

# Seminar 1: RL terminology



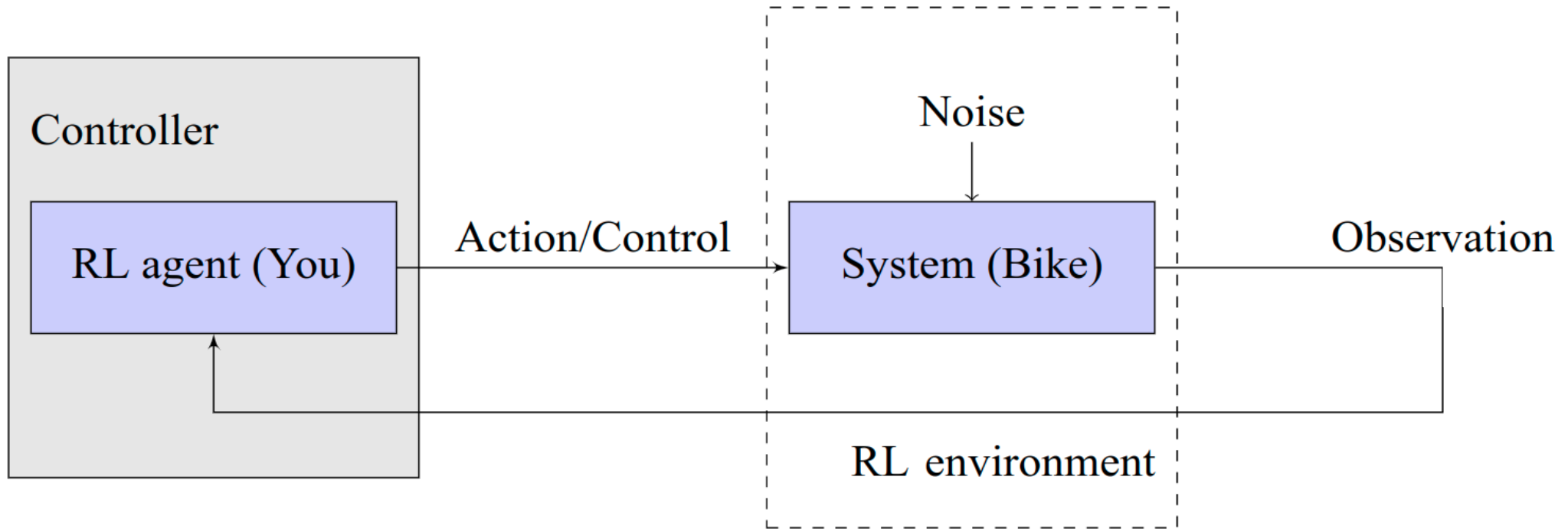
# **RL Agent & RL Environment vs. Controller & Control-system**

**RL Agent  $\stackrel{?}{=}$  Controller**

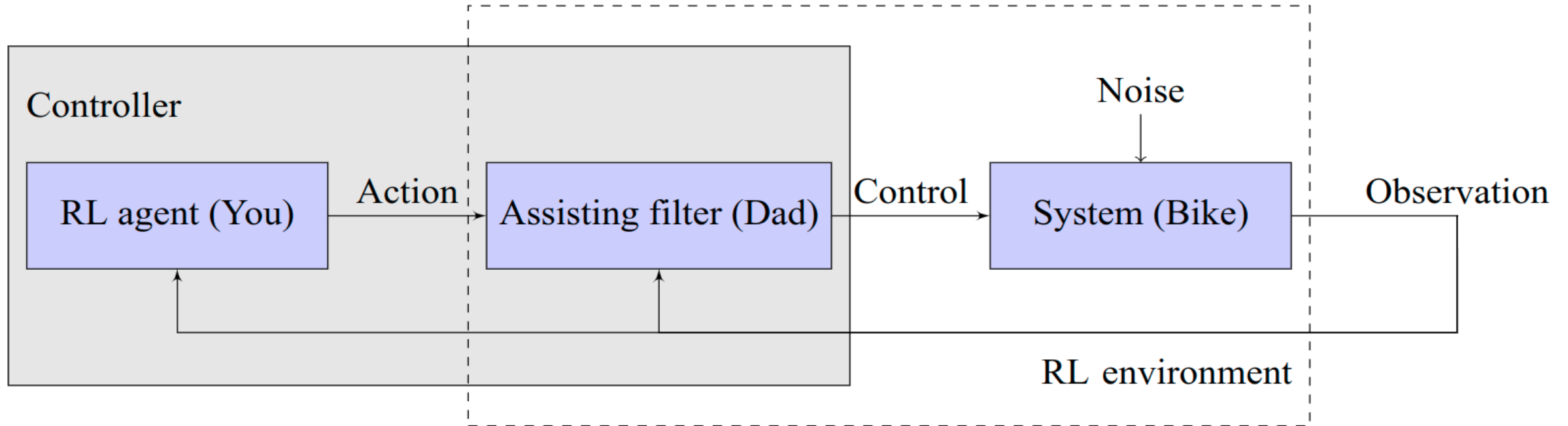
**RL Environment  $\stackrel{?}{=}$  Control-system**

**Action  $\stackrel{?}{=}$  Control input**

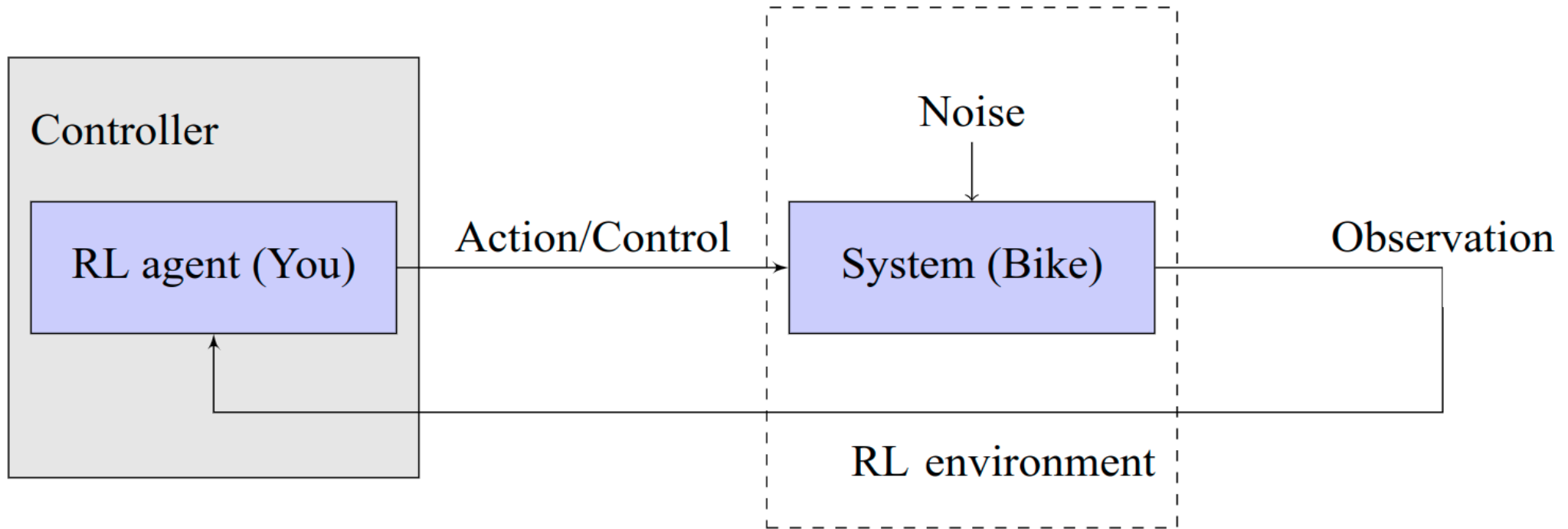
# RL Agent & RL Environment vs. Controller & Control-system



# RL Agent & RL Environment vs. Controller & Control-system



# RL Agent & RL Environment vs. Controller & Control-system





Please, split into groups of three.



# Problems and methods

## RL Terminology



Problems related



Methods related

# Problems related terminology

Optimal control  
problem



System



Objective



# Discrete time vs. Continuous time

System

Discrete time

$$T := \mathbb{Z}$$

Continuous time

$$T := \mathbb{R}$$

# Discrete time vs. Continuous time

$$f : \mathbb{R}^n \times \mathbb{U} \rightarrow \mathbb{R}^n$$

Continuous:

$$\frac{\partial}{\partial t} x(t) = f(x(t), u(t))$$

State dynamics function



Discrete:

$$x_{t+1} = f(x_t, u_t)$$

State transition function



# Discrete state space vs. Continuous state space

System

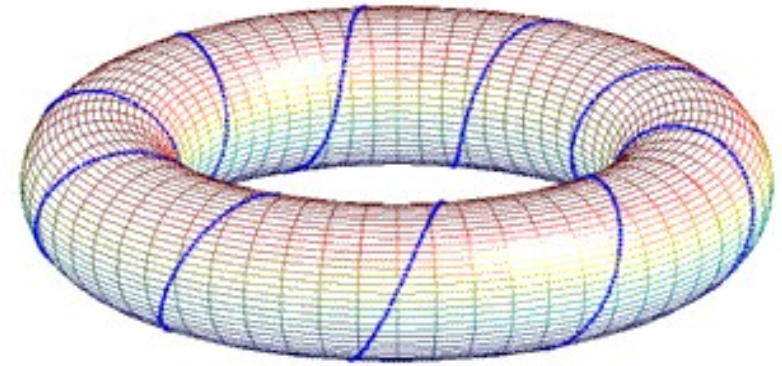
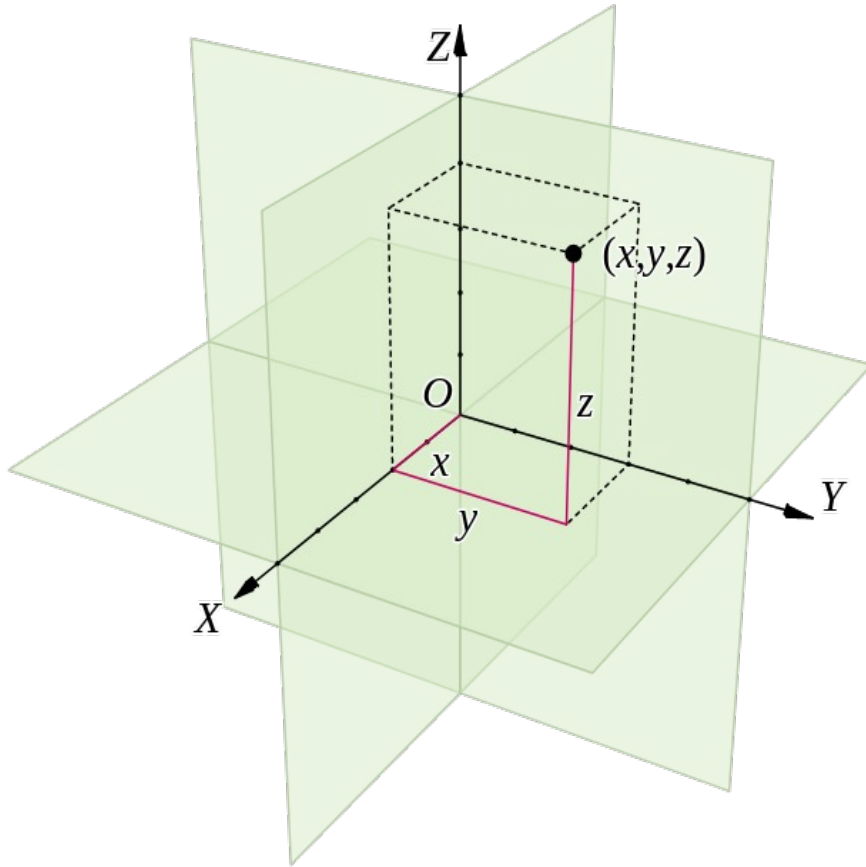


Discrete state space



Continuous state space

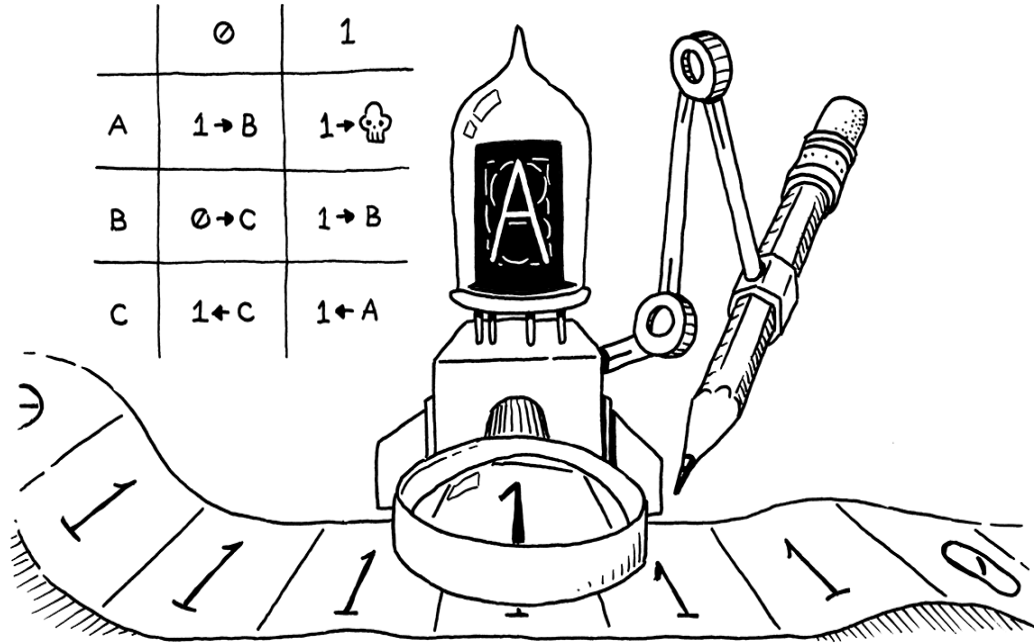
# Continuous state space



# Discrete state space

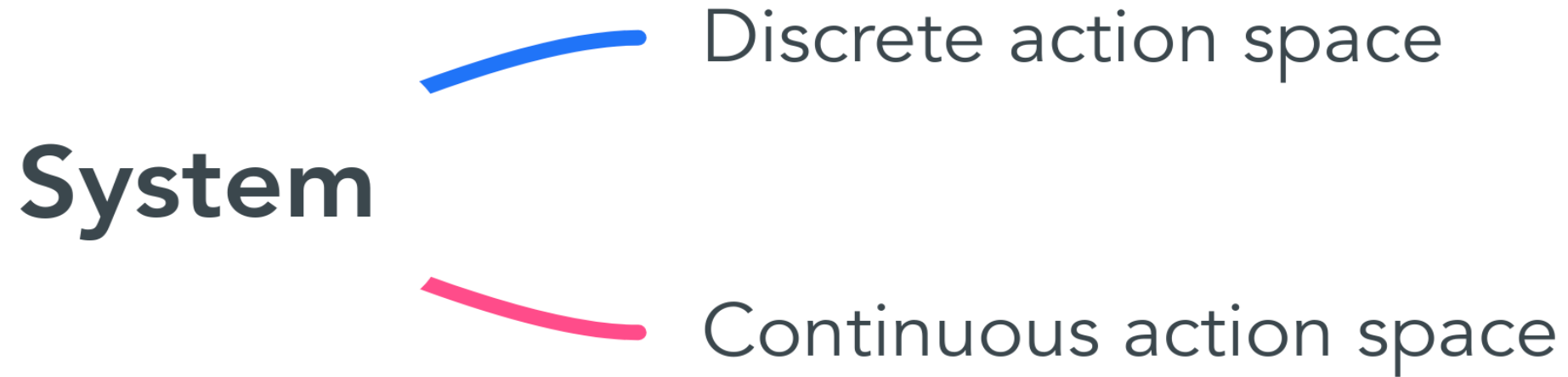


# Discrete state space



$$x_{t+1} = f(x_t, u_t),$$
$$f : \mathbb{Z} \times \mathbb{U} \rightarrow \mathbb{Z}$$

# Discrete action space vs. Continuous action space



# Discrete action space vs. Continuous action space



Continuous



Discrete

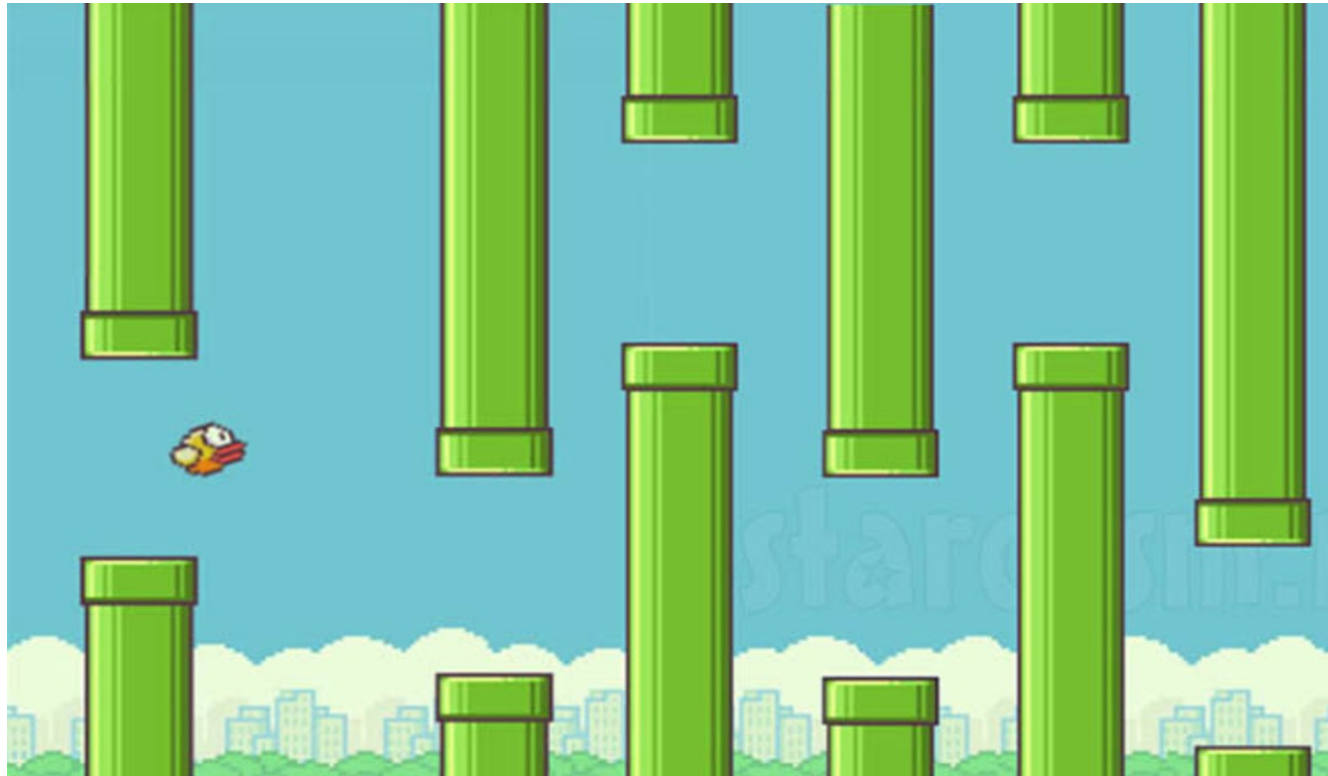




# Discrete action space vs. Continuous action space

Action space  $\approx$  Control set ( $\mathbb{U}$ )

# Discrete action space with continuous time and state space





# Continuous action space with discrete time and state space





## Continuous action space with discrete time and state space

$$x_{t+1} = f(x_t, u_t) + \lceil \sigma(x_t, u_t) \xi_t \rceil,$$

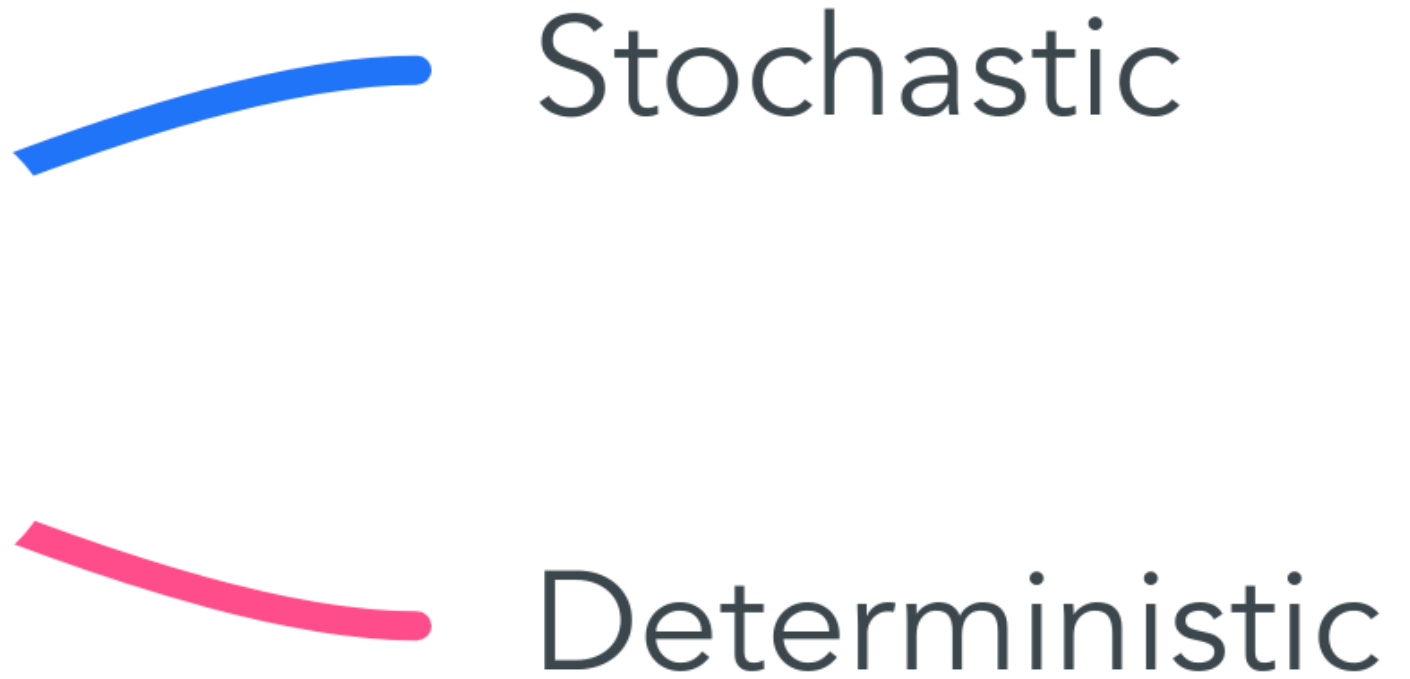
$$f : \mathbb{Z} \times \mathbb{U} \rightarrow \mathbb{Z},$$

$$\sigma : \mathbb{Z} \times \mathbb{U} \rightarrow \mathbb{R},$$

$$\xi_t \sim \mathcal{N}(0, 1)$$

# Stochastic vs. Deterministic

System





# Stochastic Systems





# Stochastic systems

Pretty much anything

# Stochastic systems

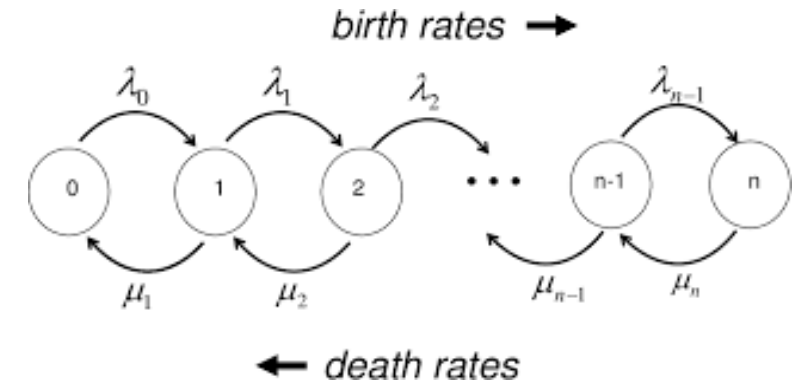
Continuous state space

Discrete state space

Continuous time

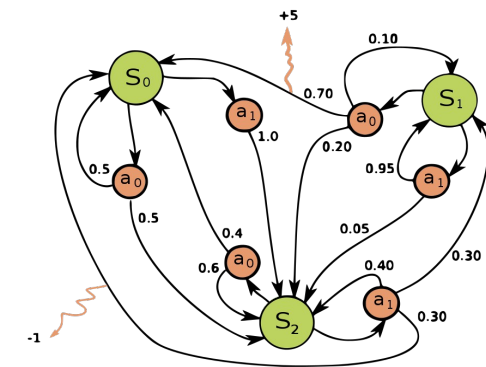
$$dX_t = f(X_t, U_t) dt + \sigma(X_t, U_t) dW_t,$$

$W_t$  – semimartingale.



Discrete time

$$x_{t+1} \sim \mathcal{F}(x_t, u_t)$$





# Full information vs. Partial information





# Full information vs. Partial information

**Observation  $\stackrel{?}{=}$  State**



# Full information vs. Partial information

Full information

**Observation = State**

Partial information

**Observation  $\neq$  State**

# Partial information examples

$\rho(\cdot)$  – feedback policy.

Full information

$$u(t) := \rho(x(t))$$

Partial information

$$u(t) := \rho(g(x(t)))$$
$$u(t) := \rho(x(t) + \xi_t), \quad \xi \sim \mathcal{N}(\mu, \sigma^2)$$

# Stationary vs. Non-stationary





# Stationary vs. Non-stationary

Non-stationary

$$x_{t+1} := f(x_t, u_t, t)$$

Stationary

$$x_{t+1} = f(x_t, u_t)$$

# Non-stationary --> stationary

$$x_{t+1} := f(x_t, u_t, t) \longrightarrow \begin{aligned} x_{t+1} &= f(x_t, u_t, y_t) \\ y_{t+1} &= y_t + 1 \end{aligned}$$



# Example of a non-stationary system





# Example of a non-stationary system



## Cost vs. Reward

Objective



Cost



Reward

# Cost vs. Reward

Cost → Minimize

Reward → Maximize

# Finite horizon vs. Infinite horizon

Problem



Finite horizon



Infinite horizon



# Finite horizon vs. Infinite horizon

## Finite-horizon

You optimize the objective over a finite time frame.

## Infinite-horizon

You optimize the objective over an infinite time frame.  
(As if your RL agent were to run for all eternity)

# Running vs. Terminal

Objective



Running



Terminal

# Running vs. Terminal

$J(\cdot, \cdot)$  – total objective.

$$J(x(\cdot), u(\cdot)) := \int_{t_1}^{t_2} r(x(t), u(t)) \, dt + T(x(t_2))$$

$$J(x., u.) := \sum_{i=t_1}^{t_2} r(x_i, u_i) + T(x_{t_2})$$

Running objective

Terminal objective



# Terminal objective





# Model-based vs. Model-free

RL Method



Model-based



Model-free

# Model-based vs. Model-free

$$\dot{x} = f(x, u)$$

## Model-based

Aware of the system's **dynamics**. Able to predict immediate outcomes of its own actions.  
Learns by numerically approximating the optimal policy.

## Model-free

Relies solely on its own **experience**.  
Learns by associating rewards with states and actions through statistical modeling.

# Offline vs. Online

RL Method



Offline



Online



# Offline vs. Online

## Offline

Learning occurs **before** the agent is deployed.

## Online

Learning occurs **while** the agent is deployed.



Q&A