# An introduction to dynamic programming in discrete time 

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Computational Aspects of Optimization

## Dynamic programming

Finite $T$ or infinite $\infty$ time horizon

$$
\begin{array}{ll}
\max _{A_{t}, c_{t}} & \sum_{t=1}^{T \vee \infty}\left(\frac{1}{1+i}\right)^{t-1} u\left(c_{t}\right) \\
\text { s.t. }
\end{array}
$$

$$
A_{t}=(1+r) A_{t-1}+Y_{t}-c_{t}
$$

- $u$ - utility function
- $A_{t}$ - state variables representing total amount of resources available to the consumer.
- $c_{t}$ - control variables maximizing the consumer's utility. It affects the resources available in the next period.
- $Y_{t}$ - exogenous income
- $1 /(1+i)$ - discount factor, $r$ - exogenous interest rate


## Dynamic programming

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

$$
\begin{aligned}
V_{1}\left(A_{0}\right)= & \max _{A_{t}, c_{t}} \sum_{t=1}^{T}\left(\frac{1}{1+i}\right)^{t-1} u\left(c_{t}\right) \\
= & \max _{A_{t}, c_{t}} u\left(c_{1}\right)+\frac{1}{1+i} u\left(c_{2}\right)+\cdots+\left(\frac{1}{1+i}\right)^{T-1} u\left(c_{T}\right) \\
= & \max _{A_{t}, c_{t}} u\left(c_{1}\right)+\frac{1}{1+i}\left[\sum_{t=2}^{T}\left(\frac{1}{1+i}\right)^{t-2} u\left(c_{t}\right)\right] \\
& \text { s.t. } \\
& A_{t}=(1+r) A_{t-1}+Y_{t}-c_{t} .
\end{aligned}
$$

## Dynamic programming

We rewrite the maximization problem recursively and obtain the Bellman equation

$$
V_{t}\left(A_{t-1}\right)=\max _{A_{t}, c_{t}} u\left(c_{t}\right)+\frac{1}{1+i} V_{t+1}\left(A_{t}\right)
$$

where $A_{t}=(1+r) A_{t-1}+Y_{t}-c_{t}$.

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

$$
\begin{aligned}
V\left(A_{t-1}\right) & =\max _{A_{t}, c_{t}} u\left(c_{t}\right)+\frac{1}{1+i} V\left(A_{t}\right), \\
& =\max _{c_{t}} u\left(c_{t}\right)+\frac{1}{1+i} V\left((1+r) A_{t-1}+Y_{t}-c_{t}\right),
\end{aligned}
$$

with $V_{T+1}\left(A_{T}\right)=V\left(A_{T}\right) \equiv 0$.

## 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.

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

## Dynamic programming

First order optimality conditions

$$
\begin{aligned}
& \frac{\partial V\left(A_{t-1}\right)}{\partial c_{t}}=0 \\
& \frac{\partial V\left(A_{t-1}\right)}{\partial A_{t-1}}=0
\end{aligned}
$$

In particular,

$$
\begin{aligned}
& \frac{\partial V\left(A_{t-1}\right)}{\partial c_{t}}=u^{\prime}\left(c_{t}\right)+\frac{1}{1+i} V^{\prime}\left(A_{t}\right) \frac{\partial A_{t}}{\partial c_{t}} \\
& \frac{\partial V\left(A_{t-1}\right)}{\partial A_{t-1}}=\frac{1}{1+i} V^{\prime}\left(A_{t}\right) \frac{\partial A_{t}}{\partial A_{t-1}},
\end{aligned}
$$

where using $A_{t}=(1+r) A_{t-1}+Y_{t}-c_{t}$ we have

$$
\frac{\partial A_{t}}{\partial c_{t}}=-1, \quad \frac{\partial A_{t}}{\partial A_{t-1}}=1+r .
$$

## Example: Cake eating problem

Cake eating problem:

- $u(c)=2 c^{1 / 2}$,
- $\Pi_{0}=1, \Pi_{T}=0$,
- $\Pi_{t}=\Pi_{t-1}-c_{t} \ldots$


## Example: Cake eating problem

Bellman equation

$$
\begin{aligned}
V\left(\Pi_{t-1}\right)= & \max _{c_{t}} u\left(c_{t}\right)+\frac{1}{1+i} V\left(\Pi_{t}\right) \\
& \text { s.t. } \Pi_{t}=\Pi_{t-1}-c_{t}
\end{aligned}
$$

Optimality conditions

$$
\begin{aligned}
& \frac{\partial V\left(\Pi_{t-1}\right)}{\partial c_{t}}=u^{\prime}\left(c_{t}\right)+\frac{1}{1+i} V^{\prime}\left(\Pi_{t}\right) \frac{\partial \Pi_{t}}{\partial c_{t}}=0 \\
& \frac{\partial V\left(\Pi_{t-1}\right)}{\partial \Pi_{t-1}}=\frac{1}{1+i} V^{\prime}\left(\Pi_{t}\right) \frac{\partial \Pi_{t}}{\partial \Pi_{t-1}}=0
\end{aligned}
$$

From $\Pi_{t}=\Pi_{t-1}-c_{t}$

$$
\begin{equation*}
\frac{\partial \Pi_{t}}{\partial c_{t}}=-1, \frac{\partial \Pi_{t}}{\partial \Pi_{t-1}}=1 \tag{2}
\end{equation*}
$$

## Example: Cake eating problem

Putting them together, we obtain

$$
\begin{align*}
& \frac{\partial V\left(\Pi_{t-1}\right)}{\partial c_{t}}=u^{\prime}\left(c_{t}\right)-\frac{1}{1+i} V^{\prime}\left(\Pi_{t}\right)=0  \tag{3}\\
& \frac{\partial V\left(\Pi_{t-1}\right)}{\partial \Pi_{t-1}}=\frac{1}{1+i} V^{\prime}\left(\Pi_{t}\right)=0 \tag{4}
\end{align*}
$$

Taking (3) for $t-1$

$$
\begin{equation*}
u^{\prime}\left(c_{t-1}\right)-\frac{1}{1+i} V^{\prime}\left(\Pi_{t-1}\right)=0 \tag{5}
\end{equation*}
$$

and plugging it into (4), we have

$$
u^{\prime}\left(c_{t-1}\right)=\frac{1}{1+i} u^{\prime}\left(c_{t}\right)
$$

which represents the optimal path of the cake consumption.

## Example: Cake eating problem

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

$$
\begin{aligned}
u^{\prime}\left(c_{t-1}\right) & =\frac{1}{1+i} u^{\prime}\left(c_{t}\right), \\
\left(c_{t-1}\right)^{-1 / 2} & =\frac{1}{1+i}\left(c_{t}\right)^{-1 / 2}, \\
c_{t} & =\left(\frac{1}{1+i}\right)^{2} c_{t-1},
\end{aligned}
$$

with initial and terminal conditions $\Pi_{0}=1, \Pi_{T}=0$. If we denote $\beta=1 /(1+i)^{2}$, 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

$$
\Pi_{0}-c_{1}-c_{2}-\cdots-c_{T}=\Pi_{T}=0,
$$

we have

$$
\left(1-\beta-\cdots-\beta^{T-1}\right) c_{1}=\Pi_{0}
$$

and finally optimal consumption

$$
\begin{aligned}
& \hat{c}_{1}=\frac{1-\beta}{1-\beta^{T}} \Pi_{0} \\
& \hat{c}_{t}=\beta \hat{c}_{t-1}=\beta^{t-1} \hat{c}_{1} .
\end{aligned}
$$

## Literature

- P. Kall, S.W. Wallace: Stochastic Programming, John Wiley \& Sons, Chichester.
- M. C. Sunny Wong: Dynamic Optimization: An Introduction, Lecture Notes University of Houston, 2013.

