Lecture 12 — Dynamic programming

- Closed loop formulation of optimal control
- Intuitive methods of solution
- Guarantees global optimality
- Iteratively solves the problem starting at the end-time

'Life can only be understood backwards;
but it must be lived forwards'

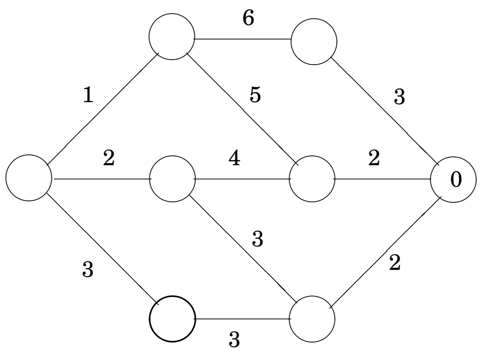
Kierkegaard

Goal

To be able to

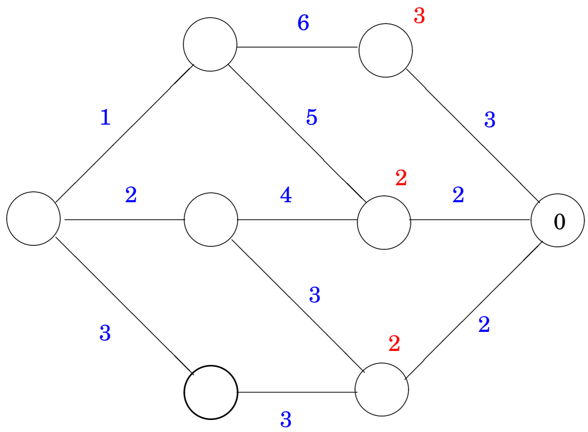
- to understand the idea of Dynamic programming
- to derive optimal feedback laws in simple cases

Example: Shortest path

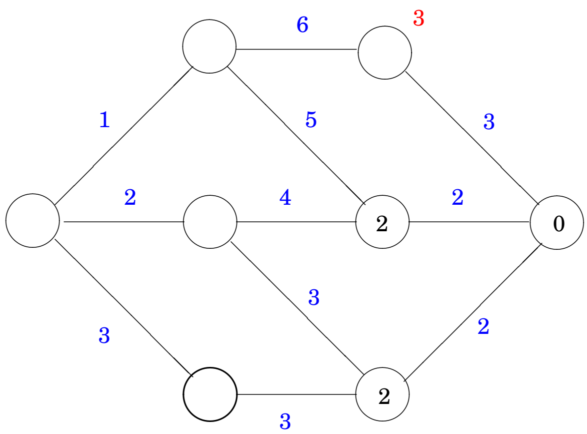


As an example we try to find the shortest path to "0" in the above graph.

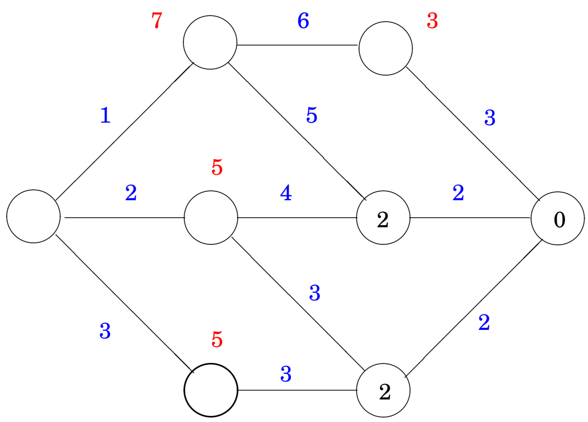
Example: Shortest path



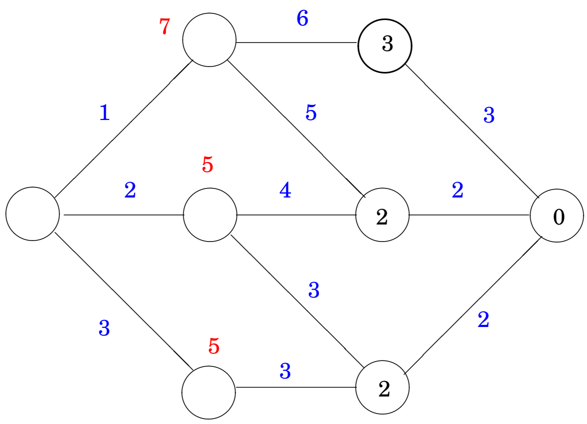
Example: Shortest path



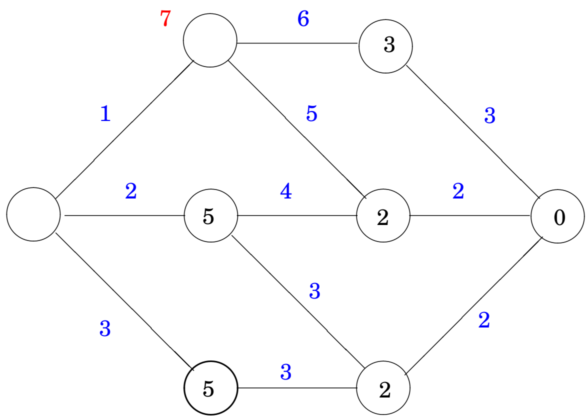
Example: Shortest path



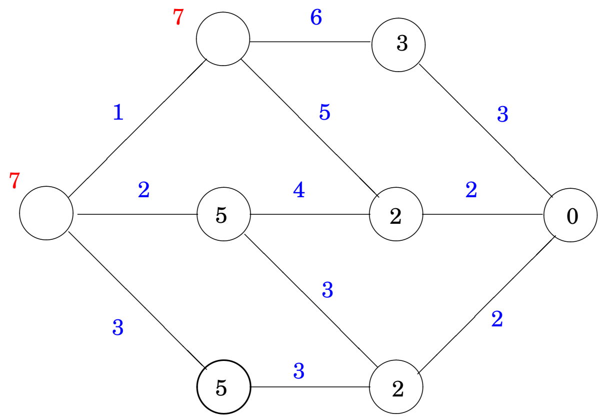
Example: Shortest path



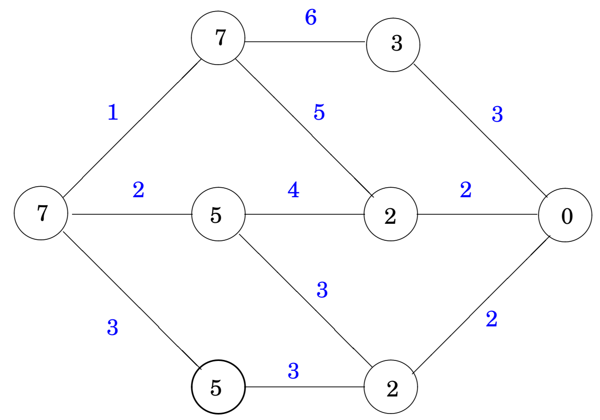
Example: Shortest path



Example: Shortest path



Example: Shortest path



Basic problem formulation: The system

- First we assume that the system is in discrete time

$$x_{k+1} = f_k(x_k, u_k), \quad k = 0, 1, \dots, N-1$$

where x_k is the state $u_k \in U(x_k)$ is the control.

- Feedback-control implies $u_k = \mu_k(x_k)$
- In closed-loop form the system can thus be written

$$x_{k+1} = f_k(x_k, \mu_k(x_k))$$

Basic problem formulation: The cost

- We let $\mu = \{\mu_0, \mu_1, \dots, \mu_{N-1}\}$ and assume that we have an additive cost

$$J_\mu(x_0) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, \mu_k(x_k))$$

- Total cost $J_\mu(x_0)$ is a function of both initial state x_0 and feedback law μ
- N is the horizon of the problem
  - Finite-horizon: $N < \infty$
  - Infinite-horizon: $N = \infty$

Basic formulation: Minimal cost and optimal strategy

- An optimal policy μ^* is one that minimizes $J_\mu(x_0)$ (for all x_0)

$$J_{\mu^*}(x_0) = \min_{\mu \in \Pi} J_\mu(x_0)$$

optimization is performed over the set Π, of admissible control policies

- For deterministic problems a control is admissible whenever

$$u_k = \mu_k(x_k) \in U(x_k)$$

The principle of optimality

Let $\mu^* = \{\mu_0^*, \mu_1^*, \dots, \mu_{N-1}^*\}$ be an optimal policy for the basic problem and assume that when applying μ^*, a given state x_i occurs at time i, when starting at x_0.

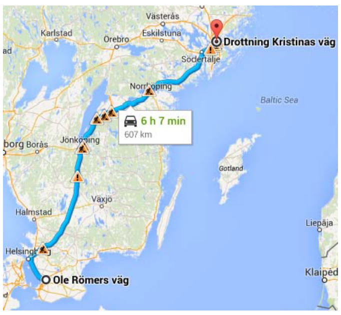
Consider the subproblem whereby we are in state x_i at time i and wish to minimize the "cost-to-go" from time i to time N

$$g_N(x_N) + \sum_{k=i}^{N-1} g_k(x_k, \mu_k(x_k)).$$

Principle of optimality

The truncated policy $\{\mu_i^*, \mu_{i+1}^*, \dots, \mu_{N-1}^*\}$ is optimal for the subproblem starting from x_i at time i.

Principle of optimality



- Google maps fastest route from LTH to KTH passes through Jönköping
- Subpath starting in Jönköping is the fastest from Jönköping to KTH

The dynamic programming algorithm

Let

$$V_k(x_k) = g_N(x_N) + \sum_{j=k}^{N-1} g_j(x_j, \mu_j^*(x_j))$$

so that $V_k(x_k)$ is the optimal "cost-to-go" from time k to time N

The Bellman equation

For every initial state x_0, the optimal cost $J^*(x_0)$ is given by the last step in the following backward-recursion.

$$V_k(x_k) = \min_{u_k \in U_k(x_k)} \left[g_k(x_k, u_k, w_k) + V_{k+1}(f_k(x_k, u_k)) \right]$$
$$V_N(x_N) = g_N(x_N)$$

We get the optimal control "for-free"

$$\mu_k^*(x_k) = \arg\min_{u_k \in U_k(x_k)} \left[g_k(x_k, u_k, w_k) + V_{k+1}(f_k(x_k, u_k)) \right]$$

Managing spending and saving

Example

An investor holds a capital sum in a building society, which gives an interest rate of $\theta \times 100\%$ on the sum held at each time $k = 0, 1, \ldots, N-1$. The investor can chose to reinvest a portion u of the interest paid which then itself attracts interest. No amounts invested can ever be withdrawn. How should the investor act so as to maximize total reward by time $N-1$?

- We take as the state x_k the present income at time $k = 0, 1, \ldots, N-1$ and let $u_k \in [0, 1]$ be the fraction of reinvested interest, hence

$$x_{k+1} = x_k + \theta u_k x_k =: f(x_k, u_k)$$

- The reward is $g_k(x, u) = (1-u)x$ and $g_N(x, u) \equiv 0$.

Managing spending and saving

- The optimality equation is $V(N, x) = 0$,

$$V(k,x) = \max_{0\le u\le 1}\{(1-u)x + V(k+1, (1+\theta u)x)\}, \quad k = 0, 1, \ldots, N-1$$

- We get

$$V(N-1, x) = \max_{0\le u\le 1}\{(1-u)x + 0\} = x$$
$$V(N-2, x) = \max_{0\le u\le 1}\{(1-u)x + (1+\theta u)x\}$$
$$= \max_{0\le u\le 1}\{2x + (\theta-1)ux\} = \max\{2, 1+\theta\}x = \rho_2 x$$

- Guess: $V(N-s+1, x) = \rho_{s-1}x$, then

$$V(N-s, x) = \max_{0\le u\le 1}\{(1-u)x + \rho_{s-1}(1+u\theta)x)\}$$
$$= \max\{1+\rho_{s-1}, (1+\theta)\rho_{s-1}\}x = \rho_s x$$

Managing spending and saving

- We have thus verified that $V(N-s, x) = \rho_s x$, and found the recursion

$$\rho_s = \rho_{s-1} + \max\{1, \theta\rho_{s-1}\}$$

- Together with $\rho_1 = 1$ this gives

$$\rho_s = \begin{cases} s & \text{for } s \le s^* \\ s^*(1+\theta)^{s-s^*} & \text{otherwise.} \end{cases} \qquad s^* = \lceil 1/\theta \rceil$$

- The optimal policy is then

$$u_k = \begin{cases} 1 & \text{for } k < N - s^* \\ 0 & \text{for } k \ge N - s^*. \end{cases}$$

Continuous time optimal control: The HJB-equation

- So far we have only considered the discrete time case
- Dynamic programming can also be applied in continuous time, this leads to the Hamilton-Jacobi-Bellman (HJB) equation:
- Benefits over PMP:
  - + Gives closed-loop optimal control in continuous time
  - + Sufficient condition of optimality
- Drawbacks:
  - – Requires solving a highly non-linear PDE
  - – Well-posedness of the PDE problem proved only in the '80s

Continuous time problem formulation

- In continuous time the system is given by

$$\dot{x}(t) = f(x(t), u(t)), \quad t \in [0, T]$$

with $x(0) = x_0$ and $u(t) \in U(x(t))$, for all $t \in [0, T]$.
- We define the cost as

$$J(x_0) = \phi(x(T)) + \int_0^T L(x(t), u(t))dt$$

- With optimal "cost-to-go" from (t, x)

$$V(t, x) = \min_u \left\{\phi(x(T)) + \int_t^T L(x(t), u(t))dt\right\}$$

The HJB-equation: Informal derivation

- divide $[0, T]$ into N subintervals of length $\delta = T/N$
- Let $x_k = x(k\delta)$ and $u_k = u(k\delta)$, for $k = 0, 1, \ldots, N$ and approximate the system by

$$x_{k+1} = x_k + f(x_k, u_k)\delta, \quad k = 0, 1, \ldots, N.$$

- The optimal "cost-to-go" is approximated by

$$V(k\delta, x) = \min_{u_0,\ldots,u_{N-1}} [\phi(x_N) + \sum_{k=0}^{N-1} L(x_k, u_k)\delta]$$

The HJB-equation: Informal derivation

- Dynamic programming now yields

$$V(k\delta, x) = \min_{u\in U}[L(x, u)\delta + V((k+1)\delta, x + f(x, u)\delta)],$$
$$V(N\delta, x) = \phi(x).$$

- For small δ we get (with $t = k\delta$)

$$V(t+\delta, x + f(x, u)\delta) \approx V(t, x) + V_t(t, x)\delta + \nabla_x V(t, x) \cdot f(x, u)\delta$$

- Inserting this in the DP equation gives

$$V(t, x) \approx \min_{u\in U}[L(x, u)\delta + V(t, x) + V_t(t, x)\delta + \nabla_x V(t, x) \cdot f(x, u)\delta]$$

The HJB-equation

The Hamilton-Jacobi-Bellman equation

For every initial state x_0, the optimal cost is given by $J^*(x_0) = V(0, x_0)$ where $V(t, x)$ is the solution to the PDE

$$V_t(t, x) = -\min_{u\in U}[L(x, u) + \nabla_x V(t, x) \cdot f(x, u)]$$
$$V(T, x) = \phi(x)$$

As before the optimal control is given in feedback form by

$$\mu^*(t, x) = \arg\min_{u\in U}[L(x, u) + \nabla_x V(t, x) \cdot f(x, u)]$$

Example: The HJB-equation

Example

Consider the simple example involving the scalar system

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

with the constraint $|u(t)| \leq 1$ for all $t \in [0, T]$ and the cost

$$J(x_0) = \frac{1}{2}(x(T))^2.$$

- The HJB equation for this problem is

$$V_t(t, x) = -\min_{|u(t)| \leq 1} [V_x(t, x)u]$$

with terminal condition $V(T, x) = x^2/2$.

Example: The HJB-equation

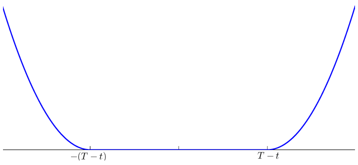
- An optimal control for this problem is

$$\mu(t, x) = \begin{cases} 1 & \text{for } x < 0 \\ 0 & \text{for } x = 0 \\ -1 & \text{for } x > 0 \end{cases}$$

- The optimal "cost-to-go" with this control is

$$V(t, x) = \frac{1}{2}(\max\{0, |x| - (T - t)\})^2$$

Example: The HJB-equation



- For $|x| > T - t$ we have $V(t, x) = 1/2(|x| - (T - t))^2$, hence

$$V_t = |x| - (T - t)$$

$$\min_{|u(t)| \leq 1} [V_x(t, x)u] = -\text{sgn}(x)V_x(t, x) = -\text{sgn}(x)^2(|x| - (T - t))$$

$$= -(|x| - (T - t))$$

- For $|x| \leq T - t$ we have $V(t, x) = 0$ and the HJB equation holds trivially

Infinite horizon problem

Assume that the final cost is $\phi(x(T)) = 0$ and the final time $T \to +\infty$, and that there exists some control such that the total cost remains bounded in the limit. Hence, we want to solve

$$\min_u \int_0^{+\infty} L(x(t), u(t))dt, \qquad x(0) = x_0$$

It is intuitive that the cost-to-go from (x, t)

$$V(x, t) = \min_u \int_t^T L(x(t), u(t))dt = V(x)$$

does not depend on the initial time but only on the initial state.

The HJB equation then becomes

$$0 = \min_u [L(x, u) + \nabla_x V(x) \cdot f(x, u)]$$

(Observe that, for scalar problems, this is an ODE!)

Infinite horizon problem: example

$$\min_u \int_0^{+\infty} (x^4(t) + u^4(t))dt, \qquad x(0) = x_0$$

From the stationary HJB eqn we get

$$0 = \min_u \left\{x^4 + u^4 + V_x(x) \cdot u\right\}$$

and putting the derivative with respect to u equal to 0

$$x^4 = 3\left(\frac{1}{4}V_x(x)\right)^{4/3}$$

which gives $V_x(x) = \pm 4(\frac{1}{3})^{3/4}x^3$ and the + sign should be chosen to have V positive definite)since L is. This gives the optimal feedback control law

$$u^*(x) = -(\frac{1}{4}V_x(x))^{1/3} = -(\frac{1}{3})^{1/4}x$$

Dynamics Programming for LQ control

Consider the optimal feedback control problem for an LTI system $\dot{x} = Ax + Bu$ with cost

$$J = \int_0^T \left(x'(t)Qx(t) + u'(t)Ru(t)\right) dt + x(T)'Mx(T)$$

where Q, R, M are symmetric positive definite. The HJB eqn reads

$$0 = \min_u \left\{x'Qx + u'Ru + V_t + V_x'(Ax + Bu)\right\}$$

with final time condition $V(T, x) = x'Mx$.

Dynamics Programming for LQ control

With the ansatz $V(x, t) = x'P(t)x$ with symmetric $P(t)$, we get that the optimal control is in the form

$$u^* = -R^{-1}B'Px$$

and $P = P(t)$ satisfies the following differential eqn

$$\dot{P} = -PA - A'P - Q + PBR^{-1}B'P \qquad P(T) = M$$

which is called the differential Riccati equation (DRE).

For the infinite horizon problem this reduces to

$$0 = -PA - A'P - Q + PBR^{-1}B'P$$

which is called the algebraic Riccati equation (ARE).

Summary — Dynamic programming

- Closed loop formulation of optimal control
- Intuitive methods of solution
- Guarantees global optimality
- Iteratively solves the problem starting at the end-time