G&CNETs

If you learn from examples, choose the best ones.

ESA Advanced Concepts Team

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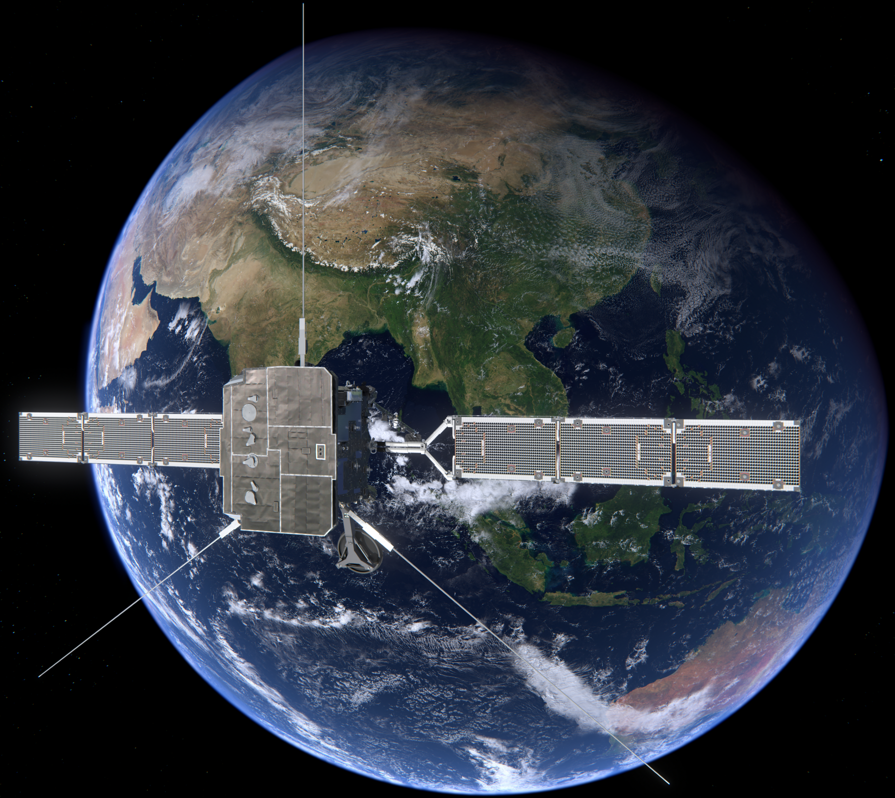
Earth vs. Space

1 - Less disturbances and stochasticity.

2 – Guarantees demanded on critical components.

3 - Need for great precisions.

4 – Scarce resources (mass, volume and power)

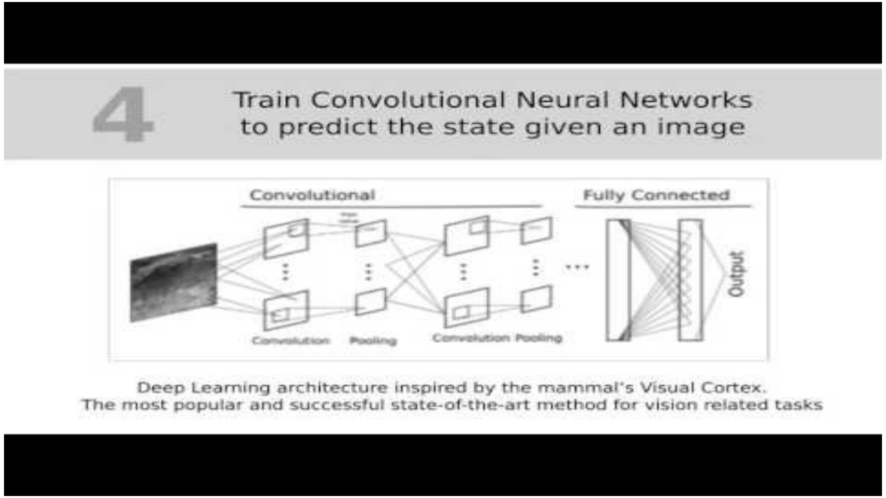


RL … sure, but … Pontryagin maximum principle CAN be used here (e.g. the absolute optimal decision can be known from any agent state)!

Guidance and Control Networks (G&CNETs)

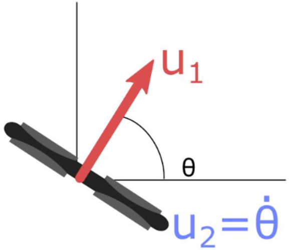
G&CNETs are Deep Neural networks (DNN) for on-board autonomous real-time optimal guidance, control (and navigation)

- A) Generate **optimal** trajectories for different initial conditions.
- B) **Imitation Learning** a.k.a **behavioural cloning**: train DNN to imitate optimal control profiles (policy and value function learning).
- C) Convolutional Neural Network for pose estimation.

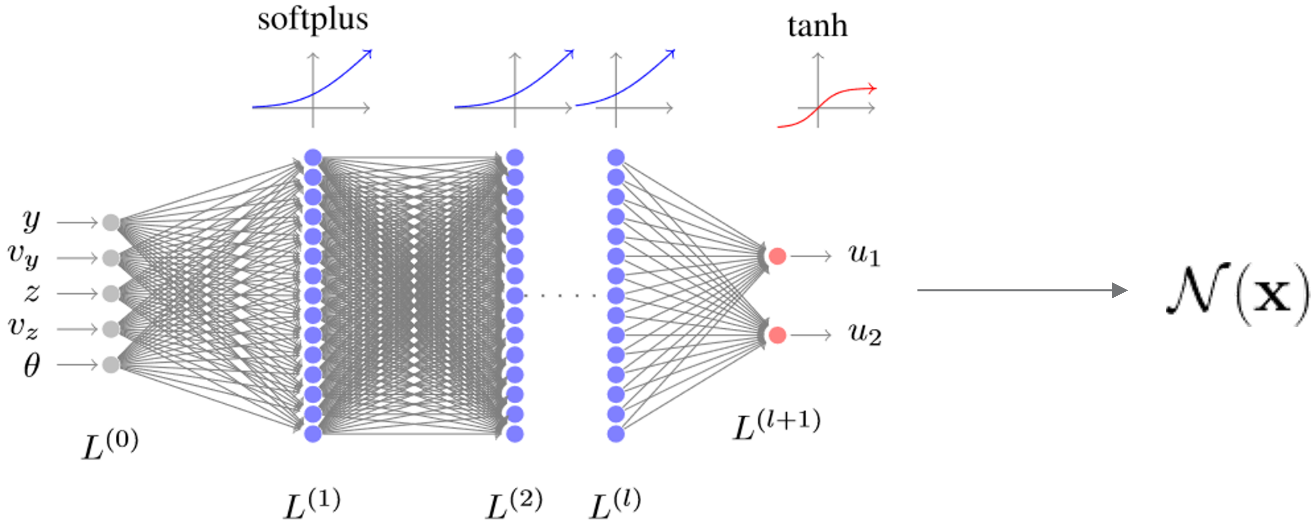


Systems studied: quadrotors, spacecraft, rockets.

Stability results obtained.



G&CNETs architecture (perception).



- A purely reactive network (unlike in behavioral cloning).
- Can it be trusted?

Stability of the neurocontrolled system

$$\mathbf{x}(t, \mathbf{x}_0) := \begin{cases} \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathcal{N}(\mathbf{x})) \\ \mathbf{x}(t_0) = \mathbf{x}_0 \end{cases}$$

$$x_i(t, \hat{\mathbf{x}}_0 + \delta\mathbf{x}_0) = x_i(t, \hat{\mathbf{x}}_0) + a_{ij}(t)\delta x_j + a_{ijk}(t)\delta x_j \delta x_k + a_{ijk\ell}(t)\delta x_j \delta x_k \delta x_\ell + \ldots$$

If:
1 - The Taylor series converges in some ball B
2 - All coefficients ->0 for t->infinity

Asymptotic stability in B!!

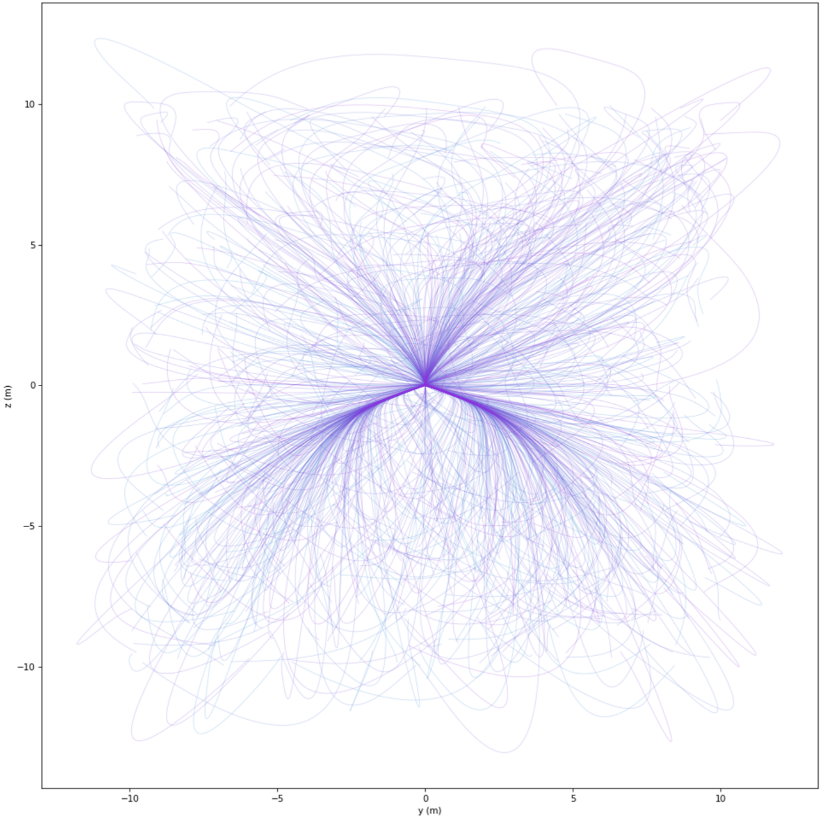
Differential algebraic techniques allow to compute automatically the coefficients and the Ball radius

Drone Racing
time is essential

Drone racing– the database

Dataset of 214,210 Optimal Trajectories of which 857 are visualised on the right.

Pontryagin maximum principle to generate the trajectories. (indirect methods have to be preferred to avoid noisy artifacts)



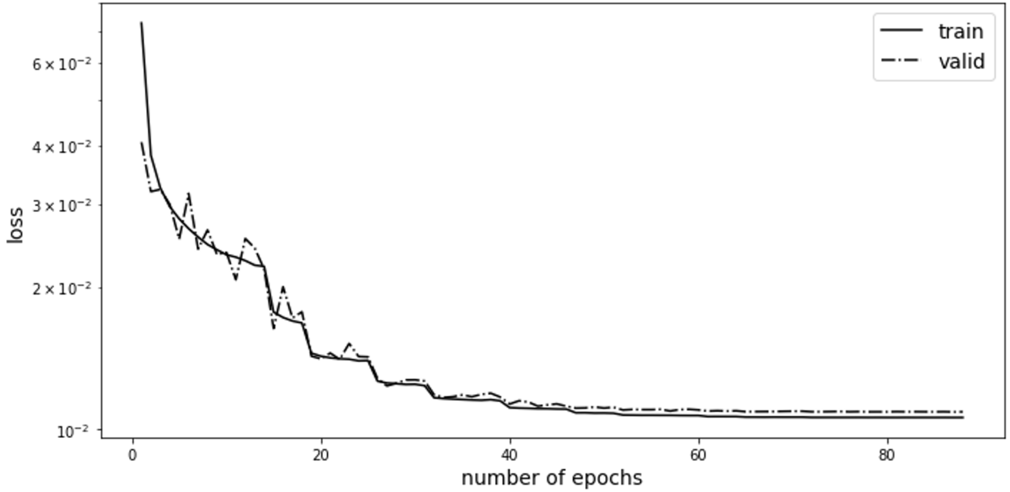
Drone racing - training

Best performing network has 7 hidden layers, softplus activations and 100 neurons per layer.

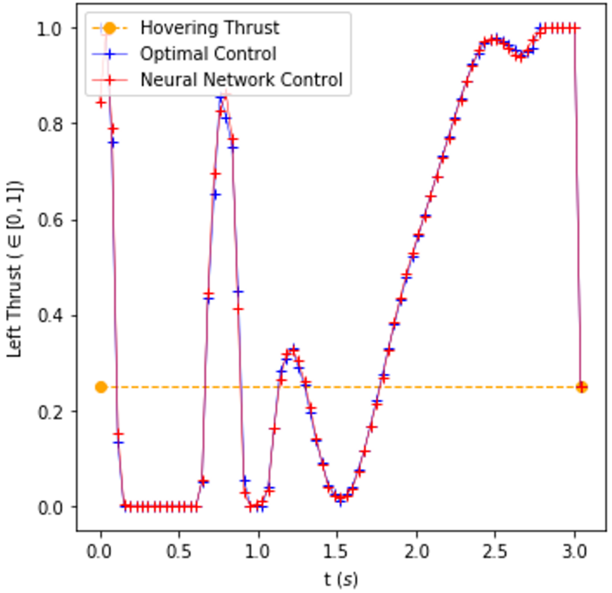
Achieves a Mean Absolute Error of

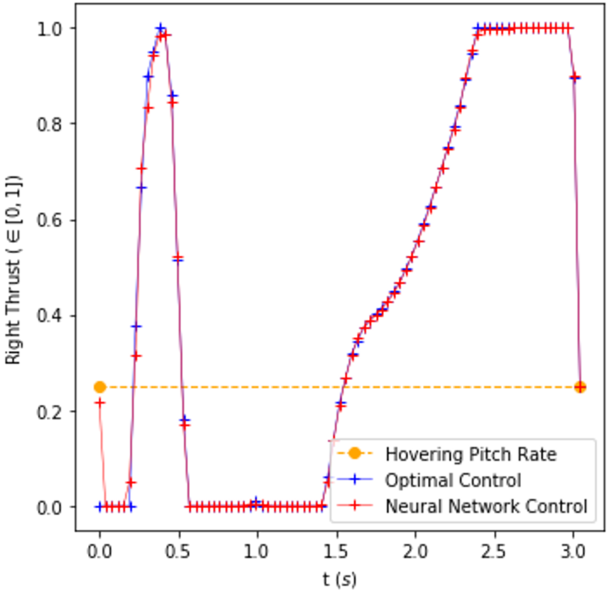
- Left Thrust: 0.0108
- Right Thrust: 0.0109
- Overall: 0.0108

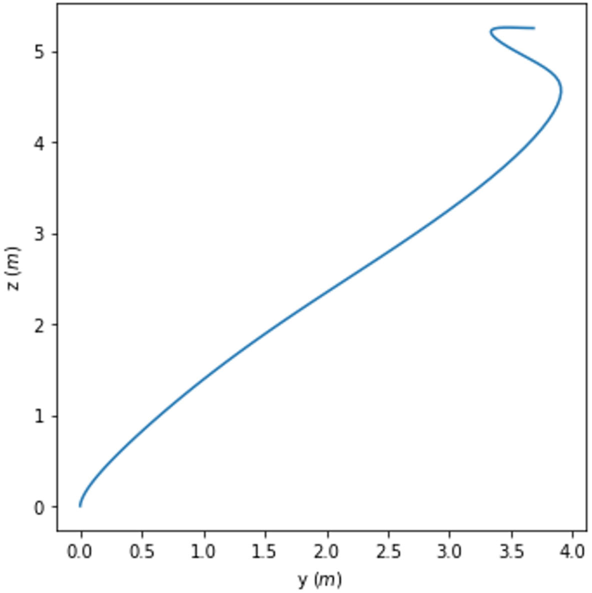
On unseen states in the test set.



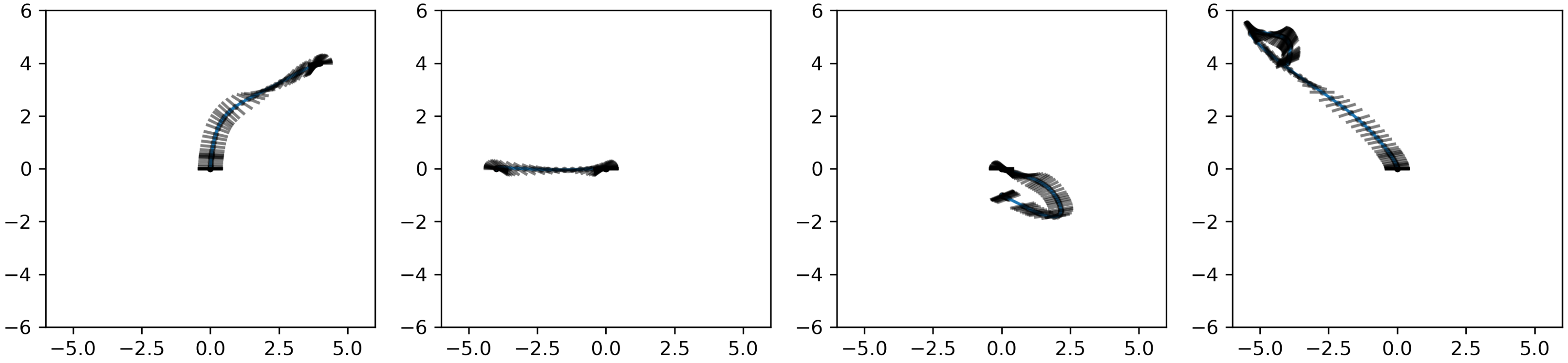
Drone racing - predictions





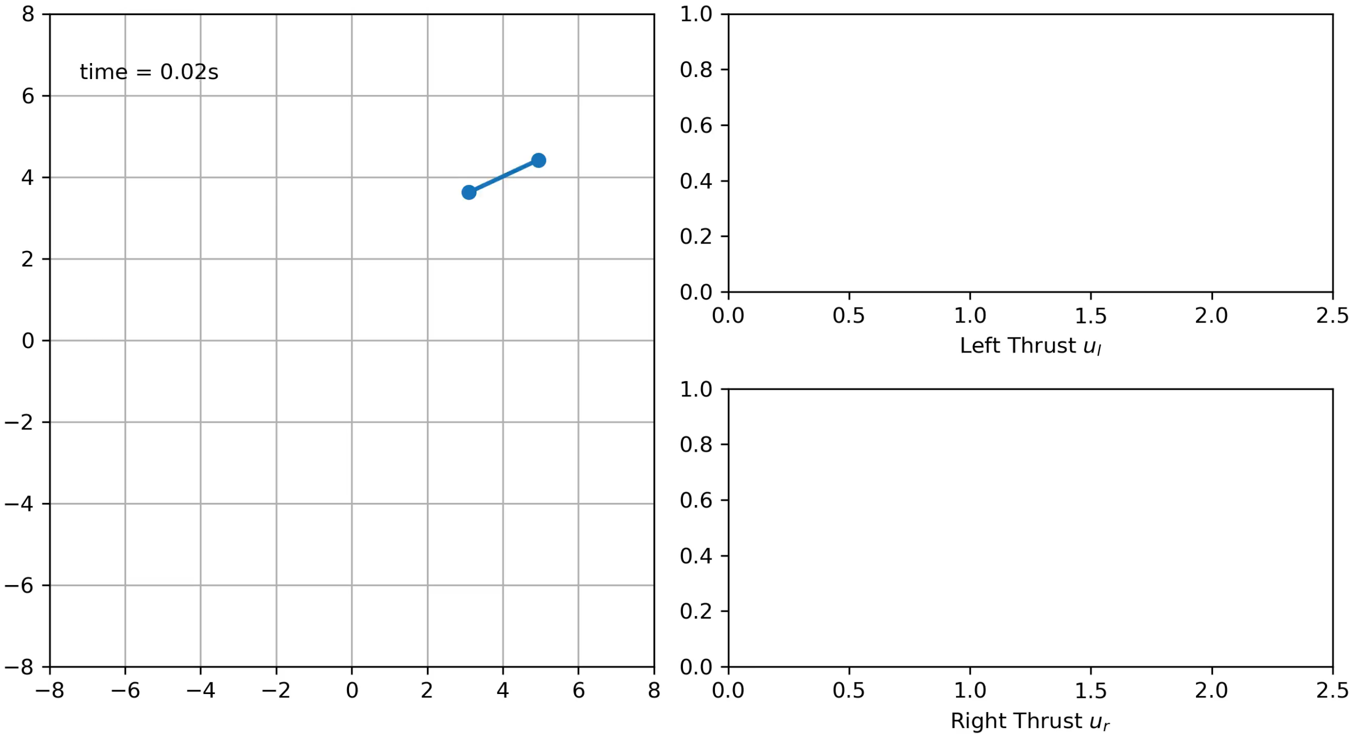


Drone racing– simulated flights

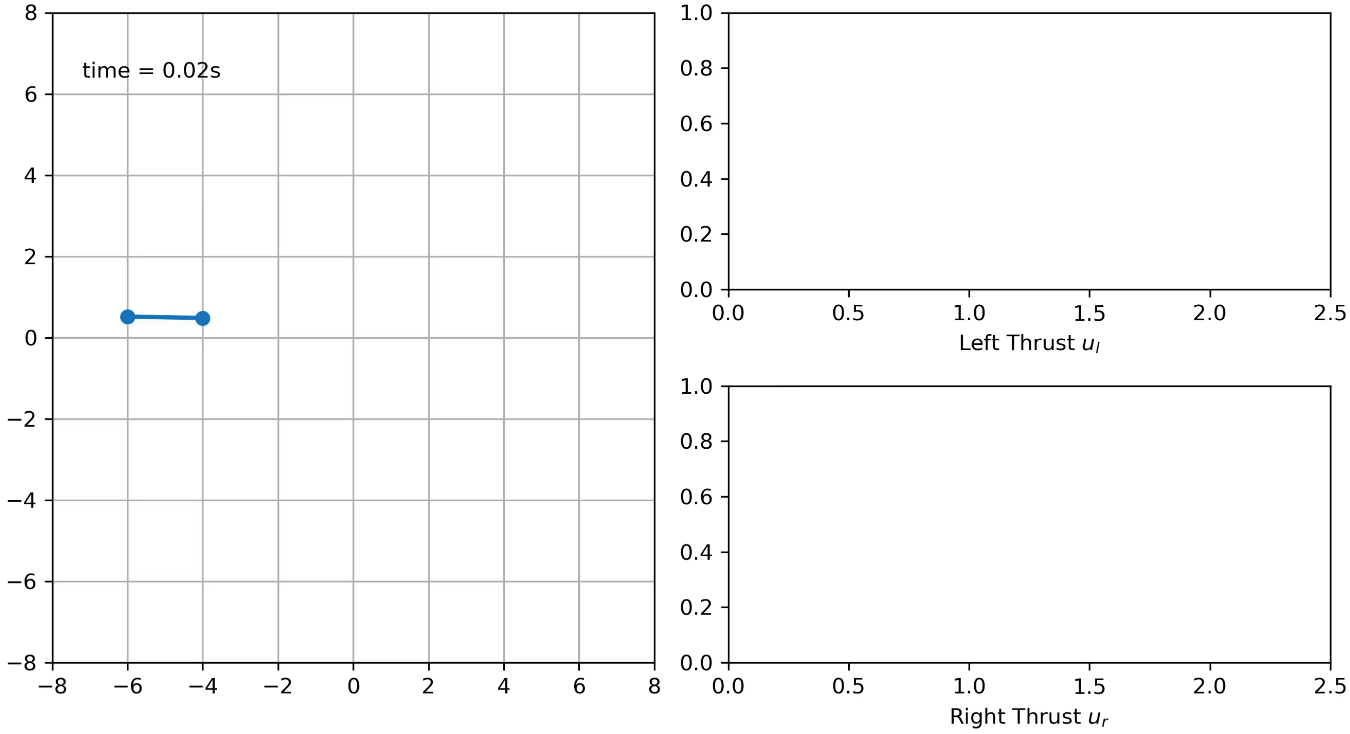


All trajectories converge to the origin regardless of starting (proved mathematically using differential algebra)

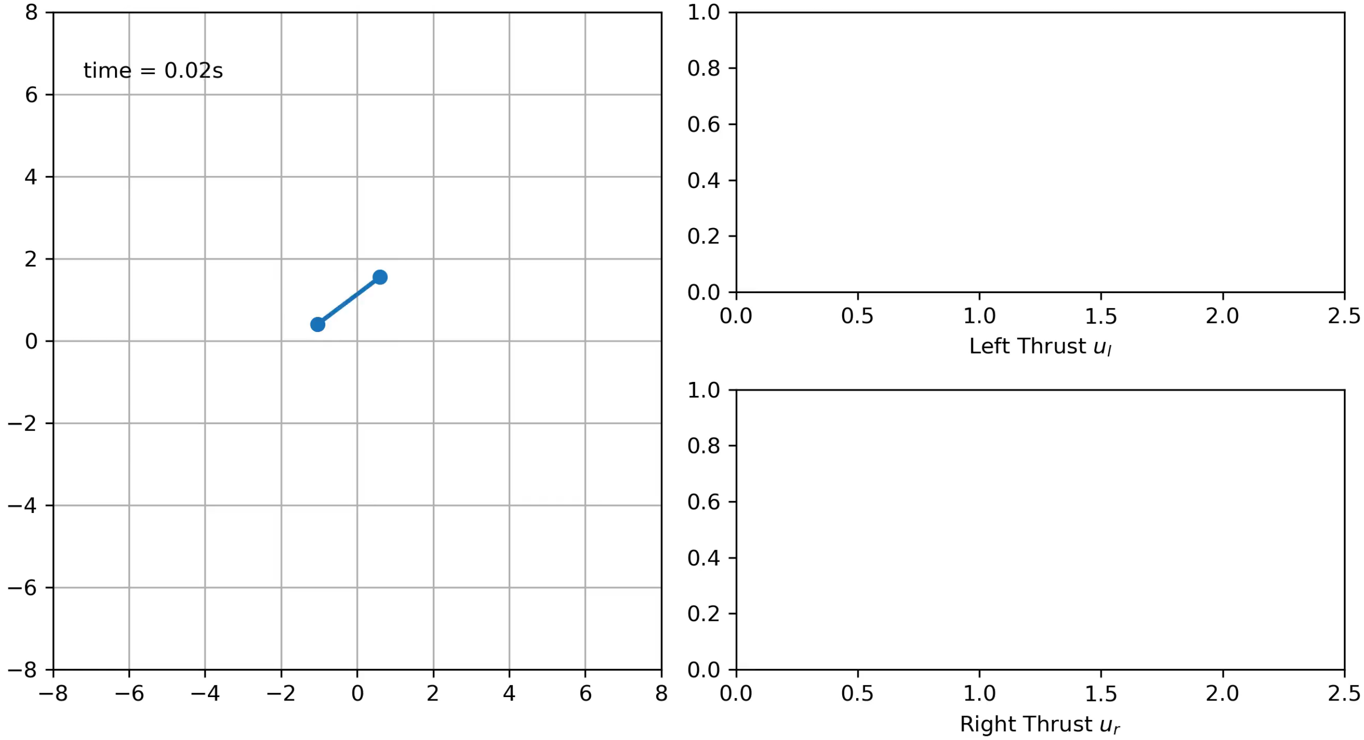
Drone racing– simulated flights 1



Drone racing– simulated flights 2



Drone racing – simulated flights 3



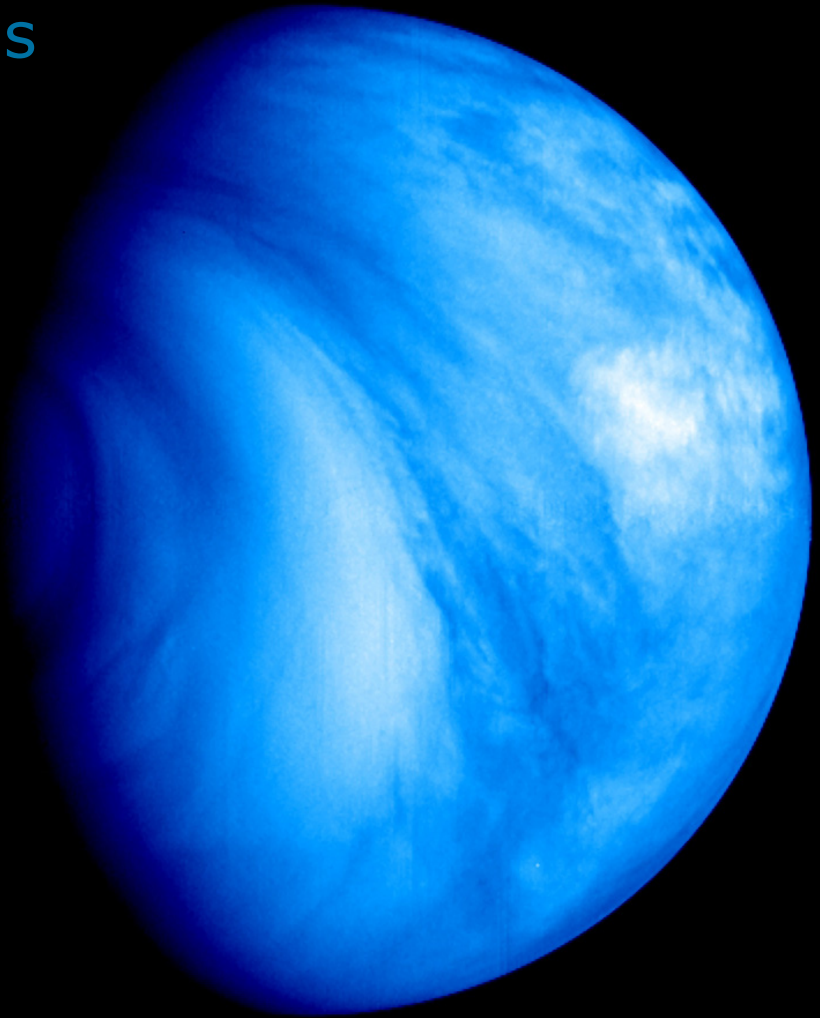
Drone racing– real flights

In collaboration with TU Delft MAVLAB (World Champions of **AIRR autonomous drone race 2019**)

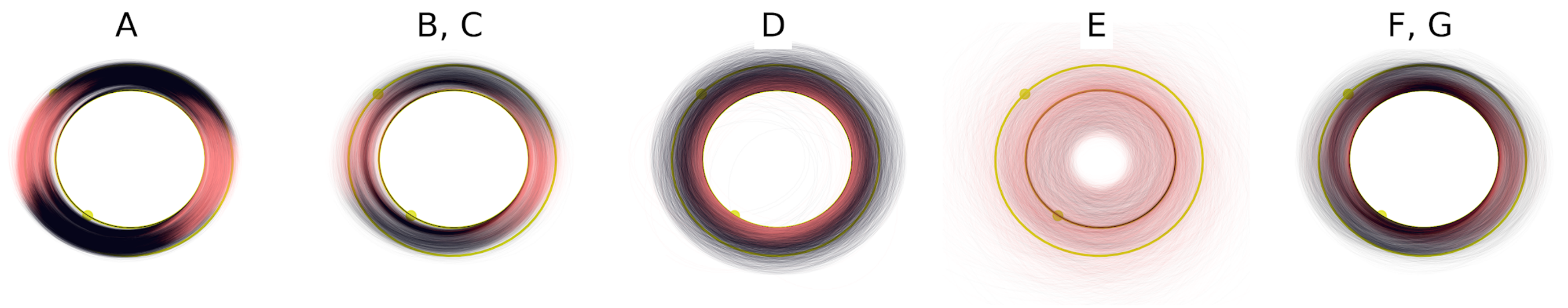
Differential Flatness

GECNET 0.2 EPSILON

Getting to Venus
minimal mass



Interplanetary transfer – the database



Deep Neural Networks (DNNs) trained on a database of **mass optimal controls** for Earth to Venus transfer. We can **Generate** a multitude of optimal trajectories perturbing one nominal optimal trajectory having solved only **one** optimal control problem.

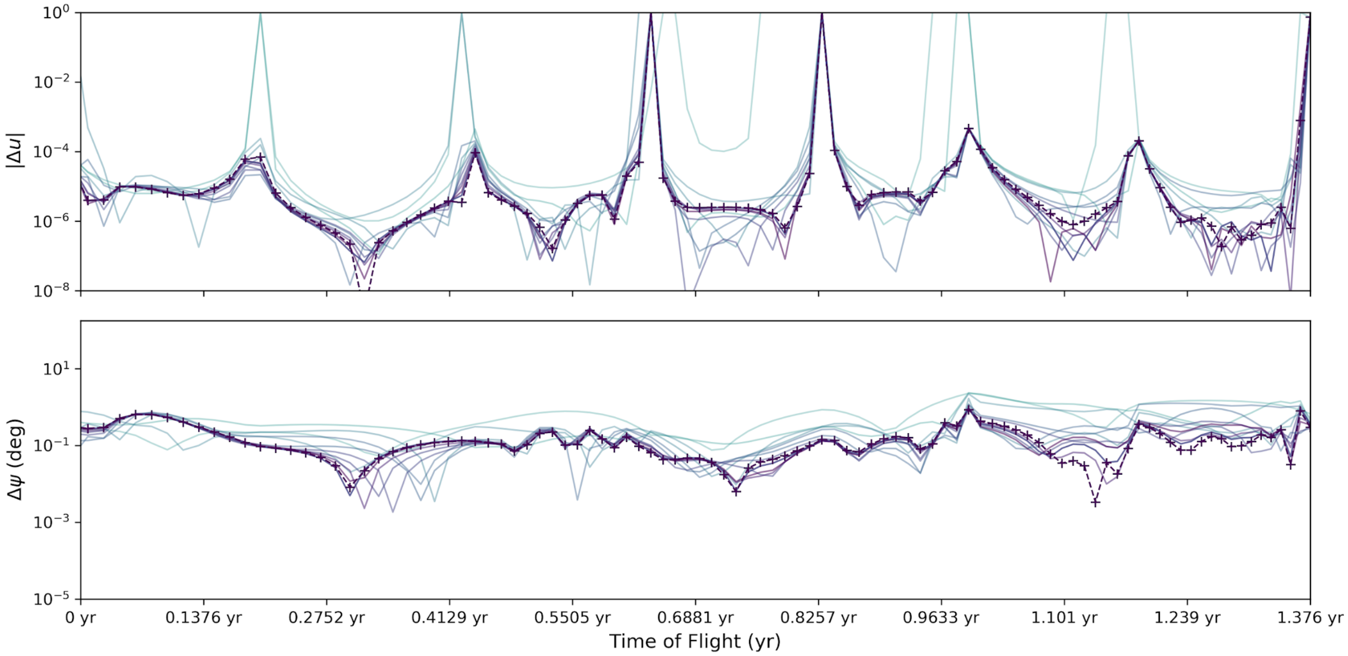
- **Policy Learning:** One neural network trained to predict optimal controls.
- **Value Function Learning:** One neural network trained to predict the value function and compute controls via Hamilton-Jacobi-Bellman Equations.

Interplanetary transfer – the database

Value Function Network:

Error in throttle

Error in thrust direction

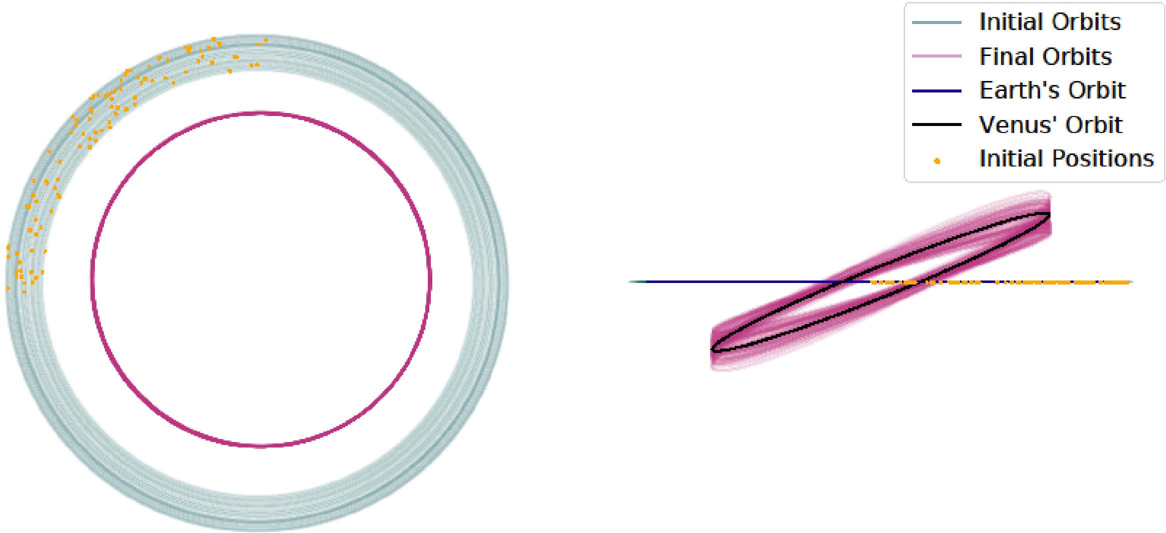


Networks perform mass optimal maneuvers with high accuracy and precision even with a bang-bang control structure.

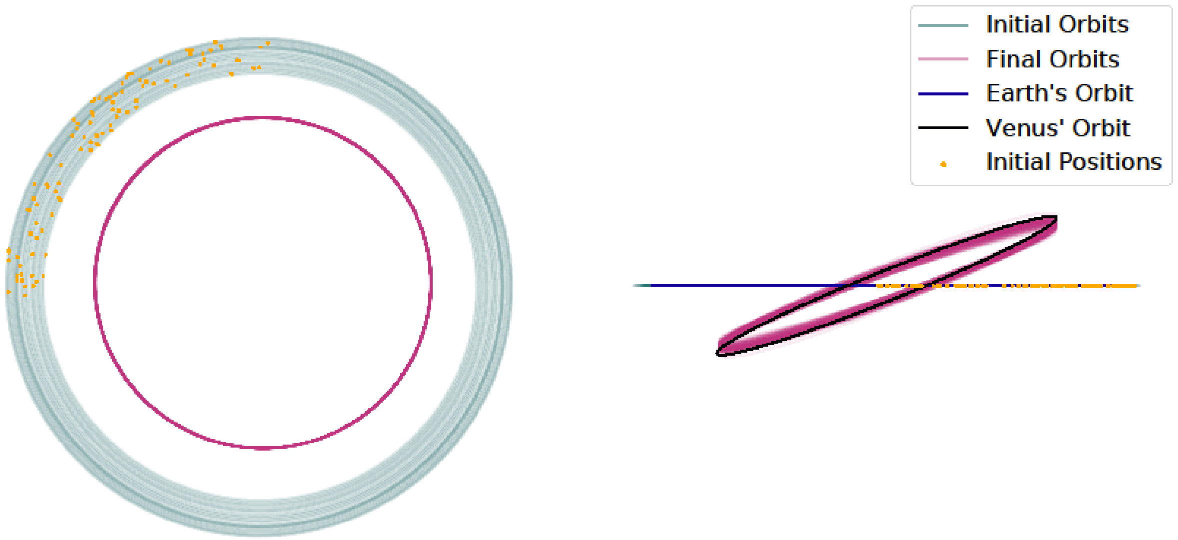
Interplanetary transfer – predictions

NN Architectures	Training Database			A	B	C	D	E	F	G
	policy network	$l_{\mathcal{N}_1}$	$\langle \Delta u \rangle$	0.027	0.037	0.044	0.062	0.12	0.042	0.035
			$\langle \psi_{i_\tau} \rangle$	0.52°	0.44°	0.68°	7.2°	11°	1.4°	1.4°
	value function network	$l_{\mathcal{N}_2}$	$\langle \Delta u \rangle$	0.46	0.39	0.42	0.19	0.13	0.43	0.42
			$\langle \psi_{i_\tau} \rangle$	11°	8.8°	9.2°	16°	15°	8.7°	8.6°
	value function network	$l_{\mathcal{N}_3}$	$\langle \Delta u \rangle$	0.041	0.057	0.049	0.029	0.029	0.046	0.030
			$\langle \psi_{i_\tau} \rangle$	0.26°	0.53°	0.49°	3.7°	4.9°	0.92°	0.45°
	value function network	$l_{\mathcal{N}_4}$	$\langle \Delta u \rangle$	0.068	0.11	0.096	0.078	0.21	0.12	0.11
			$\langle \psi_{i_\tau} \rangle$	2.7°	3.0°	2.7°	19°	17°	4.0°	4.5°

Value function network



Policy Network



References:

- Izzo, Dario, Märtens, Marcus, and Pan, Binfeng, “A Survey on Artificial Intelligence Trends in Spacecraft Guidance Dynamics and Control”, Astrodynamics, 2019.
- Dharmesh, T. and Izzo, D., “Learning the optimal state-feedback via supervised imitation learning”, arXiv preprint arXiv:1901.02369, 2019.
- Izzo, D., Öztürk, E., and Märtens, M., “Interplanetary Transfers via Deep Representations of the Optimal Policy and/or of the Value Function”, arXiv preprint arXiv:1904.08809, 2019.
- Sanchez-Sanchez, C. and Izzo, D., “Real-Time Optimal Control via Deep Neural Networks: Study on Landing Problems”, Journal of Guidance Control and Dynamics, 41 (5), pp.1122-1135, 2018.
- Izzo, D., Tailor, D., and Vasileiou, T., “On the stability analysis of optimal state feedbacks as represented by deep neural models”, arXiv preprint arXiv:1812.02532, 2018.
- Sanchez-Sanchez, C., Izzo, D., and Hennes, D., “Learning the optimal state-feedback using deep networks”, 2016 IEEE Symposium Series on Computational Intelligence (SSCI), 2016.