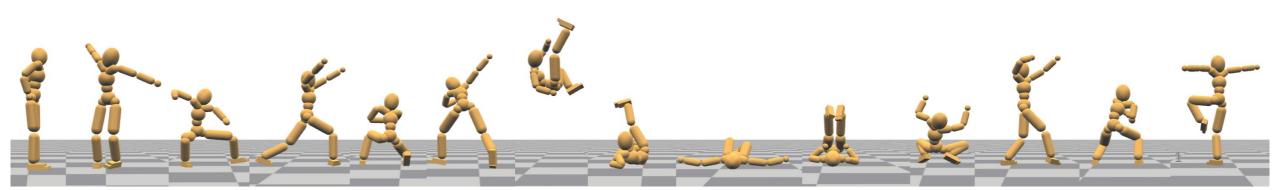
# Learning to Control Complex Human Motions Using Reinforcement Learning

Libin Liu <a href="http://libliu.info">http://libliu.info</a>

DeepMotion Inc <a href="http://deepmotion.com">http://deepmotion.com</a>



#### Physics-based Character Animation

Motion Controller



Control Signal



Physics Engine



Character Animation



[Gang Beasts]



[Totally Accurate Battle Simulator]



#### Designing Controllers for Locomotion

Hand-crafted control policy

Simulating abstract model SIMBICON, IPM, ZMP...

Optimization/policy search

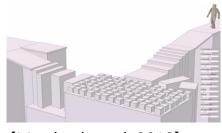
Reinforcement learning Actor-critic



[Hodgins et al. 1995]



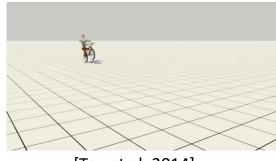
[Coros et al. 2010]



[Mordatch et al. 2010]



SIMBICON [Yin et al. 2007]

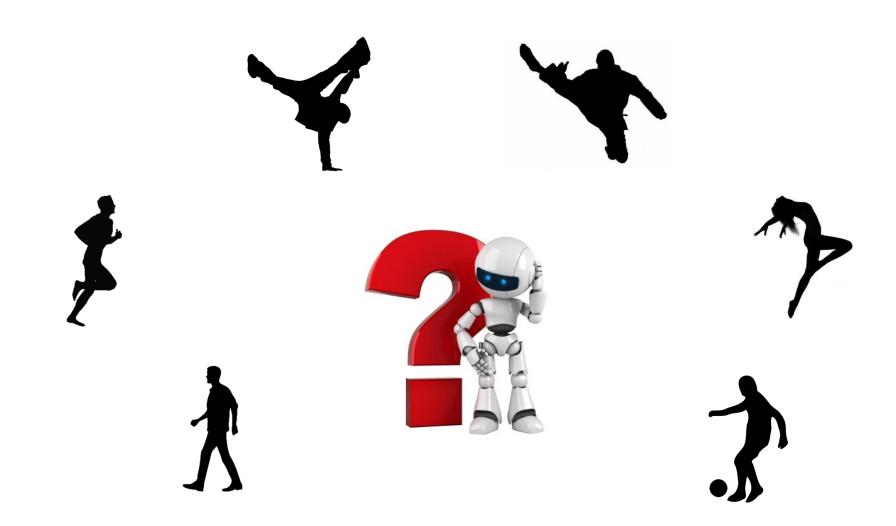


[Tan et al. 2014]

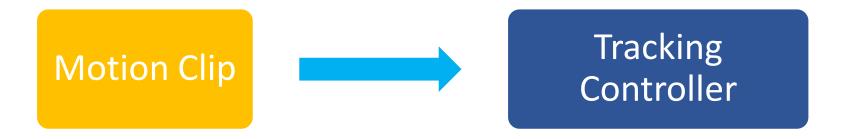


[Peng et al. 2017]

#### Designing Controllers for Complex Motions



#### Designing controllers for complex motions







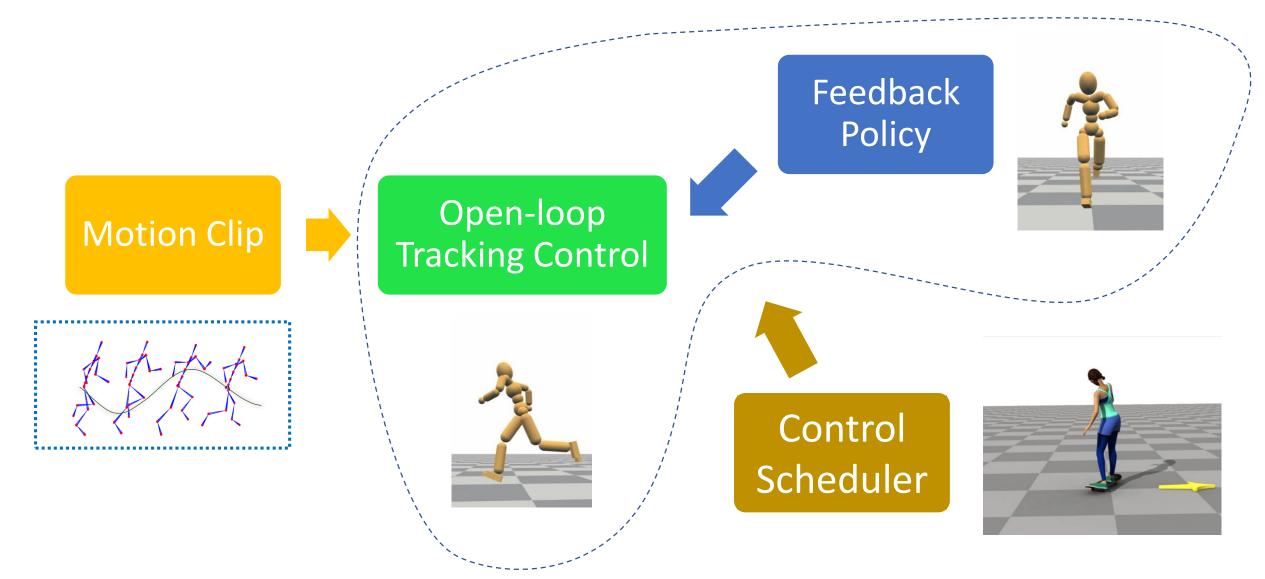




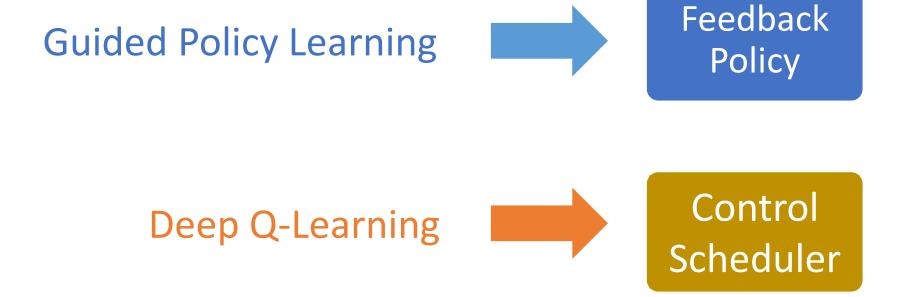




#### Tracking Control for Complex Human Motion



#### Reinforcement Learning



#### Outline

Construct open-loop control
SAMCON (Sample-based Motion Control)

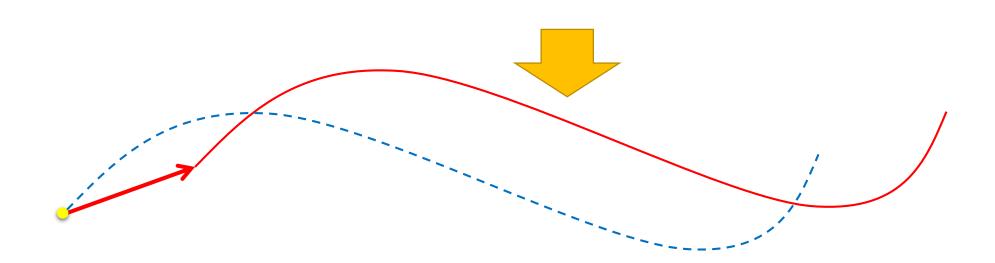
Guided learning of linear feedback policies

Learning to schedule control fragment using deep Q-learning

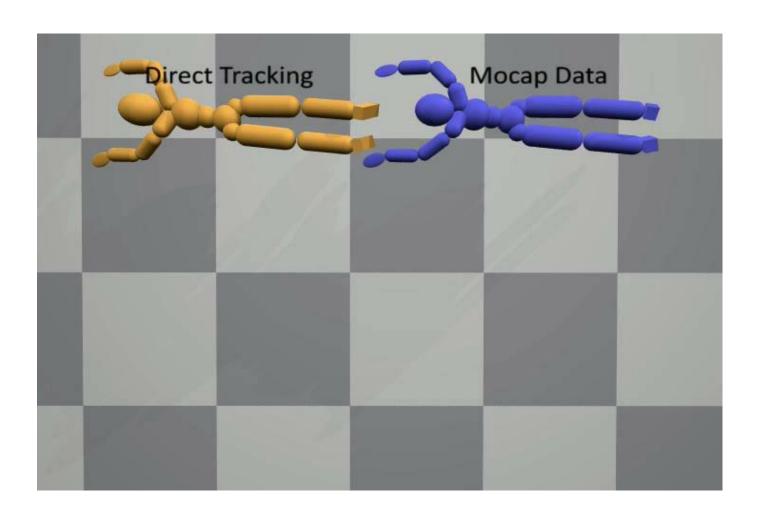
#### Tracking Control

• PD servo

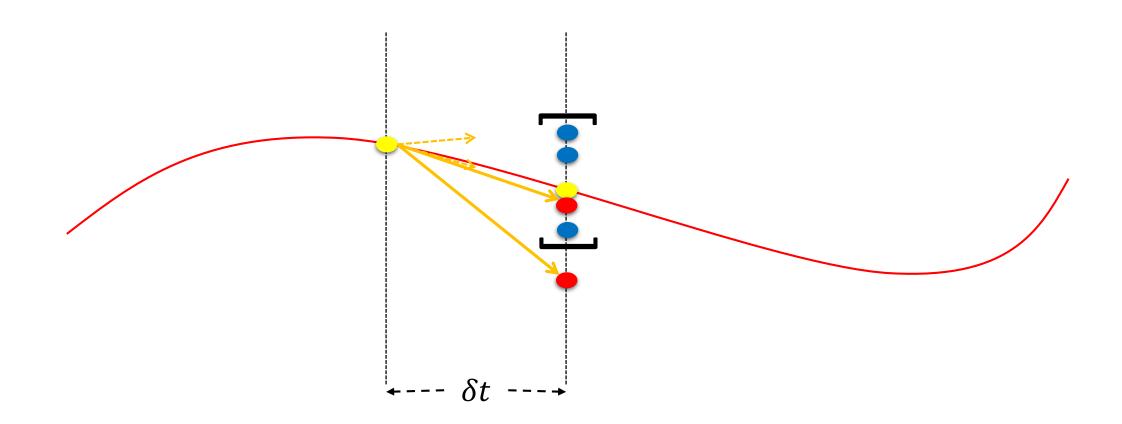
$$\tau = k_p (\tilde{\theta} - \theta) - k_d \dot{\theta}$$



## Mocap Clips as Tracking Target

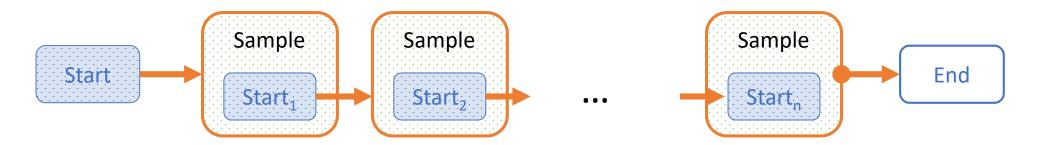


## Correction with Sampling



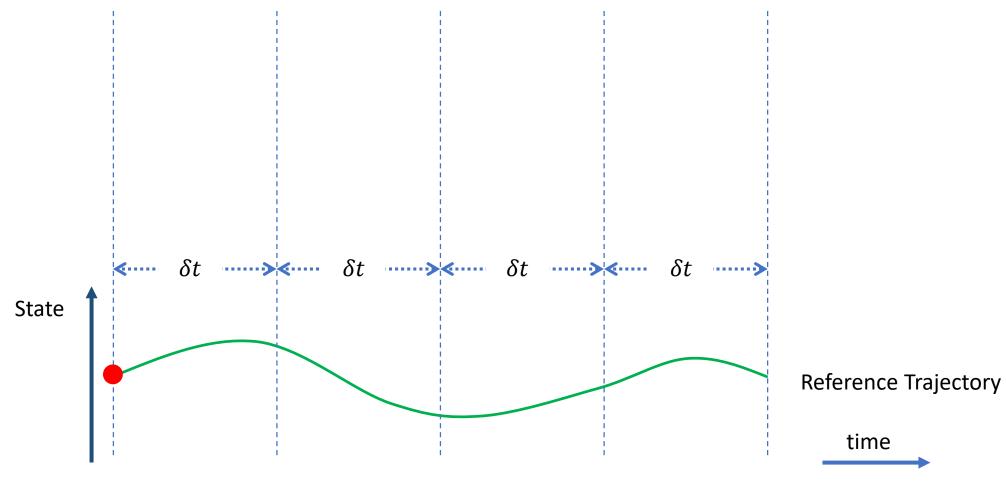
#### **SAMCON**

- SAmpling-based Motion CONtrol [Liu et al. 2010, 2015]
  - Motion Clip → Open-loop control trajectory

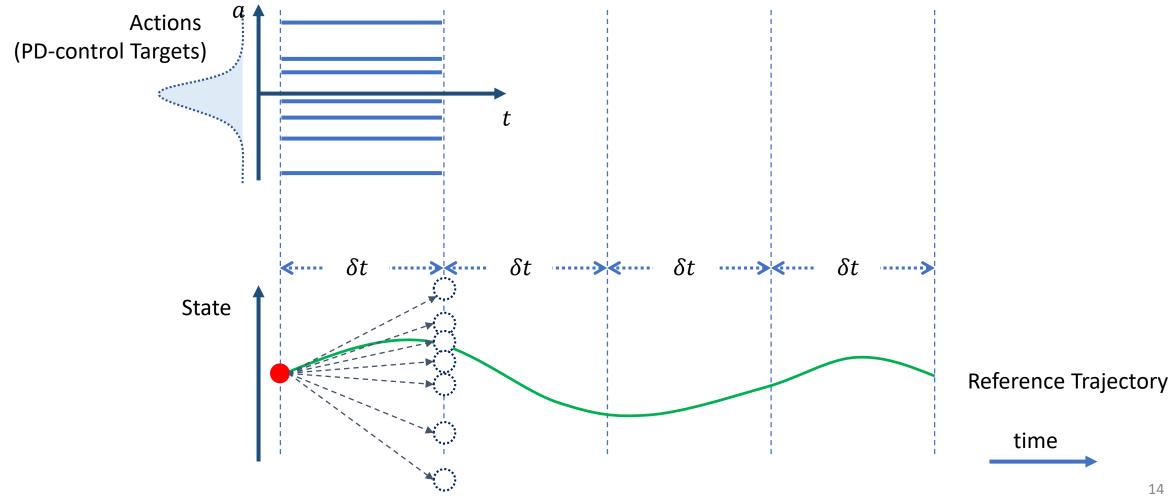


Particle filtering / Sequential Monte Carlo

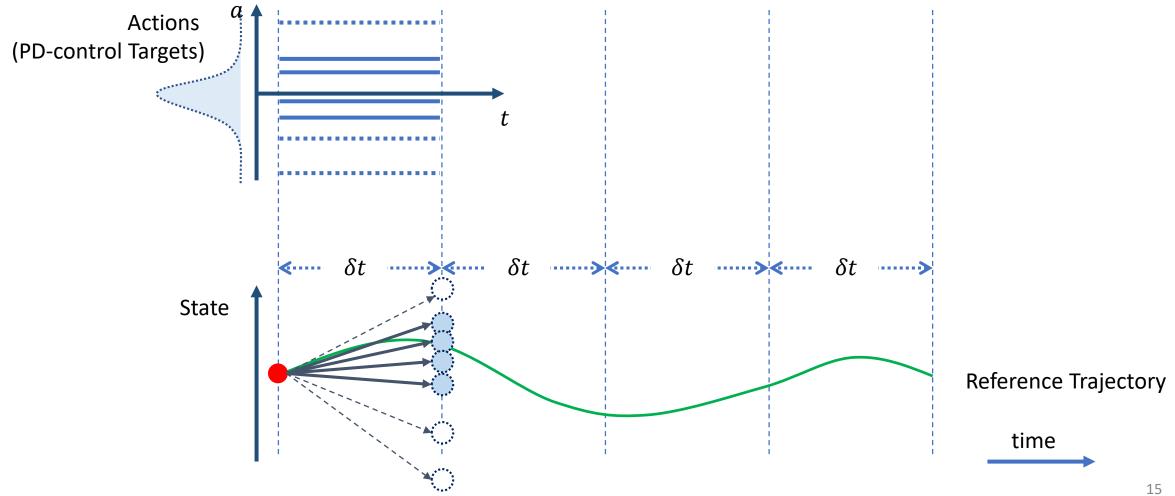
#### SAMCON



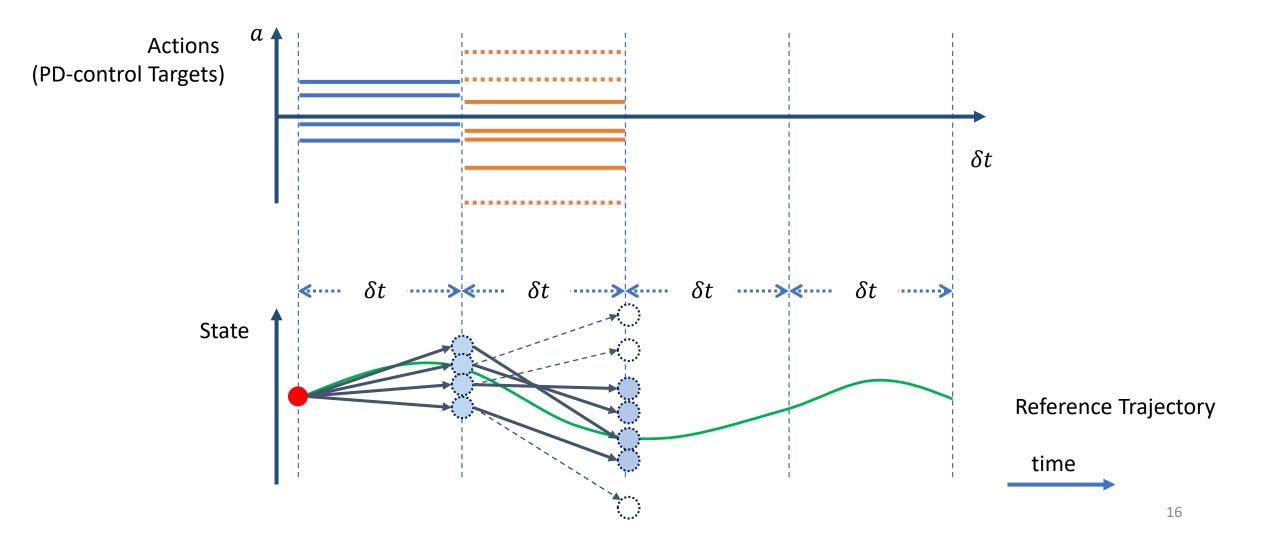
#### Sampling & Simulation



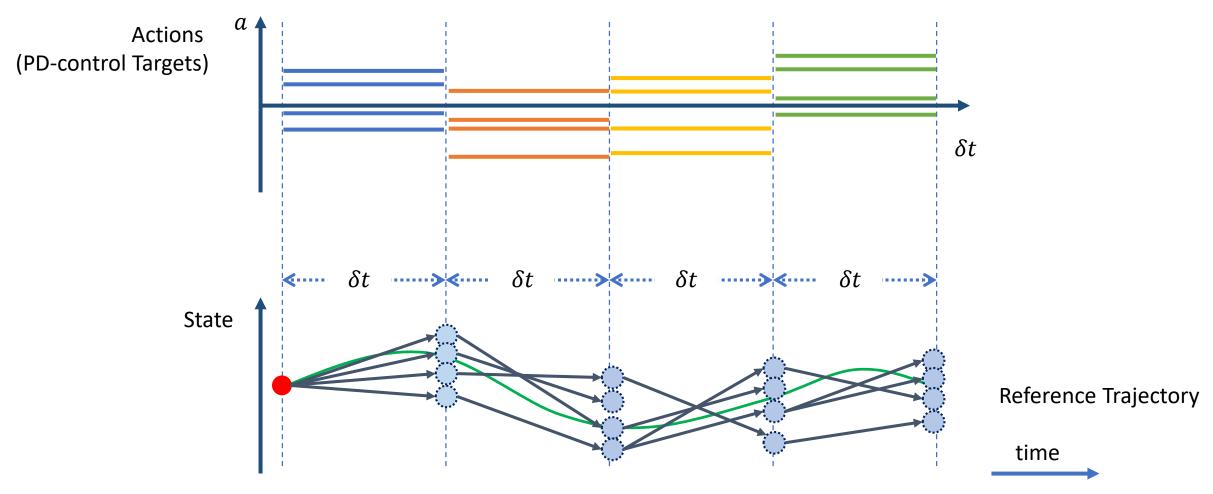
## Resampling



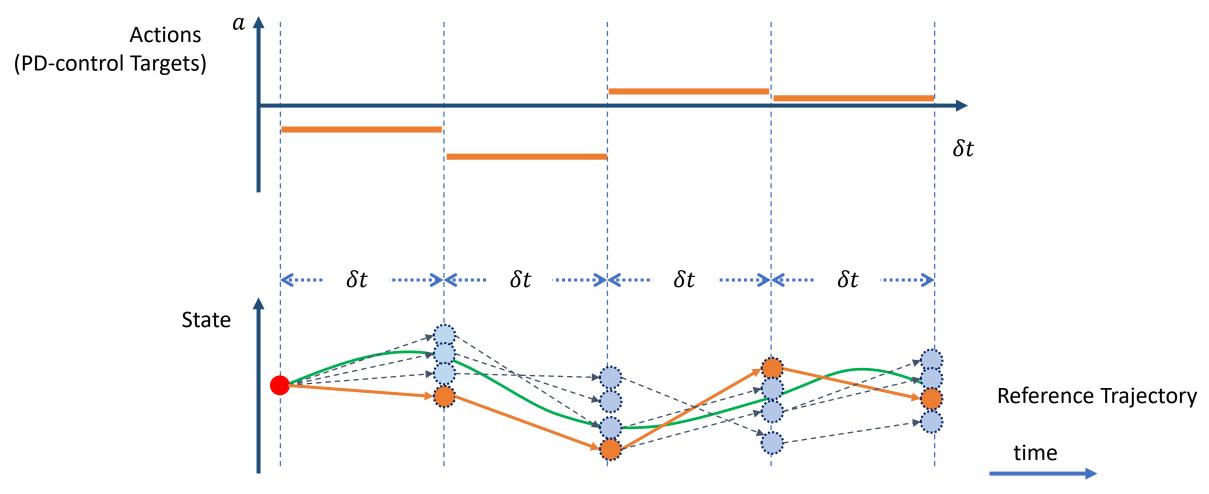
#### SAMCON Iterations



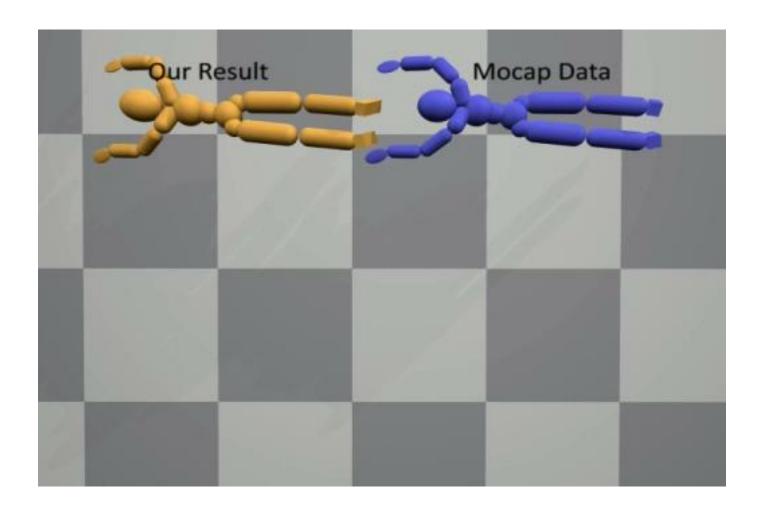
#### SAMCON Iterations



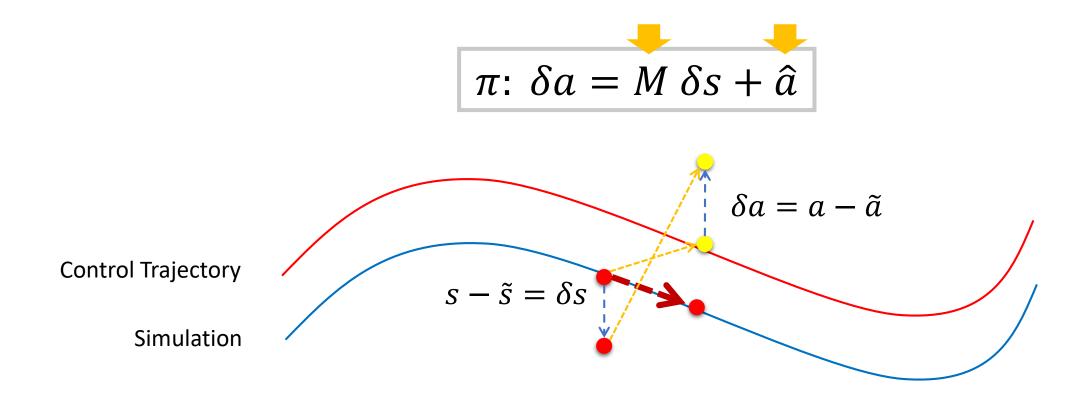
#### Constructed Open-loop Control Trajectory



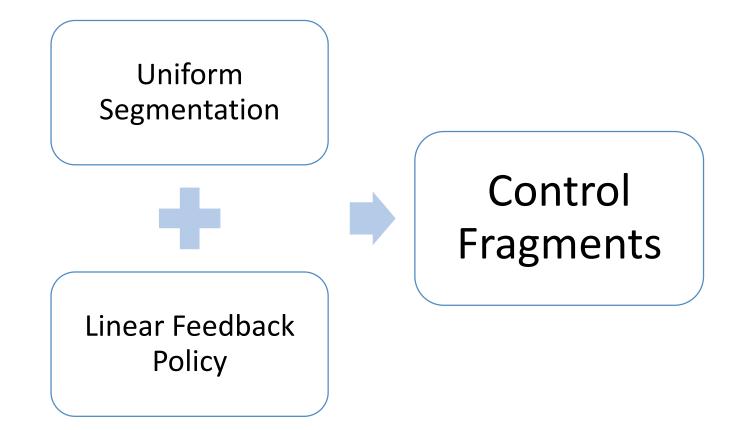
#### Control Reconstruction



#### Linear Policy

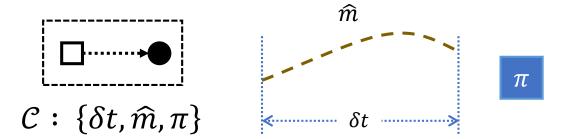


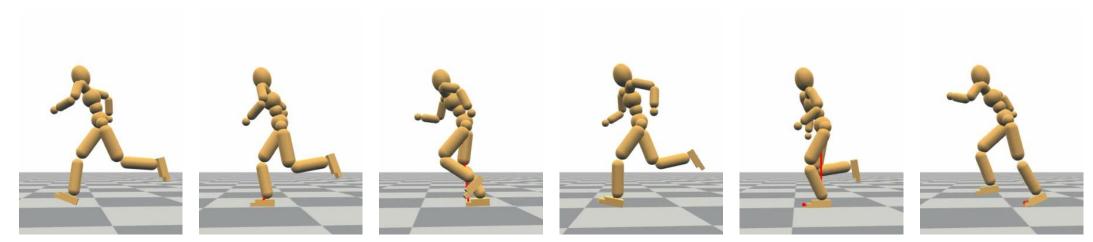
#### For complex motions



#### Control Fragment

- A short control unit:
  - $\delta t \approx 0.1$  seconds long
  - Open-loop control segment  $\widehat{m}$
  - Linear Feedback policy  $\pi$





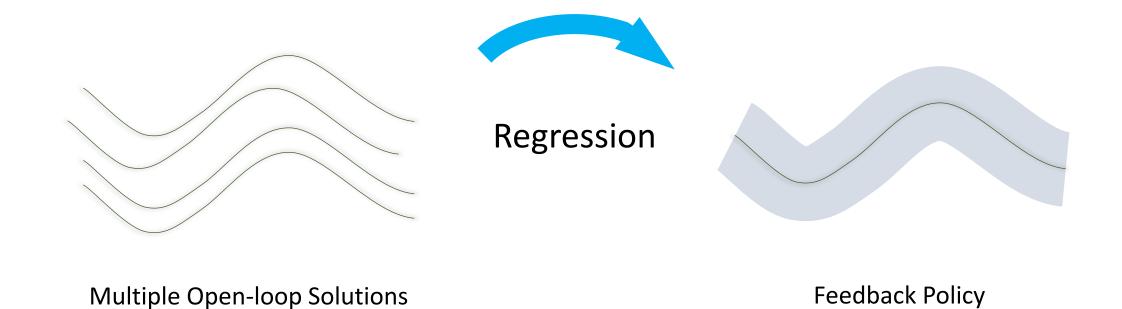
#### Controller

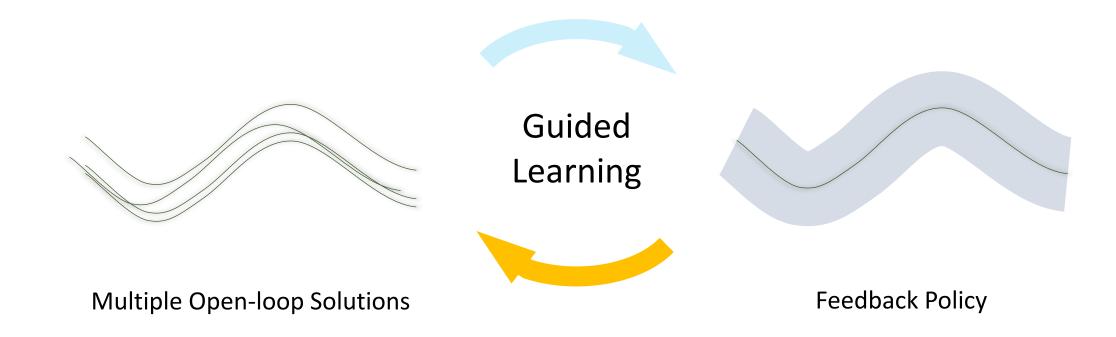
A chain of control fragments

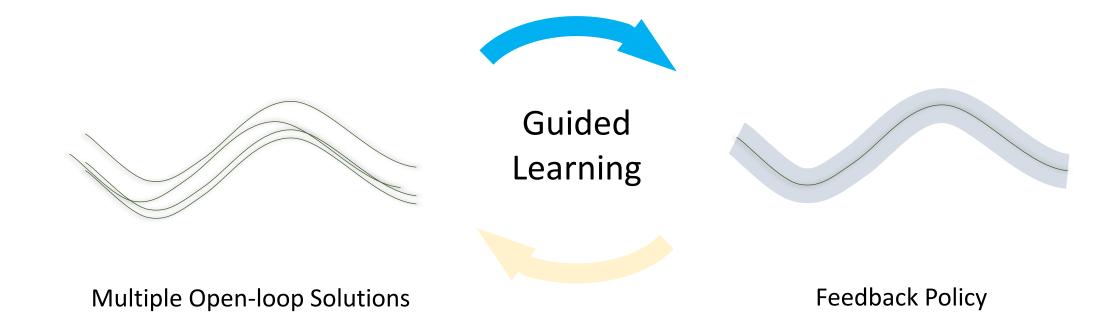


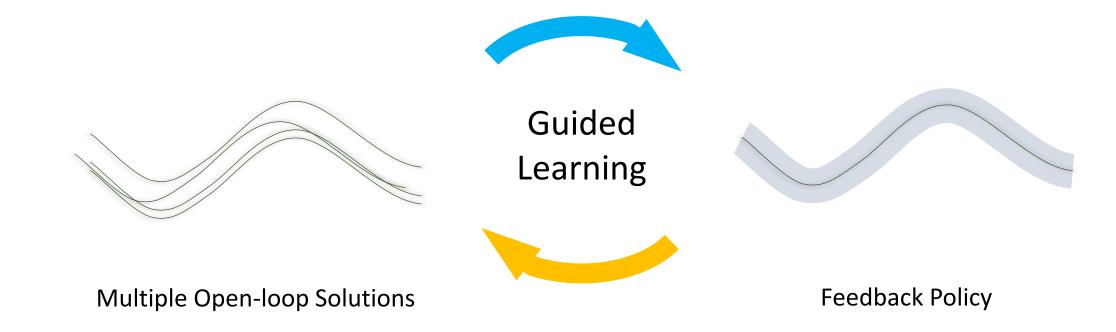




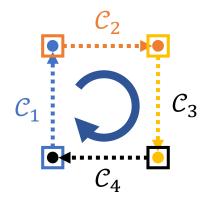




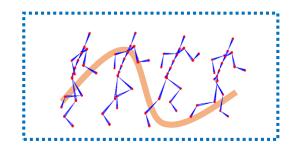


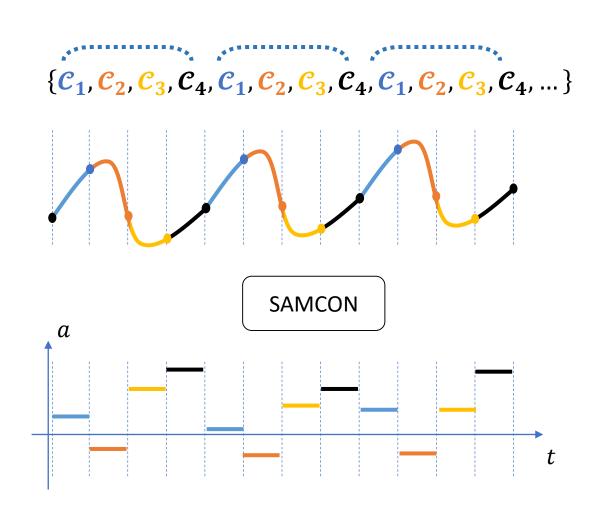


#### Example: Cyclical Motion

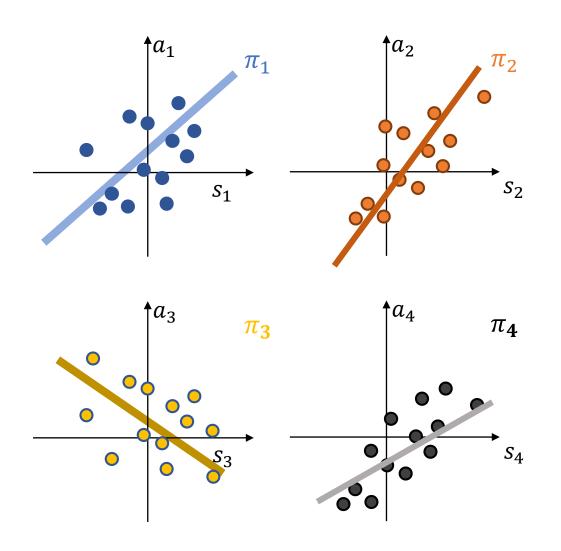


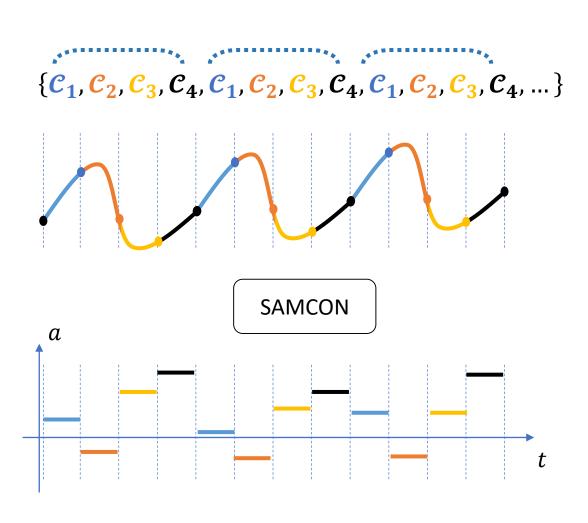
 $\mathcal{C}_k$ :  $\{\widehat{m}_k, \delta t, \pi_k\}$ 



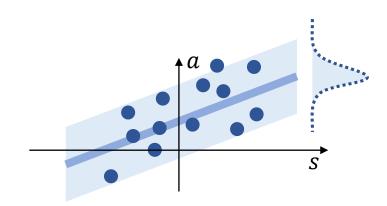


## Example: Cyclical Motion



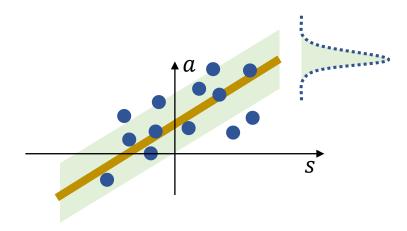


## Policy Update

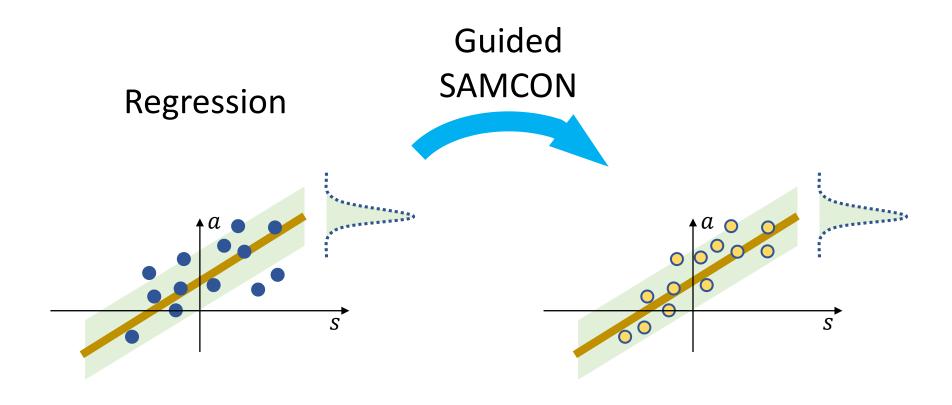


## Policy Update

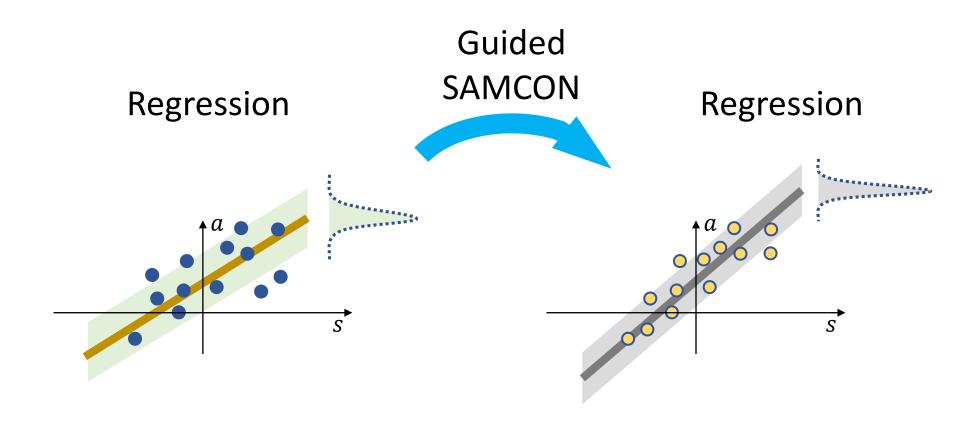
#### Regression

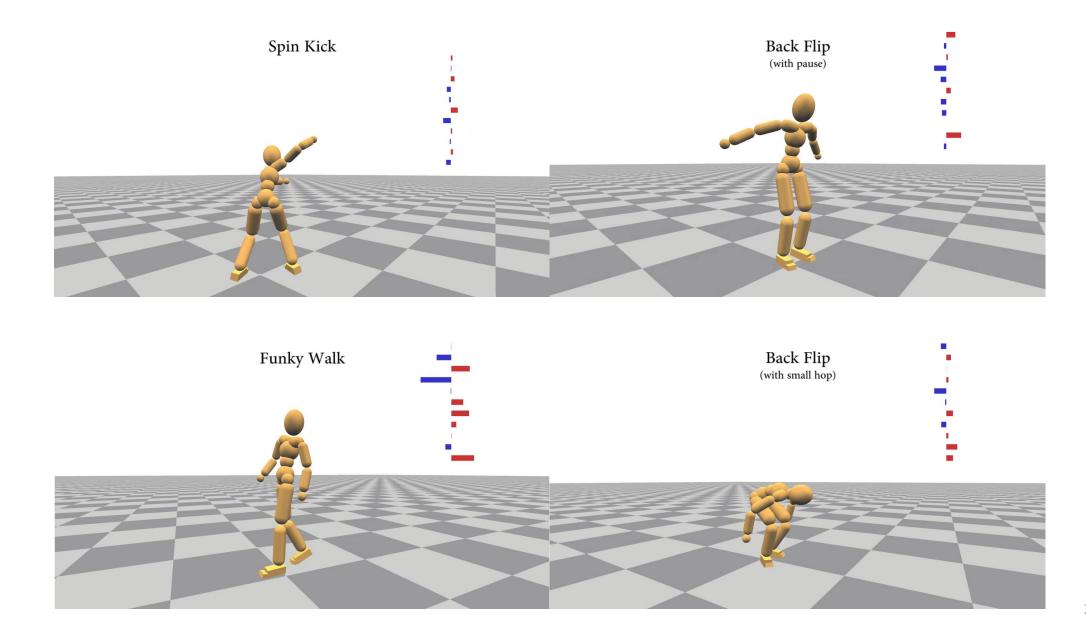


#### Guided Learning Iterations



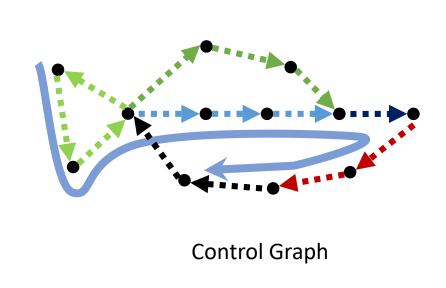
## Guided Learning Iterations

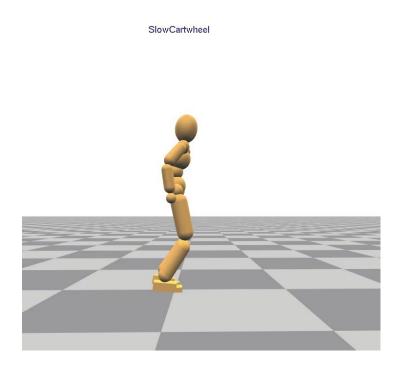




#### Control Graph

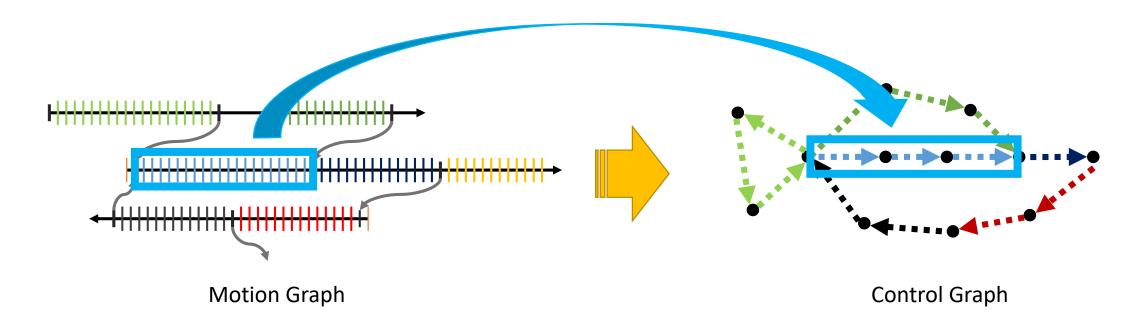
• A graph whose nodes are control fragments



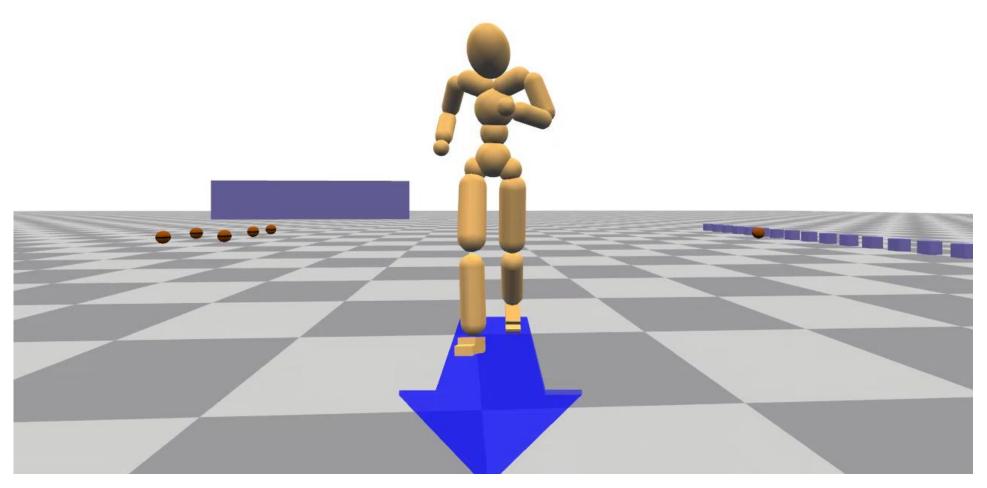


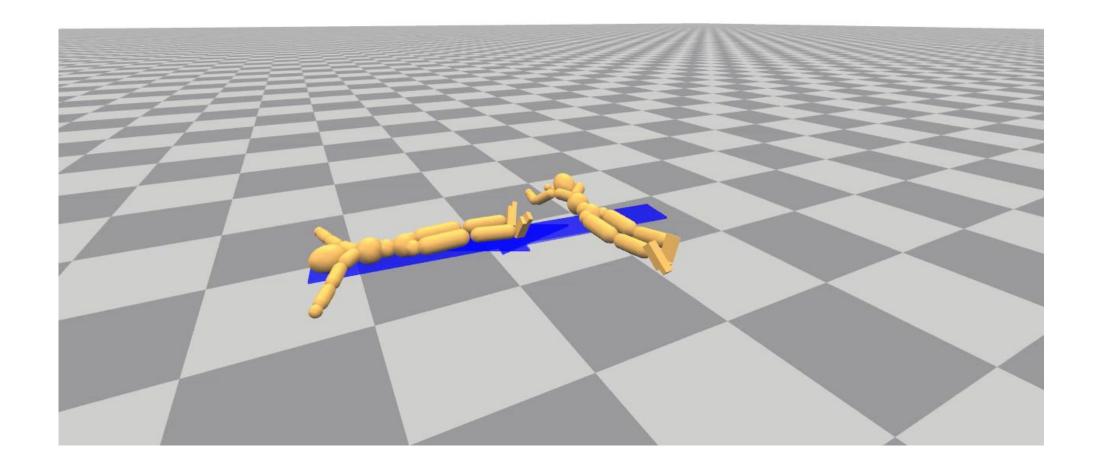
#### Control Graph

- A graph whose nodes are control fragments
- Converted from a motion graph

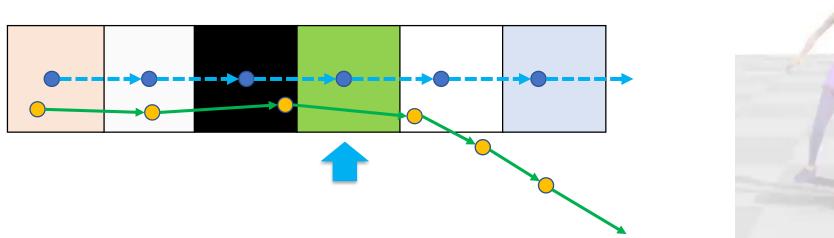


#### SlowRun





# Problem of Fixed Time-Indexed Tracking

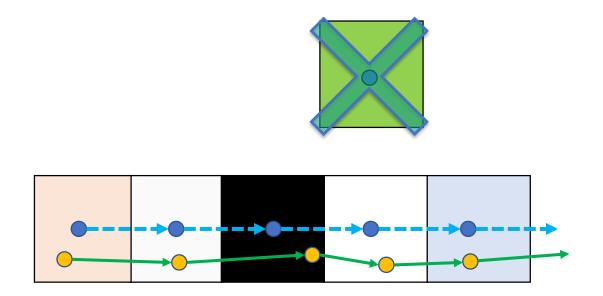








# Scheduling

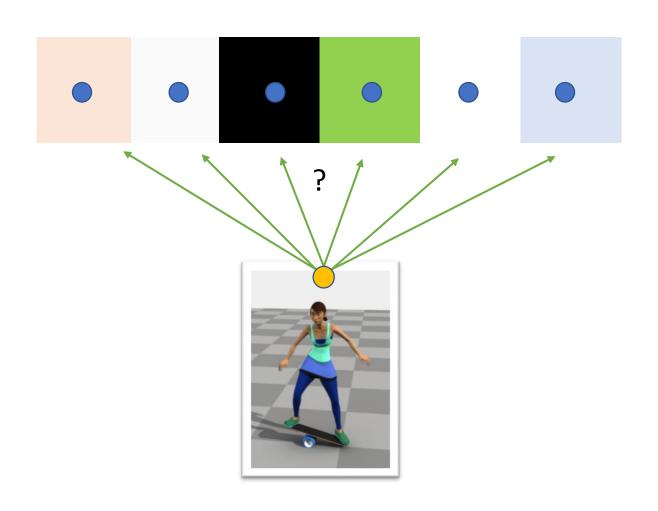








# Scheduling

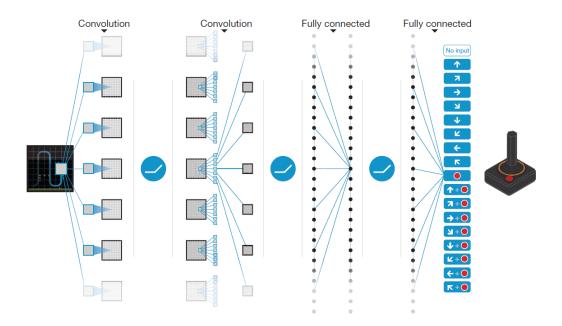


#### Deep Q-Learning

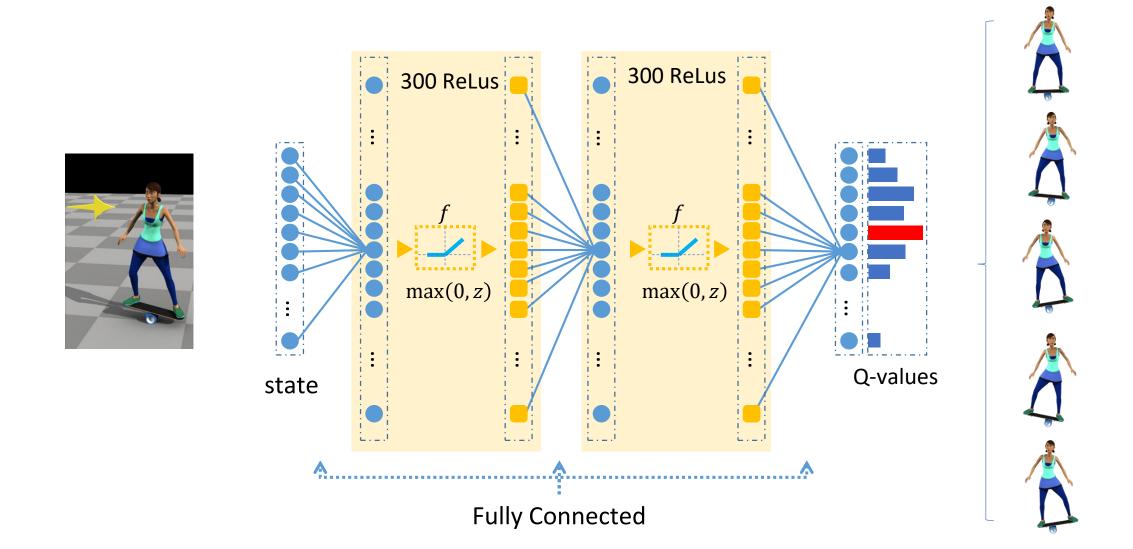
Learn to perform good actions

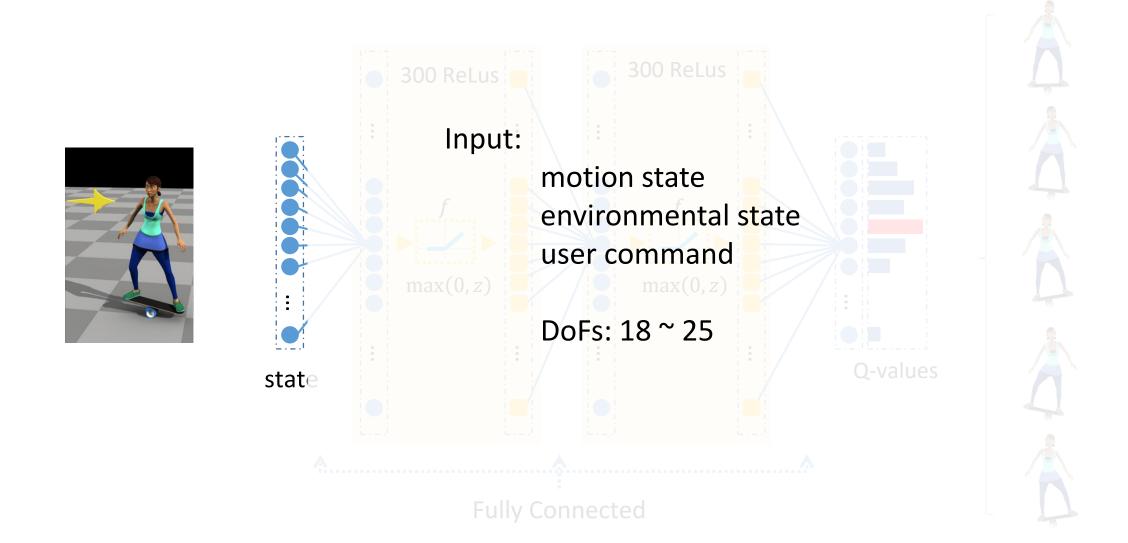
Raw image input

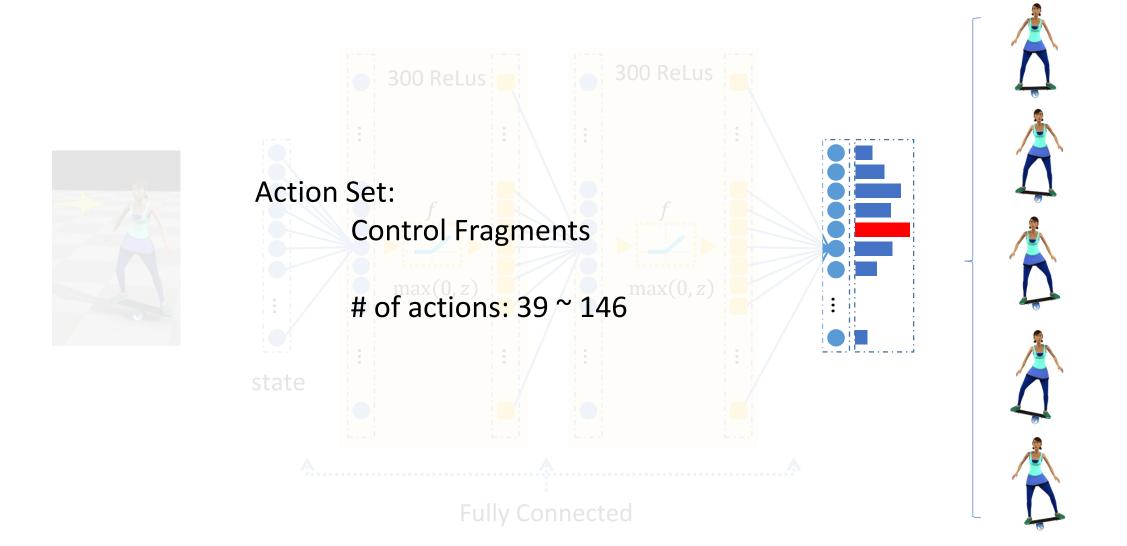
Deep convolutional network

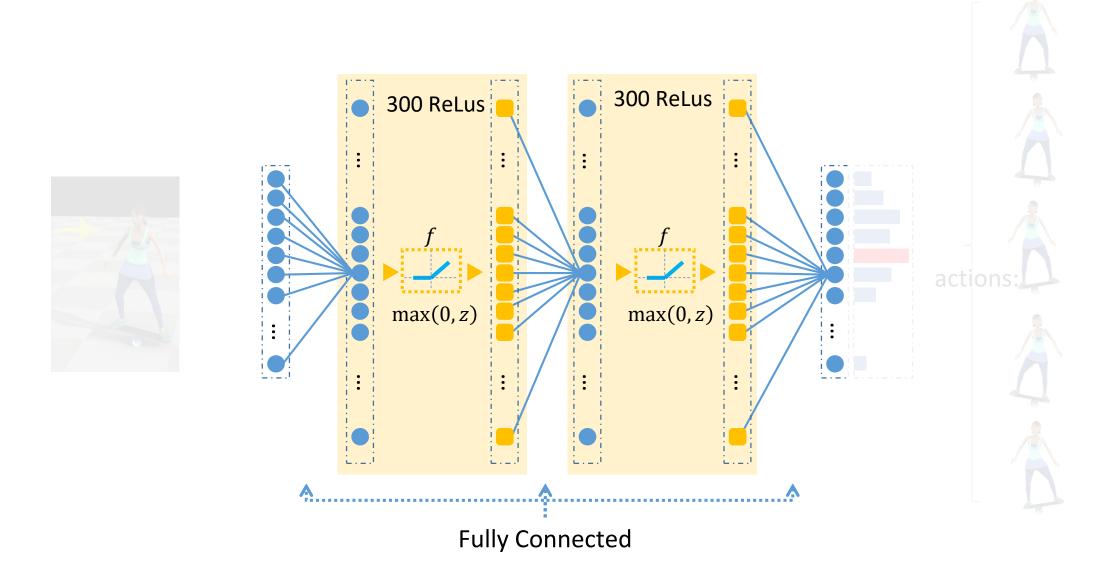


[Mnih et al. 2015, DQN]









## Training

#### Pipeline:

**Exploration / Exploitation** 

Simulation

Reward

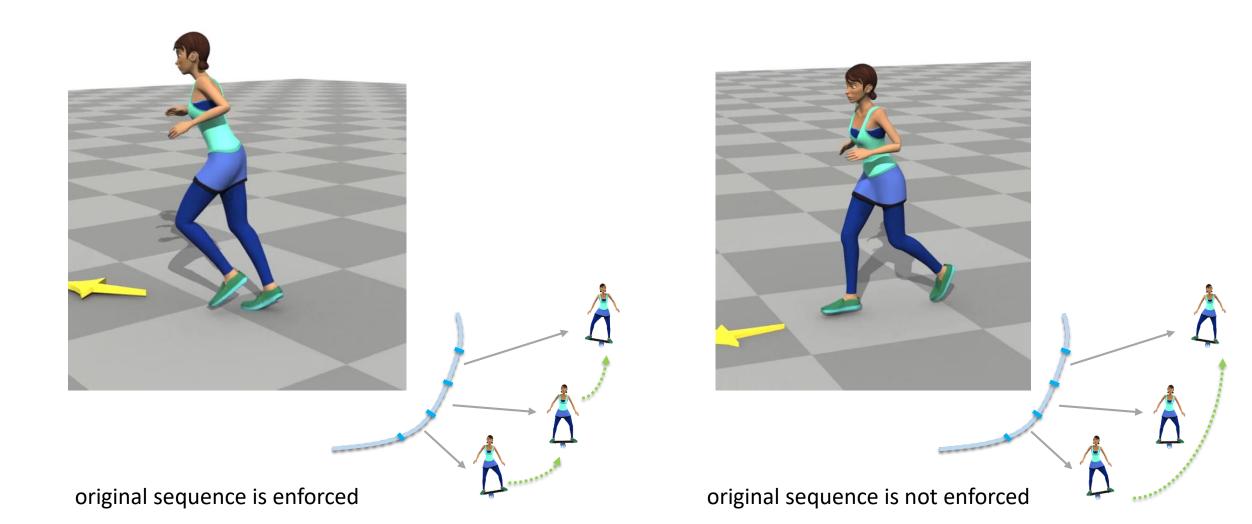
Replay Buffer

**Batch SGD** 

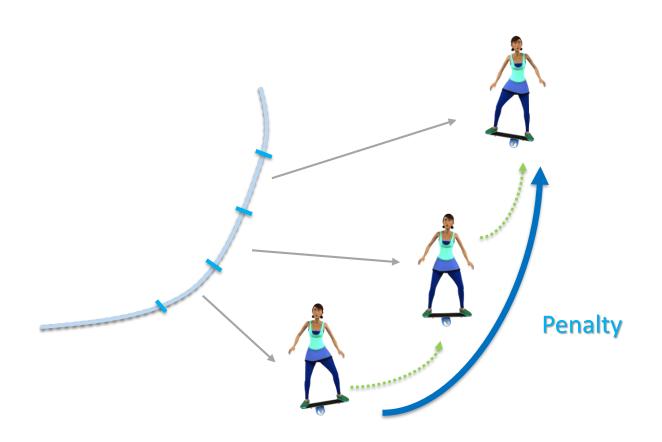
#### Reward Function

$$R = E_{\text{tracking}} + E_{\text{preference}} + E_{\text{feedback}} + E_{\text{task}} + R_0$$

## Importance of the Reference Sequence



## Tracking penalty term

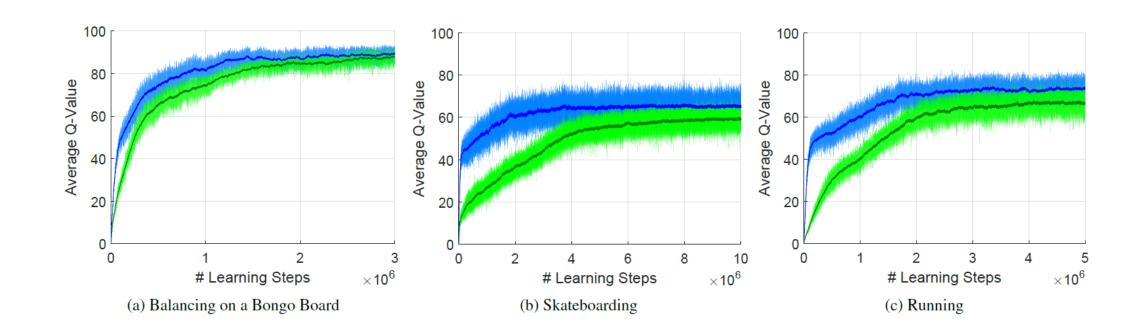


In-sequence action

Out-of-sequence action

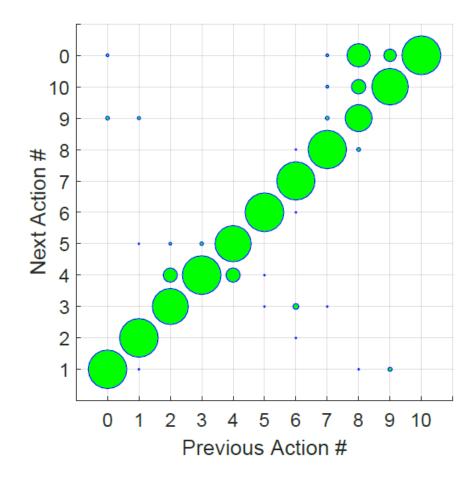
#### Tracking exploration strategy

with probability  $\varepsilon_r$  select a random action with probability  $\varepsilon_o$  select an in-sequence action



## Bongo Board Balancing



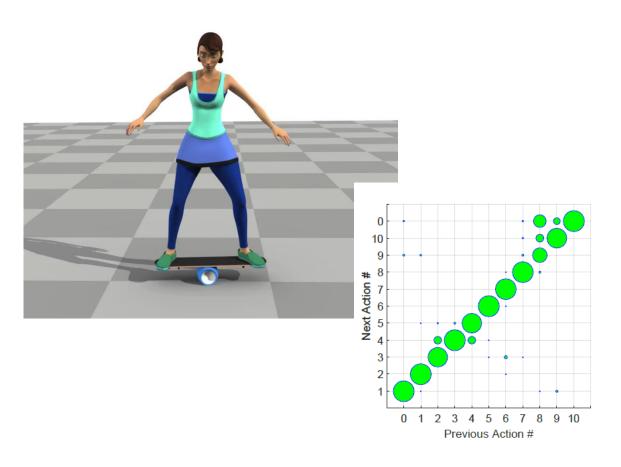


## Effect of Feedback Policy

**Open-loop Control Fragments** 

# Next Action 7 0 1 2 3 4 5 6 7 8 9 10 Previous Action #

#### Feedback-augmented Fragments



#### Discover New Transitions

Bongo Boarding Input



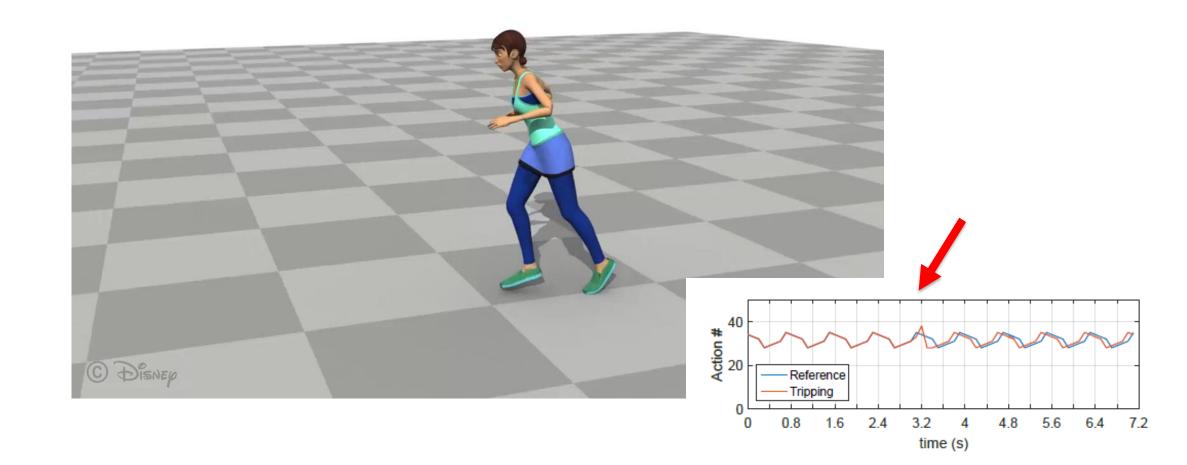




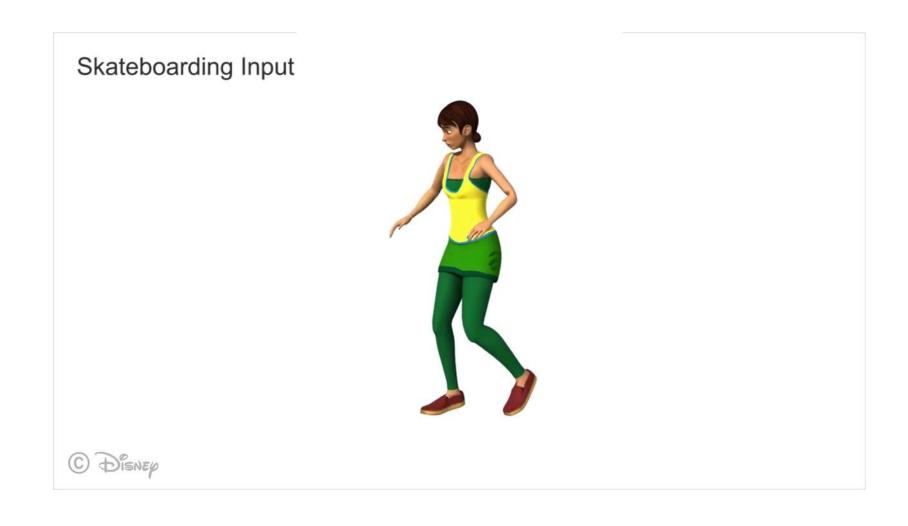
# Running



# Tripping



## Skateboarding



# Skateboarding



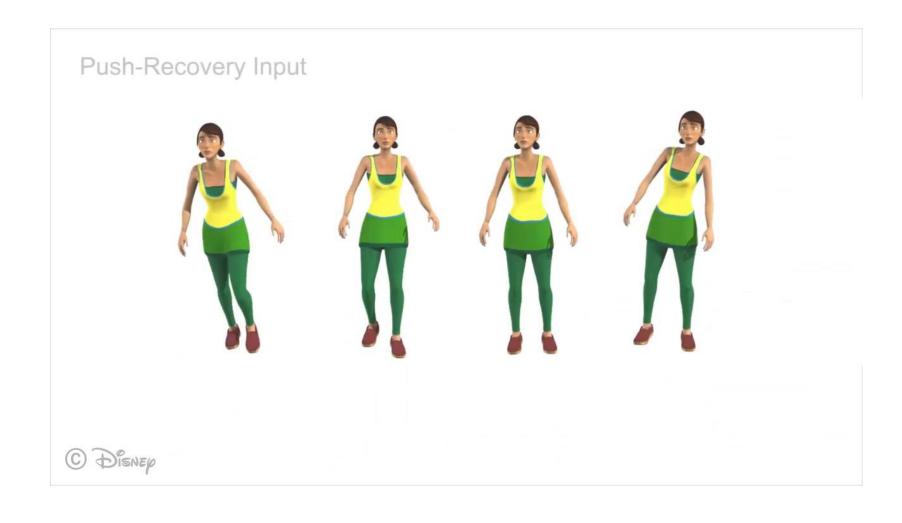
# Walking On A Ball

Ballwalker Input

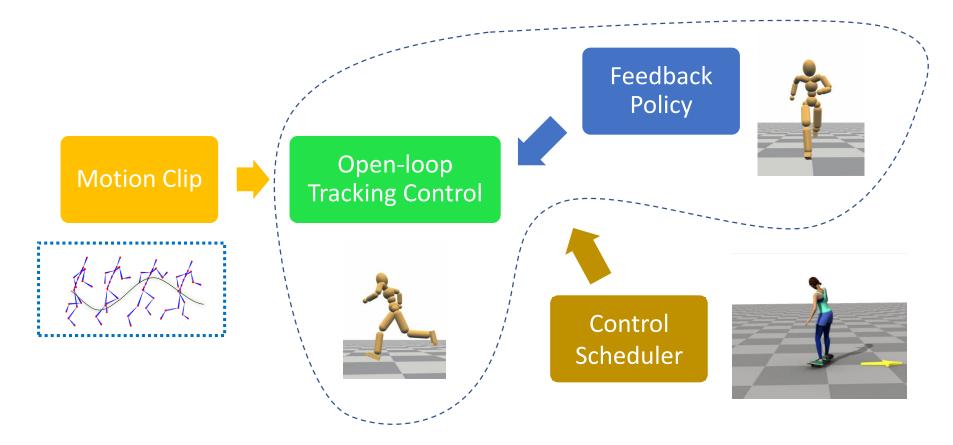




# Push-Recovery



#### Conclusion



Libin Liu, Michiel Van De Panne, and Kangkang Yin. 2016. Guided Learning of Control Graphs for Physics-Based Characters. *ACM Trans. Graph.* 35, 3, Article 29 (May 2016), 14 pages.

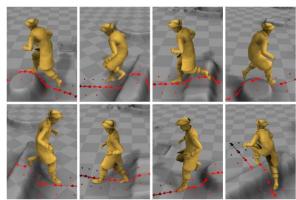
Libin Liu and Jessica Hodgins. 2017. Learning to Schedule Control Fragments for Physics-Based Characters Using Deep Q-Learning. *ACM Trans. Graph.* 36, 3, Article 29 (June 2017), 14 pages.

#### **Future Work**

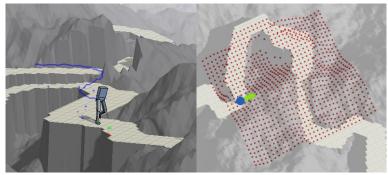
Statistical/generative model

Control with raw simulation state and terrain information

Active human-object interaction basketball, soccer dancing, boxing, martial arts



[Holden et al. 2017]



[Peng et al. 2017, DeepLoco]



[Heess et al. 2017]



#### Questions?

Libin Liu
<a href="http://libliu.info">http://libliu.info</a>

DeepMotion Inc <a href="http://deepmotion.com">http://deepmotion.com</a>

