Caltech

Learning for Safety-Critical Control in Dynamical Systems

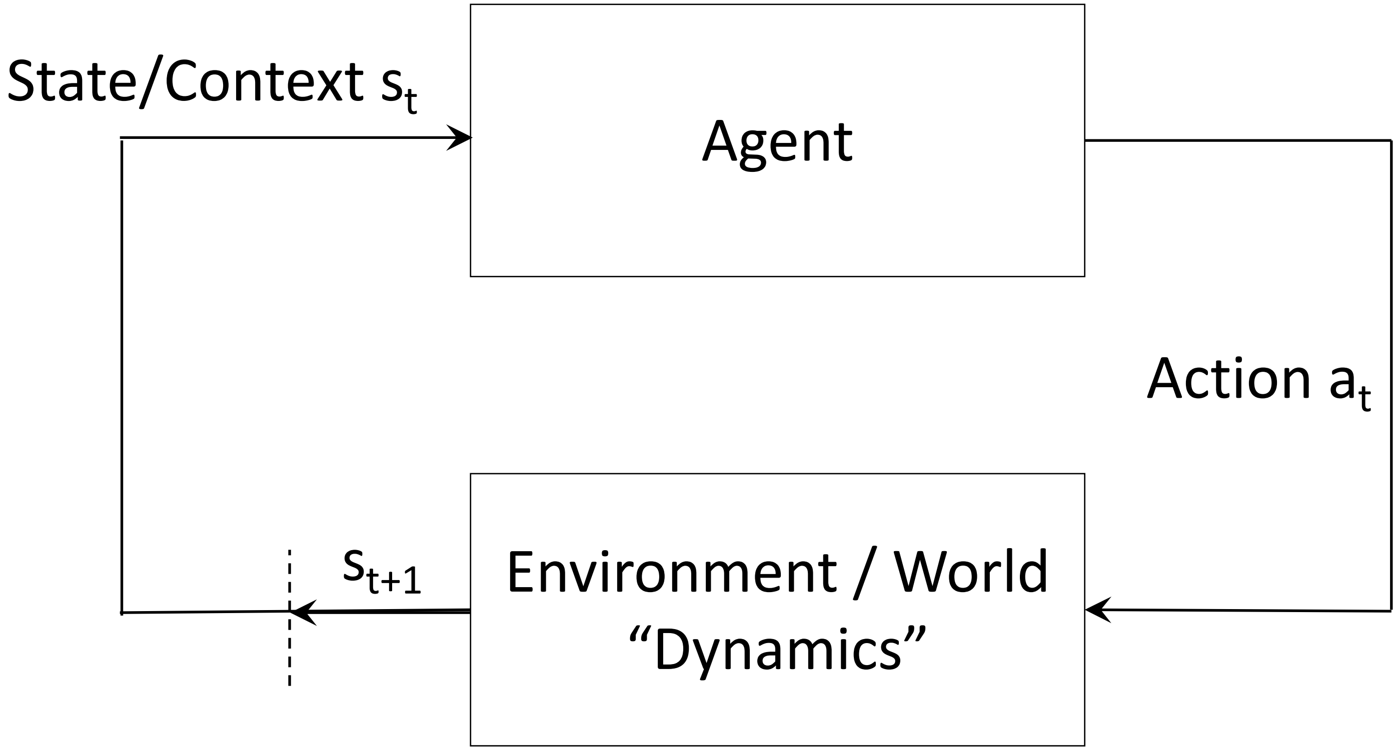
Yisong Yue

Policy/Controller Learning (Reinforcement & Imitation)

Goal: Find "Optimal" Policy

Imitation Learning:
Optimize imitation loss

Reinforcement Learning:
Optimize environmental reward



Learning-based Approach for Sequential Decision Making

Non-learning approaches include: optimal control, robust control, adaptive control, etc.

Imitation Learning Tutorial

https://sites.google.com/view/icml2018-imitation-learning/

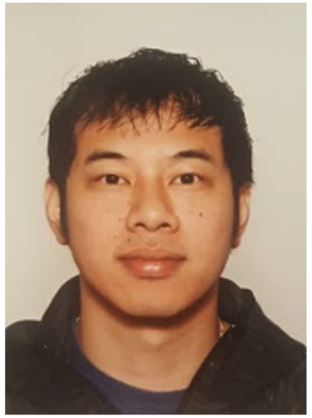
Yisong Yue

yyue@caltech.edu

@YisongYue

yisongyue.com

Hoang M. Le

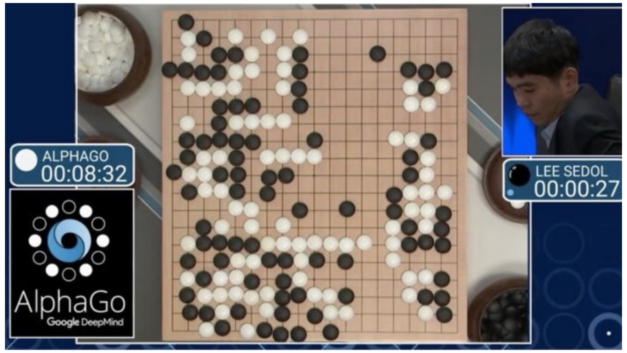


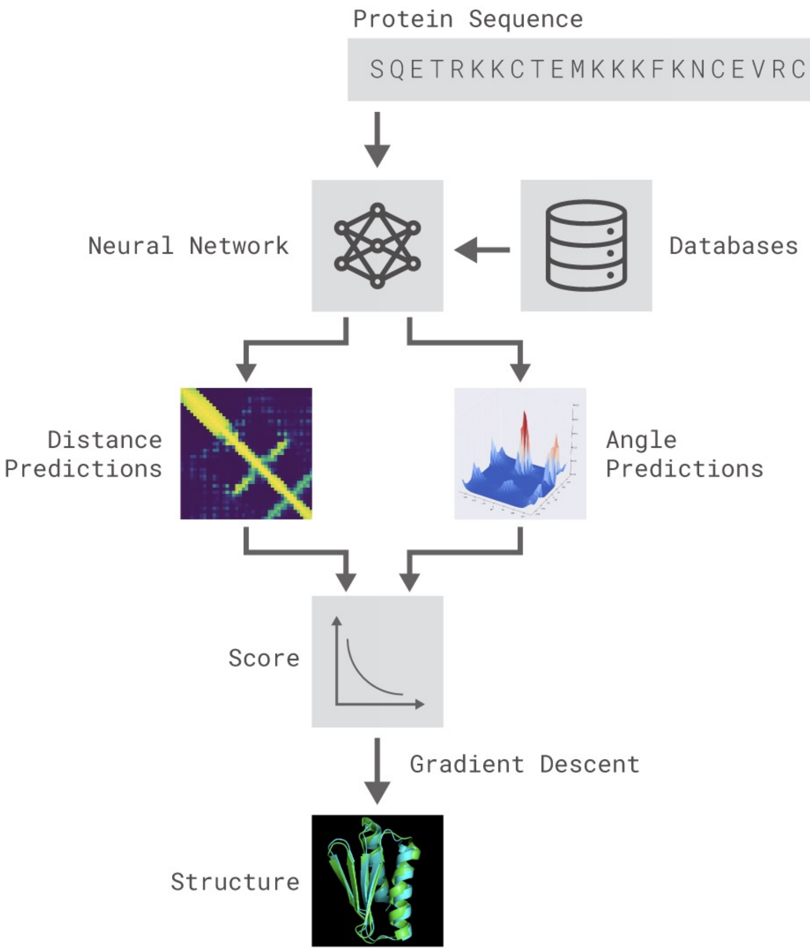
Hoang.Le@Microsoft.com

@HoangMinhLe

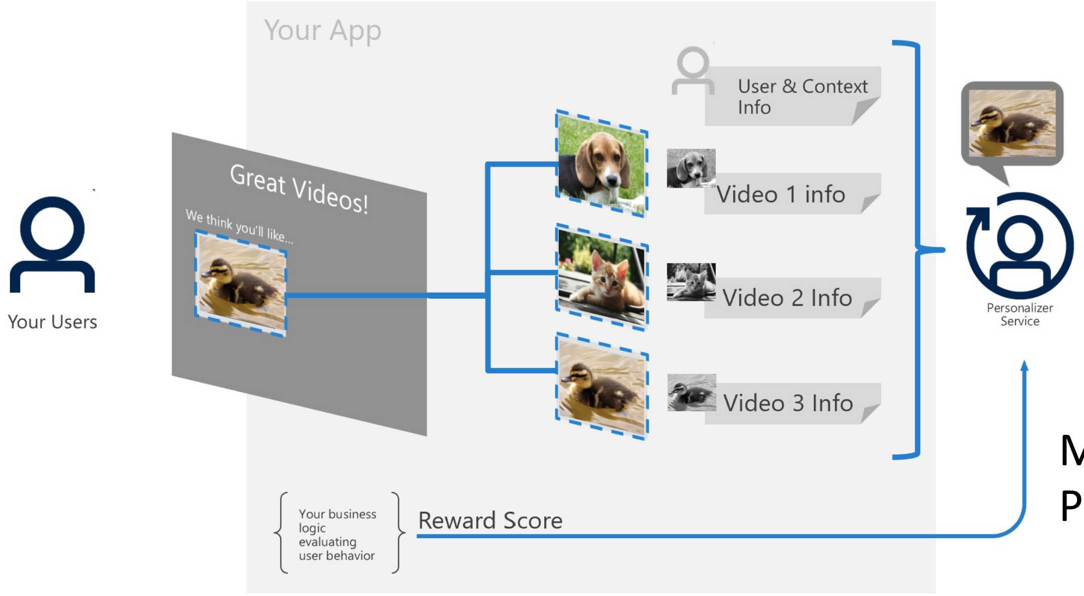
hoangle.info

Many Exciting Success Stories





AlphaFold

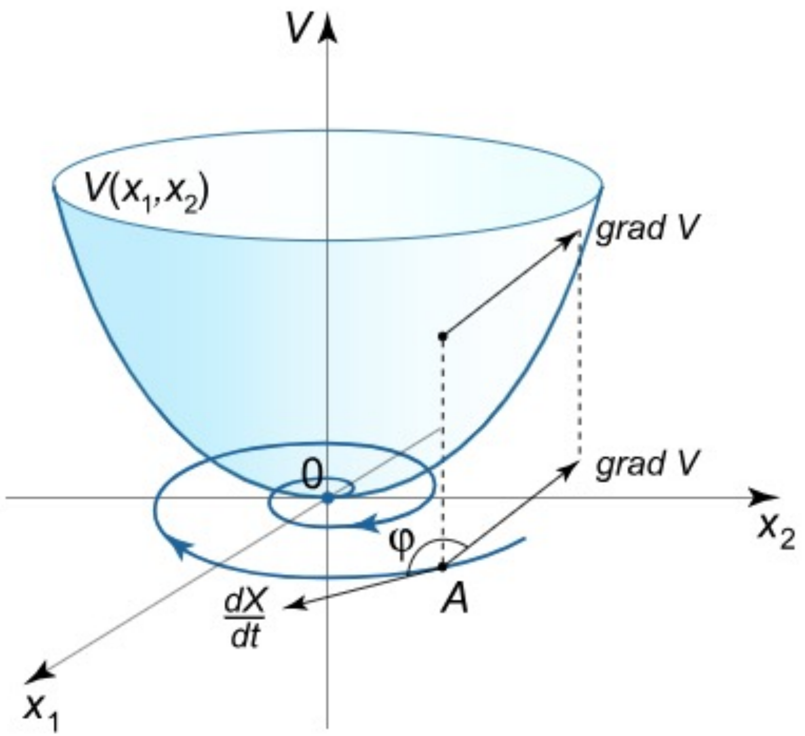


Microsoft Azure Personalizer

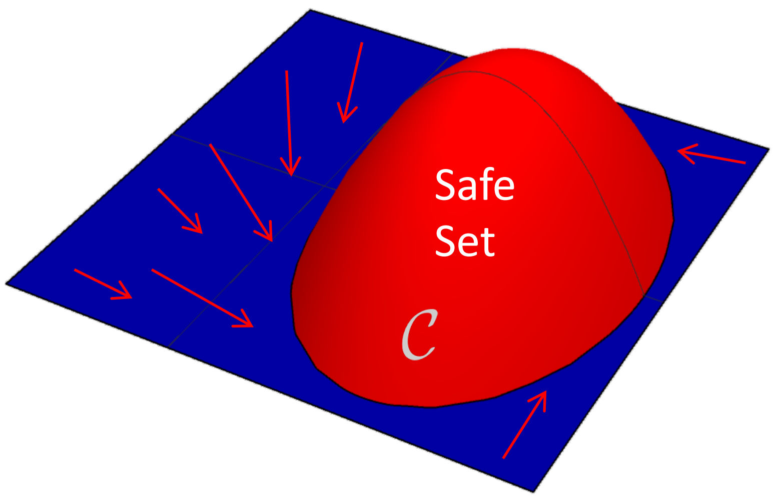
“ I want to use deep learning to optimize the design, manufacturing and operation of our aircrafts. But I need some guarantees. ” -- Aerospace Director

Behavioral Guarantees

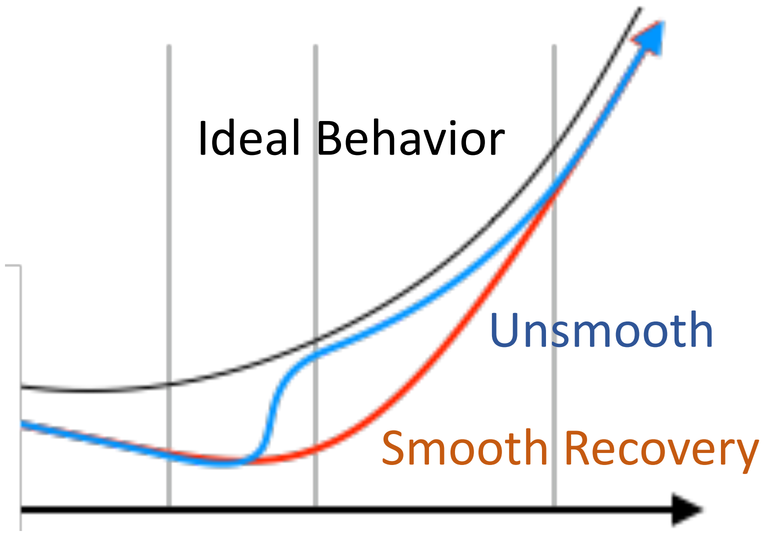
Possibly Others:
- Fairness
- Low-risk
- Temporal logic
- Etc…



Stability

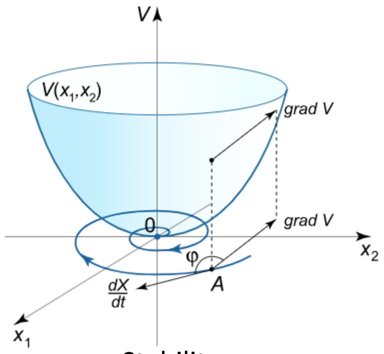


Safety

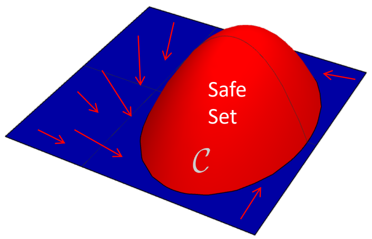


Smoothness

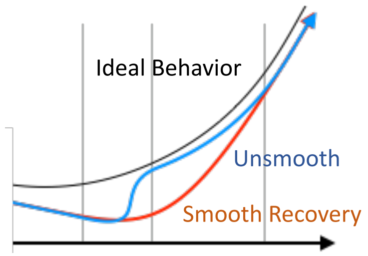
Research Questions



Stability



Safety

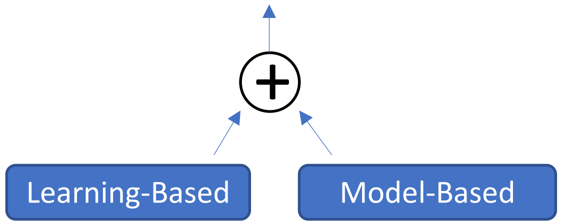


Smoothness

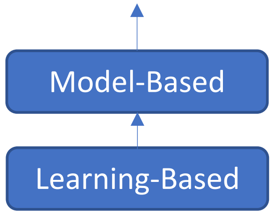
- How to constrain learning to (provably) satisfy guarantees?
- How to integrate domain knowledge from physics & control theory?
  - (Towards) a unified framework?
- How to exploit structure for faster learning?
  - (both computational & statistical)

Integration of Learning at Varying Levels

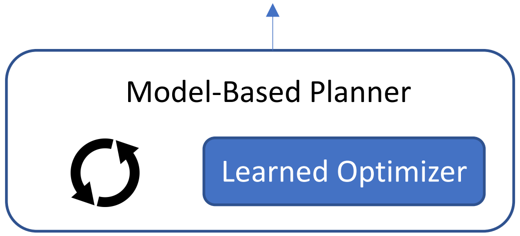
- Integration in control/action



- Integration in dynamics modeling



- Integration in optimization problem



Starting Point

Standard IL/RL Objective

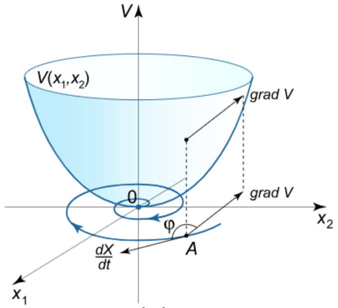
- Model-Based/Free
- On/Off Policy
- Imitation/Reinforcement
- Optimal Control

$$\underset{h}{argmin}\, L(h)$$
$$s.t.$$
$$R(h) < \kappa$$

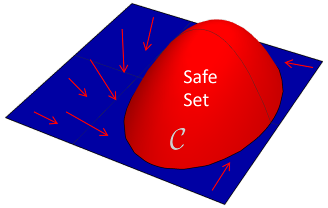
Side Constraint

In general, very hard to verify/optimize!

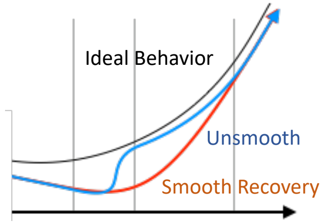
(e.g., for all inputs, h is safe)



Stability



Safety



Smoothness

Functional Regularization

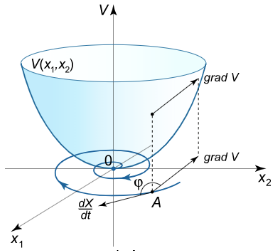
(to a certified controller)

$$\begin{aligned} &\quad argmin_h L(h) \\ &s.t. \\ &\exists g \in G: \|h - g\|^2 < \kappa \end{aligned} \quad \Longleftrightarrow \quad argmin_{h,g} L(h) + \lambda \|h - g\|^2$$

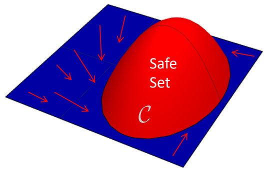
Intractable?

Model-Based Controllers

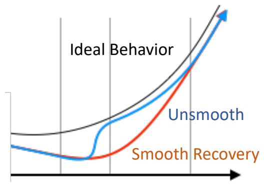
(certified by construction)



Stability



Safety



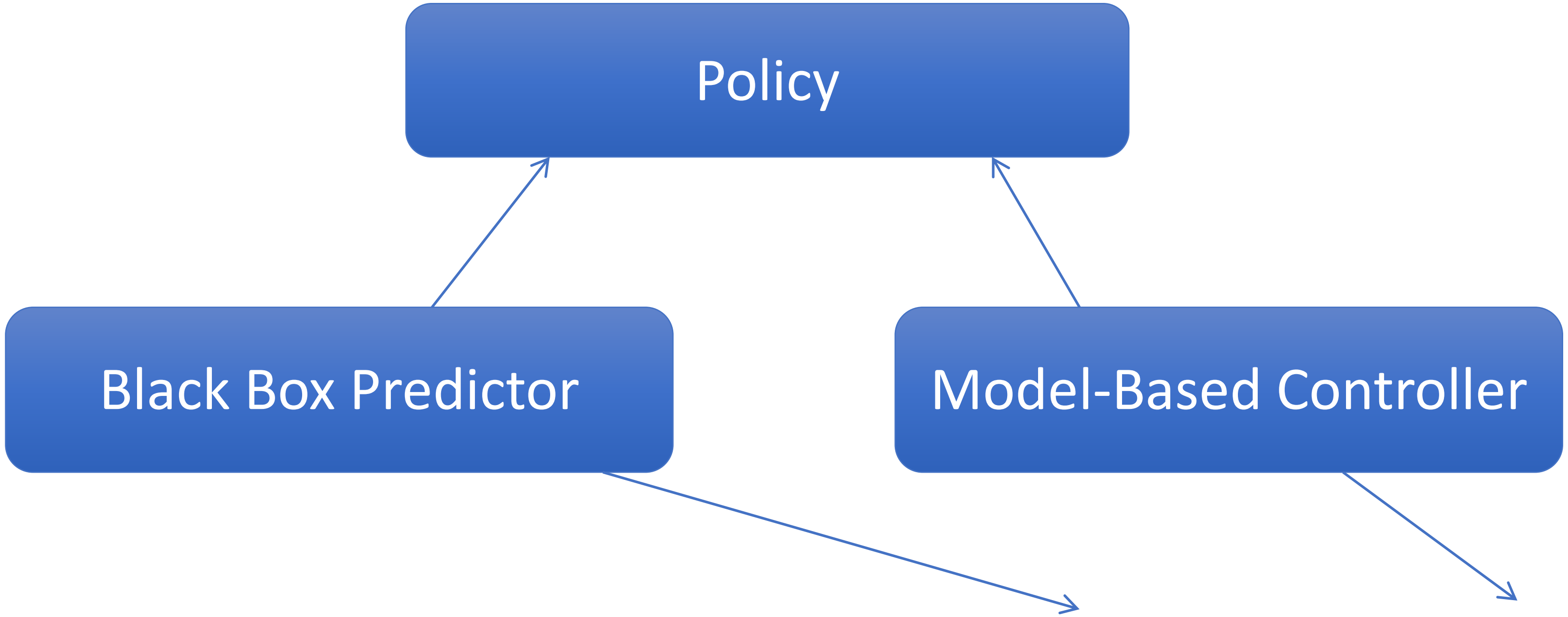
Smoothness

Key idea: G encodes domain knowledge & guarantees

Blended Policy Class (solution concept)

Hoang Le

Richard Cheng



$$\operatorname{argmin}_{h=(f,g)} L(h) \quad \text{s.t.} \quad h(s) = \operatorname{argmin}_{a'} (f(s) - a')^2 + \lambda (g(s) - a')^2$$

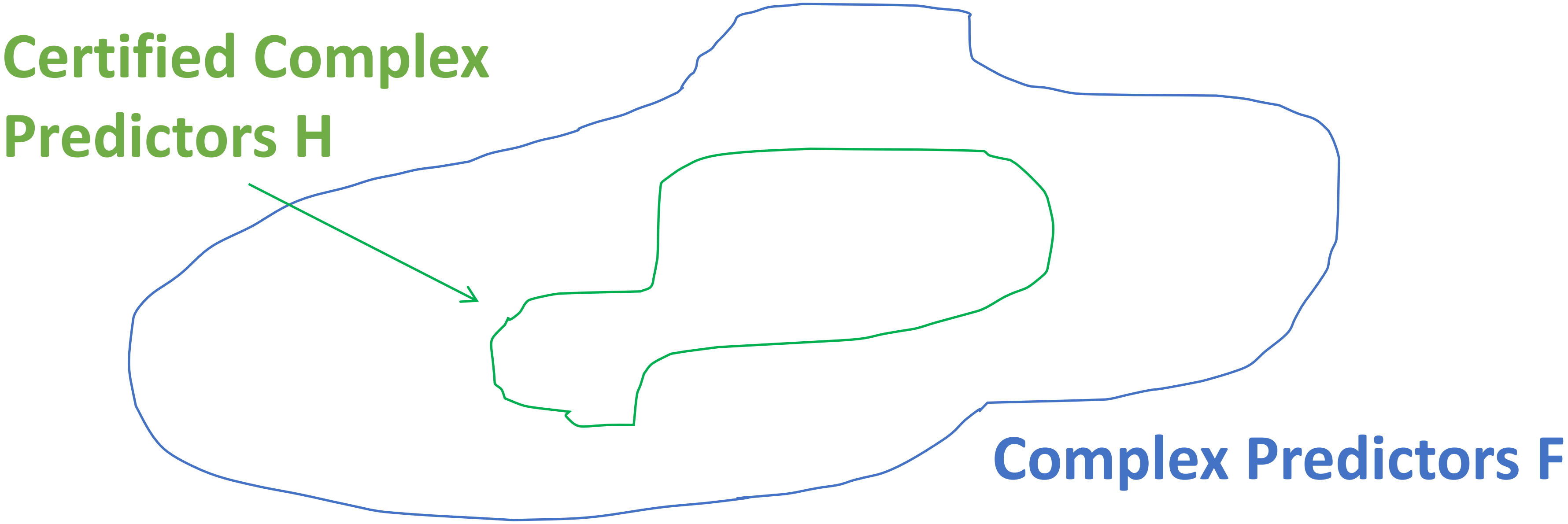
$$= \frac{f(s) + \lambda g(s)}{1+\lambda}$$

Smooth Imitation Learning for Online Sequence Prediction, Hoang Le, Andrew Kang, Yisong Yue, Peter Carr. ICML 2016

Control Regularization for Reduced Variance Reinforcement Learning, Richard Cheng, Abhinav Verma, et al. ICML 2019

Test-Time Functional Regularization

Hoang Le



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$$= \frac{f(s) + \lambda g(s)}{1 + \lambda}$$

Smooth Imitation Learning for Online Sequence Prediction
Hoang Le, Andrew Kang, Yisong Yue, Peter Carr. ICML 2016

Theoretical Guarantees

$$argmin_{h=(f,g)} L(h) \quad \text{s.t.} \quad h(s) = argmin_{a'} (f(s) - a')^2 + \lambda (g(s) - a')^2$$
$$= \frac{f(s) + \lambda g(s)}{1 + \lambda}$$

- By construction: h "close" to g
  - Certifications on g => (relaxed) certifications on h

Run-time regularization

- Compatible with IL/RL
  - New learning approaches

Convergence analysis

- Very data efficient

Low-Variance Gradients

Comments on Certified by Construction

$$h(s) = \frac{f(s)+\lambda g(s)}{1+\lambda}$$

- **Assumption:** all $g \in G$ are certified by construction
  - Robust against disturbances
  - Satisfied for many physical systems
- **Disturbance:** Black box predictor $f \in F$ is a "disturbance" of g
  - Worst-case disturbance depends $\max_s f(s)$ and λ
  - Guarantees worsen as λ decreases
- **Note:** local guarantee at the per-state level

Comments on Optimization/Learning

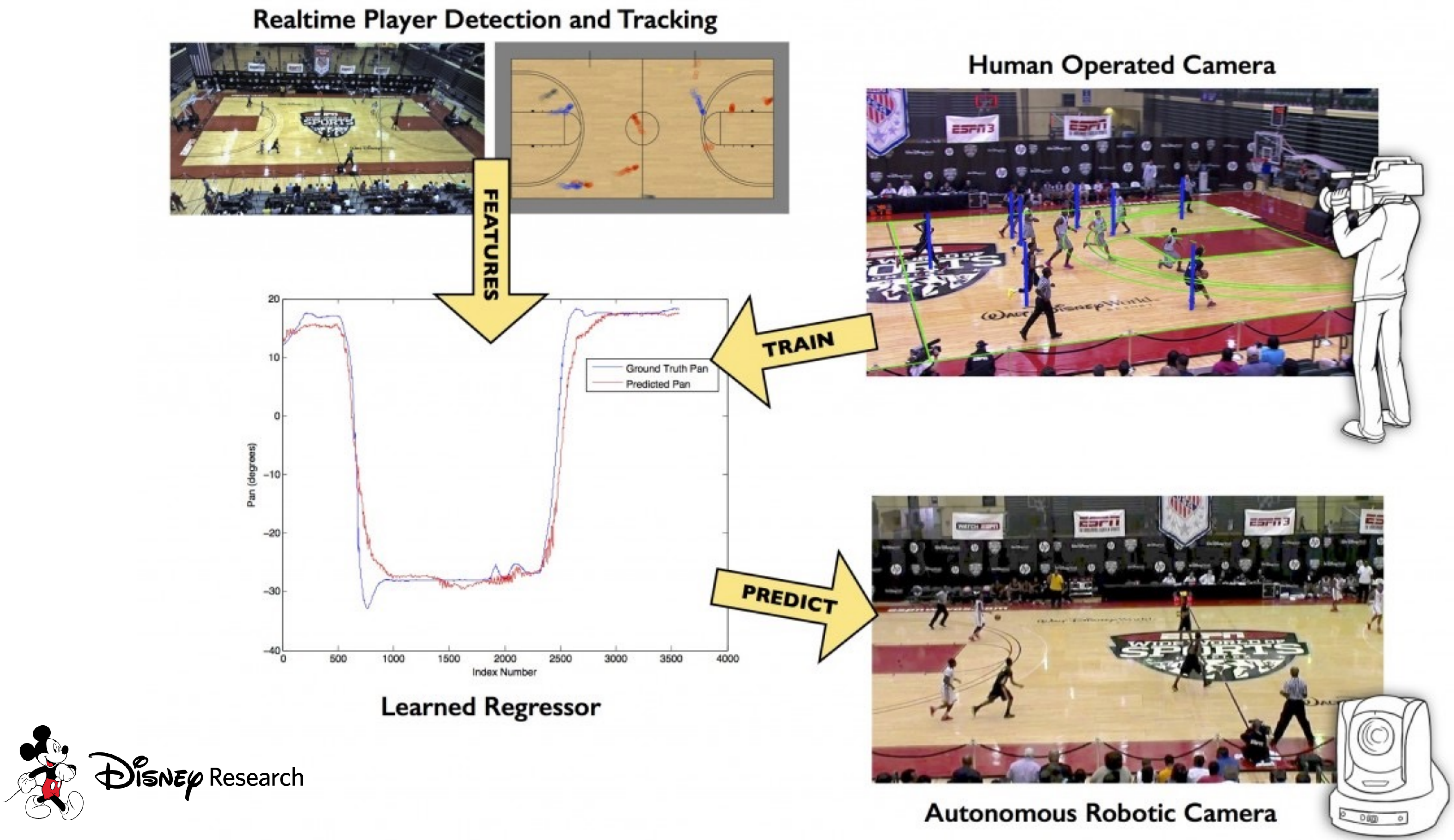
$$argmin_{h=(f,g)} L(h) \quad \text{s.t.} \quad h(s) = argmin_{a'} (f(s) - a')^2 + \lambda (g(s) - a')^2$$

$$= \frac{f(s)+\lambda g(s)}{1+\lambda}$$

- Alternating optimization
  - Hold g fixed, optimize f
  - Hold h fixed, optimize g
  - (see NeurIPS 2019 paper for clean treatment)

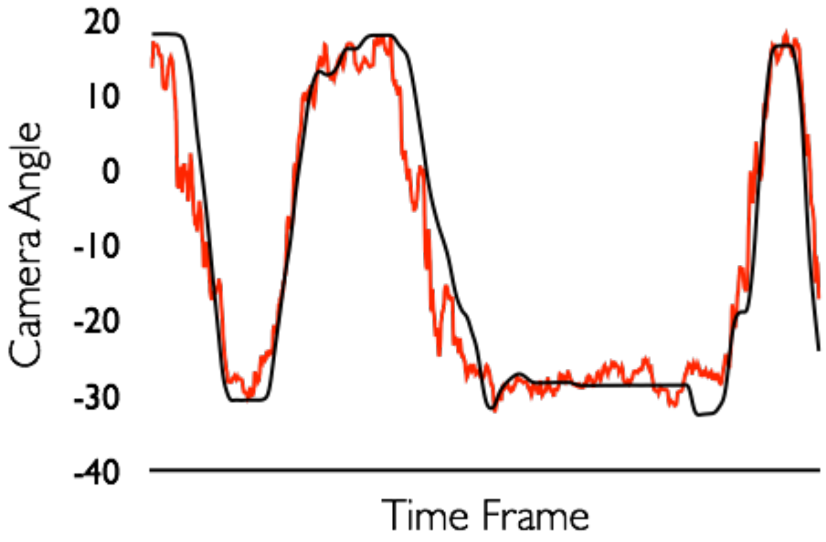
Reduces to "standard" approaches

Imitation-Projected Programmatic Reinforcement Learning
Abhinav Verma, Hoang Le, Yisong Yue, Swarat Chaudhuri. NeurIPS 2019

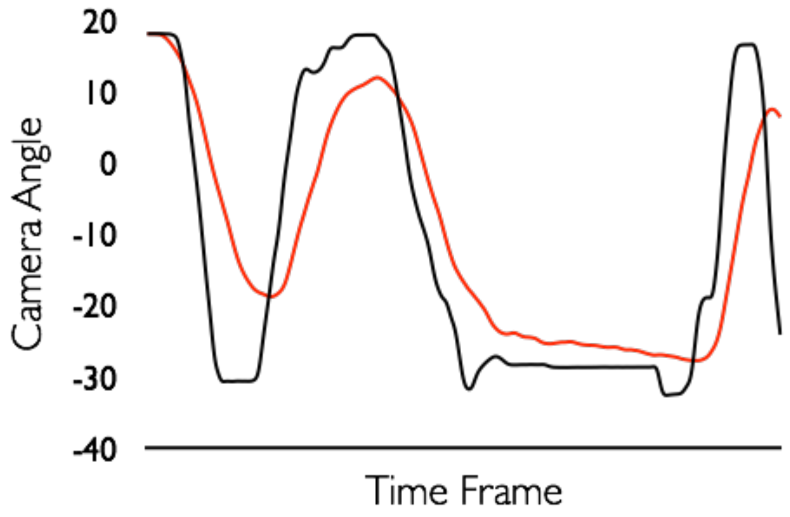

Realtime Player Detection and Tracking
FEATURES
Human Operated Camera
TRAIN
Ground Truth Pan
Predicted Pan
20
10
0
−10
−20
−30
−40
Pan (degrees)
0
500
1000
1500
2000
2500
3000
3500
4000
Index Number
Learned Regressor
PREDICT
Autonomous Robotic Camera
Disney Research

Naïve Approach

- Supervised learning of demonstration data
  - Train predictor per frame
  - Predict per frame

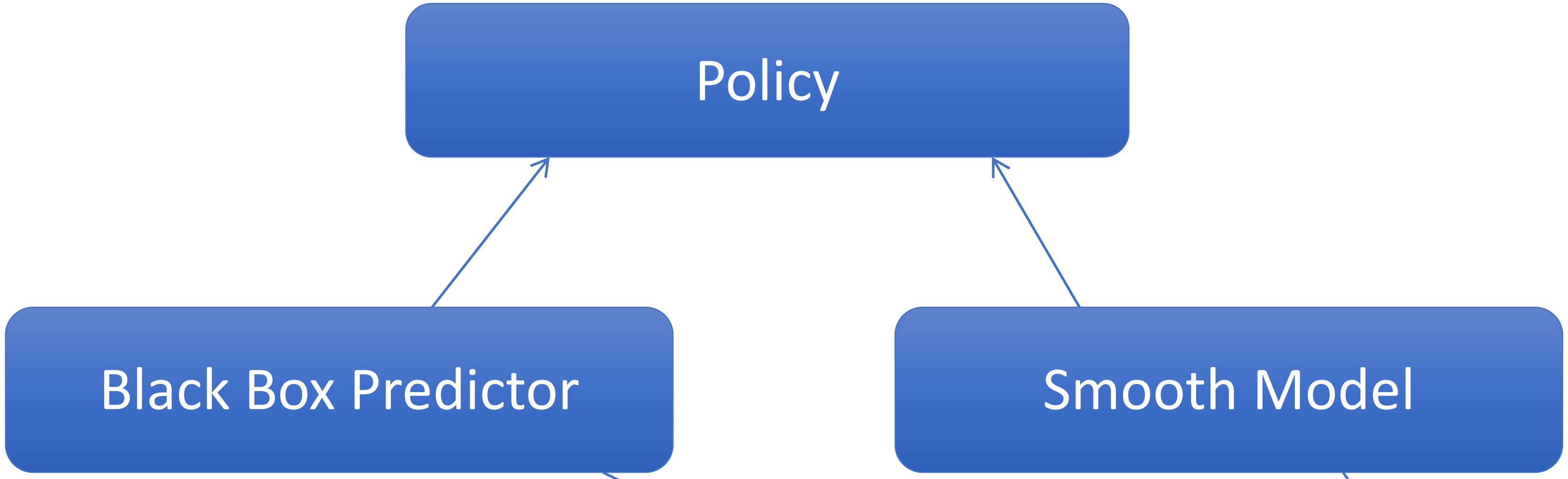


In practice, 2-step smoothing:



Smooth Policy Class

Hoang
Le



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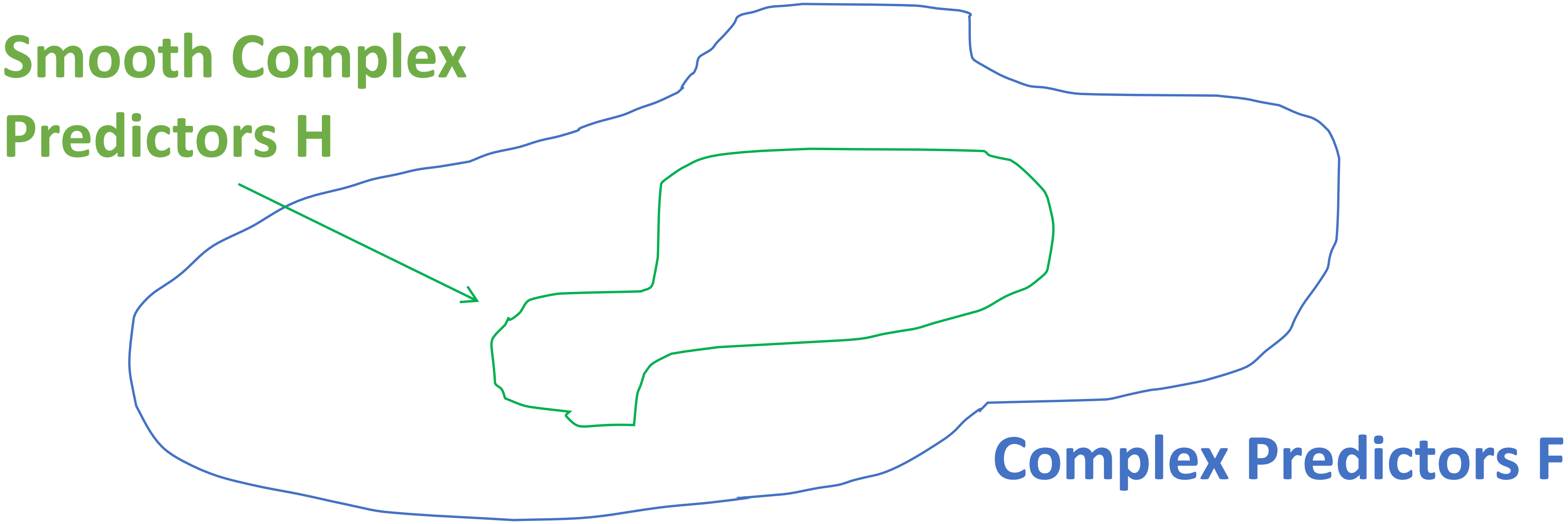
Test-Time Functional Regularization


Hoang
Le



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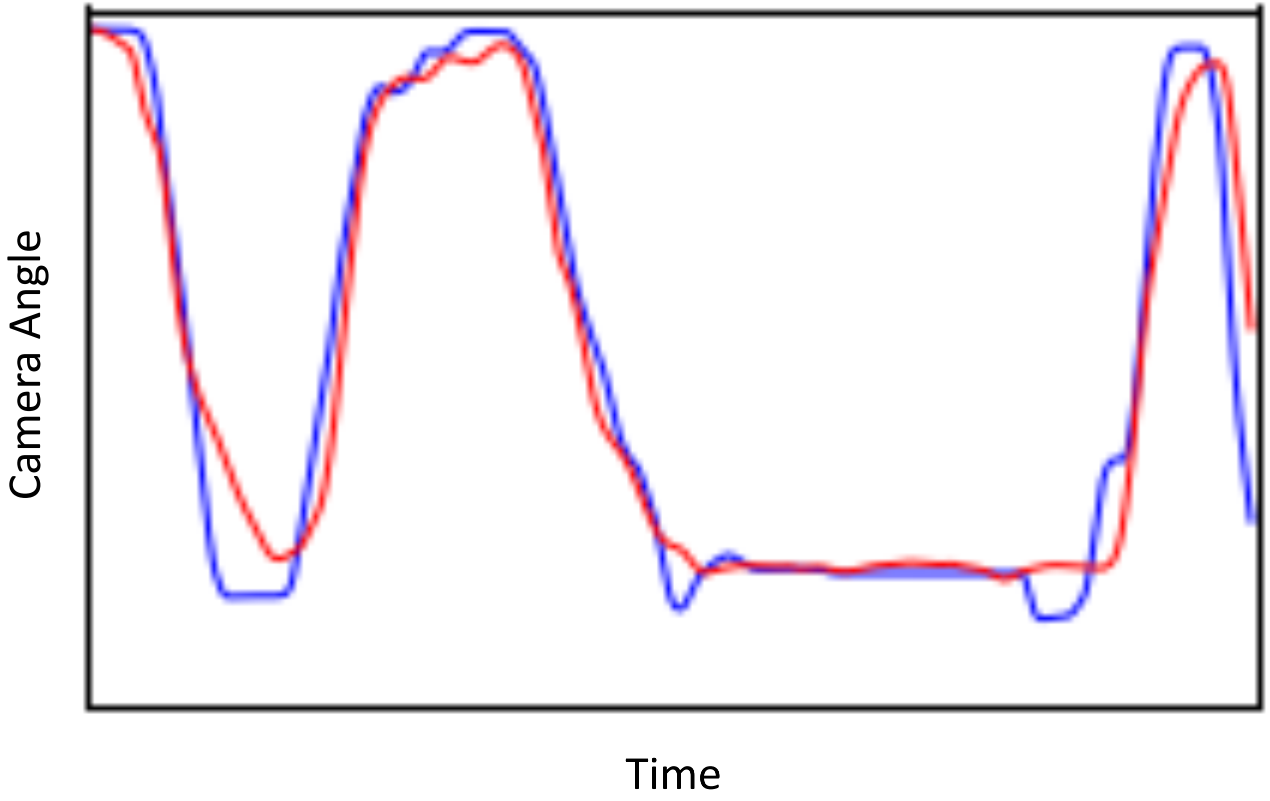
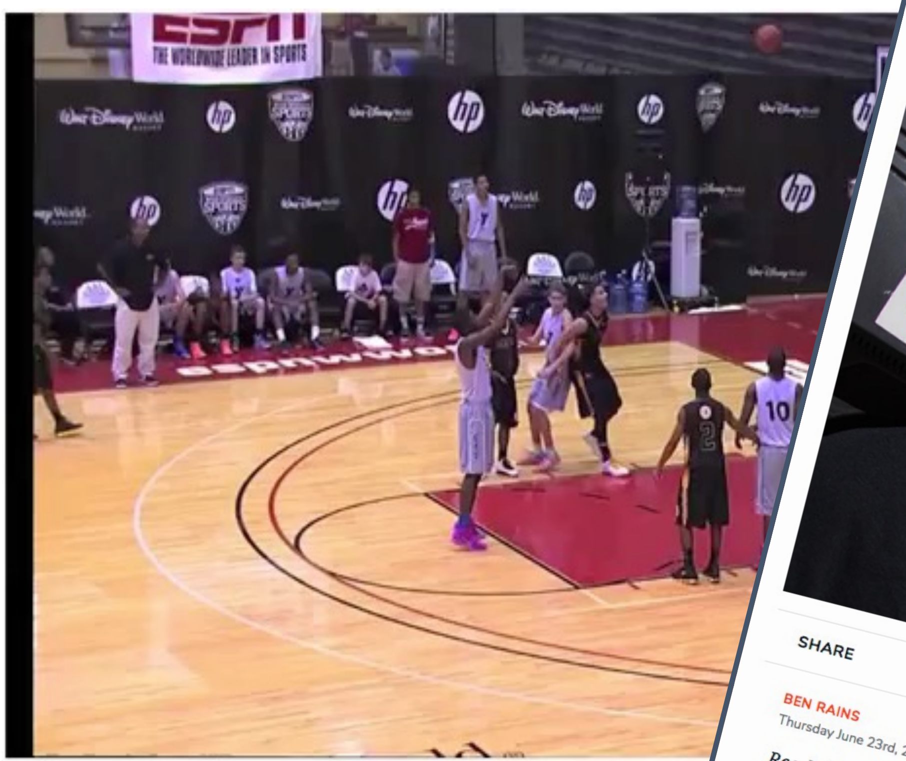
Smooth Imitation Learning for Online Sequence Prediction
Hoang Le, Andrew Kang, Yisong Yue, Peter Carr. ICML 2016

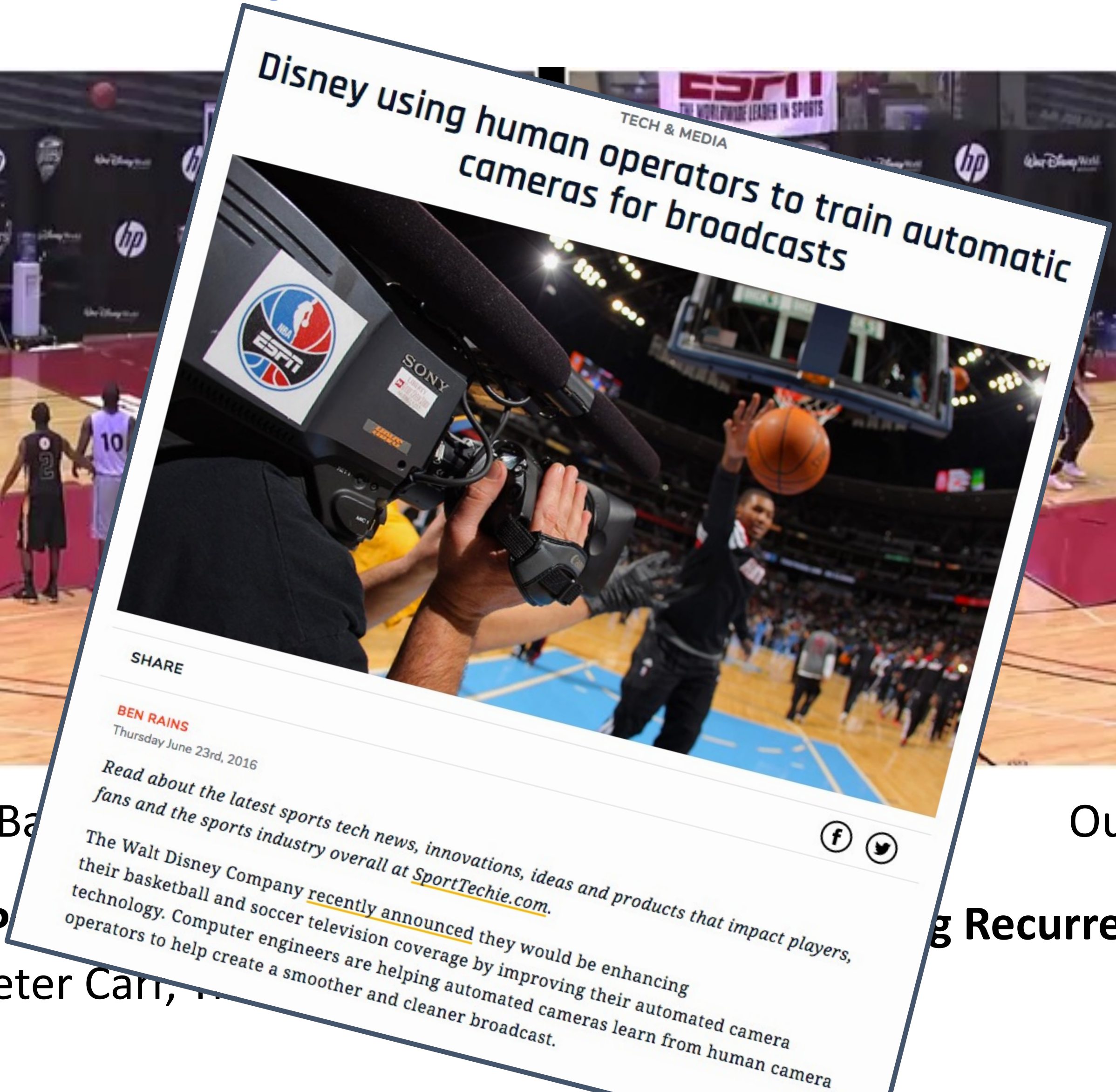
Our Results



Smooth Imitation Learning for Online Sequence Prediction
Hoang Le, Andrew Kang, Yisong Yue, Peter Carr. ICML 2016

Qualitative Comparison





Disney using human operators to train automatic cameras for broadcasts

TECH & MEDIA

SHARE

BEN RAINS
Thursday June 23rd, 2016

Read about the latest sports tech news, innovations, ideas and products that impact players, fans and the sports industry overall at SportTechie.com.

The Walt Disney Company recently announced they would be enhancing their basketball and soccer television coverage by improving their automated camera technology. Computer engineers are helping automated cameras learn from human camera operators to help create a smoother and cleaner broadcast.

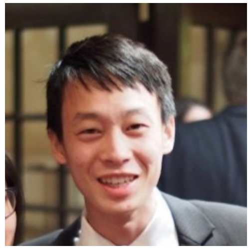
2-Step Ba

Our Approach

Learning Online Smooth P **g Recurrent Decision Trees**

Jianhui Chen, Hoang Le, Peter Carr,

Control Regularization



Richard Cheng

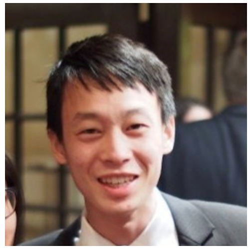
$$h(s) = \frac{f(s)+\lambda g(s)}{1+\lambda}$$

- f is black box
- g is "control prior"   (e.g., H-infinity controller)

- Learn f using any RL method

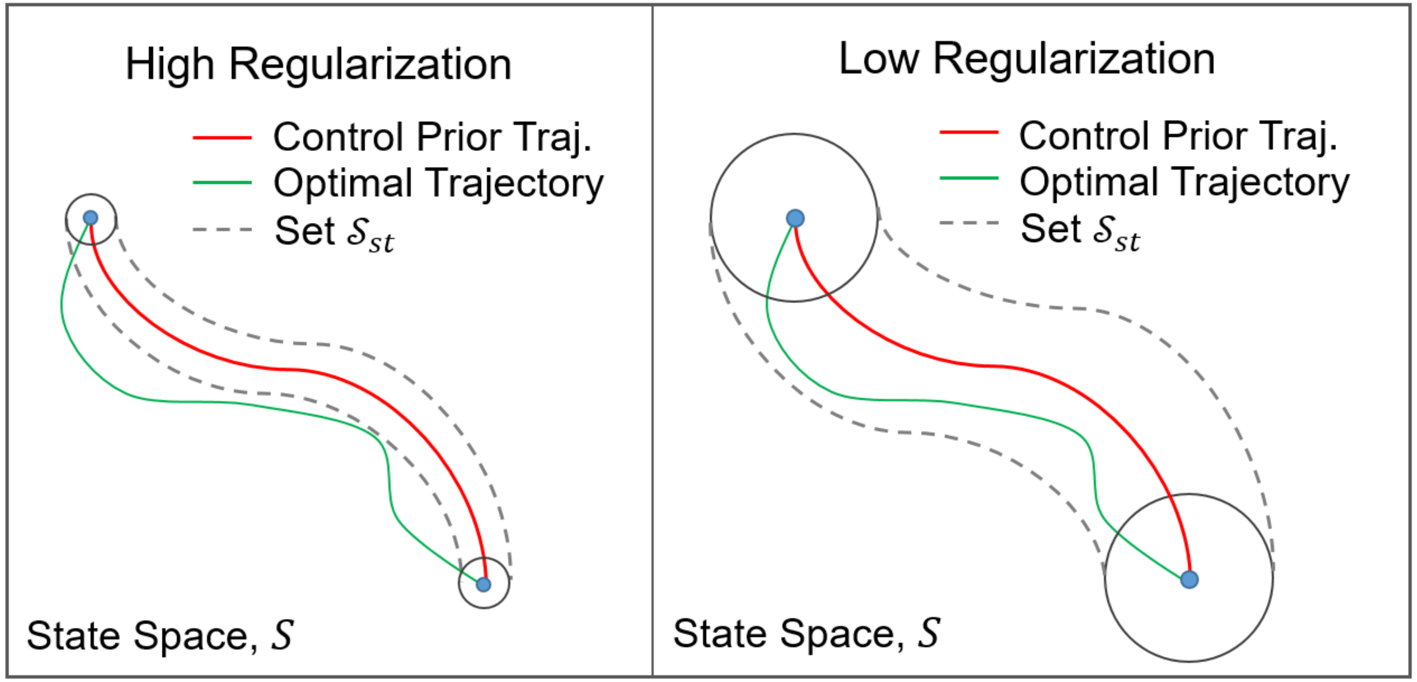
Control Regularization for Reduced Variance Reinforcement Learning
Richard Cheng, Abhinav Verma, Gabor Orosz, Swarat Chaudhuri, Yisong Yue, Joel Burdick. ICML 2019

Control Regularization



Richard Cheng

- (Relaxed) Lyapunov stability bounds:



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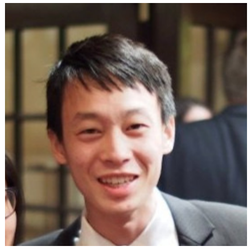


Richard Cheng

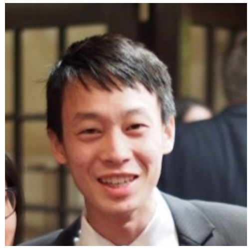
$$h(s) = \frac{f(s)+\lambda g(s)}{1+\lambda}$$

- Theorem (informal):
  - Variance of policy gradient decreases by factor of: $\left(\frac{1}{1+\lambda}\right)^2$
  - Bias converges to: $\left(\frac{\lambda}{1+\lambda}\right) D_{TV}(h^*, g)$

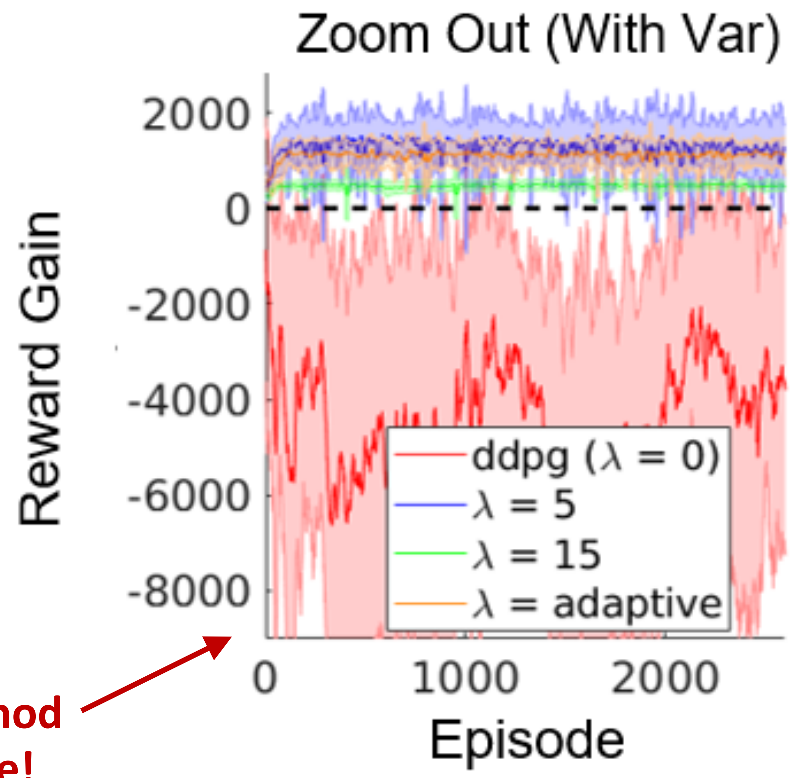
Implies much faster learning!

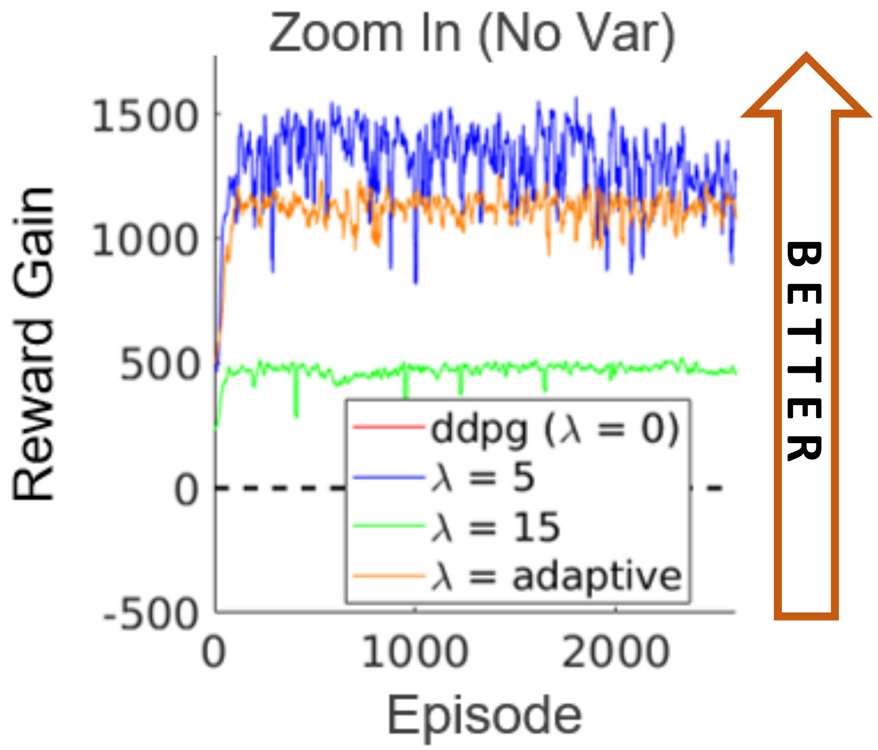
Control Regularization for Reduced Variance Reinforcement Learning
Richard Cheng, Abhinav Verma, Gabor Orosz, Swarat Chaudhuri, Yisong Yue, Joel Burdick. ICML 2019

Control Regularization



Richard Cheng





Baseline RL Method has High Variance!

Control Regularization for Reduced Variance Reinforcement Learning
Richard Cheng, Abhinav Verma, Gabor Orosz, Swarat Chaudhuri, Yisong Yue, Joel Burdick. ICML 2019


Ready
3 4 5 6 7
120 180 240

Ready
3 4 5 6 7
120 180 240

Summary: Functional Regularization

Regularization ↔ Constrained Learning

$$argmin_h L(h)$$
$$s.t.$$
$$R(h) < \kappa$$

⟺

$$argmin_h L(h) + \lambda R(h)$$

IL/RL Objective

Side Guarantees

Hybrid Policy Solution Concept

$$h(s) = argmin_{a'} (f(s) - a')^2 + \lambda (g(s) - a')^2$$
$$= \frac{f(s) + \lambda g(s)}{1 + \lambda}$$

Summary: Functional Regularization (cont.)

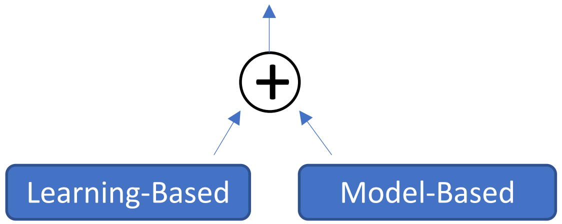
- Control methods => analytic guarantees (side guarantees)
- Blend w/ learning => improve precision/flexibility (real-world improvements)
- Preserve side guarantees (possibly relaxed)
- Interpret as functional regularization (speeds up learning)
- Other directions:

  Batch Policy Learning under Constraints
  Hoang Le, Cameron Voloshin, Yisong Yue. ICML 2019 (offline learning)

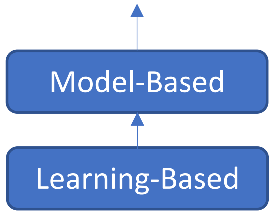
  Imitation-Projected Programmatic Reinforcement Learning
  Abhinav Verma, Hoang Le, Yisong Yue, Swarat Chaudhuri. NeurIPS 2019 (programmatic controllers)

Integration of Learning at Varying Levels

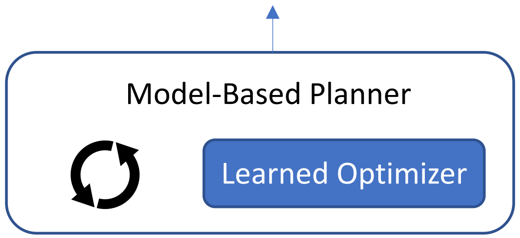
- Integration in control/action



- Integration in dynamics modeling



- Integration in optimization problem



Model-Based Control

New State

Current Action (aka control input)

$$s_{t+1} = F(s_t, u_t) + \epsilon$$

Current State

Unmodeled Disturbance / Error

(Value Iteration is also contraction mapping)

Robust/Optimal Control (fancy contraction mappings)

- Stability guarantees (e.g., Lyapunov)
- Precision/optimality depends on error

Learning Residual Dynamics

F = nominal dynamics
$\tilde{F}$ = learned dynamics

New State

Current Action (aka control input)

$$s_{t+1} = F(s_t, u_t) + \tilde{F}(s_t, u_t) + \epsilon(s_t, u_t)$$

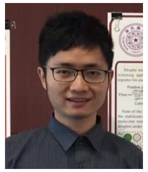
Current State

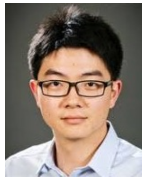
Unmodeled Disturbance / Error

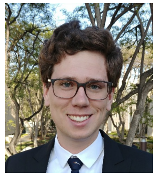
Leverage robust/optimal control (fancy contraction mappings)

- Preserve stability (even using deep learning)
- Requires $\tilde{F}$ Lipschitz & bounded error

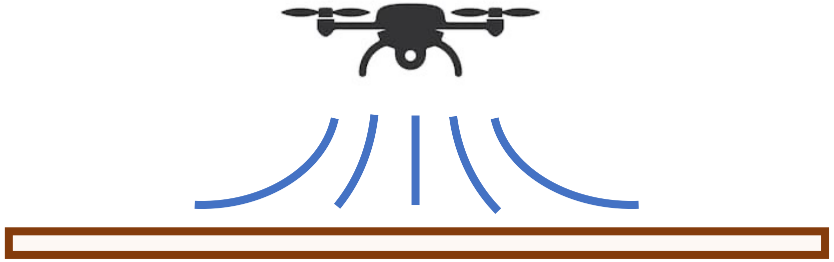
Stable Drone Landing

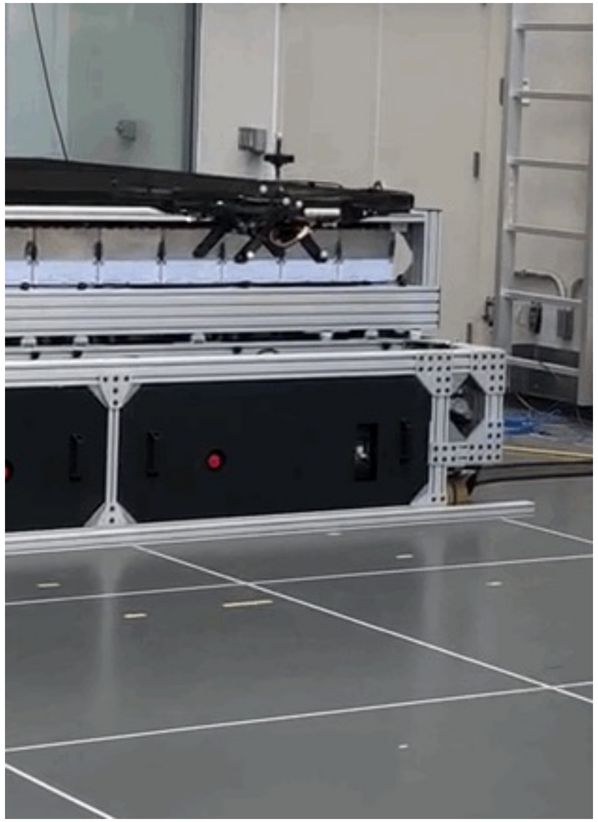

Guanya Shi


Xichen Shi


Michael O'Connell

Ground effect





Neural Lander: Stable Drone Landing Control using Learned Dynamics
Guanya Shi, Xichen Shi, Michael O'Connell, Rose Yu, Kamyar Azizzadenesheli, Anima Anandkumar, Yisong Yue, Soon-Jo Chung. ICRA 2019

Control System Formulation

Learn the Residual

- Dynamics:

$$\begin{cases} \dot{\mathbf{p}} = \mathbf{v}, & m\dot{\mathbf{v}} = m\mathbf{g} + R\mathbf{f}_u + \mathbf{f}_a \\ \dot{R} = RS(\boldsymbol{\omega}), & J\dot{\boldsymbol{\omega}} = J\boldsymbol{\omega} \times \boldsymbol{\omega} + \boldsymbol{\tau}_u + \boldsymbol{\tau}_a \end{cases}$$

- Control:

$$\begin{cases} \mathbf{f}_u = [0, 0, T]^\top \\ \boldsymbol{\tau}_u = [\tau_x, \tau_y, \tau_z]^\top \\ \begin{bmatrix} T \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} = \begin{bmatrix} c_T & c_T & c_T & c_T \\ 0 & c_T l_{\text{arm}} & 0 & -c_T l_{\text{arm}} \\ -c_T l_{\text{arm}} & 0 & c_T l_{\text{arm}} & 0 \\ -c_Q & c_Q & -c_Q & c_Q \end{bmatrix} \begin{bmatrix} n_1^2 \\ n_2^2 \\ n_3^2 \\ n_4^2 \end{bmatrix} \end{cases}$$

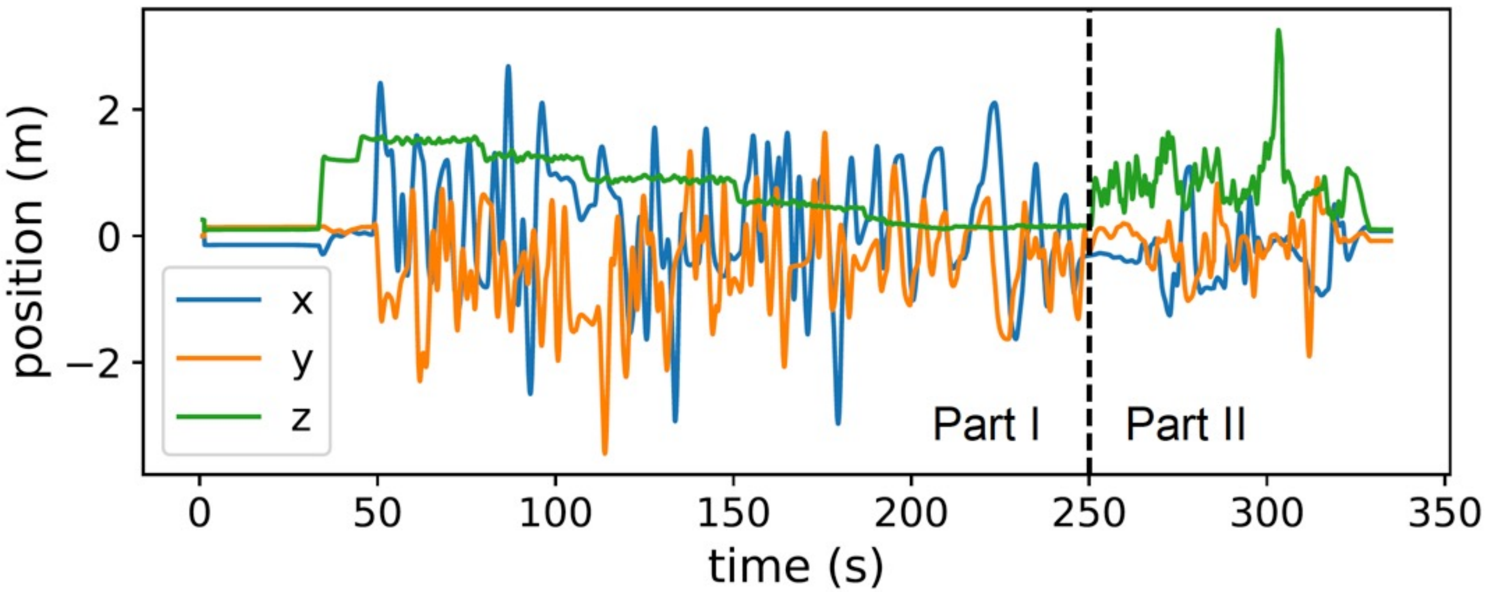
- Unknown forces & moments:

$$\begin{cases} \mathbf{f}_a = [f_{a,x}, f_{a,y}, f_{a,z}]^\top \\ \boldsymbol{\tau}_a = [\tau_{a,x}, \tau_{a,y}, \tau_{a,z}]^\top \end{cases}$$

Learn the Residual

Data Collection (Manual Exploration)

Notable Extension:
Safe Exploration

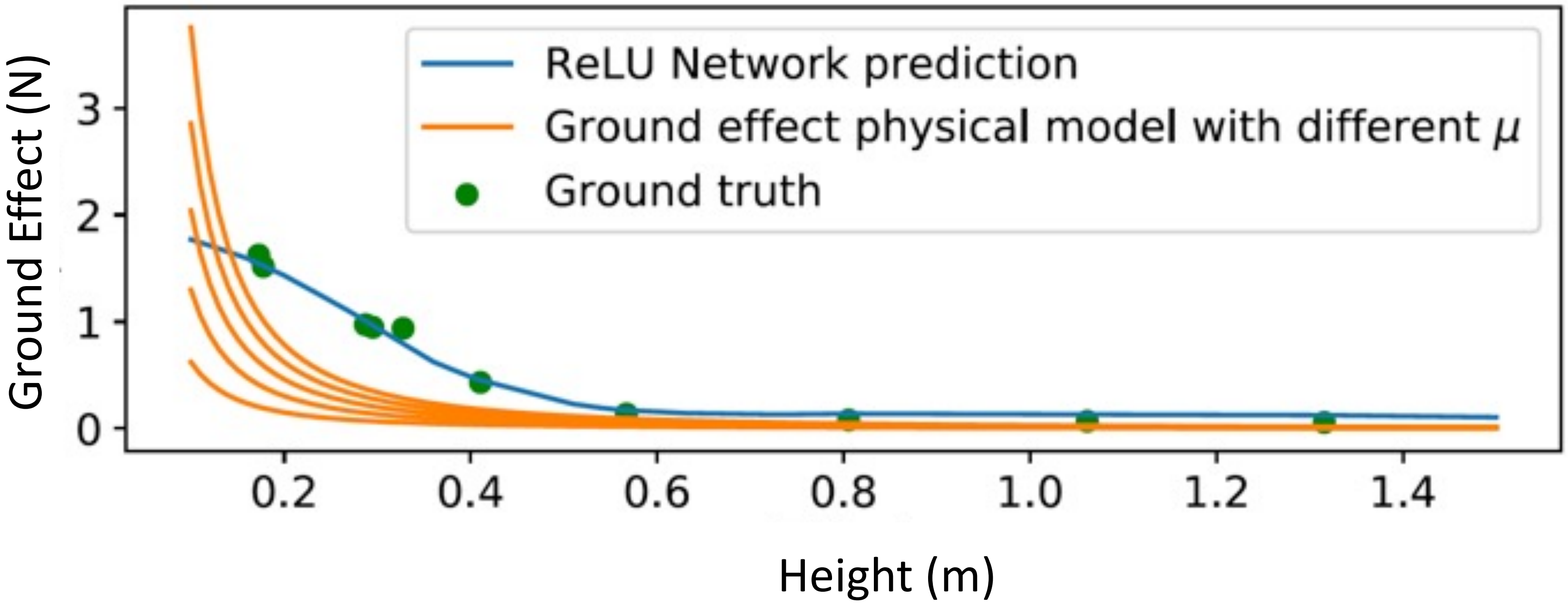


Ensures $\widetilde{F}$ is Lipshitz
[Bartlett et al., NeurIPS 2017]
[Miyato et al., ICLR 2018]

Spectral-Normalized 4-Layer Feed-Forward

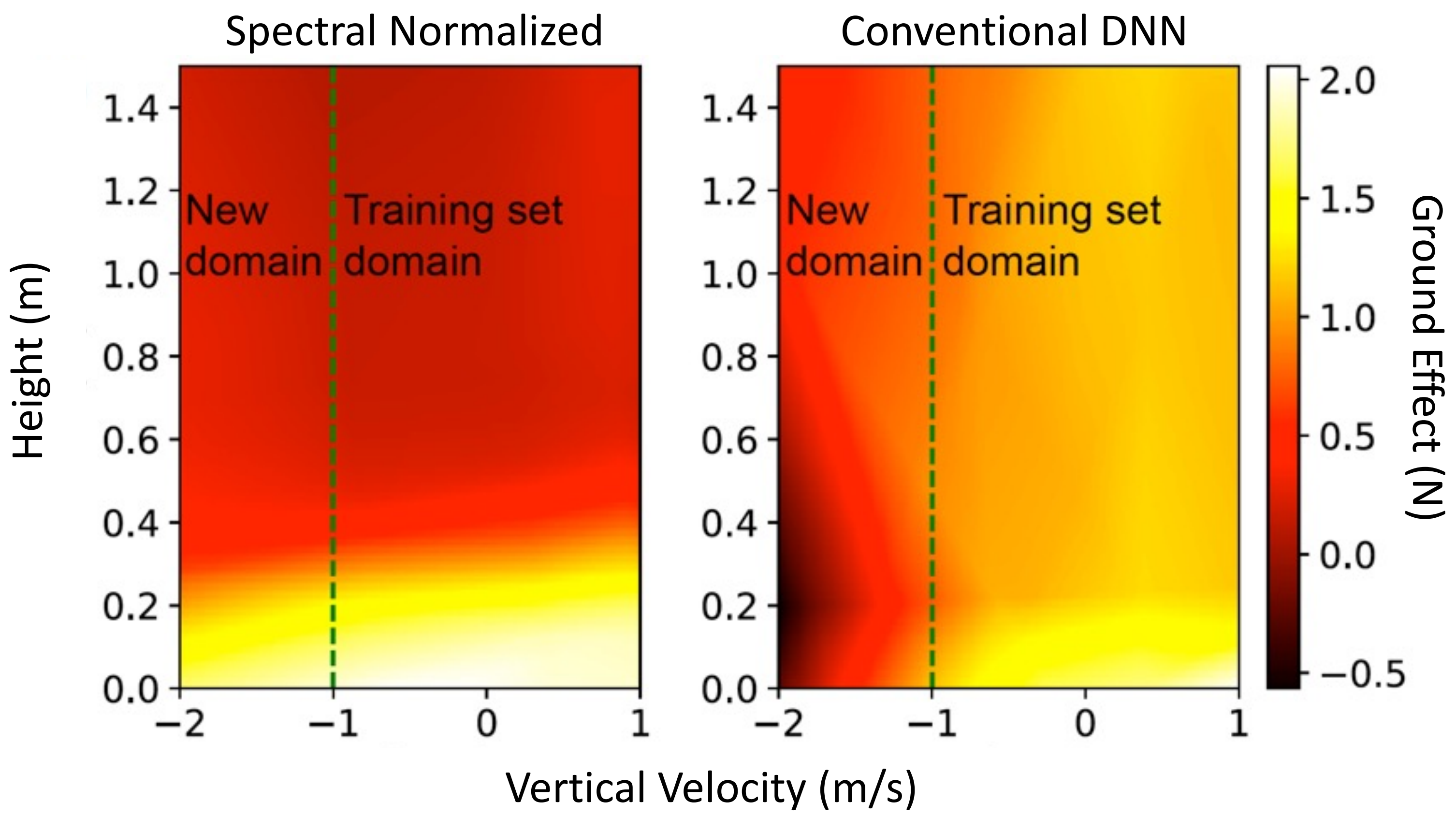
- Learn ground effect: $\tilde{F}(s,u) \rightarrow \quad \mathbf{f}_a = [f_{a,x}, f_{a,y}, f_{a,z}]^\top$
- (s,u): height, velocity, attitude and four control inputs

Prediction Results



Neural Lander: Stable Drone Landing Control using Learned Dynamics
Guanya Shi, Xichen Shi, Michael O'Connell, Rose Yu, Kamyar Azizzadenesheli, Anima Anandkumar, Yisong Yue, Soon-Jo Chung. ICRA 2019.

Prediction Results



Neural Lander: Stable Drone Landing Control using Learned Dynamics
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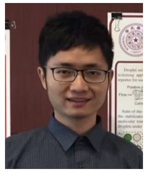
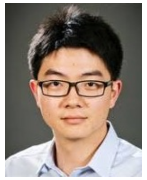
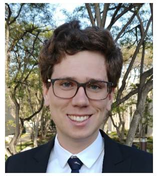

Guanya Shi


Xichen Shi


Michael O'Connell

Controller Design (simplified)

- Nonlinear Feedback Linearization:

$$u_{nominal} = K_s \eta \qquad \eta = \begin{bmatrix} p - p^* \\ v - v^* \end{bmatrix}$$

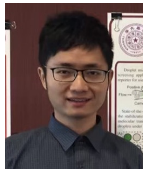
Desired Trajectory
(tracking error)

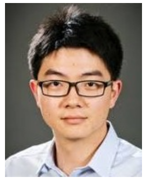
Feedback Linearization (PD control)

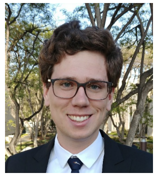
- Cancel out ground effect $\tilde{F}(s, u_{old})$: $u = u_{nominal} + u_{residual}$

Requires Lipschitz & small time delay

Controller Design (simplified)


Guanya Shi


Xichen Shi


Michael O'Connell

- Nonlinear Feedback Linearization:

$$u_{nominal} = K_s \eta \qquad \eta = \begin{bmatrix} p - p^* \\ v - v^* \end{bmatrix}$$

Desired Trajectory
(tracking error)

Stability Guarantee:
(simplified)

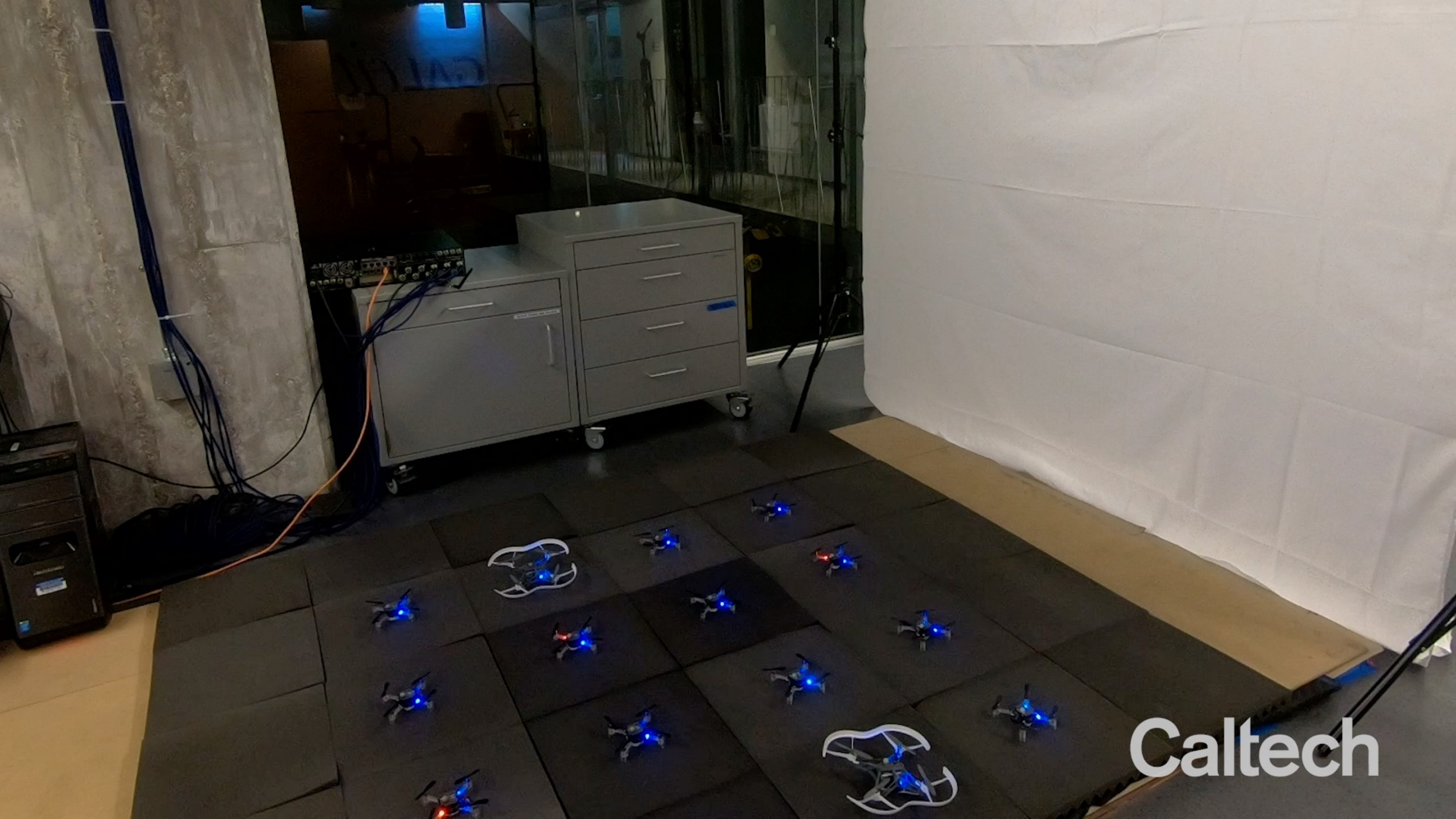
Time delay

Unmodeled disturbance

$$\|\eta(\mathrm{t})\| \le \|\eta(0)\| \exp\left\{\frac{\lambda_{min}(K) - \tilde{L}\rho}{C} t\right\} + \frac{\epsilon}{\lambda_{min}(K) - \tilde{L}\rho}$$

Lipschitz of NN

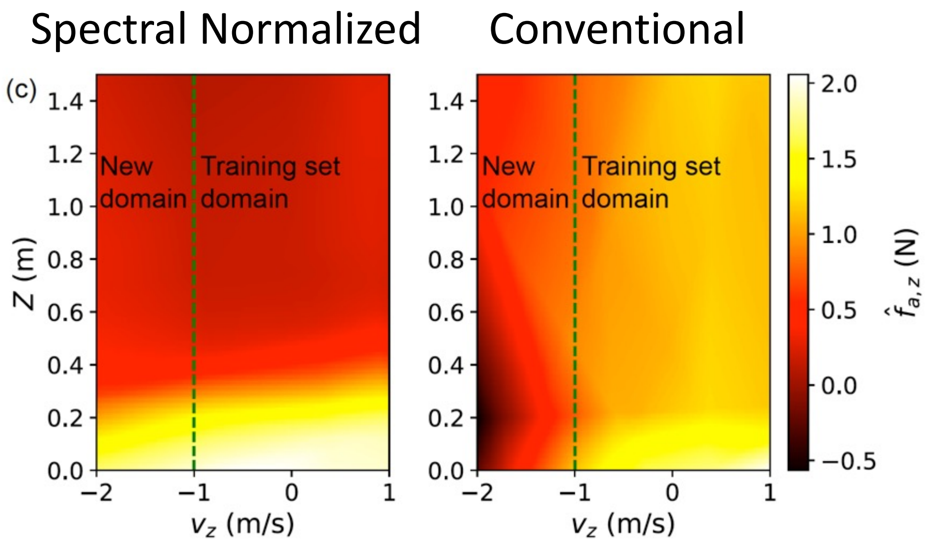
$$\Longrightarrow \|\eta(\mathrm{t})\| \to \frac{\epsilon}{\lambda_{min}(K) - \tilde{L}\rho}$$ Exponentially fast

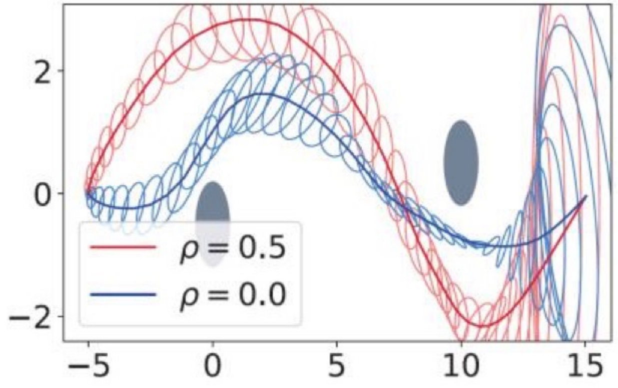

Caltech

Aside: Robust Regression for Safe Exploration

- Robust regression for provable extrapolation => Safe Exploration!

Robust regression guarantees low error!

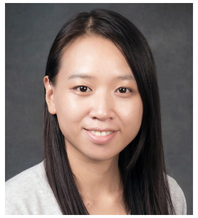




Provably safe trajectory planning for exploration!

Robust Regression for Safe Exploration in Control,
Angie Liu, Guanya Shi, Soon-Jo Chung, Anima Anandkumar, Yisong Yue, L4DC 2020

Chance-Constrained Trajectory Optimization for Safe Exploration and Learning of Nonlinear Systems,
Yashwanth Kumar Nakka, Angie Liu, Guanya Shi, Anima Anandkumar, Yisong Yue, Soon-Jo Chung, R-AL 2021



Angie Liu

Yashwanth Nakka

Aside: Learning Control Lyapunov/Barrier Functions

- CLFs & CBFs encode low-dimensional projection of dynamics
  - DOF of action space rather than state space
  - Can be easier to learn than full dynamics

- How to learn CLF/CBF for controller design?
- How to analyze stability/safety under uncertainty?

Andrew Taylor

Victor Dorobantu

Episodic Learning with Control Lyapunov Functions for Uncertain Robotic Systems
Andrew J. Taylor, Victor D. Dorobantu, Hoang M. Le, Yisong Yue, Aaron D. Ames. IROS 2019.

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Learning for Safety-Critical Control with Control Barrier Functions
Andrew Taylor, Andrew Singletary, Yisong Yue, Aaron Ames. L4DC 2020.

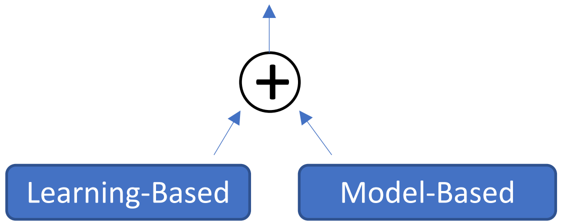
A Control Barrier Perspective on Episodic Learning via Projection-to-State Safety
Andrew J. Taylor, Andrew Singletary, Yisong Yue, Aaron D. Ames. L-CSS 2020.

Summary: Dynamics Learning

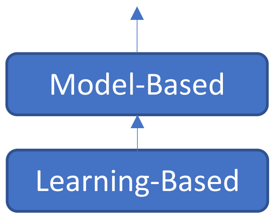
- Learn residual dynamics (data efficient)
- Control Lipschitz constant (imposes compatible structure)
- Standard controller design (inherits guarantees)
- Robust regression for safe exploration (provable limited extrapolation)

Integration of Learning at Varying Levels

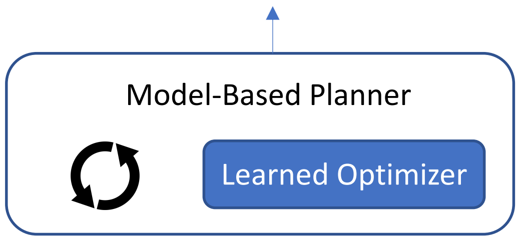
- Integration in control/action



- Integration in dynamics modeling



- Integration in optimization problem

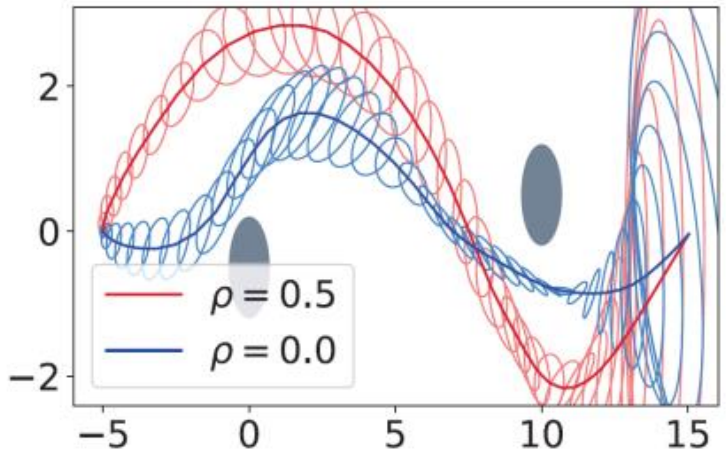


Model-Based Planning

- Environment model is given

$$s_{t+1} = F(s_t, u_t) + \epsilon$$

- Design global plan (aka trajectory)
- Satisfy global constraints
  - Previous topics only ensured local constraints
  - E.g., Lyapunov stability, smoothness
- **NP-Hard optimization problem!**



Optimization as Sequential Decision Making

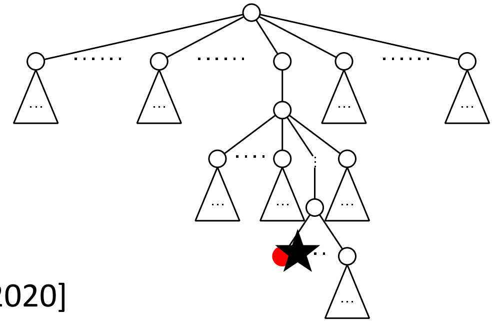
- Many Solvers are Sequential
  - Tree-Search
  - Greedy
  - Gradient Descent

- Can view solver as “agent” or “policy”
  - State = intermediate solution
  - Find a state with high reward (solution)
  - **Learn better local decision making**

Optimization as Sequential Decision Making

Learning to Search/Plan

- **Learning to Search via Retrospective Imitation** [arXiv]
- **Co-training for Policy Learning** [UAI 2019]
- **GLAS: Global-to-Local Safe Autonomy Synthesis** [RA-L 2020]
- **A General Large Neighborhood Search Framework for Solving Integer Programs** [NeurIPS 2020]

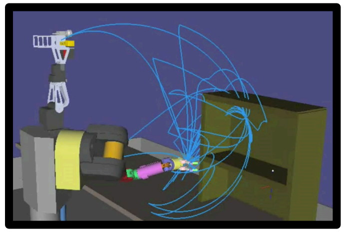


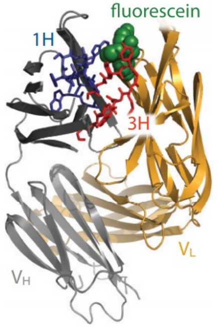
Jialin Song

Ben Riviere

Submodular Maximization

- **Learning Policies for Contextual Submodular Prediction** [ICML 2013]
- **Learning to Make Decisions via Submodular Regularization** [ICLR 2021]



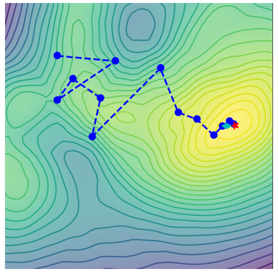


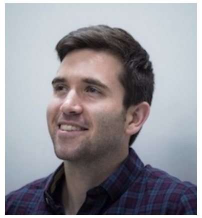
Ayya Alieva

Stephane Ross

Learning to Infer

- **Iterative Amortized Inference** [ICML 2018]
- **A General Method for Amortizing Variational Filtering** [NeurIPS 2018]
- **Iterative Amortized Policy Optimization** [arXiv]





Joe Marino

Optimization as Sequential Decision Making

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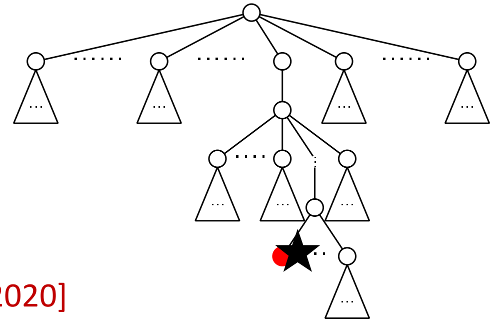

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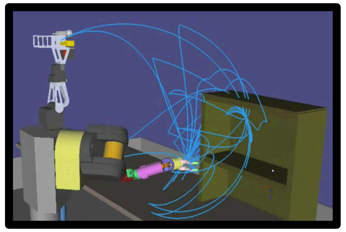

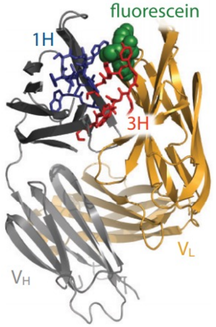

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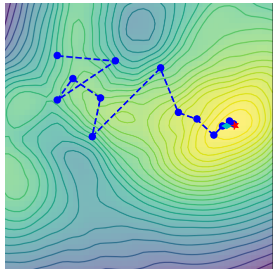
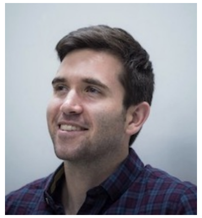
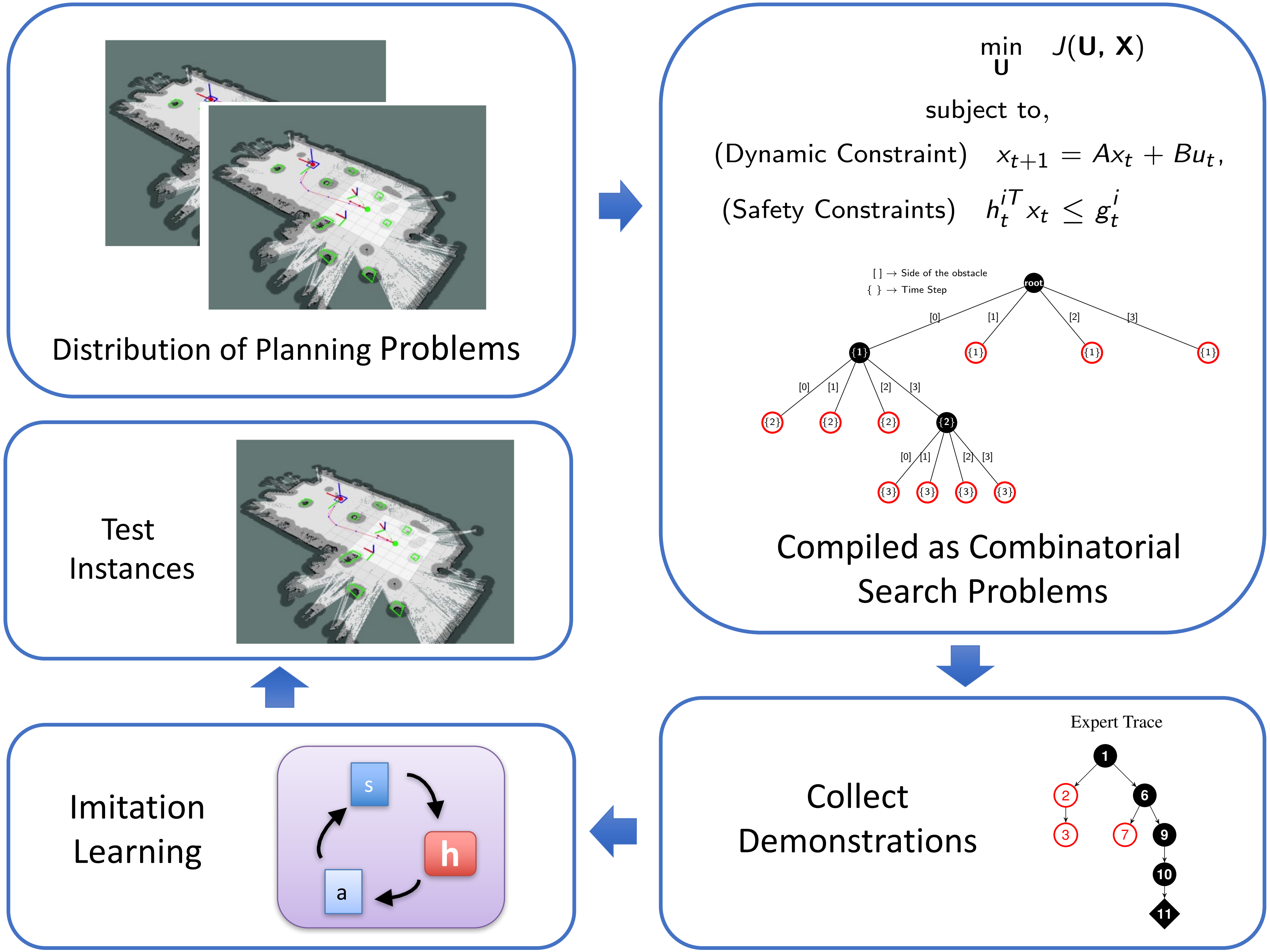




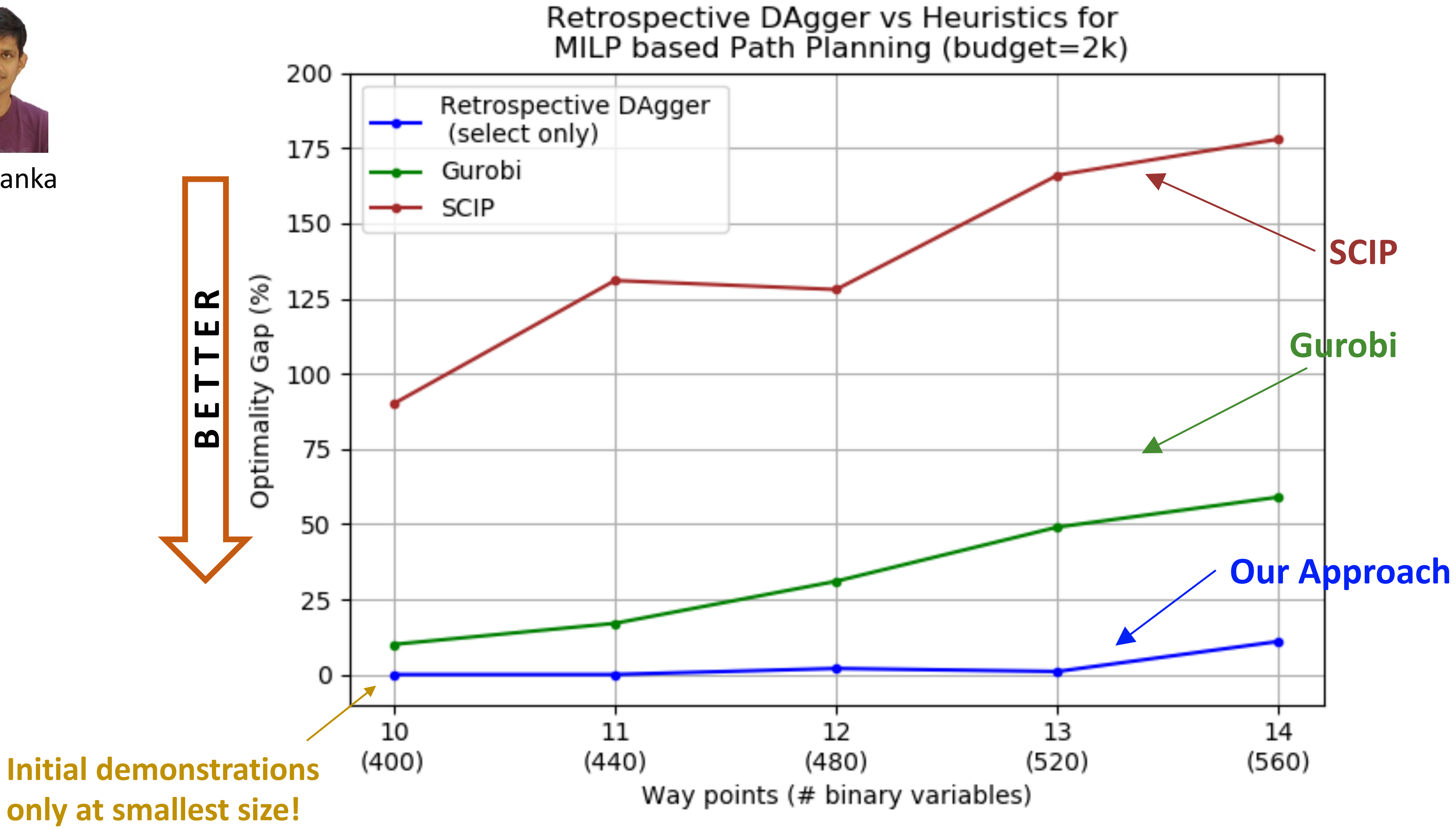
Joe Marino

Ravi Lanka



Jialin Song

Ravi Lanka

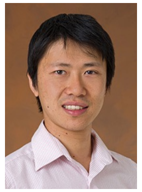


Jialin Song

Learning to Search via Retrospective Imitation, Jialin Song, Ravi Lanka, et al., arXiv

Ongoing: ENav Integration

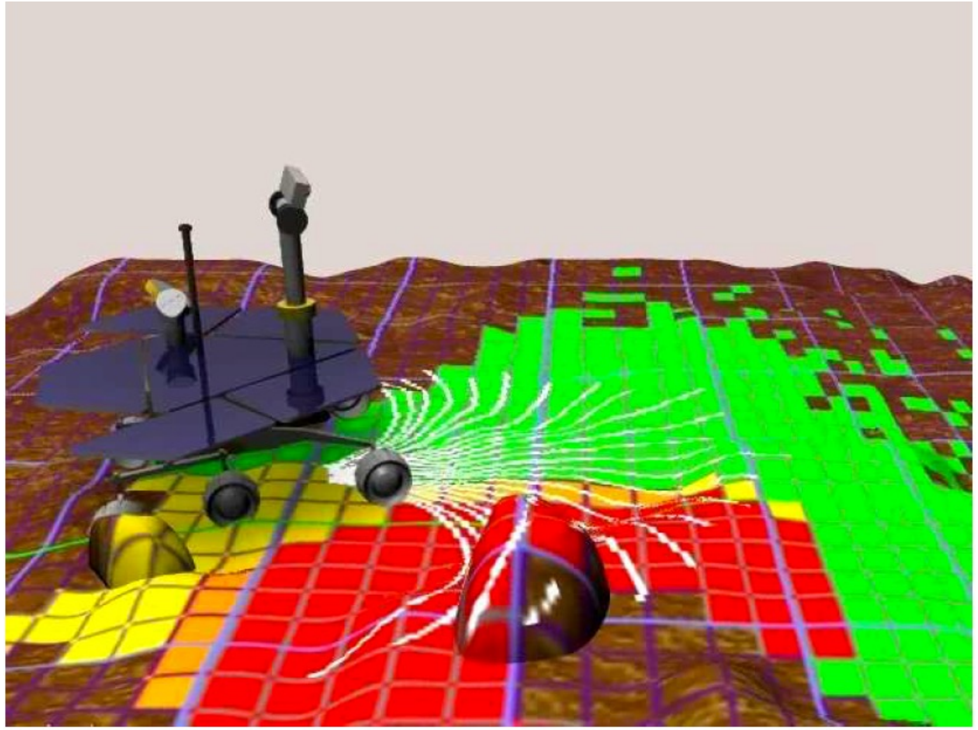

Shreyansh Daftry

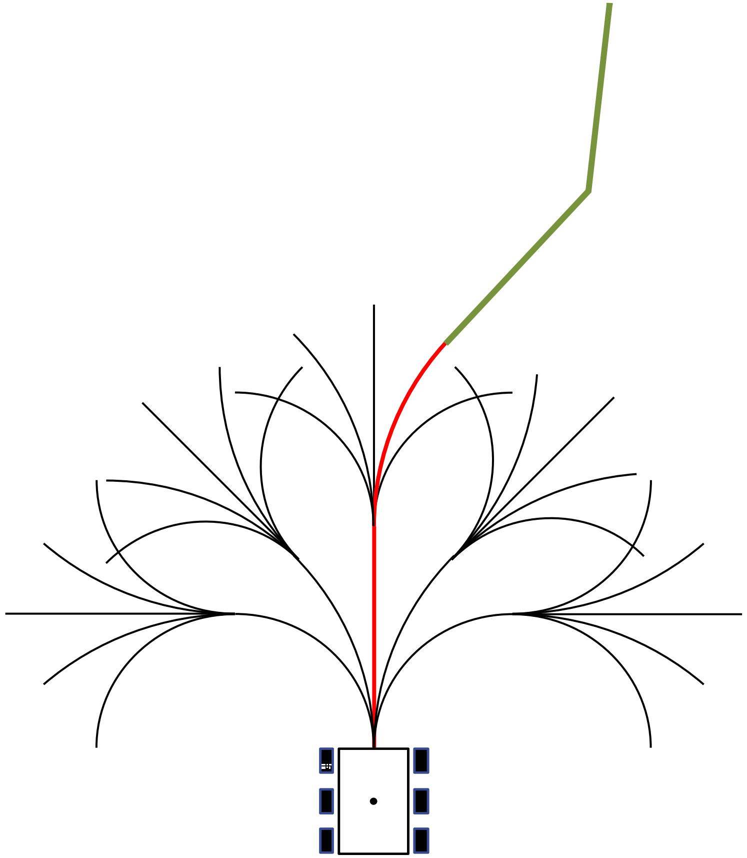

Hiro Ono

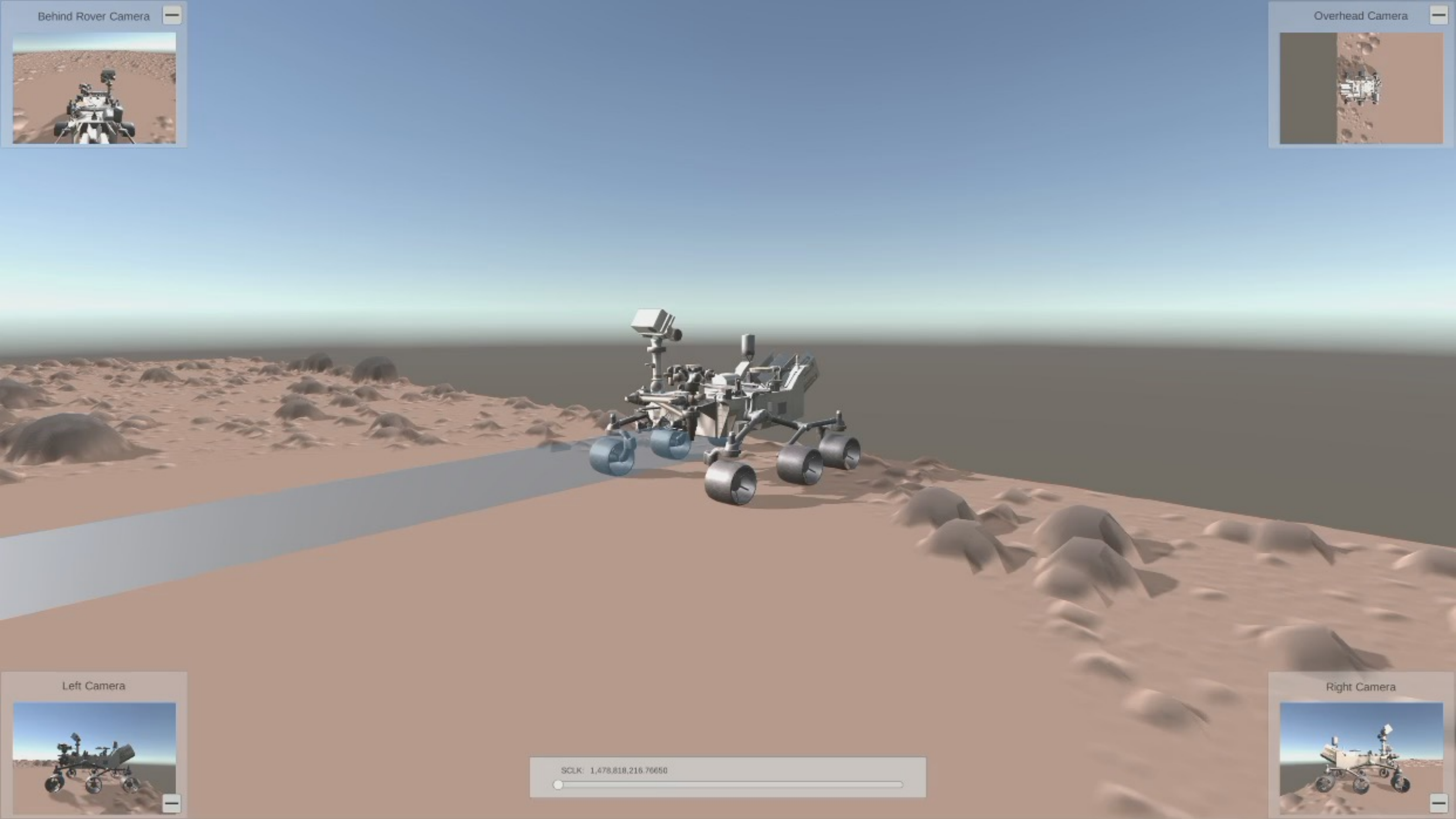

Olivier Toupet


Neil Abcouwer


Siddarth Venkatraman



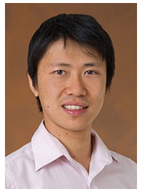




Behind Rover Camera
Overhead Camera
Left Camera
Right Camera
SCLK: 1,478,818,216.76650

Preliminary Results


Shreyansh Daftry


Hiro Ono


Olivier Toupet


Neil Abcouwer


Siddarth Venkatraman

Baseline ENav (Cycle Time(s))

	7 %	10 %	12 %	15 %
20 deg.	1.45	3.38	n/a	n/a
15 deg.	1.00	2.49	2.89	3.58
10 deg.	0.99	2.39	3.17	2.06
5 deg.	0.77	2.38	3.79	2.09
0 deg.	0.98	2.57	3.44	5.18

MLNav (Cycle Time(s))

	7 %	10 %	12 %	15 %
20 deg.	0.80	0.99	n/a	n/a
15 deg.	0.48	0.99	1.20	1.45
10 deg.	0.47	1.20	1.38	1.41
5 deg.	0.54	0.93	1.25	1.28
0 deg.	0.47	1.11	1.33	1.78

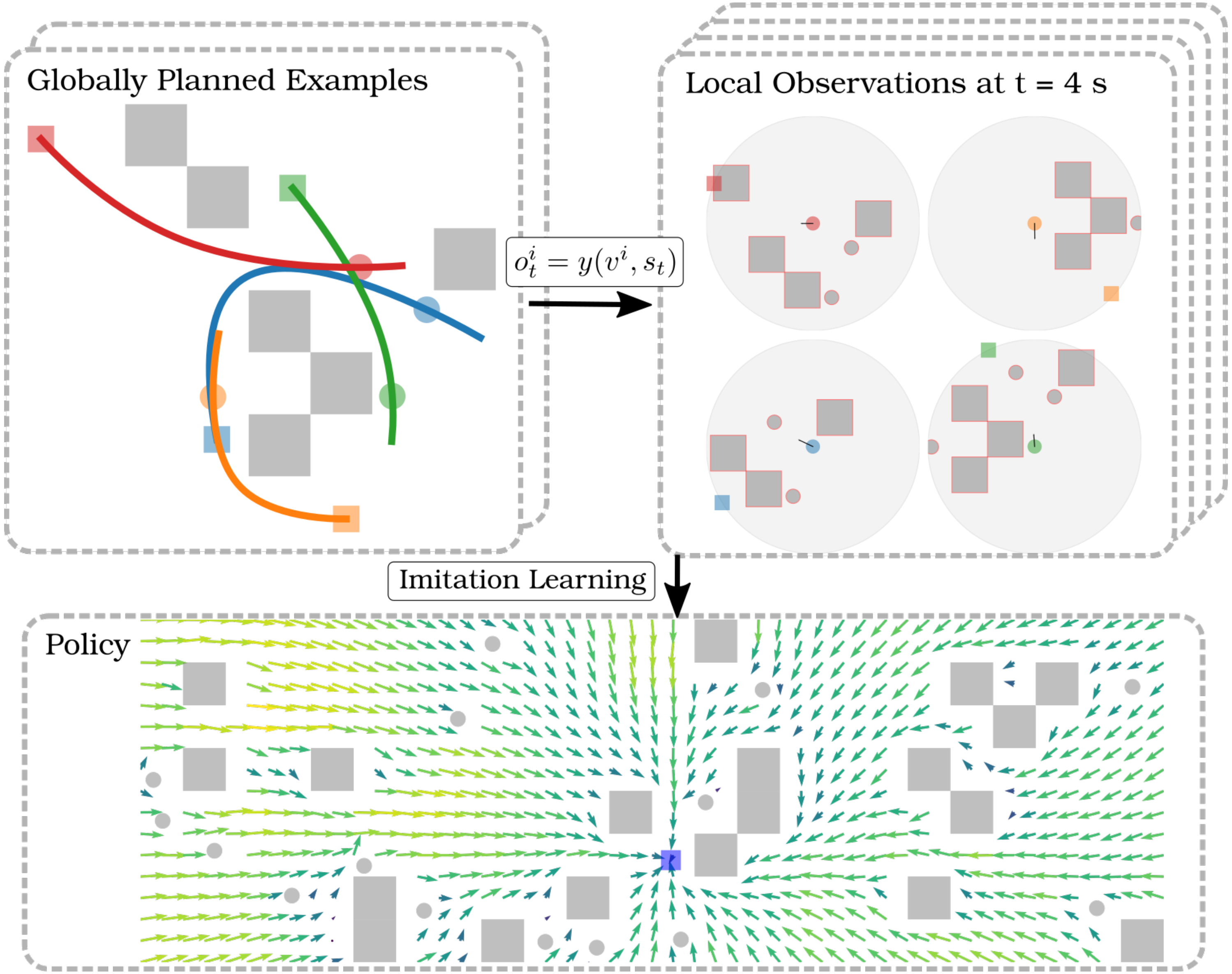
Machine Learning Based Path Planning for Improved Rover Navigation, Neil Abcouwer et al., IEEE AeroConf 2021.

Learned Decentralized Planner

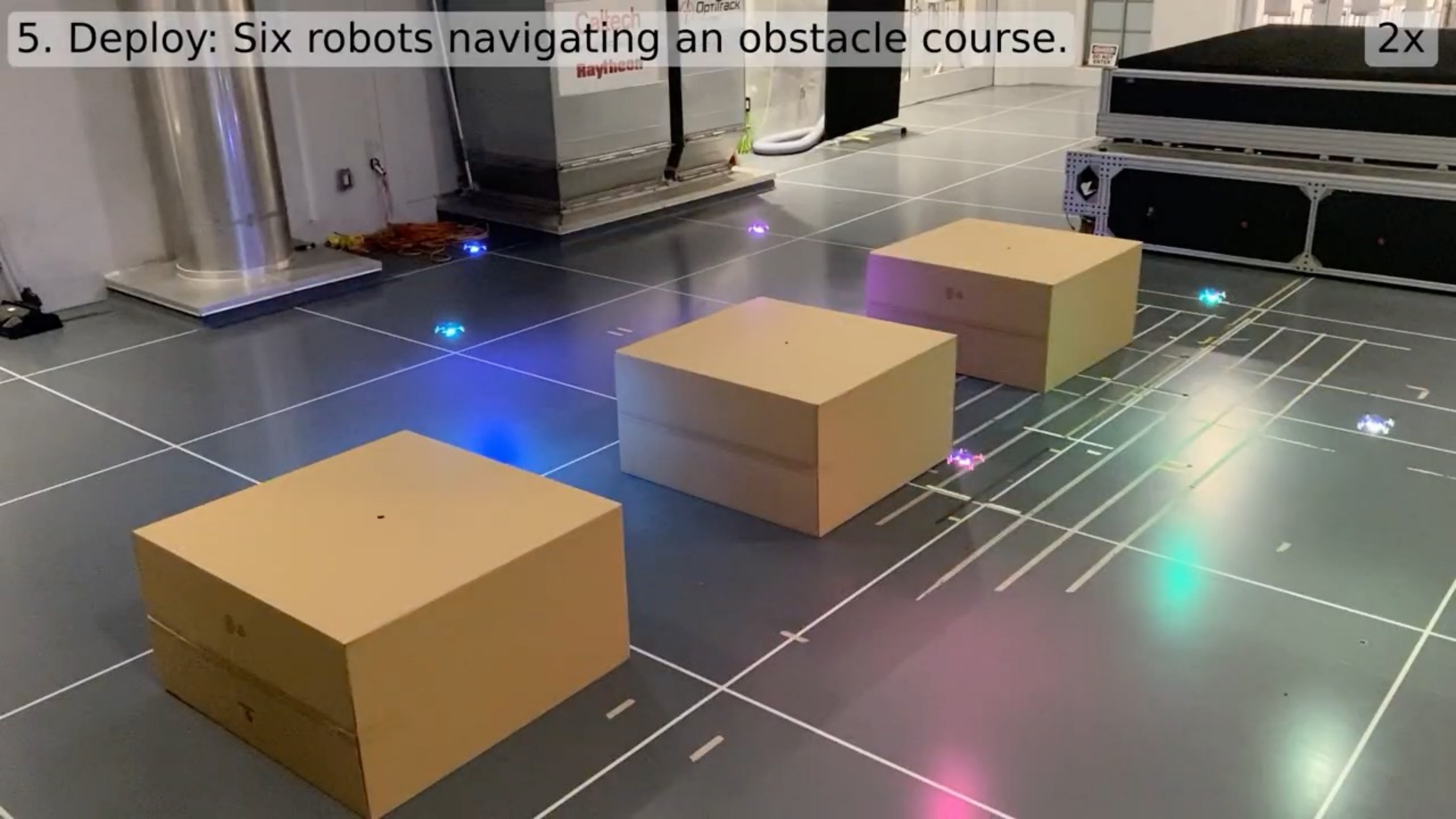
(enforcing safety)

Ben Riviere

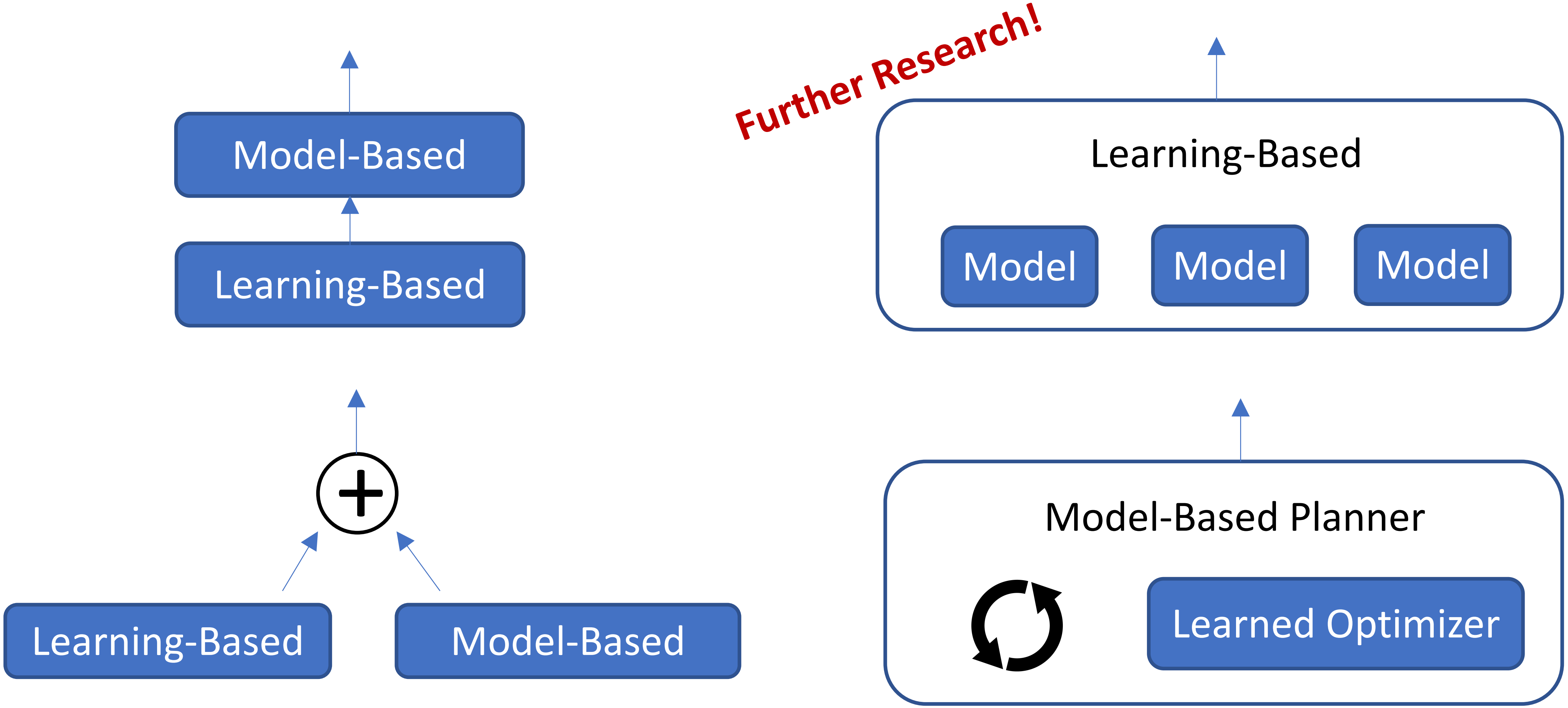
Wolfgang Hoenig



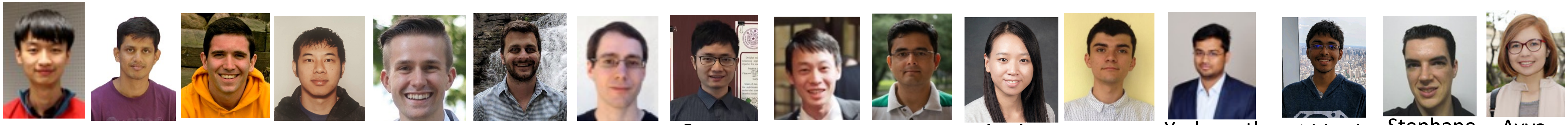
GLAS: Global-to-Local Safe Autonomy Synthesis for Multi-Robot Motion Planning with End-to-End Learning,
Benjamin Rivière, et al., R-AL 2020


5. Deploy: Six robots navigating an obstacle course.
2x

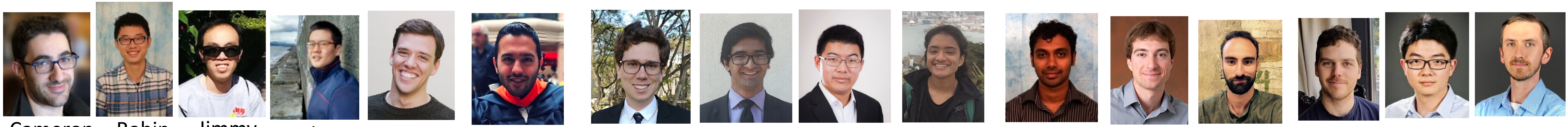
Blending Models/Rules & Black-Box Learning



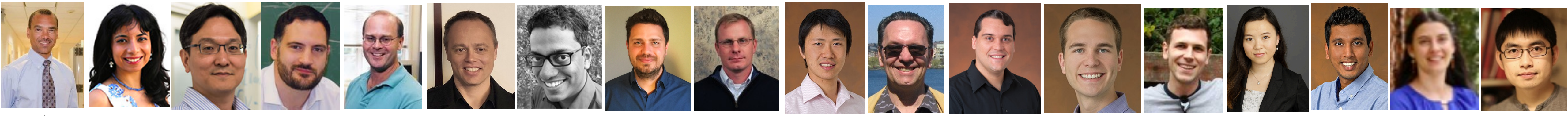
Collaborators



Jialin Song, Ravi Lanka, Joe Marino, Hoang Le, Andrew Taylor, Victor Dorobantu, Wolfgang Hoenig, Guanya Shi, Richard Cheng, Abhinav Verma, Angie Liu, Ben Riviere, Yashwanth Nakka, Siddarth Venkatraman, Stephane Ross, Ayya Alieva



Cameron Voloshin, Robin Zhou, Jimmy Chen, Andrew Kang, Milan Cvitkovic, Kamyar Azizzadenesheli, Michael O'Connell, Aadyot Bhatnagar, Albert Zhao, Meera Krishnamoorthy, Debadeepta Dey, Tyler del Sesto, Alessandro Ialongo, Alex Piche, Xichen Shi, Aiden Aceves



Stephen Mayo, Anima Anandkumar, Soon-Jo Chung, Aaron Ames, Joel Burdick, Gabor Orosz, Swarat Chaudhuri, Stephan Mandt, Drew Bagnell, Hiro Ono, Jim Little, Olivier Toupet, Neil Abcouwer, Peter Carr, Rose Yu, Shreyansh Daftry, Bistra Dilkina, Yuxin Chen

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Batch Policy Learning under Constraints, Hoang Le, et al. ICML 2019

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Imitation-Projected Programmatic Reinforcement Learning, Abhinav Verma, Hoang Le, et al., NeurIPS 2019

Neural Lander: Stable Drone Landing Control using Learned Dynamics, Guanya Shi, et al., ICRA 2019

Neural-Swarm: Decentralized Close-Proximity Multirotor Control Using Learned Interactions, Guanya Shi et al., ICRA 2020

Neural-Swarm2: Planning and Control of Heterogeneous Multirotor Swarms using Learned Interactions, Guanya Shi et al., arXiv

Robust Regression for Safe Exploration in Control, Angie Liu, Guanya Shi, et al., L4DC 2020

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