ADVANCING IDENTIFICATION METHODOLOGIES THROUGH IN-CONTEXT DYNAMICAL METALEARNING

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Introduction

System identification, which has not benefited from recent surges of interest in **in-context learning**, is an ample playground for **metalearning** where high amounts of extrapolation is required to ensure **flexible** and **descriptive** models.

These models can be developed using various contemporary **neural architectures** where **autoregressive** and **non-autoregressive** properties allow unique modes of inference, corresponding to broader sets of dynamical identification.

Methodology

Our dynamical identification methodology focuses on modeling the relation between **temporal high dimensional input/output trajectories** from a **horizon estimation perspective** where **contextual information** (until *m*) is parsed to make **estimations** over the **horizon** (until *N*) through the black box model (*M*),

$$y_{m:N} = M_\phi(y_{1:m}, u_{1:m}, u_{m:N})$$

The candidate systems for dynamical identification are **feedforward / feedback control systems on Franka robotic manipulators.**

These systems are used to generate synthetic data that in turn is utilized in training and testing **autoregressive** or **non-autoregressive neural architectures.**

In the end, we identify **forward kinematic behavior** of our candidate systems. Joint torques and joint/cartesian variables are, respectively, the input/outputs that facilitate this.

Simulation models use **dynamical parameters** from optimization studies

Real tests benefit from such **dynamically feasible selection of parameters**

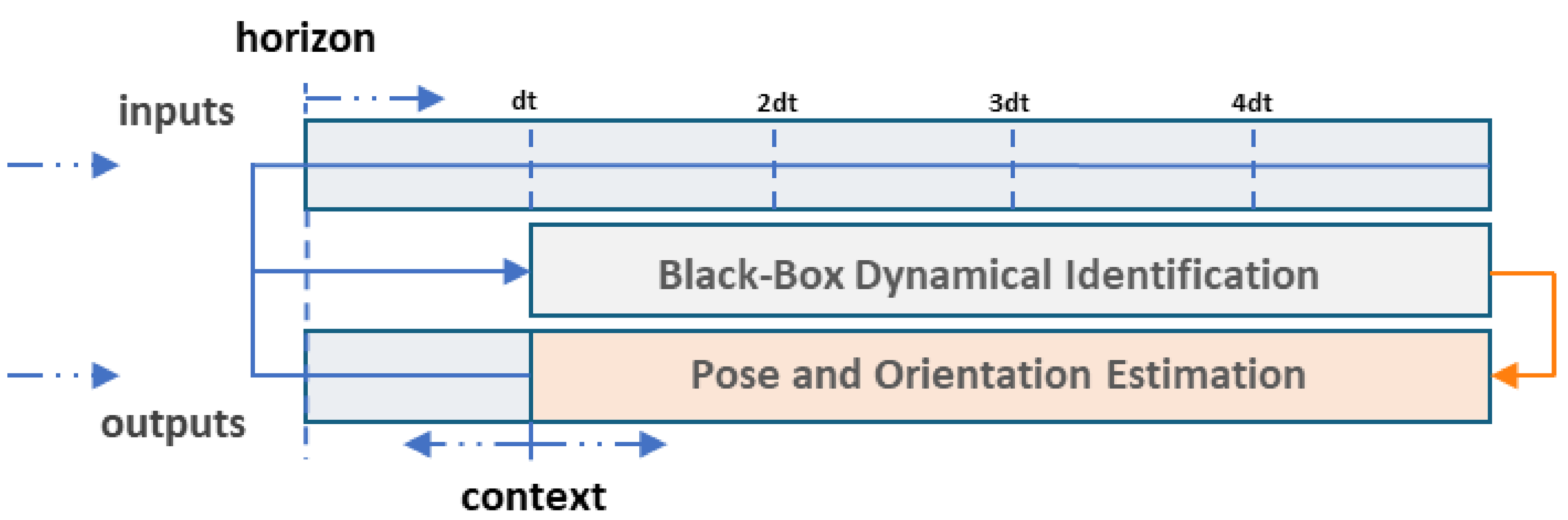
Domain exploration is key to the success of this methodology. We train our identification module on multitudes of frequencies and dynamic properties.

Framework

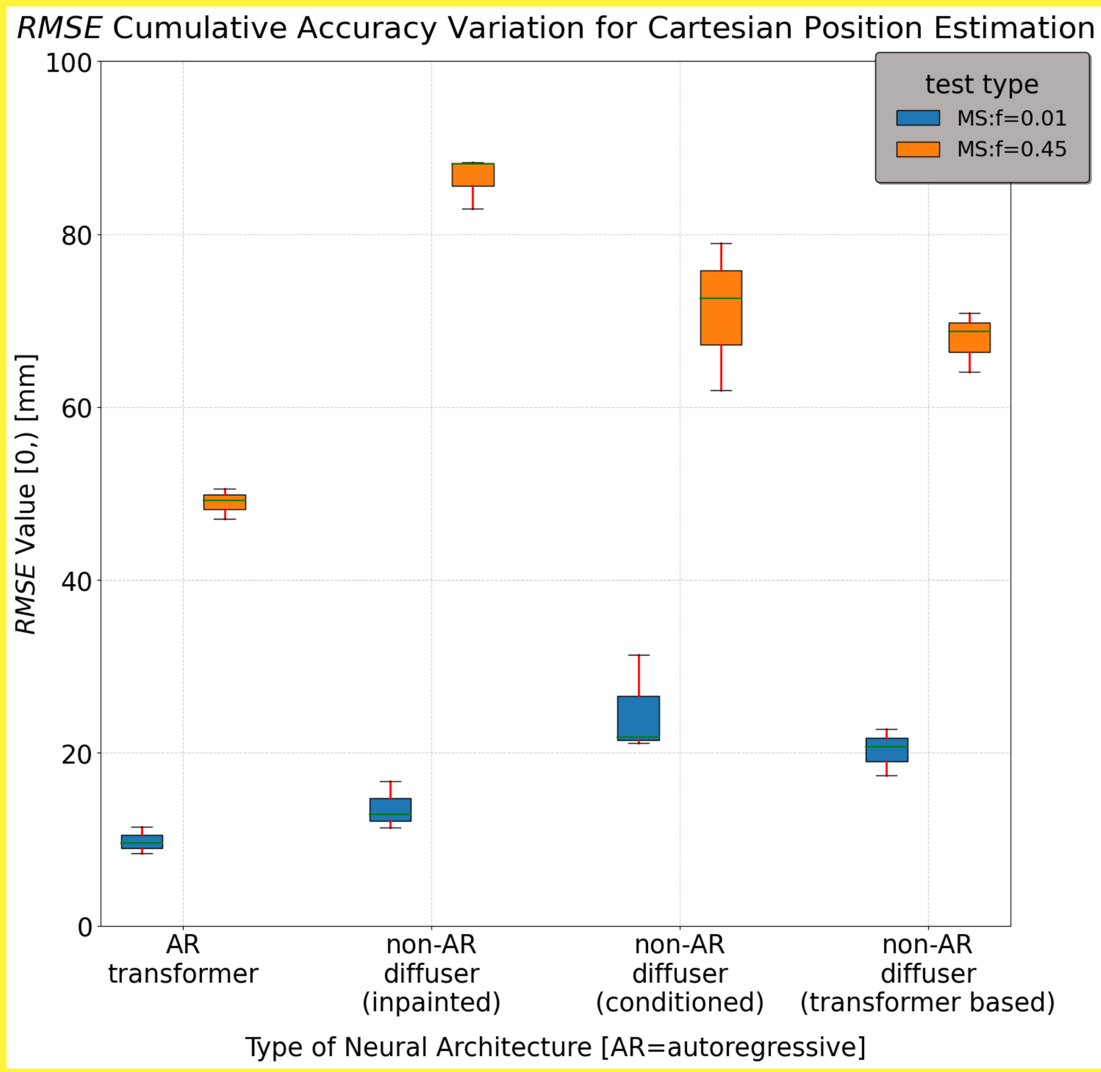
Horizon estimations from our **dynamic models** are tested through **simulation** and **real** data, constituting to an MPC-like **online controller scenario**.

We train our models on a combination of **multisinusoidal(MS)** and **chirp (CH)** tasks in joint space and **circular (FC)** tasks in cartesian space and benchmark in **out-of-distribution scenarios**.

To extentuate the capabilities of our models, we propose seperate benchmarks for simulation and real trajectories.



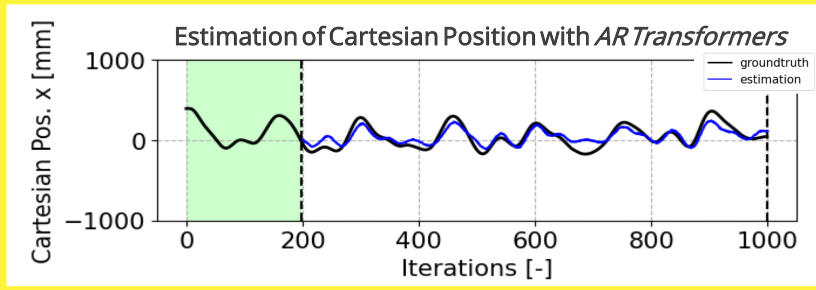
Results

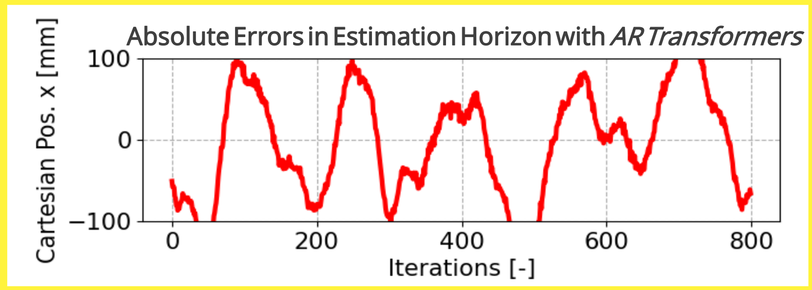


Autoregressive architectures are better in **sequential processing** whereas **non-autoregressive** architectures are flexible in **inference time.**

Mean errors are not that substantial, hinting possibilities of **sim2real implementations.**

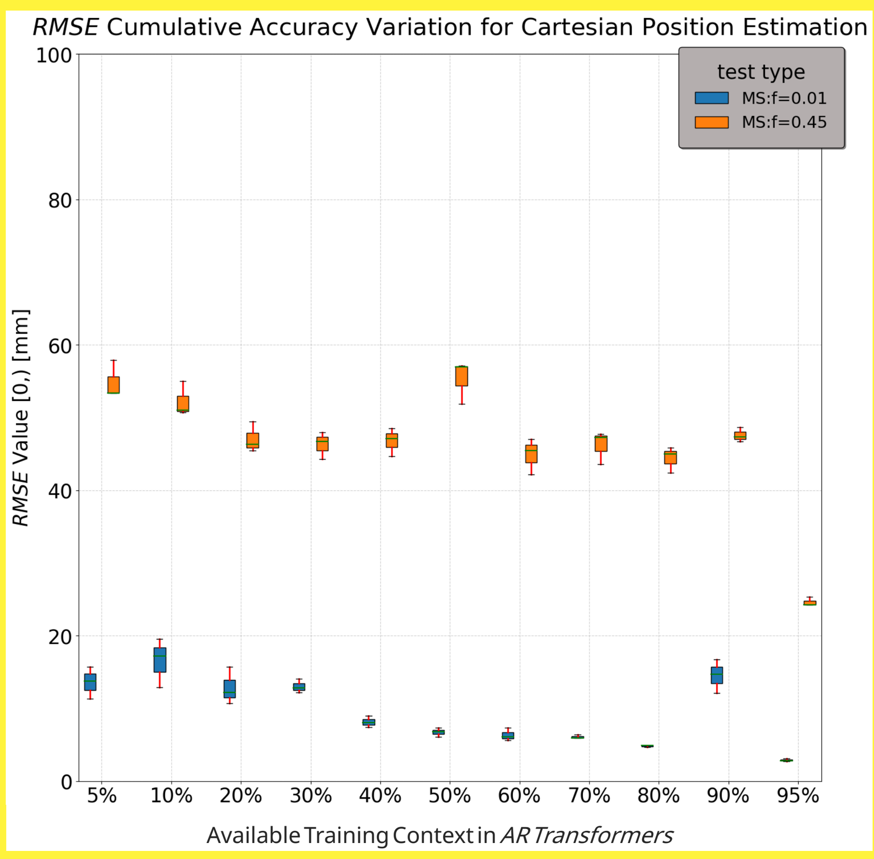
Not all parts of the domain are explored with equivalent accuracy, necessitating **finetuning** or **transfer learning.**



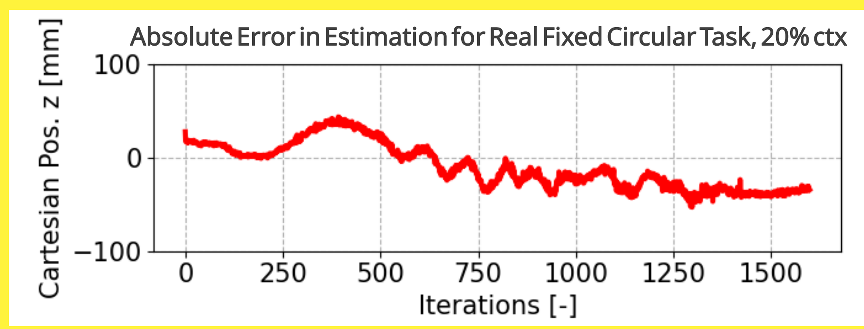


Contextual changes are useful in online control scenarios where horizon predictions may be updated with **more(or less) information.**

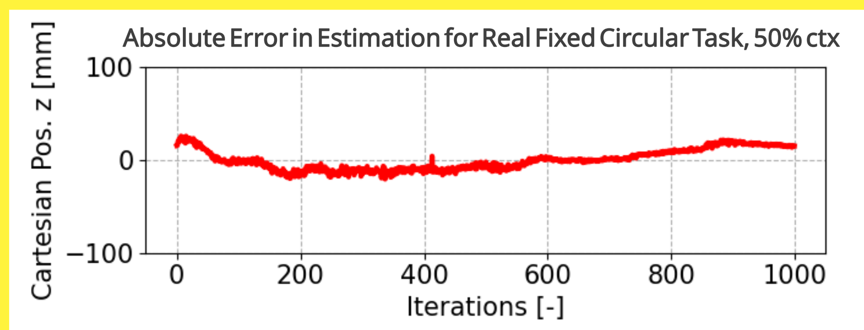
As expected, with more available information (higher contexts), **mean errors are reduced**. For real systems, this proposes a comprimise between **computational power** and **estimation accuracy** with increasing contexts.



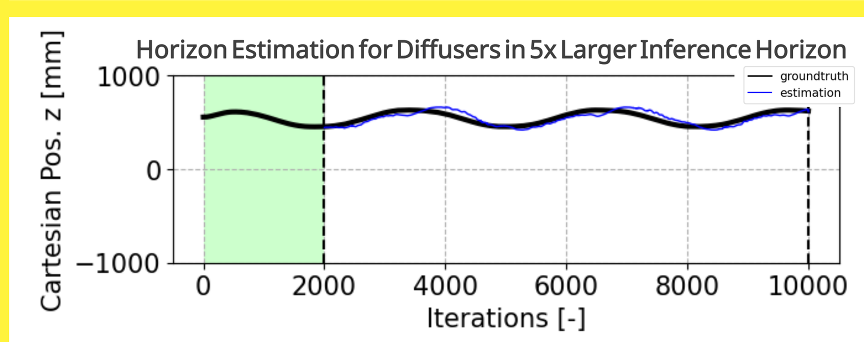
Real tests show a similar trend. Simulation models subjected to real tests manage to **extrapolate well** with less than 10% errors in comparison scales



Increasing **context size** to **1000 steps (50%)** from 400 **400 steps (20%)** allows better approximations in real trajectories.



Diffusers can be selectively modified in **inference time** for **larger horizons** and **contexts**. The right model is capable of guessing **10000 points** only by being trained on **2000.**



Conclusion

Through this work, we pinpoint the effect of different neural architectures in dynamical identification and horizon estimation tasks. Apart from simulation accuracy of our models, we obtain promising results on real data which necessitate future research on this nascent topic.

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