Neural properties underlying the efficiency-robustness trade-off in motor control: insights from RNNs

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THE BRAIN IN ACTION

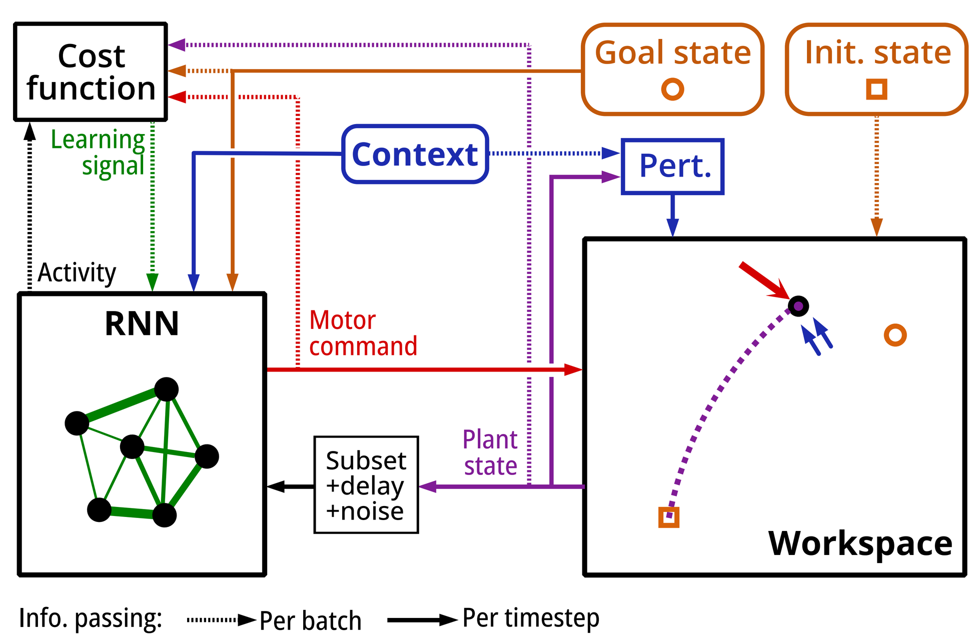
Background

- **Robust control**: *model-free* methods to modify optimal controllers to mitigate unmodeled perturbations [4]
  → higher sensory gains, larger maximal forces
- More robust policies are **more costly** to execute.
  → **tradeoff**: *How uncertain is my model, right now?*
- Apparent in human reaching [2] and familiar situations (e.g. driving a car in high winds), but neural basis unclear.

Conclusions

- Single RNNs learn to scale the robustness of their policies based on an input signal of model uncertainty.
- More-robust policies show higher sensory gains, matching theoretical predictions.
- The input signal of model uncertainty (i.e. context) drives systematic changes in network dynamics and stability.

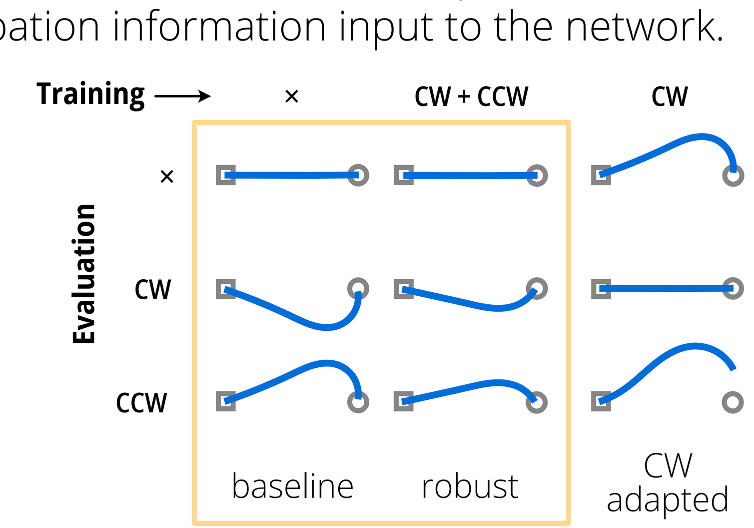
Training a recurrent neural network as an optimal feedback controller for reaching



Training experiments

Perturbations (**curl force fields**) are fixed for each trial, after sampling amplitude/direction from a zero-mean Gaussian distribution with given standard deviation (std).

1. **Fixed context**: Train *one model per std.*, with no perturbation information input to the network.

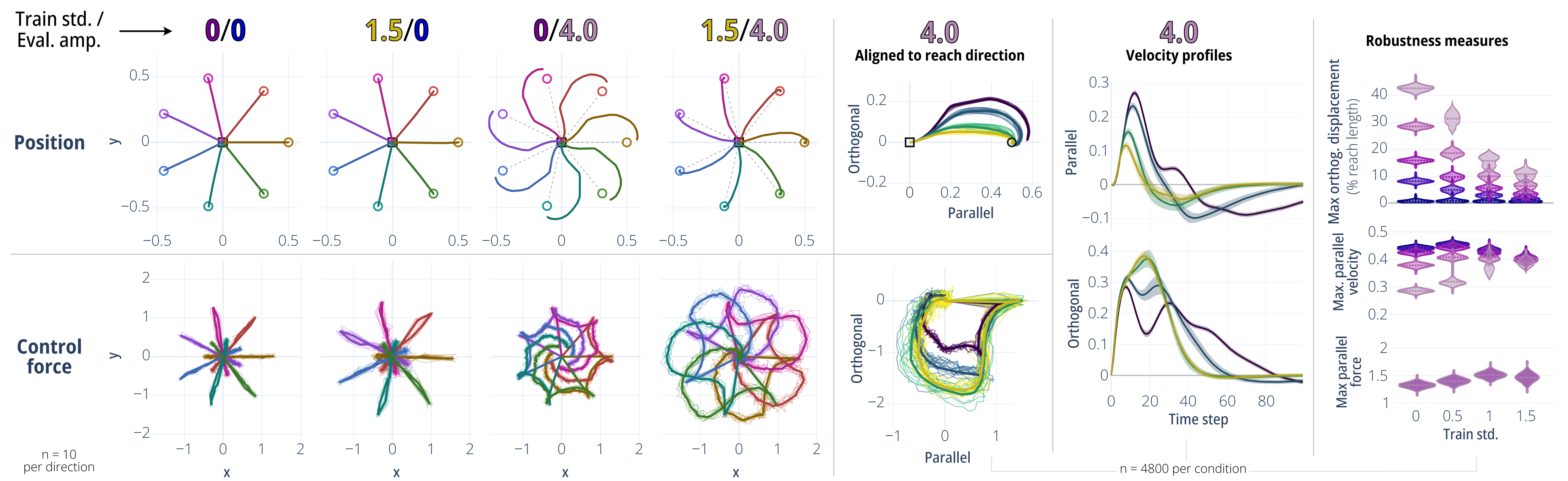


2. **Variable context**: Train one model per std., but the perturbation is scaled on each trial by an additional uniformly-sampled (in $[0, 1]$) **context signal** provided as input to the network.

Methods details

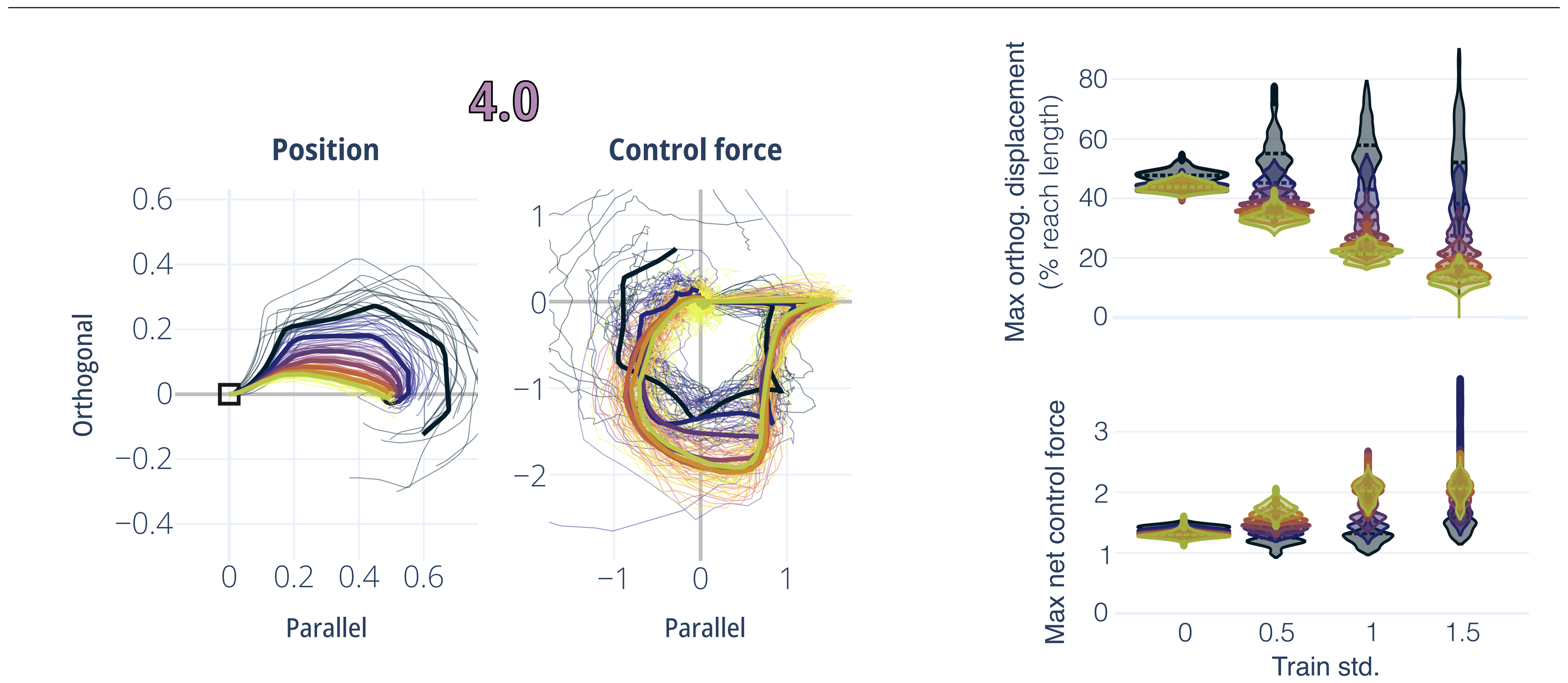
- **Cost function**: Quadratic in position errors, final velocities, control forces, and network activities.
- **Network**: 100 gated recurrent units [1]; linear readout.
- **Biomechanics**: Point mass with drag force.
- **Sensory feedback**: Position and velocity. Zero delay.
- **System noise**: Gaussian. Sensory → additive. Motor → additive + multiplicative.
- **Training**: Adam optimizer; 10,000 batches × 250 trials.
- **Software**: Python; JAX + Equinox + Feedbax.

1. Fixed context: Models trained with stronger unpredictable perturbations are more robust.



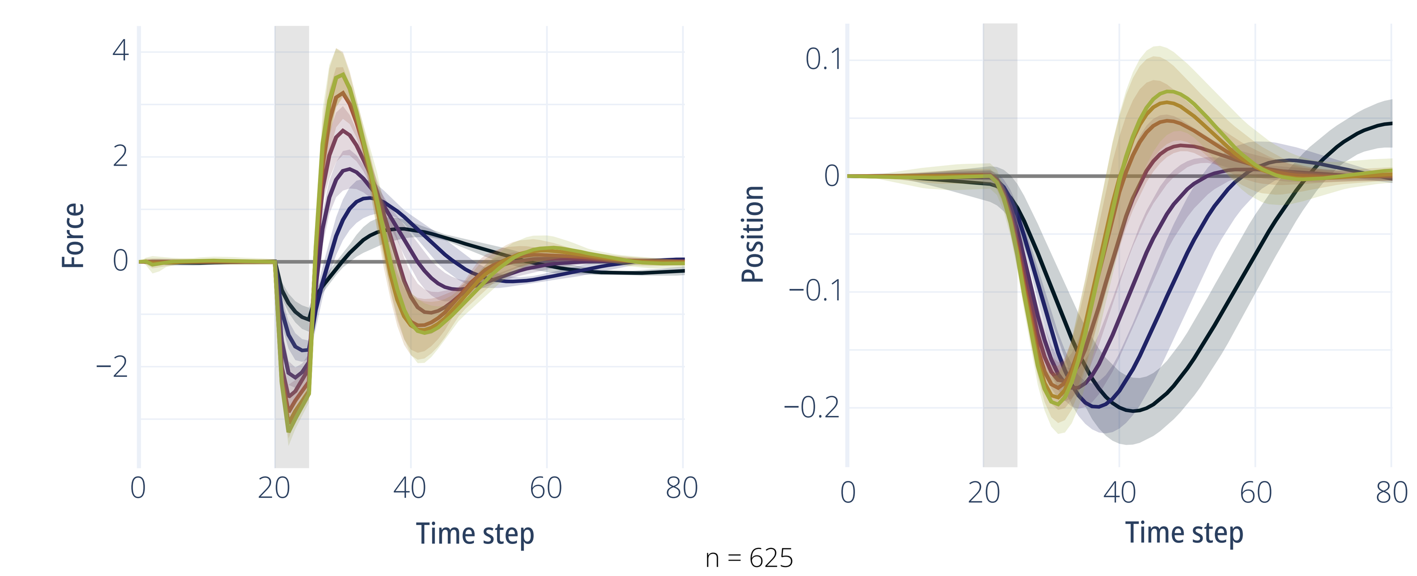
2. Variable context: With increasing context signal during evaluation, a single model's...

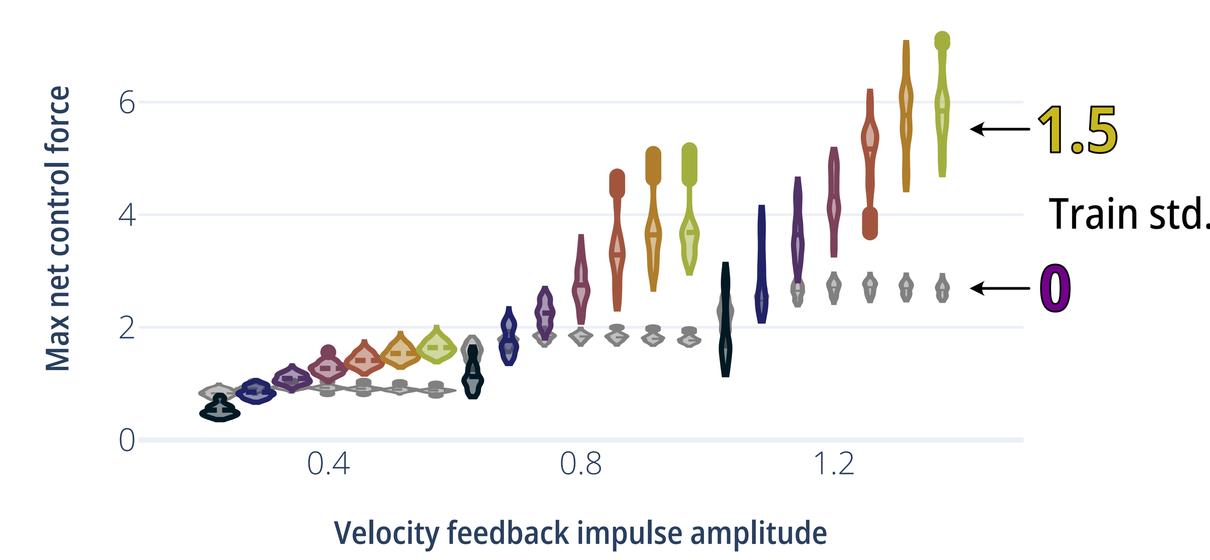
... reaches become more robust to perturbations.



... sensory gains increase.

At steady state (i.e. already at goal) apply a step-change to the velocity feedback, in a random direction, for 5 time steps. Align the responses to impulse direction.





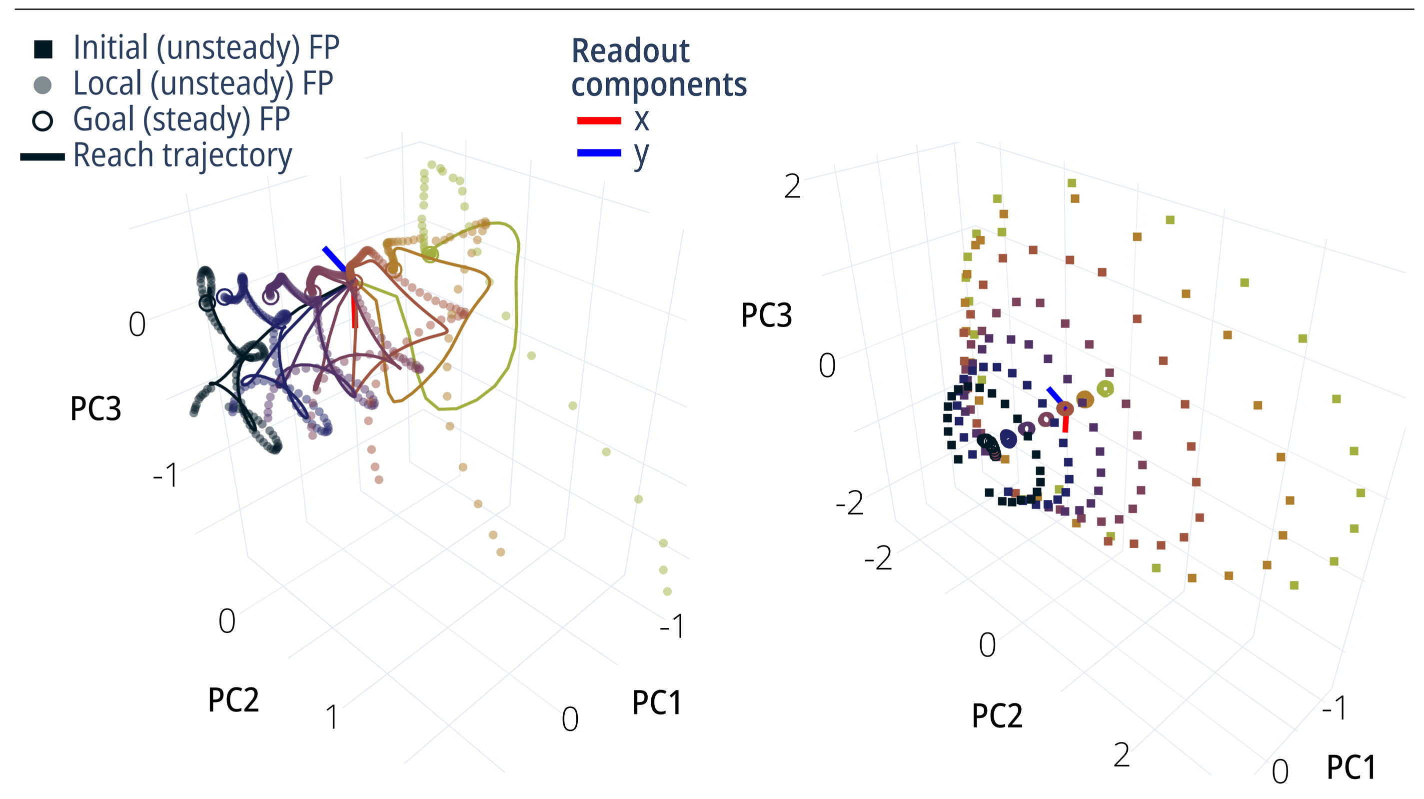
Legend

Reach endpoints	Train std.
□ Start	0.0
○ Goal	0.5
	1.0
	1.5

Context	Eval. amp.
-3.0	0.0
-2.0	0.5
-1.0	1.0
0.0	2.0
1.0	4.0
2.0	
3.0	

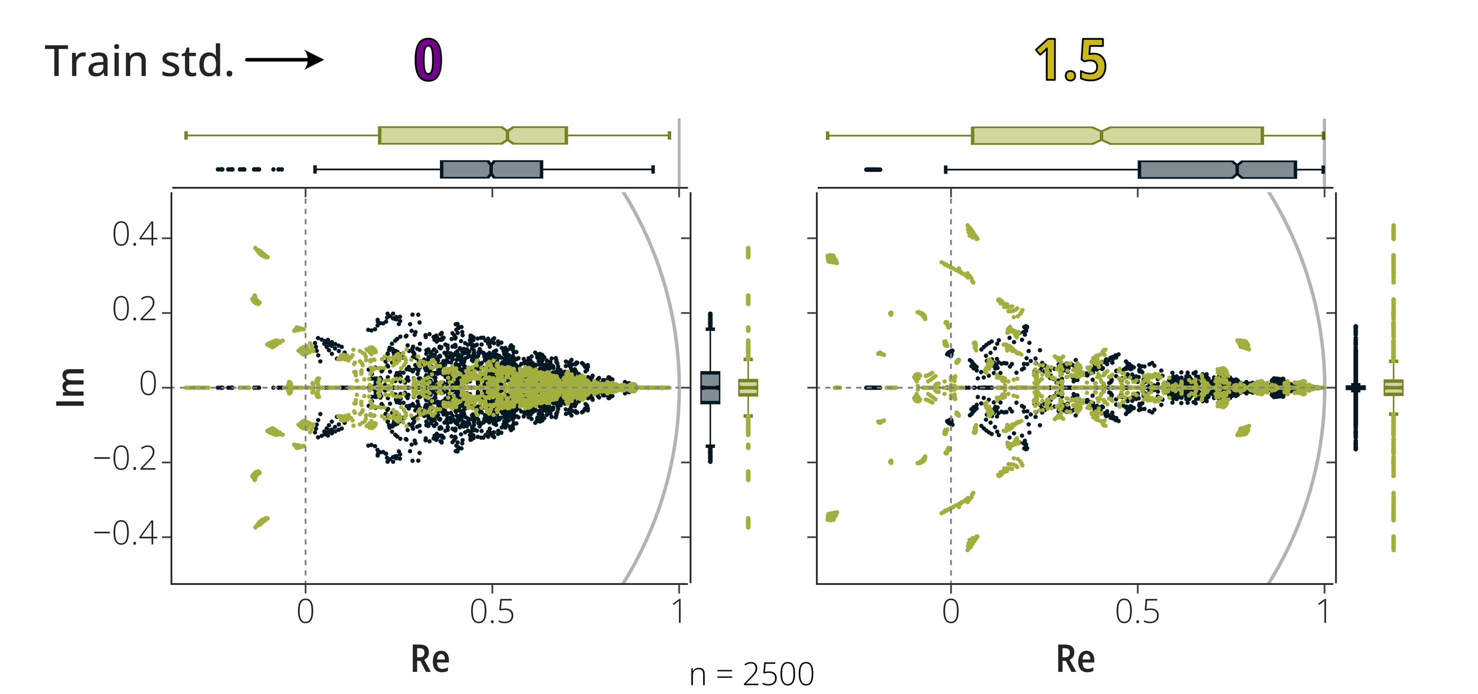
Colors in center-out example sets are solely for comparing position and force.

... network activity arranges along a principal component.



... steady-state fixed points become more stable.

Eigenvalues of the linearized network, comparing lowest and highest context values across train stds.



References

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