



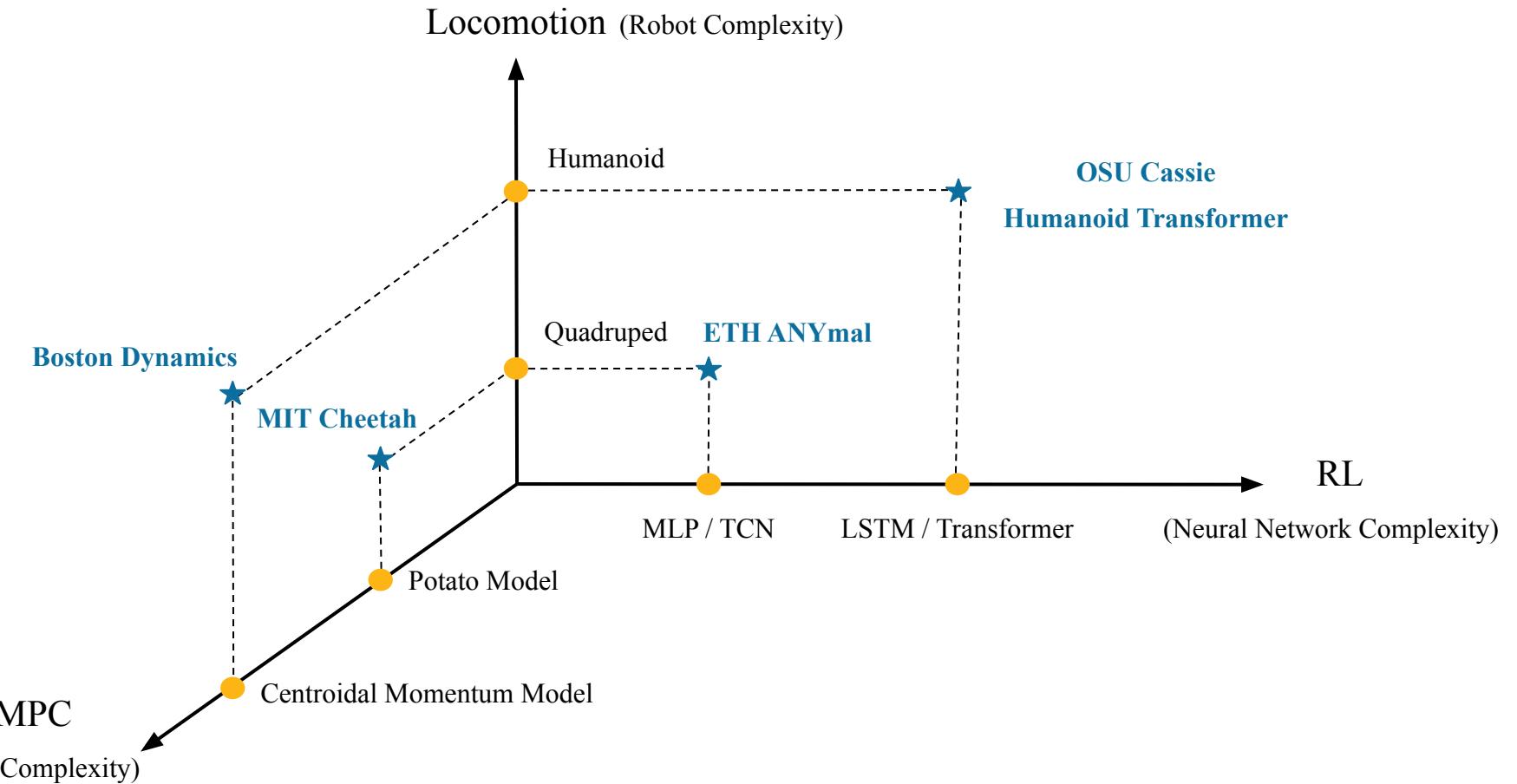
# Predictive Control and Reinforcement Learning for Legged Robots: Part 2

Bike Zhang

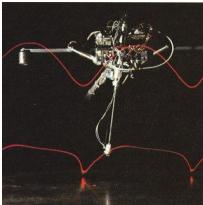


Berkeley Mechanical Engineering

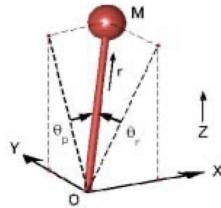
Apr. 20, 2023  
EECS 206B Guest Lecture



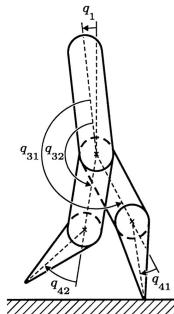
# History of legged robot



Legged Robots that Balance  
Marc Raibert



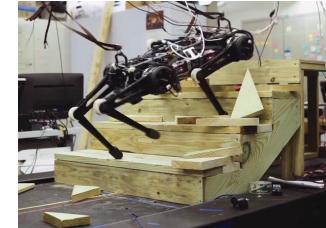
Linear Inverted Pendulum  
Shuuji Kajita



Hybrid Zero Dynamics  
Jessy Grizzle



DARPA Robotics Challenge



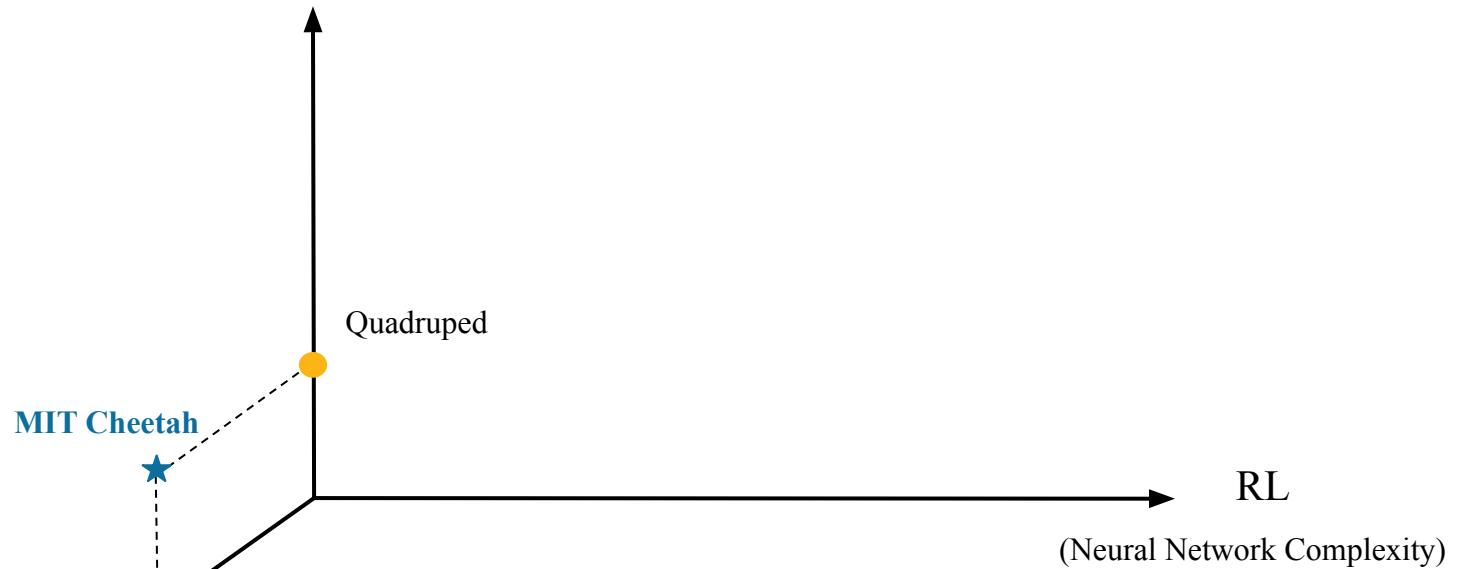
Model Predictive Control  
Sangbae Kim



Reinforcement Learning  
Marco Hutter



Locomotion (Robot Complexity)



MPC

(Model Complexity)

RL

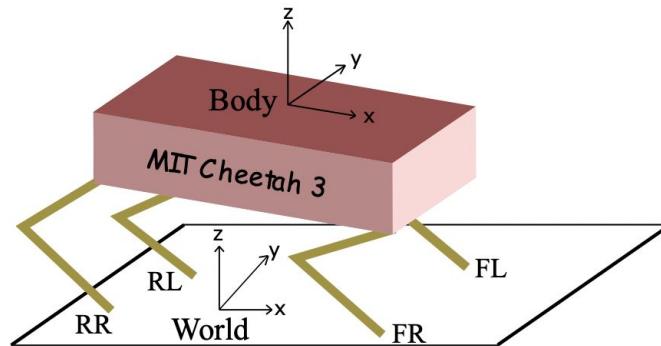
(Neural Network Complexity)

# MIT Cheetah



# Convex Model Predictive Control

## Stance Phase



Potato Model

## Assumption:

- Ignore leg dynamics
- Base roll and pitch are small

## Output:

- Ground reaction force

## Swing phase:

- Raibert heuristic

# Convex Model Predictive Control

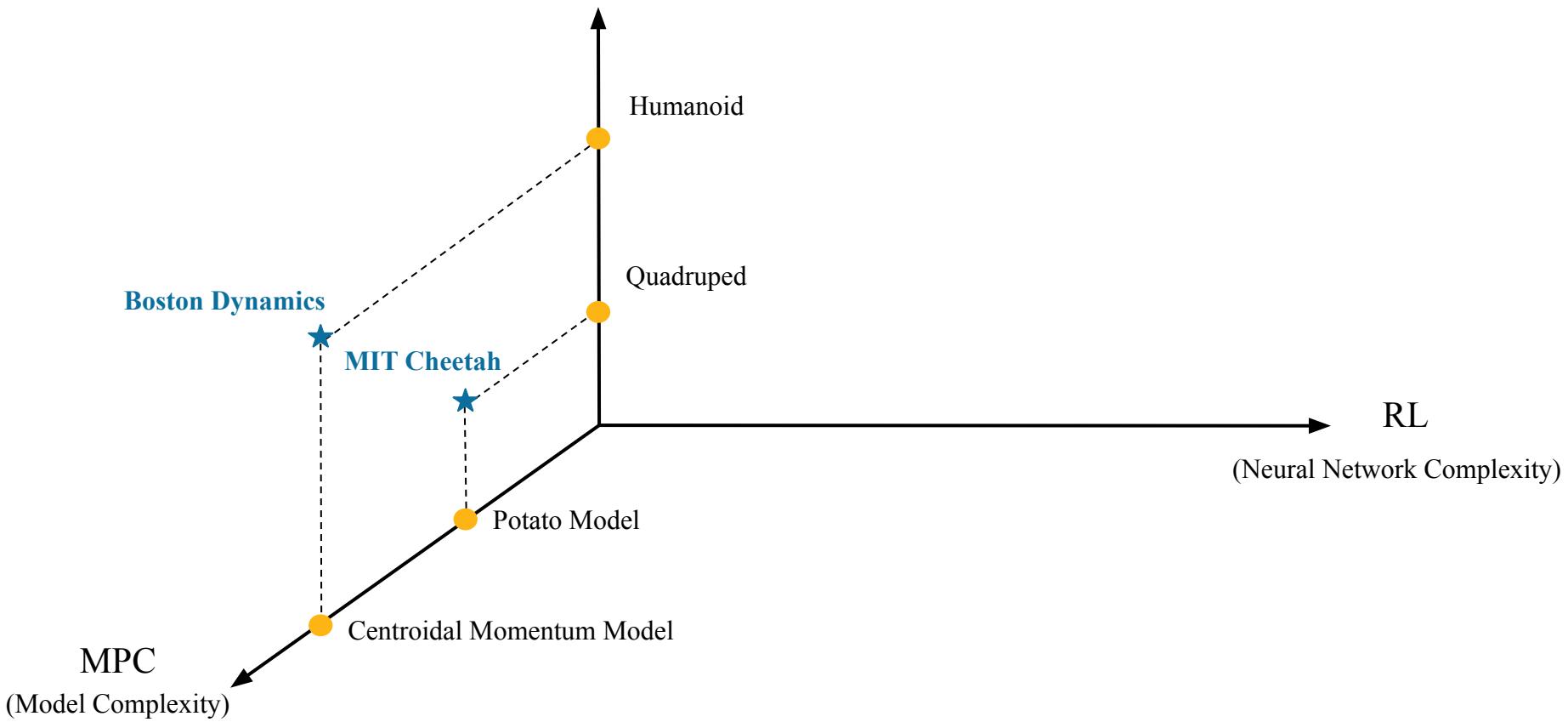
## **Advantages:**

- Potato model
- Convex MPC

## **Disadvantages:**

- Strong assumptions
- Swing phase

## Locomotion (Robot Complexity)

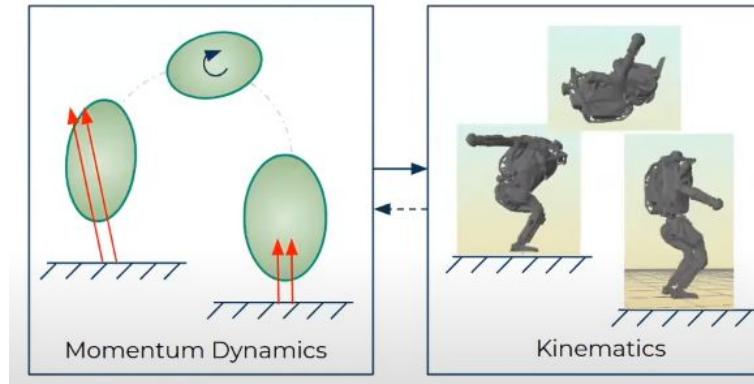


# Boston Dynamics Atlas



[https://youtu.be/-e1\\_QhJ1EhQ](https://youtu.be/-e1_QhJ1EhQ)

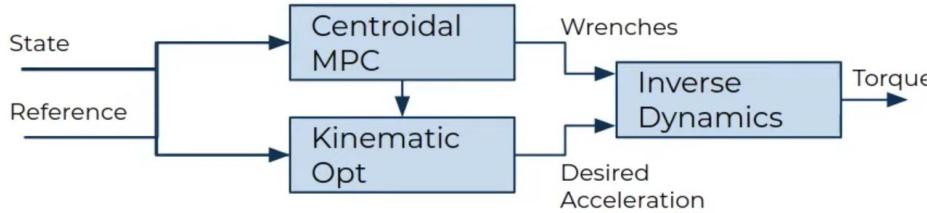
# Boston Dynamics Atlas



**Offline nonlinear trajectory optimization**  
Create template behaviors

**Online model predictive control**  
Adapt & execute behaviors

# Boston Dynamics Atlas



- *Variables:* wrenches, COM, linear/angular momentum, angular excursion, contact positions, dt
- *Cost:* track [retargeted] reference
- Linearize and solve at every control tick
- Exploit problem structure for speed
- Solve kinematic optimization to derive consistent touchdown configurations

# Boston Dynamics Atlas

## **Advantages:**

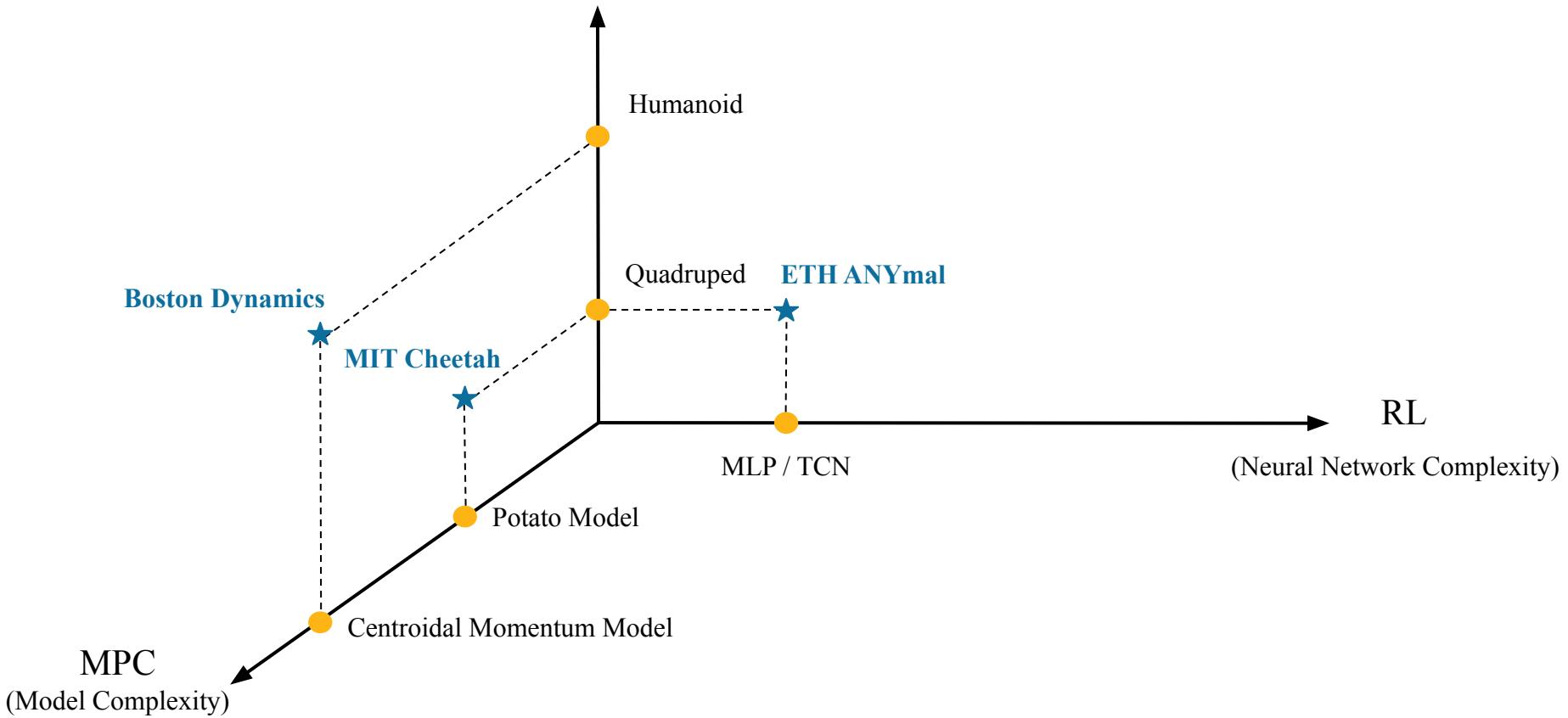
- Centroidal momentum + kinematics
- Online linearized MPC
- For both stance and swing phases

## **Disadvantages:**

- Contact assumptions
- Structured terrain

# Gol Demo

## Locomotion (Robot Complexity)



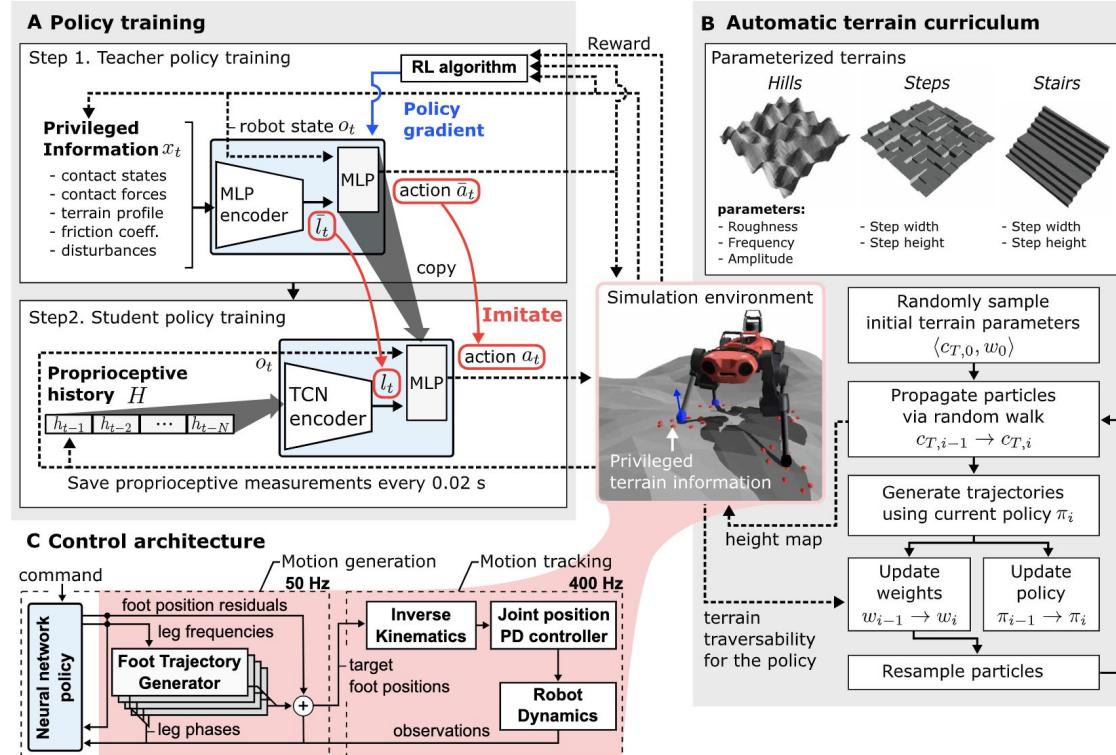
MPC  
(Model Complexity)

ETH ANYmal

Learning  
Quadrupedal  
Locomotion  
over  
Challenging  
Terrain

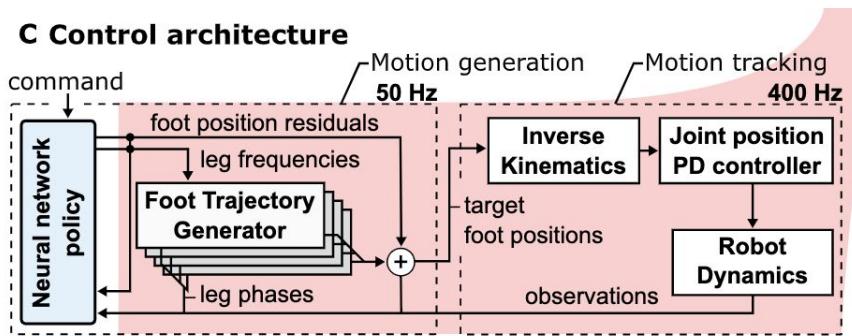


# ETH ANYmal



# ETH ANYmal

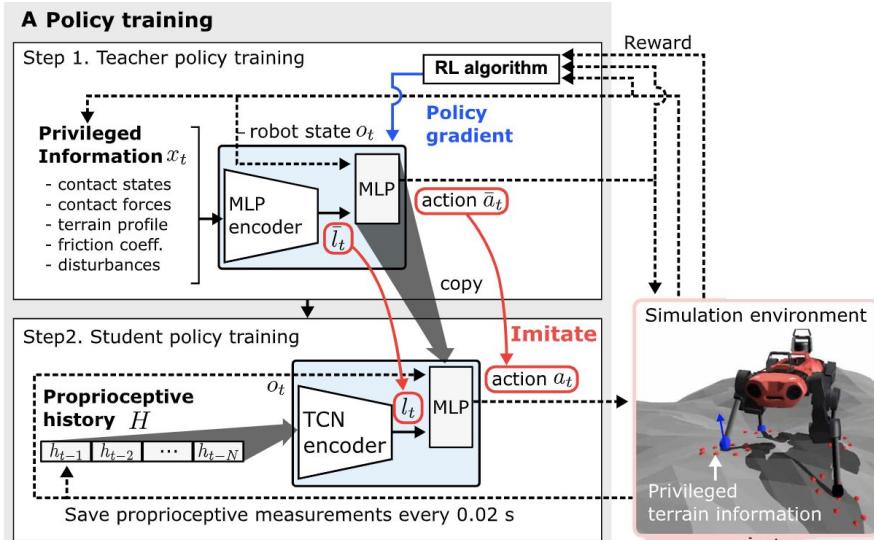
## C Control architecture



## Discussion:

- Multi-rate architecture
- Joint position control

# ETH ANYmal



## Discussion:

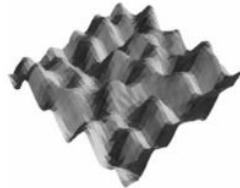
- Teacher-student structure
- Privileged information
- Proprioceptive history

# ETH ANYmal

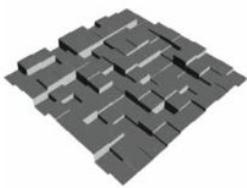
## B Automatic terrain curriculum

Parameterized terrains

*Hills*



*Steps*



*Stairs*

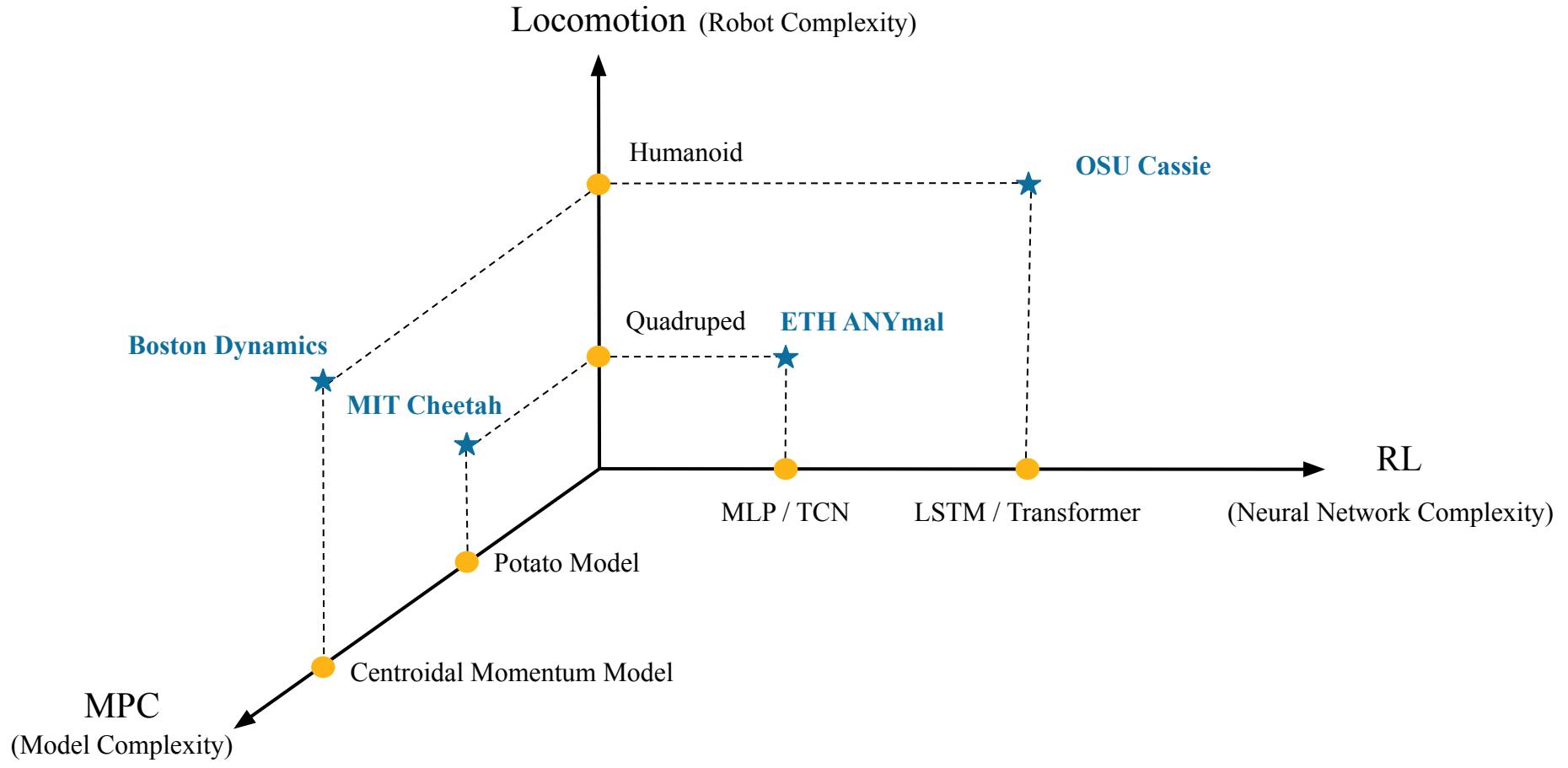


**parameters:**

- |             |               |               |
|-------------|---------------|---------------|
| - Roughness | - Step width  | - Step height |
| - Frequency | - Step height |               |
| - Amplitude |               |               |

### Discussion:

- Domain randomization
- Curriculum learning



# OSU Cassie

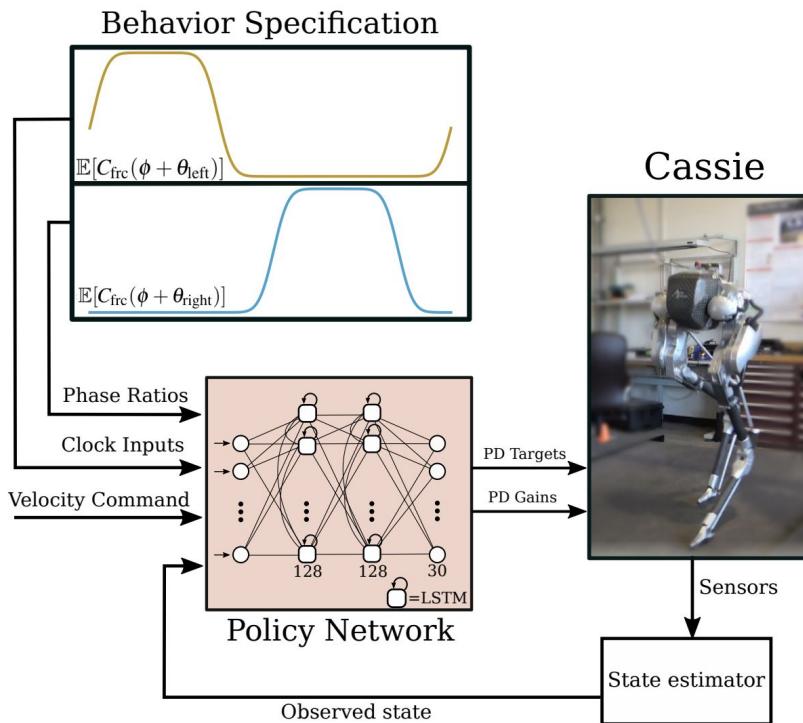


In addition, the neural network can switch between behaviors seamlessly, even while in motion.

# OSU Cassie



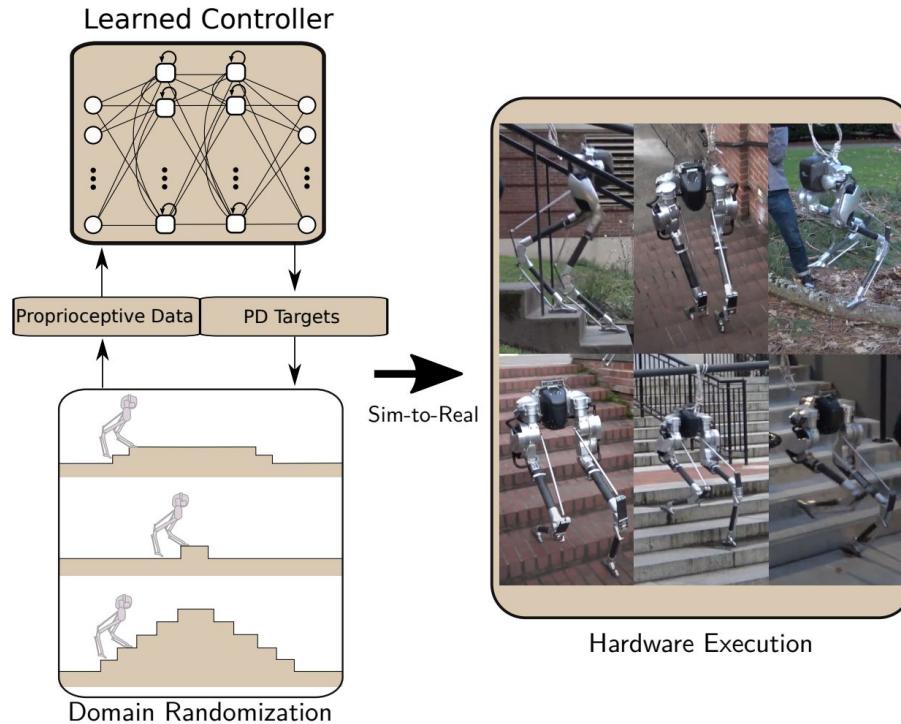
# OSU Cassie



## Discussion:

- Periodic reward
- LSTM

# OSU Cassie



## Discussion:

- Domain randomization

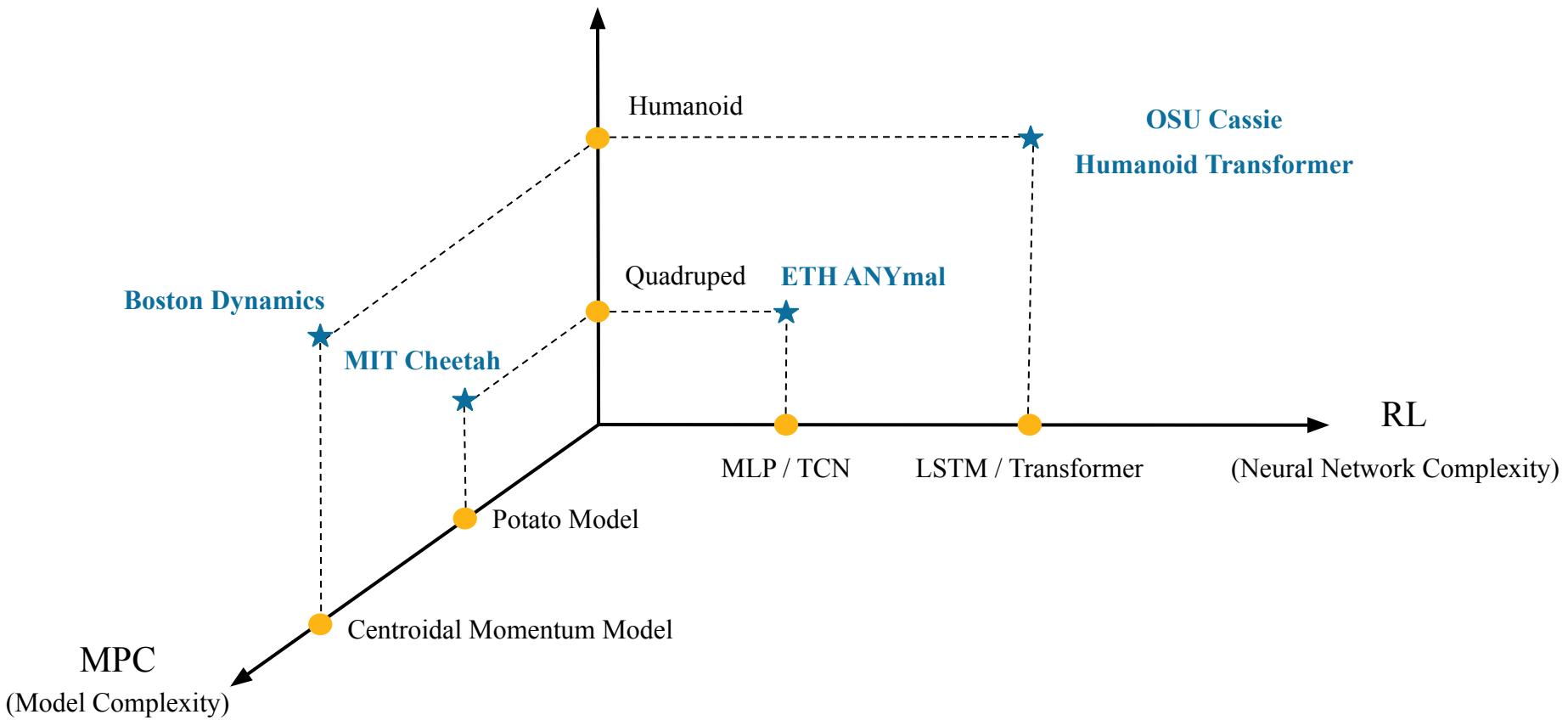
# OSU Cassie Runs a 5k



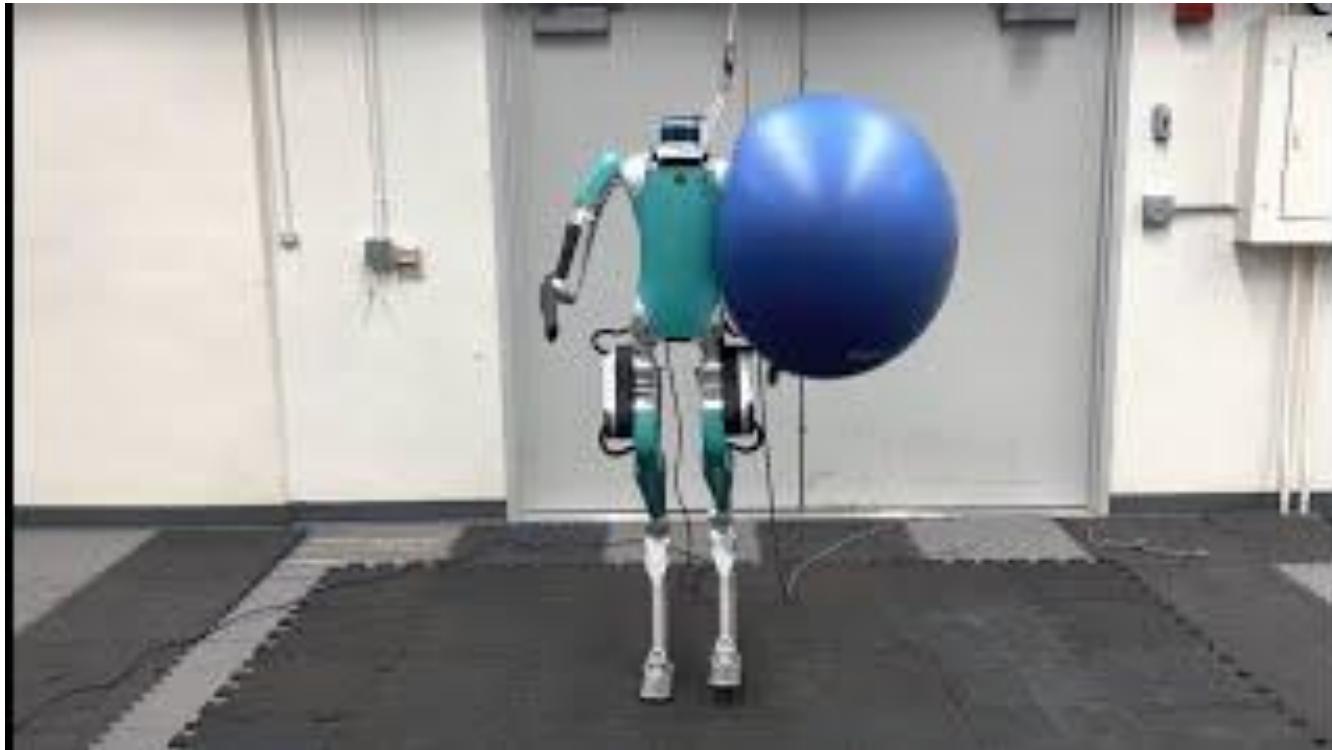
# OSU Cassie for 100M Run



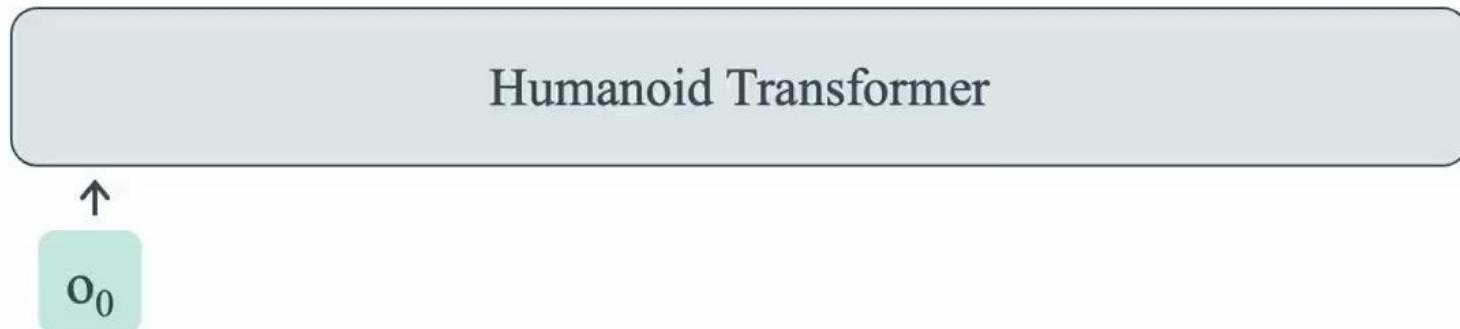
Locomotion (Robot Complexity)



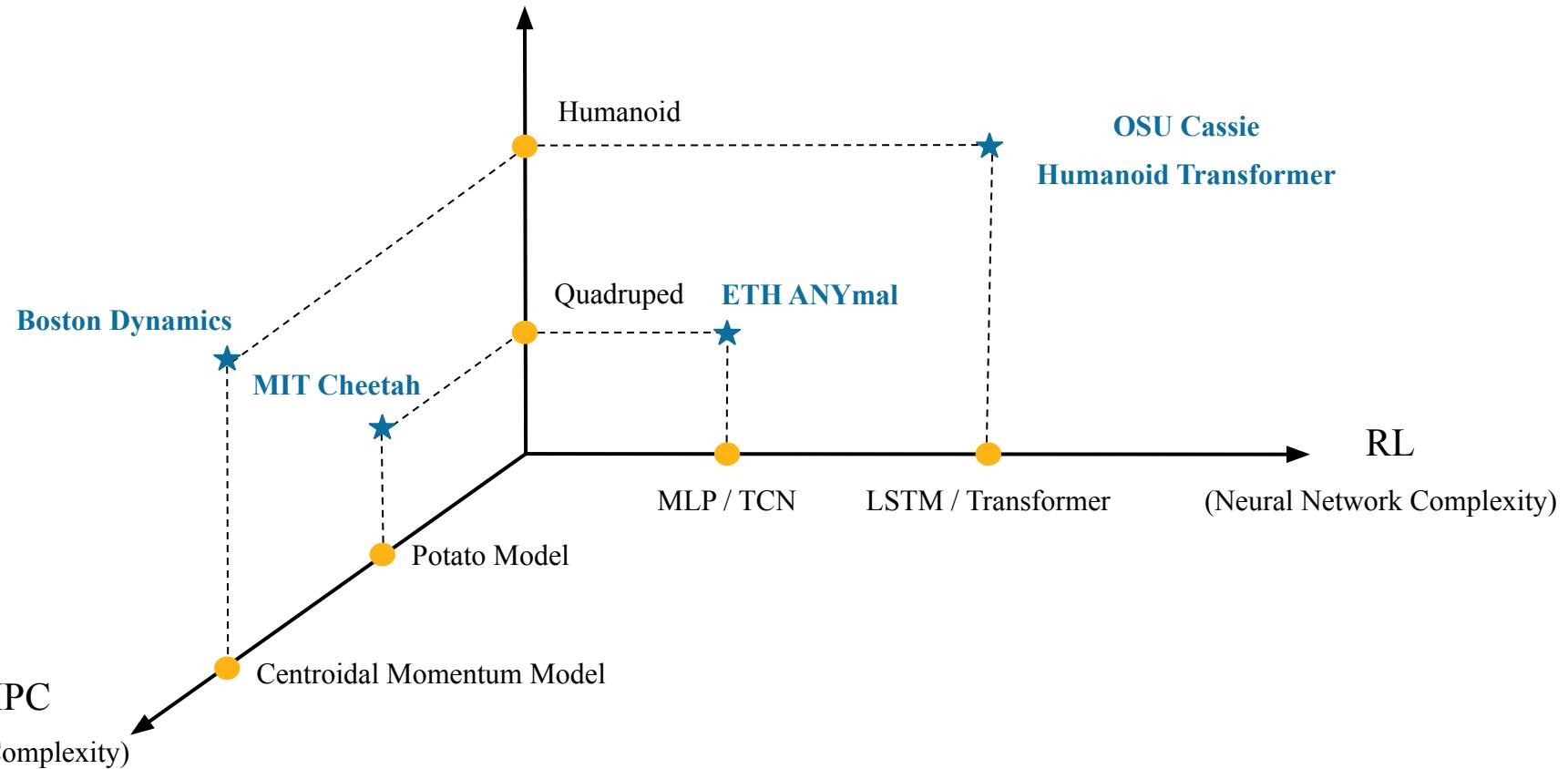
# Humanoid Transformer



# Humanoid Transformer



## Locomotion (Robot Complexity)



# Discussion: MPC & RL for Legged Robots

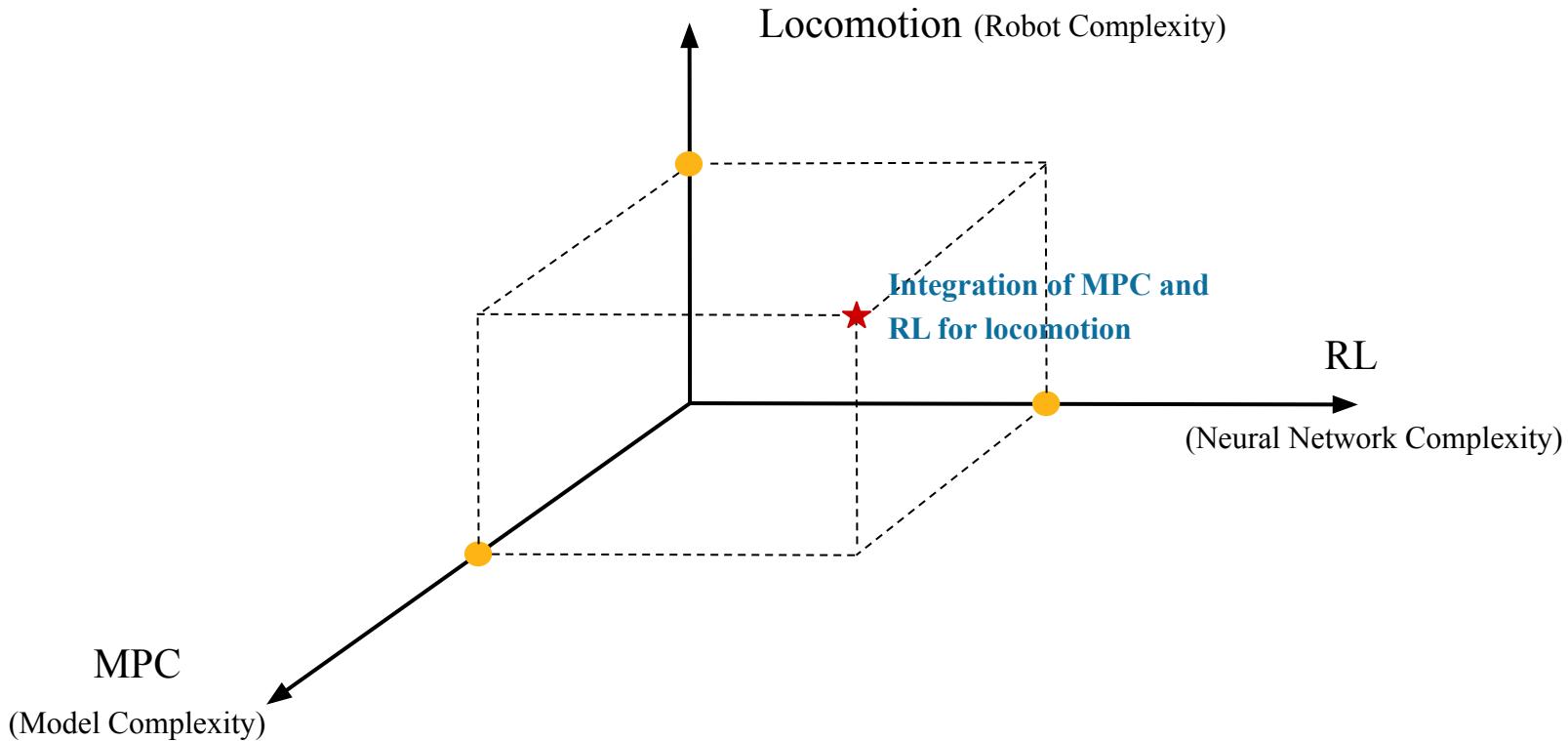
MPC:

- Explicit formulation with guarantee
- Good choice for engineering product

RL:

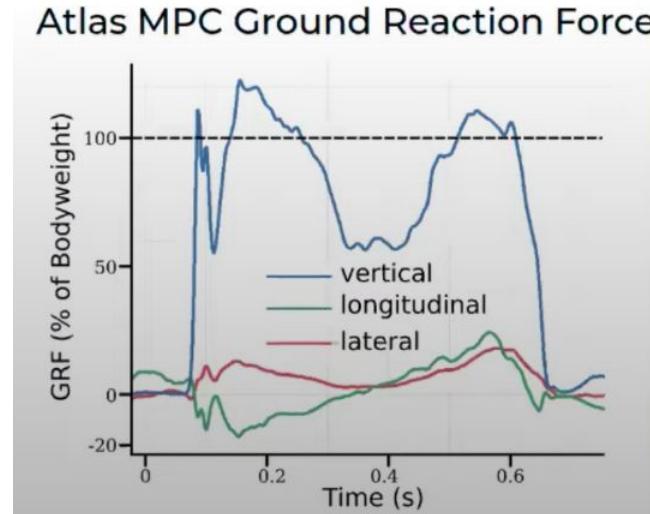
- Easy to robustify a policy
- Easy to integrate with vision, etc

# Discussion: MPC & RL for Legged Robots



# Special Topic: Contact

- Discussion on contact sequence, contact position and contact timing
- Contact detection

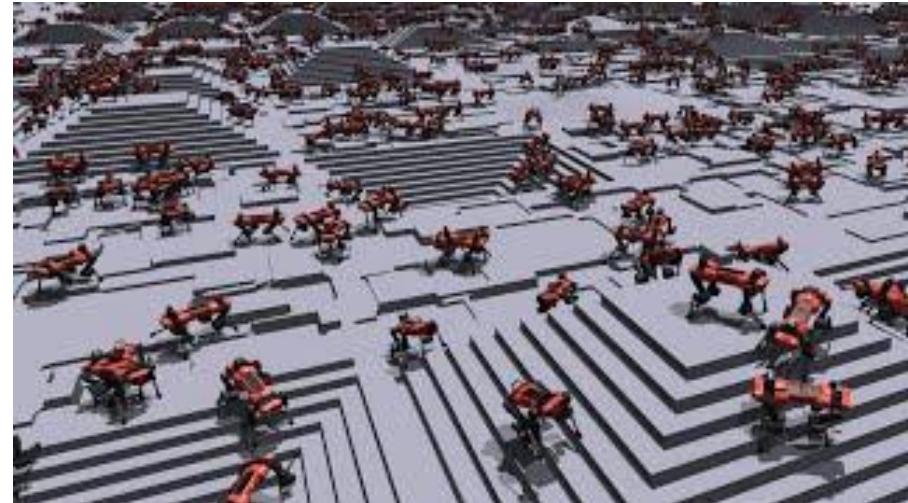


# Special Topic: Simulator

- MuJoCo v.s. Isaac Gym



MuJoCo



Isaac Gym