

Lecture VI

Numerical Integration

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Quantitative Macroeconomics

Reservation wage equation

$$w^* = b + \frac{\lambda}{r + \delta} \int_{w^*}^{\bar{w}} (w - w^*) dG(w)$$

- How do we solve for w^* ? We need a method that computes numerically the integral inside a root finding algorithm
- Three approaches to computing integral:
 1. **Newton-Cotes methods**: employ piecewise polynomial approximations to the integrand with evenly spaced nodes
 2. **Gaussian Quadrature**: choose nodes and weights efficiently, i.e. they satisfy some moment-matching conditions
 3. **Monte-Carlo methods**: use equally weighted random nodes

Newton-Cotes: Trapezoid rule

- Approximate f with a **piecewise linear polynomial** \tilde{f} whose integral is easy to compute:

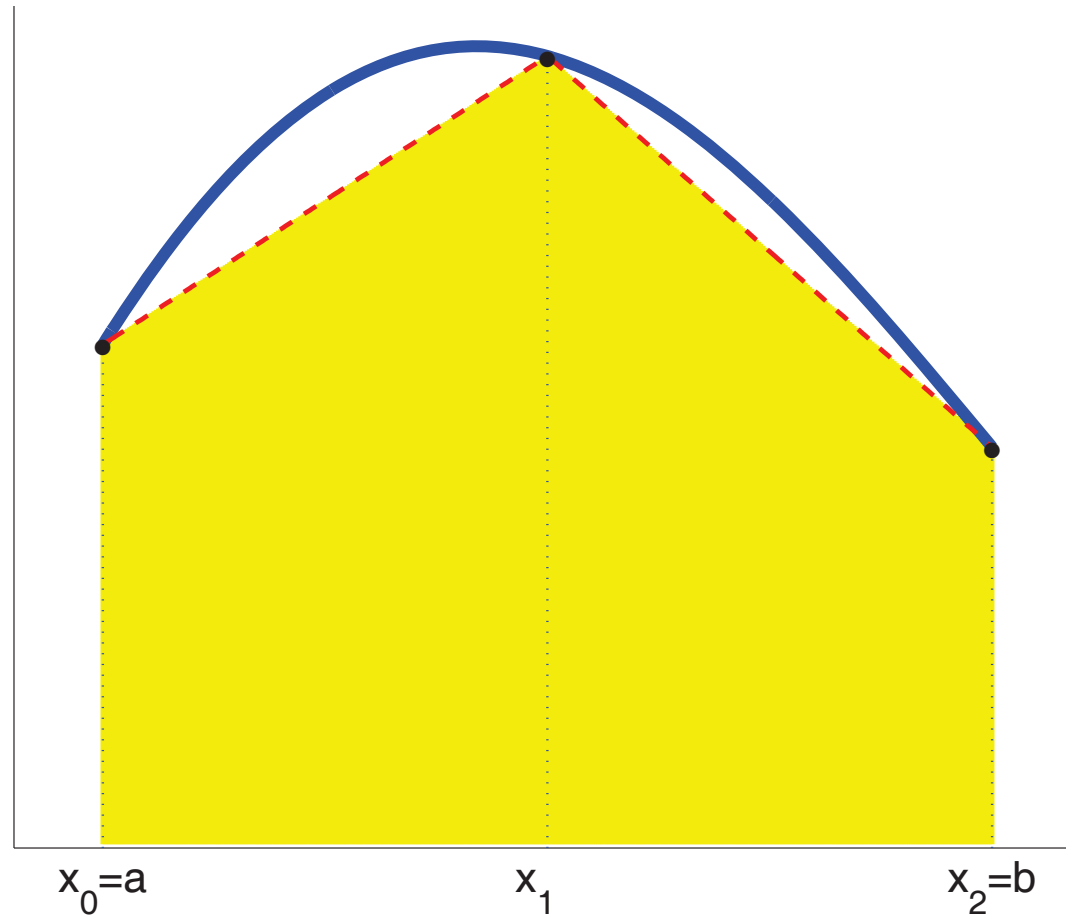
$$\int_a^b f(x) dx \simeq \int_a^b \tilde{f}(x) dx$$

- Partition the integration interval $[a, b]$ into n subintervals of equal length $h = (b - a)/n$ and endpoint nodes $x_i = a + ih$
- Compute the function values $y_i = f(x_i)$ at nodes i .
- Form a piecewise linear approximation of the function between successive points (x_i, x_{i+1})

$$f(x) \simeq f(x_i) + \frac{f(x_{i+1}) - f(x_i)}{x_{i+1} - x_i} (x - x_i)$$

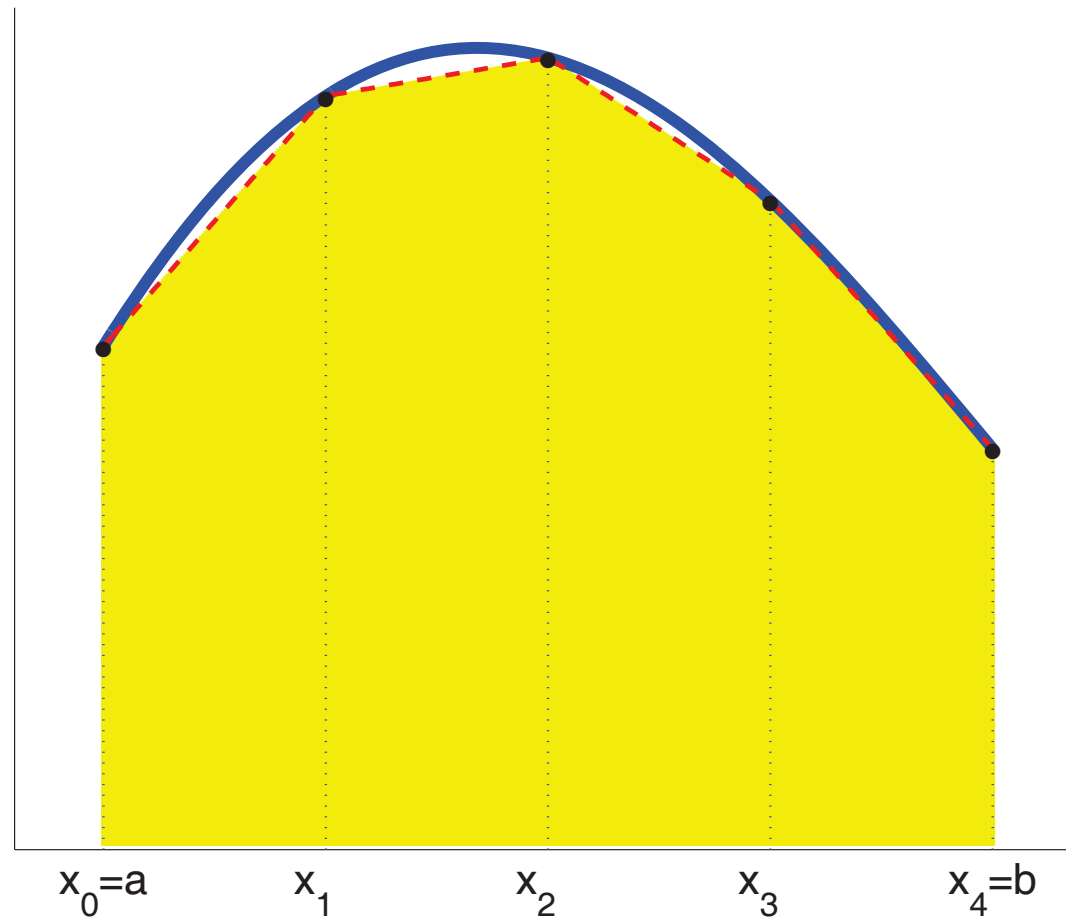
Example: 2 nodes

Trapezoid Rule, $n = 2$.



Example: 4 nodes

Trapezoid Rule, $n = 4$.



Newton-Cotes: Trapezoid rule

- The area under the piecewise linear appx. for subinterval i is:

$$\int_{x_i}^{x_{i+1}} \tilde{f}(x) dx \simeq \left[\frac{f(x_{i+1}) + f(x_i)}{2} \right] \cdot h$$

and hence

$$\int_{x_i}^{x_{i+1}} f(x) dx \simeq \sum_{i=0}^N w_i f(x_i)$$

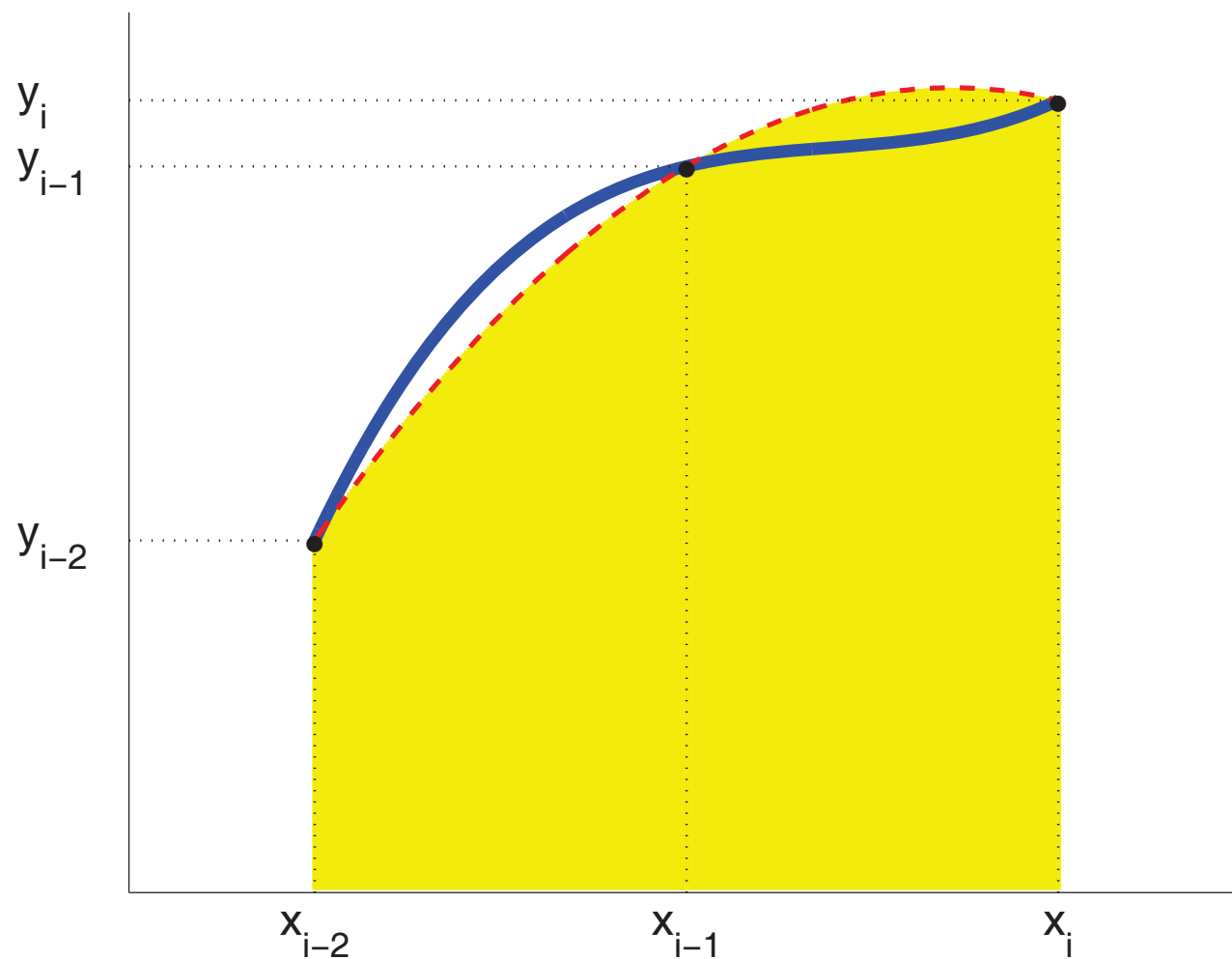
where $w_i = h$ for all i , unless $\{i = 0, N\}$ where $w_i = 1/2$

- Simple and robust
- Increasing nodes from N to $M * N$ reduces error by factor of M^2

Newton-Cotes: Simpson rule

- Simpson rule based on **quadratic approximation** of the function
- Form a piecewise quadratic approximation \tilde{f} that interpolates f at successive triplets of (x_{i-1}, x_i, x_{i+1}) with quadratic functions
- Similar expression as above. Figure out what w_i need to be
- If f is smooth, Simpson rule is preferred because approximation error is square of Trapezoid rule error, hence more accurate
- But if f is nondifferentiable at some points, then trapezoid rule may be better

Example: 2 nodes



Gaussian quadrature

- It builds on idea that (i) a function can be approx. by a polynomial and (ii) weights and quadrature points are chosen efficiently
- Let $\Phi = \{\varphi_k(x)\}_{k=0}^{\infty}$ be a family of polynomials defined on $[a, b]$ with typical element

$$\varphi_k(x) = \sum_{i=0}^k \alpha_{k,i} x^i, \text{ with } \alpha_{k,k} = 1 \quad (\text{normalization})$$

- Definition: Φ is orthogonal w.r.t. the weight function $w(x)$ if

$$\langle \varphi_k, \varphi_j \rangle = \int_a^b \varphi_k(x) \varphi_j(x) w(x) dx = 0 \text{ for } k \neq j$$

- Moreover, if $\langle \varphi_k, \varphi_k \rangle = 1$, for all k , then Φ is also said to be orthonormal with respect to $w(x)$

Gaussian quadrature

- **Theorem:** Suppose that Φ is orthonormal w.r.t. $w(x)$ on $[a, b]$. Let $\{x_i\}_{i=1}^n$ be the zeros of $\varphi_n(x)$. Then $x_i \in [a, b]$. If $f \in C^{(2n)}[a, b]$:

$$\int_a^b f(x) w(x) dx = \sum_{i=1}^n \omega_i f(x_i) + \frac{f(\xi)^{2n}}{(2n)!}$$

for some $\xi \in [a, b]$. The residual is "small". And the weights are:

$$\omega_i = -\frac{1}{\varphi'_n(x_i) \varphi_{n+1}(x_i)} > 0$$

- **Corollary:** if f is a polynomial of degree $(2n - 1)$, then the integration is exact (residual term is zero)
- Theorem gives us zeros of orthogonal polynomials as quadrature nodes and weights (a.k.a. abscissae).
- In practice, nodes/weights **tabulated for known polynomial families**

Example of exact approximation

- We want to evaluate the definite integral

$$I = \int_{-1}^1 f(x) dx, \quad \text{where} \quad f(x) = c_0 + c_1x + c_2x^2 + c_3x^3$$

- Set $n = 2$ since $(2n - 1 = 3)$
- The Gaussian approximation of the integral is:

$$\hat{I} = \sum_{i=1}^2 \omega_i (c_0 + c_1x_i + c_2x_i^2 + c_3x_i^3)$$

- Set $I = \hat{I}$

Example of exact approximation

$$\begin{aligned}\int_{-1}^1 (c_0 + c_1 x + c_2 x^2 + c_3 x^3) dx &= \sum_{i=1}^2 \omega_i (c_0 + c_1 x_i + c_2 x_i^2 + c_3 x_i^3) \\ 2c_0 + 0c_1 + \frac{2}{3}c_2 + 0c_3 &= c_0 (\omega_1 + \omega_2) + c_1 (\omega_1 x_1 + \omega_2 x_2) + \\ &\quad c_2 (\omega_1 x_1^2 + \omega_2 x_2^2) + c_3 (\omega_1 x_1^3 + \omega_2 x_2^3)\end{aligned}$$

- The last equation is satisfied if and only if:

$$\begin{aligned}2 &= \omega_1 + \omega_2 \\ 0 &= \omega_1 x_1 + \omega_2 x_2 \\ \frac{2}{3} &= \omega_1 x_1^2 + \omega_2 x_2^2 \\ 0 &= \omega_1 x_1^3 + \omega_2 x_2^3\end{aligned}$$

- System of 4 equations into 4 unknowns $(\omega_1, \omega_2, x_1, x_2)$ that gives weights and quadrature points.

Gauss-Chebyshev quadrature on $[-1,1]$

- Consider an integral of the form:

$$\int_{-1}^1 f(x) (1 - x^2)^{-1/2} dx$$

- The weighting function is the one that defines **Chebyshev polynomials** as orthogonal family. Thus, we know that:

$$\int_{-1}^1 f(x) (1 - x^2)^{-1/2} dx \simeq \sum_{i=1}^n \omega_i f(x_i)$$

$$\omega_i = \frac{\pi}{n}, \quad x_i = \cos\left(\frac{2i-1}{2n}\pi\right)$$

- Convenient because the weight is constant and the abscissas have simple formula

Gauss-Chebyshev quadrature on $[a,b]$

$$I = \int_a^b f(x) dx$$

- Linear change of variable from $x \in (a, b)$ to $y \in (-1, 1)$:

$$x = a + \frac{(1+y)(b-a)}{2}$$

- Multiply and divide by $(1-y^2)^{-1/2}$:

$$\begin{aligned} I &= \int_{-1}^1 f\left(a + \frac{(1+y)(b-a)}{2}\right) \frac{(1-y^2)^{-1/2}}{(1-y^2)^{-1/2}} \left(\frac{b-a}{2} dy\right) \\ &= \frac{b-a}{2} \int_{-1}^1 \left[f\left(a + \frac{(1+y)(b-a)}{2}\right) (1-y^2)^{1/2} \right] (1-y^2)^{-1/2} dy \\ &\simeq \frac{\pi(b-a)}{2n} \sum_{i=1}^n \left[f\left(a + \frac{(1+y_i)(b-a)}{2}\right) (1-y_i^2)^{1/2} \right] \end{aligned}$$

Other quadrature methods

- In general, suppose you want to compute an integral of the type

$$\int_a^b f(x) \omega(x) dx \simeq \sum_{i=1}^n \omega_i f(x_i)$$

Range	$\omega(x)$	Polynomial family	Quadrature method
$[-1, 1]$	1	Legendre	Gauss-Legendre
$(-1, 1)$	$(1 - x^2)^{1/2}$	Chebyshev	Gauss-Chebyshev
$[0, \infty)$	e^{-x}	Laguerre	Gauss-Laguerre
$(-\infty, \infty)$	e^{-x^2}	Hermite	Gauss-Hermite

- ... after an appropriate change of variable
- Nodes and weights already tabulated

Monte-Carlo Integration

- Gaussian approach to multi-dimensional integrals OK up to 3 dimensions: then, it requires too many functional evaluations
- Monte-Carlo **useful for multi-dimensional integration**
- LLN: if $\{x_i\}$ are iid realizations of a random variable $x \in [0, 1]$ and f is continuous, then with probability one:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n f(x_i) = \int_0^1 f(x) dx$$

- Draw n realizations of x from $U[0, 1]$ and compute the sum:

$$I_n = \frac{1}{n} \sum_{i=1}^n f(x_i)$$

- Integral is a random var. and value depends on realizations

Variance-reduction techniques

- **Stratified sampling:** divide $[0, 1]$ into two subintervals $[0, \alpha]$ and $[\alpha, 1]$ in order to avoid concentration of draws in one subregion by bad luck and use:

$$I_n = \frac{\alpha}{n} \sum_{i=1}^n f(x_{1i}) + \frac{(1 - \alpha)}{n} \sum_{i=1}^n f(x_{2i})$$

so you weight more the larger section

- **Antithetic variance:** if f is weakly increasing then $f(x)$ and $f(1 - x)$ are negatively correlated.

$$I_n = \frac{1}{2n} \sum_{i=1}^n [f(x_i) + f(1 - x_i)]$$

produces smaller variance because covar. btw. terms negative