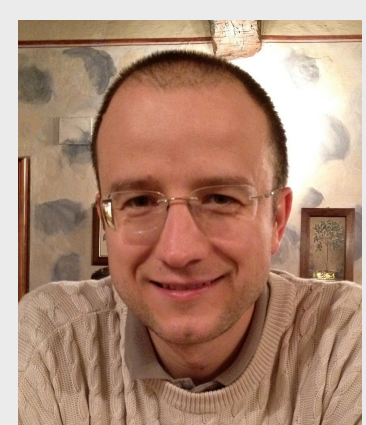


Data-Driven Cyberphysical Systems



Topcu



Fish



Dillig



Caramanis



Sangiovanni-Vincentelli



Sznaier



Mishra



Yue

Univ of Texas at Austin

Univ of California at Berkeley

Northeastern Univ

Rensselaer Polytechnic Inst

California Inst of Technology

The central question

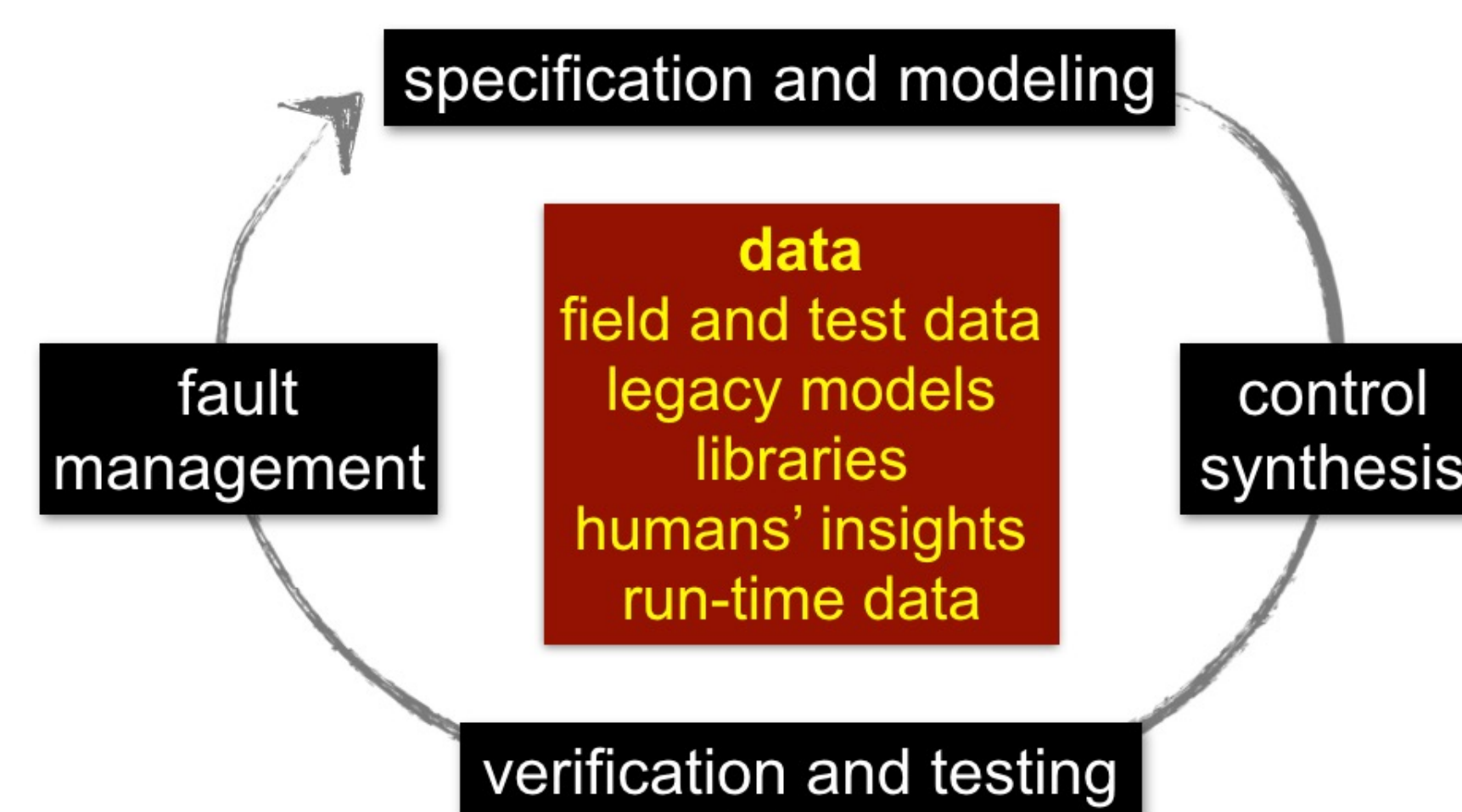
How can we, *in a data-aware world*, design and operate CPS differently?

Why?

Increasingly difficult and costly to develop CPS.

The approach

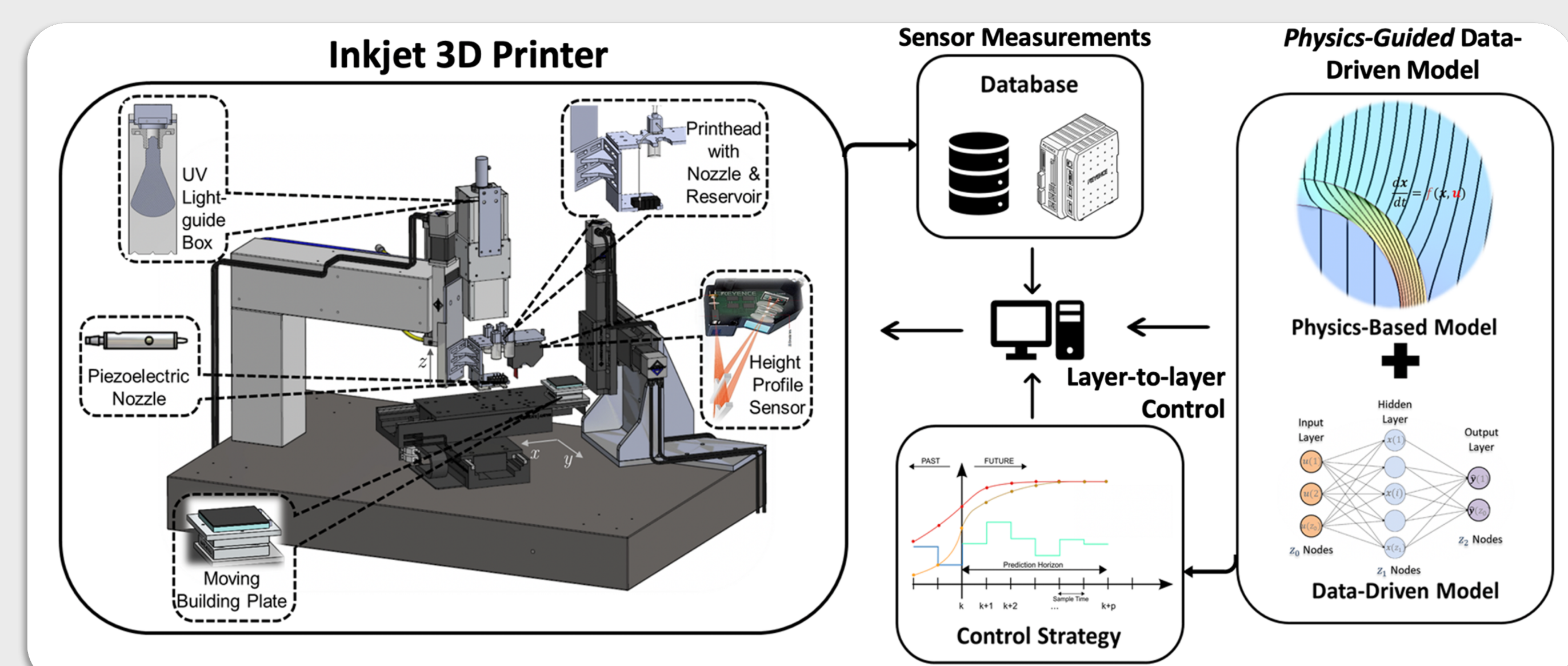
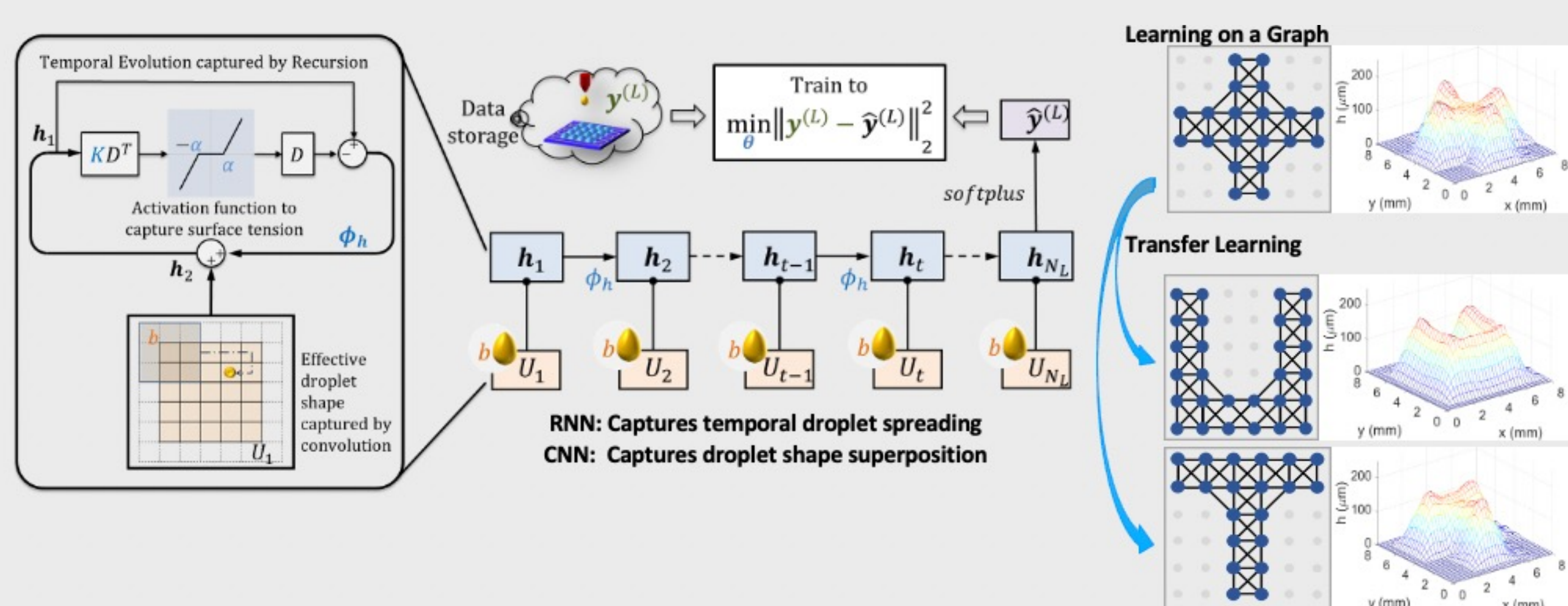
Data-driven methods complementing model-based design and **respecting the needs of CPS**



What is different in CPS?

- Safety-criticality
- Obey the laws of physics
- Heterogenous data at run time while closing the loop
- Possibility for proactive data collection
- Sometimes “big” yet often scarce data

Physics-guided, data-driven modeling and control for inkjet 3D printing



- Based on conservation laws: guaranteed stability, input output passivity
- Needs 60x less training data because of embedded structure
- Geometry-agnostic: train on geometry, transfer to a different geometry by changing the graph

Safety-guaranteed, data-driven control

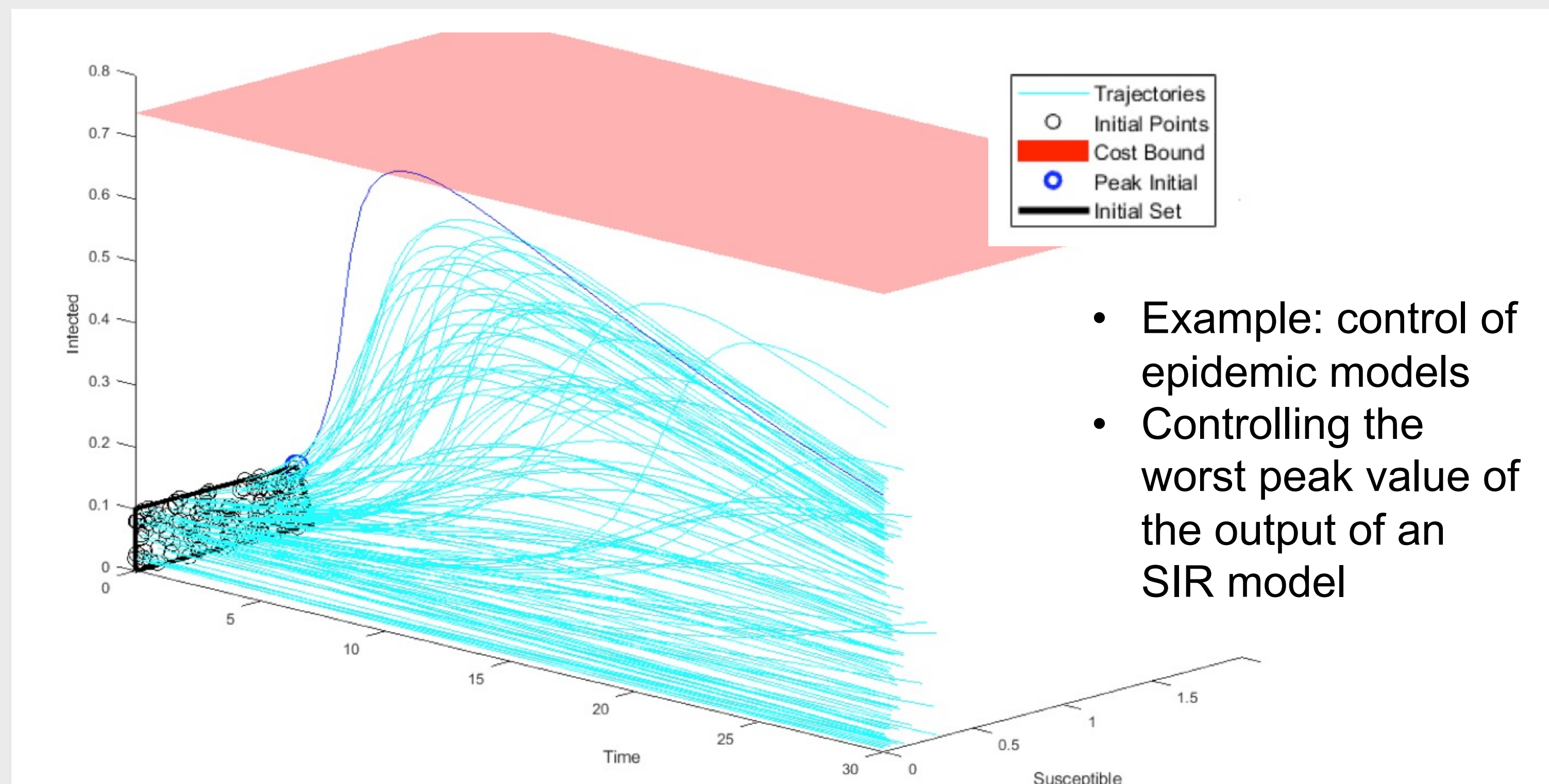
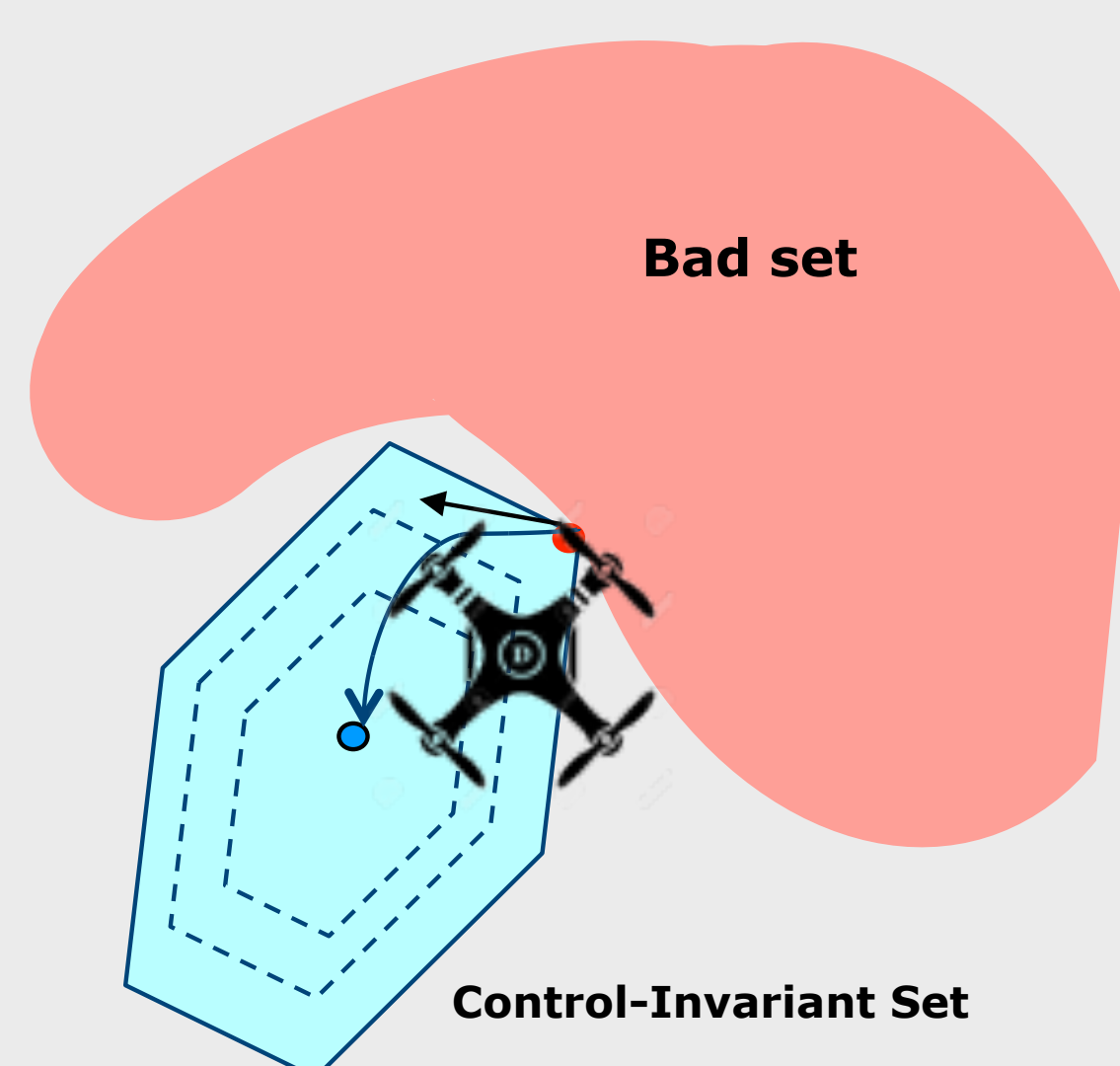
Control a system with unknown dynamics while avoiding an unsafe set

Key enabler for learning based control

- Stay safe while learning about the system
- Provides a “safety guard” that can be easily incorporated into existing learning-based framework

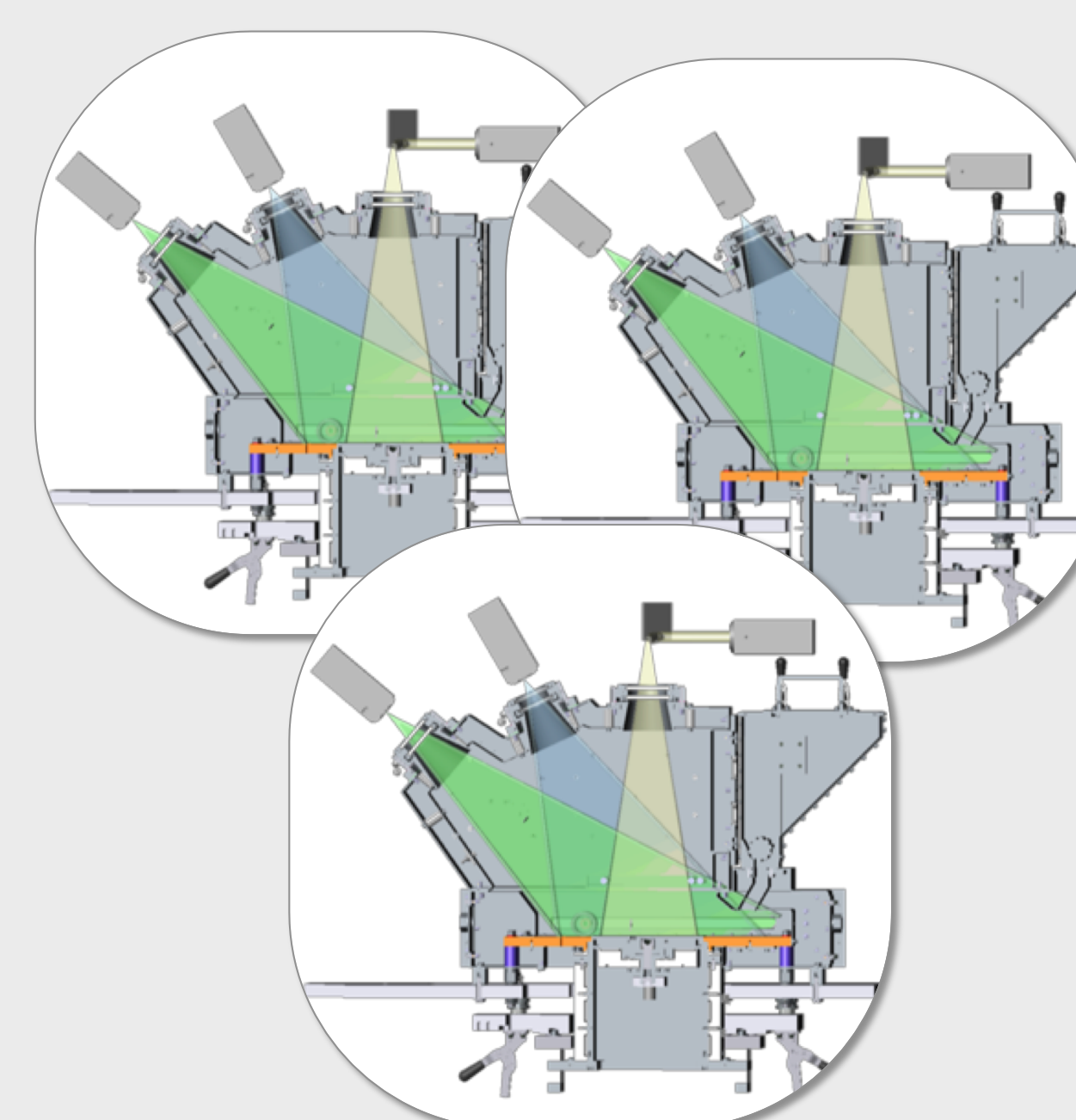
Key ideas

- Reduces to a tractable convex optimization
- The structure of the optimization can be exploited to reduce computational complexity

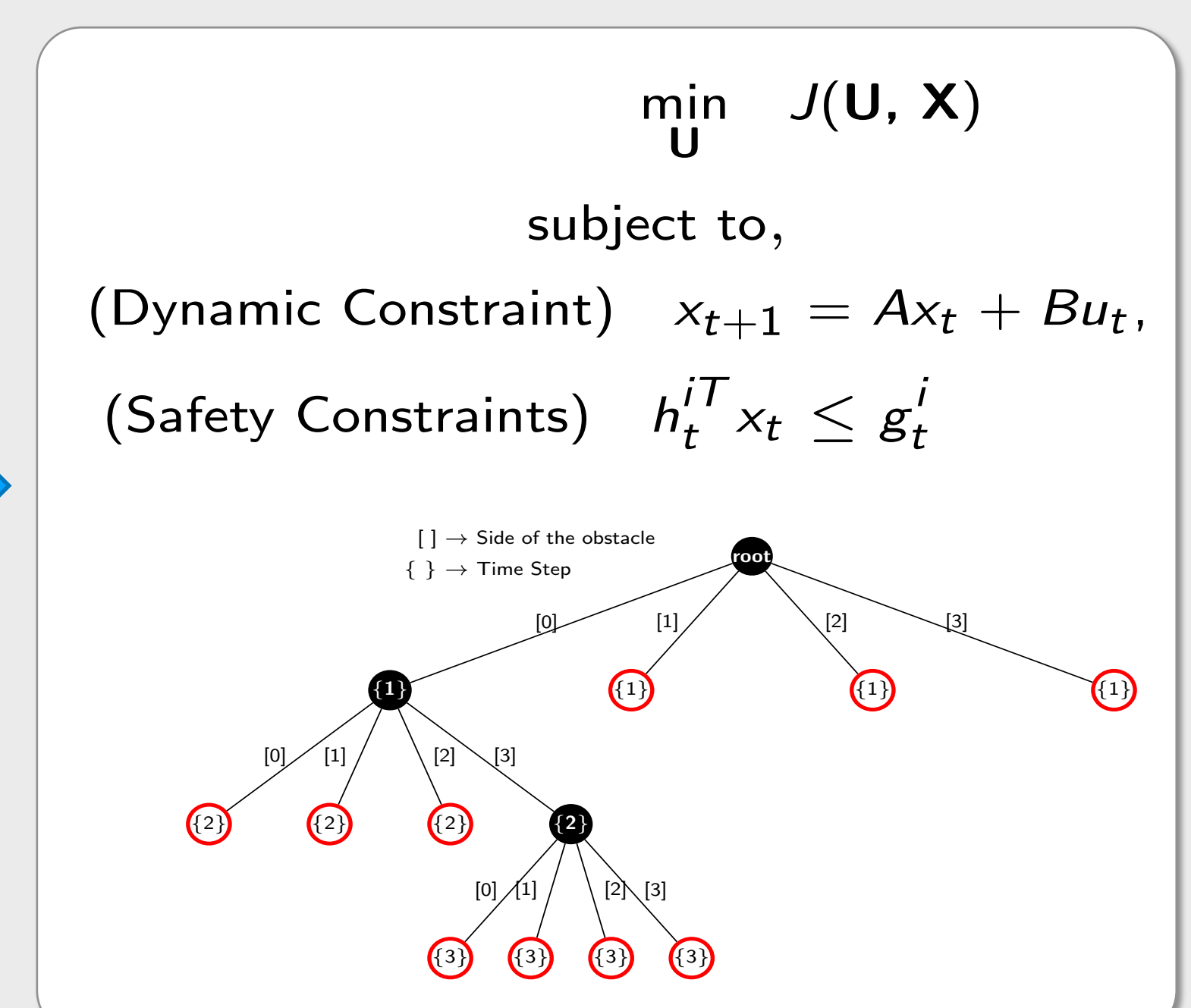


- Example: control of epidemic models
- Controlling the worst peak value of the output of an SIR model

Learning to optimize



Distribution of planning instances



Compiled as combinatorial optimization problems

Key insight

- Many solvers are sequential, e.g., gradient- or coordinate-descent
- Can view a solver as “agent” or “policy” making decisions

