

Week 5

2. Consider the integral:

$$\theta = \int_0^{10} x \ln(x) dx$$

- (a) Use the simple Monte Carlo estimator to estimate the expected value, where the importance function is the $Uniform(0, 10)$ distribution. Call this $\hat{\theta}$.
- (b) Write an exact expression for $\text{Var}[\hat{\theta}]$. You do not need to evaluate this integral by hand. Then, compute this integral using `integrate()` in R.
- Disclaimer:** you need to know how to integrate for the tests; we also just want you to learn the `integrate()` function as well. You will not be using the `integrate()` function in R for the term tests or exam.
- (c) Recall in lecture, we said the Monte Carlo estimate for the variance of the estimator for the integral is:

$$\widehat{\text{Var}}[\hat{\theta}] = \frac{\hat{\sigma}^2}{n} = \frac{\sum_{i=1}^n [g(x_i) - \bar{g}(x)]^2}{n^2}$$

Using this equation, compute $\widehat{\text{Var}}[\hat{\theta}]$ in R. Use $n = 10^4$.

- (d) Compare the MC estimator against the theoretical variance of $\hat{\theta}$. Use `all.equal()`, which will report the mean relative difference.

$$(a) \quad \theta = 10 \int_0^{10} \left(\frac{1}{10} \cdot x \cdot \ln(x) \right) dx$$

$$= 10 E_{U(0,10)} [x \cdot \ln(x)]$$

Samples from $U \sim \text{Uniform}(0, 10)$.

by SLN, the sample MC estimator is

$$\hat{\theta} = 10 \times \frac{1}{n} \sum_{i=1}^n u_i \cdot \ln(u_i)$$

(b).

$$\begin{aligned} \text{Var}[\hat{\theta}] &= \text{Var}\left[\frac{10}{n} \sum_{i=1}^n u_i \cdot \ln(u_i)\right] \\ &= \frac{100}{n^2} \text{Var}\left[\sum_{i=1}^n u_i \cdot \ln(u_i)\right] \\ &= \frac{100}{n^2} \sum_{i=1}^n \text{Var}[u_i \cdot \ln(u_i)] \end{aligned}$$

$$= \frac{100}{n^2} \sum_{i=1}^n \left(E[(u_i \cdot \ln(u_i))^2] - (E[u_i \cdot \ln(u_i)])^2 \right)$$

$$\text{Var}(X+Y)$$

$$= \text{Var}(X) + \text{Var}(Y)$$

$$\text{Var}(Y) = E(Y^2) - (E(Y))^2$$

$$E(Y) = \int y \cdot f(y) dy$$

$$= \frac{100}{n^2} \sum_{i=1}^n \left(\int_0^{10} (u_i \cdot \ln(u_i))^2 \cdot \frac{1}{10} du_i - \left(\int_0^{10} u_i \cdot \ln(u_i) \cdot \frac{1}{10} du_i \right)^2 \right)$$

C

$$= \frac{100}{n^2} n \cdot C = \frac{100}{n} \left(\int_0^{10} (u_i \cdot \ln(u_i))^2 \cdot \frac{1}{10} du_i - \left(\int_0^{10} u_i \cdot \ln(u_i) \cdot \frac{1}{10} du_i \right)^2 \right)$$



(C)

$$\widehat{\text{Var}}[\hat{\theta}] = \frac{\hat{\sigma}^2}{n} = \frac{\sum_{i=1}^n \left[g(x_i) - \bar{g}(x) \right]^2}{n^2}$$

$$n = 10^4$$

$$n \leftarrow 10^4$$

$$u \leftarrow \text{runif}(n, 0, 10)$$

Uniform (0, 1)
 $u \leftarrow \text{runif}(n)$

$$\text{mc-est} \leftarrow \text{sum}\left((10 * \log(u) * u - \text{mean}(10 * \log(u) * u))^2 \right) / n^2$$

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n 10 u_i \cdot \ln(u_i)$$

$f(x)$

(b) Integrate ()

$$\text{fun1} = \int_0^{10} (u_i \ln(u_i))^2 \cdot \frac{1}{10} du_i \quad E(Y^2)$$

$$\text{fun2} = \int_0^{10} (u_i \ln(u_i)) \cdot \frac{1}{10} du_i \quad E(Y)$$

```
fun1 <- function(x){log(x)^2*x^2/10}  
fun2 <- function(x){log(x)*x/10}
```

```
ex2 <- integrate(fun1, 0, 10)  
ex_sq <- integrate(fun2, 0, 10)  
exact <- 100 * (ex2$value - (ex_sq$value)^2) / n
```

↗ .

$$\frac{100}{n} \left(\int_0^{10} (u_i \ln(u_i))^2 \cdot \frac{1}{10} du_i - \left(\int_0^{10} u_i \ln(u_i) \cdot \frac{1}{10} du_i \right)^2 \right)$$

Test 1

Q3.

$z_1, z_2 \dots z_n$ i.i.d. $z_i \sim N(0, 1)$ for all $i = 1, 2 \dots n$.

chi-squared distribution

$$\sum_{i=1}^n z_i^2 \sim \chi_n^2$$

Use rnorm() ... $n = 10^4$ samples from the $\chi_{(30)}^2$.

R codes

$$n \leftarrow 10^4$$

vector. values \leftarrow numeric(n)

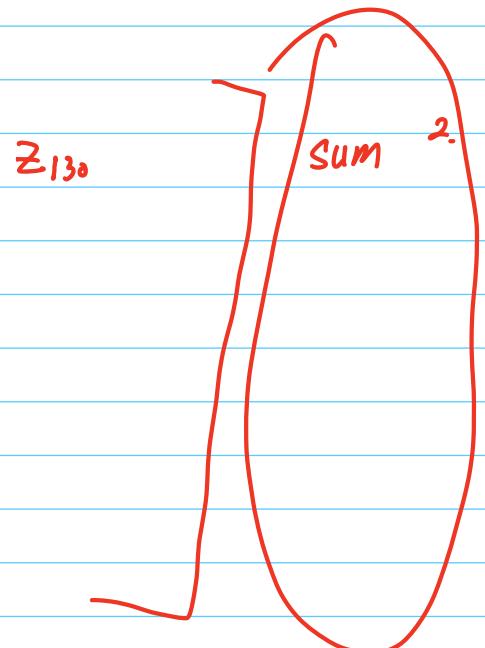
loop for (i in 1:n) {

values[i] \leftarrow sum(rnorm(30, mean=0, sd=1)^2)

}

SumRow

1 $z_1 \quad z_2 \dots \dots$
2
3
:
 10^4



Q4. $f_i(x)$ density $i = 1, 2 \dots k$.

$f_1(x), \dots, f_k(x)$.

π_1, \dots, π_k weights.

$$f(x) := \sum_{i=1}^k \pi_i f_i(x)$$

where $0 \leq \pi_i \leq 1$ & $\sum_{i=1}^k \pi_i = 1$

(a) $f(x)$ non-negative

$$\int_{-\infty}^{\infty} f(x) dx = 1$$

(D) Non-negative.

Since $f_i(x)$ is valid density $\Rightarrow 0 \leq f_i(x)$

And $0 \leq \pi_i \leq 1$

$$\Rightarrow 0 \leq \sum_{i=1}^n \pi_i f_i(x)$$

$$\int(A+B)$$

$$= \int A + \int B$$

$$\textcircled{2} \quad \int_{-\infty}^{\infty} f(x) dx = \int_{-\infty}^{\infty} \sum_{i=1}^n \pi_i f_i(x) dx$$

$$= \sum_{i=1}^n \int_{-\infty}^{\infty} \pi_i \cdot f_i(x) dx.$$

$$= \sum_{i=1}^n \pi_i \underbrace{\int_{-\infty}^{\infty} f_i(x) dx}_{1} = \sum_{i=1}^n \pi_i = 1$$

(b) suppose X_i has f_i .

$$\mu_i = E[X_i] = \int_{-\infty}^{\infty} x \cdot f_i(x) dx.$$

$$\sigma_i^2 := V[X_i]$$

$$WTS \Rightarrow \sigma^2: V[X] = \sum_{i=1}^k \pi_i \sigma_i^2 + \sum_{i=1}^k \pi_i (\mu_i - \mu)^2$$

$$V[X] = E[(X - \mu)^2]$$

$$= \int_{-\infty}^{\infty} (x - \mu)^2 \cdot \sum_{i=1}^k \pi_i \cdot f_i(x) dx$$

$$= \int_{-\infty}^{\infty} (x^2 - 2x\mu + \mu^2) \cdot \sum_{i=1}^k \pi_i \cdot f_i(x) dx$$

$$= \sum_{i=1}^k \pi_i \int_{-\infty}^{\infty} (x^2 - 2x\mu + \mu^2) f_i(x) dx$$

$$= \sum_{i=1}^k \pi_i \left[\int_{-\infty}^{\infty} x^2 \cdot f_i(x) dx - \int_{-\infty}^{\infty} 2x\mu \cdot f_i(x) dx + \int_{-\infty}^{\infty} \mu^2 \cdot f_i(x) dx \right]$$

$$= \sum_{i=1}^k \pi_i \left[E[X_i^2] - 2\mu\mu_i + \mu^2 \right]$$

$$= \sum_{i=1}^k \pi_i \left[V[X_i] + (E[X_i])^2 - 2\mu\mu_i + \mu^2 \right]$$

$$= \sum_{i=1}^k \pi_i \left[\sigma_i^2 + \mu_i^2 - 2\mu\mu_i + \mu^2 \right]$$

$$= \sum_{i=1}^k \pi_i (\sigma_i^2 + (\mu_i - \mu)^2)$$

$$= \sum_{i=1}^k \pi_i \sigma_i^2 + \sum_{i=1}^k \pi_i (\mu_i - \mu)$$