Pacific Northwest
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Fieldable AI for Robotics

Wenceslao Shaw Cortez, *Data Scientist*
w.shawcortez@pnnl.gov

Soumya Vasisht, Ján Drgoňa, Draguna Vrabie, Aaron Tuor, Jan Strube

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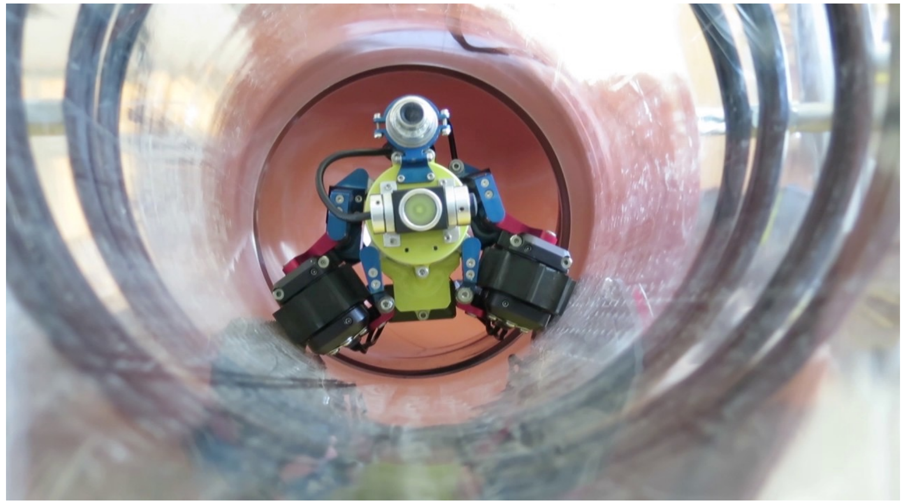
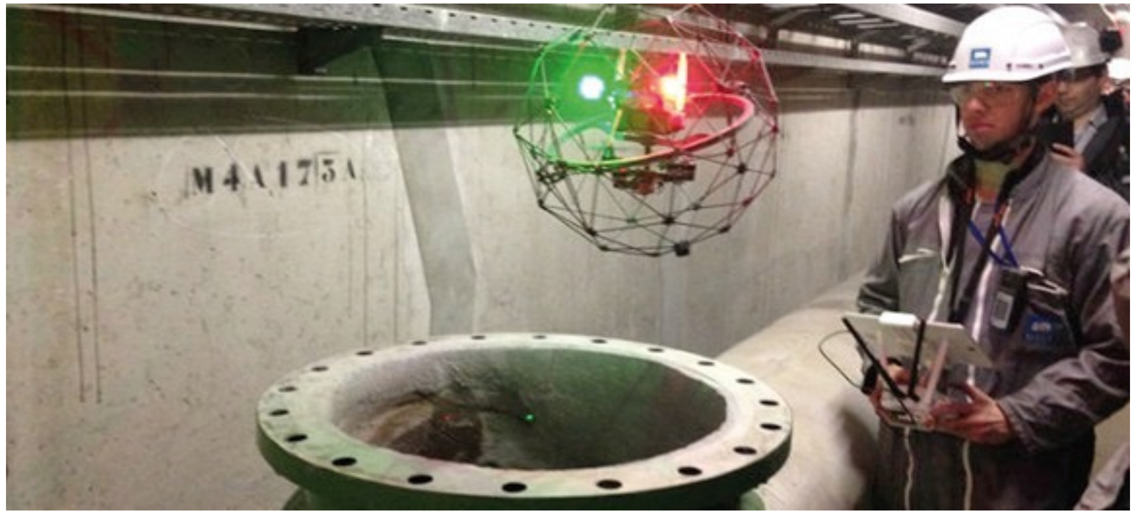
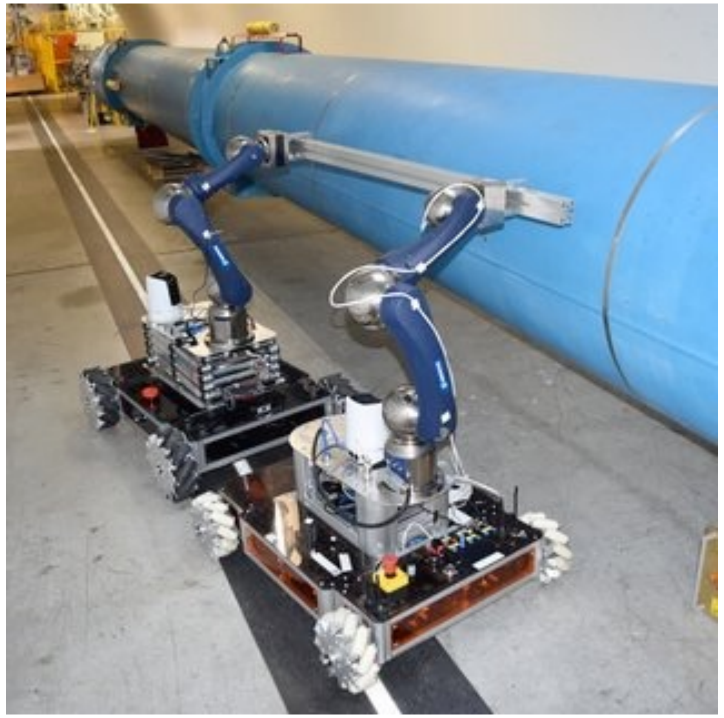
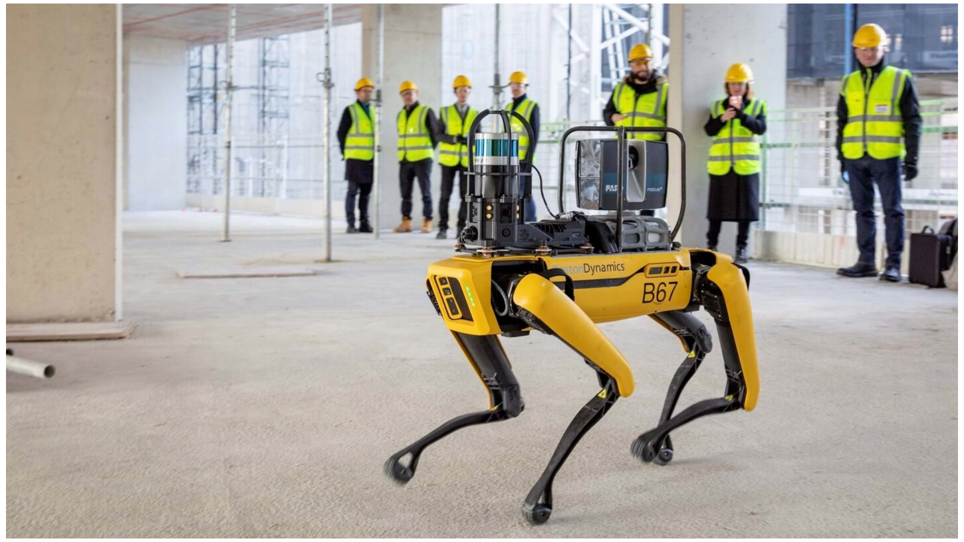
Motivation: Robots in Unstructured Environments









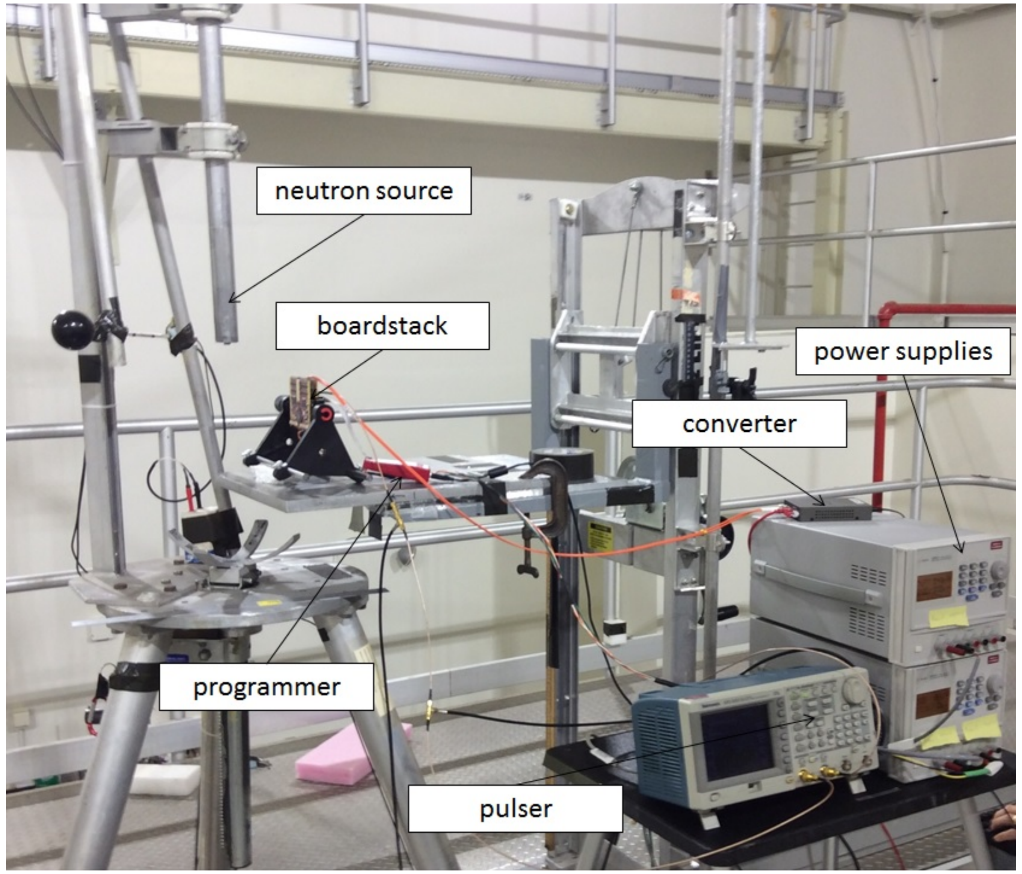
Challenges: Robots in Unstructured Environments

- Unstructured environments
- Uncertain models
- From simulation to the real environment

"It worked in rehearsal."

Radiation Hardness Tests

- Disturbances:
  - Magnetic fields
  - Communication loss
  - Radiation damage
- Radiation damages electronics components
  - Instantaneous bit-flips
  - Long-term performance deterioration



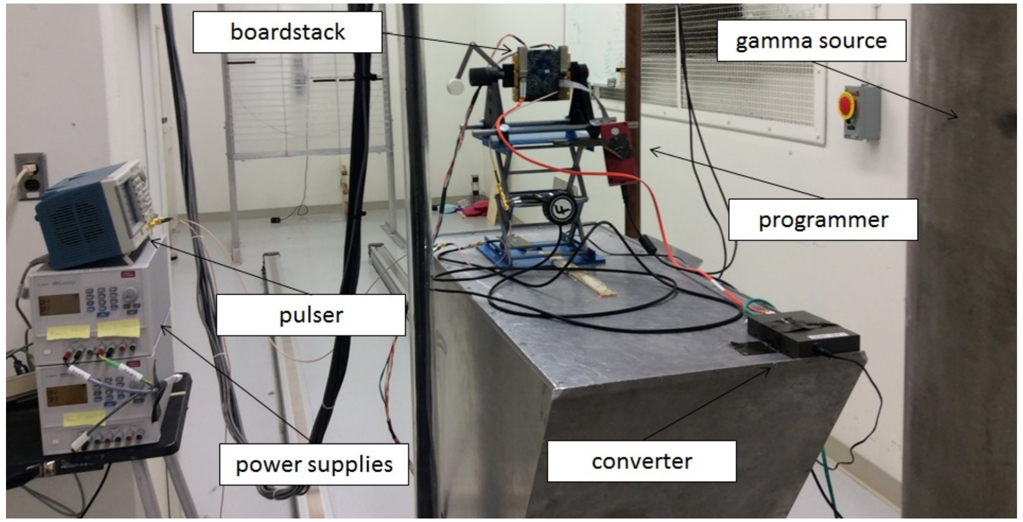
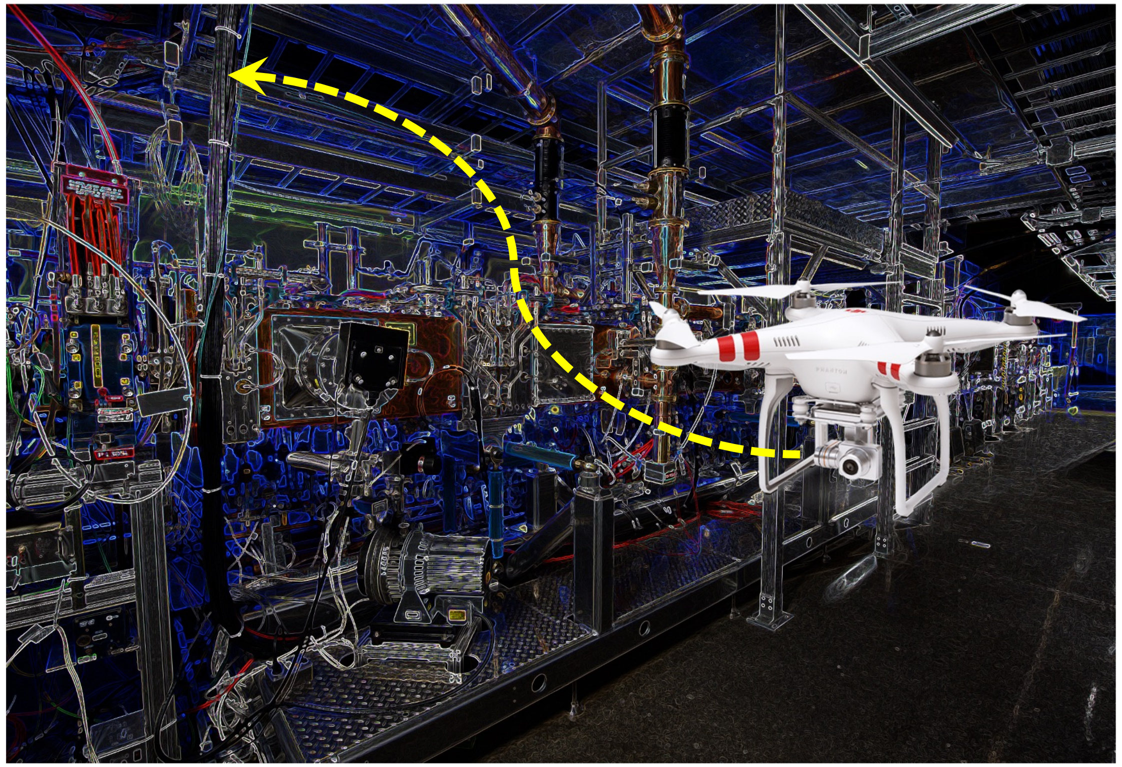


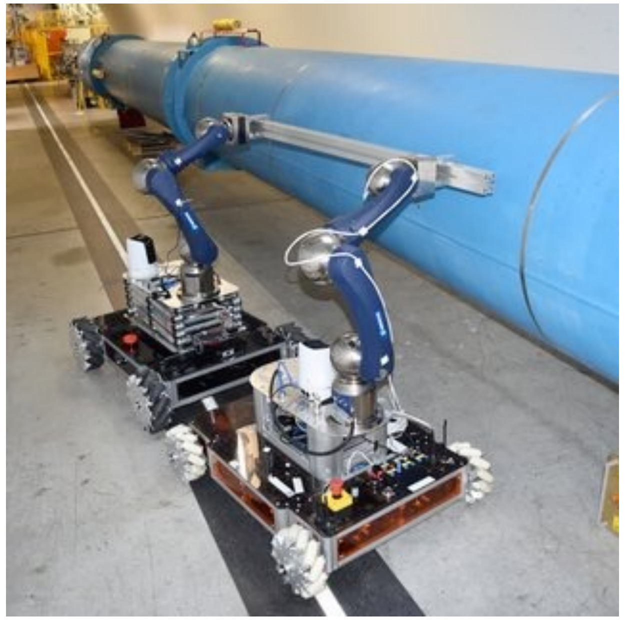
Image source: *Radiation hardness testing of iTOP SCROD and carrier boards*, PNNL, 2015 (link)

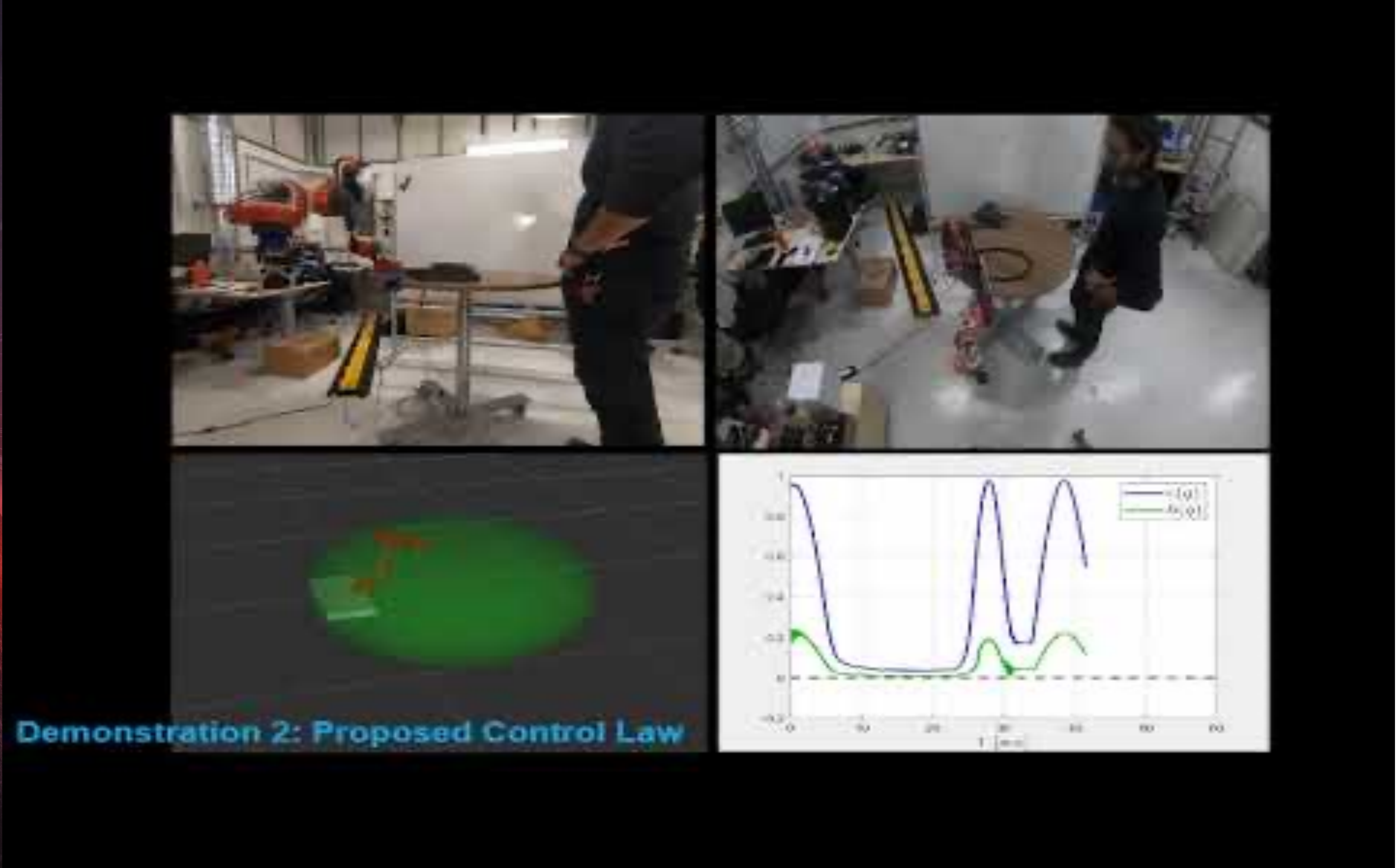
Tackling Challenges in Unstructured Environments

- **Stability:**
  - Trajectory tracking, i.e., "perform the task"
  - Provides measure of robustness

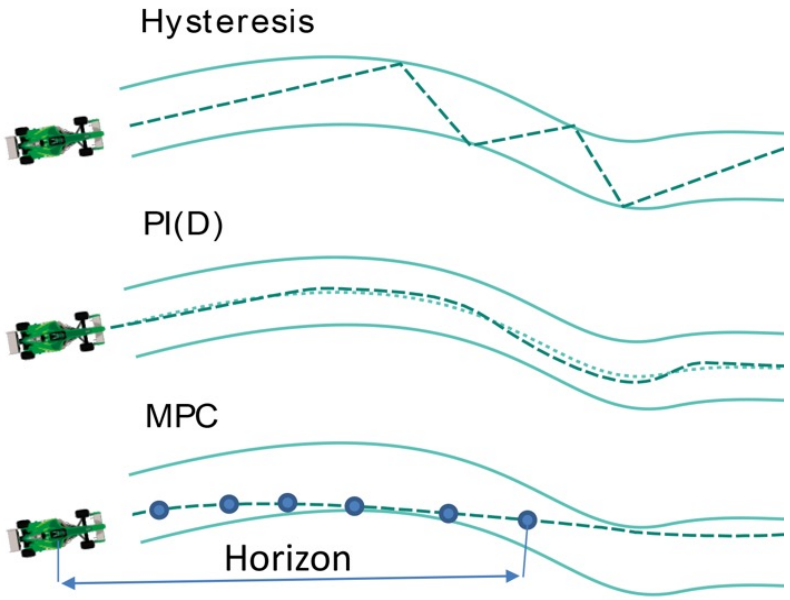
- **Safety:**
  - Constraint satisfaction
  - Collision avoidance





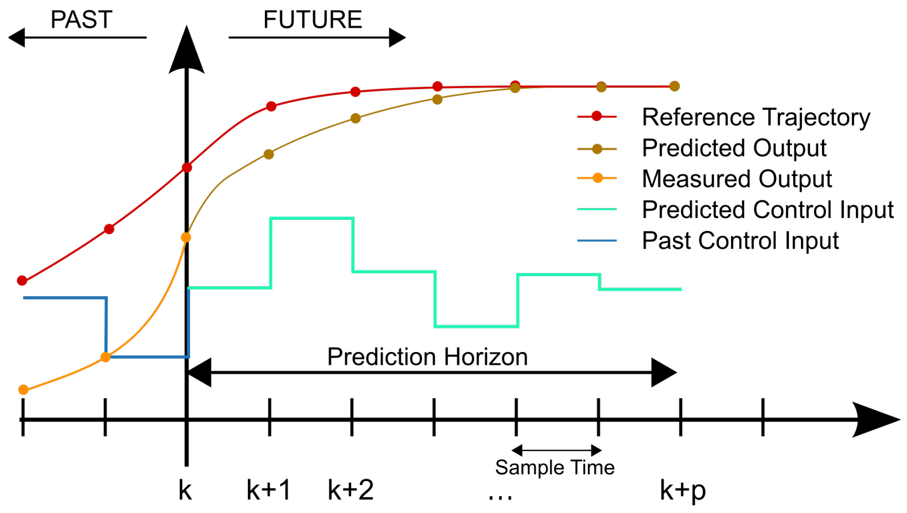

Demonstration 2: Proposed Control Law

Let's talk control



Model Predictive Control

- Advanced optimal control
- First devised for process control in 1970's
- Handles constraints and optimality
- Computationally expensive



Cost: $\min_{\tilde{\mathbf{u}}(k)} J(\tilde{\mathbf{x}}(k+1), \tilde{\mathbf{z}}(k), \tilde{\mathbf{u}}(k))$

subject to

Model: $\tilde{\mathbf{x}}(k+1) = \tilde{\mathbf{f}}(\tilde{\mathbf{x}}(k), \tilde{\mathbf{z}}(k), \tilde{\mathbf{u}}(k))$

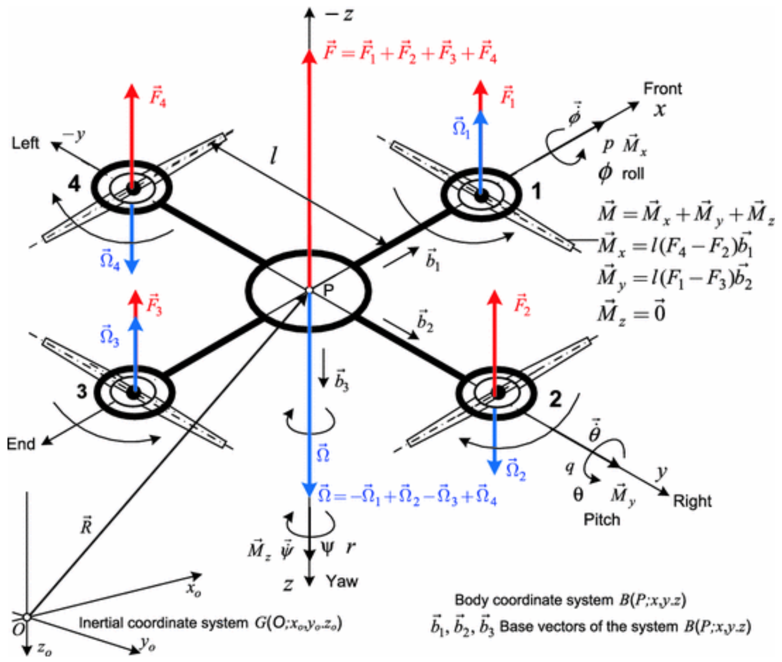
Constraints: $\tilde{\mathbf{g}}(\tilde{\mathbf{x}}(k), \tilde{\mathbf{z}}(k), \tilde{\mathbf{u}}(k)) = \mathbf{0}$

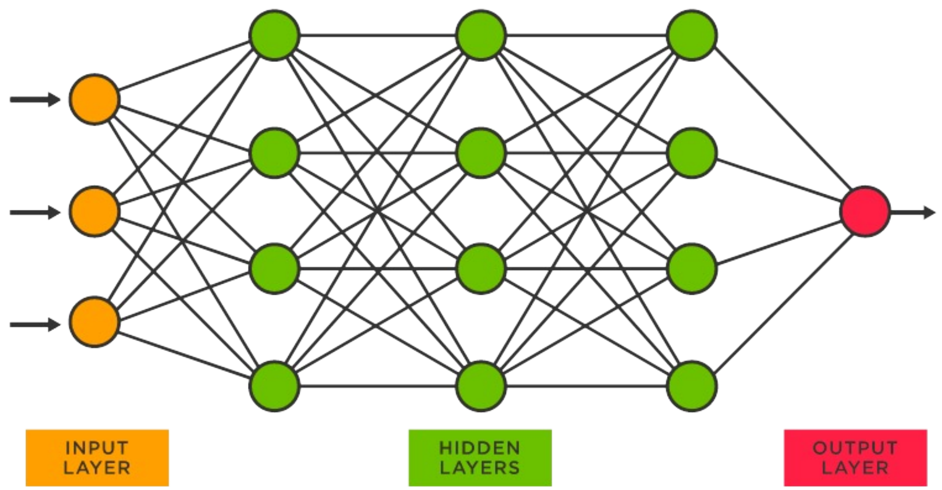
$\tilde{\mathbf{h}}(\tilde{\mathbf{x}}(k), \tilde{\mathbf{z}}(k), \tilde{\mathbf{u}}(k)) \leq \mathbf{0},$

Assumption: Reliable and accurate system dynamics model is available

Drgona J., J. Arroyo, I.C. Figueroa, D. Blum, K. Arendt, D. Kim, and E.P. Olle, J. Oravec, M. Wetter, D. L. Vrabie, L. Helsen. 2020. "All You Need to Know About Model Predictive Control for Buildings." Annual Reviews in Control, September 29, 2020

Modeling challenges: Nonlinear system identification





Physics-based modeling is useful but tedious

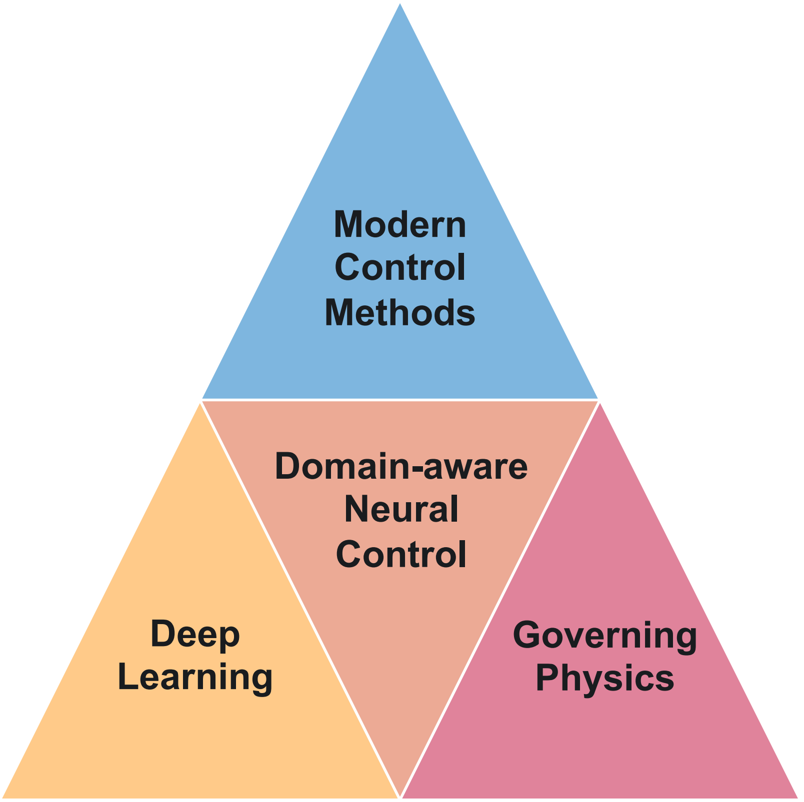
- Unknown underlying system dynamics
- Incomplete knowledge of model state-space
- Limited availability of operational data

Purely data driven models are unreliable

- Poor sampling efficiency
- Lack of operational safety guarantees
- Opaque and difficult to interpret

Data-driven Control Methods

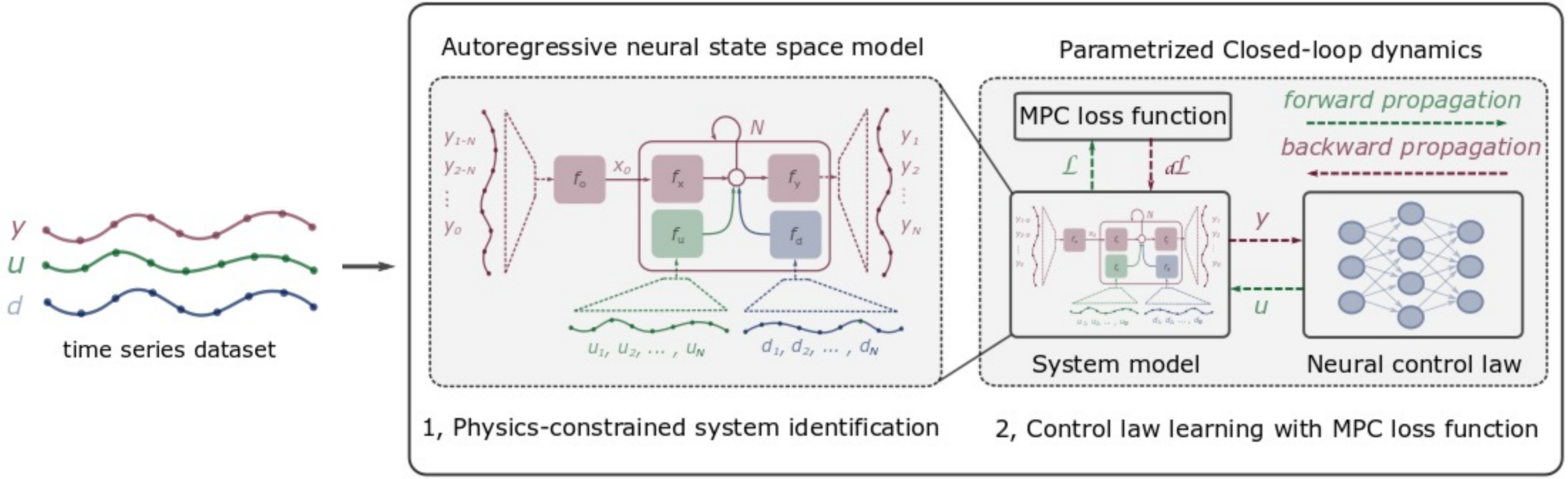
Integrate Deep Learning with MPC and Physics



- Automate learning of the system dynamics and model-based control policy
- Automated installation: from data to optimal control policy
- Endow with lifelong learning and provide performance guarantees during the learning process

Differentiable Predictive Control

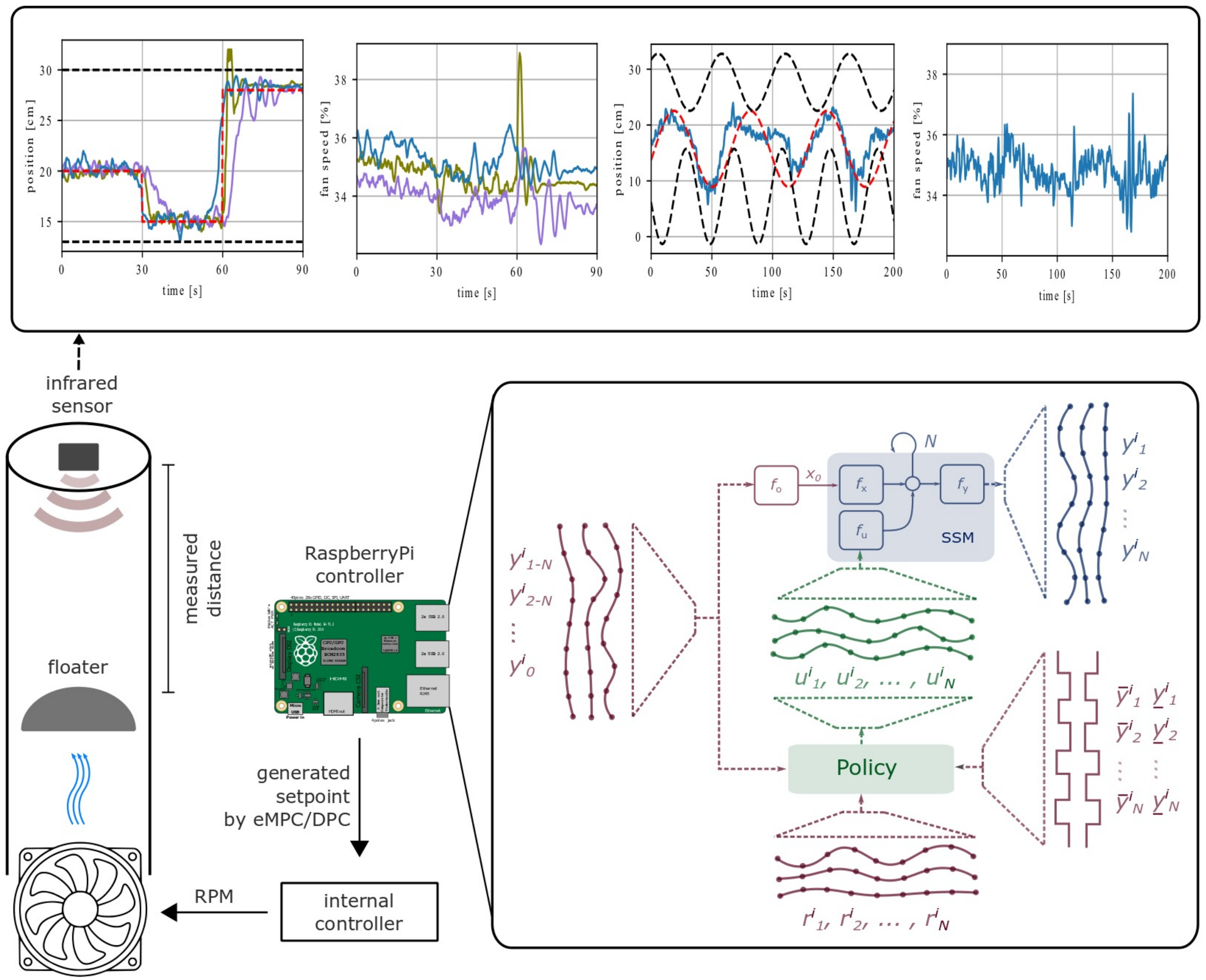
From data to optimized control policy

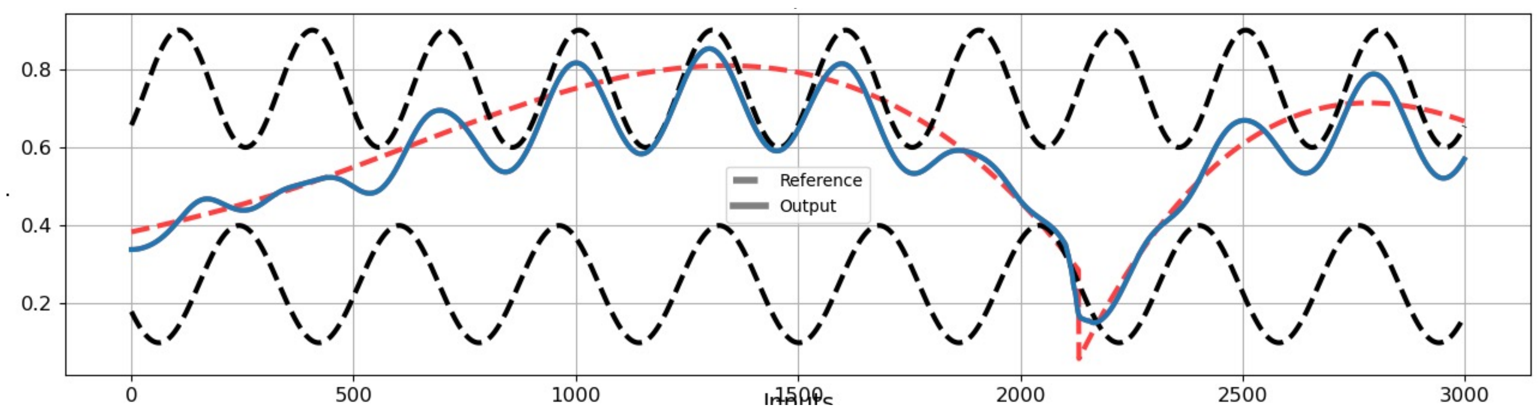


- Theoretical connection with MPC
- Neural state space models
- Differentiable closed-loop model
- Model-based policy optimization

DPC Applications

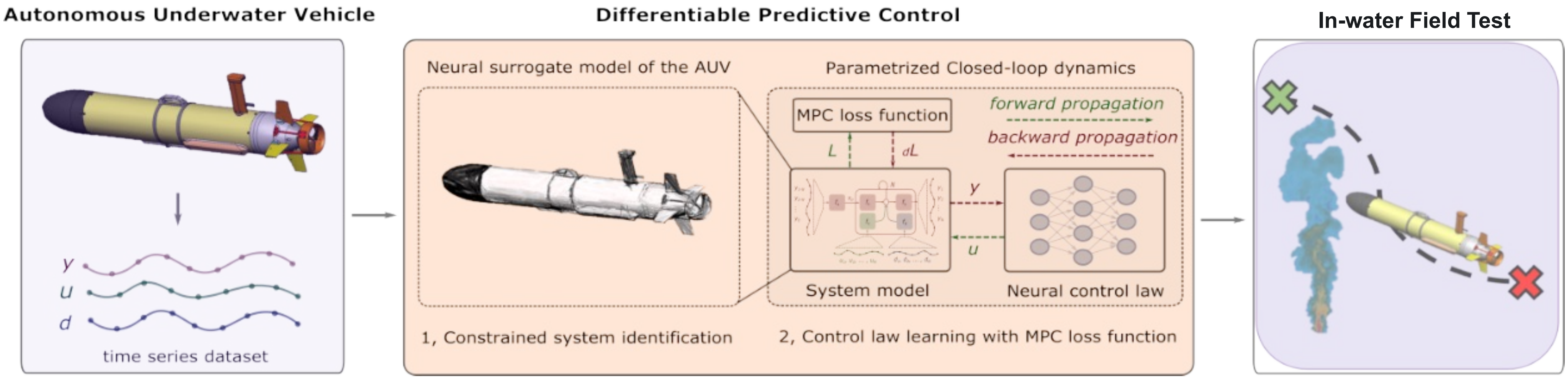
- Constrained optimization
- Dynamical modeling and control
  - Buildings
  - Power Systems
  - Embedded systems
  - Autonomous vehicles





Software products:
https://github.com/pnnl/neuromancer
https://github.com/pnnl/slim

Underwater Robotics use case

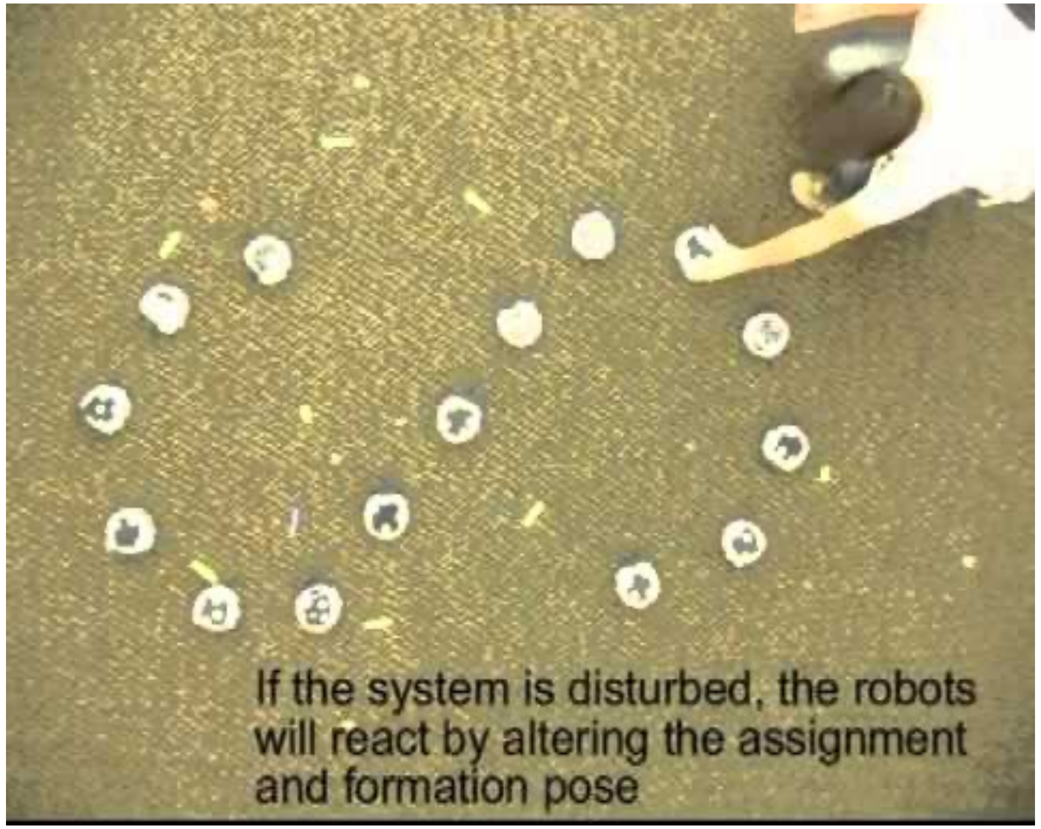


- Adapt to changing environment: ocean currents, changing salinity
- Apply to different robot types:

Drgona J., et al., Differentiable Predictive Control: An MPC Alternative for Unknown Nonlinear Systems using Constrained Deep Learning, 2021. (link)

Future Directions

- Robots in unstructured environments
- Apply DPC for different robot dynamics
- Federated learning
- Multi-agent systems approach
- Heterogeneous cooperative robots



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Thank you