


Autoencoders used as a non-linear mapping

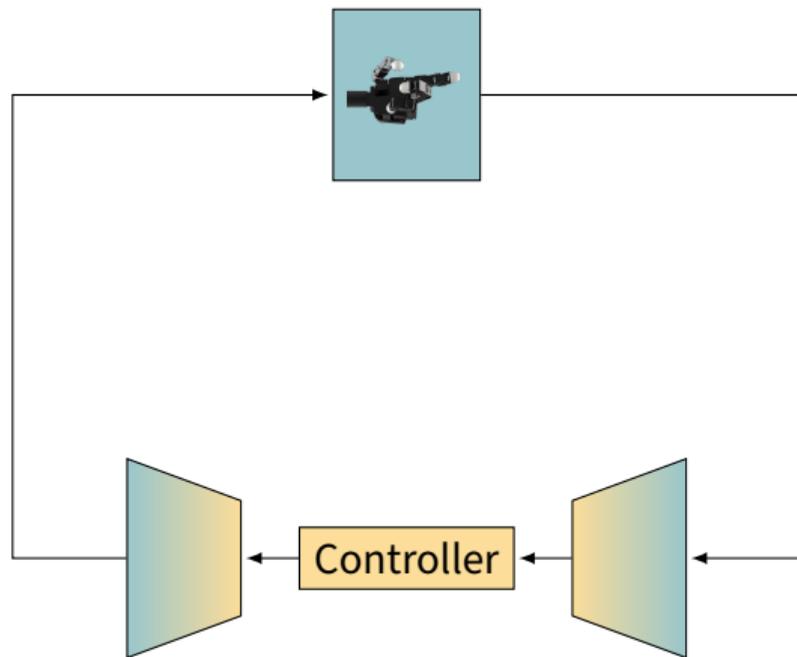
Classic Autoencoder



Classic autoencoder has no guarantees on the projection

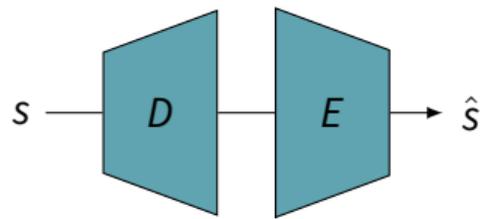


$$s \stackrel{?}{=} \hat{s}$$



Constrained autoencoder ensures projection property

- ▶ Decoder is left inverse of Encoder



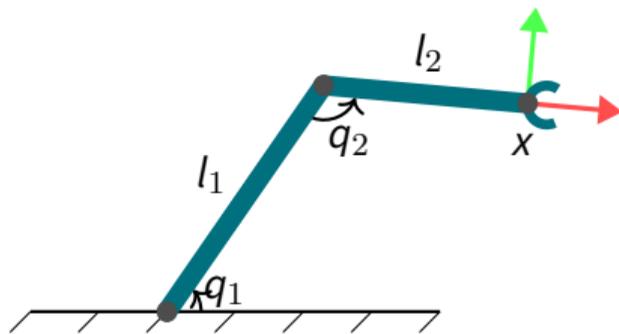
- ▶ Autoencoder's structure is constrained

$$s = \hat{s}$$

(Friedl et al., 2025; Otto et al., 2023)

Classic autoencoder loss ignores manipulator structure

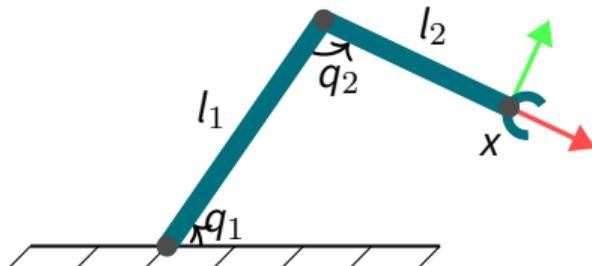
Classic AE treats the error on q_1 and q_2 similarly.



BUT

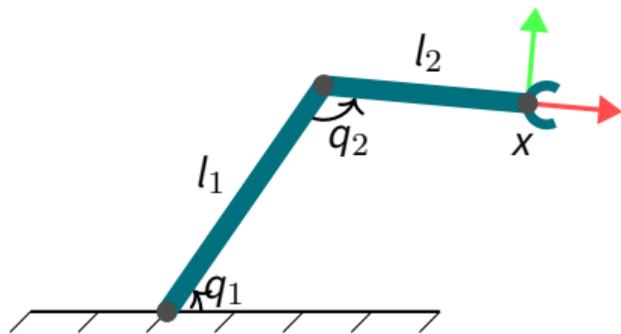
Errors on q_1 and q_2 are not equivalent w.r.t the end-effector position x .

Error on q_2



Classic autoencoder loss ignores manipulator structure

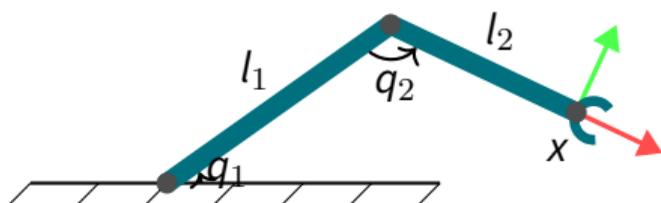
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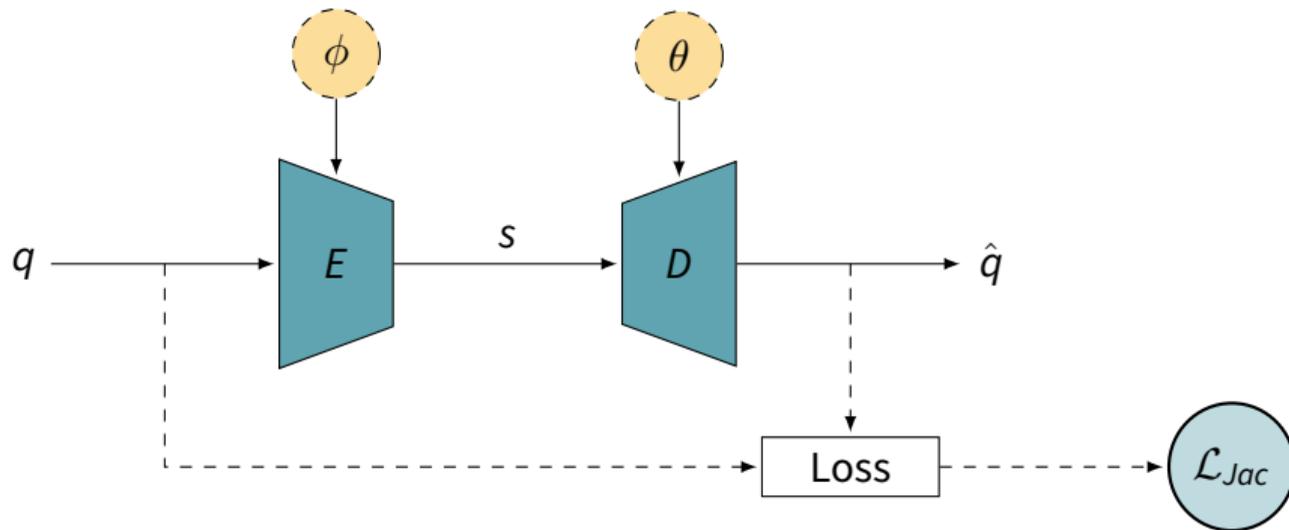
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Error on q_1



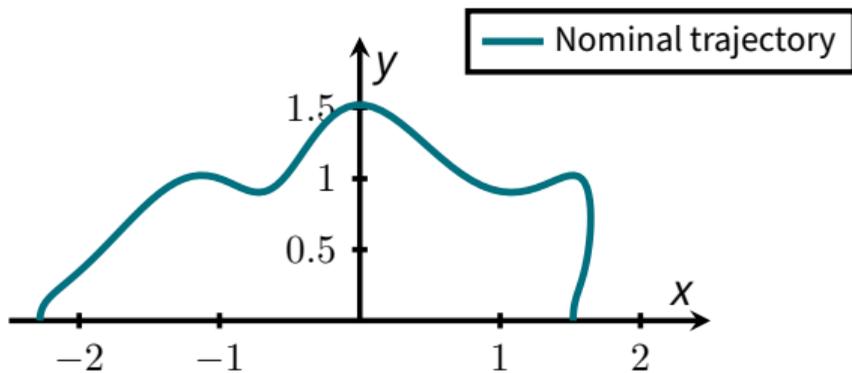
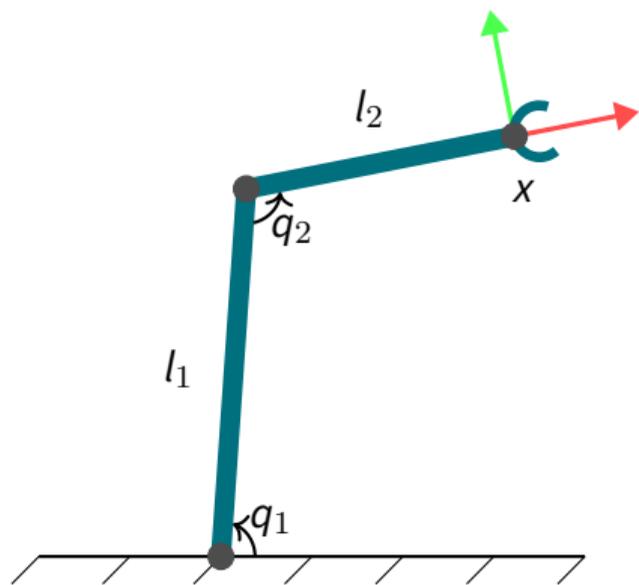
The jacobian can be used as an optimization weight

Our Autoencoder

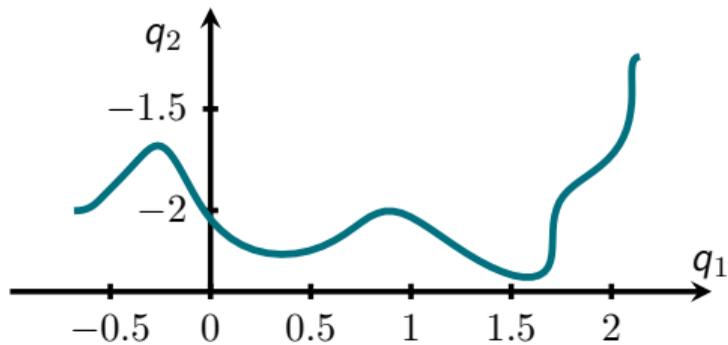


$$\text{Loss}(q, \hat{q}) = (q - \hat{q})^T J^T(q) J(q) (q - \hat{q})$$

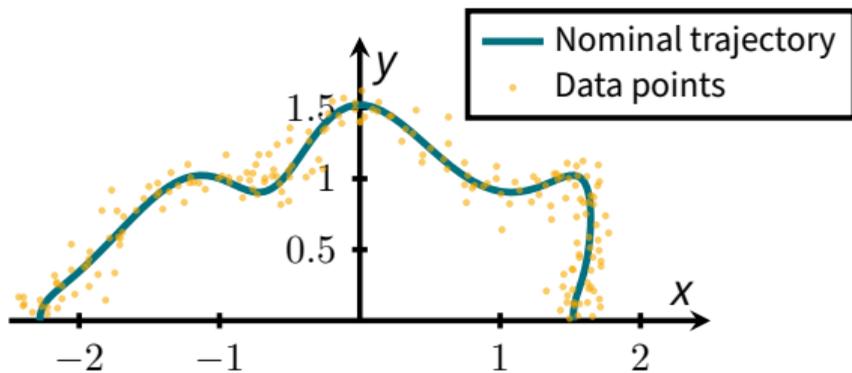
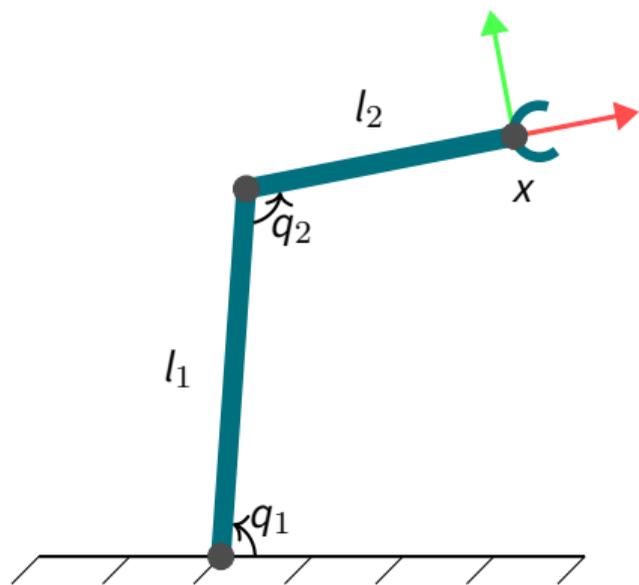
We can apply this to a 2 DoF manipulator



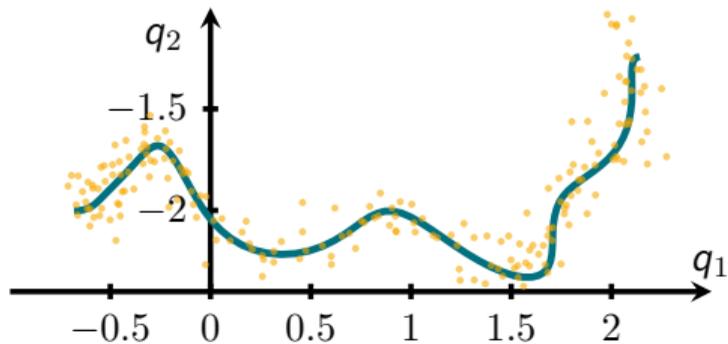
Inverse Kinematics ↓



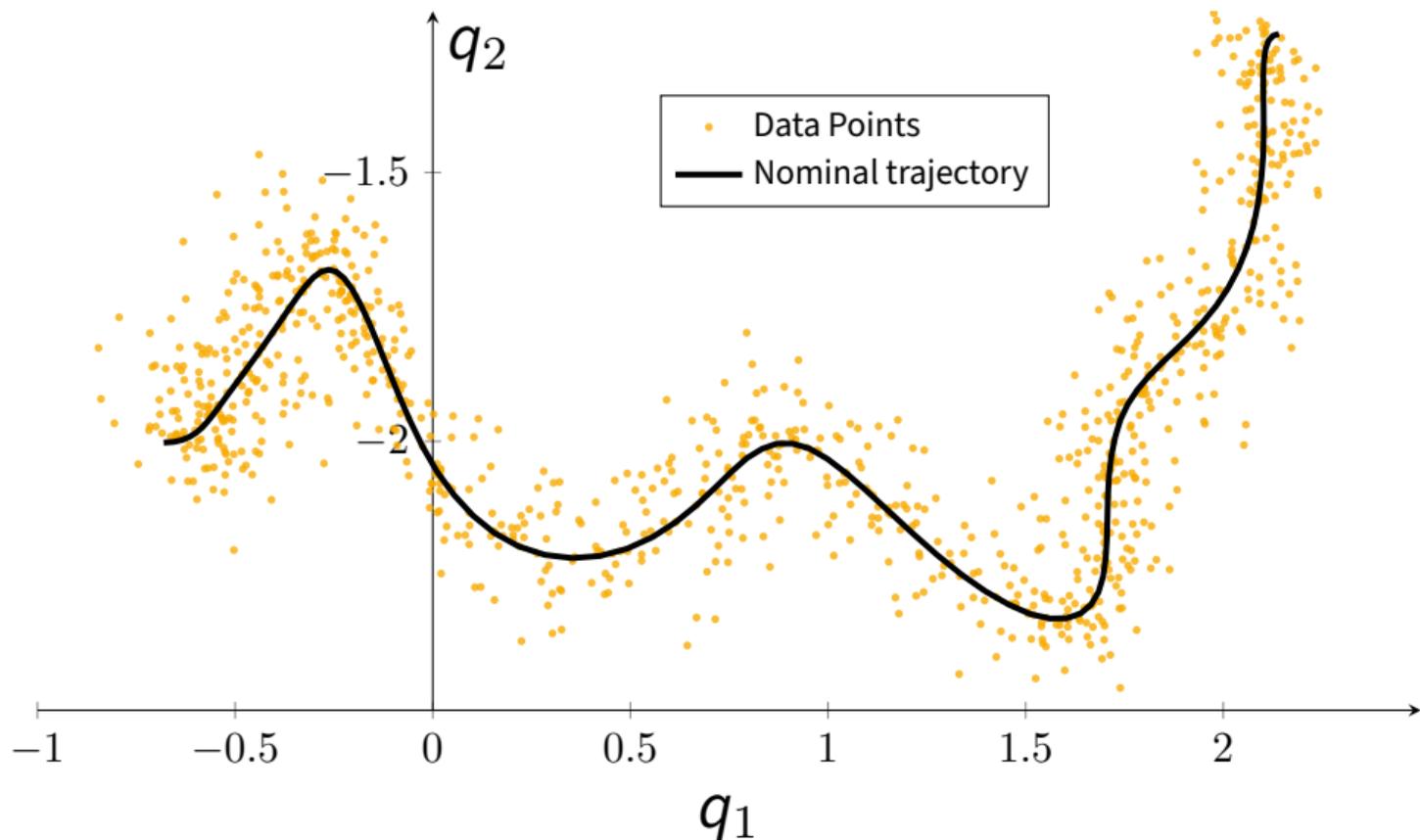
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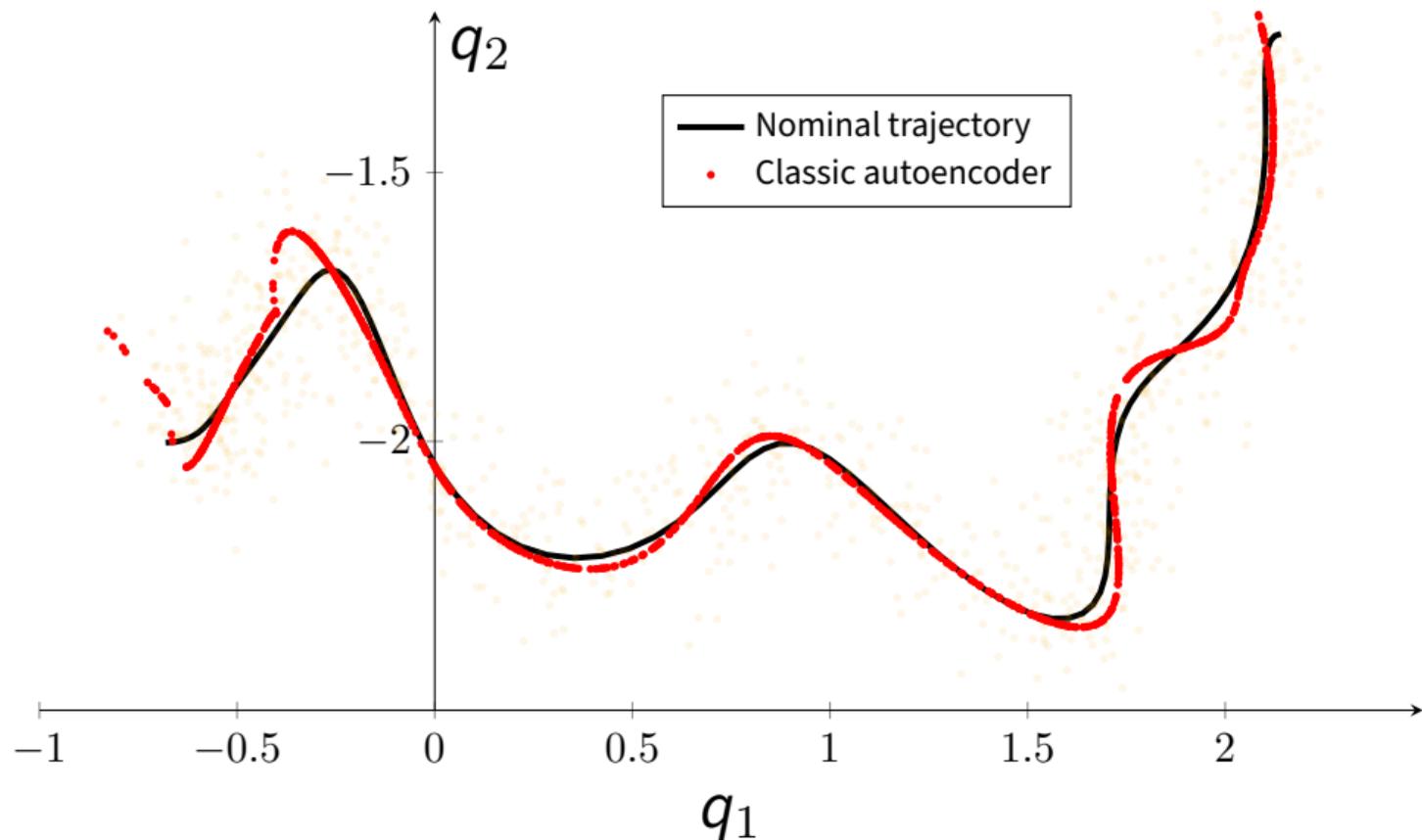
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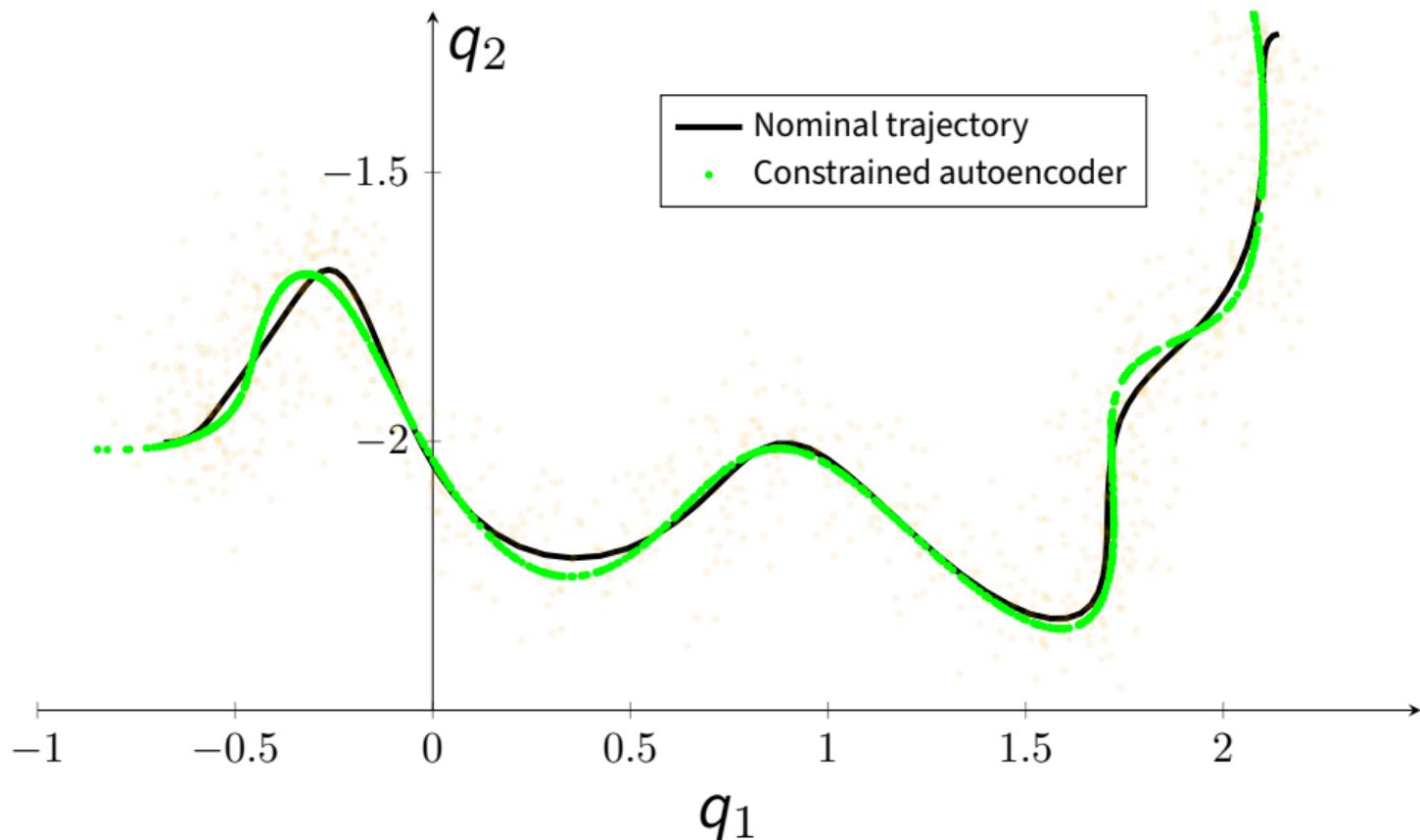
Our learned representation is close to nominal joint trajectory



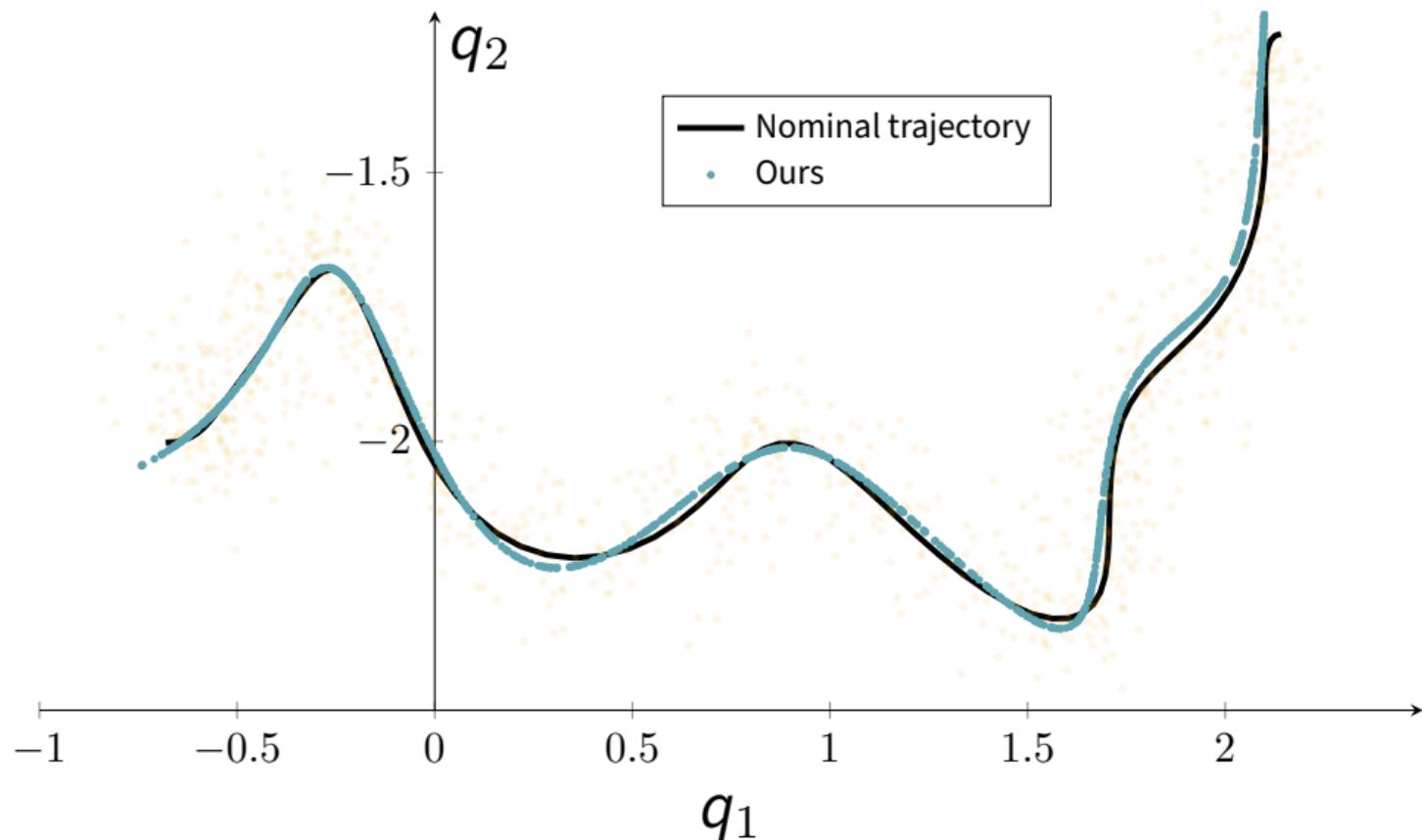
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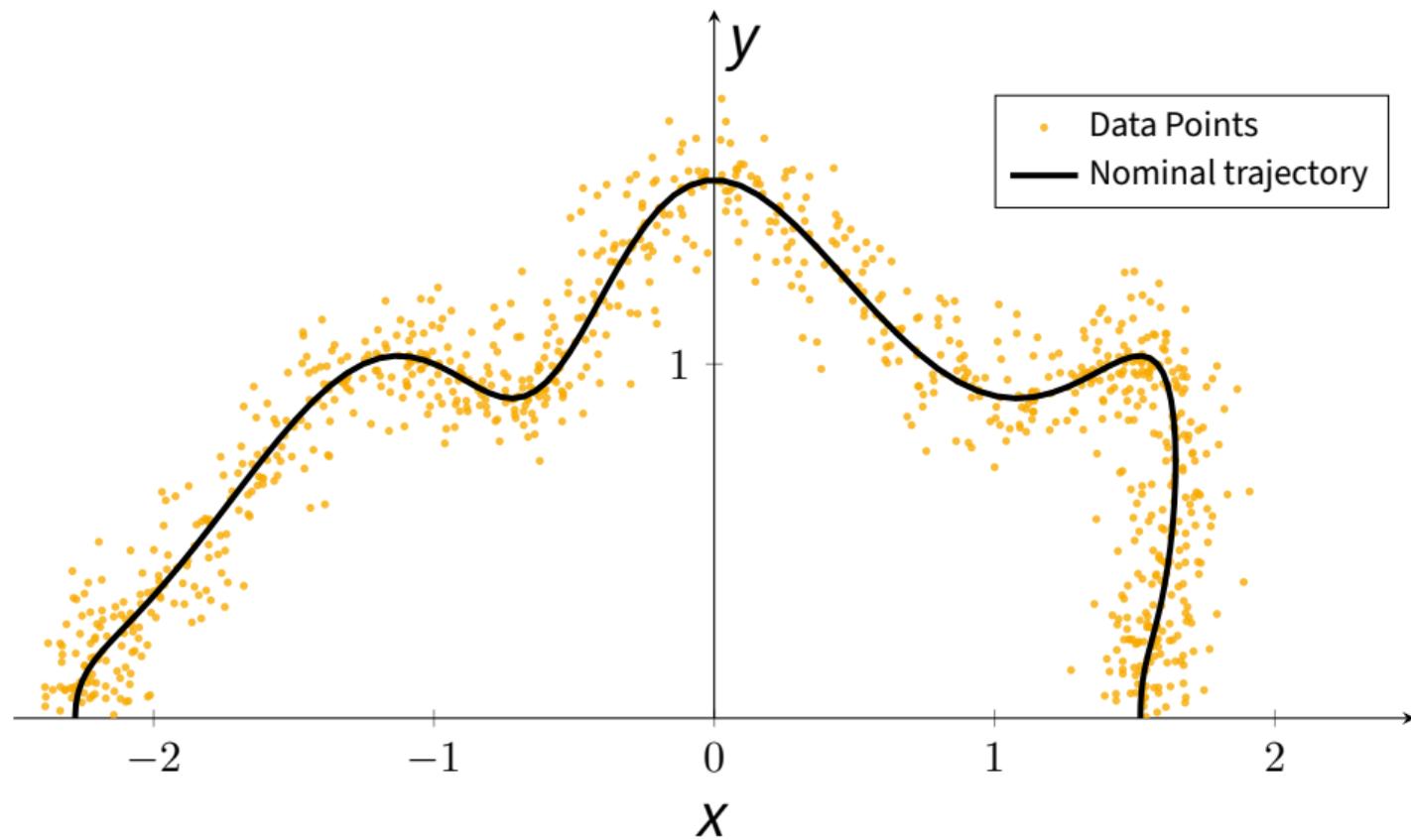
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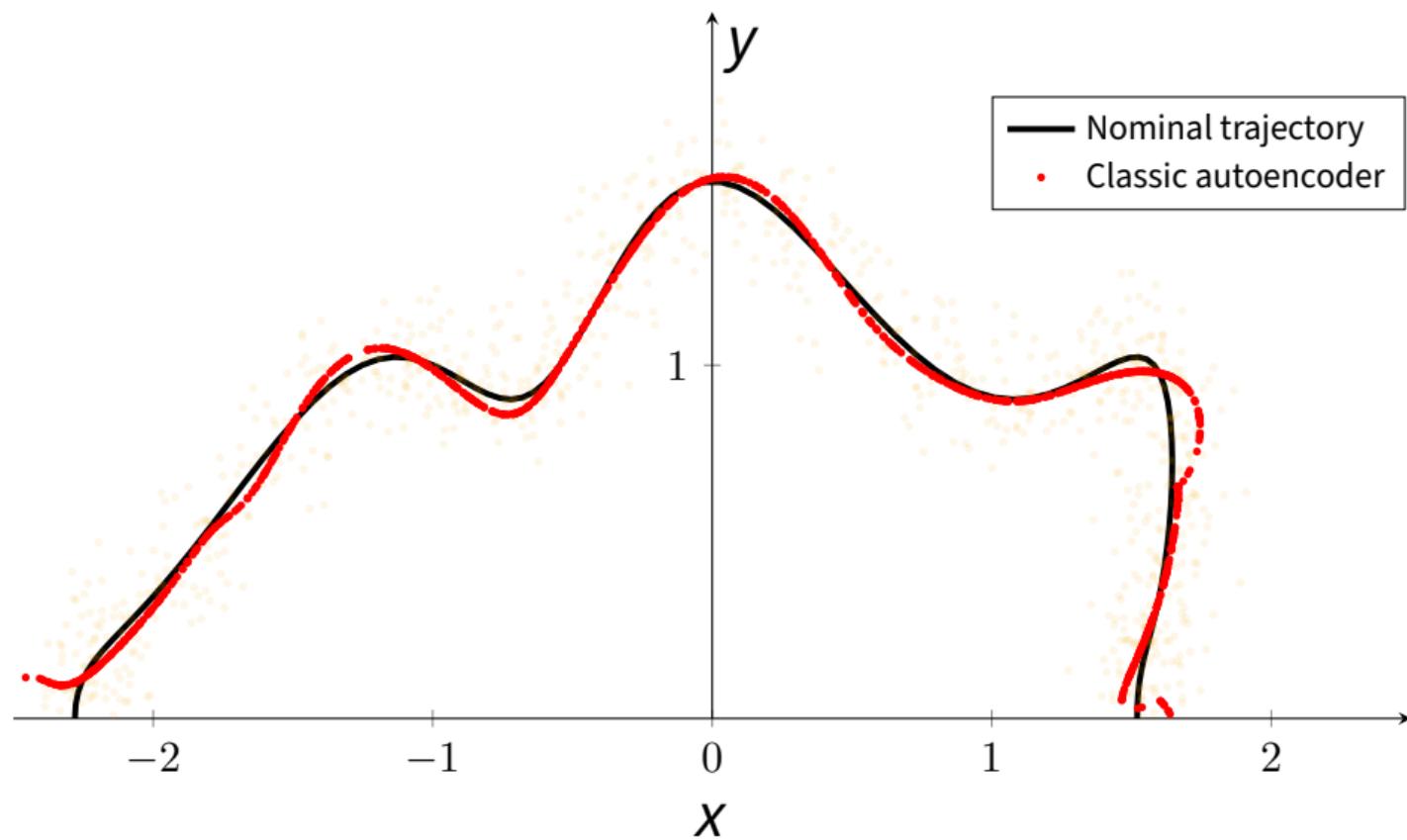
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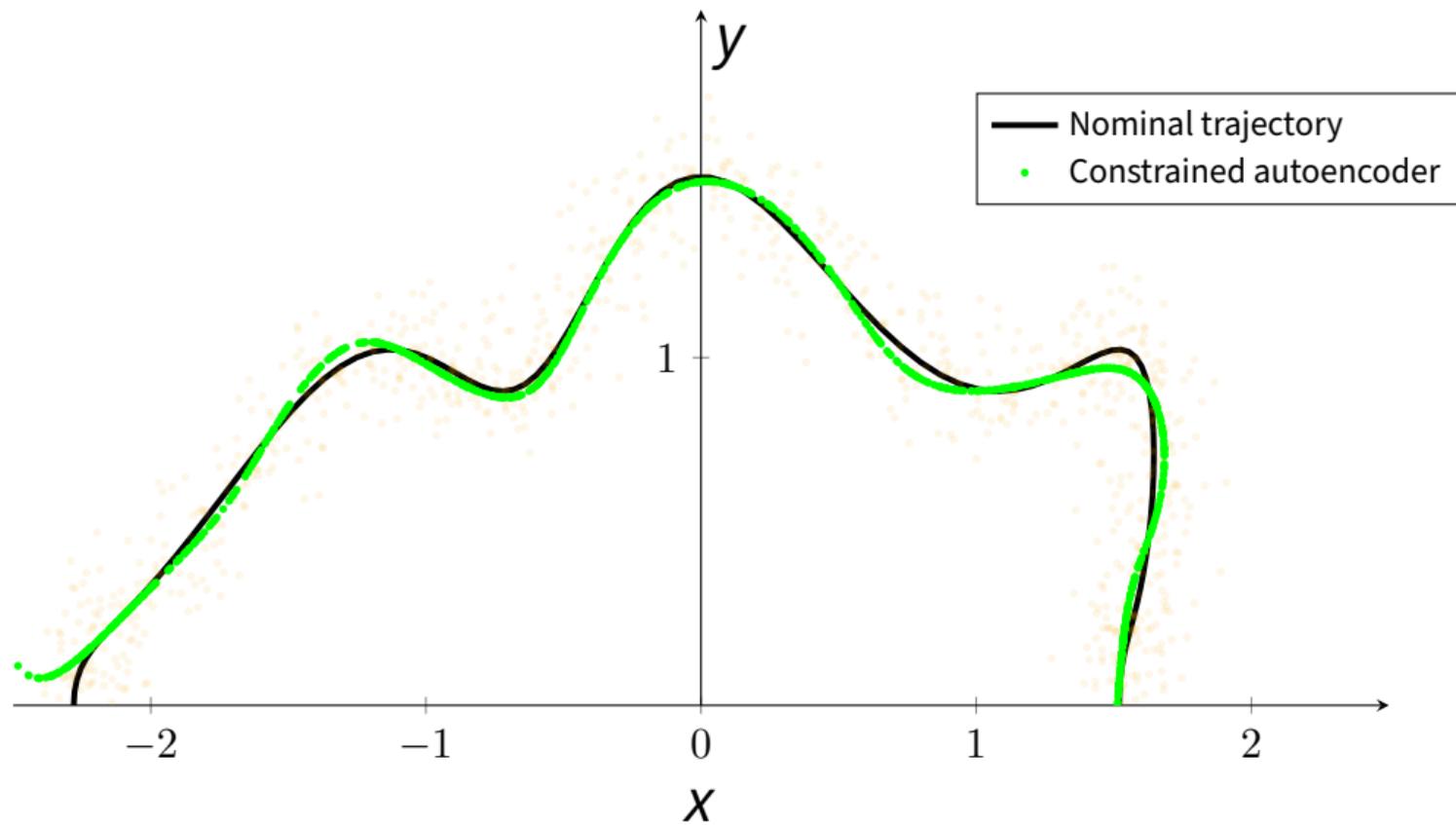
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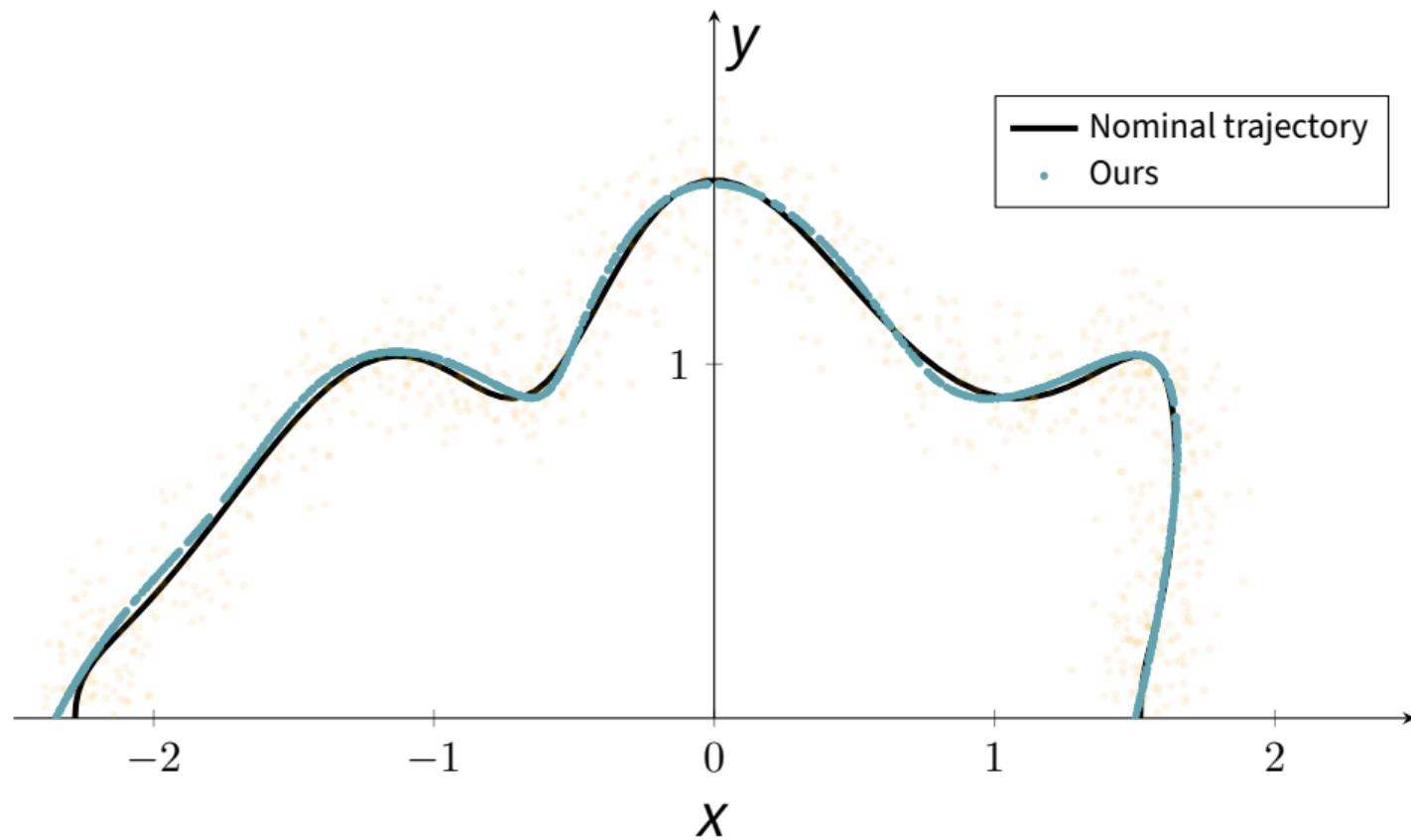
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Further perspectives

- ▶ Increase the number of DoF
- ▶ Analysis of dynamic behaviour
- ▶ Control the manipulator using the reduced coordinates
- ▶ Experiment on a real robot

References I

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-  Feix, T., Romero, J., Schmiedmayer, H.-B., Dollar, A. M., & Kragic, D. (2016). The GRASP Taxonomy of Human Grasp Types. *IEEE Transactions on Human-Machine Systems*, 46(1), 66–77. <https://doi.org/10.1109/THMS.2015.2470657>
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-  OpenAI, Akkaya, I., Andrychowicz, M., Chociej, M., Litwin, M., McGrew, B., Petron, A., Paino, A., Plappert, M., Powell, G., Ribas, R., Schneider, J., Tezak, N., Tworek, J., Welinder, P., Weng, L., Yuan, Q., Zaremba, W., & Zhang, L. (2019). Solving Rubik's Cube with a Robot Hand. <https://doi.org/10.48550/arXiv.1910.07113>

References II



Otto, S. E., Macchio, G. R., & Rowley, C. W. (2023). Learning Nonlinear Projections for Reduced-Order Modeling of Dynamical Systems using Constrained Autoencoders. <https://doi.org/10.48550/arXiv.2307.15288>

Singularities

