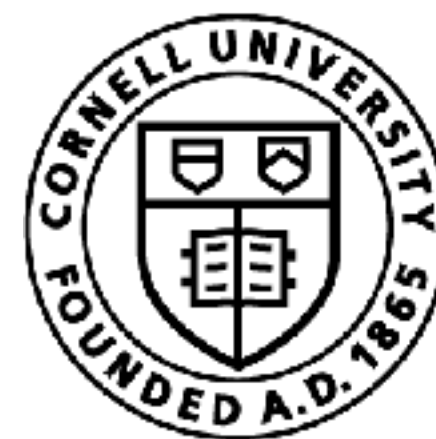


# Linear Quadratic Regulator:

# The Analytic MDP

Sanjiban Choudhury



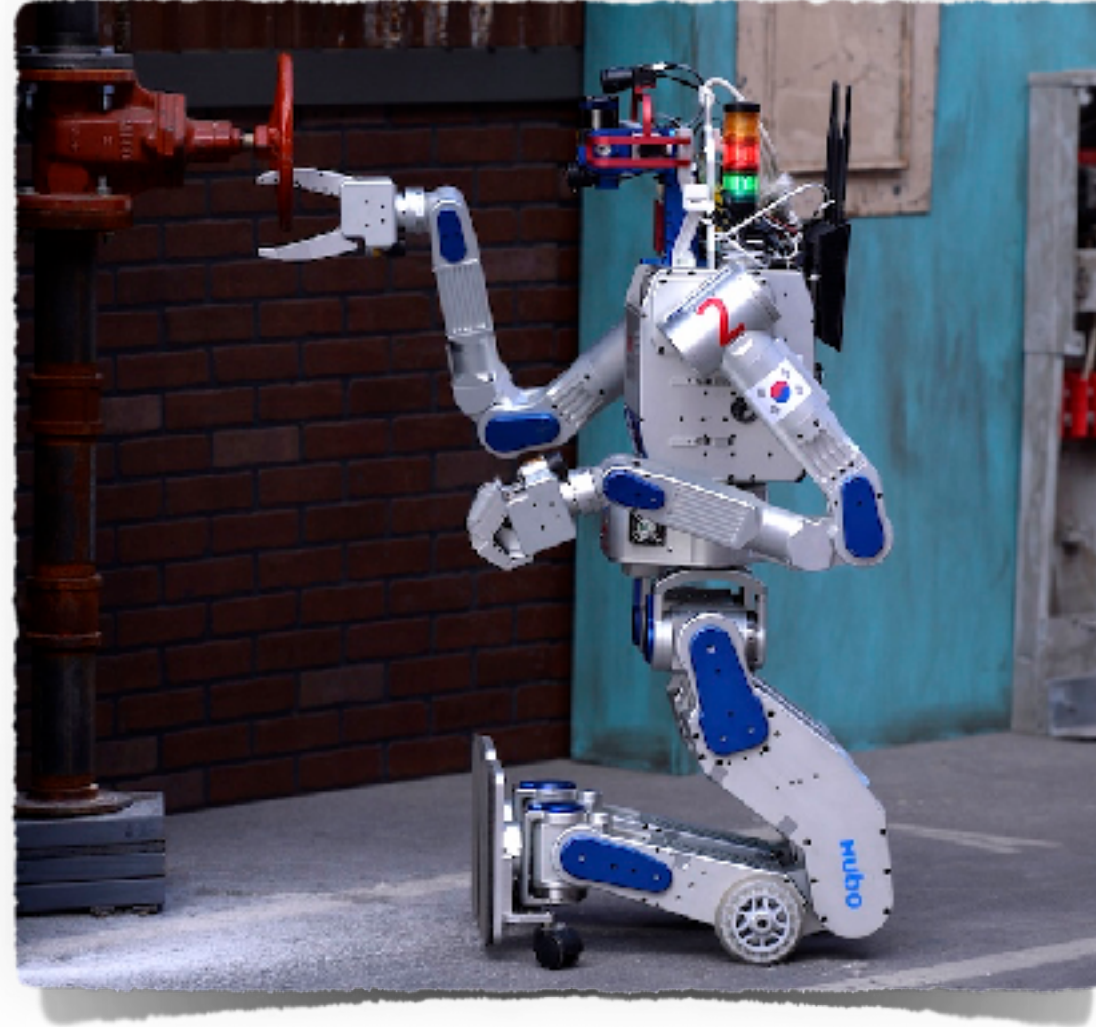
Cornell Bowers CIS  
**Computer Science**

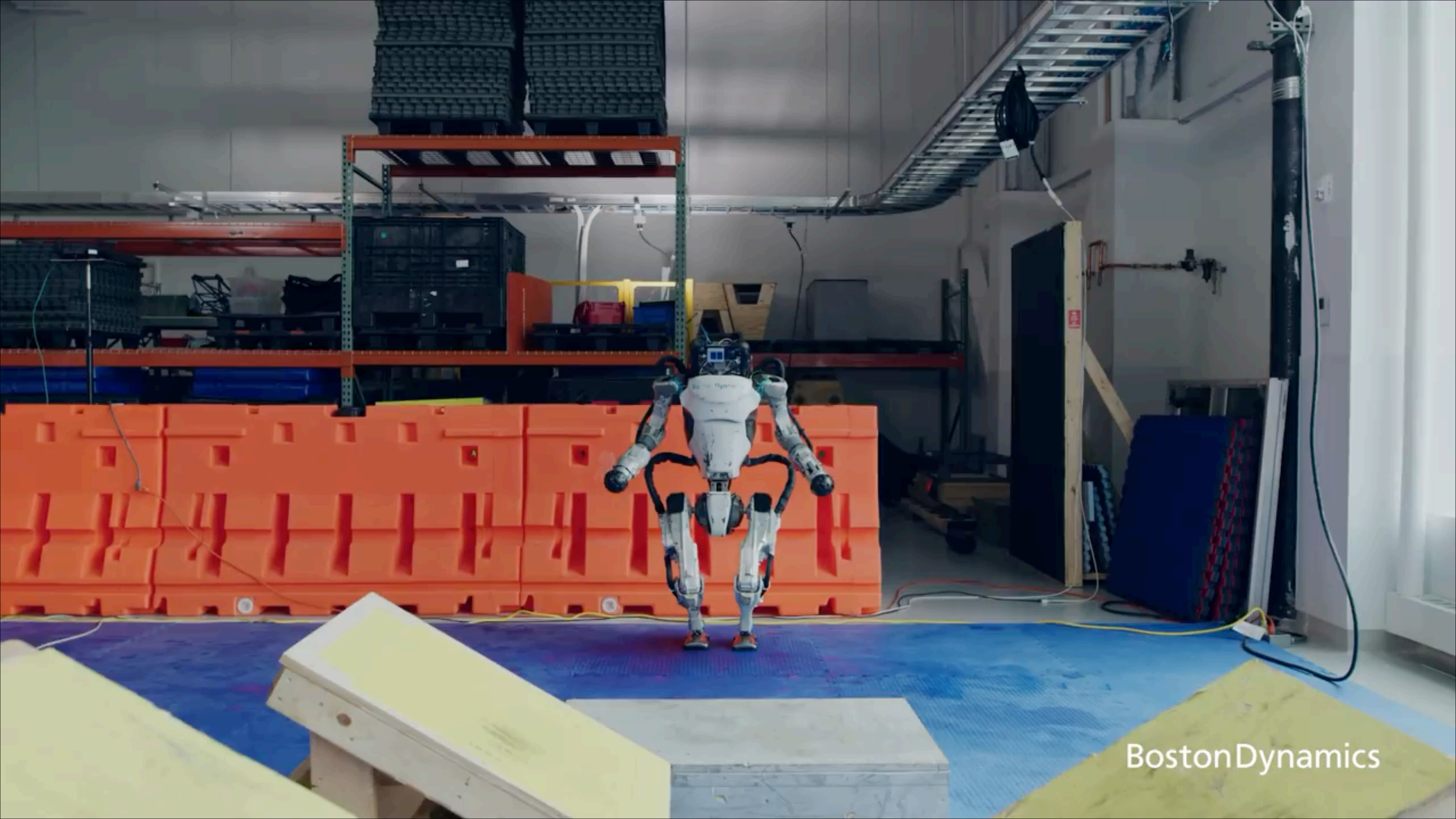
# Announcements



1. No office hours for Sanjiban on Thursday this week :(

# It's time to bring in the robots!





BostonDynamics

Activity!



# Think-Pair-Share

Think (30 sec): How do we model the Atlas backflip as a Markov Decision Problem  $\langle S, A, C, T \rangle$ ?

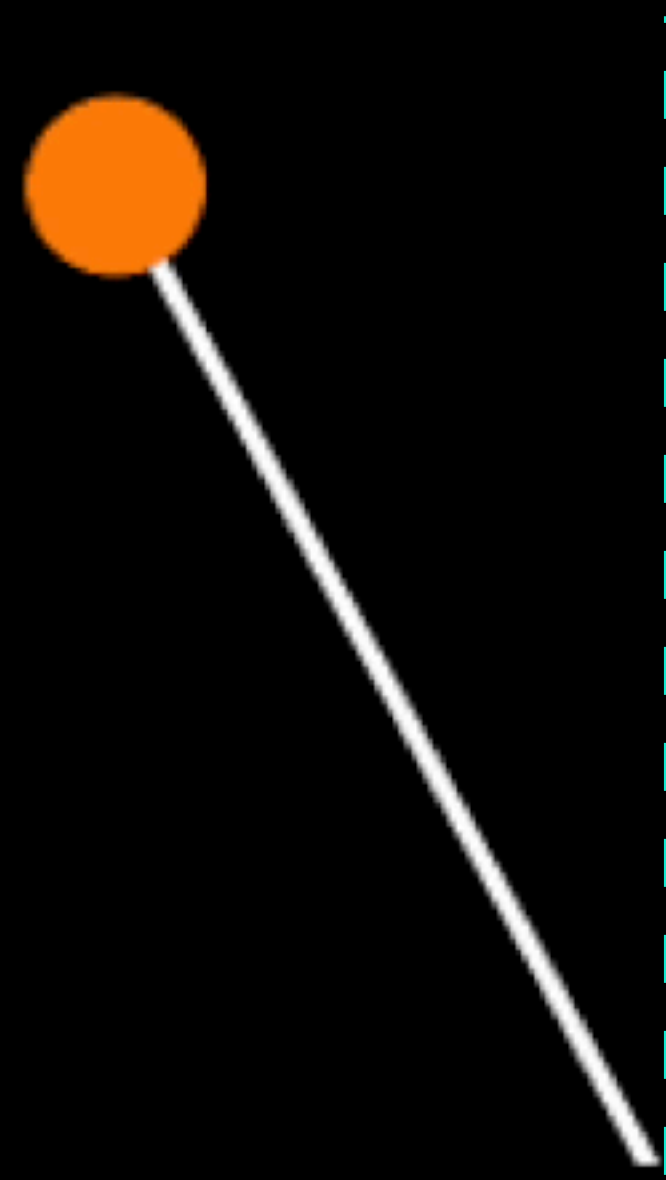
Pair: Find a partner

Share (45 sec): Partners exchange ideas





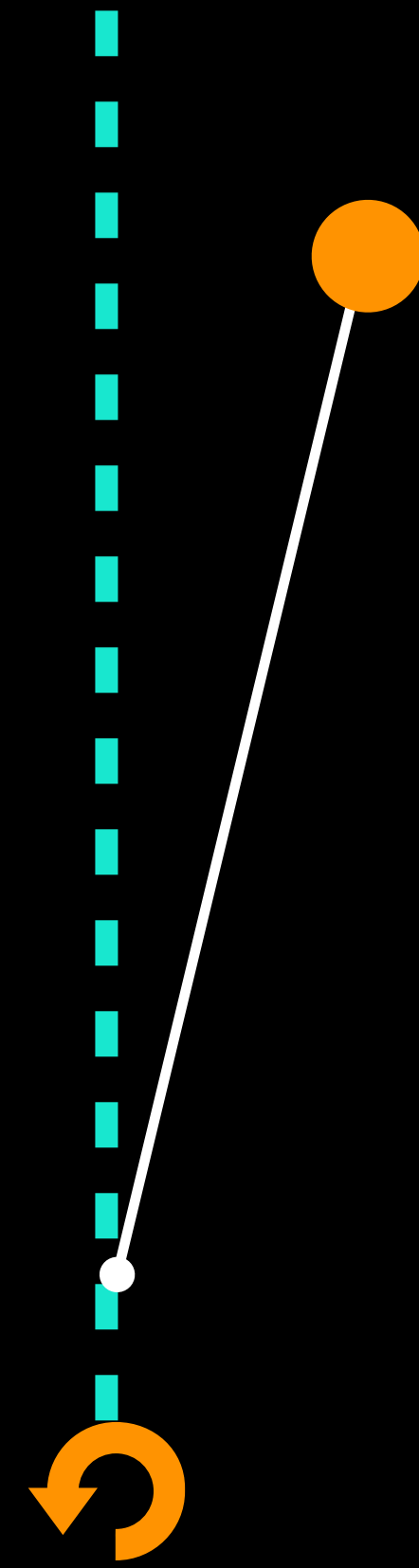
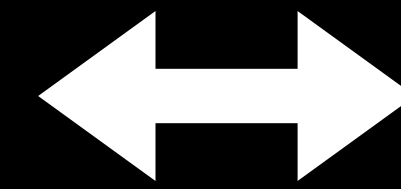
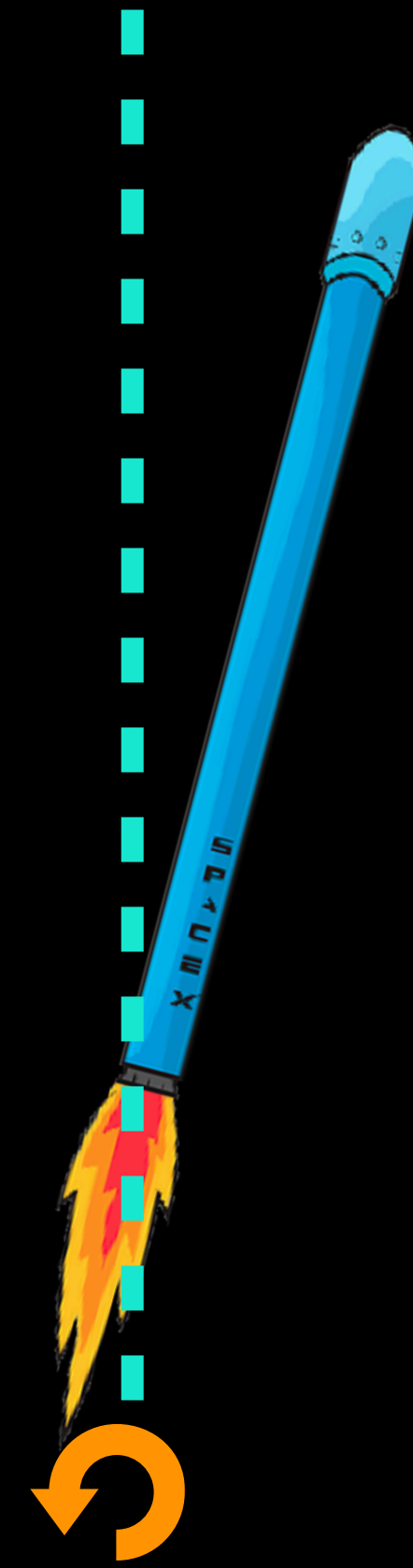
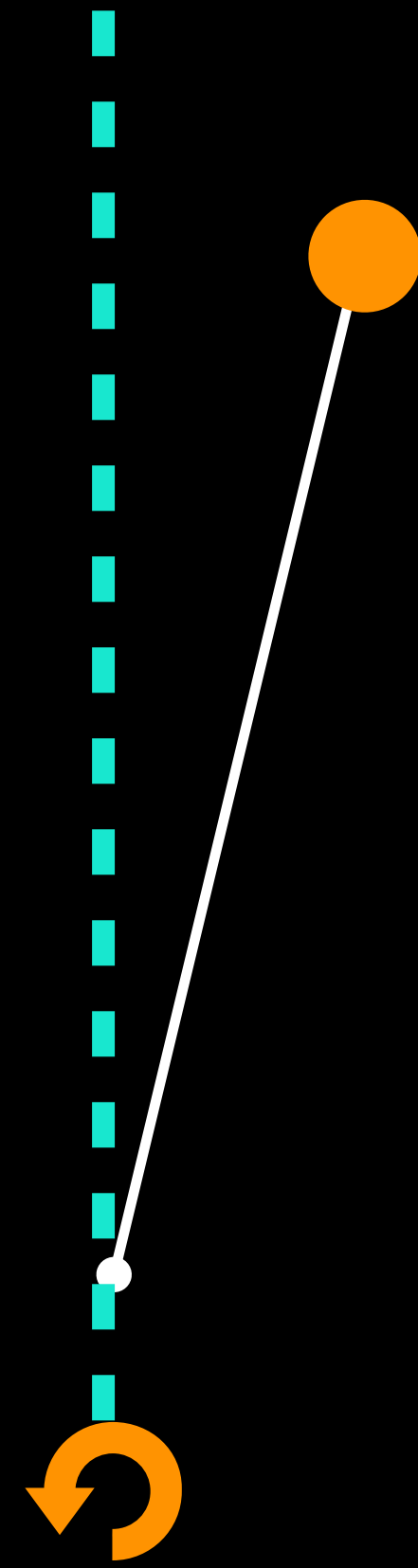
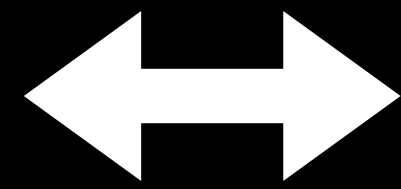
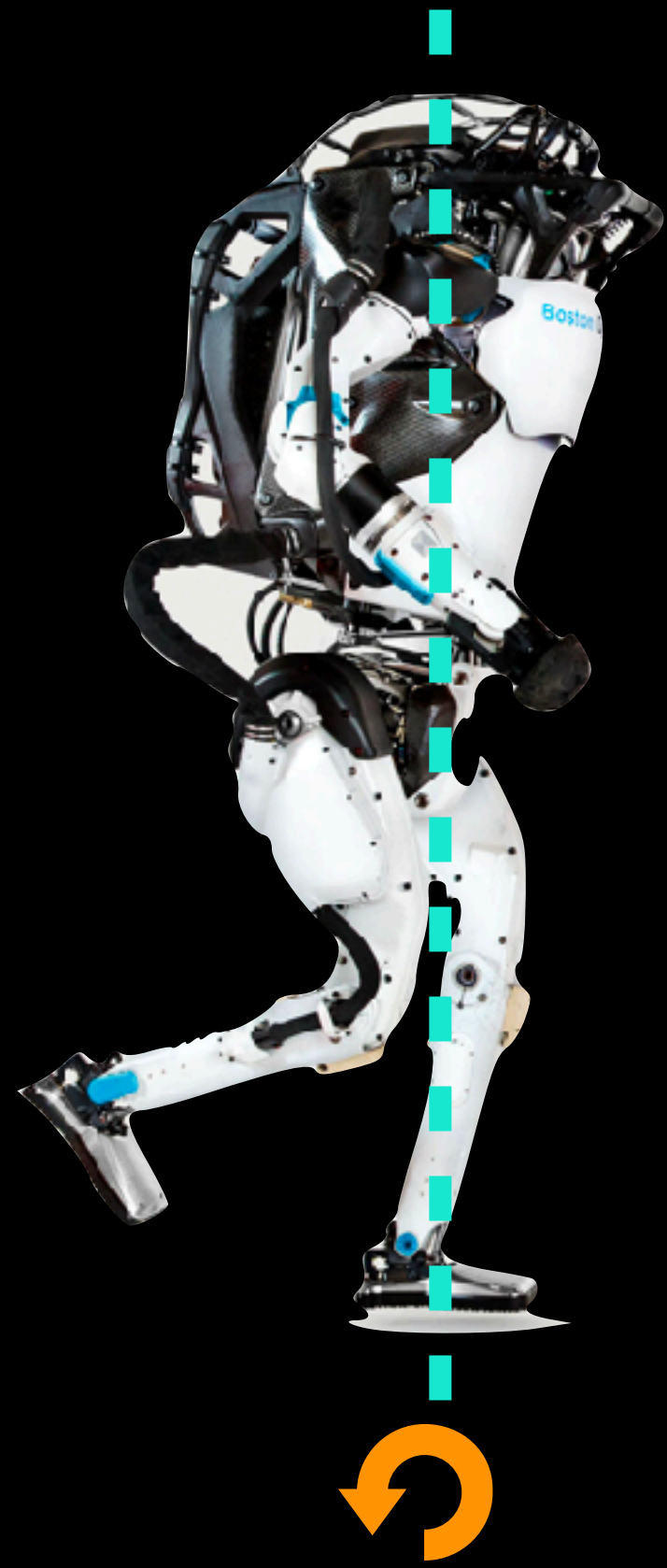
# The Inverted Pendulum: A fundamental dynamics model





# Humanoid balancing

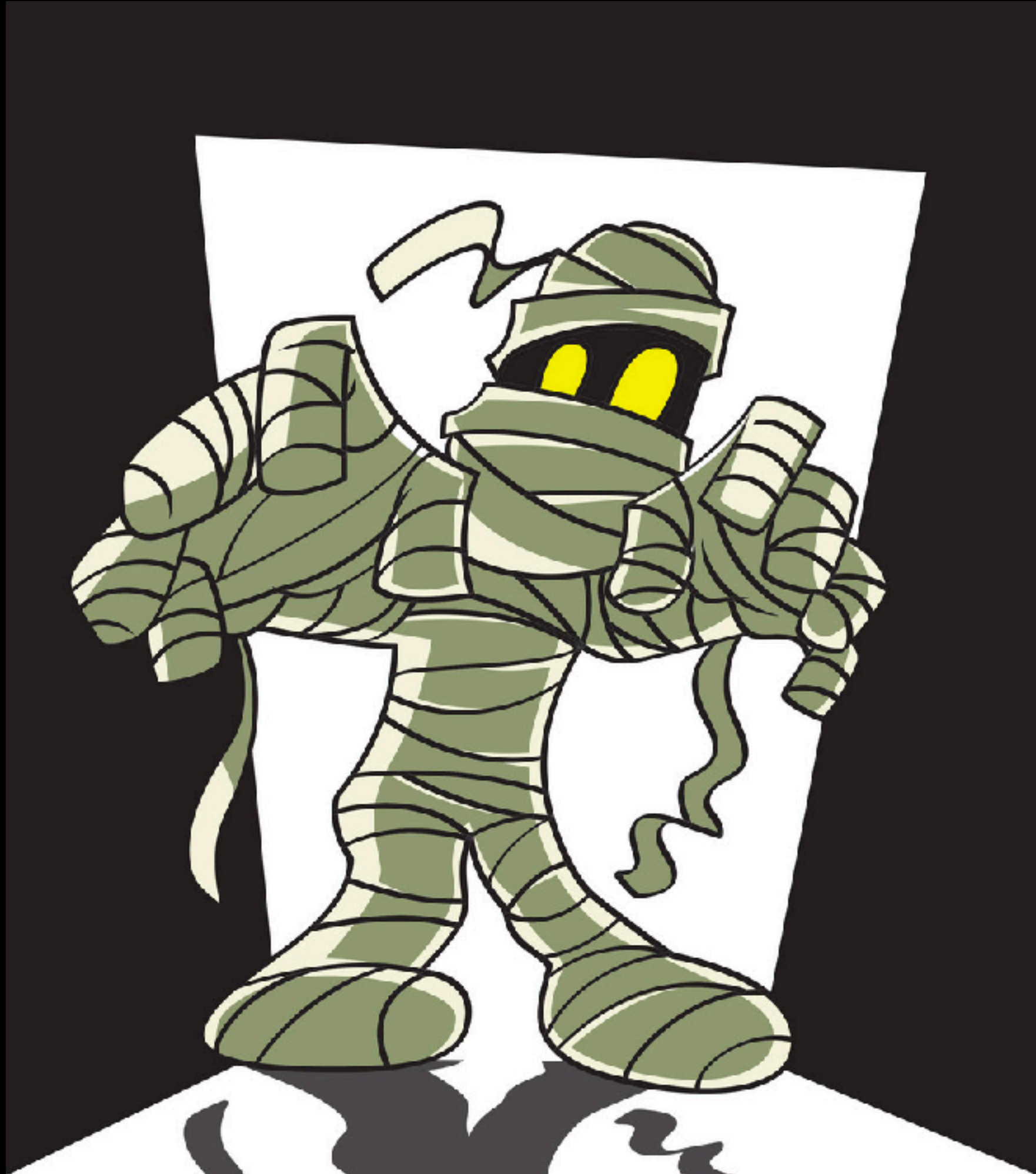
# Rocket landing



Why not discretize  
the dynamics and  
apply value / policy  
iteration?



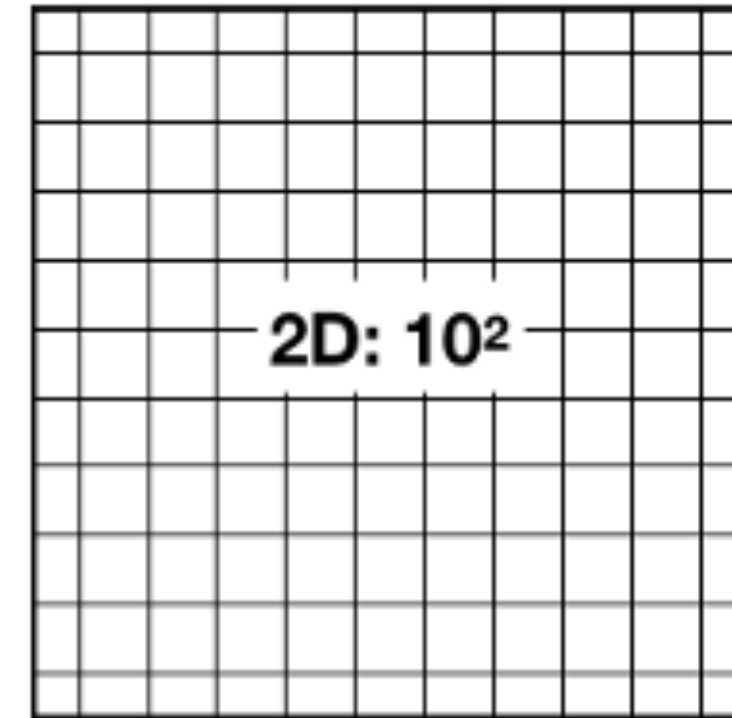
# THE CURSE OF DIMENSIONALITY



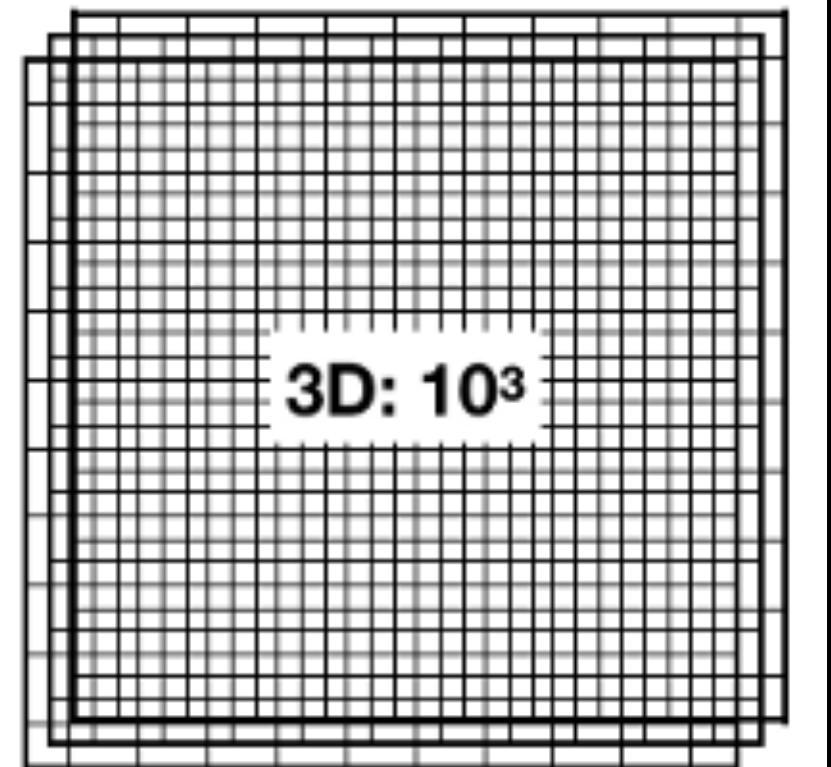
1D:  $10^1$



2D:  $10^2$



3D:  $10^3$

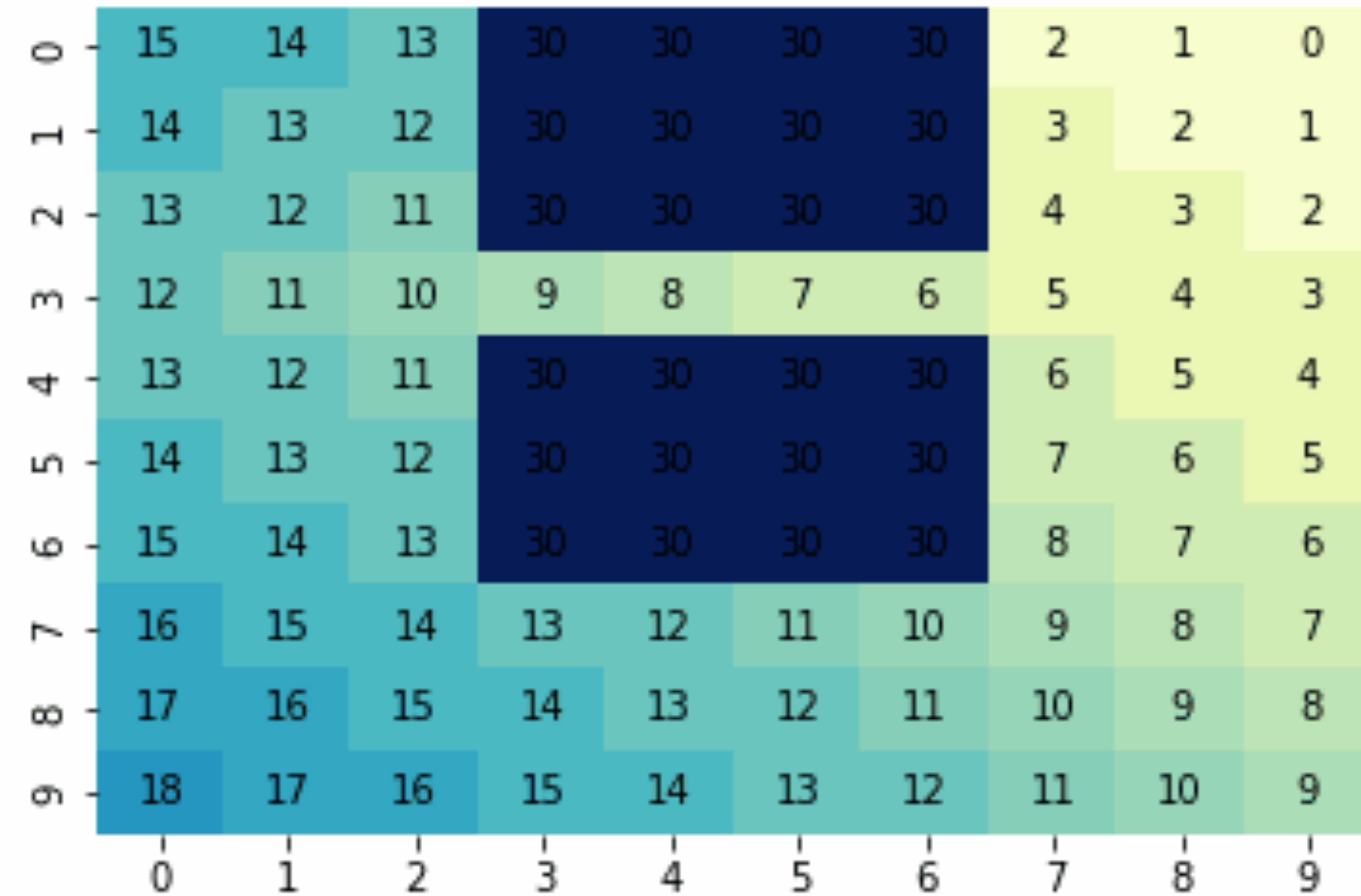


# No Discretization!

Can we **analytically** *represent* and *update* the value function?

$$V^*(s) = \min_a [c(s, a) + \gamma \mathbb{E}_{s' \sim \mathcal{T}(s, a)} V^*(s)]$$

Time: 0



Can represent analytically ...  
(piecewise linear?)

But updating seems hard!

$$V^*(s) = \min_a [c(s, a) + \gamma \mathbb{E}_{s' \sim \mathcal{T}(s, a)} V^*(s)]$$

Can we **analytically** represent and  
*update* the value function?

Yes\*

\*linear dynamics, quadratic costs

Let's formalize!

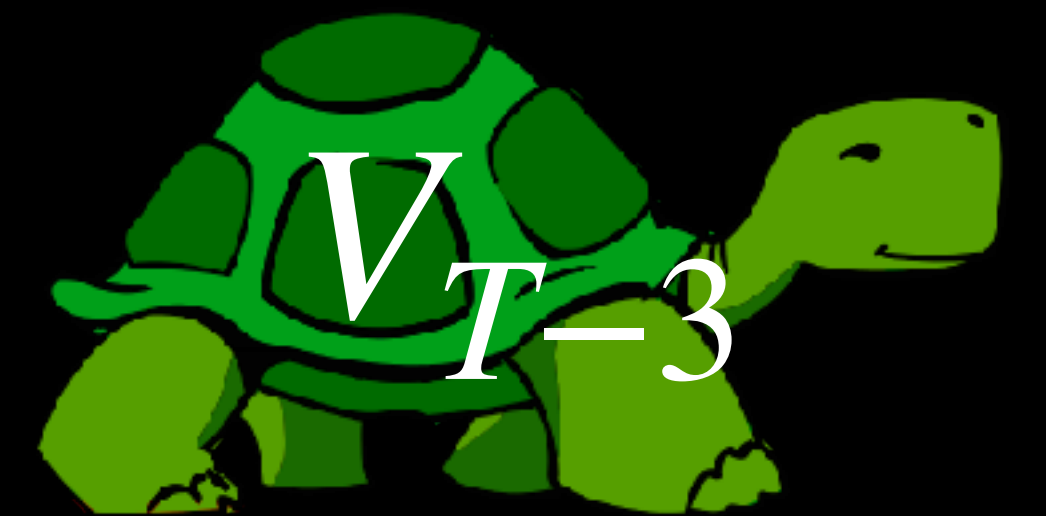
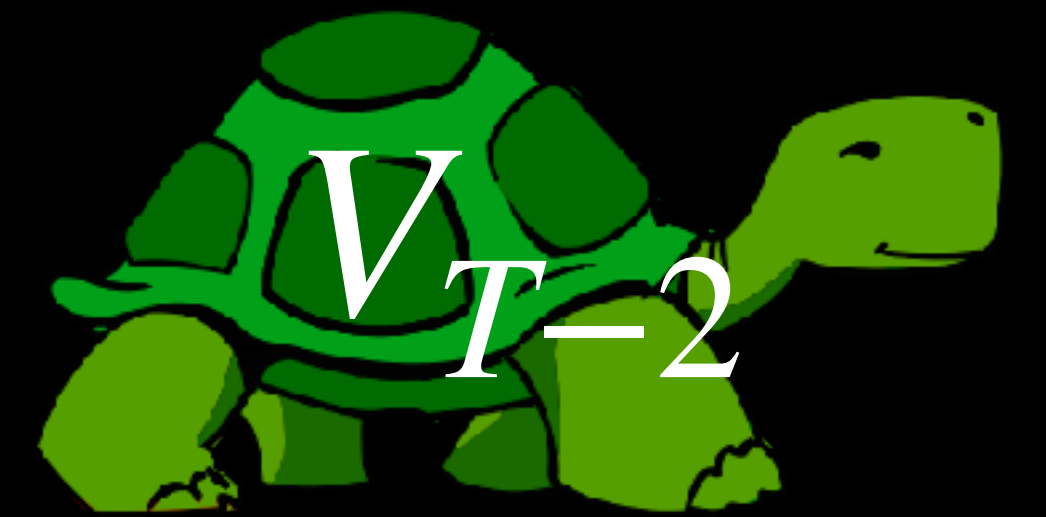
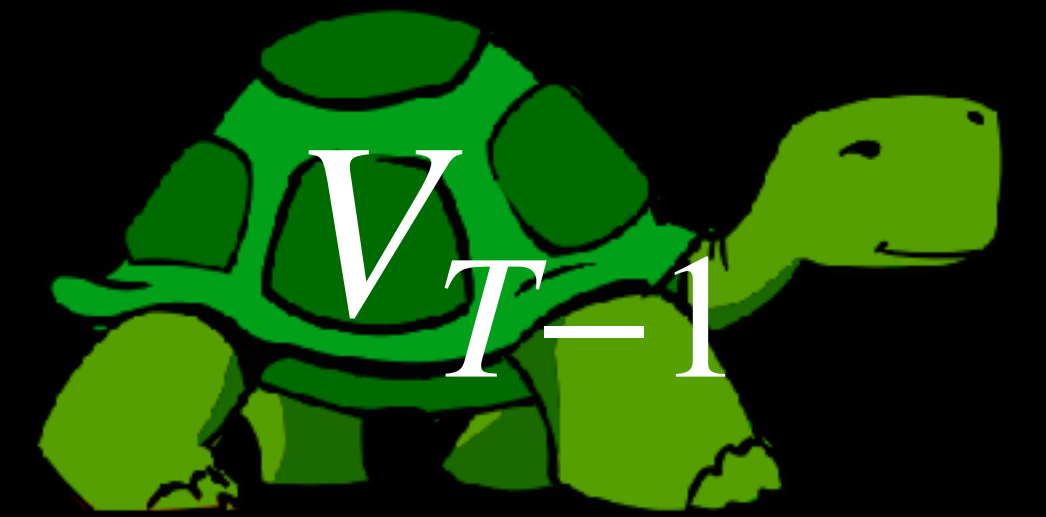


# It's quadratics all the way down!



$$K_t = (R + B^T V_{t+1} B)^{-1} B^T V_{t+1} A$$

$$V_t = Q + K_t^T R K_t + (A + B K_t)^T V_{t+1} (A + B K_t)$$





# The LQR Algorithm

Initialize  $V_T = Q$

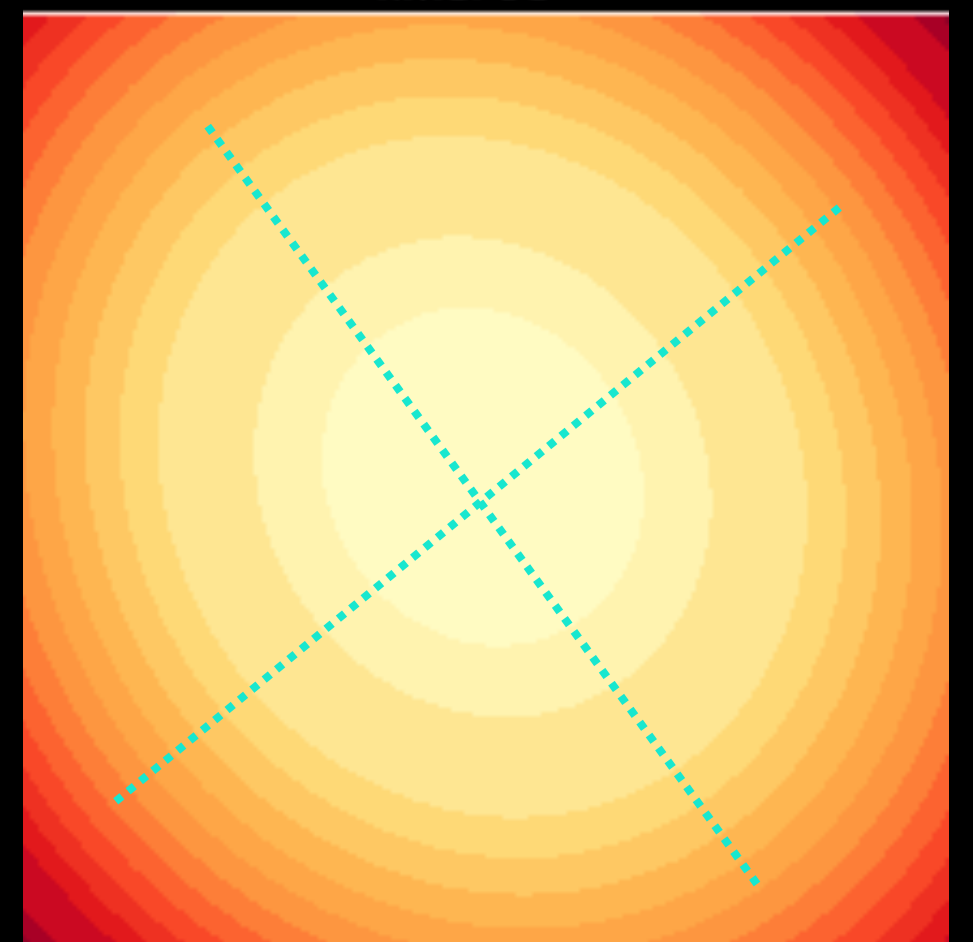
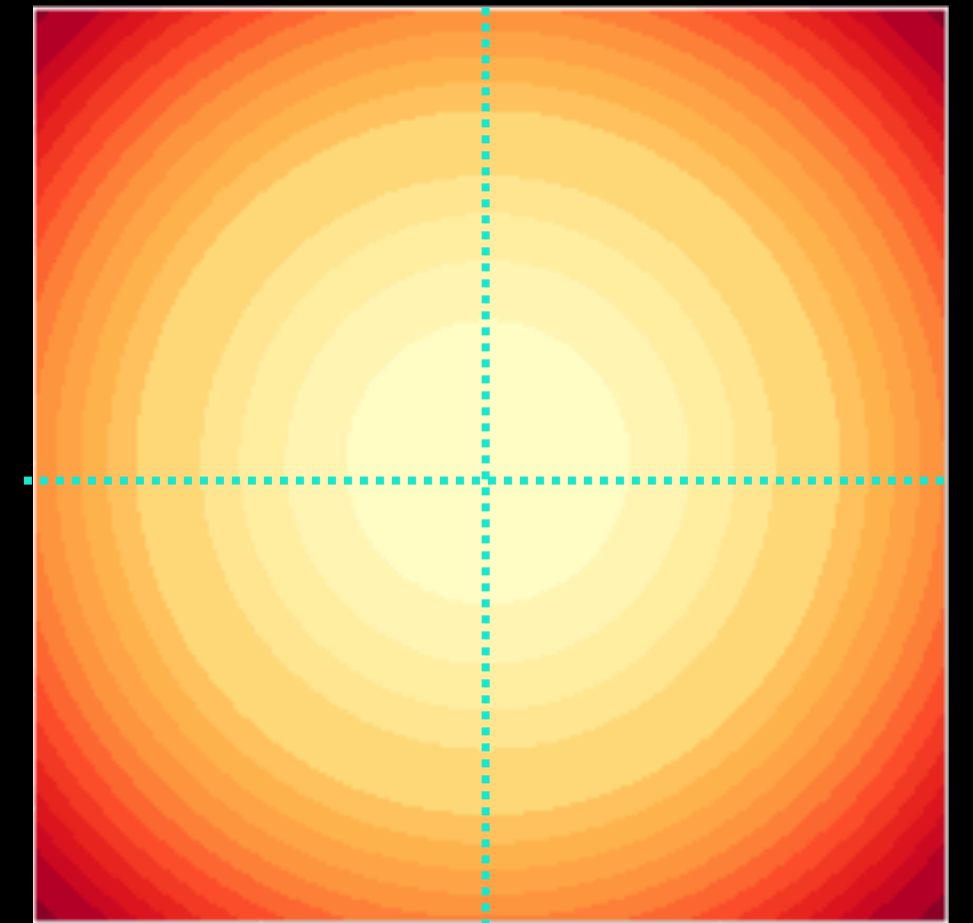
For  $t = T \dots 1$

Compute gain matrix

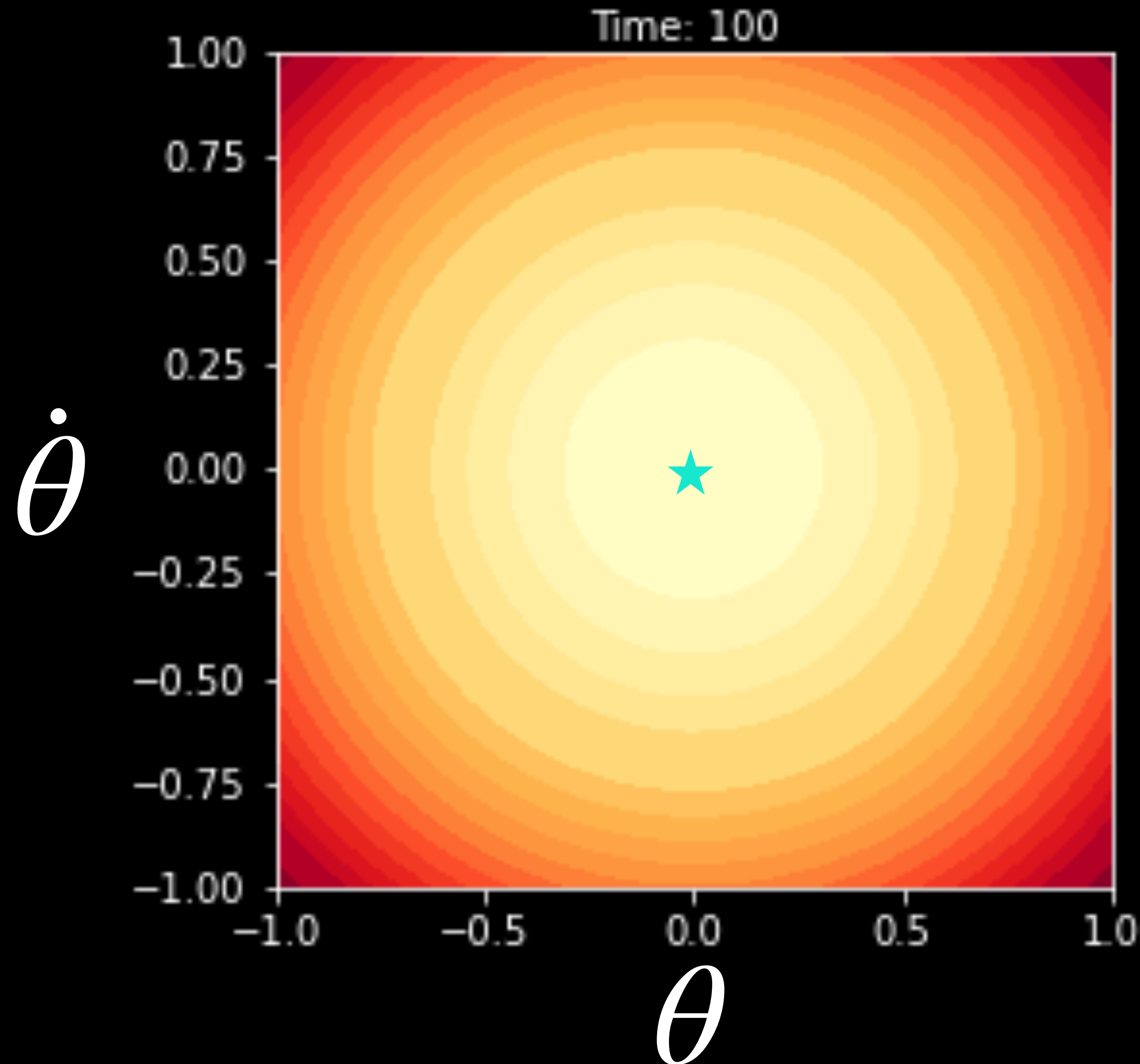
$$K_t = (R + B^T V_{t+1} B)^{-1} B^T V_{t+1} A$$

Update value

$$V_t = Q + K_t^T R K_t + (A + B K_t)^T V_{t+1} (A + B K_t)$$



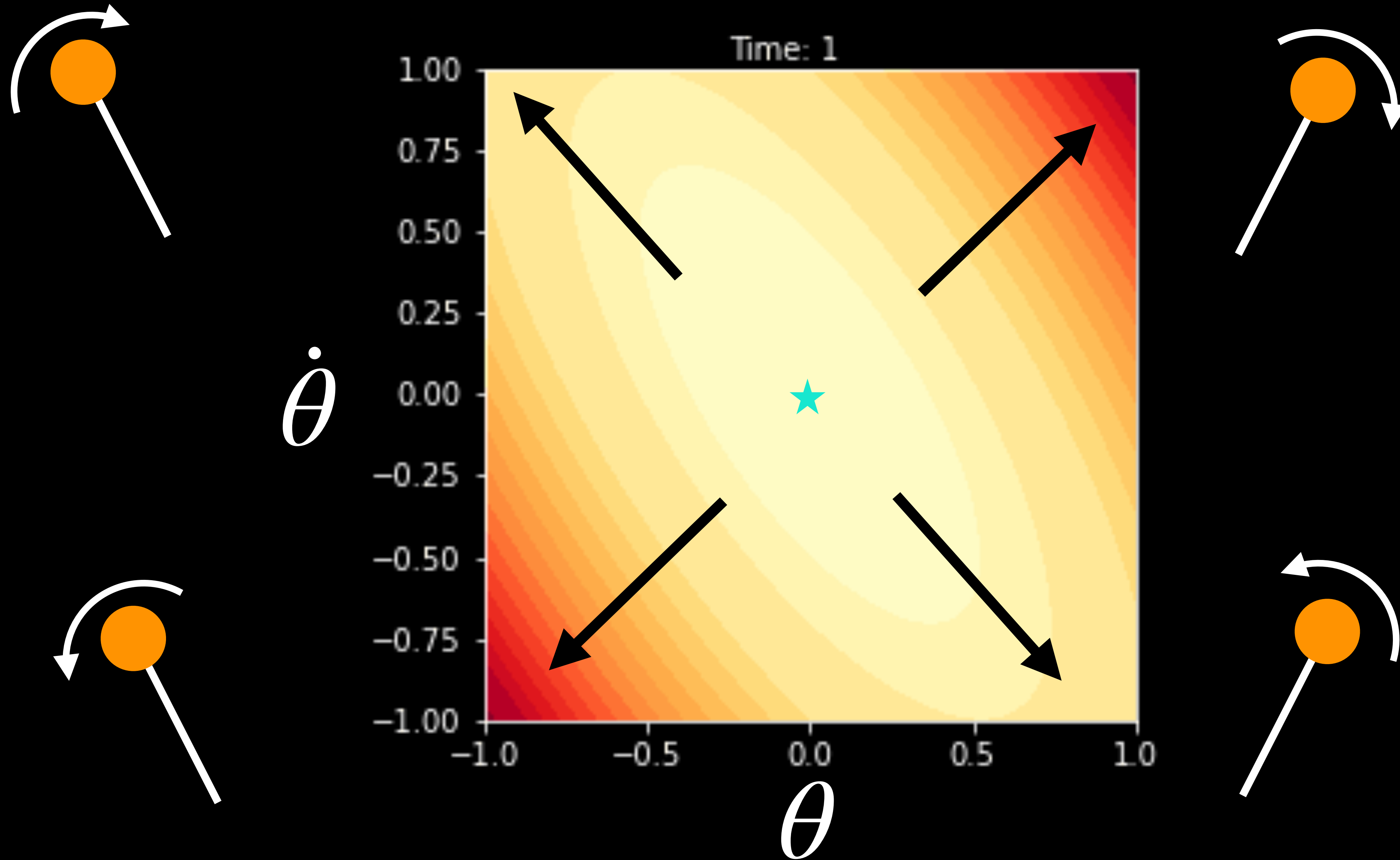
# Value Iteration for Inverted Pendulum



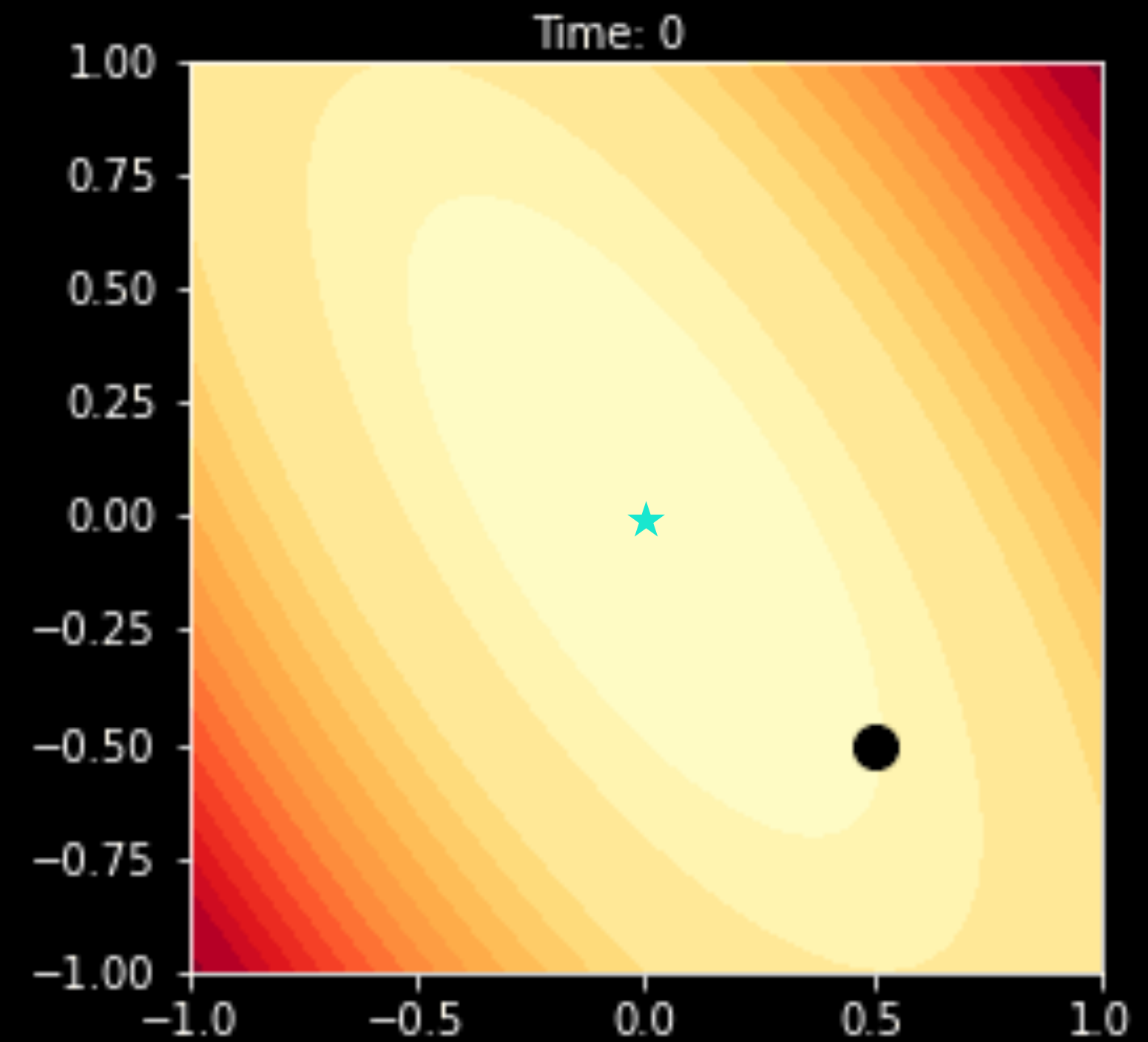
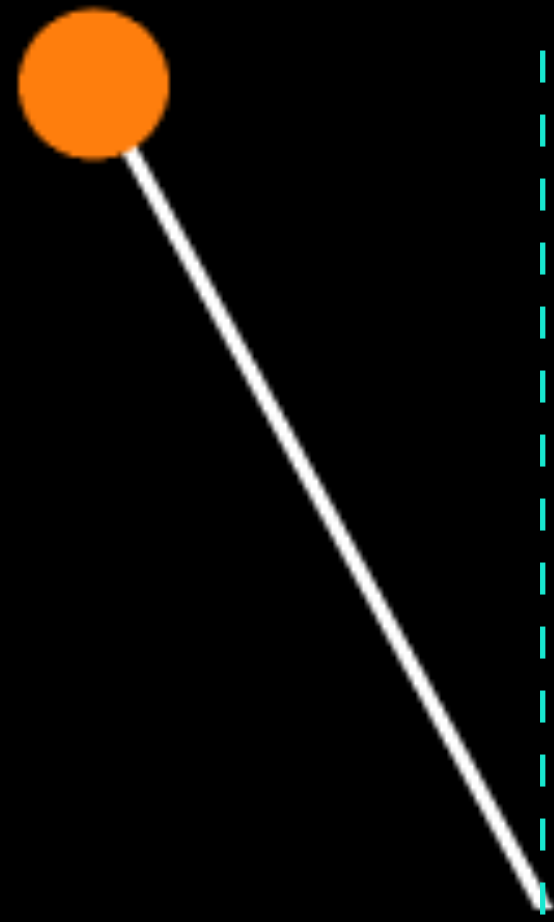
*Value  
converges  
when system  
is stabilizable*

*Can solve  
Ricatti  
equations for  
fixed point*

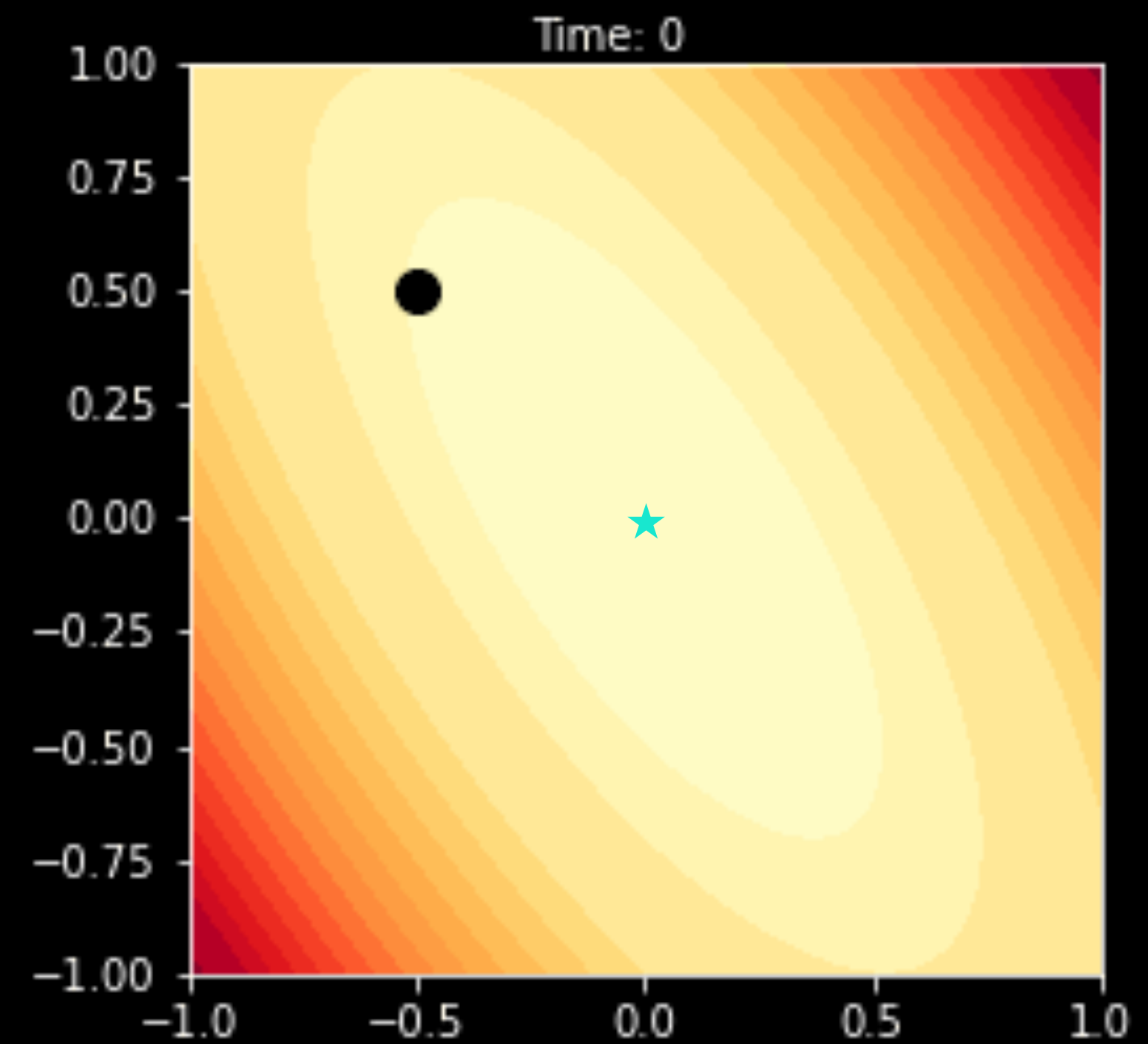
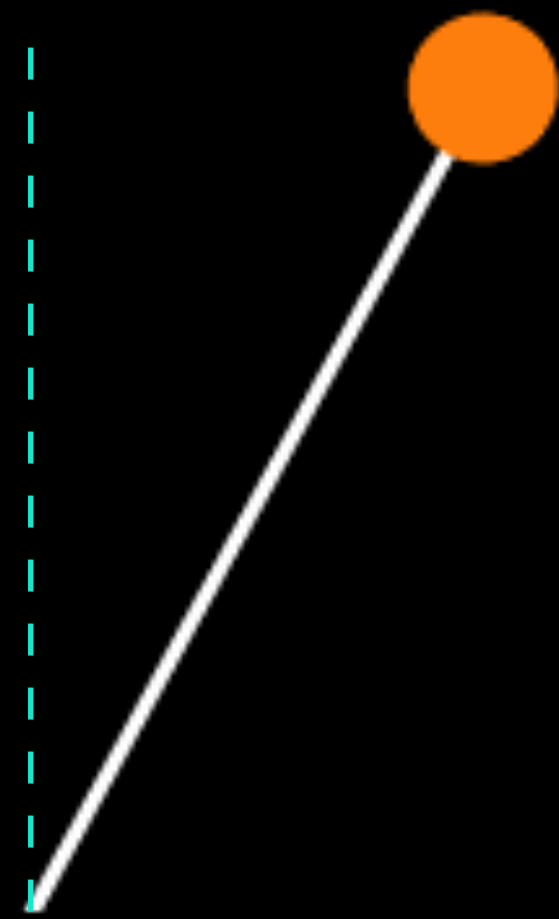
# Value Iteration for Inverted Pendulum



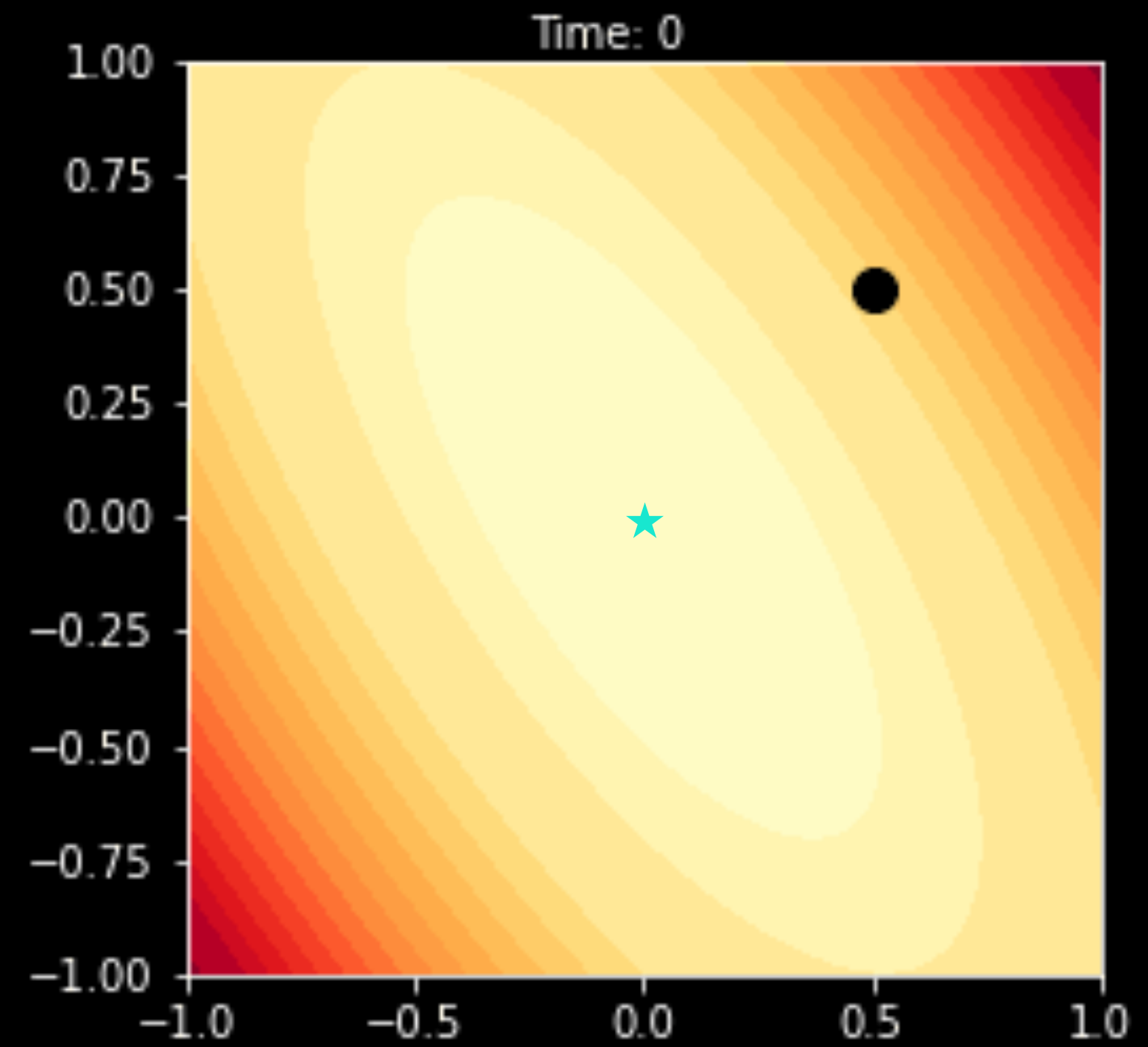
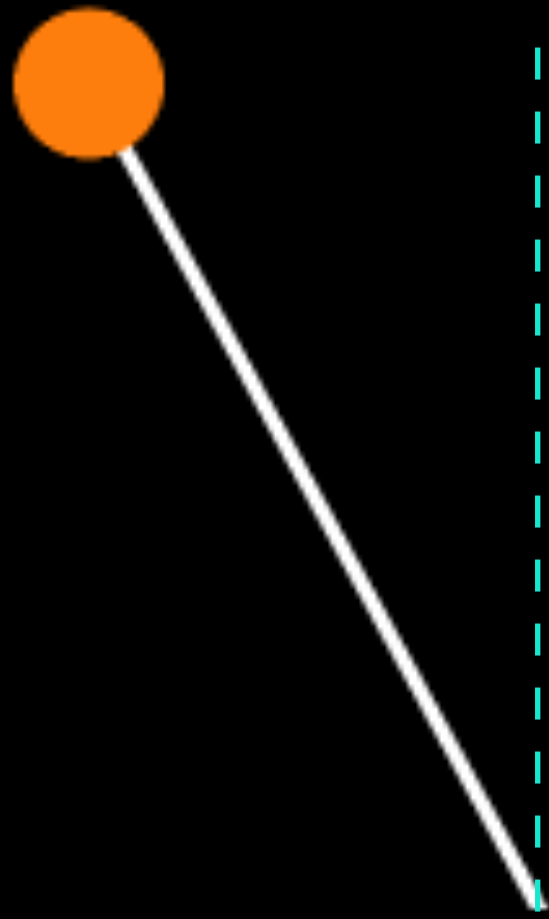
# An Easy Starting Point



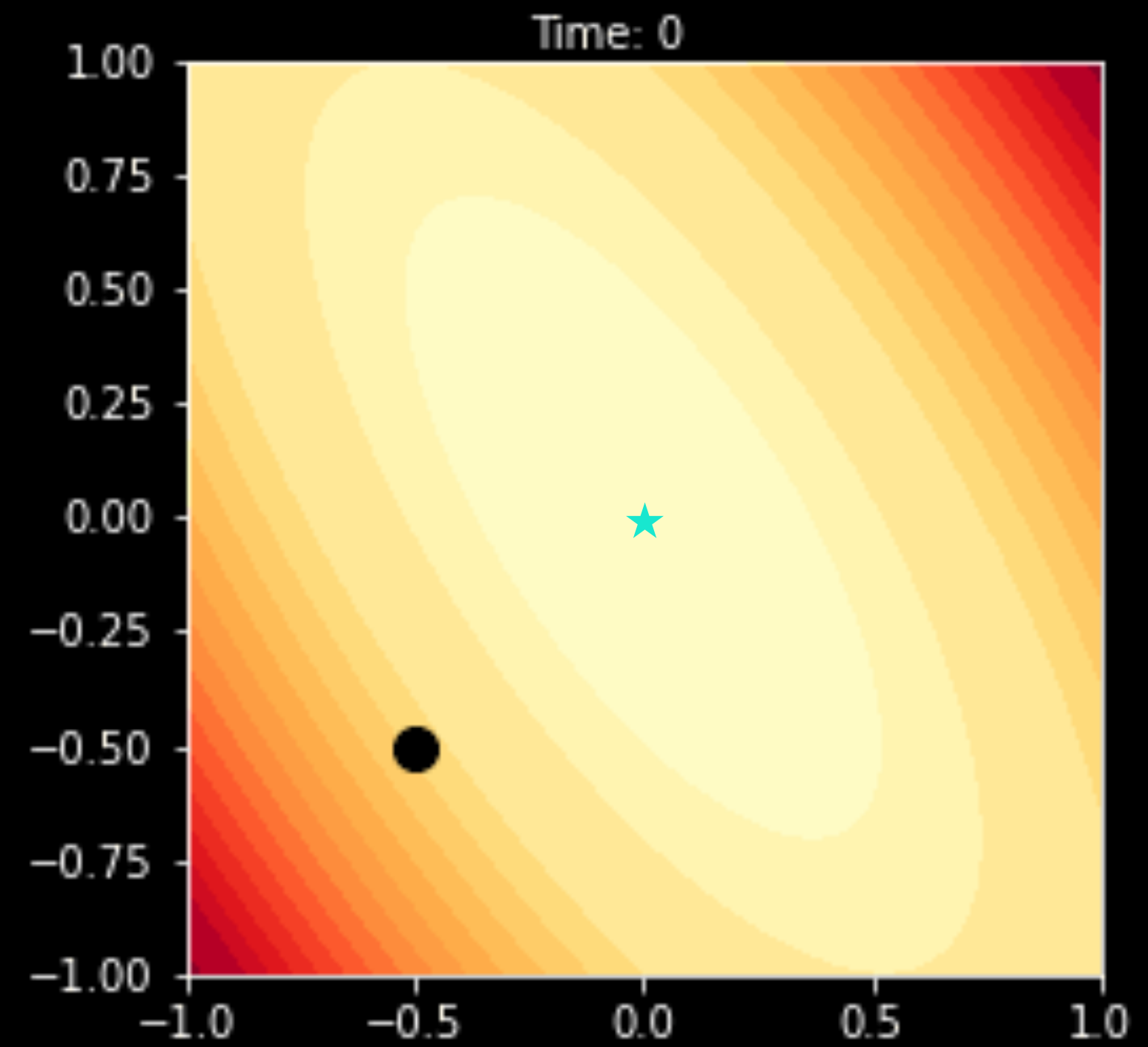
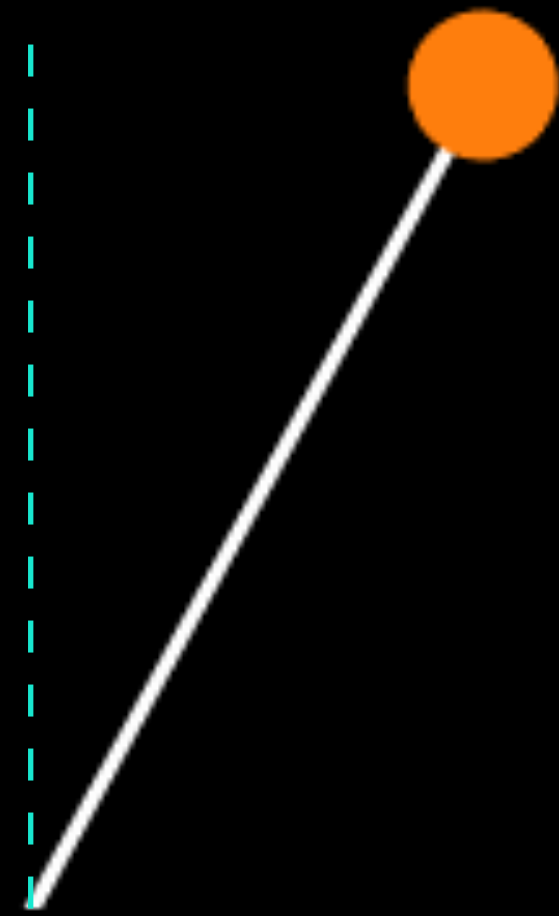
# Another Easy Starting Point



# A Hard Starting Point



# Another Hard Starting Point



When does LQR converge?

$$V = Q + K^T R K + (A + BK)^T V (A + BK)$$

$$K = (R + B^T V B)^{-1} B^T V A$$

When the closed loop system is stable, i.e.

Eigen values of  $(A+BK)$  are inside the unit circle on the complex plane



When does LQR converge?

$$V = Q + K^T R K + (A + BK)^T V (A + BK)$$

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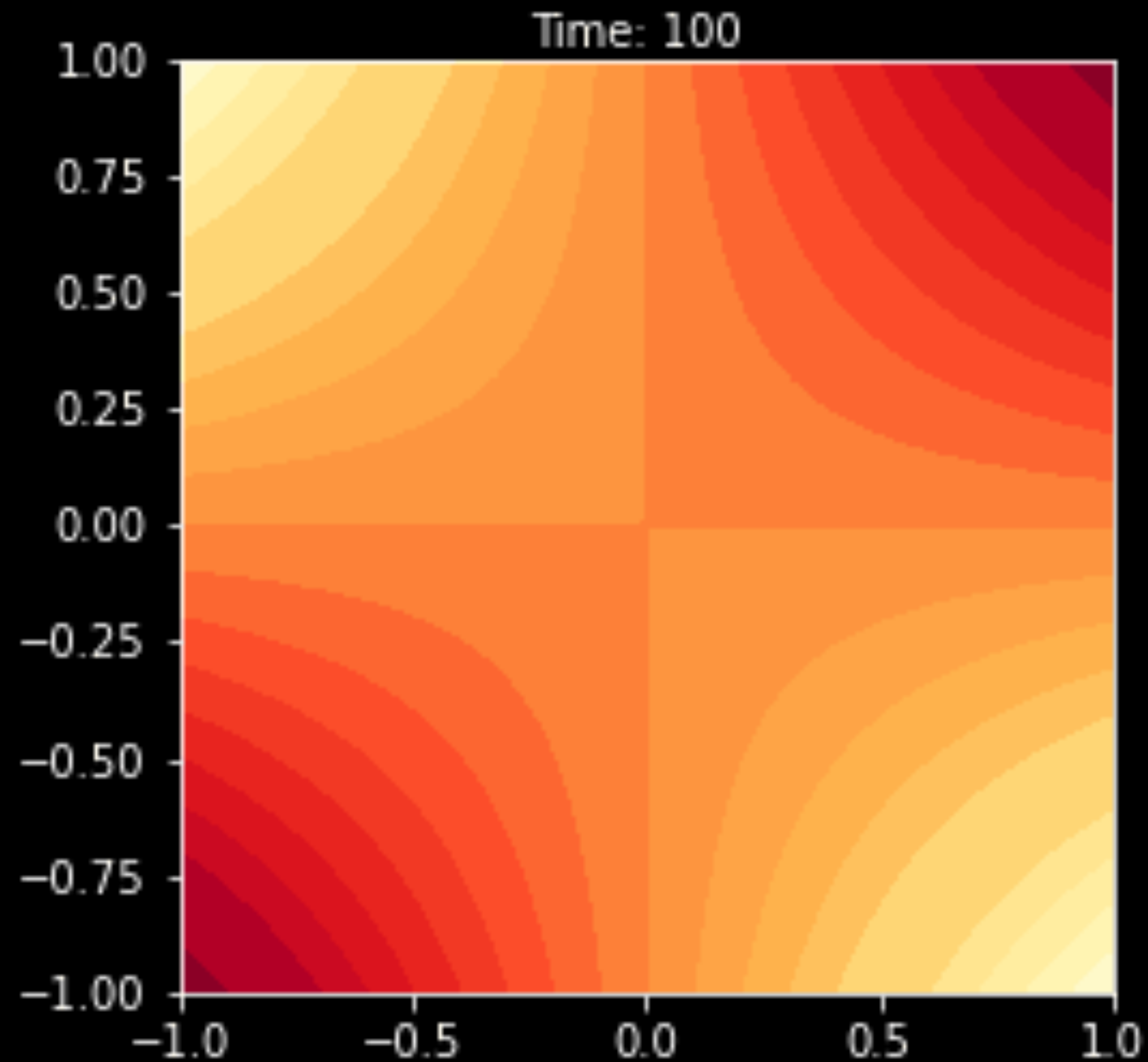
Eigen values of  $(A+BK)$  are inside the unit circle on the complex plane

*How can we find the fixed point of this equation?*

Discrete time algebraic ricatti equation (DARE)



# What if $Q$ is not PSD?



$$x^T Q x \neq 0$$

$$Q = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

What if  $R$  is not positive definite?

$$u^T R u \neq 0 \quad R = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

Hint: Gain matrix update?

$$K_t = (R + B^T V_{t+1} B)^{-1} B^T V_{t+1} A$$

# What about handling uncertainty?

Gaussian noise in dynamics ?

$$x_{t+1} \sim \mathcal{N}(Ax_t + Bu_t, \Sigma)$$

# Some Trivia!

## *A productive year from Kalman*

In 1960 three major papers were published by R. Kalman and coworkers...

1. One of these [Kalman and Bertram 1960], publicized the vital work of Lyapunov in the time-domain control of nonlinear systems.
2. The next [Kalman 1960a] discussed the optimal control of systems, providing the design equations for the linear quadratic regulator (LQR).
3. The third paper [Kalman 1960b] discussed optimal filtering and estimation theory, providing the design equations for the discrete Kalman filter.

# Trivia: Duality between control and estimation

R. Kalman "A new approach to linear filtering and prediction problems." (1960)

**linear-quadratic  
regulator**

**Kalman-Bucy  
filter**

$V$

$\Sigma$

(state variance)

$A$

$A^T$

(dynamics)

$B$

$H^T$

(dynamics noise)

$R$

$DD^T$

(measurement)

$Q$

$CC^T$

(motion noise)

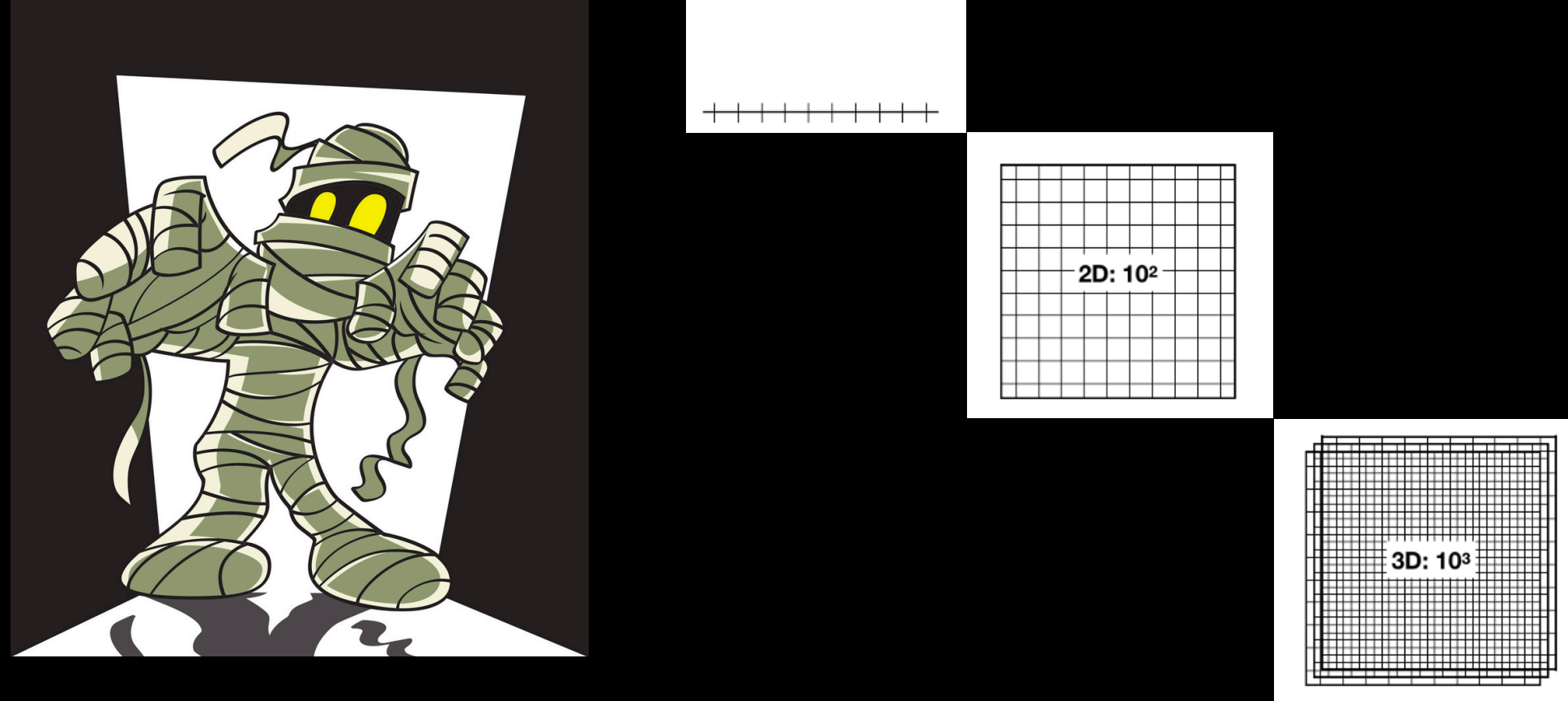
$t$

$t_f - t$

(Table from E.Todorov "General duality between optimal control and estimation", CDC, 2008)

# tl;dr

## THE CURSE OF DIMENSIONALITY

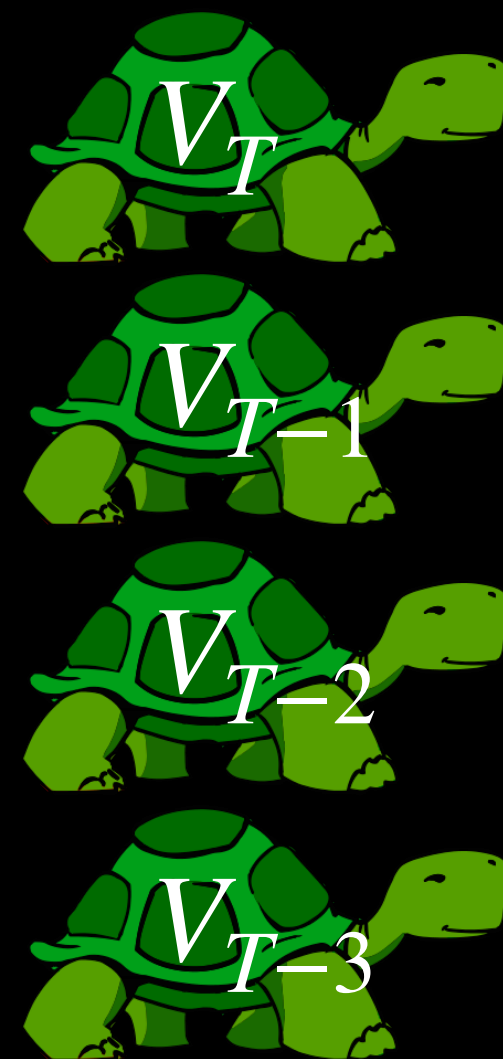


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