An introduction to dynamic programming in discrete time

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Computational Aspects of Optimization

Content

Transportation problem – deterministic

- x_{ij} – decision variable: amount transported from i to j
- c_{ij} – costs for transported unit
- a_i – capacity
- b_j – demand

ASS. $\sum_{i=1}^{n} a_i \geq \sum_{j=1}^{m} b_j$.

$$\begin{aligned}
\min \ & \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \\
\text{s.t.} \ & \sum_{j=1}^{m} x_{ij} \leq a_i, \ i = 1, \dots, n, \\
& \sum_{i=1}^{n} x_{ij} \geq b_j, \ j = 1, \dots, m, \\
& x_{ij} \geq 0.
\end{aligned}$$

Transportation problem – stochastic

- x_{ij} – amount transported from i to j
- c_{ij} – costs for transported unit
- a_i – capacity
- B_j – **random demand** with known distribution, $\mathbb{E}[B_j] < \infty$
- q_j^+, q_j^- – price for unit shortage, surplus

Two-stage problem with simple recourse

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \mathbb{E}\left[\sum_{j=1}^{m} q_j^+ \left(B_j - \sum_{i=1}^{n} x_{ij}\right)_+ + \sum_{j=1}^{m} q_j^- \left(B_j - \sum_{i=1}^{n} x_{ij}\right)_-\right]$$

$$\text{s.t.} \sum_{j=1}^{m} x_{ij} \le a_i,\ \ i = 1, \dots, n,$$

$$x_{ij} \ge 0.$$

Transportation problem – stochastic

Let the distribution of B_j be finite discrete b_{js}, $s = 1, \dots, S$, with probabilities p_s:

$$\begin{aligned}
\min_{x_{ij}, y_{js}} \; & \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} + \sum_{s=1}^{S} p_s \left[\sum_{j=1}^{m} q_j^+ y_{js}^+ + q_j^- y_{js}^- \right] \\
\text{s.t.} \; & \sum_{j=1}^{m} x_{ij} \le a_i, \;\; i = 1, \dots, n, \\
& x_{ij} \ge 0, \\
& y_{js}^+ - y_{js}^- = b_{js} - \sum_{i=1}^{n} x_{ij}, \; j = 1, \dots, m, \;\; s = 1, \dots, S, \\
& y_{js}^+, y_{js}^- \ge 0.
\end{aligned}$$

Benders decomposition (L-shaped algorithm)

Master problem

$$\begin{aligned}\min_{x_{ij}} \ & \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \sum_{s=1}^{S} p_s f^s(x)\\ \text{s.t.}\ & \sum_{j=1}^{m} x_{ij} \le a_i,\ \ i = 1,\dots,n,\\ & x_{ij} \ge 0.\end{aligned}$$

Slave (second-stage) problems

$$\begin{aligned}f^s(x) = \min_{y_{js}} \ & \sum_{j=1}^{m} q_j^+ y_{js}^+ + q_j^- y_{js}^-\\ \text{s.t.}\ & y_{js}^+ - y_{js}^- = b_{js} - \sum_{i=1}^{n} x_{ij},\ \ j = 1,\dots,m,\\ & y_{js}^+, y_{js}^- \ge 0.\end{aligned}$$

Transportation problem – stochastic

Two-stage problem with simple recourse

$$
\begin{aligned}
\min\ & \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \\
& + \sum_{j=1}^{m} q_j^{+}\mathbb{E}\left[\left(B_j - \sum_{i=1}^{n} x_{ij}\right)_+\right] + \sum_{j=1}^{m} q_j^{-}\mathbb{E}\left[\left(B_j - \sum_{i=1}^{n} x_{ij}\right)_-\right] \\
\text{s.t. } & \sum_{j=1}^{m} x_{ij} \le a_i,\ \ i = 1, \dots, n, \\
& x_{ij} \ge 0.
\end{aligned}
$$

Explicit formula for $\mathbb{E}\left[\left(B - x\right)_+\right]$ ...

Transportation problem – stochastic

Explicit formula for $\mathbb{E}\left[(B-x)_+\right]$ under uniform distribution $B \sim U(\underline{b}, \overline{b})$

- $= 0$, if $x \geq \overline{b}$,
- $= \mathbb{E}[B] - x$, if $x \leq \underline{b}$,
- if $x \in (\underline{b}, \overline{b})$, then

$$\begin{aligned}
\mathbb{E}\left[(B-x)_+\right] &= \frac{1}{\overline{b}-\underline{b}} \int_x^{\overline{b}} z - x \, dz \\
&= \frac{1}{\overline{b}-\underline{b}} \left(\left[\frac{z^2}{2} \right]_x^{\overline{b}} - x \, [z]_x^{\overline{b}} \right) \\
&= \frac{(\overline{b}-x)^2}{2(\overline{b}-\underline{b})}.
\end{aligned}$$

Transportation problem – stochastic

Explicit formula for $\mathbb{E}\left[\left(B-x\right)_+\right]$ under normal distribution $B \sim N(\mu, \sigma^2)$

$$\begin{aligned}
\mathbb{E}\left[\left(B-x\right)_+\right] &= \int_x^\infty b - x \, dF(b) \\
\int_x^\infty b \, dF(b) &= \int_{\frac{x-\mu}{\sigma}}^\infty (\mu + z\sigma)\varphi(z)\, dz \\
&= \int_{\frac{x-\mu}{\sigma}}^\infty \mu\varphi(z)\, dz + \int_{\frac{x-\mu}{\sigma}}^\infty z \frac{\sigma}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \, dz \\
&= \mu\left(1 - \Phi\left(\frac{x-\mu}{\sigma}\right)\right) + \frac{\sigma}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \\
\int_x^\infty x \, dF(b) &= x\left(1 - \Phi\left(\frac{x-\mu}{\sigma}\right)\right)
\end{aligned}$$

Content

Dynamic programming – Bellman principle

Reward maximization problem:

$$\max_{c\in\mathcal{C},s\in\mathcal{S}} \mathbb{E}_W \left[\sum_{t=1}^{T\vee\infty} v^{t-1} r(s_{t-1}, c_t)\right] \tag{1}$$
$$\text{s.t. } s_t = f(s_{t-1}, c_t, W_t),\ t = 1, \ldots, T \vee \infty.$$

- $s_t \in \mathcal{S}$ – **state variables** at the end of period t,
- $c_t \in \mathcal{C}$ – **control variables**,
- $r : \mathcal{S} \times \mathcal{C} \to \mathbb{R}$ – **reward** under state s_{t-1} and control c,
- v – **discount factor**,
- $f : \mathcal{S} \times \mathcal{C} \times \mathcal{W} \to \mathcal{S}$ – **transition function**
- W_t – **random variable** $=$ information random until period t, i.e., $W_t \in \mathcal{F}_t$ for a filtration $(\mathcal{F}_t)$.

Dynamic programming – Bellman principle

Bellman equation

$$\begin{aligned} V_t(s_{t-1}) = \max_{c_t \in \mathcal{C}} \ & r(s_{t-1}, c_t) + v\, \mathbb{E}_{W_{t\bullet}}[V_{t+1}(s_t) | s_{t-1}] \\ \text{s.t. } & s_t = f(s_{t-1}, c_t, W_t) \end{aligned} \tag{2}$$

- $s_t \in \mathcal{S}$ – **state variables** at the end of period t,
- $c_t \in \mathcal{C}$ – **control variables**,
- $r : \mathcal{S} \times \mathcal{C} \to \mathbb{R}$ – **reward** under state s_{t-1} and control c,
- v – **discount factor**,
- $f : \mathcal{S} \times \mathcal{C} \times \mathcal{W} \to \mathcal{S}$ – **transition function**
- W_t – **random variable** $=$ information random until period t, i.e., $W_t \in \mathcal{F}_t$ for a filtration $(\mathcal{F}_t)_t$.
- V_t – **value function** (cost-to-go function)

Dynamic programming

Consider $|\mathcal{C}| = 10$, and $|\mathcal{S}| = 10$. Then the reward maximization problem grows by a factor 100 every time stage. Represent the dynamics as a decision tree over 10 periods. Full enumeration leads to 10^{20} nodes.

Whereas, dynamic programming collapses all the nodes of the tree that represent the same state.

Dynamic programming – Example 1

Finite T or infinite ∞ time horizon

$$\begin{aligned} \max_{s_t, c_t} \sum_{t=1}^{T \vee \infty} v^{t-1} u(c_t) \\ \text{s.t.} \\ s_t = (1+r)s_{t-1} + Y_t - c_t. \end{aligned} \tag{3}$$

- u – **utility function**
- s_t – **state variables** representing total amount of resources available to the consumer (initial state s_0).
- c_t – **control variables** maximizing the consumer's utility. It affects the resources available in the next period.
- Y_t – **exogenous income** (deterministic for now)
- $v = 1/(1+i)$ – discount factor, r – exogenous interest rate

Dynamic programming

If we assume that there is a finite terminal period T:

$$\begin{aligned}
V_1(s_0) &= \max_{s_t, c_t} \sum_{t=1}^{T} v^{t-1} u(c_t) \\
&= \max_{s_t, c_t} u(c_1) + v\, u(c_2) + \cdots + v^{T-1} u(c_T) \\
&= \max_{s_t, c_t} u(c_1) + v \left[\sum_{t=2}^{T} v^{t-2} u(c_t) \right] \\
& \text{s.t.} \\
& s_t = (1+r)s_{t-1} + Y_t - c_t.
\end{aligned}$$

Dynamic programming

We rewrite the maximization problem recursively and obtain the **Bellman equation**

$$V_t(s_{t-1}) = \max_{s_t, c_t} u(c_t) + v\ V_{t+1}(s_t),$$

where $s_t = (1+r)s_{t-1} + Y_t - c_t$.

Moreover, since u does not depend on the time period, we can write

$$\begin{aligned} V(s_{t-1}) &= \max_{s_t, c_t} u(c_t) + v\ V(s_t), \\ &= \max_{c_t} u(c_t) + v\ V\Big((1+r)s_{t-1} + Y_t - c_t\Big), \end{aligned}$$

with $V_{T+1}(s_t) = V(s_T) \equiv 0$.

Bellman principle of optimality

An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an **optimal policy** with regard to the state resulting from the first decision, i.e.,

$$\hat{c}_t(s_{t-1}) \in \arg\max_{c_t} u(c_t) + v \ V\Big((1+r)s_{t-1} + Y_t - c_t\Big).$$

This principle is applied recursively (forward/backward recursion)...

Dynamic programming

First order optimality conditions

$$\frac{\partial V(s_{t-1})}{\partial c_t} = 0, \quad \frac{\partial V(s_{t-1})}{\partial s_{t-1}} = 0.$$

In particular,

$$\begin{aligned} \frac{\partial V(s_{t-1})}{\partial c_t} &= u'(c_t) + v\ V'(s_t)\frac{\partial s_t}{\partial c_t}, \\ \frac{\partial V(s_{t-1})}{\partial s_{t-1}} &= v\ V'(s_t)\frac{\partial s_t}{\partial s_{t-1}}, \end{aligned}$$

where using $s_t = (1+r)s_{t-1} + Y_t - c_t$ we have

$$\frac{\partial s_t}{\partial c_t} = -1, \quad \frac{\partial s_t}{\partial s_{t-1}} = 1 + r.$$

A stochastic extension

Let $Y_t(\xi)$ be random. We can obtain the **Bellman equation**

$$V(s_{t-1}) = \max_{c_t} u(c_t) + v\, \mathbb{E}_{Y_{t\bullet}} \left[V\Big((1+r)s_{t-1} + Y_t(\xi) - c_t \Big) \right].$$

Content

Dynamic programming – Example 2: Cake eating problem

Cake eating problem:

- $u(c) = 2c^{1/2}$,
- $s_0 = 1$, $s_T = 0$,
- $s_t = s_{t-1} - c_t$ ...

Example: Cake eating problem

Bellman equation

$$V(s_{t-1}) = \max_{c_t} u(c_t) + v\ V(s_t),$$
$$\text{s.t. } s_t = s_{t-1} - c_t.$$

Optimality conditions

$$\begin{aligned} \frac{\partial V(s_{t-1})}{\partial c_t} &= u'(c_t) + v\ V'(s_t) \frac{\partial s_t}{\partial c_t} = 0, \\ \frac{\partial V(s_{t-1})}{\partial s_{t-1}} &= v\ V'(s_t) \frac{\partial s_t}{\partial s_{t-1}} = 0, \end{aligned}$$

From $s_t = s_{t-1} - c_t$

$$\frac{\partial s_t}{\partial c_t} = -1,\ \frac{\partial s_t}{\partial s_{t-1}} = 1. \tag{4}$$

Example: Cake eating problem

Putting them together, we obtain

$$\begin{aligned} \frac{\partial V(s_{t-1})}{\partial c_t} &= u'(c_t) - v\ V'(s_t) = 0, & (5) \\ \frac{\partial V(s_{t-1})}{\partial s_{t-1}} &= v\ V'(s_t) = 0, & (6) \end{aligned}$$

Taking (5) for $t-1$

$$u'(c_{t-1}) - v\ V'(s_{t-1}) = 0, \tag{7}$$

and plugging it into (6), we have

$$u'(c_{t-1}) = v\ u'(c_t),$$

which represents the **optimal path of the cake consumption**.

Example: Cake eating problem

For $u(c) = 2c^{1/2}$, we have

$$\begin{aligned} u'(c_{t-1}) &= v\, u'(c_t), \\ (c_{t-1})^{-1/2} &= v\, (c_t)^{-1/2}, \\ c_t &= v^2 c_{t-1}, \end{aligned}$$

with initial and terminal conditions $s_0 = 1$, $s_T = 0$. If we denote $\beta = v^2$, we obtain

$$c_t = \beta c_{t-1} = \beta^{t-1} c_1.$$

Using

$$c_t = \beta c_{t-1} = \beta^{t-1} c_1.$$

and

$$s_0 - c_1 - c_2 - \cdots - c_T = s_T = 0,$$

we have

$$(1 - \beta - \cdots - \beta^{T-1}) c_1 = s_0,$$

and finally **optimal consumption**

$$\begin{aligned} \hat{c}_1 &= \frac{1-\beta}{1-\beta^T} s_0, \\ \hat{c}_t &= \beta \hat{c}_{t-1} = \beta^{t-1} \hat{c}_1. \end{aligned}$$

Content

Gambling game

The gambler wins/looses a bet. The goal is to maximize the probability that the gambler reaches at least bankroll G.

- T – number of periods (games)
- b_t – **bet** at period (game) t
- s_t – state of **bankroll** at the end of period t
- p – **winning probability**
- G – **bankroll goal**

Recursion

$$V_t(s) = \max_{b_t(s)} p\, V_{t+1}(s + b_t) + (1 - p)\, V_{t+1}(s - b_t),$$

with boundary conditions $V_T(s) = 0$ for $s \leq \lfloor G/2 \rfloor$, $V_T(s) = 1$ for $s \geq G$, and $V_T(s) = p$ otherwise.

The value function expresses the accumulated probability of reaching the goal G from actual state s.

Gambling game

Let

- $T = 3$ – number of periods (games)
- $s_0 = 2$ – state of bankroll at the beginning
- $p = 0.4$ – probability of winning
- $G = 4$ – goal bankroll

Forward recursion

b	$V_1(2)$
0	$0.4V_2(2+0) + 0.6V_2(2-0)$
1	$0.4V_2(2+1) + 0.6V_2(2-1)$
2	$0.4V_2(2+2) + 0.6V_2(2-2)$

b	$V_2(0)$
0	$0.4V_3(0+0)+0.6V_3(0-0)$

b	$V_2(1)$
0	$0.4V_3(1+0)+0.6V_3(1-0)$
1	$0.4V_3(1+1)+0.6V_3(1-1)$

b	$V_2(2)$
0	$0.4V_3(2+0)+0.6V_3(2-0)$
1	$0.4V_3(2+1)+0.6V_3(2-1)$
2	$0.4V_3(2+2)+0.6V_3(2-2)$

b	$V_2(3)$
0	$0.4V_3(3+0)+0.6V_3(3-0)$
1	$0.4V_3(3+1)+0.6V_3(3-1)$

b	$V_2(4)$
0	$0.4V_3(4+0)+0.6V_3(4-0)$

Gambling game

Boundary conditions

$$
\begin{aligned}
V_3(0) &= 0\\
V_3(1) &= 0\\
V_3(2) &= 0.4\\
V_3(3) &= 0.4\\
V_3(4) &= 1
\end{aligned}
$$

$$\begin{array}{clll} b & V_2(0) & & \\ 0 & 0.4V_3(0+0)+0.6V_3(0-0) & =0.4\cdot 0+0.6\cdot 0 & =0 \end{array}$$

$$\begin{array}{clll} b & V_2(1) & & \\ 0 & 0.4V_3(1+0)+0.6V_3(1-0) & =0.4\cdot 0+0.6\cdot 0 & =0 \\ 1 & 0.4V_3(1+1)+0.6V_3(1-1) & =0.4\cdot 0.4+0.6\cdot 0 & =0.16 \end{array}$$

$$\begin{array}{clll} b & V_2(2) & & \\ 0 & 0.4V_3(2+0)+0.6V_3(2-0) & =0.4\cdot 0.4+0.6\cdot 0.4 & =0.4 \\ 1 & 0.4V_3(2+1)+0.6V_3(2-1) & =0.4\cdot 0.4+0.6\cdot 0 & =0.16 \\ 2 & 0.4V_3(2+2)+0.6V_3(2-2) & =0.4\cdot 1+0.6\cdot 0 & =0.4 \end{array}$$

$$\begin{array}{clll} b & V_2(3) & & \\ 0 & 0.4V_3(3+0)+0.6V_3(3-0) & =0.4\cdot 0.4+0.6\cdot 0.4 & =0.4 \\ 1 & 0.4V_3(3+1)+0.6V_3(3-1) & =0.4\cdot 1+0.6\cdot 0.4 & =0.64 \end{array}$$

$$\begin{array}{clll} b & V_2(4) & & \\ 0 & 0.4V_3(4+0)+0.6V_3(4-0) & =0.4\cdot 1+0.6\cdot 1 & =1 \end{array}$$

Gambling game

b	$V_1(2)$		
0	$0.4V_2(2+0)+0.6V_2(2-0)$	$=0.4\cdot 0.4+0.6\cdot 0.4$	$=0.4$
1	$0.4V_2(2+1)+0.6V_2(2-1)$	$=0.4\cdot 0.64+0.6\cdot 0.16$	$=0.352$
2	$0.4V_2(2+2)+0.6V_2(2-2)$	$=0.4\cdot 1+0.6\cdot 0$	$=0.4$

Curse of dimensionality

If s_t is multidimensional and/or continuous, enumerating all states is difficult or impossible. Instead of solving

$$\begin{aligned} V_t(s_{t-1}) = \max_{c_t} \; & r(s_{t-1}, c_t) + v\,\mathbb{E}_{W_{t\bullet}}[V_{t+1}(s_t)|s_{t-1}] \\ \text{s.t. } & s_t = f(s_{t-1}, c_t, W_t) \end{aligned} \tag{8}$$

create sample paths (scenarios) $(W_\bullet^n)_{n=1}^N$ and solve iteratively for $n = 1, \ldots, N$ and $t = 1, \ldots, T$

$$\begin{aligned} \overline{V}_t^n(s_{t-1}^n) = \max_{c_t} \; & r(s_{t-1}^n, c_t) + v\,\mathbb{E}_{W_{t\bullet}}\left[\overline{V}_{t+1}^{n-1}(s_t)|s_{t-1}^n\right] \\ \text{s.t. } & s_t = f(s_{t-1}^n, c_t, W_t^n), \end{aligned} \tag{9}$$

where $\overline{V}_t^n$ is an approximated value function based on first n paths, see Powell (2009) for details.

Literature

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