HW8

2024-11-06

$\mathbf{Q}\mathbf{1}$

Write a function which takes 2 arguments n and k which are positive integers. It should return the nXn matrix:

$$\begin{pmatrix} k & 1 & 0 & 0 & \dots & 0 & 0 \\ 1 & k & 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & k & 1 & \dots & 0 & 0 \\ 0 & 0 & 1 & k & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & k & 1 \\ 0 & 0 & 0 & 0 & \dots & 1 & k \end{pmatrix}$$

Call the function defined above for n = 6 and k = 5, and provide the matrix you obtain.

One with a for loop, one without.

```
# nkMatFor <- function(n, k) {</pre>
#
    mat \leftarrow matrix(0, n, n)
#
   diag(mat) \leftarrow k
#
   for (i in 1:(n-1)) {
      mat[i, i+1] \leftarrow 1
#
      mat[i+1, i] <- 1
#
#
#
    return(mat)
# }
#
# n6k5 <- nkMatFor(n = 6,
# n6k5
```

```
nkMat <- function(n, k) {
  mat <- matrix(0, n, n)

diag(mat) <- k

mat[row(mat) == col(mat) + 1] <- 1
  mat[row(mat) == col(mat) - 1] <- 1

return(mat)</pre>
```

```
## [1,1] [,2] [,3] [,4] [,5] [,6]
## [1,1] 5 1 0 0 0 0 0
## [2,1] 1 5 1 0 0 0 0
## [3,1] 0 1 5 1 0 0
## [4,1] 0 0 1 5 1 0
## [5,1] 0 0 0 1 5 1 5
## [6,1] 0 0 0 0 1 5
```

Consider the continuous function

$$f(x) = \begin{cases} x^2 + 2x + 3 & \text{if } x < 0\\ x + 3 & \text{if } 0 \le x < 2\\ x^2 + 4x - 7 & \text{if } 2 \le x \end{cases}$$

Write a function tmpFn which takes a single argument xVec. The function should return the vector of values of the function f(x) evaluated at the values xVec. Plot the function f(x) for -3 < x < 3.

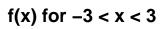
```
tmpFn <- function(xVec) {
  result <- numeric(length(xVec))

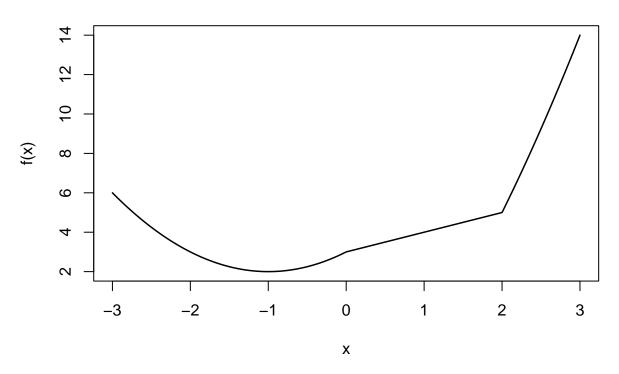
result[xVec < 0] <- xVec[xVec < 0]^2 + 2 * xVec[xVec < 0] + 3
  result[xVec >= 0 & xVec < 2] <- xVec[xVec >= 0 & xVec < 2] + 3
  result[xVec >= 2] <- xVec[xVec >= 2]^2 + 4 * xVec[xVec >= 2] - 7

result
}
```

[1] TRUE

```
plot(x = xValues, y = yValues,
    type = "l",
    col = "black",
    lwd = 1.5,
    xlab = "x",
    ylab = "f(x)",
    main = "f(x) for -3 < x < 3")</pre>
```





$\mathbf{Q3}$

[1] 1

Greatest common divisor of two integers The greatest common divisor (gcd) of two integers m and n can be calculated using Euclid's Algorithm: Divide m by n. If the remainder is zero, the gcd is n. If not, divide n by the remainder. If the remainder is zero, then the previous remainder is the gcd. If not, continue dividing the remainder into previous remainder until a remainder of zero is obtained. The gcd is the value of the last nonzero remainder. Write a function gcd(m,n) using a while loop to find the gcd of two integers m and n.

```
gcd <- function(m, n) {
    m <- abs(m)
    n <- abs(n)

while (n != 0) {
        remainder <- m %% n
        m <- n
        n <- remainder
    }

# Testing examples
gcd(m = 4*7,
        n = 4*4*4*7)

## [1] 28
gcd(m = 47,
        n = 93)</pre>
```

$\mathbf{Q4}$

eQTL mapping. (The following problem was suggested by Professor Dan Nettleton.) Write a function order.matrix which takes in a matrix x and returns a matrix containing the row and column indices of the sorted values of x. Test this function on a 4X3 matrix of independent χ_1^2 pseudo-random deviates.

```
order.matrix <- function(mat) {
  sorted.indices <- order(mat)
  result <- arrayInd(sorted.indices, dim(mat))
  colnames(result) <- c("row", "col")
  result
}</pre>
```

Had a previous version of this before discovering arrayInd:

[1] 4 3

testMat

```
## [,1] [,2] [,3]
## [1,] 1.521034 4.268462e-01 3.0177684
## [2,] 0.587395 4.222746e-01 0.4038763
## [3,] 3.732687 4.370368e-05 0.5225843
## [4,] 2.963479 1.507955e-04 0.3116673

testResults <- order.matrix(mat = testMat)
testResults</pre>
```

```
## row col

## [1,] 3 2

## [2,] 4 2

## [3,] 4 3

## [4,] 2 3

## [5,] 2 2
```

```
## [6,] 1
           2
## [7,] 3
          3
## [8,]
          1
## [9,]
       1
          1
## [10,]
       4
          1
## [11,]
       1
          3
## [12,] 3
          1
```

dim(testResults)

[1] 12 2

Polar representation of a number. Let $x \in \mathbb{R}^p$. The polar respresentation of $\mathbf{x} = (x_1, x_2, ..., x_p)$ is given by $(R, \theta_1, \theta_2, ..., \theta_{p-1})$, where:

$$x_1 = R \cos \theta_1$$

$$x_2 = R \sin \theta_1 \cos \theta_2$$

$$x_3 = R \sin \theta_1 \sin \theta_2 \cos \theta_3$$

$$\dots = \dots$$

$$x_{p-1} = R \prod_{i=1}^{p-2} \sin \theta_i \cos \theta_{p-1}$$

$$x_p = R \prod_{i=1}^{p-1} \sin \theta_i,$$

where $0 \le R < \infty, 0 \le \theta_1 < 2\pi$ and $0 \le \theta_i < \pi$ i = 2, 3, . . . , p - 1.

(a)

Write a function polaroid which takes in an arbitrary p-dimensional vector \mathbf{x} and provides its polar representation as a vector, with the first element as R and the remainder being $\theta_1, \theta_2, \dots, \theta_{p-1}$.

```
polaroid <- function(x) {</pre>
  R \leftarrow sqrt(sum(x^2))
  # if radius is length 0, then no angles
  if (R == 0) return(c(R))
  # for an n length input, return length n, but n-1 are thetas
  theta <- numeric(length(x) - 1)
  # atan for arctan
  theta[1] \leftarrow atan2(x[2], x[1])
  if (theta[1] < 0) {</pre>
    theta[1] <- theta[1] + 2 * pi
  }
  p <- length(x)</pre>
  # only need to do function once if input is 2
  # else need to start iterating
  if (p > 2) {
    for (i in 2:(p - 1)) {
      numerator <- sqrt(sum(x[i:p]^2))</pre>
      denominator <- sqrt(sum(x[(i-1):p]^2))</pre>
      theta[i] <- acos(numerator / denominator)</pre>
    }
  }
  dat <- c(R, theta)
  dat
}
```

```
x \leftarrow c(1, 2, 3)
polarRep <- polaroid(x)</pre>
polarRep
## [1] 3.7416574 1.1071487 0.2705498
```

(b)

##

Write a function normalize which takes in a matrix and returns its normalized form: i.e., the matrix with rows scaled such that the sum of squares of each row is equal to 1.

```
normalize <- function(x) {</pre>
  rowNorm <- sqrt(rowSums(x^2))</pre>
  normMat <- x / rowNorm</pre>
  normMat[is.nan(normMat)] <- 0</pre>
  normMat
}
# here's one using sweep
# normalize <- function(x) {</pre>
# rowNorm <- sqrt(rowSums(x^2))
   normMat \leftarrow sweep(x, 1, row_norms, FUN = "/")
    normMat[is.nan(normMat)] <- 0</pre>
    normMat
# }
set.seed(42)
testMat <- matrix(data = rnorm(12),</pre>
                   nrow = 4,
                   ncol = 3)
testMat
                            [,2]
##
               [,1]
## [1,] 1.3709584 0.40426832 2.0184237
## [2,] -0.5646982 -0.10612452 -0.0627141
## [3,] 0.3631284 1.51152200 1.3048697
## [4,] 0.6328626 -0.09465904 2.2866454
rowSums(testMat^2)
## [1] 6.1169942 0.3340795 4.1192458 5.6382226
normMatEx <- normalize(x = testMat)</pre>
normMatEx
                                        [,3]
```

[,2]

[,1]

[1,] 0.5543132 0.16345593 0.8160999 **##** [2,] -0.9769930 -0.18360767 -0.1085026 **##** [3,] 0.1789169 0.74474161 0.6429220 **##** [4,] 0.2665252 -0.03986493 0.9630032

```
rowSums(normMatEx^2)
```

```
## [1] 1 1 1 1
```

(c)

Obtain a 1000X5 matrix \mathbf{y} of N(0,1) pseudo-random deviates. Use apply and normalize to obtain the normalized values. Call this matrix \mathbf{z} . We test whether the columns of \mathbf{z} are uniform on U(-1,1). One may test whether a sample $x \sim U(-1,1)$ using ks.test(x, "punif", min=-1, max=1) where punif represents the cumulative distribution function of the uniform over range (-1,1). Summarize your results.

```
set.seed(42)
y \leftarrow matrix(data = rnorm(1000 * 5),
             nrow = 1000,
             ncol = 5)
z \leftarrow apply(X = y,
            MARGIN = 2,
            FUN = function(col) {
              normalize(x = matrix(col, ncol = 1))
            )
ksTests \leftarrow apply(X = z,
                    MARGIN = 2,
                    FUN = function(col) {
                      ks.test(col, "punif", min = -1, max = 1)
                      }
                    )
ksTests
```

```
## [[1]]
##
   Asymptotic one-sample Kolmogorov-Smirnov test
##
##
## data: col
## D = 0.515, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
##
## [[2]]
##
##
   Asymptotic one-sample Kolmogorov-Smirnov test
##
## data: col
## D = 0.503, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
##
## [[3]]
```

```
##
    Asymptotic one-sample Kolmogorov-Smirnov test
##
##
## data: col
## D = 0.505, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
##
## [[4]]
##
##
    Asymptotic one-sample Kolmogorov-Smirnov test
##
## data: col
## D = 0.52, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
##
## [[5]]
##
##
    Asymptotic one-sample Kolmogorov-Smirnov test
##
## data: col
## D = 0.501, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

The KS tests provide small p-values, which is evidence to support rejecting the null hypothesis that the column vectors are distributed by U(-1,1), each of the five vectors each column. As we have evidence to suggest the vectors are not distributed by U(-1,1), then we have evidence that our efforts to normalize the vectors did not effectively transform the data into a uniform distribution over this range (at least when normalizing the sum of squares of each row).

(d)

Obtain polar representations of y using your function polaroid and test whether $R^2 \sim \chi_5^2$ distribution.

Provide a page of histograms or boxplots of $\theta_1, \theta_2, \theta_3, \theta_4$. Test whether these are from the uniform distributions on their respective ranges, i.e., $[0, 2\pi)$ for θ_1 , and $[0, \pi)$ for $\theta_2, \theta_3, \theta_4$.

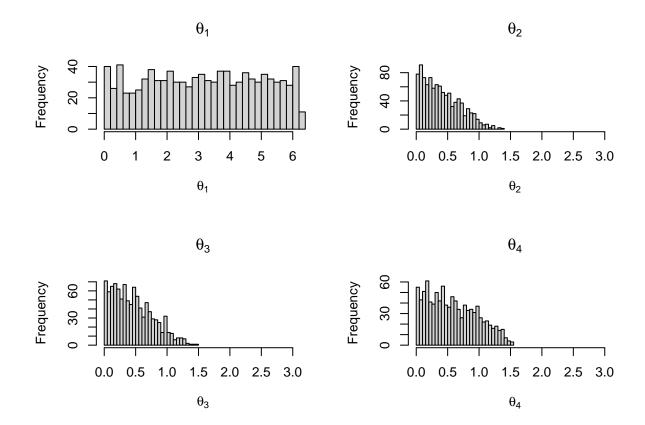
```
rSq <- rVal^2
csTest <- ks.test(rSq, "pchisq", df = 5)
csTest</pre>
```

```
##
## Asymptotic one-sample Kolmogorov-Smirnov test
##
```

```
## data: rSq
## D = 0.017123, p-value = 0.9311
## alternative hypothesis: two-sided
```

The large p-value provides evidence in support of not rejecting the null hypothesis that $R^2 \sim \chi_5^2$, such that we have evidence that $R^2 \sim \chi_5^2$.

```
par(mfrow = c(2, 2))
hist(thetaVal[, 1],
    breaks = 30,
    main = expression(theta[1]),
    xlab = expression(theta[1]),
     xlim = c(0, 2 * pi))
hist(thetaVal[, 2],
     breaks = 30,
     main = expression(theta[2]),
    xlab = expression(theta[2]),
     xlim = c(0, pi)
hist(thetaVal[, 3],
    breaks = 30,
     main = expression(theta[3]),
    xlab = expression(theta[3]),
    xlim = c(0, pi)
hist(thetaVal[, 4],
    breaks = 30,
    main = expression(theta[4]),
    xlab = expression(theta[4]),
    xlim = c(0, pi)
```



```
theta1Test <- ks.test(x = thetaVal[, 1] / (2 * pi),</pre>
                        y = "punif",
                       min = 0,
                       max = 1)
theta2Test <- ks.test(x = thetaVal[, 2] / pi,</pre>
                        y = "punif",
                       min = 0,
                       max = 1)
theta3Test <- ks.test(x = thetaVal[, 3] / pi,</pre>
                        y = "punif",
                       min = 0,
                       max = 1)
theta4Test <- ks.test(x = thetaVal[, 4] / pi,</pre>
                        y = "punif",
                       min = 0,
                       max = 1)
list(theta1 = theta1Test,
     theta2 = theta2Test,
     theta3 = theta3Test,
     theta4 = theta4Test)
```

```
## $theta1
##

## Asymptotic one-sample Kolmogorov-Smirnov test
##
```

```
## data: thetaVal[, 1]/(2 * pi)
## D = 0.017778, p-value = 0.9101
## alternative hypothesis: two-sided
##
##
## $theta2
##
   Asymptotic one-sample Kolmogorov-Smirnov test
##
##
## data: thetaVal[, 2]/pi
## D = 0.65547, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
## $theta3
##
   Asymptotic one-sample Kolmogorov-Smirnov test
##
##
## data: thetaVal[, 3]/pi
## D = 0.62241, p-value < 2.2e-16
## alternative hypothesis: two-sided
##
## $theta4
##
##
   Asymptotic one-sample Kolmogorov-Smirnov test
##
## data: thetaVal[, 4]/pi
## D = 0.54649, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

The above statistical tests may be summarized as follows:

```
H_0: \theta_1 \sim U[0, 2\pi)
```

 H_0 : individually and respectively $\theta_2, \theta_3, \theta_4 \sim U[0, \pi)$

We do not have evidence in support or rejecting the null hypothesis that $\theta_1 \sim U[0, 2\pi)$ such that we have evidence in support of $\theta_1 \sim U[0, 2\pi)$.

However, we have small p-values in evidence of rejecting the null hypotheses that individually and respectively $\theta_2, \theta_3, \theta_4 \sim U[0, \pi)$, which is evidence in support of θ_2, θ_3 , and θ_4 not having distributions of $U[0, \pi)$.