

Chapter 3 Numerical Integration

3.1 Newton-Côtes Quadrature

- We want to calculate integration $\int_{\mathcal{X}} g(x) dx$ for some function $g(x)$ defined on $\mathcal{X} \subset \mathbb{R}$.

- Let $f_X(x)$ be the PDF of random variable X , we may want to know

$$F_X(x) = P(X \leq x) = \int_{-\infty}^x f_X(u) du$$

or

$$E[h(X)] = \int_{-\infty}^{\infty} h(x) f_X(x) dx.$$

- Let $f_{XY}(x, y)$ be the joint PDF of (X, Y) , we often need to calculate $f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$.

3.1 Newton-Côtes Quadrature

- **Bayesian Inference:** In Bayesian approaches, the parameter $\boldsymbol{\theta}$ is considered as a random variable.

- Suppose $\boldsymbol{\theta}$ has a *prior distribution* with PDF $\pi(\theta)$. Given $\boldsymbol{\theta} = \theta$, the observed data X follows a distribution with PDF $f_{X|\boldsymbol{\theta}}(x|\theta)$.
- The distribution of $\boldsymbol{\theta}$ conditional on the the observed data is called the *posterior distribution* of the parameter $\boldsymbol{\theta}$.
- Let $f_{\boldsymbol{\theta}|X}(\theta|x)$ be the PDF of the posterior distribution of $\boldsymbol{\theta}$. Then

$$f_{\boldsymbol{\theta}|X}(\theta|x) = \frac{f_{X\boldsymbol{\theta}}(x, \theta)}{f_X(x)} = \frac{f_{X\boldsymbol{\theta}}(x, \theta)}{\int f_{X\boldsymbol{\theta}}(x, \theta) d\theta} = \frac{\pi(\theta)f_{X|\boldsymbol{\theta}}(x|\theta)}{\int \pi(\theta)f_{X|\boldsymbol{\theta}}(x|\theta) d\theta}.$$

- Suppose we want to calculate the probability $P(a < \boldsymbol{\theta} < b|X = x)$, then

$$P(a < \boldsymbol{\theta} < b|X = x) = \int_a^b f_{\boldsymbol{\theta}|X}(\theta|x) d\theta = \frac{\int_a^b \pi(\theta)f_{X|\boldsymbol{\theta}}(x|\theta) d\theta}{\int \pi(\theta)f_{X|\boldsymbol{\theta}}(x|\theta) d\theta}.$$

3.1 Newton-Côtes Quadrature

- **Example:** Suppose that X_1, \dots, X_n are i.i.d. from the Poisson(θ) distribution given that $\boldsymbol{\theta} = \theta > 0$. Assume that the prior distribution of θ has the PDF $\pi(\theta) = \frac{1}{\Gamma(\alpha)\beta^\alpha} \theta^{\alpha-1} e^{-\theta/\beta}$, $\theta > 0$ (the Gamma(α, β) distribution with $\alpha > 0$ and $\beta > 0$), where $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt$.

- The distribution of $X_1 = x_1, \dots, X_n = x_n$ given $\boldsymbol{\theta} = \theta$ is

$$P(X_1 = x_1, \dots, X_n = x_n | \boldsymbol{\theta} = \theta) = \prod_{i=1}^n P(X_i = x_i | \boldsymbol{\theta} = \theta) = \frac{e^{-n\theta} \theta^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}.$$

- The posterior distribution of $\boldsymbol{\theta}$ is

$$\begin{aligned} f_{\boldsymbol{\theta}|X}(\theta | X = x) &= \frac{\pi(\theta) P(X_1 = x_1, \dots, X_n = x_n | \boldsymbol{\theta} = \theta)}{\int_{\Theta} \pi(\theta) P(X_1 = x_1, \dots, X_n = x_n | \boldsymbol{\theta} = \theta) d\theta} \\ &= \frac{\frac{1}{\Gamma(\alpha)\beta^\alpha} \theta^{\alpha-1} e^{-\theta/\beta}}{\int_{\Theta} \pi(\theta) P(X_1 = x_1, \dots, X_n = x_n | \boldsymbol{\theta} = \theta) d\theta} \cdot \frac{e^{-n\theta} \theta^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!} \\ &= c(x_1, \dots, x_n) \cdot \theta^{\alpha + \sum_{i=1}^n x_i - 1} e^{-(n\beta+1)\theta/\beta}, \end{aligned}$$

which is the Gamma($\alpha + \sum_{i=1}^n x_i, \frac{\beta}{n\beta+1}$) distribution.

3.1 Newton-Côtes Quadrature

- When $\int_{-\infty}^{\infty} g(x) dx$ exists, we have $\int_a^b g(x) dx \rightarrow \int_{-\infty}^{\infty} g(x) dx$ when $a \rightarrow -\infty$ and $b \rightarrow \infty$. So we can choose $a < b$ so that $\int_a^b g(x) dx \approx \int_{-\infty}^{\infty} g(x) dx$. We focus on calculate $\int_a^b g(x) dx$ in the following.

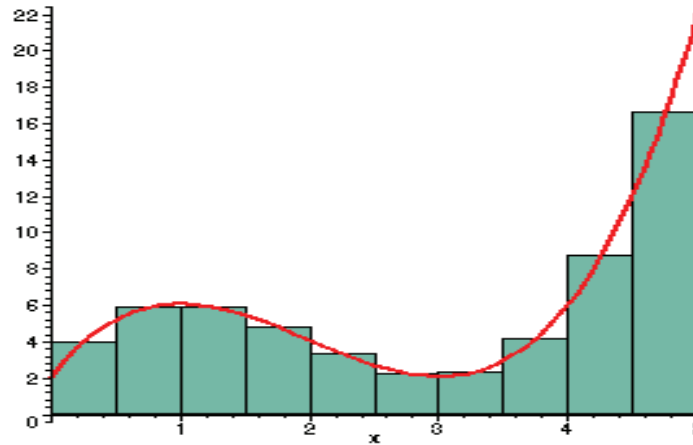
- **Riemann Rule:** Let $a = x_0 < x_1 < \cdots < x_{n-1} < x_n = b$ be a partition of interval $[a, b]$ and let ξ_i be any point between x_i and x_{i+1} . Then

$$\sum_{i=0}^{n-1} g(\xi_i)(x_{i+1} - x_i) \rightarrow \int_a^b g(x) dx$$

as $\max \{|x_1 - x_0|, \cdots, |x_n - x_{n-1}|\} \rightarrow 0$.

- Assume that x_0, x_1, \cdots, x_n are equally spaced in the following. That is,
 $x_i = a + i(b - a)/n$ for $i = 0, 1, \cdots, n$.
- For simplicity, we use h_n to denote $(b - a)/n$ in the following.

3.1 Newton-Côtes Quadrature



- – If we let $\xi_i = x_i$, then $\int_a^b g(x) dx$ is estimated by

$$R_{1,n} = h_n \sum_{i=0}^{n-1} g(x_i).$$

- If we let $\xi_i = (x_i + x_{i+1})/2$, then $\int_a^b g(x) dx$ is estimated by

$$R_{2,n} = h_n \sum_{i=0}^{n-1} g((x_i + x_{i+1})/2).$$

3.1 Newton-Côtes Quadrature

- – We say $a_n = O(b_n)$ if we can find $c > 0$ such that $|a_n/b_n| < c$ for all n , and $a_n = o(b_n)$ if $\lim_{n \rightarrow \infty} a_n/b_n = 0$.
- Assume that $g''(x)$ is continuous on $[a, b]$. For $R_{1,n}$, we have

$$\begin{aligned} & \left| R_{1,n} - \int_a^b g(x) dx \right| \\ &= \left| h_n \sum_{i=0}^{n-1} g(x_i) - \sum_{i=0}^{n-1} \int_{x_i}^{x_{i+1}} g(x) dx \right| \leq \sum_{i=0}^{n-1} \left| h_n g(x_i) - \int_{x_i}^{x_{i+1}} g(x) dx \right| \\ &= \sum_{i=0}^{n-1} \left| h_n g(x_i) - \int_{x_i}^{x_{i+1}} \left[g(x_i) + g'(x_i)(x - x_i) + \frac{1}{2} g''(u_i)(x - x_i)^2 \right] dx \right| \\ &= \sum_{i=0}^{n-1} \left| -\frac{1}{2} g'(x_i) h_n^2 - \int_{x_i}^{x_{i+1}} \frac{1}{2} g''(u_i)(x - x_i)^2 dx \right| \\ &\leq c \sum_{i=0}^{n-1} h_n^2 = O(h_n) = O(1/n), \end{aligned}$$

where u_i is a point between x and x_i .

3.1 Newton-Côtes Quadrature

- – For $R_{2,n}$, we have

$$\begin{aligned} \left| R_{2,n} - \int_a^b g(x) dx \right| &= \left| h_n \sum_{i=0}^{n-1} g\left(\frac{x_i + x_{i+1}}{2}\right) - \sum_{i=0}^{n-1} \int_{x_i}^{x_{i+1}} g(x) dx \right| \\ &\leq \sum_{i=0}^{n-1} \left| h_n g\left(\frac{x_i + x_{i+1}}{2}\right) - \int_{x_i}^{x_{i+1}} g(x) dx \right| \\ &= \sum_{i=0}^{n-1} \left| h_n g\left(\frac{x_i + x_{i+1}}{2}\right) - \int_{x_i}^{x_{i+1}} \left[g\left(\frac{x_i + x_{i+1}}{2}\right) + g'\left(\frac{x_i + x_{i+1}}{2}\right) \cdot \left(x - \frac{x_i + x_{i+1}}{2}\right) \right. \right. \\ &\quad \left. \left. + \frac{1}{2} g''(u_i) \cdot \left(x - \frac{x_i + x_{i+1}}{2}\right)^2 \right] dx \right| \\ &= \sum_{i=0}^{n-1} \left| 0 - \int_{x_i}^{x_{i+1}} \frac{1}{2} g''(u_i) \cdot \left(x - \frac{x_i + x_{i+1}}{2}\right)^2 dx \right| \\ &\leq c \sum_{i=0}^{n-1} h_n^3 = O(h_n^2) = O(1/n^2). \end{aligned}$$

- Hence, $R_{2,n}$ converges faster than $R_{1,n}$.

3.1 Newton-Côtes Quadrature

- **Newton-Côtes Quadrature:** The Newton-Côtes quadrature proposes to use a m th degree polynomial (**instead of a constant**) to approximate $g(x)$ in each subinterval $[x_i, x_{i+1}]$, $i = 1, \dots, n$.

– We insert $m - 1$ equally spaced points in the interval $[x_i, x_{i+1}]$. Define

$x_{ij}^* = x_i + jh_n/m$, $j = 0, \dots, m$. Then $x_{i0}^* = x_i$ and $x_{im}^* = x_{i+1}$.

– Define

$$p_{ij}(x) = \prod_{k=0, k \neq j}^m \frac{x - x_{ik}^*}{x_{ij}^* - x_{ik}^*}.$$

It is easy to find that $p_{ij}(x)$ is a m th degree polynomial, $p_{ij}(x_{ij}^*) = 1$ and $p_{ij}(x_{ik}^*) = 0$ for $k = 0, \dots, m$ and $k \neq j$.

- Let $\hat{g}_i(x) = \sum_{j=0}^m g(x_{ij}^*)p_{ij}(x)$. Then $\hat{g}_i(x)$ is a m th degree polynomial, and it satisfies $\hat{g}_i(x_{ij}^*) = g(x_{ij}^*)$ for $j = 0, \dots, m$.

3.1 Newton-Côtes Quadrature

- – The Newton-Côtes quadrature proposes to calculate $\int_a^b g(x) dx$ by

$$\begin{aligned}\int_a^b g(x) dx &= \sum_{i=0}^{n-1} \int_{x_i}^{x_{i+1}} g(x) dx \\ &\approx \sum_{i=0}^{n-1} \int_{x_i}^{x_{i+1}} \hat{g}_i(x) dx = \sum_{i=0}^{n-1} \sum_{j=0}^m g(x_{ij}^*) \int_{x_i}^{x_{i+1}} p_{ij}(x) dx.\end{aligned}$$

- When $m = 1$, we have $x_{i0}^* = x_i$, $x_{i1}^* = x_{i+1}$ and $p_{i0}(x) = \frac{x-x_{i+1}}{x_i-x_{i+1}}$, $p_{i1}(x) = \frac{x-x_i}{x_{i+1}-x_i}$. Note that $x_{i+1} - x_i = h_n$, we have

$$\int_{x_i}^{x_{i+1}} p_{i0}(x) dx = \frac{h_n}{2} \quad \text{and} \quad \int_{x_i}^{x_{i+1}} p_{i1}(x) dx = \frac{h_n}{2}.$$

Then $\int_a^b g(x) dx$ is estimated by

$$T_n = \sum_{i=0}^{n-1} \left[\frac{h_n}{2} g(x_i) + \frac{h_n}{2} g(x_{i+1}) \right] = \frac{h_n}{2} g(x_0) + h_n \sum_{i=1}^{n-1} g(x_i) + \frac{h_n}{2} g(x_n).$$

This method is called the *trapezoidal rule*.

3.1 Newton-Côtes Quadrature

- – When $m = 2$, $x_{i0}^* = x_i$, $x_{i1}^* = (x_i + x_{i+1})/2$, and $x_{i2}^* = x_{i+1}$. We can show that (**Homework**)

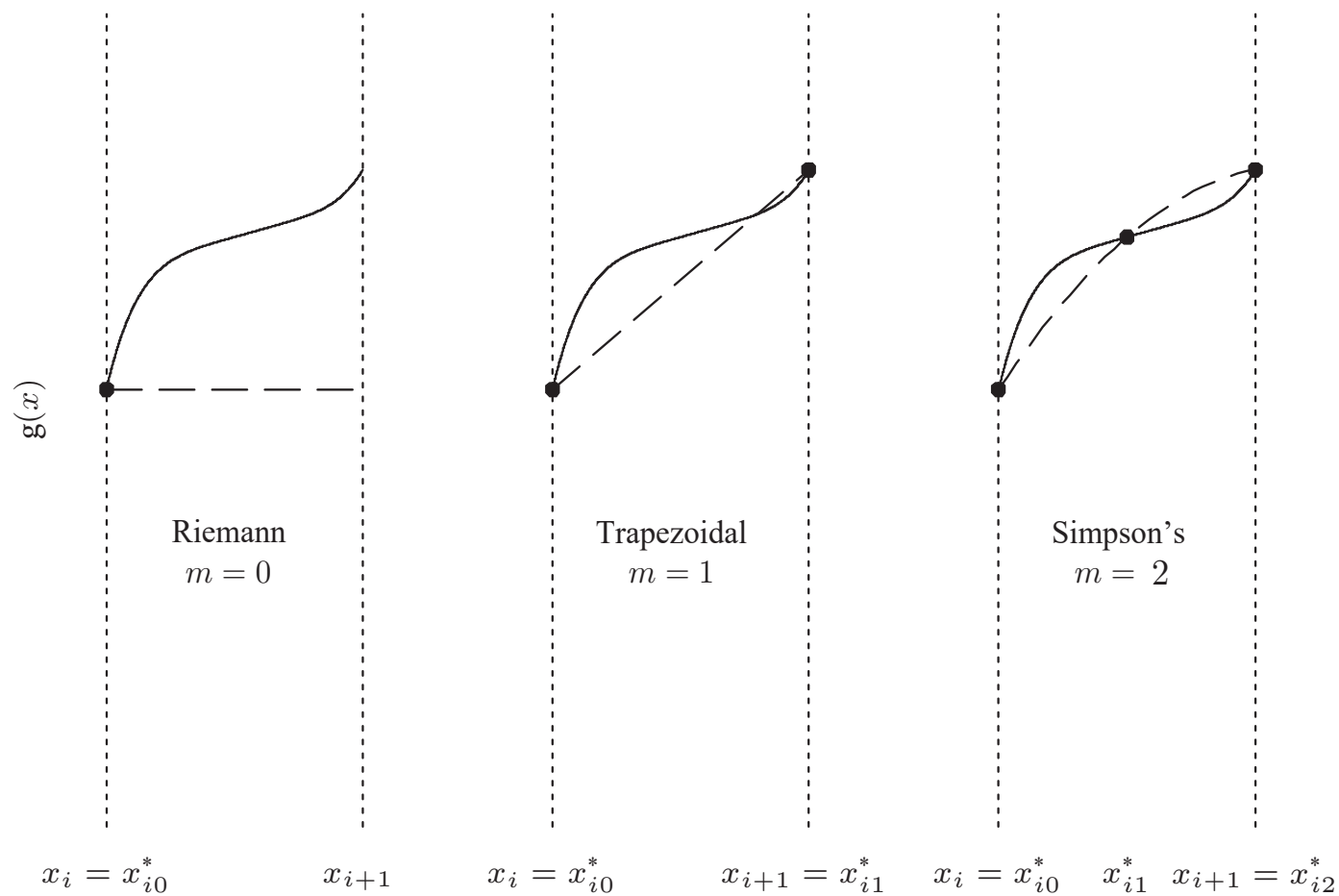
$$\int_{x_i}^{x_{i+1}} p_{i0}(x) dx = \int_{x_i}^{x_{i+1}} p_{i2}(x) dx = \frac{h_n}{6} \quad \text{and} \quad \int_{x_i}^{x_{i+1}} p_{i1}(x) dx = \frac{2h_n}{3}.$$

Then $\int_a^b g(x) dx$ is estimated by

$$\begin{aligned} S_n &= \sum_{i=0}^{n-1} \left[\frac{h_n}{6} g(x_i) + \frac{2h_n}{3} g\left(\frac{x_i + x_{i+1}}{2}\right) + \frac{h_n}{6} g(x_{i+1}) \right] \\ &= \frac{h_n}{6} g(x_0) + \frac{h_n}{3} \sum_{i=1}^{n-1} g(x_i) + \frac{2h_n}{3} \sum_{i=0}^{n-1} g\left(\frac{x_i + x_{i+1}}{2}\right) + \frac{h_n}{6} g(x_n). \end{aligned}$$

This method is called the *Simpson's rule*.

3.1 Newton-Côtes Quadrature



Riemann Rule, trapezoidal rule and Simpson's rule

3.1 Newton-Côtes Quadrature

- Next, we consider the convergence rates of different rules.
- **Bernoulli Polynomials:** The *Bernoulli polynomials* $\{B_k(x), 0 \leq x \leq 1\}$ are defined recursively by $B_0(x) = 1$, and for $k \geq 1$,

$$B'_k(x) = kB_{k-1}(x) \quad \text{and} \quad \int_0^1 B_k(x) dx = 0.$$

- **Remarks:**

- By definition, we have $B_1(x) = x - 1/2$, $B_2(x) = x^2 - x + 1/6$, \dots
- Each $B_k(x)$ is a polynomial of order k . We need the condition $\int_0^1 B_k(x) dx = 0$ to determine the constant term in the polynomial.
- Note that by definition,

$$[B_{k+1}(1) - B_{k+1}(0)] = (k+1) \int_0^1 B_k(x) dx.$$

The condition $\int_0^1 B_k(x) dx = 0$ guarantees that $B_{k+1}(1) = B_{k+1}(0)$ for $k = 1, 2, \dots$.

3.1 Newton-Côtes Quadrature

- **Eular-Maclaurin Formula:** Let $m < n$ be two integers and let $g(x)$ be a p -times continuously differentiable function on the interval $[m, n]$. Then

$$\begin{aligned} \sum_{i=m+1}^n g(i) &= \int_m^n g(x) dx + \frac{g(n) - g(m)}{2} + \sum_{k=1}^{p-1} \frac{(-1)^{k+1} B_{k+1}(0)}{(k+1)!} (g^{(k)}(n) - g^{(k)}(m)) \\ &\quad + (-1)^{p+1} \sum_{i=m+1}^n \int_{i-1}^i \frac{g^{(p)}(x)}{p!} B_p(x+1-i) dx. \end{aligned}$$

- **Proof.**

– We first consider $\int_{i-1}^i g(x) dx$ for $i = m+1, \dots, n$. Then

$$\begin{aligned} \int_{i-1}^i g(x) dx &= \int_{i-1}^i g(x) d(x - i + 1/2) \\ &= g(x)(x - i + 1/2) \Big|_{x=i-1}^i - \int_{i-1}^i (x - i + 1/2) dg(x) \\ &= \frac{g(i) + g(i-1)}{2} - \int_{i-1}^i B_1(x+1-i) g'(x) dx. \end{aligned}$$

3.1 Newton-Côtes Quadrature

- – Thus, we have

$$\begin{aligned}
g(i) &= \int_{i-1}^i g(x) dx + \frac{g(i) - g(i-1)}{2} + \int_{i-1}^i B_1(x+1-i)g'(x) dx \\
&= \int_{i-1}^i g(x) dx + \frac{g(i) - g(i-1)}{2} + \int_{i-1}^i g'(x)dB_2(x+1-i)/2 \\
&= \int_{i-1}^i g(x) dx + \frac{g(i) - g(i-1)}{2} + \frac{g'(i)B_2(1) - g'(i-1)B_2(0)}{2!} - \frac{1}{2} \int_{i-1}^i B_2(x+1-i)g''(x)dx \\
&= \int_{i-1}^i g(x) dx + \frac{g(i) - g(i-1)}{2} + \frac{B_2(0)}{2!}(g'(i) - g'(i-1)) - \frac{1}{2} \int_{i-1}^i B_2(x+1-i)g''(x)dx \\
&= \dots\dots \\
&= \int_{i-1}^i g(x) dx + \frac{g(i) - g(i-1)}{2} + \sum_{k=1}^{p-1} \frac{(-1)^{k+1}B_{k+1}(0)}{(k+1)!} (g^{(k)}(i) - g^{(k)}(i-1)) \\
&\quad + (-1)^{p+1} \int_{i-1}^i \frac{g^{(p)}(x)}{p!} B_p(x+1-i) dx.
\end{aligned}$$

- Take sum of both sides for $i = m+1, \dots, n$, we obtain

$$\begin{aligned}
\sum_{i=m+1}^n g(i) &= \int_m^n g(x) dx + \frac{g(n) - g(m)}{2} + \sum_{k=1}^{p-1} \frac{(-1)^{k+1}B_{k+1}(0)}{(k+1)!} (g^{(k)}(n) - g^{(k)}(m)) \\
&\quad + (-1)^{p+1} \sum_{i=m+1}^n \int_{i-1}^i \frac{g^{(p)}(x)}{p!} B_p(x+1-i) dx.
\end{aligned}$$

3.1 Newton-Côtes Quadrature

- **Remarks:**

- $B_k(0)$ are called *Bernoulli numbers*. The Bernoulli numbers from $B_1(0)$ to $B_7(0)$ are $\frac{1}{2}, \frac{1}{6}, 0, -\frac{1}{30}, 0, \frac{1}{42}, 0$.
- We can show that $B_k(0)=0$ for $k=3,5,7,9, \dots$.
- The Euler-Maclaurin formula can also be written as

$$\begin{aligned} \sum_{i=m}^n g(i) &= \int_m^n g(x) dx + \frac{g(n) + g(m)}{2} + \sum_{s=1}^q \frac{B_{2s}(0)}{(2s)!} (g^{(2s-1)}(n) - g^{(2s-1)}(m)) \\ &\quad + \sum_{i=m+1}^n \int_{i-1}^i \frac{g^{(2q+1)}(x)}{p!} B_{2q+1}(x + 1 - i) dx. \end{aligned}$$

3.1 Newton-Côtes Quadrature

- Now we consider $\int_a^b g(x) dx$ for $-\infty < a < b < \infty$. Set $x_i = a + \frac{i(b-a)}{n}$ for $i = 0, 1, \dots, n$. Then $a = x_0 < x_1 < \dots < x_n = b$ forms a partition of the interval $[a, b]$.

– Let $h_n = (b - a)/n$. Define $\varphi(u) = g(a + h_n u)$. It is easy to know that

$$\int_a^b g(x) dx = \int_0^n g(a + h_n u) d(a + h_n u) = h_n \int_0^n \varphi(u) du.$$

– Applying the Euler-Maclaurin formula to $\int_0^n \varphi(u) du$, we obtain

$$\begin{aligned} \int_a^b g(x) dx &= h_n \sum_{i=0}^n \varphi(i) - h_n \cdot \frac{\varphi(0) + \varphi(n)}{2} - h_n \cdot \sum_{s=1}^q \frac{B_{2s}(0)}{(2s)!} (\varphi^{(2s-1)}(n) - \varphi^{(2s-1)}(0)) \\ &\quad - h_n \cdot \sum_{i=1}^n \int_{i-1}^i \frac{\varphi^{(2q+1)}(u)}{p!} B_{2q+1}(u + 1 - i) dx. \end{aligned}$$

3.1 Newton-Côtes Quadrature

- – Note that $\varphi(0) = g(a)$, $\varphi(i) = g(x_i)$, $\varphi(n) = g(b)$, $\varphi^{(k)}(u) = h_n^k g^{(k)}(a + h_n u)$. Then

$$\begin{aligned} \int_a^b g(x) dx &= h_n \sum_{i=0}^n g(x_i) - h_n \cdot \frac{g(a) + g(b)}{2} \\ &\quad - \sum_{s=1}^q h_n^{2s} \cdot \frac{B_{2s}(0)}{(2s)!} (g^{(2s-1)}(b) - g^{(2s-1)}(a)) + O(h_n^{2q+1}) \\ &= h_n \sum_{i=0}^n g(x_i) - h_n \cdot \frac{g(a) + g(b)}{2} - \frac{h_n^2}{12} (g'(b) - g'(a)) \\ &\quad + \frac{h_n^4}{720} (g^{(3)}(b) - g^{(3)}(a)) - \frac{h_n^6}{720 \cdot 42} (g^{(5)}(b) - g^{(5)}(a)) + \dots \end{aligned}$$

3.1 Newton-Côtes Quadrature

- Consider the convergence rates of different rules to estimate $\int_a^b g(x) dx$.
 - According to the Euler-Maclaurin formula, we have

$$\begin{aligned} h_n \sum_{i=0}^n g(x_i) &= \int_a^b g(x) dx + h_n \cdot \frac{g(a) + g(b)}{2} + \frac{h_n^2}{12} (g'(b) - g'(a)) \\ &\quad - \frac{h_n^4}{720} (g^{(3)}(b) - g^{(3)}(a)) + \frac{h_n^6}{720 \cdot 42} (g^{(5)}(b) - g^{(5)}(a)) + \cdots . \end{aligned}$$

- For the Riemann rule,

$$\begin{aligned} R_{1,n} &= h_n \sum_{i=0}^{n-1} g(x_i) = h_n \sum_{i=0}^n g(x_i) - h_n g(b) \\ &= \int_a^b g(x) dx + h_n \cdot \frac{g(a) + g(b)}{2} + O(h_n^2) - h_n g(b) \\ &= \int_a^b g(x) dx + O(1/n). \end{aligned}$$

3.1 Newton-Côtes Quadrature

- – Note that $h_n = (b - a)/n$, so $h_n = 2 \cdot h_{2n}$. We have

$$\begin{aligned} R_{2,n} &= h_n \sum_{i=0}^{n-1} g((x_i + x_{i+1})/2) \\ &= 2 \cdot h_{2n} \left[\sum_{i=0}^n g(x_i) + \sum_{i=0}^{n-1} g((x_i + x_{i+1})/2) \right] - h_n \sum_{i=0}^n g(x_i) \\ &= 2 \left[\int_a^b g(x) dx + h_{2n} \cdot \frac{g(a) + g(b)}{2} + \frac{h_{2n}^2}{12} (g'(b) - g'(a)) + O(h_n^4) \right] \\ &\quad - \left[\int_a^b g(x) dx + h_n \cdot \frac{g(a) + g(b)}{2} + \frac{h_n^2}{12} (g'(b) - g'(a)) + O(h_n^4) \right] \\ &= \int_a^b g(x) dx - \frac{h_n^2}{24} (g'(b) - g'(a)) + O(h_n^4) \\ &= \int_a^b g(x) dx + O(1/n^2). \end{aligned}$$

3.1 Newton-Côtes Quadrature

- – For the trapezoidal rule, we have

$$\begin{aligned}T_n &= \frac{h_n}{2}g(x_0) + h_n \sum_{i=1}^{n-1} g(x_i) + \frac{h_n}{2}g(x_n) \\&= h_n \sum_{i=0}^n g(x_i) - h_n \cdot \frac{g(a) + g(b)}{2} \\&= \int_a^b g(x) dx + h_n \cdot \frac{g(a) + g(b)}{2} + \frac{h_n^2}{12}(g'(b) - g'(a)) + O(h_n^4) - h_n \cdot \frac{g(a) + g(b)}{2}.\end{aligned}$$

- For the Simpson's rule, we have

$$\begin{aligned}S_n &= \frac{h_n}{6}g(x_0) + \frac{h_n}{3} \sum_{i=1}^{n-1} g(x_i) + \frac{2h_n}{3} \sum_{i=0}^{n-1} g\left(\frac{x_i + x_{i+1}}{2}\right) + \frac{h_n}{6}g(x_n) \\&= \frac{4}{3} \cdot h_{2n} \left[\sum_{i=0}^n g(x_i) + \sum_{i=0}^{n-1} g((x_i + x_{i+1})/2) \right] - \frac{h_n}{3} \sum_{i=0}^n g(x_i) \\&\quad - \frac{h_n}{3} \cdot \frac{g(a) + g(b)}{2}.\end{aligned}$$

3.1 Newton-Côtes Quadrature

- – Applying the Euler-Maclaurin formula, we have

$$\begin{aligned} S_n &= \frac{4}{3} \left[\int_a^b g(x) dx + \frac{h_n}{2} \cdot \frac{g(a) + g(b)}{2} + \frac{h_n^2/4}{12} (g'(b) - g'(a)) + O(h_n^4) \right] \\ &\quad - \frac{1}{3} \left[\int_a^b g(x) dx + h_n \cdot \frac{g(a) + g(b)}{2} + \frac{h_n^2}{12} (g'(b) - g'(a)) + O(h_n^4) \right] \\ &\quad - \frac{h_n}{3} \cdot \frac{g(a) + g(b)}{2} \\ &= \int_a^b g(x) dx + O(h_n^4) \\ &= \int_a^b g(x) dx + O(1/n^4). \end{aligned}$$

- **Choice of n :** Let Π_n be the Newton-Côtes quadrature estimates using n subintervals. In practice, we can choose n so that the relative error $\frac{|\Pi_n - \Pi_{n/2}|}{\Pi_{n/2}}$ is less than a given threshold value.

3.2 Gaussian Quadrature*

- In general, if we use $m + 1$ equally spaced points x_0, \dots, x_m , we can approximate $\int_a^b g(x) dx$ by $\sum_{i=0}^m a_i g(x_i)$, so that

$$\int_a^b g(x) dx = \sum_{i=0}^m a_i \cdot g(x_i)$$

whenever g is a polynomial of **degree not exceeding** m .

– Define

$$\bar{p}_i(x) = \prod_{k=0, k \neq i}^m \frac{x - x_k}{x_i - x_k}.$$

Then $p_i(x_i) = 1$ and $p_i(x_k) = 0$ for $k = 0, \dots, m$ and $k \neq i$.

– Let

$$\hat{g}(x) = \sum_{i=0}^m g(x_i) \bar{p}_i(x).$$

We have that $\hat{g}(x)$ is a m th degree polynomial (its degree may be less than m), and it satisfies $\hat{g}(x_i) = g(x_i)$ for $j = 0, \dots, m$.

3.2 Gaussian Quadrature*

- – Note that there is **only one** m th degree polynomial $p(\cdot)$ satisfying $p(x_i) = g(x_i)$ for $j = 0, \dots, m$. If g is a also m th degree polynomial, we have $g(x) = \hat{g}(x)$ and

$$\int_a^b g(x) dx = \int_a^b \hat{g}(x) dx = \sum_{i=0}^m \int_a^b \bar{p}_i(x) dx \cdot g(x_i).$$

- If the constraint of equally spaced points is removed, we can choose specially designed x_0, x_1, \dots, x_m so that the equality may hold for higher order polynomials.

3.2 Gaussian Quadrature*

- The *Gaussian quadrature* proposes to choose x_0, \dots, x_m so that

$$\int g(x)w(x) dx = \sum_{i=0}^m a_i \cdot g(x_i)$$

whenever g is a polynomial of **degree not exceeding** $2m + 1$.

- Here $w(x)$ is a nonnegative function and $\int |x^k|w(x) dx < \infty$ for $k \geq 0$.
- When $w(x) = I(a \leq x \leq b)$, $\int g(x)w(x) dx = \int_a^b g(x) dx$.
- When $w(x) = e^{-x}I(0 \leq x < \infty)$,

$$\int g(x)w(x) dx = \int_0^\infty g(x)e^{-x} dx = E[g(X)],$$

where X follows an exponential distribution.

- When $w(x) = \frac{1}{\sqrt{2\pi}}e^{-x^2/2}$ for $-\infty < x < \infty$,

$$\int g(x)w(x) dx = \int_{-\infty}^\infty g(x)\frac{1}{\sqrt{2\pi}}e^{-x^2/2} dx = E[g(X)], \quad \text{where } X \sim N(0, 1).$$

3.2 Gaussian Quadrature*

- **Orthogonal Polynomials:** Given nonnegative $w(x)$ satisfying $\int |x^k| w(x) dx < \infty$ for $k \geq 0$, we can find a series of polynomials $q_0(x)$, $q_1(x)$, $q_2(x)$, \dots that satisfy the following conditions.

- Each $q_k(x)$ is a k th degree polynomial.
- For $i \neq j$, $q_i(x)$ and q_j are *orthogonal* with respect to $w(x)$, that is

$$\langle q_i, q_j \rangle_w := \int q_i(x) q_j(x) w(x) dx = 0.$$

- **Remark:** When $q_k(x)$ also satisfies $\langle q_k, q_k \rangle_w = 1$ for all k , we call $q_0(x)$, $q_1(x)$, $q_2(x)$, \dots as *ortho-normal bases* with respect to $w(x)$.

3.2 Gaussian Quadrature*

- A orthogonal polynomials with respect to $w(x)$ can be constructed by applying the *Gram-Schmidt process* to $\{1, x, x^2, \dots\}$. Specifically, we let $q_0(x) = 1$ and let

$$q_k(x) = x^k - \frac{\langle q_{k-1}, x^k \rangle_w}{\langle q_{k-1}, q_{k-1} \rangle_w} \cdot q_{k-1}(x) - \dots - \frac{\langle q_0, x^k \rangle_w}{\langle q_0, q_0 \rangle_w} \cdot q_0(x).$$

- When $w(x) = I(-1 \leq x \leq 1)$, the polynomials are called the *Legendre polynomials*.
- When $w(x) = e^{-x}I(0 \leq x < \infty)$, the polynomials are called the *Laguerre polynomials*.
- When $w(x) = e^{-x^2/2}$, the polynomials are called the *corrected Hermite polynomials*.

3.2 Gaussian Quadrature*

- **Gaussian Quadrature:** Given $w(x) \geq 0$ and $m > 0$, find the orthogonal polynomials $q_0(x), \dots, q_{m+1}(x)$ with respect to $w(x)$.

– Let $x_0 < x_1 < \dots < x_m$ be the solutions of $q_{m+1}(x) = 0$.

– We estimate $\int g(x)w(x) dx$ by

$$\sum_{i=0}^m \int \bar{p}_i(x)w(x) dx \cdot g(x_i),$$

where $\bar{p}_i(x) = \prod_{k=0, k \neq i}^m \frac{x-x_k}{x_i-x_k}$.

- **Remark:**

– Here $x_0 < x_1 < \dots < x_m$ and $\int \bar{p}_i(x)w(x) dx$ do not depend on g , they can be calculated in advance.

– Usually, we will not use large m due to potential numerical imprecision introduced by computer roundoff error, for example, $m \leq 8$.

3.2 Gaussian Quadrature*

- – When g is a $(2m + 1)$ th degree polynomial, it can be written as

$$g(x) = s(x)q_{m+1}(x) + r(x),$$

where s and r are polynomials with degree not exceeding m .

- * Note that $s(x) = b_m q_m(x) + \cdots + b_0 q_0(x)$ for some b_0, \cdots, b_m . Then

$$\int s(x)q_{m+1}(x)w(x) dx = 0.$$

- * Since r is a polynomial with degree not exceeding m , we have

$$r(x) = \sum_{i=0}^m \bar{p}_i(x)r(x_i).$$

- * Also note that $x_0 < x_1 < \cdots < x_m$ are the roots of $q_{m+1}(x)$. Hence,

$$g(x_i) = s(x_i)q_{m+1}(x_i) + r(x_i) = r(x_i).$$

3.2 Gaussian Quadrature*

- – * Finally, we have

$$\begin{aligned}\int g(x)w(x) dx &= \int [s(x)q_{m+1}(x) + r(x)]w(x) dx \\ &= \int r(x)w(x) dx \\ &= \int \left[\sum_{i=0}^m \bar{p}_i(x)r(x_i) \right] w(x) dx \\ &= \int \left[\sum_{i=0}^m \bar{p}_i(x)g(x_i) \right] w(x) dx \\ &= \sum_{i=0}^m \int \bar{p}_i(x)w(x) dx \cdot g(x_i).\end{aligned}$$

3.3 Frequently Encountered Problems

- **Range of Integration:** Consider integrals over infinite ranges.

- We can choose $a < b$ so that $\int_a^b g(x) dx \approx \int_{-\infty}^{\infty} g(x) dx$.
- We can also turn the infinite range to a finite range through one-to-one transformations. For example, we have

$$\begin{aligned}\int_{-\infty}^{\infty} g(x) dx &= \int_0^1 g\left(\log \frac{u}{1-u}\right) d\log \frac{u}{1-u} \\ &= \int_0^1 g\left(\log \frac{u}{1-u}\right) \cdot \frac{d\log \frac{u}{1-u}}{du} du\end{aligned}$$

by letting $u = e^x/(1 + e^x)$. Some other useful transformations include $1/x$, $x/(1 + x)$ and $\exp\{-x\}$.

3.3 Frequently Encountered Problems

- **Multiple Integrals:** Consider calculation of $\int_a^b \int_c^d g(x, y) dy dx$.
 - Define $x_i = a + i(b - a)/n$ for $i = 0, 1, \dots, n$ and $y_j = c + j(d - c)/m$ for $j = 0, 1, \dots, m$. Then

$$\int_a^b \int_c^d g(x, y) dy dx \approx \frac{b - a}{n} \cdot \frac{d - c}{m} \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} g\left(\frac{x_i + x_{i+1}}{2}, \frac{y_j + y_{j+1}}{2}\right).$$

- We can also consider $\int_c^d g(x, y) dy$ as $\varphi(x)$. Then

$$\int_a^b \int_c^d g(x, y) dy dx = \int_a^b \varphi(x) dx \approx \sum_{i=0}^n a_i \cdot \varphi(x_i).$$

We can use univariate quadrature approximations (*e.g.*, the Simpson's rule) to calculate $\varphi(x_i) = \int_c^d g(x_i, y) dy$ for each x_i .

Homework

1. Suppose that X_1, \dots, X_n are i.i.d. from the $N(\theta, 4)$ distribution. Assume that the prior distribution of θ is $N(0, 10)$. Find the posterior distribution of θ given $X_1 = x_1, \dots, X_n = x_n$.

2. To derive the Simpson's rule, prove that

$$\int_{x_i}^{x_{i+1}} p_{i0}(x) dx = \int_{x_i}^{x_{i+1}} p_{i2}(x) dx = \frac{h_n}{6} \quad \text{and} \quad \int_{x_i}^{x_{i+1}} p_{i1}(x) dx = \frac{2h_n}{3}.$$

3. Let X follow a Uniform $[1, 3]$ distribution. Compute $E(2/X) = \int_1^3 (1/x) dx$ using the Riemann rule (*i.e.*, $R_{1,n}$ and $R_{2,n}$), the trapezoidal rule (*i.e.*, T_n) and the Simpsons rule (*i.e.*, $S_{n/2}$) with $n = 4, 8, 16, 32, 64$. Discuss your results.

Homework

4. Suppose that X is from the $N(\mu, 9/7)$ distribution and assume that the prior distribution of μ is the Cauchy(5,2) distribution with density $f_{\mu}(\mu) = \frac{1}{2\pi \left[1 + \left(\frac{\mu-5}{2}\right)^2\right]}$ for $-\infty < \mu < \infty$. Assume that $X = 5.3871$ is observed.
- (a) Using a numerical integration method of your choice, show that the proportionality constant k is roughly 7.84654. (In other words, find k such that $k \times \int (\text{prior}) \times (\text{likelihood}) d\mu = 1$.)
- (b) Using the value 7.84654 from (a), determine the posterior probability that $2 \leq \mu \leq 8$ using the Riemann rule (*i.e.*, $R_{1,n}$ and $R_{2,n}$), the trapezoidal rule (*i.e.*, T_n) and the Simpsons rule (*i.e.*, $S_{n/2}$). Compute the estimates until relative error within 0.0001 is achieved for the slowest method. Table the results.

Homework

4. (c) Use the transformation $u = 1/\mu$ to calculate the posterior probability that $\mu > 3$.