



Safe Learning in Unmanned and Autonomous Systems

Claire Tomlin, EECS, UC Berkeley
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Economic Incentives

Game theory // Mechanism design // Interdependent risk management

😊 Reliability and Security Risk Management



Internet

😊 Diagnosis, Response, and Reconfiguration



Control Network

😊 Detection and Regulation



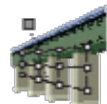
Sensor Actuator Network



Electric Power

Buildings

😊 Physical Infrastructures



Water & Gas

Transportation

Resilient CPS design

Robust Control

Fault/attack diagnostics // Control of ActionWebs // Model-based design

Economic Incentives

Game theory // Mechanism design // Interdependent risk management

Resilient CPS design

😊 Reliability and Security Risk Management

Residential DR

👹 Internet

😊 Diagnosis, Response, and Reconfiguration

👹 Control Network

😊 Detection and Regulation

Secure Estimation for CPS
Fully decentralized policies

👹 Sensor Actuator Network

Electric Power

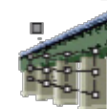
Distributed Power

😊 Physical Infrastructures

Buildings

UAV networks

Water & Gas



Resilient Stormwater Mgmt

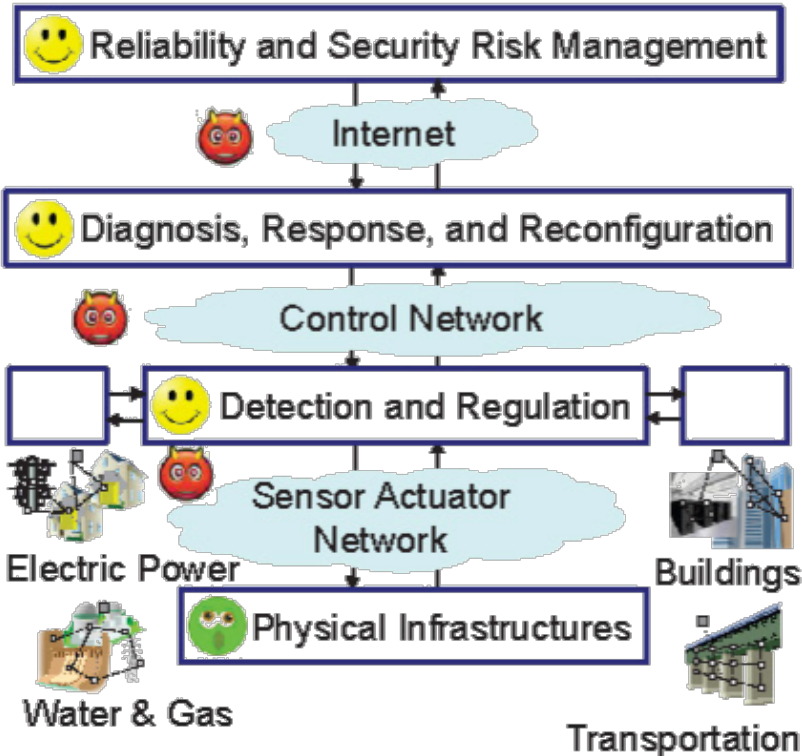
Transportation

Robust Control

Fault/attack diagnostics // Control of ActionWebs // Model-based design

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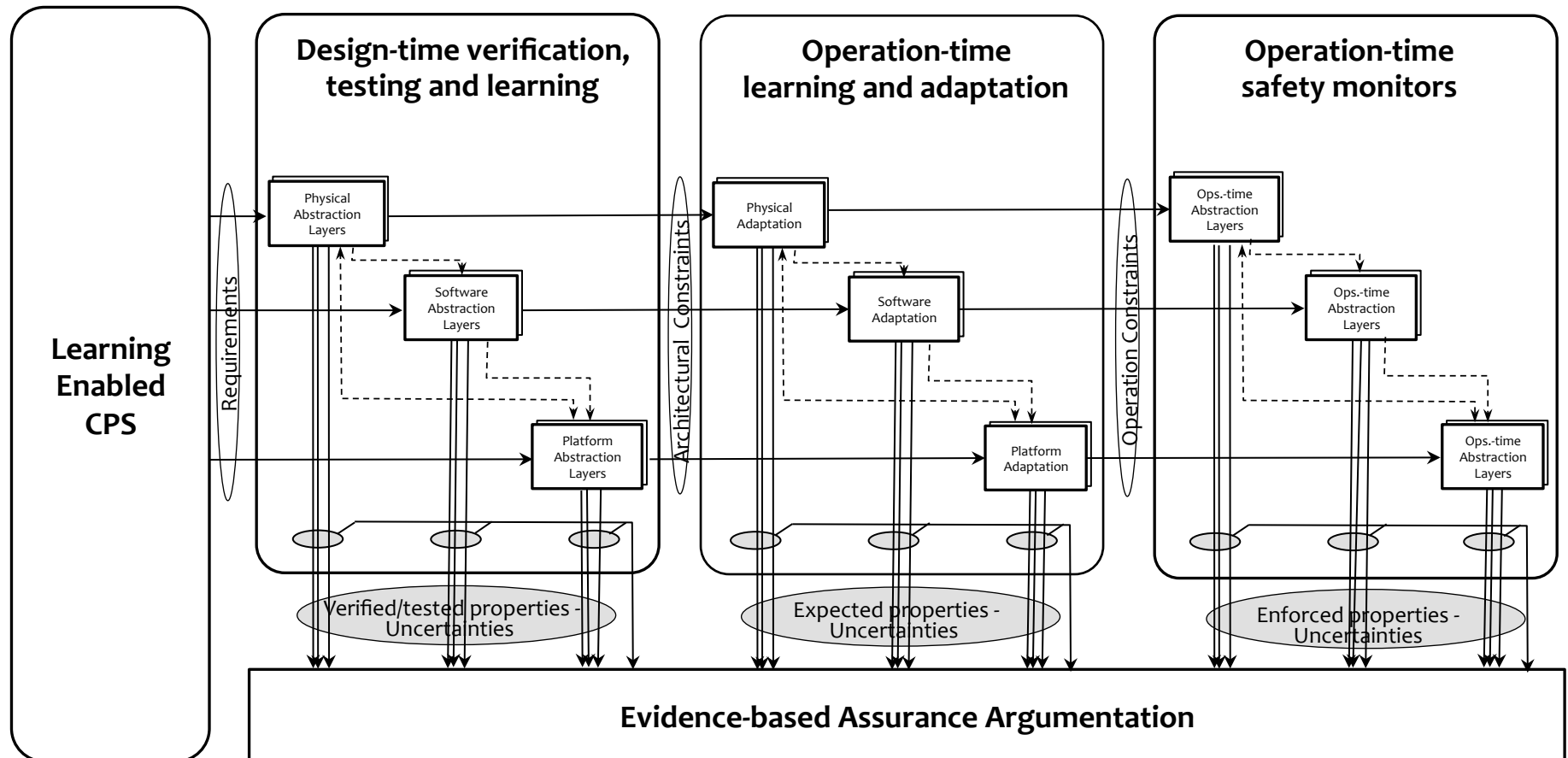
Learning-Enabled
Components

Resilient CPS design

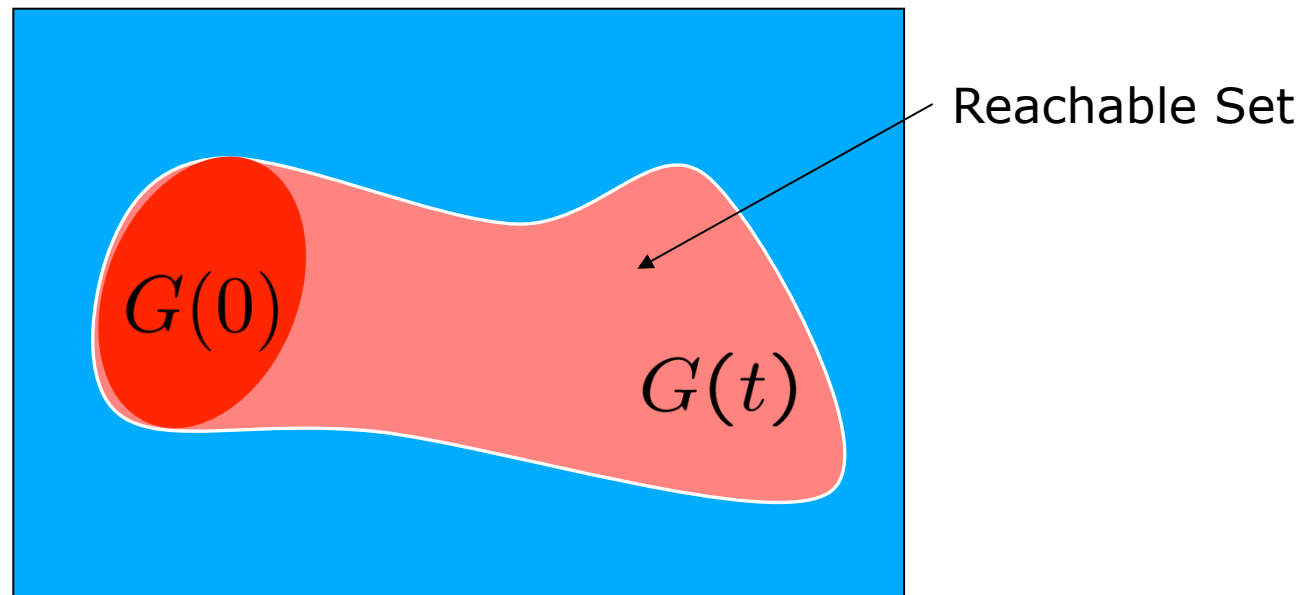
Robust Control

Fault/attack diagnostics // Control of ActionWebs // Model-based design

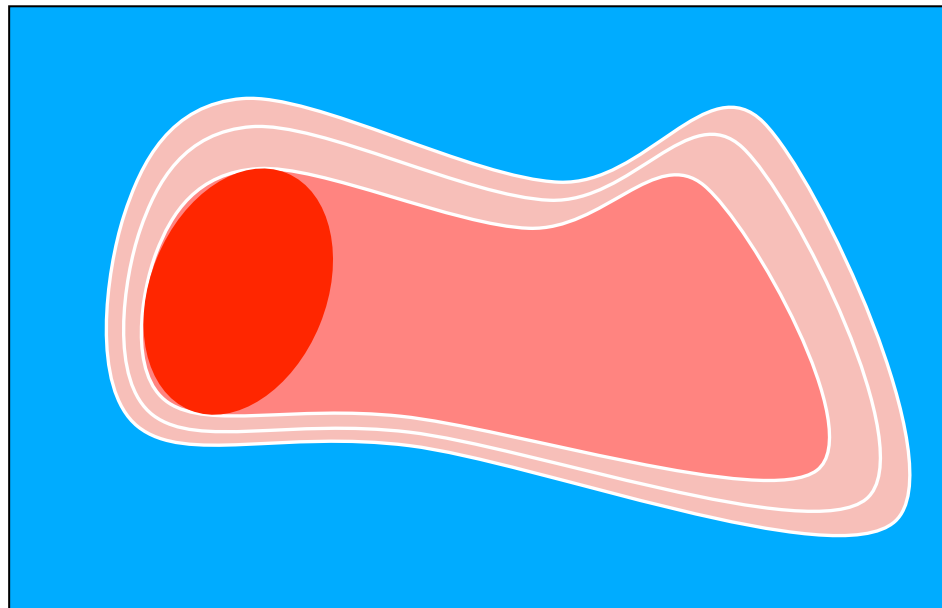
Designing high confidence systems that can learn



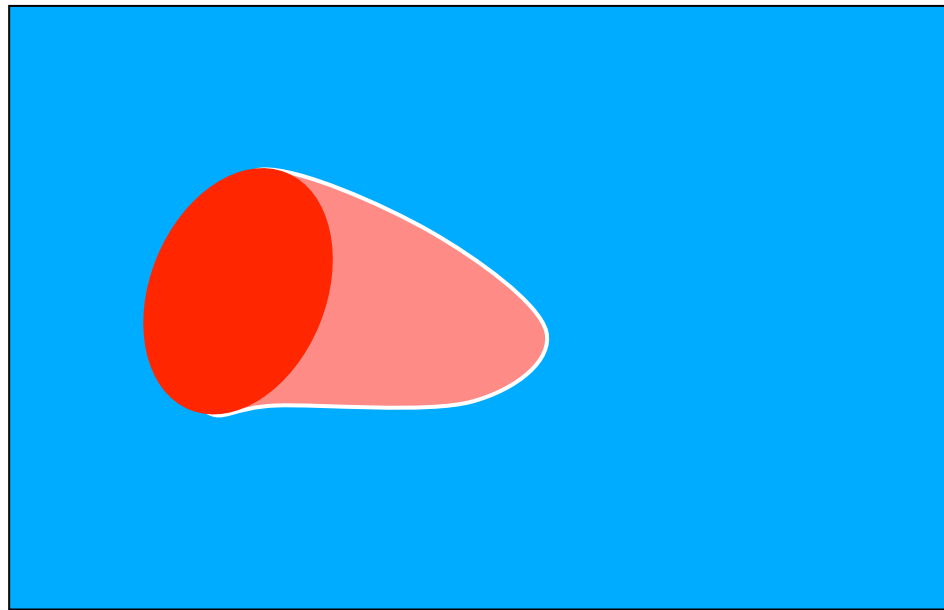
Model Checking using Reachability



Overapproximations as certificates



Learning can reduce conservatism



Scalability

- **Impose practical constraints**
 - Roads, highways, protocols...
- **Approximations**
 - Bisimulations (Girard, Pappas, Tabuada)
 - Linear, piecewise and multi-affine systems (Morari, Borrelli, Krogh, Johansson, Rantzer, Belta, Ozay, Darbon, Osher)
 - Ellipsoidal and polyhedral sets (Kurzhanski , Varaiya, Stipanovic)
 - Polynomial systems, barrier certificates (Parillo, Majumdar, Tedrake, Pappas, Papachristodoulou, Julius, Lall, Topcu, Frehse, Le Guernic, Donzé, Girard, Dang, Maler, Dreossi, Sankaranarayanan)
 - Decoupling disturbances (Chen, Herbert)
- **Mathematical structure**
 - Monotone systems (Sontag, Hafner, Del Vecchio, Arcak, Coogan)
 - LTL specifications (Kress-Gazit, Raman, Murray, Wongpiromsarn, Belta)
- **Decompositions** (Mitchell, Del Vecchio, Chen, Herbert, Grizzle, Ames, Tabuada)
- **Machine learning** (Lygeros, Djeridane, Niarchos, Seshia, Chen)

Learning a controller



Sinusoid + Yaw:

- Trained on each component separately
- Asked to fly combination
- Used Cascade FF neural net (ReLU), 2 layers, 3000 units

... but stay safe while learning

- * **Safety:**

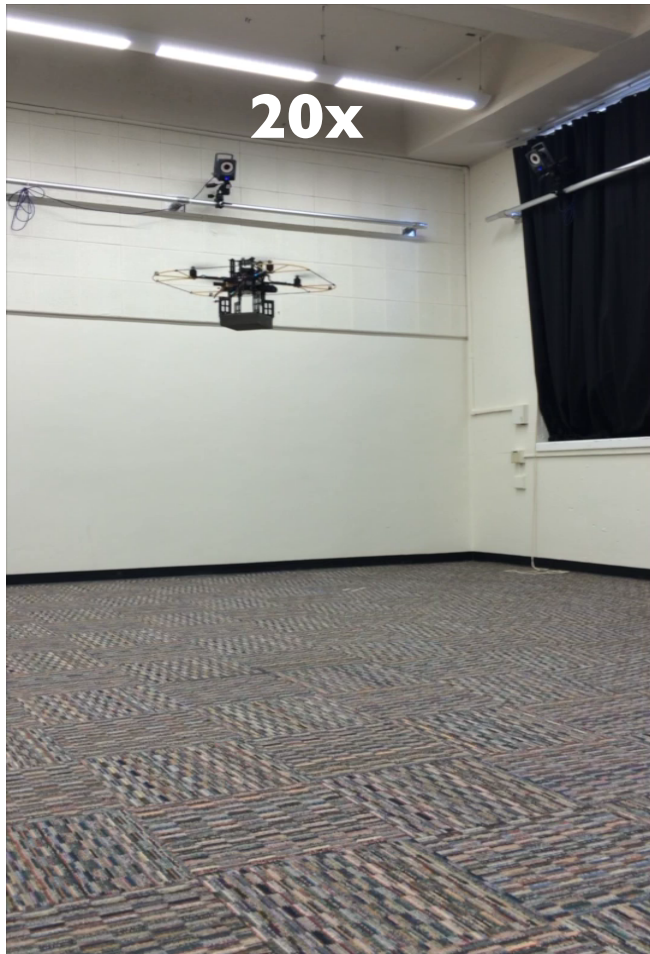
- * A nominal model with error bounds
- * Reachable sets computed to ensure safety in worst case

- * **Performance:**

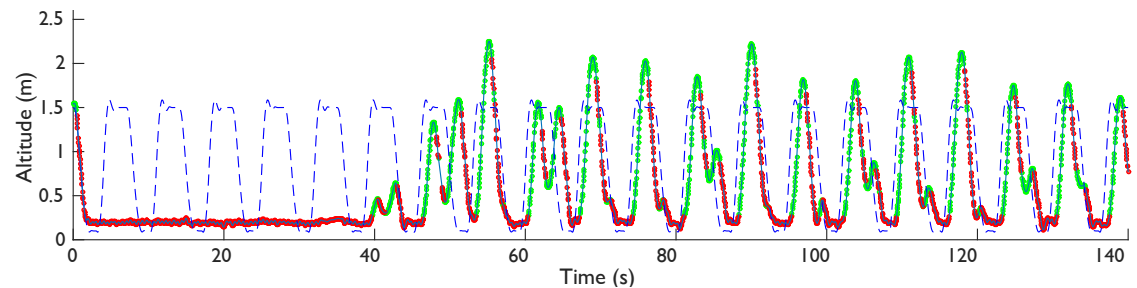
- * Use online learning to update model
- * Cost function used to generate control action within the safe set

Safe Policy Gradient Reinforcement Learning

The quadrotor first:



drops

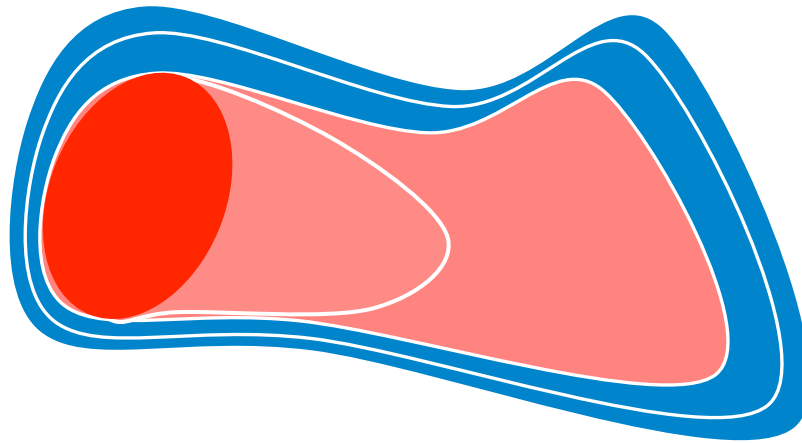


After about 1 minute,
it can roughly track the trajectory

Soon, it starts experimenting

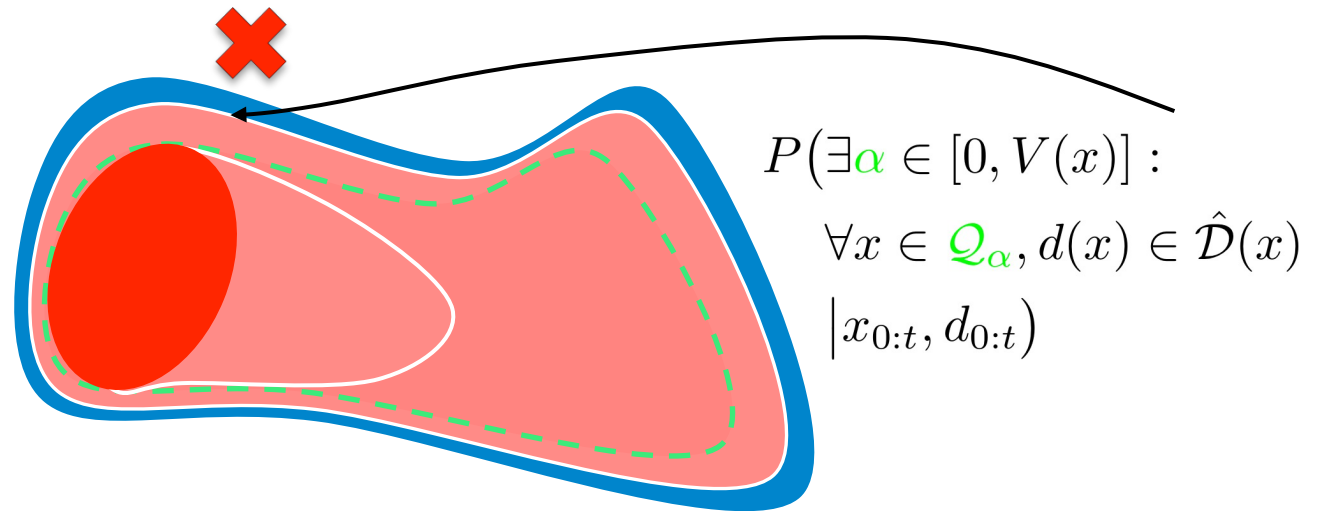
...but the safe controller steps in

Online Safety Guarantee Validation



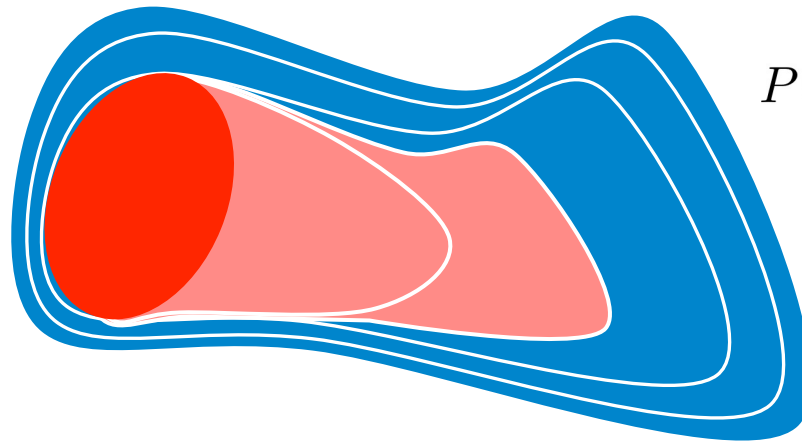
- Initialize active unsafe set = smallest candidate set

Online Safety Guarantee Validation



- Measure disturbance
- Compute Bayesian posterior on existence of a usable level set
- If posterior is low (weak safety guarantee), update unsafe set
- Update disturbance model

Online Safety Guarantee Validation



$$P(\exists \alpha \in [0, V(x)] : \\ \forall x \in \mathcal{Q}_\alpha, d(x) \in \hat{\mathcal{D}}(x) \\ | x_{0:t}, d_{0:t})$$

- Measure disturbance
- Compute Bayesian posterior on existence of a usable level set
- If posterior is low (weak safety guarantee), update unsafe set
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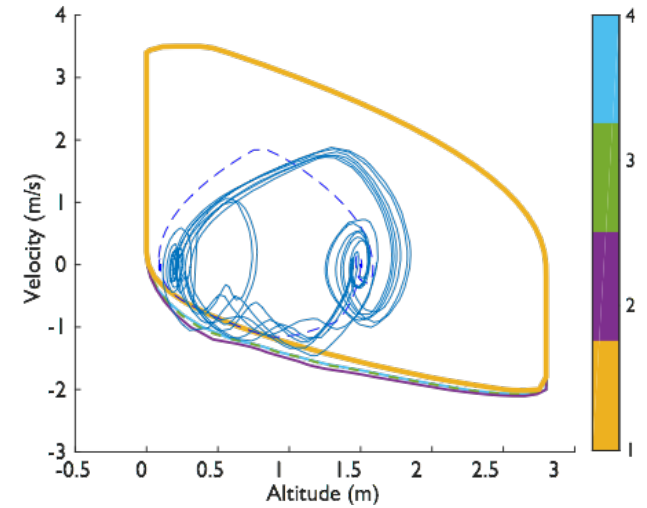
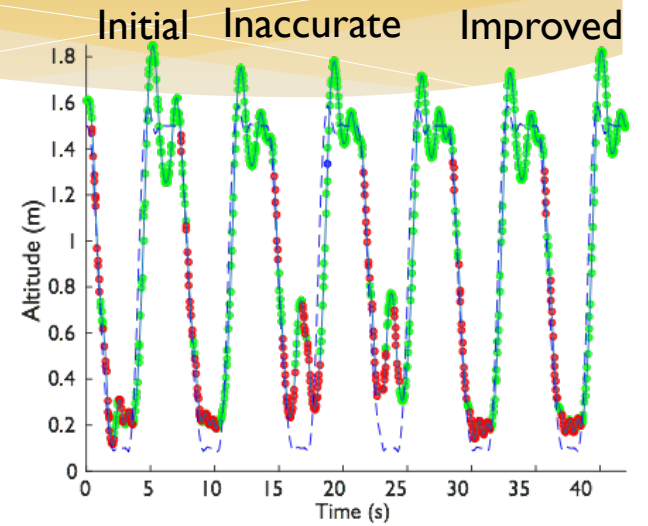
Safe Learning




First computed model is locally inaccurate

System detects inconsistency, slightly contracts safe set

Tracking resumes after a better model is computed





Safe Learning

with online model validation

Berkeley
University of California

Research Challenges

- * Models of unknown environments
 - * Scalability and compositional safety
 - * Safe exploration
 - * Sample efficiency: design-time vs operation-time
 - * Mixed initiative and collaborative learning
 - * Risk models
-
- * Safe Learning: Kene Akametalu, Somil Bansal, Jaime Fisac
 - * **Max Balandat, Young Hwan Chang, Margaret Chapman, Roel Dobbe, David Fridovich-Keil, Qie Hu, Insoon Yang, Datong-Paul Zhou**