

# Dynamic Programming

Part 1: Exercise 3, 4 & 5 (week 8)

Mikkel Reich

University of Copenhagen, Department of Economics

# Plan for today

- Continuous states and choices
- 1D Interpolation
- Models with shocks
- Numerical integration
- Exercise 3, 4 & 5

## Exercise 3: Cake-eating with continuous choice (+ states)

You can split a slice of cake! You can eat, say, 0.3 of a cake slice.

$V_t(W_t)$  is then defined for  $W_t \geq 0$  and not “only”  $W_t \in \mathbb{N}_0$ .

→ Implement using **grids**, e.g:  $W_t \in \{0, 0.2, 0.4, \dots\} \forall t$

Similarly, we can do grid search on “share of total cake to eat”, i.e.  
when we reach cake size  $W_t$ , we search over:

$$c_t \in \{0 * W_t, 0.01 * W_t, 0.02 * W_t, \dots, 1 * W_t\}$$

**Small modification of Bellman equation:**

$$V_t(W_t) = \max_{0 \leq c_t \leq W_t} \{\sqrt{c_t} + \beta V_{t+1}(W_{t+1})\} \quad \text{s.t. } W_{t+1} = W_t - c_t$$

(implement in infinite horizon in ex. 3 and finite horizon in ex. 4)

## Exercise 3: Interpolation

$V_{t+1}(W_{t+1})$  is only known on the grid for  $W_{t+1}$  but  $0 \leq c_t \leq W_t$

→ Next period state  $W_{t+1} = W_t - c_t$  can “fall” outside its grid.

→ Use interpolation / function approximation for  $V_{t+1}(W_{t+1})$

(Simple + useful) **linear interpolation algorithm** (`np.interp`):

1. Ensure that  $W_{t+1}$  is within two points in the grid (otherwise “extrapolation”)
2. Find the two “neighbouring points” to  $W_{t+1}$  in the grid
3. Compute “weighted average” of  $V_{t+1}(W_{t+1})$  in these two points (see [link](#))

Many alternatives: polynomial, neural nets, ... (next week)

## Exercise 4: Cake-eating with uncertainty

What if your cake could (stochastically) grow over-night with  $\epsilon$ ?

→ Make state transition stochastic:  $W_{t+1} = W_t - c_t + \epsilon$

→ Form expectation over future value in Bellman equation:

$$V_t(W_t) = \max_{0 \leq c_t \leq W_t} \left\{ \sqrt{c_t} + \beta \underbrace{\mathbb{E}[V_{t+1}(W_t - c_t + \epsilon)]}_{=\sum_{i=1}^K \pi_i V_{t+1}(W_t - c_t + \epsilon_i)} \right\}$$

, when  $\epsilon$  is discretely uniform on  $\{0, 1, 2, \dots, K-1\}$  (ex. 4).

$\epsilon$  continuously distributed with PDF  $p(\epsilon)$  → evaluate integral:

$$\mathbb{E}[V_{t+1}(W_t - c_t + \epsilon)] = \int_{\mathbb{R}} p(\epsilon) V_{t+1}(W_t - c_t + \epsilon) d\epsilon$$

Analytical expressions are hopeless → **Numerical integration**

## Exercise 5: Numerical integration

Compute  $\mathbb{E}[f(X)] = \int_{\mathbb{R}} p(x)f(x)dx$ , where  $p(x)$  is PDF of r.v.  $X$

**Monte Carlo:** Draw  $N$  (large) number of  $X$ :  $\{x_i\}_{i=1}^N$  and compute

$$\int_{\mathbb{R}} p(x)f(x)dx \approx \frac{1}{N} \sum_{i=1}^n f(x_i)$$

Works across distributions, no curse of dimensionality but slow

If  $X \sim \mathcal{N}(\mu, \sigma^2)$ , we can do much better!

**Gauss-Hermite Quadrature:** Deterministic method for approximating integrals like

$$\int_{\mathbb{R}} \exp(-x^2)f(x)dx \approx \sum_{i=1}^n w_i f(x_i)$$

, where  $w_i$  is computed using Hermite polynomials and  $x_i$  are the  $n$  roots of the Hermite polynomial  $H_n$ .

## Exercise 5: Intuition for Gauss-Hermite Quadrature

In practice: “import” raw pairs  $\{(w_i, x_i)\}_{i=1}^n$  by using `gauss_hermite(n)` from `tools.py` (uses [Golub-Welsch algorithm](#))

Exact integration if  $\deg(f) \leq 2n - 1$

→ Polynomials are universal function approximators

→  $f(x)$  as approx. to non-polynomial value/policy function

“Under the hood” (**Advanced**):

1. Polynomial division of  $f(x)$  with  $H_n(x)$
2. Choose nodes  $\{x_i\}_{i=1}^n$  as roots of  $H_n(x)$
3. Use orthogonality of Hermite polynomials to reduce to “weighted integration” wrt.  $r(x)$  with  $\deg(r) \leq n - 1$
4. Interpolate  $r(x)$  exactly using  $n$ -degree Lagrange polynomial

## Exercise 5: Gauss-Hermite for normally distributed r.v.

Consider  $X \sim \mathcal{N}(\mu, \sigma^2)$ , function  $f(\cdot)$  and compute expectation:

$$\begin{aligned}\mathbb{E}[f(X)] &= \int f(x) \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \int f(x) \exp\left(-\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)^2\right) dx\end{aligned}$$

Change variables  $z = \frac{x-\mu}{\sqrt{2\sigma^2}} \Rightarrow dz = \frac{1}{\sqrt{2\sigma^2}} dx \Leftrightarrow dx = \sqrt{2\sigma^2} dz$

$$\begin{aligned}\Rightarrow \mathbb{E}[f(x)] &= \frac{1}{\sqrt{\pi}} \int f(\mu + \sqrt{2}\sigma z) \exp(-z^2) dz \\ &\approx \frac{1}{\sqrt{\pi}} \sum_{i=1}^n w_i f(\mu + \sqrt{2}\sigma z_i)\end{aligned}$$

→ Can “integrate out” normal r.v.  $X$  by using Gauss-Hermite

→ Choose weights as  $\left\{\frac{w_i}{\sqrt{\pi}}\right\}_{i=1}^n$

→ Choose nodes as  $\{\mu + \sqrt{2}\sigma z_i\}_{i=1}^n$



Your time to shine!