

Methods to compute value function — continuous time

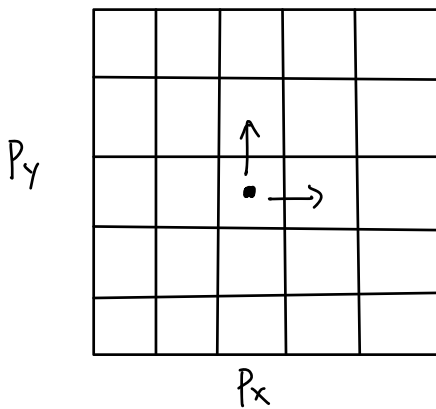
$$\text{HJB - PDE} : \frac{\partial V(x,t)}{\partial t} + \min_u \{ L(x,u) + \frac{\partial V(x,t)}{\partial x} \cdot f(x,u) \} = 0$$

$$V(x,T) = l(x)$$

(1) Closed-form computation of V

- LQR
- can be very restrictive

(2) Mesh/grid-based methods: These methods solve the PDE numerically over a grid of state and time.



$\frac{\partial V}{\partial x}$, $\frac{\partial V}{\partial t}$ are approximately numerically over the grid

- level set toolbox / helperOC (Matlab)
- BEACLS (C++)
- OptimizeDP (Python)
- julia Reach (Julia)

(3) Function approximation-based methods

- represent the value function as a parametrized function, compute the parameters to satisfy the PDE as closely as possible.

$$\theta^* = \arg \min_{\theta} \left(\left\| \frac{\partial V_{\theta}(x,t)}{\partial t} + \min_u \{ L(x,u) + \frac{\partial V_{\theta}(x,t)}{\partial x} \cdot f(x,u) \} \right\| + \lambda \| V_{\theta}(x,t) - l(x) \| \right)$$

Physics-informed Neural Network	other approximation :	- polynomials	- zonotopes
Deep Reach		- ellipsoids	

Robust Optimal Control → zero-sum dynamic games

$$\min_{u(\cdot) \in \Gamma_u} \max_{d(\cdot) \in \Gamma_d} J(x(t), u(\cdot), d(\cdot), t)$$

$$\text{s.t. } \dot{x}(s) = f(x(s), u(s), d(s))$$

$$\underline{u} \leq u(s) \leq \bar{u}$$

$$\underline{d} \leq d(s) \leq \bar{d}$$

→ this is a game between control and disturbance

→ dynamic game (evolving over time)

→ zero-sum game

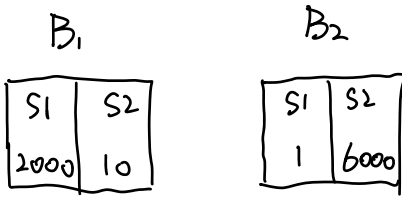
- Control is trying to minimize the worst-case cost incurred under uncertainty.

instance of zero-sum dynamic games

Rufus Isaacs (1950)

- The order of play is important $\max \min \neq \min \max$
- d has a slight informational advantage

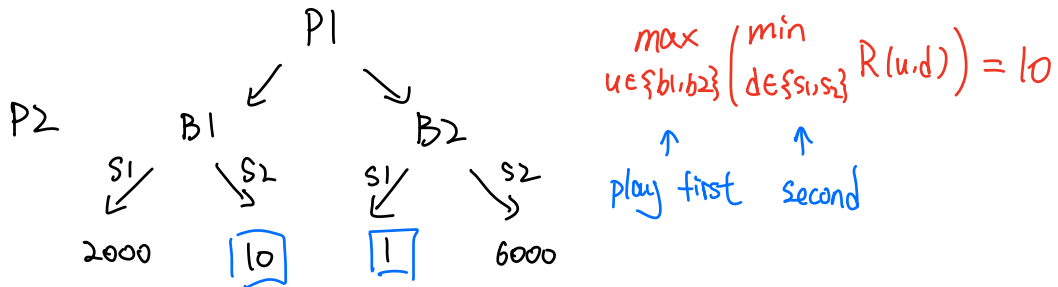
Importance of information pattern



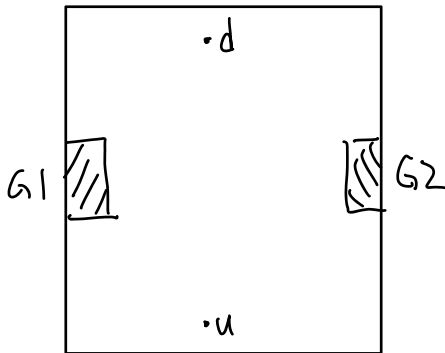
P1: choose which box to open (maximize reward)

P2: choose slot (minimize reward)

suppose P1 goes first



P1 should pick B1, P2 picks S2.



u → wants to reach G1/G2 without being intercepted by d

d → intercept u

(1) $\min_{u(\cdot)} \max_{d(\cdot)} J \dots$ } overly pessimistic

(2) $\max_{d(\cdot)} \min_{u(\cdot)} J \dots$ } overly optimistic

open-loop formulation

close-loop formulation

At any given time t , only information upto time t is known.

Such strategies are called non-anticipative strategies.

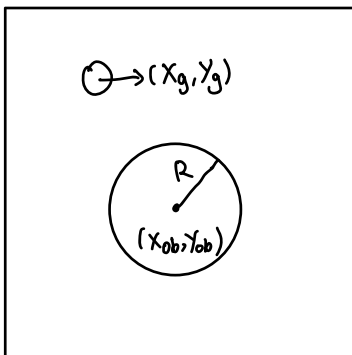
$$\begin{aligned} V(x, t) &= \min_{u(\cdot) \in \Gamma_u} \max_{d(\cdot) \in \Gamma_d} J(x, u(\cdot), d(\cdot), t) \\ &= \min_{u(\cdot) \in \Gamma_u} \max_{d(\cdot) \in \Gamma_d} \left\{ L(x, u(t), d(t)) \delta + V(x(t+\delta), t+\delta) \right\} \end{aligned}$$

$$\frac{\partial V(x, t)}{\partial t} + \min_{u(t)} \max_{d(t)} \left\{ L(x, u(t), d(t)) + \frac{\partial V(x, t)}{\partial x} \cdot f(x, u, d) \right\} = 0$$

$$V(x, T) = \ell(x)$$

Hamilton - Jacobi - Isaacs PDE

Demo:



Dynamics:

$$\dot{P}_x = V_x + dx$$

$$\dot{P}_y = V_y + dy$$

Control: V_x, V_y $|V_x|, |V_y| \leq 1$ m/s

disturbance: dx, dy $|dx|, |dy| \leq 0.2$ m/s

Cost function:

$$J(x, u(\cdot), d(\cdot), t) = \int_t^T \left(\text{dist}^2(x(s), \text{goal}) + \lambda \cdot \text{obs-penetration}(x(s)) \right) ds$$

+

$$\left(\text{dist}^2(x(T), \text{goal}) + \lambda \cdot \text{obs-pene}(x(T)) \right)$$

$$\text{dist}^2(x(s), \text{goal}) = (P_x(s) - X_g)^2 + (P_y(s) - Y_g)^2$$

$$\text{obs-pene} = \max \{ R - \text{sqrt}((P_x(s) - X_{\text{obs}})^2 + (P_y(s) - Y_{\text{obs}})^2), 0 \}$$

$$\text{Hamiltonian} = L(x) + \min_{u(t)} \max_{d(t)} \underbrace{\frac{\partial V(x,t)}{\partial x} \cdot f(x,u,d)}$$

$$\Downarrow$$
$$\begin{bmatrix} P_1(x) & P_2(x) \end{bmatrix} \begin{bmatrix} V_x + dx \\ V_y + dy \end{bmatrix}$$

$$= P_1(x)V_x + P_2(x)V_y + P_1(x)dx + P_2(x)dy$$