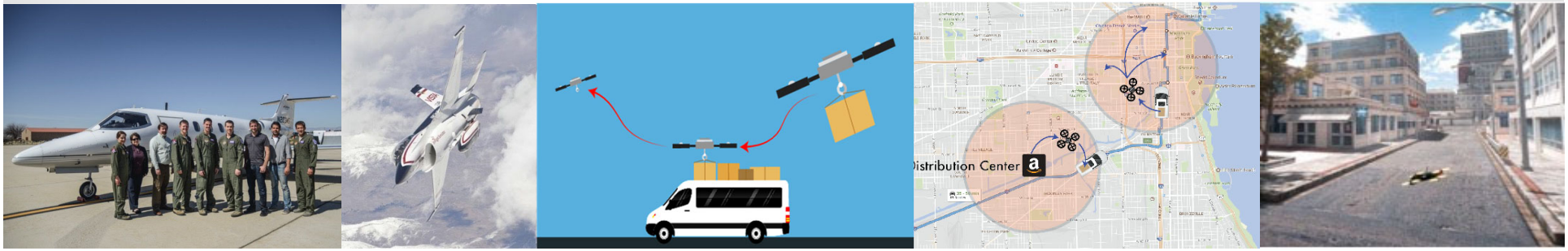
# Safe Learning and Control with $\mathcal{L}_1$-Adaptation

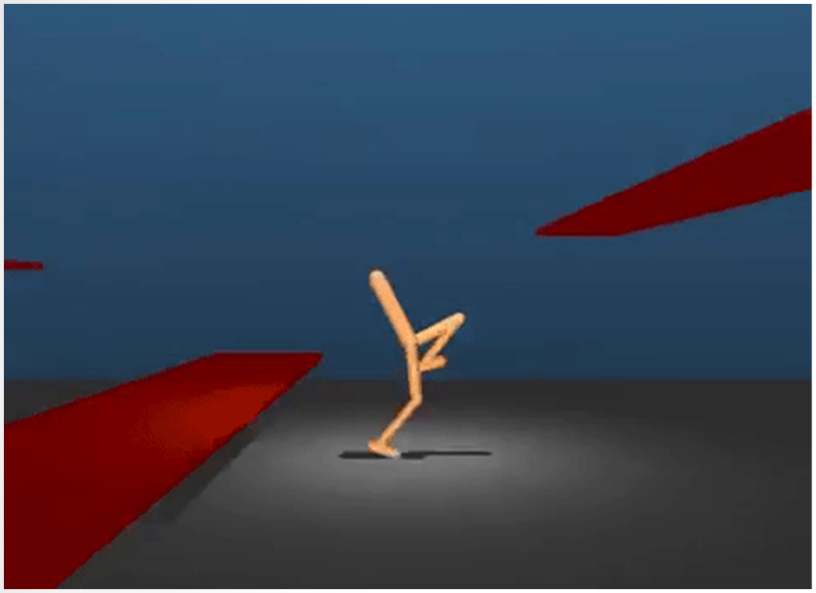
**Naira Hovakimyan**

**Mechanical Science and Engineering**
**University of Illinois at Urbana-Champaign**

**June 3, 2021**

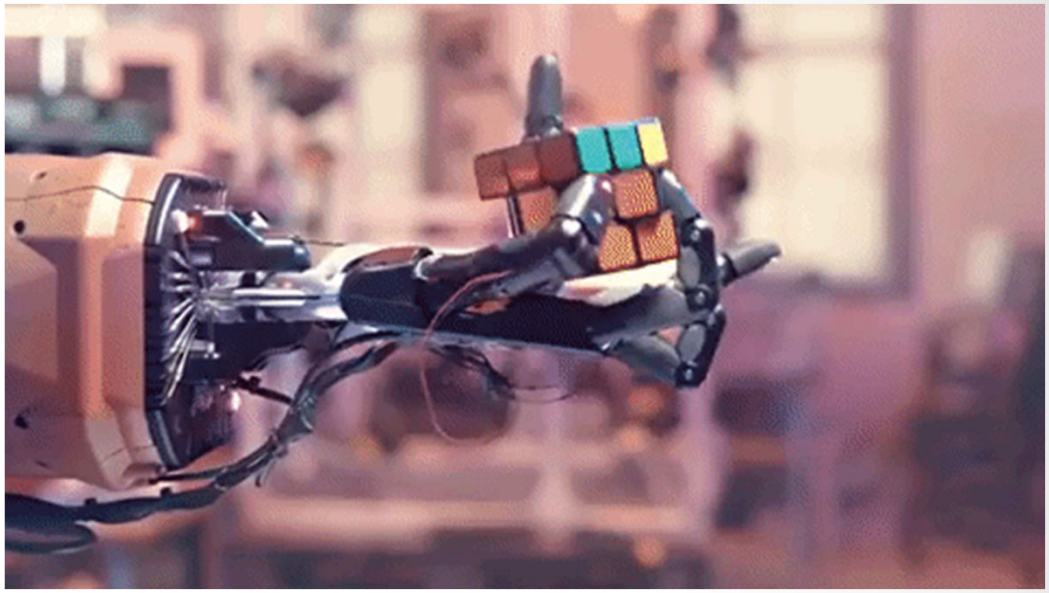


# Recent Advances in Learning-Based Control



Source: Deepmind (Alphabet Inc.)

*Heess et al. "Emergence of Locomotion Behaviours in Rich Environments." arXiv preprint arXiv:1707.02286 (2017)*



Source: OpenAI Inc.

*Akkaya et al. "Solving rubik's cube with a robot hand." arXiv preprint arXiv:1910.07113 (2019).*

# Safety-Critical Systems



*Learjet 45*



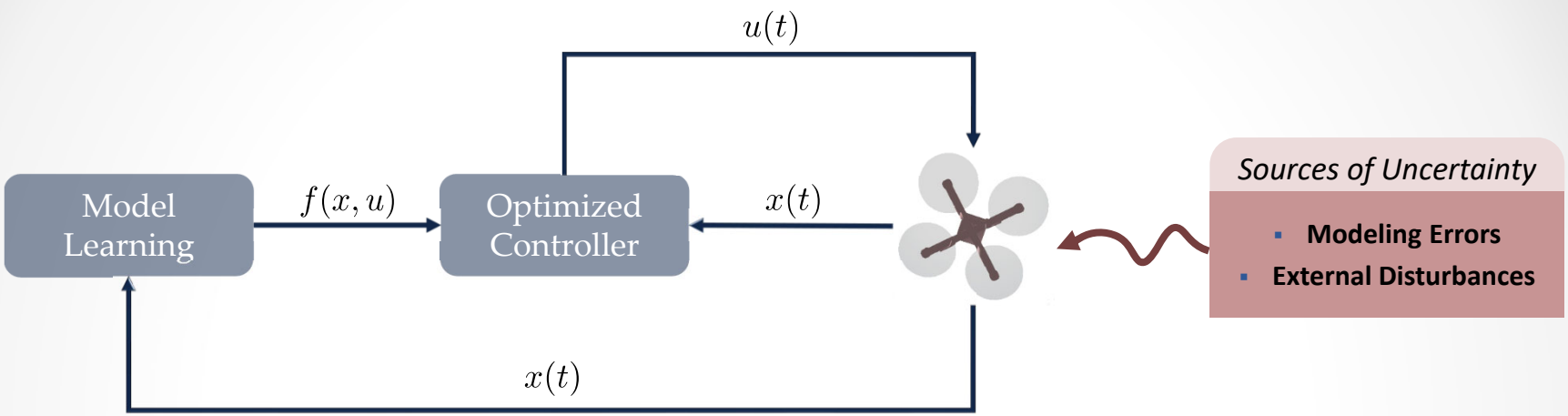
*Aerial robots*



*Self-driving cars (credit: Daniel Lu)*

- Difficult to ***safely*** obtain a large amount of data required by RL methods to produce good control policies.
- Accidents can be expensive and sometimes even deadly.

# Learning-Based Control Setup



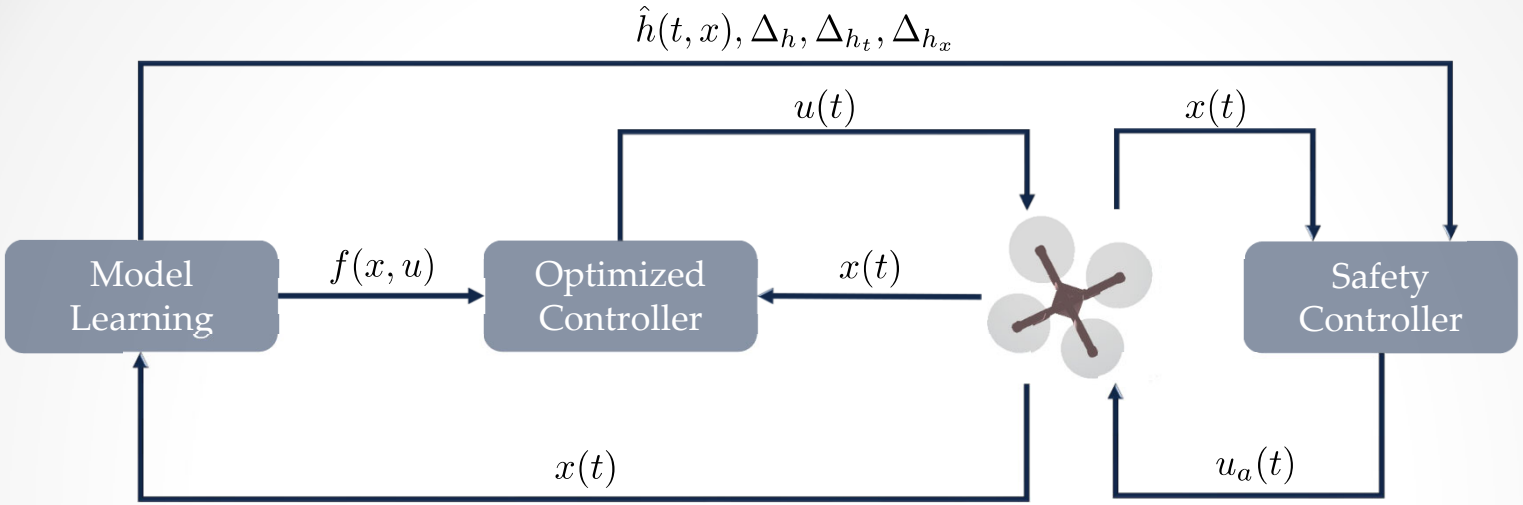

Loss of performance and stability guarantees for robots under uncertainty!


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Safety ***must*** be built into control architecture


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# Safe Learning and Control Setup




$$\dot{x}(t) = f(x,u) + h(t,x)$$

Nominal Model

Uncertainty

$$\Delta_h, \Delta_{h_t}, \Delta_{h_x}$$

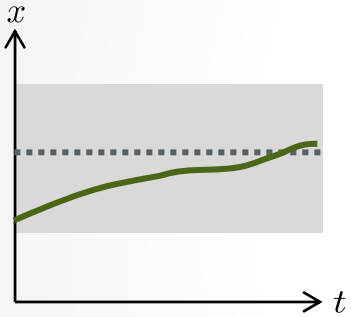
Bounds on the uncertainty and its growth in t and x.



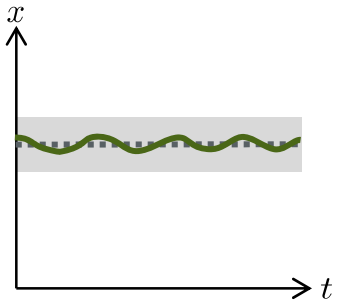
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# Safe Learning and Control Setup

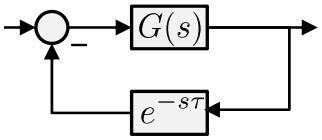
The safety controller must provide ***certificates of performance and robustness:***



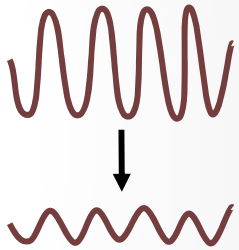

Transient performance




Steady-state performance




Time-delay margin



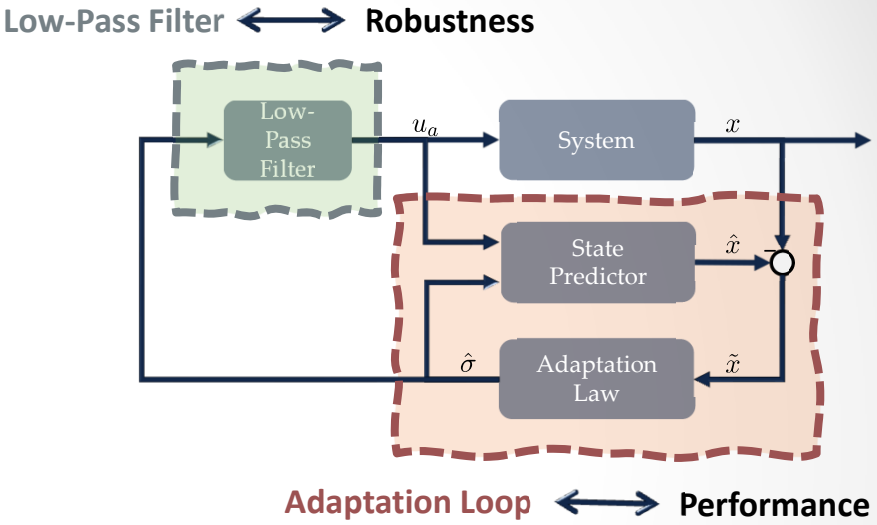
Disturbance rejection

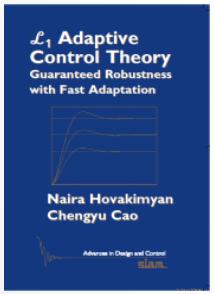


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# $\mathcal{L}_1$-Adaptive Control Architecture

- **Guaranteed uniform performance bounds and robustness margins**
- Validated for manned and unmanned aerial vehicles, oil drilling operations, hydraulic pumps, etc.
- Commercialized by various industries, including Raymarine, Caterpillar, etc.






intelinair

Statoil

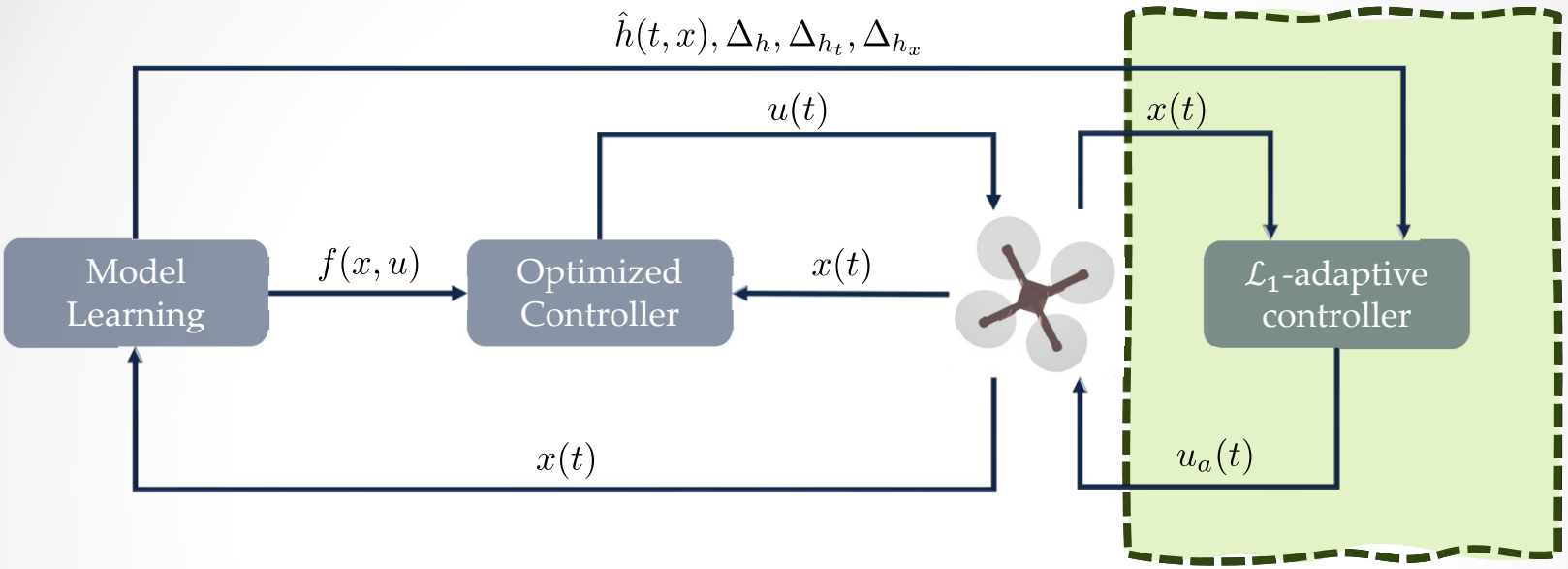




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# Safe Learning and Control Setup




- **Retaining the key features of performance and robustness guarantees of $\mathcal{L}_1$- adaptive controllers**
- **Benefitting from the versatility offered by machine learning methods**


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# Guarantees Provided by $\mathcal{L}_1$ Theory

- $x^\star$: Desired system trajectory
- $x_r$: Reference system (best performance achieved using the $\mathcal{L}_1$ framework with known uncertainties*, but non-implementable*)
- $x$ : Actual system trajectory

$$\|x_r(t) - x(t)\| \leq \rho_a(\Gamma^{-1})$$

*Performance*: Adaptation rate Γ

**Decoupling**

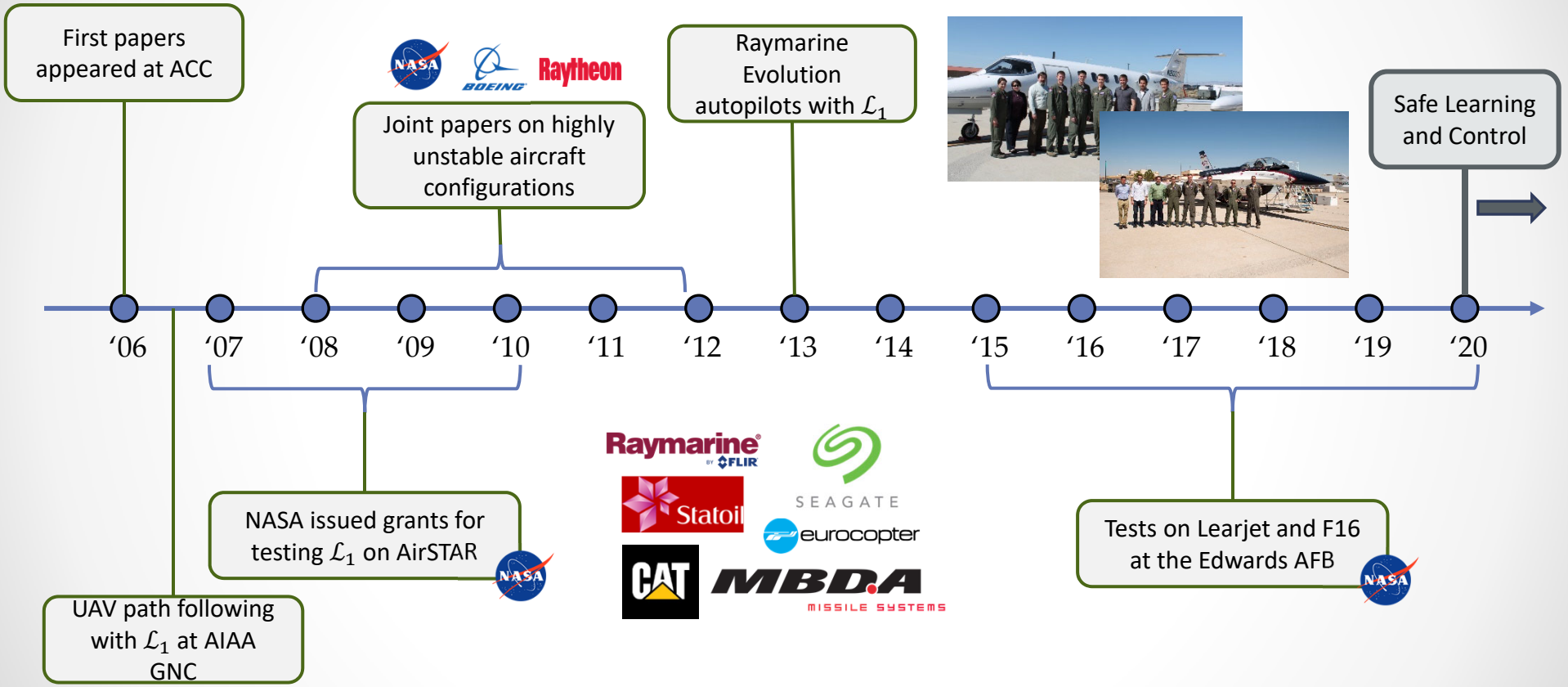
$$\|x^\star(t) - x_r(t)\| \leq \sqrt{ke^{-2\lambda t}\|x^\star(0) - x(0)\| + \rho_r(\omega^{-1})}$$

*Robustness*: Filter bandwidth ω

*Exponential decay of error due to the difference in initial conditions*


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# A Timeline of $\mathcal{L}_1$-Adaptive Control Theory






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# Robust Flight Control: Learjet at Edwards AFB

- **Recovered flying qualities** of different Variable Stability System configurations
- **Restored handling qualities to a safe and consistent level** despite the off-nominal dynamics
- The controller was shown to be **easily adjusted to improve handling qualities**.









Calspan




Ackerman, et al. "Evaluation of an $\mathcal{L}_1$ Flight Control Law on Calspan's Variable-Stability Learjet." AIAA Journal of Guidance, Control and Dynamics, vol. 40, No. 4, pp. 1051-1060, 2017.



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# "Can we get $\mathcal{L}_1$ on?" from the 2015 Flight Test





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AVIATION WEEK NETWORK

# USAF Test Pilots School Vets Safer Adaptive Flight Controller

April 06, 2015



Credit: Calspan

"The $\mathcal{L}_1$ controller is designed to automatically intervene in the case of control problems, immediately reconfiguring the flight control system to compensate for degraded flying qualities from mechanical failure or battle damage to a control surface, or even the unintended result of shifting center-of-gravity inflight for better cruise performance. Acting as a backup to the standard flight control system, the $\mathcal{L}_1$ is **designed to provide safe, predictable, reliable** and repeatable responses that would free up pilots to deal with the emergency and further compensate for reduced performance."

Guy Norris, Aviation Week and Space Technology.
Published on April 6, 2015.


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# Lifting Body Incident (1967) and the 2018 Flight Test




Puig-Navarro et al. "An $\mathcal{L}_1$ Adaptive Stability Augmentation System Designed to MIL-HDBK-1797 Level 1 Specifications." *In Proceedings of* AIAA Guidance, Navigation and Control Conference, San Diego, CA, 2019.


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## Flight Control System Virtually Eliminates Pilot Error




The $\mathcal{L}_1$ adaptive flight control system installed in an aircraft. (Maj. Miguel J. Carreras)

"$\mathcal{L}_1$ adaptive control has overcome some of the major limitations of conventional adaptive control systems by providing **predictable robustness guarantees in the presence of a large class of uncertainties**. It has the potential to revolutionize aircraft safety by greatly diminishing the possibility of pilot error during high workload maneuvers."

Published on April 3, 2018.

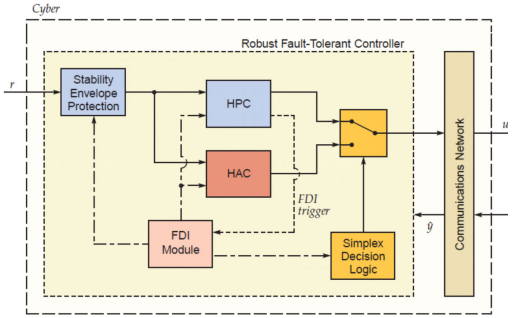


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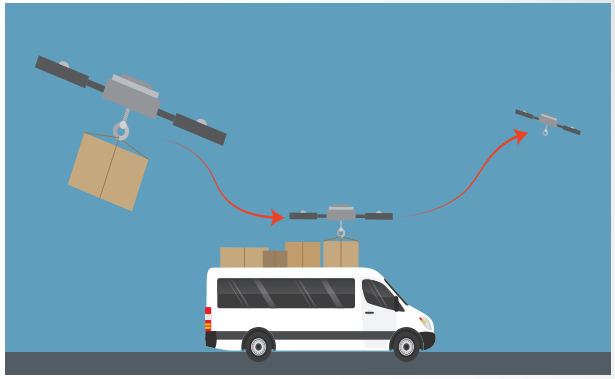
# ... and many other applications



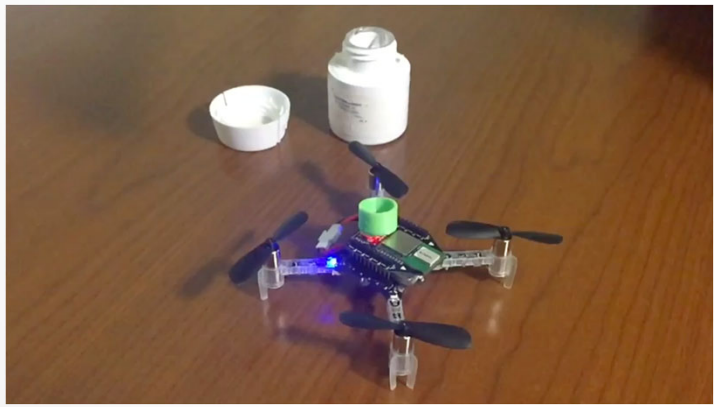
Time-critical coordination



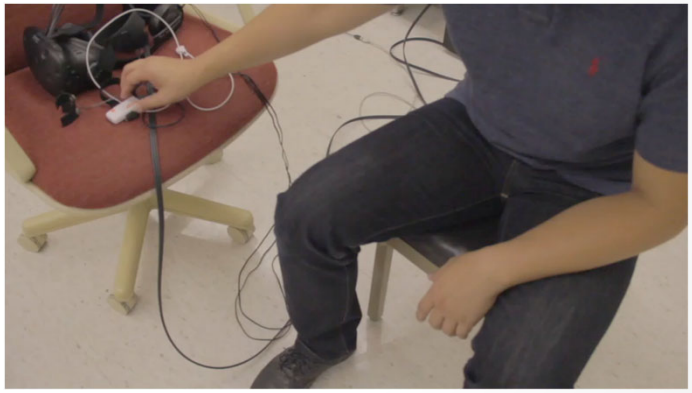

Fault-tolerant software



Drone—based package delivery



Indoor aerial vehicles



Human-centered (perceived) safety



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# Complex Environments

**New challenges**

- Unpredictable environments
- Uncertain nonlinear dynamics
- Dynamic & clustered environments
- Nonlinear uncertain dynamics

**New requirements**

- Fast re-planning
- Safe planning
- Safe control
- Learning for high performance

*with guaranteed robustness*

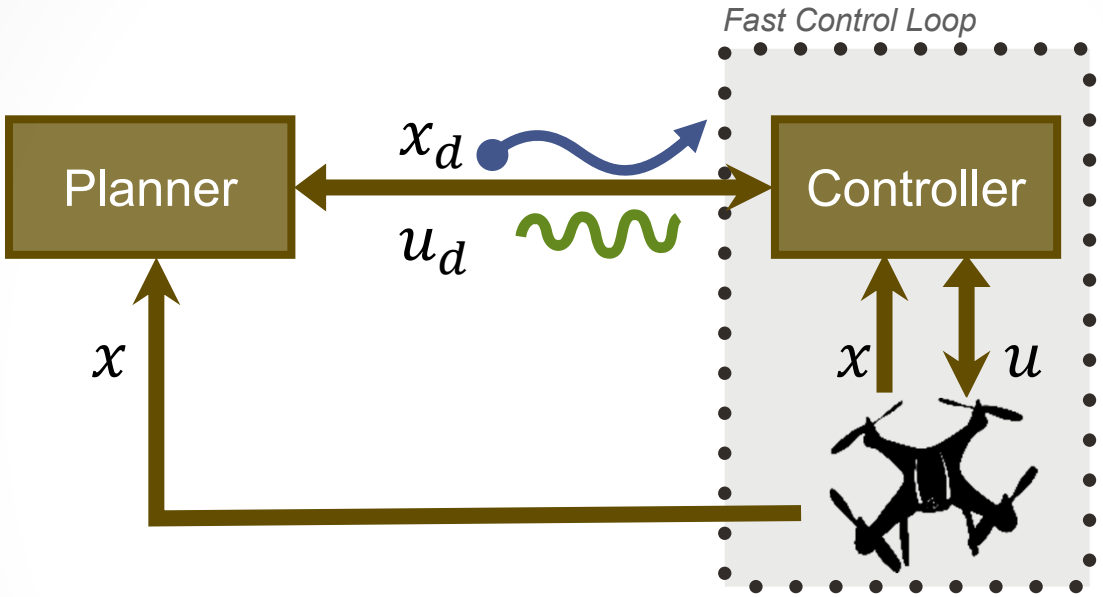
Alphabet Hoc Simulation challenge: camera views

Massachusetts Institute of Technology

Guerra, Tal, Murali, Ryou, and Karaman. "FlightGoggles: Photorealistic Sensor Simulation for Perception-driven Robotics using Photogrammetry and Virtual Reality." International Conference on Intelligent Robots and Systems (IROS), 2019.

# The Autonomy Stack

## Planning and Control Pipeline




**Standard architecture**

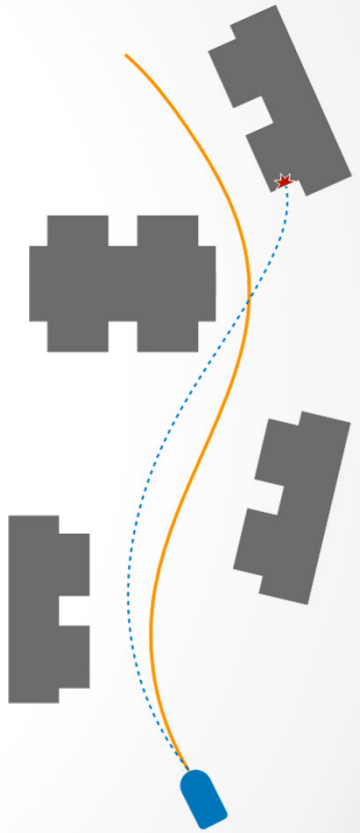
- Planner generates desired $x_d$ and open loop $u_d$
- Controller attempts to track using feedback law $u = k(u_d, x_d, x)$


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# Planning and Control Pipeline

**Challenges**:

- Uncertainties can drive the system to failure.
- Controller needs to compensate for uncertainties
- Can the compensation be provided in the form of certificates?
- If yes, enables two-way communication between planner and controller for safety!



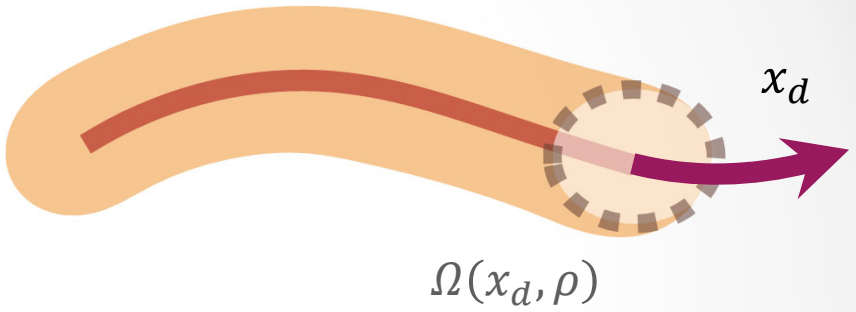

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# Planning and Control Pipeline

## Example Scenario

- Controller guarantees $x \in \Omega(x_d, \rho)$
  - A tube centered on desired $x_d$
  - Radius $\rho$
- Two-way communication
  - Controller communicates $\rho$ to the planner
  - Planner communicates $x_d$ and $u_d$ such that

    $x(t) \in \Omega(x_d, \rho) \subset \mathcal{X}_{safe}$
- Planner aware of the controller capabilities
  - Safety is guaranteed



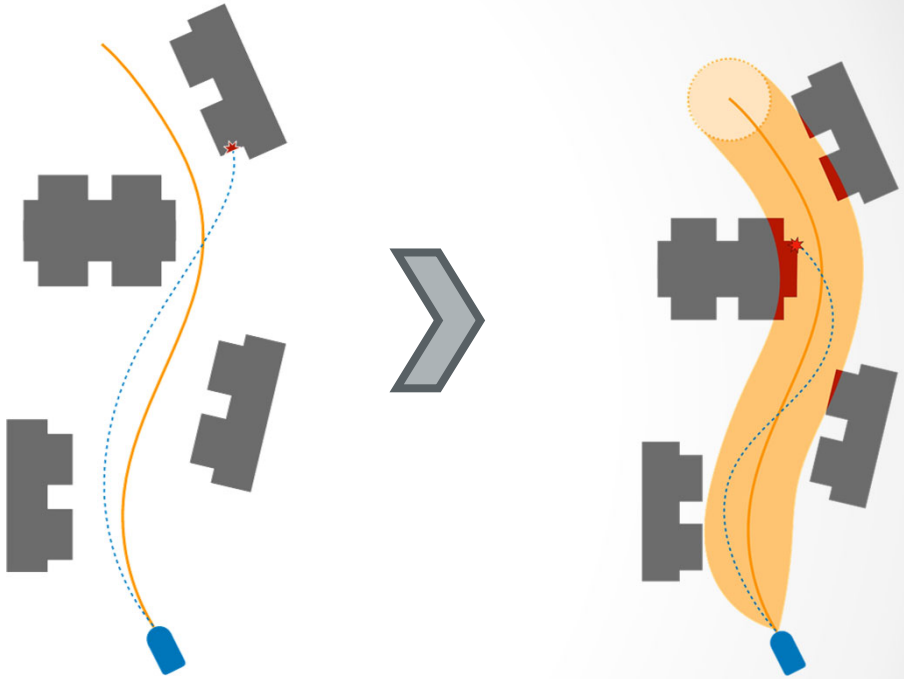

Safety: Existence of $\Omega(x_d, \rho)$


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# Planning and Control Pipeline

## What about performance?

- Overly conservative designs → large $\rho$
  - Practically unusable!



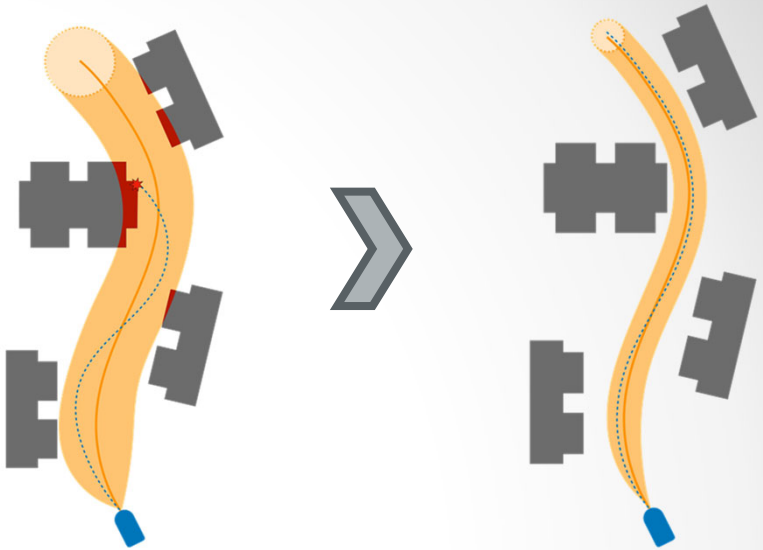
Performance: Radius $\rho$


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# Planning and Control Pipeline

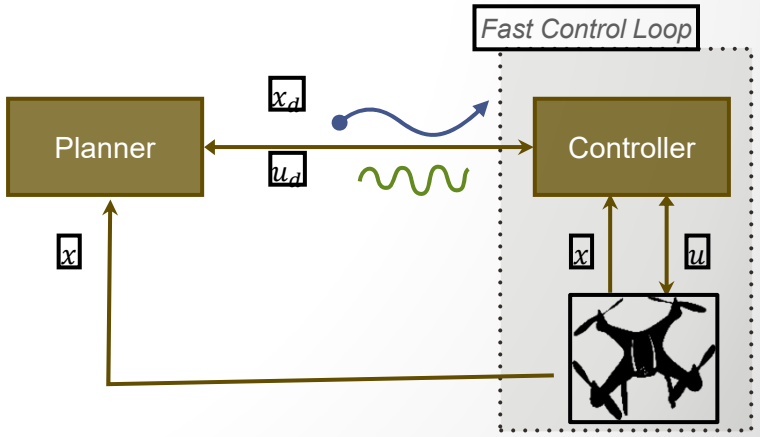
Can we use ML to improve performance?

- ML has shown impressive empirical performance



**However:**

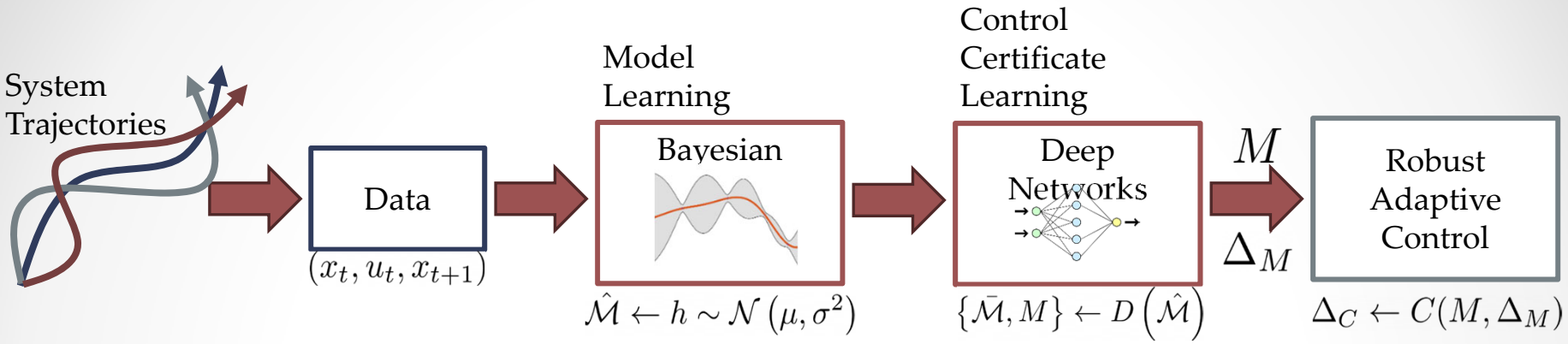
- Can we still generate certificates?
- **Safety cannot depend on learning!**
  - Data intensive and computationally intensive!
- Decoupling of safety from learning?
  - **Safety is a necessity**
  - **Performance is a luxury**
- Task appropriateness of ML tools?
  - DNNs, Bayesian Learning etc.
- **Can learned models always be usable?**





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# Learning-Based Control Pipeline




A bottom-up approach

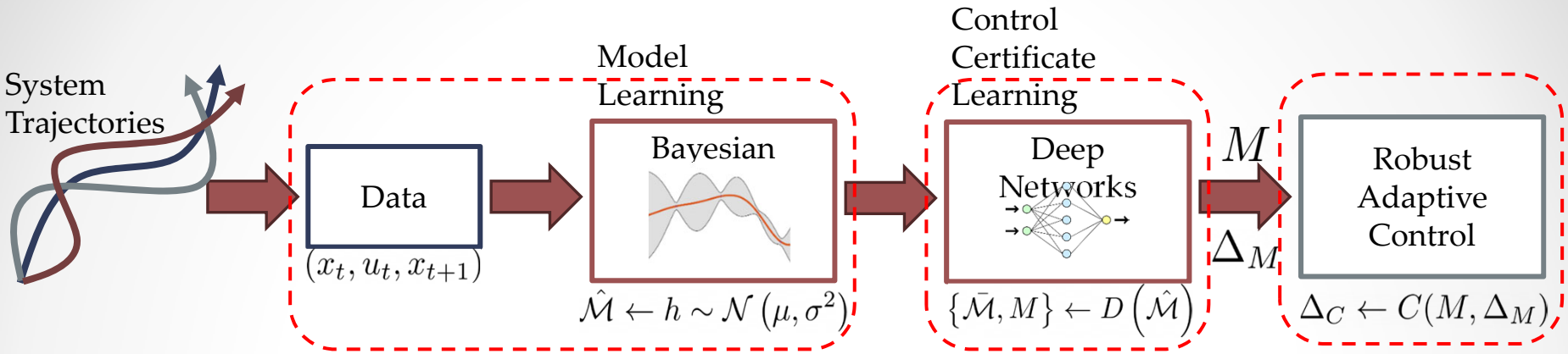
- Foundation based on Control theory: Safety
- Build-up based on ML: Performance

Unified in an architecture that decouples safety from learning

- Learning does not affect safety, only performance


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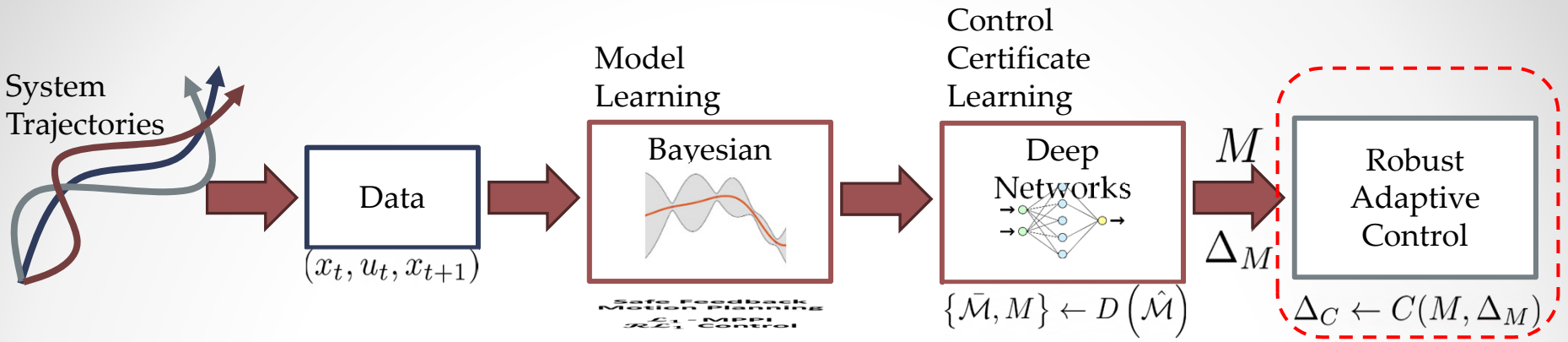
# Learning-Based Control Pipeline



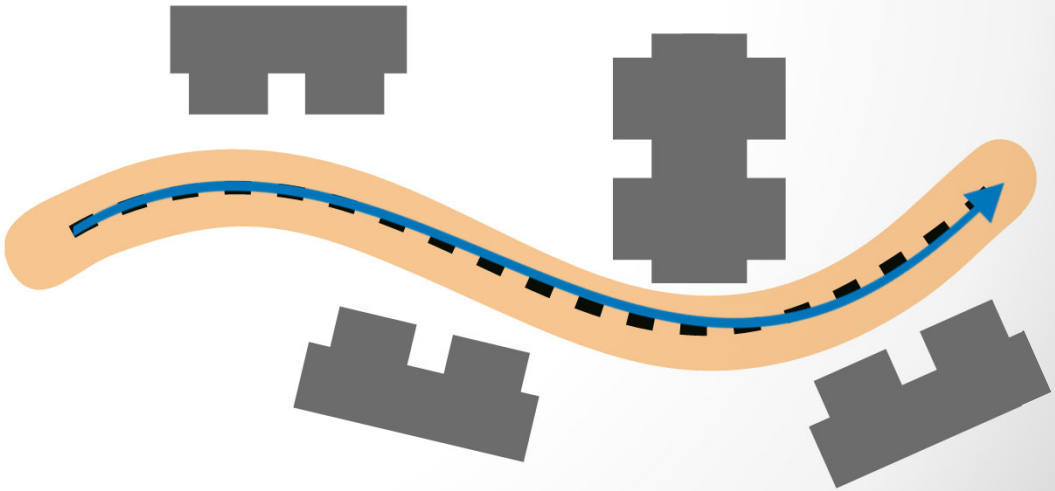

The building blocks

- $\mathcal{L}_1$ - MPPI and Riemannian-energy $\mathcal{L}_1$ ($\mathcal{RL}_1$) Control: Safety
- Bayesian learning of dynamics - $\mathcal{RL}_1 - GP$ control: Performance
- Deep incrementally stabilizing control: Usability


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# Safe Feedback Motion Planning



# $\mathcal{L}_1$-MPPI

# Contraction $\mathcal{L}_1$ Control

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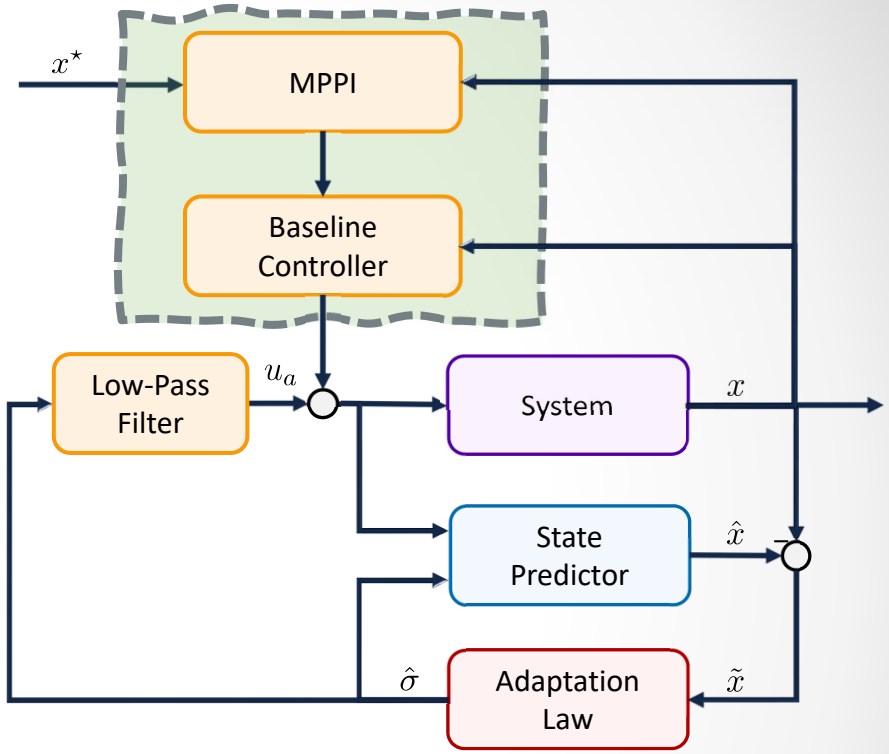
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# $\mathcal{L}_1$ coupled with state-of-the-art stochastic planners


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# $\mathcal{L}_1$-MPPI: Fast and **Safe** Re-Planning

- **Fast and robust re-planning** is needed for mission success in complex, dynamic and uncertain environments.
- **Model predictive path integral (MPPI)** control provides a framework for solving nonlinear MPC with complex constraints in **near real-time.**
- **Robustness** against dynamic uncertainties and disturbances is achieved through an $\mathcal{L}_1$ **augmentation.**





Pravitra, J., Ackerman, K. A., Cao, C., Hovakimyan, N., and Theodorou, E. A. L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors. International Conference on Intelligent Robots and Systems, 2020.




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# $\mathcal{L}_1$-MPPI: Fast and **Safe** Re-Planning

Nonlinear system

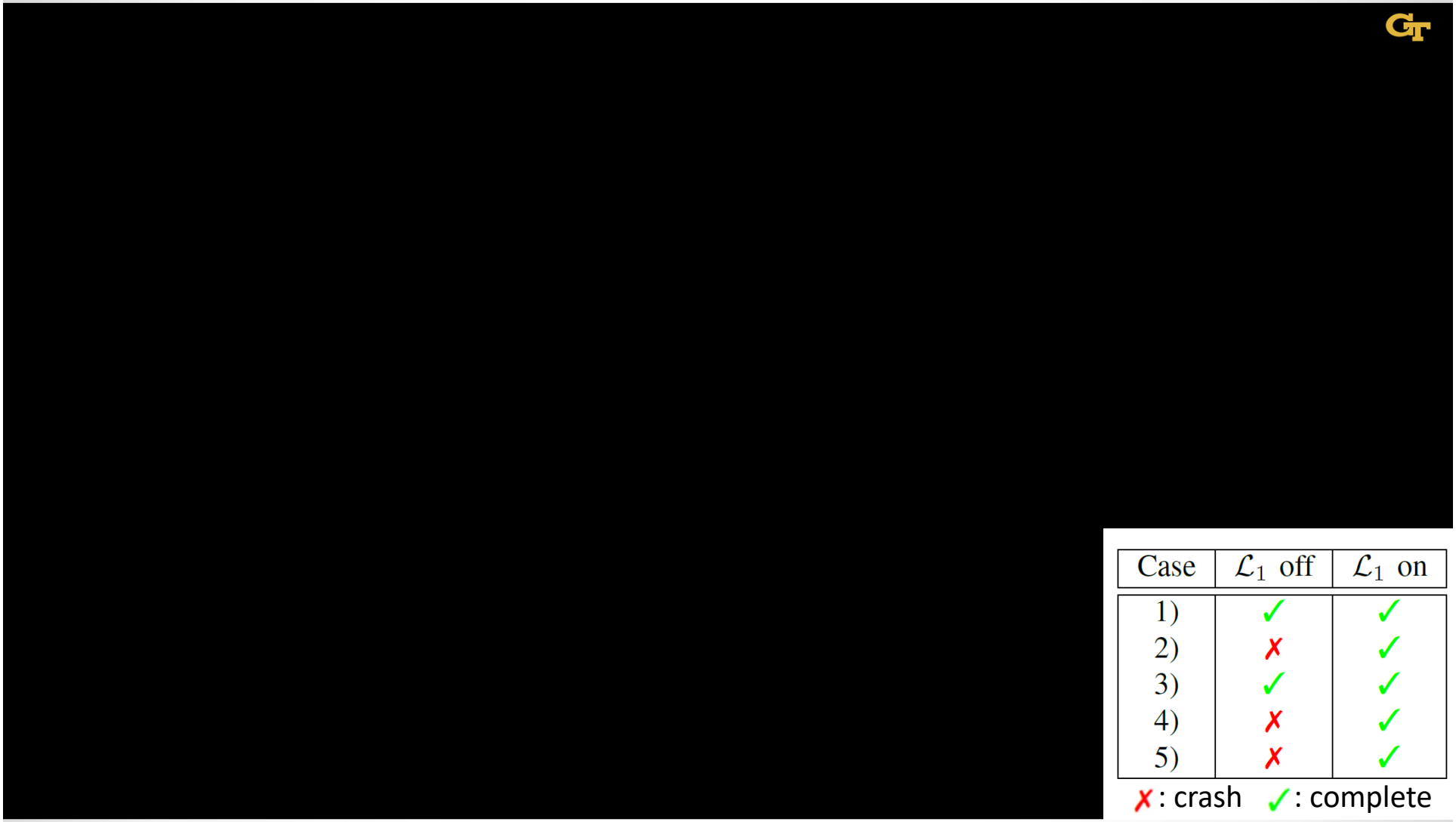
$$\dot{x}_{t+1} = f(x_t, u_t + \epsilon) + h(x_t . u_t)$$

Nominal system — Unknown nonlinearity, disturbance

| MPPI | $\mathcal{L}_1$ adaptive control |
|---|---|
| ▪ Optimal control computation forward in time for nominal system<br>▪ Update the control sequence iteratively by **sampling** (thousands of) trajectories | ▪ Robustifies against the **discrepancy**<br>▪ Guaranteed robustness and transient and steady-state bounds for performance |

- Can leverage **parallel sampling** for modern GPUs
- Can handle **complex** (possibly non-differentiable) dynamics and cost functions

# Goggle Environment



| Case | $\mathcal{L}_1$ off | $\mathcal{L}_1$ on |
|---|---|---|
| 1) | ✓ | ✓ |
| 2) | ✗ | ✓ |
| 3) | ✓ | ✓ |
| 4) | ✗ | ✓ |
| 5) | ✗ | ✓ |

✗ : crash ✓ : complete

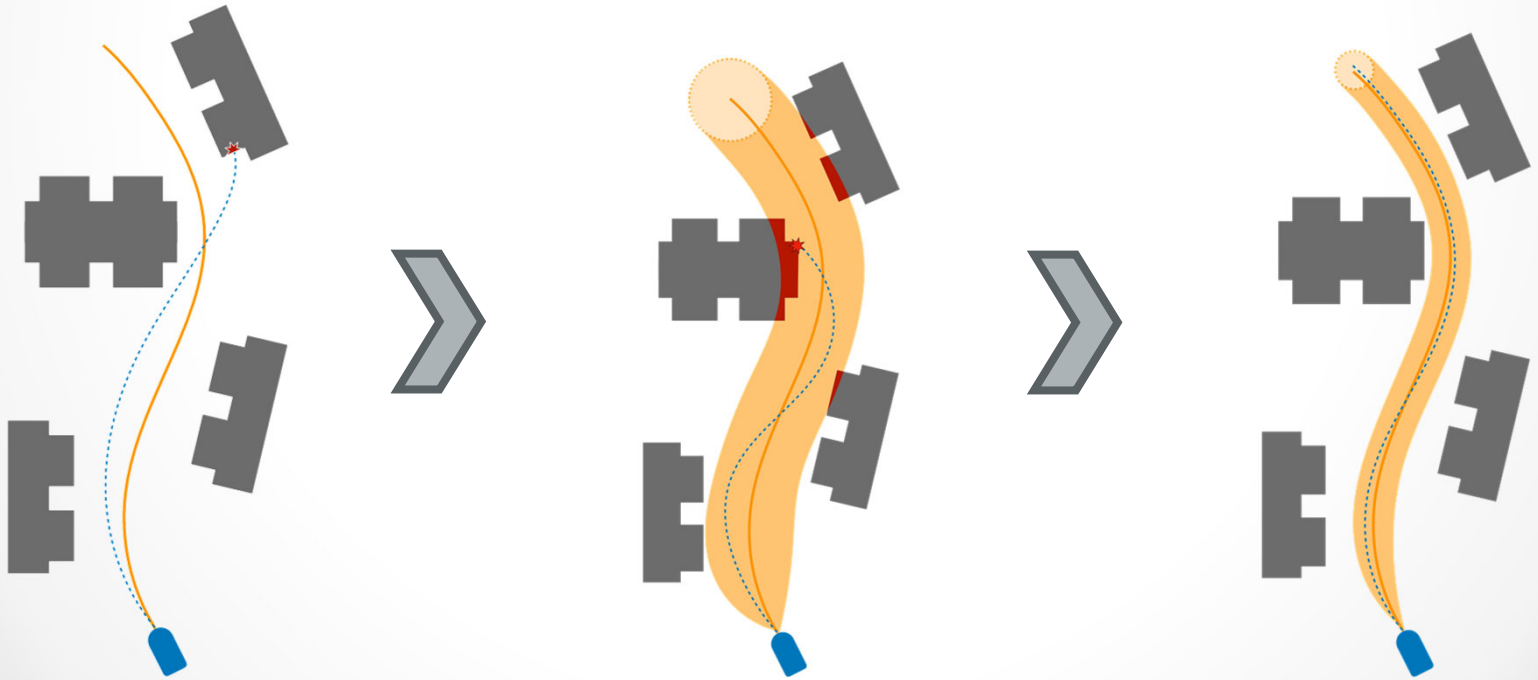
Pravitra, J., Ackerman, K. A., Cao, C., Hovakimyan, N., and Theodorou, E. A. L1-Adaptive MPPI Architecture for Robust and Agile Control of Multirotors. International Conference on Intelligent Robots and Systems, 2020.

Quantifiable safety certificates for nonlinear systems that enable ***safe motion planning***.


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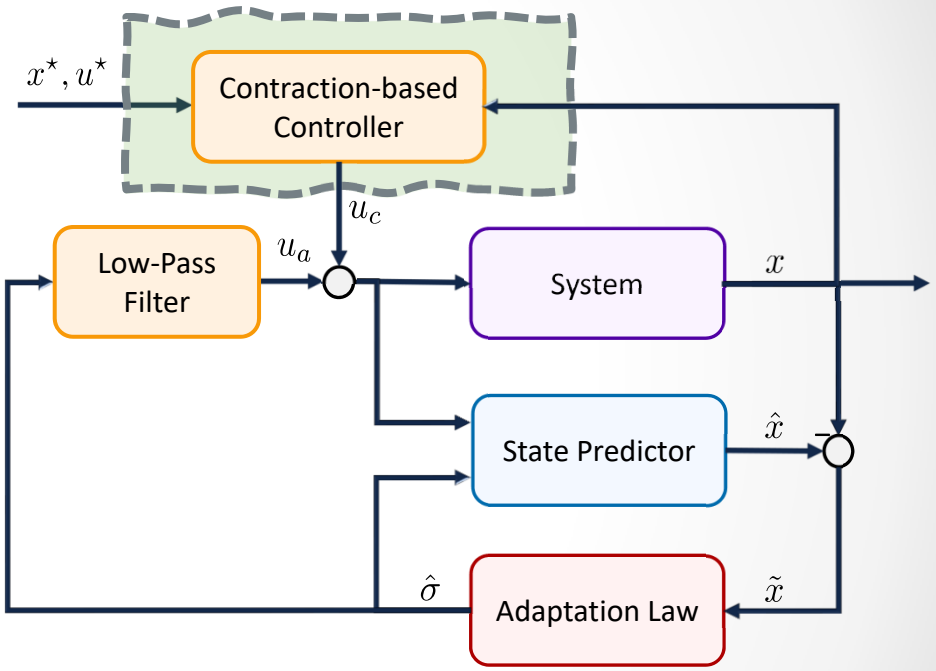
# Challenges in Safe Planning

- Planning under uncertainty is of vital importance for **safety critical applications**
- A planner-agnostic approach to certify **safe tubes** around desired trajectories, that the UAV is **guaranteed to remain inside**
- Tuning knobs that allow **tubes** to be made arbitrarily **small** as a **trade-off between performance and robustness.**



# Contraction $\mathcal{L}_1$- Architecture: Safe Planning

- Contraction theory enables consideration of **nonlinear reference systems**
  - applies to **a large class of nonlinear systems.**
- $\mathcal{L}_1$ **adaptive control** compensates for uncertainties with **guaranteed robustness.**
- Combined architecture allows for publishing **certificates of performance and robustness**.




Lakshmanan, A., Gahlawat, A., & Hovakimyan, N. (2020). "Safe feedback motion planning: A contraction theory and L1-adaptive control based approach." Conference on Decision and Control (CDC) 2020.

# Overview of Contraction Theory*

Nonlinear system

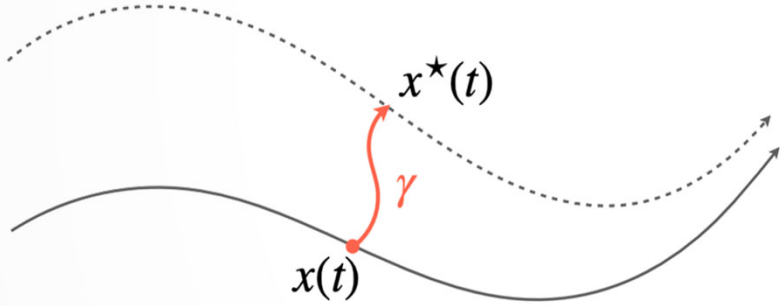
$$\dot{x}(t) = f(x) + B(x)(u(t) + h(t,x))$$
$$y(t) = x(t)$$

Contraction controller for nominal system

$$u_c(t) = u^*(t) + \Delta u(x^*(t), x(t))$$
$$h(t,x) = 0$$

- **Riemannian energy**

$$\mathcal{E}(x^*, x) = \int_0^1 \gamma(s,t)^\top M(\gamma(s,t))\gamma(s,t)ds$$




$\gamma$ : The shortest path on the manifold defined by $M(x)$

$M(x)$ : Control contraction metric that satisfies Lyapunov-like conditions

- $\underline{\alpha}\mathbb{I}_n \preceq M(x) \preceq \mathbb{I}_n\overline{\alpha}$,
- $\delta_x^\top M(x)B(x) = 0 \Rightarrow$

$$\delta_x^\top \left( \partial_f M(x) + \left[ M(x)\frac{\partial f(x)}{\partial x} \right]_{\mathbb{S}} + 2\lambda M(x) \right) \delta_x \leq 0$$

where $\delta_x$ is the differential.

Choose $\Delta u(x^*(t), x(t))$ to ensure that the gradient of the **Riemannian energy** is negative definite, so that **the energy of the shortest path on the manifold acts as Lyapunov function**:

$$V(\gamma) = \mathcal{E}(x^*, x)$$

*S. Singh, A. Majumdar, J.-J. Slotine, and M. Pavone. "Robust online motion planning via contraction theory and convex optimization." in IEEE International Conference on Robotics and Automation (ICRA), 2017.

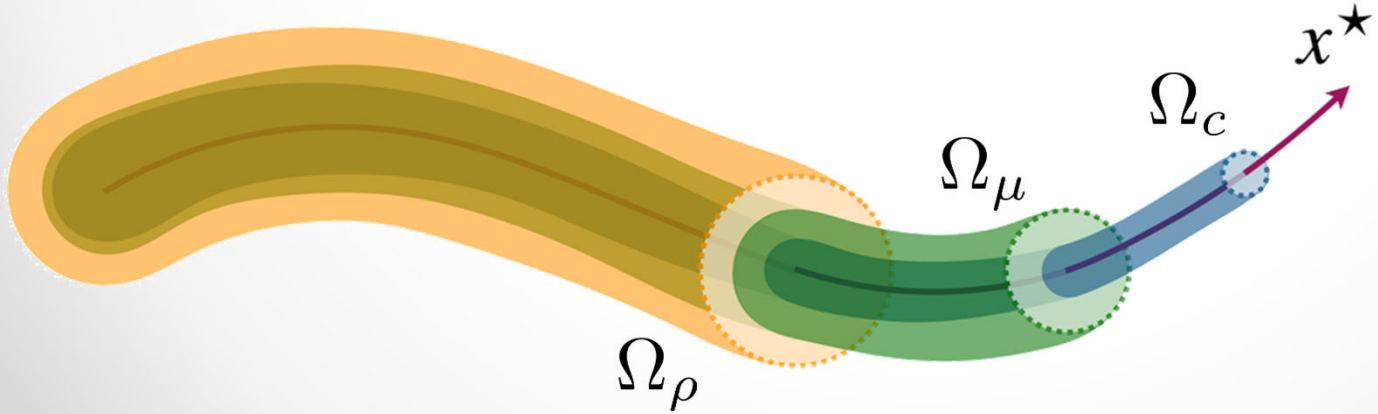
# Contraction $\mathcal{L}_1$- Architecture: Safe Planning

**Assumption 5** *The nominal dynamics $\dot{x}(t) = f(x) + B(x)u(t)$ admits a control contraction metric $M(x)$ for all $x \in \mathcal{X}$.*

**Theorem 4** *Suppose that Assumption 5 holds. Consider a desired state trajectory $x^*(t)$ and the state of the $\mathcal{L}_1$ closed-loop system of $\dot{x}(t) = f(x) + B(x)(u(t)+h(t,x))$ with baseline contraction controller $u_c(t)$. Then we have*

| | | |
|---|---|---|
| UB | $x(t) \in \Omega(\rho, x^*(t)),$ | $t \geq 0,$ |
| UUB | $x(t) \in \Omega(\delta(\omega, T), x^*(t)) \subset \Omega(\rho, x^*(t)),$ | $t \geq T > 0.$ |

*where* $\delta(\omega, T) = \mu(\omega, T) + \rho_a.$



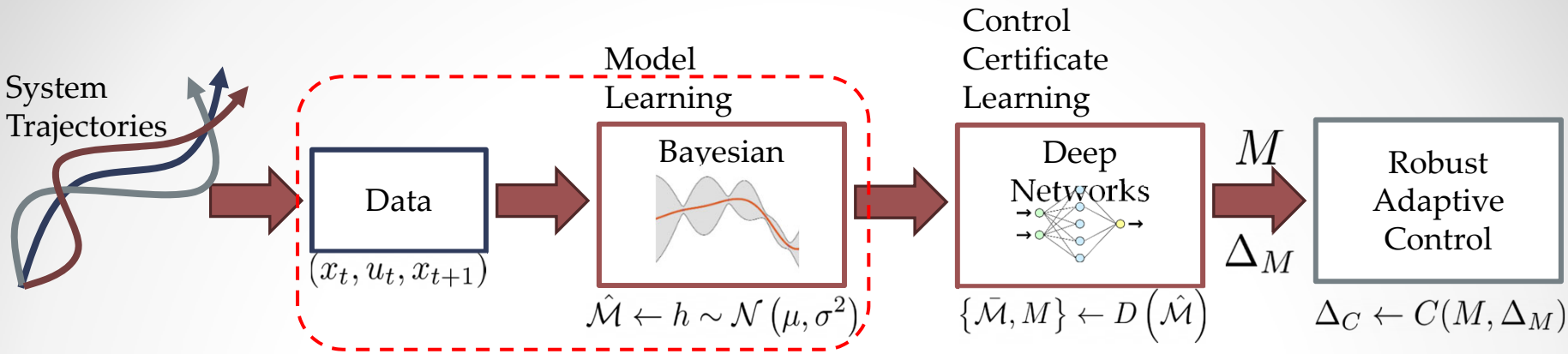

$\Omega_c$ : decaying error

$\Omega_\mu \propto$ filter bandwidth

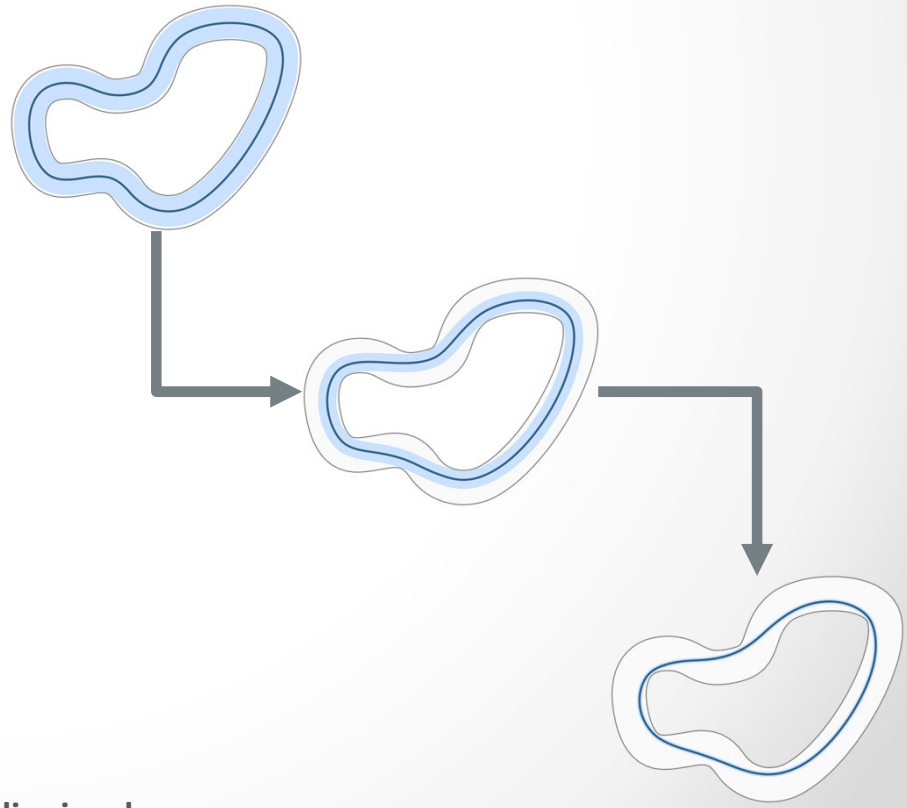
$\Omega_\rho \propto$ adaptation rate

Quantifiable safety certificates for nonlinear systems for ***safe learning and control***.


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# Safe Simultaneous Learning and Control

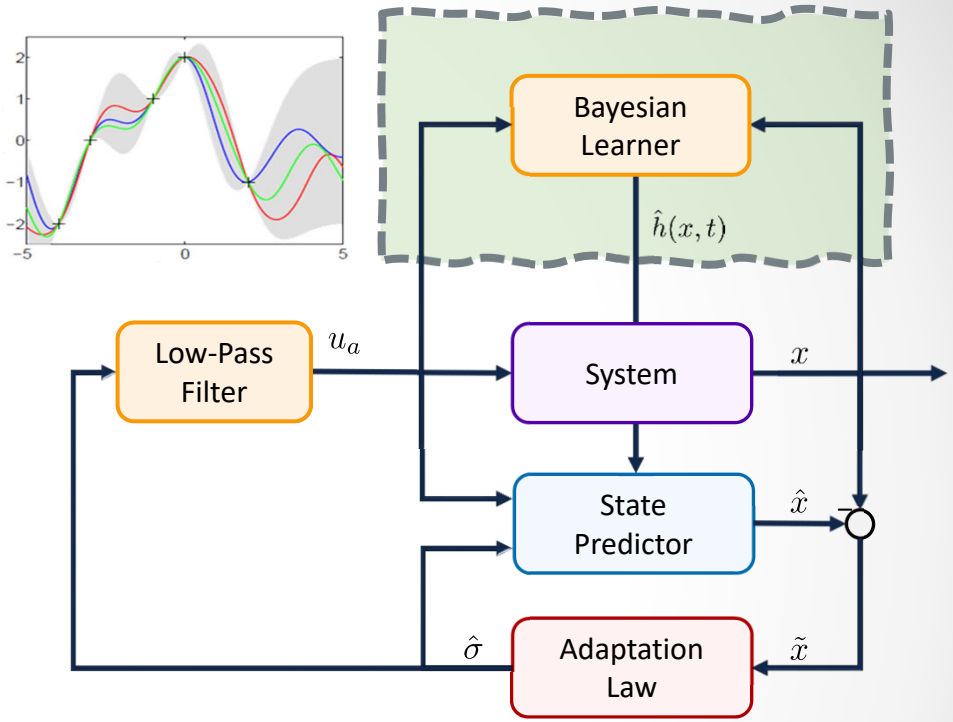


## Contraction $\mathcal{L}_1$- $\mathcal{GP}$

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# $\mathcal{L}_1$-$\mathcal{GP}$: Safe Bayesian Learning

- Gaussian process ($\mathcal{GP}$) learns model uncertainties
  - **No need for persistent excitation**
  - No need for parametric models
  - The kernel function **integrates prior model knowledge**
  - **High probability error bounds** on the prediction*
- $\mathcal{L}_1$ augmentation
  - Ensures safety during learning
  - Vanishes once learning is complete




*A. Lederer, J. Umlauft, and S. Hirche. "Uniform error bounds for Gaussian process regression with application to safe control." In the Advances in Neural Information Processing Systems." 2019

A. Gahlawat, P. Zhao, A. Patterson, N. Hovakimyan, E. Theodorou, "$\mathcal{L}_1$-$\mathcal{GP}$: $\mathcal{L}_1$ Adaptive Control with Bayesian Learning." In the Learning for Dynamics and Control (L4DC) Conference, Berkeley, CA, 2020

# $\mathcal{L}_1$-$\mathcal{GP}$: Safe Bayesian Learning

**Bayesian learner**

- Use GPR
- **Estimate** of nonlinearity $\hat{h}(x(t),t)$
- **High probability error bounds** $\hat{e}_h(x(t),t)$

**$\mathcal{L}_1$ adaptive control**

- Filter bandwidth adjusted based on error bounds
- Learned filtered nonlinearity as feedforward term



$$\{\hat{h}(x(t),t), \hat{e}_h(x(t),t)\}$$

Gaussian process regression (GPR)

- Under the assumption that $h(x)$ is a **Gaussian process ($\mathcal{GP}$)**, we have

$$h(x^{test})|Y \sim \mathcal{N}(\mu(x^{test}), \sigma^2(x^{test}))$$

where $Y$ represents the input-output data.

# $\mathcal{L}_1$-$\mathcal{GP}$: Safe Bayesian Learning

**Assumption 6** *The kernels $K$ are Lipschitz.*

**Assumption 7** *The continuous function $h(x)$ is sampled from Gaussian process $GP(0, K)$.*

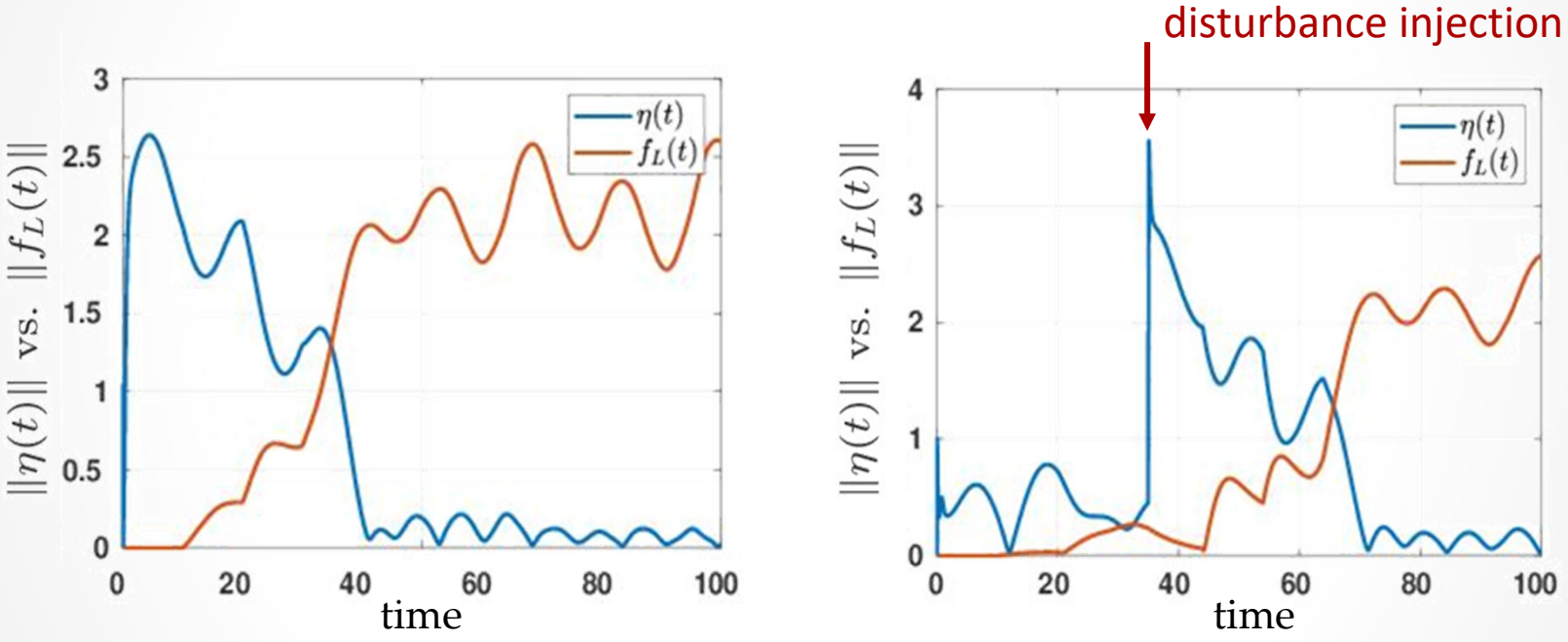
**Theorem 5 (Learning performance)** *Let the model uncertainty $h(x)$ satisfy Assumptions 6 and 7. Given the posterior distribution $h(x^*)|Y$, for any $\delta \in (0, 1)$, we have*

$$Pr\{\|h(x) - \mu(x)\|_\infty \leq \sqrt{\beta}\|\sigma(x)\|_\infty + \gamma\} \geq 1 - \delta.$$

$\mu(x)$ : Mean prediction of learned $\mathcal{GP}$ model
$\sigma(x)$ : Variance prediction of learned $\mathcal{GP}$ model
$\gamma$ : Error induced by state prediction

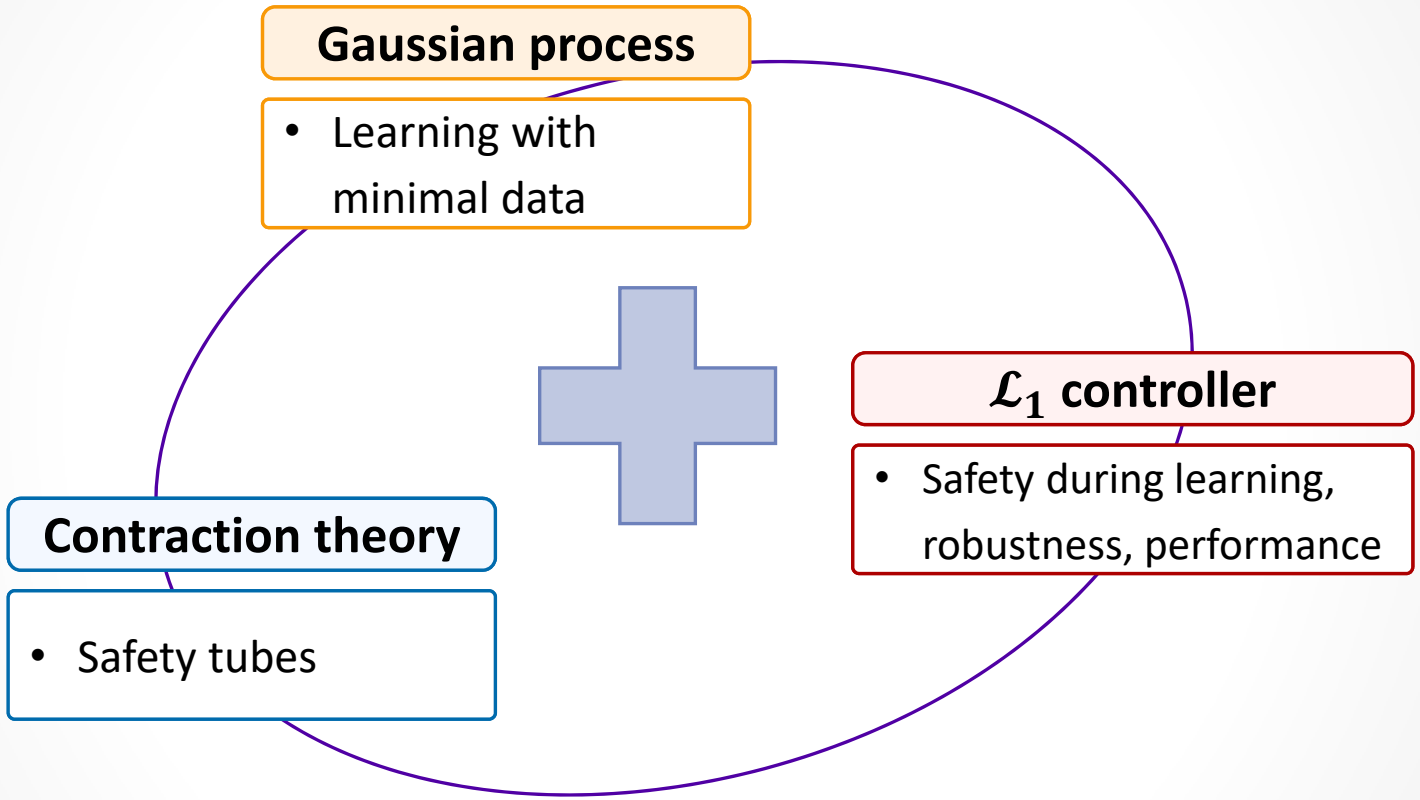
# $\mathcal{L}_1$-$\mathcal{GP}$: Safe Bayesian Learning

- Angular rate control of a quadrotor
- **Switched** state-dependent uncertainties starting at 35s
- Collect data at 1 Hz, and update Bayesian model at 0.1 Hz




When model uncertainties switch, $\mathcal{L}_1$ **adaptive element immediately steps in** to compensate for the new (yet unlearned) uncertainties.

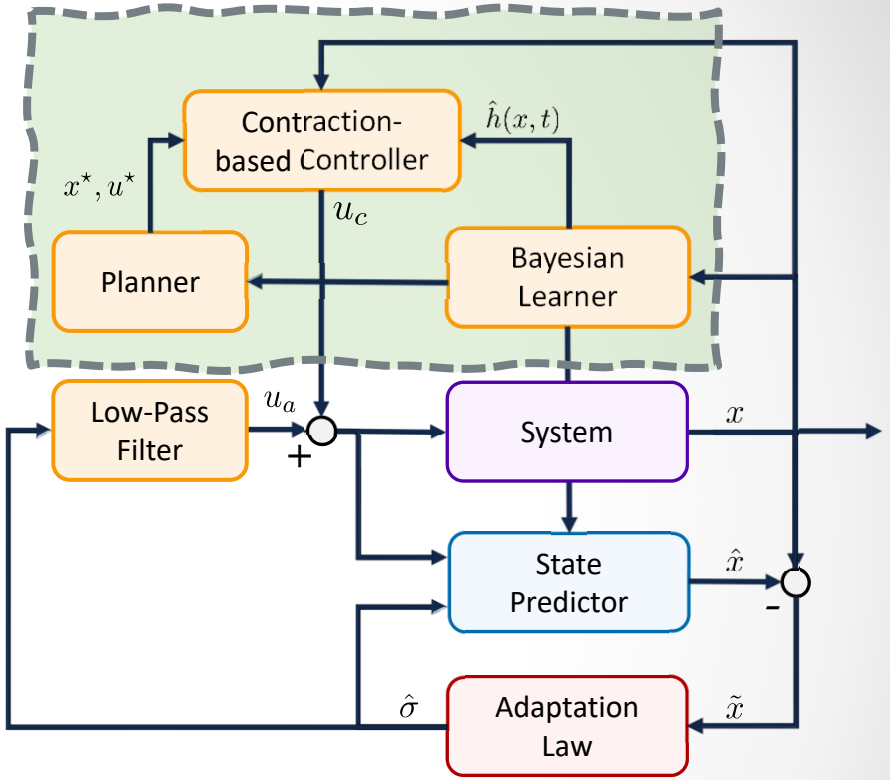
# Safe Simultaneous Learning, Planning and Control



# Contraction $\mathcal{L}_1$- $\mathcal{GP}$ Architecture: Safe Learning and Control

- **Safety certificates** in the form of tubes from the $\mathcal{RL}_1$- $\mathcal{GP}$ framework which **enables safety during learning**

- Natural framework for learning using $\mathcal{GP}$ :
  - **guaranteed performance** during the learning transients
  - improved performance of the $\mathcal{L}_1$ adaptive controller, i.e., **smaller tubes**
  - **improved quality** of the planned trajectory



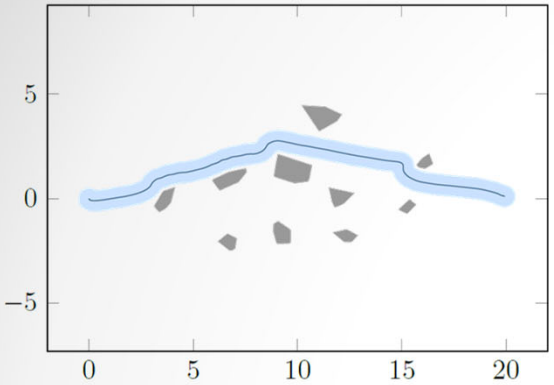


Gahlawat, A., Lakshmanan, A., Song, L., Patterson, A., Wu, Z., Hovakimyan, N., & Theodorou, E. "Contraction $\mathcal{L}_1$ Adaptive Control with Gaussian Processes ." Learning for Dynamics and Control (L4DC) Conference (To Appear). 2021.



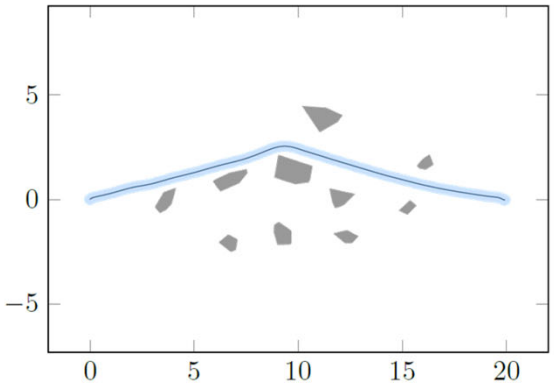

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# Contraction $\mathcal{L}_1$- $\mathcal{GP}$ Architecture: Safe Learning and Control

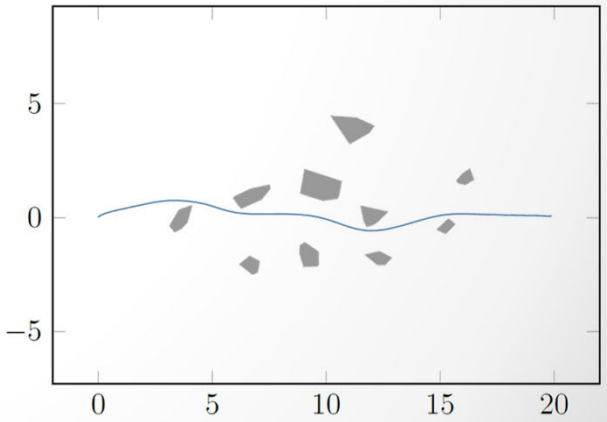



(a) Episode 1: $\omega = 90$ rad/s, $\Gamma = 7e10$, $N = 0$.
Traverse time: 27secs.

Learning **kicks in** ⟹ tube **shrinks** ⟹ **better** planning

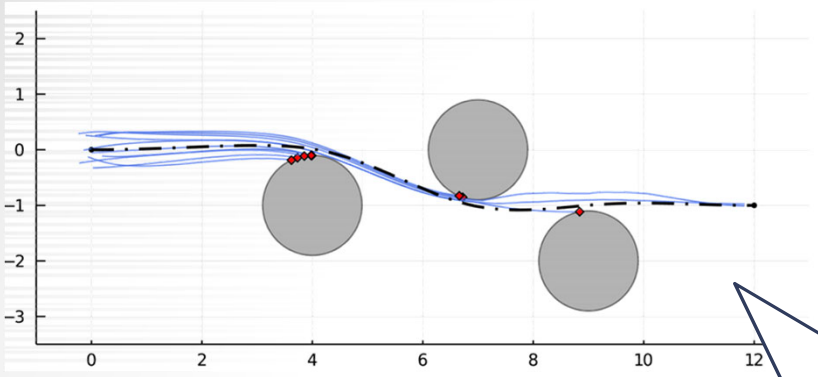



(b) Episode 2: $\omega = 30$ rad/s, $\Gamma = 2e6$, $N = 25$.
Traverse time: 16secs.

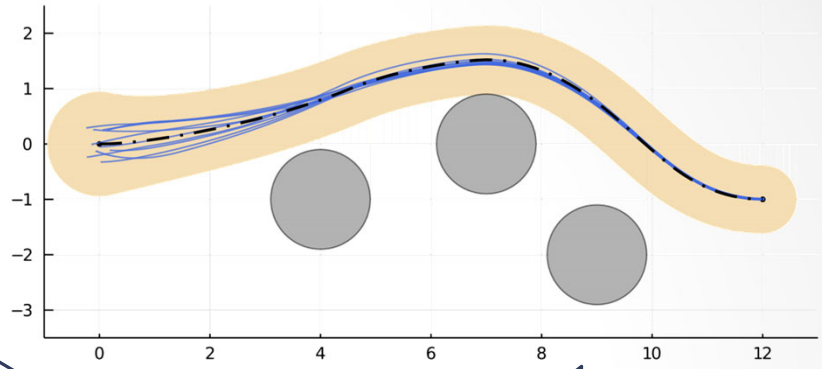



(c) Episode 3: $\omega = 30$ rad/s, $\Gamma = 2e6$, $N = 100$.
Traverse time: 14secs.

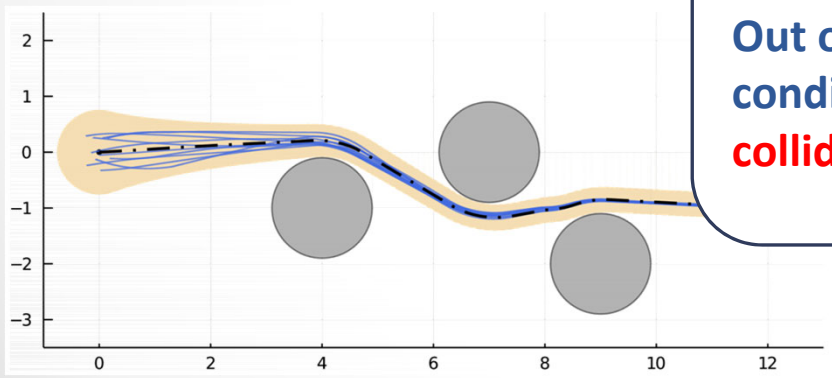
# Contraction $\mathcal{L}_1$-$\mathcal{GP}$ Architecture: Safe Learning and Control



(a) Contraction-based feedback



$\mathcal{RL}_1$



(c) $\mathcal{RL}_1$-$\mathcal{GP}$

**No** safety guarantees!

Out of ten random initia
conditions, **8 trajectorie**
**collide** with obstacles.

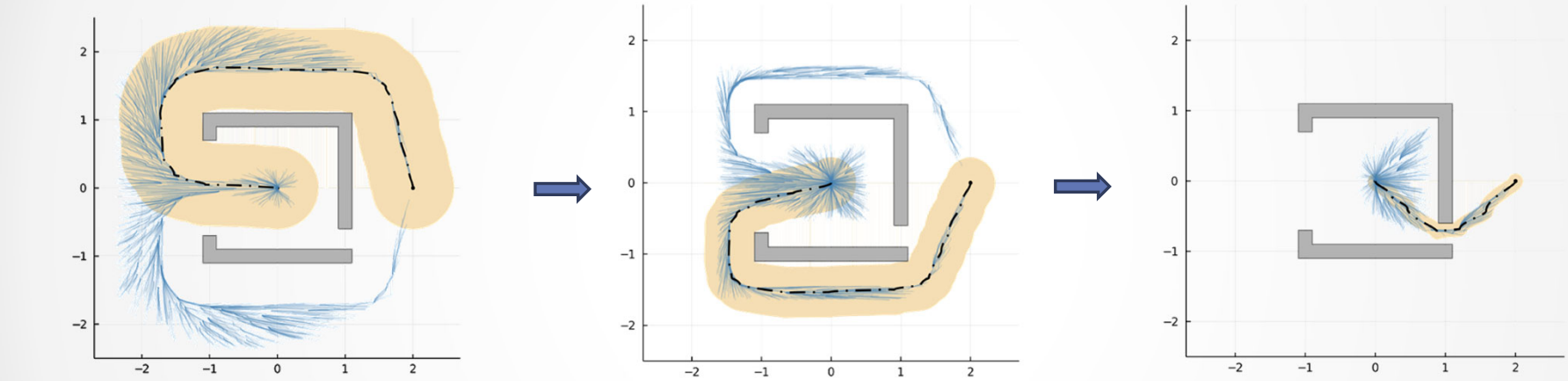
Uses a conservative knowledge of the uncertainty.

**teed**!

As the uncertainty is learned, performance is improved **without** sacrificing robustness.

# Contraction $\mathcal{L}_1$- $\mathcal{GP}$ Architecture: Safe Learning and Control

Learning **kicks in** ⟹ tube **shrinks** ⟹ **better** planning



(a) only a deterministic knowledge of the uncertainty

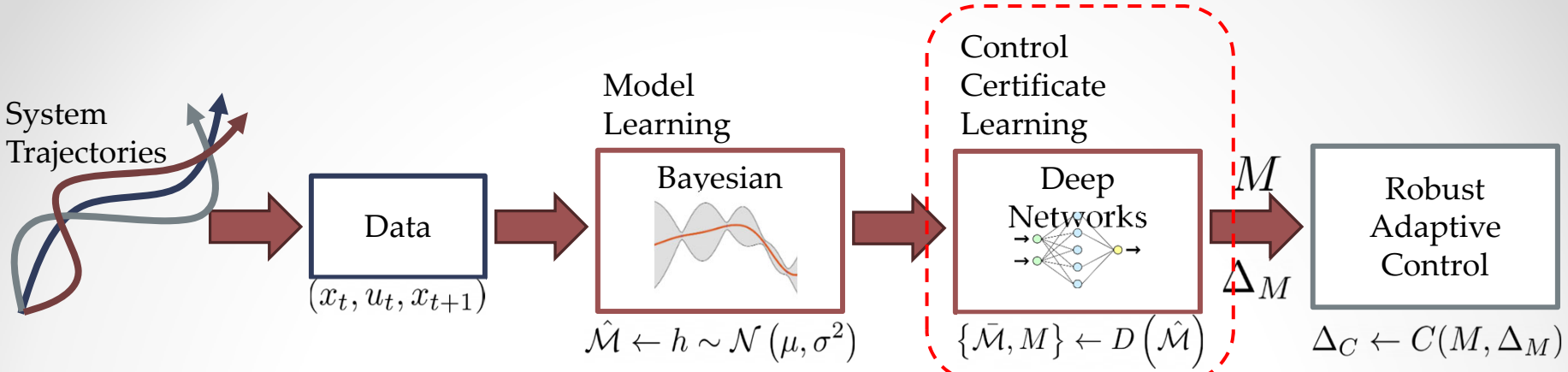
(b) model learned with N = 25 dataset

(c) model learned with N = 100 dataset

**When learned model updates, no retuning required for $\mathcal{RL}_1$**

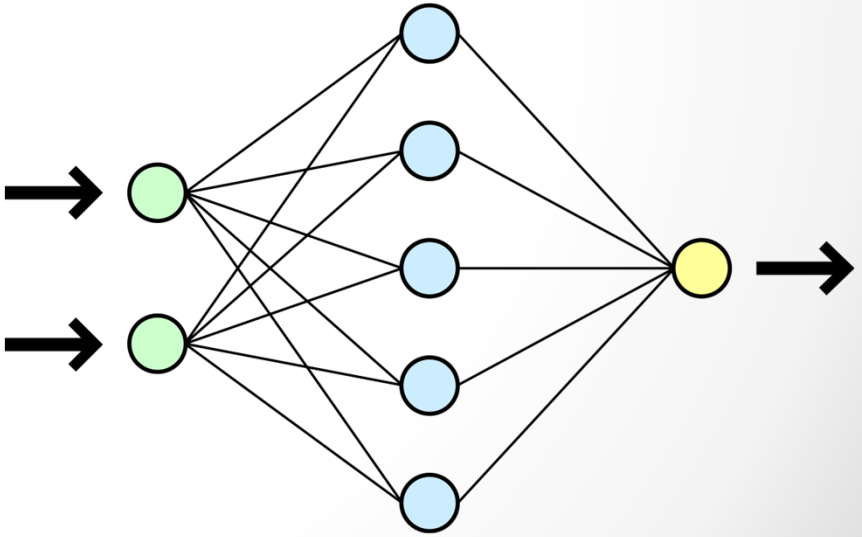
⟹

**Safety is decoupled from learning!**




# Learning the Control Certificates

# DISCO





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Learning accurate models by themselves is **not** enough!

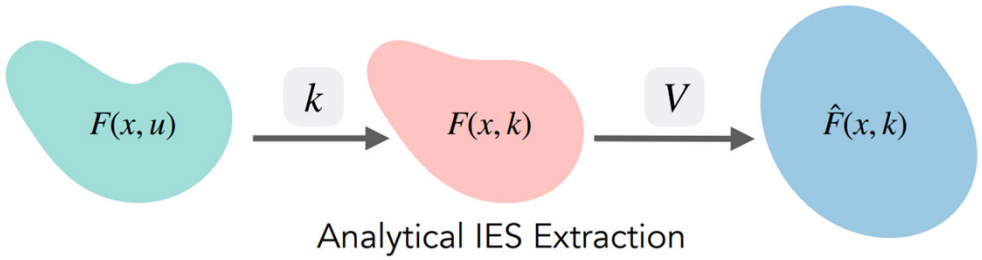
The accuracy of the learned models is **not sufficient** to guarantee that controllers can be synthesized.


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# Deep Incrementally Stabilizing Control

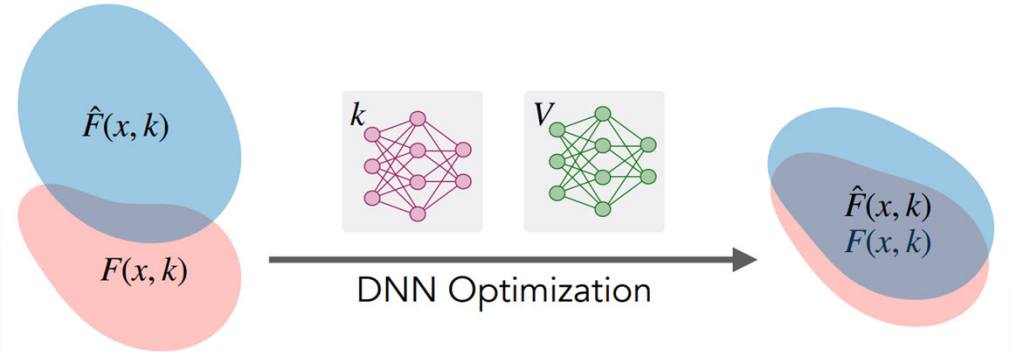
Our approach: Optimization-based relaxation of the feasibility problem
Design spaces of valid CCMs/ILFs and feedback laws

- Extract models that are analytically verified to be IES
- A projection-based approach



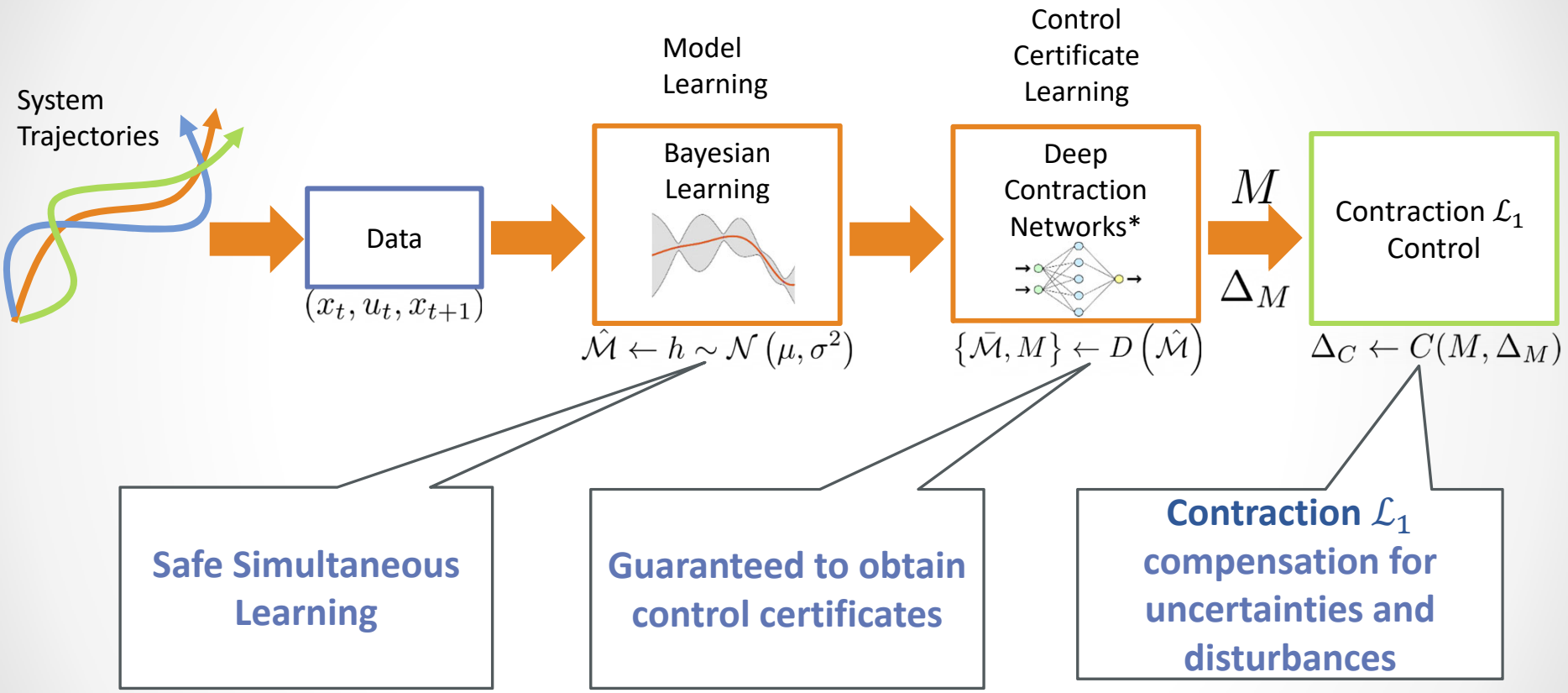

Parameterize the space of valid candidates using DNNs

- DNN opt. minimizes model-mismatch between learned and extracted models




*Gahlawat, A., Lakshmanan, A., Vlahov, B. Gandhi, M. Song, L, Hovakimyan, N., and Theodorou, E. "Deep Incrementally Stabilizing Control. *Under Review.*

# Control Pipeline



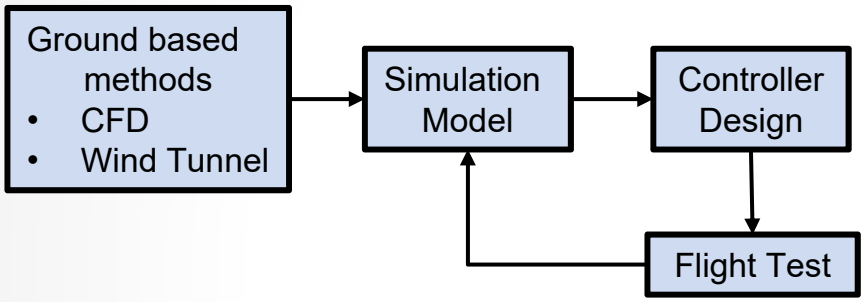

*Gahlawat, A., Lakshmanan, A., Vlahov, B. Gandhi, M. Song, L, Hovakimyan, N., and Theodorou, E. "Deep Incrementally Stabilizing Control. "*In preparation.*

A few ***real-world problems*** that need the robustness and performance guarantees provided by our safe learning and control framework.


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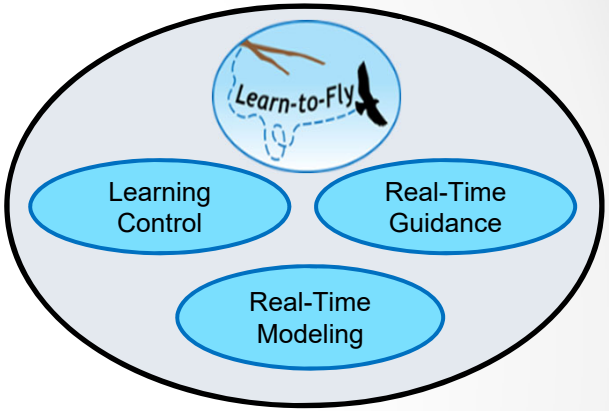
# Learn-to-Fly (L2F)

Conventional aircraft development process





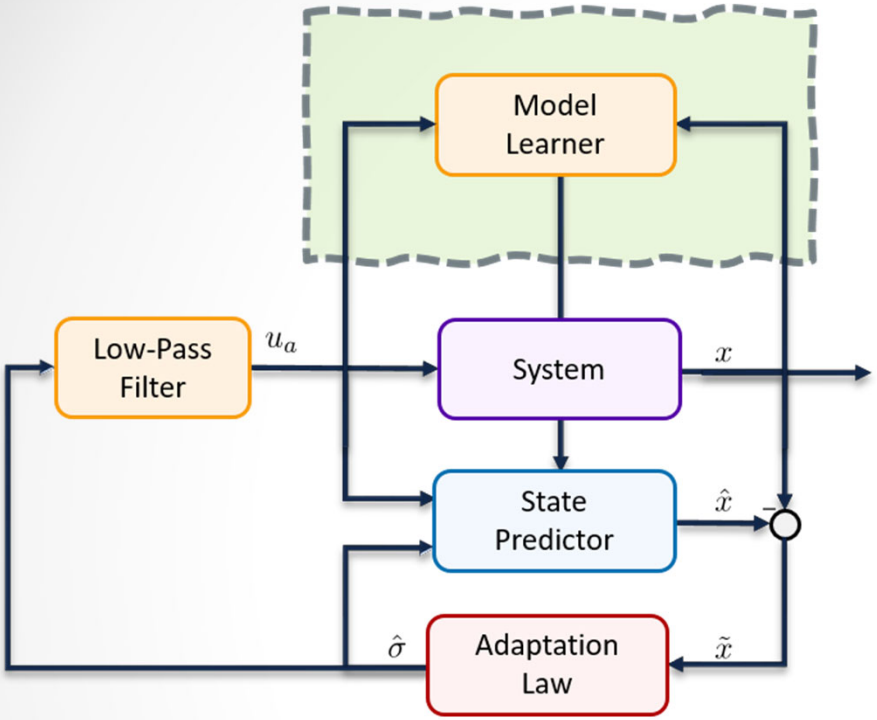

L2F concept*



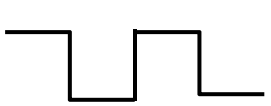



*E. H. Heim, et al. "NASA's Learn-to-Fly Project Overview." In *2018 Atmospheric Flight Mechanics Conference*, 2018.

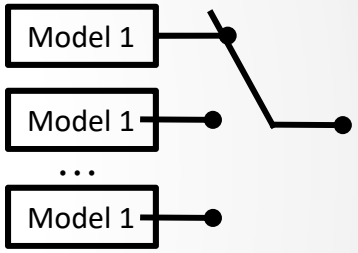
# Learn-to-Fly (L2F)




Periodic model update



Switched nom. dynamics




$$\dot{x}(t) = A_p x(t) + B_p \left(\omega_p u(t) + f_p(t, x)\right)$$

- Learned model is used to update the nominal dynamics
- Adaptive control handles the discrepancy between the learned model and the actual dynamics
- Periodic model update leads to switched nominal dynamics


S. Snyder, P. Zhao and N. Hovakimyan. L1 adaptive control for switching reference systems: Application to flight control. *IFAC-PapersOnLine*, 52(16), pp.718-723, 2019.

S. Snyder, P. Zhao*, N. Hovakimyan. L1 adaptive control for learn-to-fly validated by flight tests. *In preparation*.

# Flight Tests at NASA LaRC

- Flight tests on NASA Woodstock and E-1 aircraft performed at NASA LaRC



E1


Woodstock

This video demonstrates the flight test of a Learn-to-Fly system supported by an L1 adaptive augmentation on the E-1 aircraft.

Unstable aircraft emulation by activating the hidden feedback

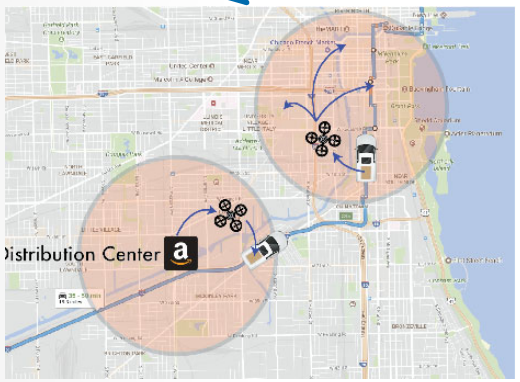
- Challenging for the pilot to control
- L2F able to achieve level flight after initial learning phase

S. Snyder, P. Zhao*, N. Hovakimyan. L1 adaptive control for learn-to-fly validated by flight tests. *In preparation*.

# Last Mile Delivery Problem

The **rapid growth of e-commerce** demands has resulted in **increased traffic of delivery** trucks while **slowing down the pace** of delivery operations.

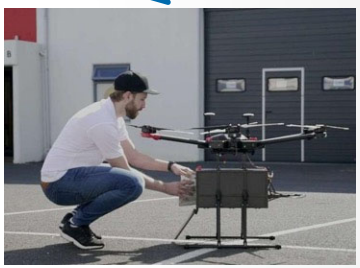
**Dispatch** a package over the delivery network




**Use space** on a ground vehicle's roof



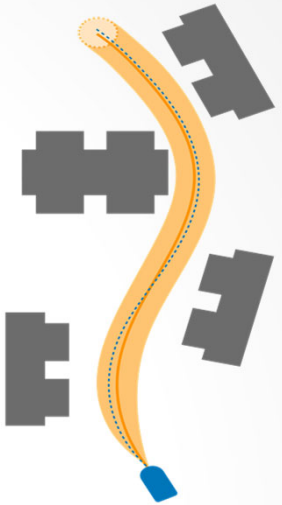
**Fly last-mile** to the target position



- Handling packages of unknown sizes and masses
  - Leverage robust adaptive control to guarantee mission success while simultaneously and safely learning the uncertainties to improve the energy efficiency
- Safe and robust rendezvous in the presence of uncertainties with the ground vehicles
  - Use Bayesian learning to predict the movement of ground vehicles and incorporate the uncertainty into a planner (e.g., MPPI) for risk-sensitive planning.

# Deep Perceptual Adaptive Control

- Uncertainty-driven safety guarantees for the full autonomy stack from perception to low-level control
- Quantify performance as a function of available hardware and software resources
- Dynamic resource allocation:
  - **Fast environment**: Perception, high-rate planning, and adaptation prioritized.
  - **Slow environment**: Safe model learning.



A. Lakshmanan, A. Gahlawat and N. Hovakimyan, Safe Feedback Motion Planning: A Contraction Theory and L1-Adaptive Control Based Approach, In Proceedings of Control and Decision Conference, Jeju Island, Korea, 2020, accepted.



NASA's Urban Aerial Mobility platforms

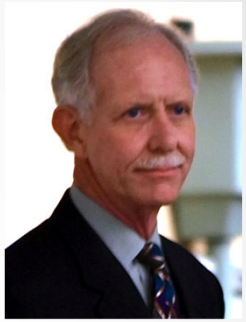


P. Drews, G. Williams, B. Goldfain, E. A., Theodorou, and J. M. Rehg, "Vision-based high-speed driving with a deep dynamic observer." IEEE Robotics and Automation Letters, 4(2), 1564-1571, 2019

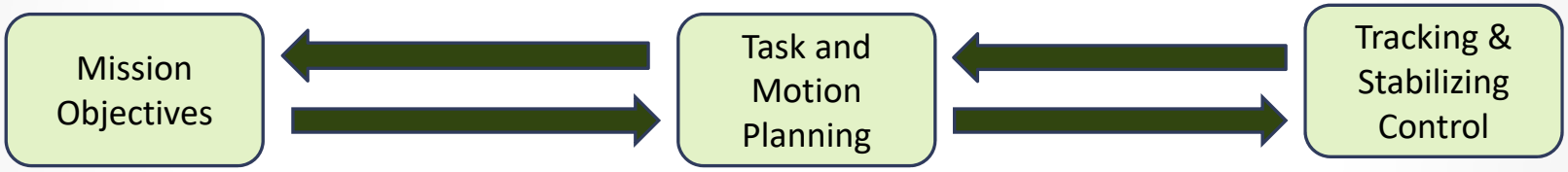
# Virtual Sully: Towards Full Pilotless Autonomy

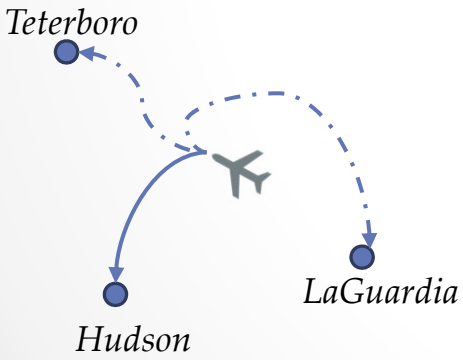
- Airbus 320 lost both engines shortly after takeoff due to bird strike.
- Captain Sullenberger made the **correct decision** by landing on the Hudson river instead of attempting return to LaGuardia
- Long years of experience and training of neurons in human brain lead to correct decisions (**what can we learn from neuroscience?**)



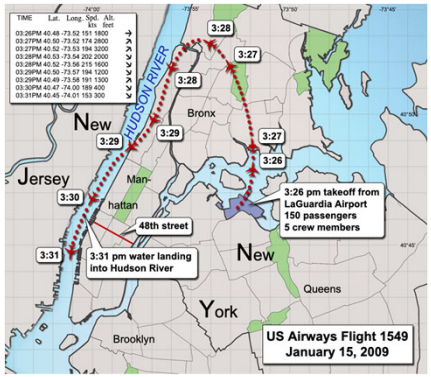


Credits: (left) Greg L., (right) I. Talyar

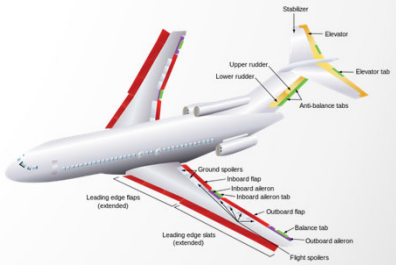



**Safest landing option**




**Safe path to the Hudson river**



**Safe landing with just the available control surfaces**

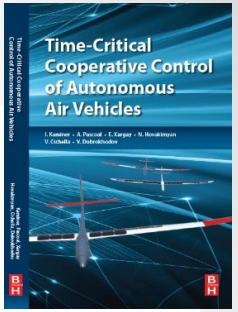


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# Cooperative Path Generation and Path Following











J. Puig-Navarro et al. "Silhouette-Informed Trajectory Generation through a Wire Maze for UAS." *In the* Aviation Technology, Integration, and Operations Conference, 2018.

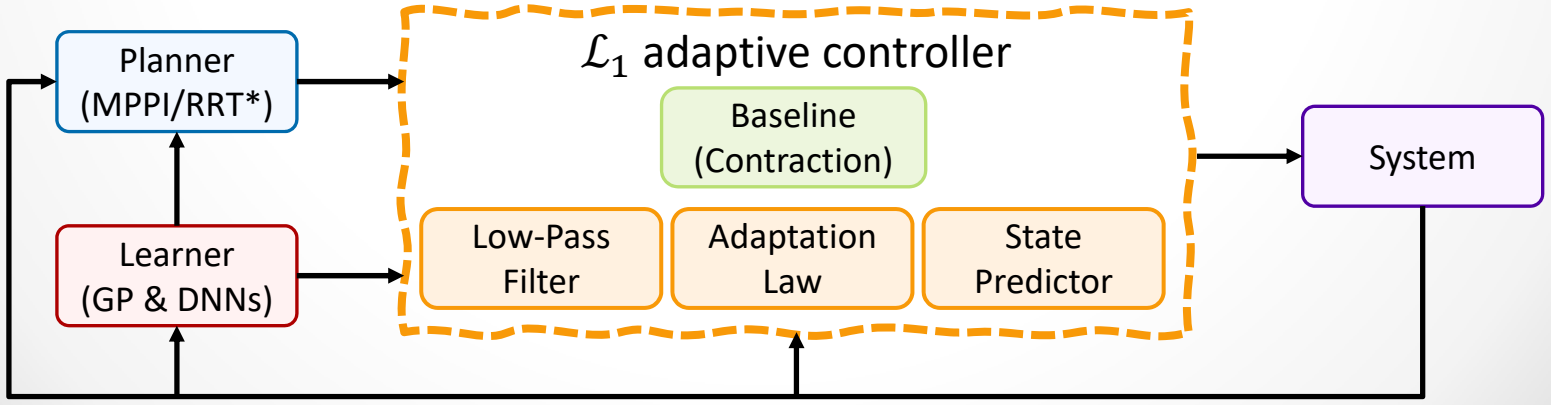
V. Cichella et al. Safe Coordinated Maneuvering of Teams of Multirotor UAVs: A Cooperative Control Framework for Multi-Vehicle Time-Critical Missions, IEEE Control Systems Magazine, vol. 36, No. 4, pp. 59-82, 2016.

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# Conclusions

- Developed advanced **safe trajectory tracking** control algorithms for complex and uncertain environments.
- **Contraction-based control** ensures exponential convergence of the nominal system to some planned trajectory.
- Relies on **fast adaptation** to immediately compensate for disturbances and **slow adaptation** to learn the unmodeled dynamics over time.
- Performance guarantees (as tubes) and robustness margins (as filter design) can be tuned to **ensure safety during the entire learning process.**



# Current collaborators

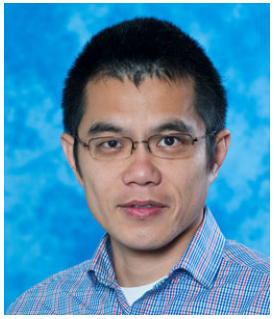
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Petros Voulgaris



Xiaofeng Wang



Lui Sha



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# An incomplete list of acknowledgements


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Vijay Patel (Indian Ministry of Defense)
Vahram Stepanyan (NASA Ames)
Jiang Wang (Apple)
Amanda Dippold (Howard Community College)
Dapeng Li (JD.com)
Enric Xargay (Barcelona, Spain)
Zhiyuan Li (DJI)
Evgeny Kharisov (Seagate)
Hui Sun (Marvell Semiconductor)
Venanzio Cichella (University of Iowa)
Syed Bilal Mehdi (GM)
Hanmin Lee (Korean Defense Agency)
Ronald Choe (Singapore Defense Agency)
Hamidreza Jafarnejadsani (Stevens Institute of Technology)
Steve Snyder (NASA)
Thiago Marinho (Waymo, Alphabet)
Hyung-Jin Yoon (University of Nevada)
Alexandre Barbosa (Amazon Robotics)

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Petros Voulgaris, UNR
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Lui Sha, UIUC
Tarek Abdelzaher, UIUC
Evangelos Theodorou, Georgia Tech
Marco Pavone, Stanford
Zsolt Kira, Georgia Tech
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Tryphon Georgiou, UC Irvine
Alex Kirlik, UIUC
Frances Wang, UIUC
Dusan Stipanovic, UIUC
Lavanya Marla, UIUC
Tamer Basar, UIUC
Honghui Shi, University of Oregon
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*Learjet 1*



*F-16*



*Learjet 2*



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