

Tristan De Alwis
DSC 465: Intermediate Statistics
Assignment #2
April 16th, 2020

Q1:

$$\pi(\theta | x) = \frac{f(x|\theta) \pi(\theta)}{\int_{\theta=0}^1 f(x|\theta) \pi(\theta) d\theta} = \frac{f(x|\theta) \pi(\theta)}{\sum_{\theta} f(x|\theta) \pi(\theta)}$$

posterior

$$f(x|\theta) = \binom{n}{x} \theta^x (1-\theta)^{n-x}$$

$$\Rightarrow \pi(\theta | x) = \frac{\binom{n}{x} \theta^x (1-\theta)^{n-x} \pi(\theta)}{\sum_{\theta} \binom{n}{x} \theta^x (1-\theta)^{n-x} \pi(\theta)}$$

$$\theta\left(\frac{1}{4}, \frac{1}{2}, \frac{3}{4}\right) = \frac{1}{3}$$

$$\pi(\theta | x) = \frac{\theta^x (1-\theta)^{n-x}}{\left(\frac{1}{4}\right)^4 \left(\frac{3}{4}\right)^6 + \left(\frac{1}{2}\right)^4 \left(\frac{1}{2}\right)^6 + \left(\frac{3}{4}\right)^4 \left(\frac{1}{4}\right)^6}$$

$$\pi(\theta | x) = \begin{cases} .397 & \text{for } \theta = \frac{1}{4} \\ .558 & \text{for } \theta = \frac{1}{2} \\ .044 & \text{for } \theta = \frac{3}{4} \end{cases}$$

Assignment #2: R code

Tristan De Alwis

4/16/2020

Loading Neccessary Libraries

```
suppressPackageStartupMessages(library(MASS))
suppressPackageStartupMessages(library(dplyr))
suppressPackageStartupMessages(library("Rlab"))
suppressPackageStartupMessages(library(class))
```

Q2

Let λ be the traffic flow rate in vehicles per hour and M be the number of available toll

(c)

```
prior_m <- function(m) {
  if (m == 8) {
    return(4/7)
  } else if (m == 9) {
    return(2/7)
  } else {
    return(1/7)
  }
}

q_m <- function(m, mNew) {
  if (m == 9) {
    return(1)
  } else if (mNew == 9) {
    return(0.5)
  }
}

prior_lam <- function(lambda) {
  return(1/((lambda + 10) - max(c(0, lambda - 10))))
}

get_lam <- function(lambdaOld) {
  return(max(c(0, lambdaOld + runif(1, -10, +10), 1)))
}

q_lam <- function(lambdaOld, lambdaNew) {
  if (lambdaOld == 0) {
    return(abs(lambdaNew - 10)/20)
  } else {
    return(1/20)
  }
}
```

```

}

get_m <- function(mOld) {
  if (mOld == 9) {
    return(sample(c(8, 10), 1))
  } else {
    return(9)
  }
}

xDist <- function(x, lambda, m) {
  poisson <- 1 - exp(-1 * lambda * 15 * (1/3600)/m)
  return(max(dbinom(x, m, poisson, 1e-06)))
}

acceptanceProb <- function(lambdaNew, mNew, lambdaOld, mOld, X) {
  pPrime <- xDist(X, lambdaNew, mNew) * prior_m(mNew) * prior_lam(lambdaNew)
  p <- xDist(X, lambdaOld, mOld) * prior_m(mOld)
  rNum <- pPrime * q_lam(lambdaOld, lambdaNew) * q_m(mOld, mNew)
  rDenom <- p * q_lam(lambdaNew, lambdaOld) * q_m(mNew, mOld)
  r <- rNum/rDenom

  return(min(1, r))
}

MCMC <- function(M, x, ntrace, interval) {
  mOld <- M
  lambdaOld <- x * 240

  Ms <- c(mOld)
  Lambdas <- c(lambdaOld)

  for (i in 1:ntrace) {
    lambdaNew <- get_lam(lambdaOld)
    mNew <- get_m(mOld)

    if (acceptanceProb(lambdaNew, mNew, lambdaOld, mOld, x) >= runif(1,
      min = 0, max = 1)) {
      mOld <- mNew
      lambdaOld <- lambdaNew
    }
    if (i%interval == 0) {
      Ms <- c(Ms, mOld)
      Lambdas <- c(Lambdas, lambdaOld)
    }
  }
  return(list(Ms = Ms, Lambdas = Lambdas))
}

# (iv)
ntrace <- 5e+06
interval = 1000
x2 <- MCMC(8, 2, ntrace, interval)

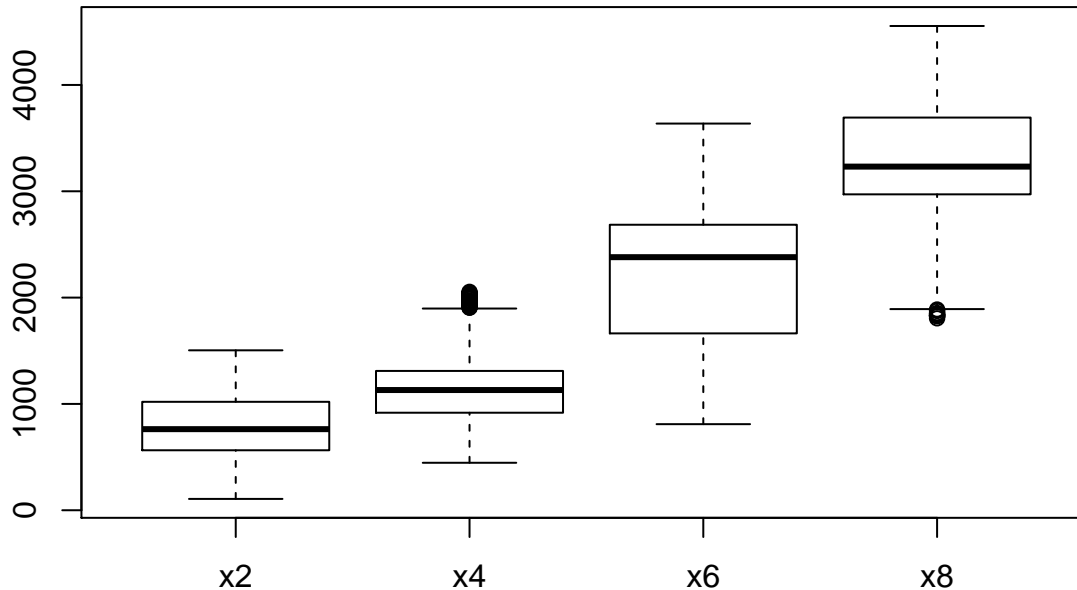
```

```

x4 <- MCMC(8, 4, ntrace, interval)
x6 <- MCMC(8, 6, ntrace, interval)
x8 <- MCMC(8, 8, ntrace, interval)

dF = c(x2[2], x4[2], x6[2], x8[2])
boxplot(dF, names = c("x2", "x4", "x6", "x8"))

```



Q3

```

carsb = Cars93[, c(4, 5, 6, 7, 8, 12, 13, 14, 15, 17, 19:22, 25, 26)]
names(carsb)

```

```

## [1] "Min.Price"      "Price"          "Max.Price"
## [4] "MPG.city"       "MPG.highway"    "EngineSize"
## [7] "Horsepower"     "RPM"            "Rev.per.mile"
## [10] "Fuel.tank.capacity" "Length"         "Wheelbase"
## [13] "Width"          "Turn.circle"    "Weight"
## [16] "Origin"

```

```
carsb[, -16] = log(carsb[, -16])
```

(a)

```

lrfp = function(m) {
  (m[1, 1]/(m[1, 1] + m[2, 1]))/(m[1, 2]/(m[2, 2] + m[1, 2]))
}
lrfn = function(m) {
  (m[2, 1]/(m[1, 1] + m[2, 1]))/(m[2, 2]/(m[2, 2] + m[1, 2]))
}
f0 = function(m) {
  c(1 - sum(diag(m))/sum(m), lrfp(m), lrfn(m))
}

```

(b)

```
fit.lda = lda(Origin ~ ., data = carsb)

confusion.matrix.lda = table(predict(fit.lda)$class, carsb$Origin)

m = confusion.matrix.lda

vector = f0(m)
cat("CE: ", vector[1], "\n")

## CE: 0.1075269
cat("LR+: ", vector[2], "\n")

## LR+: 8.0625
cat("LR-: ", vector[3], "\n")

## LR-: 0.1171875
```

(c)

```
fit.qda = qda(Origin ~ ., data = carsb)

confusion.matrix.qda = table(predict(fit.qda)$class, carsb$Origin)

m = confusion.matrix.qda

vector = f0(m)
cat("CE: ", vector[1], "\n")

## CE: 0.03225806
cat("LR+: ", vector[2], "\n")

## LR+: 43.125
cat("LR-: ", vector[3], "\n")

## LR-: 0.04261364
```

Yes, the QDA appears to produce less error

(d)

```
fit.lda = lda(Origin ~ ., data = carsb, CV = TRUE)

confusion.matrix.lda = table(fit.lda$class, carsb$Origin)

m = confusion.matrix.lda

vector = f0(m)
cat("CE: ", vector[1], "\n")

## CE: 0.1397849
```

```

cat("LR+: ", vector[2], "\n")

## LR+: 6.40625
cat("LR-: ", vector[3], "\n\n")

## LR-: 0.1682692

fit.qda = qda(Origin ~ ., data = carsb, CV = TRUE)

confusion.matrix.qda = table(fit.qda$class, carsb$Origin)

m = confusion.matrix.qda

vector = f0(m)
cat("CE: ", vector[1], "\n")

## CE: 0.2473118
cat("LR+: ", vector[2], "\n")

## LR+: 3.068182
cat("LR-: ", vector[3], "\n")

## LR-: 0.3308824

```

lda() does better than qda() with CV because it is better at generalizing

Q4

```

pima1 = rbind(Pima.tr)[, c(2, 3, 4, 5, 6, 8)]
names(pima1)

## [1] "glu" "bp" "skin" "bmi" "ped" "type"

```

(a)

```

yes = length(which(pima1$type == "Yes"))
yes <- yes/200
cat("yes: ", yes, "\n")

## yes: 0.34

no = length(which(pima1$type == "No"))
no <- no/200
cat("no: ", no, "\n")

## no: 0.66

```

The classifier would be incorrect 34% of the time.

(b)

```

knn.function = function(k.list, xtrain, gr) {

  pr.tab = matrix(NA, length(k.list), 3)

```

```

for (i in 1:length(k.list)) {

  knn.fit = knn.cv(xtrain, gr, k = k.list[i], use.all = TRUE)
  cm = table(knn.fit, gr)
  # print(cm)
  pr.tab[i, ] = f0(cm)
}
cm
return(pr.tab)
}

```

(c)

```

k.list = seq(1, 125, 2)
cv.tab = knn.function(k.list, pima1[, 1:5], pima1[, 6])
cv.tab

```

```

##      [,1]      [,2]      [,3]
## [1,] 0.300 1.639118 0.3974026
## [2,] 0.295 1.768687 0.3931419
## [3,] 0.275 1.754735 0.3291246
## [4,] 0.270 1.663203 0.2966024
## [5,] 0.260 1.803030 0.2861953
## [6,] 0.265 1.677922 0.2809917
## [7,] 0.255 1.742424 0.2575758
## [8,] 0.265 1.748393 0.2943723
## [9,] 0.275 1.681818 0.3181818
## [10,] 0.265 1.645623 0.2736742
## [11,] 0.250 1.795225 0.2502165
## [12,] 0.245 1.772727 0.2272727
## [13,] 0.250 1.757576 0.2424242
## [14,] 0.250 1.757576 0.2424242
## [15,] 0.255 1.707359 0.2497704
## [16,] 0.240 1.787879 0.2121212
## [17,] 0.250 1.722078 0.2341598
## [18,] 0.260 1.692641 0.2653811
## [19,] 0.255 1.742424 0.2575758
## [20,] 0.255 1.742424 0.2575758
## [21,] 0.275 1.617003 0.3058712
## [22,] 0.260 1.692641 0.2653811
## [23,] 0.265 1.615070 0.2658847
## [24,] 0.260 1.599681 0.2404040
## [25,] 0.270 1.545455 0.2664577
## [26,] 0.265 1.615070 0.2658847
## [27,] 0.265 1.615070 0.2658847
## [28,] 0.250 1.688552 0.2253788
## [29,] 0.250 1.656839 0.2160313
## [30,] 0.255 1.613238 0.2232323
## [31,] 0.270 1.519697 0.2575758
## [32,] 0.270 1.519697 0.2575758
## [33,] 0.270 1.519697 0.2575758
## [34,] 0.275 1.506818 0.2759740
## [35,] 0.265 1.532576 0.2391775

```

```
## [36,] 0.265 1.532576 0.2391775
## [37,] 0.265 1.532576 0.2391775
## [38,] 0.260 1.571873 0.2309300
## [39,] 0.260 1.571873 0.2309300
## [40,] 0.260 1.571873 0.2309300
## [41,] 0.265 1.532576 0.2391775
## [42,] 0.265 1.532576 0.2391775
## [43,] 0.265 1.532576 0.2391775
## [44,] 0.265 1.532576 0.2391775
## [45,] 0.275 1.459596 0.2575758
## [46,] 0.270 1.495196 0.2480359
## [47,] 0.275 1.459596 0.2575758
## [48,] 0.270 1.471861 0.2377622
## [49,] 0.275 1.416667 0.2361111
## [50,] 0.270 1.449612 0.2266667
## [51,] 0.285 1.355072 0.2575758
## [52,] 0.280 1.366271 0.2341598
## [53,] 0.280 1.348162 0.2207792
## [54,] 0.280 1.348162 0.2207792
## [55,] 0.315 1.198718 0.3541667
## [56,] 0.320 1.119122 0.3090909
## [57,] 0.335 1.055230 0.4292929
## [58,] 0.340 1.007237 0.5151515
## [59,] 0.340 1.000000      NaN
## [60,] 0.340 1.000000      NaN
## [61,] 0.340 1.000000      NaN
## [62,] 0.340 1.000000      NaN
## [63,] 0.340 1.000000      NaN
```

```
cat("Min C.E.: ", min(cv.tab[, 1]), "\n")
```

```
## Min C.E.: 0.24
```

```
cat("Min LR+: ", min(cv.tab[, 2]), "\n")
```

```
## Min LR+: 1
```

```
cat("Max LR+: ", max(cv.tab[, 2]), "\n")
```

```
## Max LR+: 1.80303
```

```
cat("Min LR-: ", min(cv.tab[, 3], na.rm = TRUE), "\n")
```

```
## Min LR-: 0.2121212
```

```
cat("Max LR-: ", max(cv.tab[, 3], na.rm = TRUE), "\n")
```

```
## Max LR-: 0.5151515
```

```
# plot(seq(1, 125, 2), cv.tab[,1], pch=16, ylab='Classification Error',
# xlab='K', main='Normalized Features') lines(seq(1, 125, 2), cv.tab[,1],
# lty=1) abline(h = 0.34, lty = 2, lwd = 3, col = 'dark blue')
```


Using only odd numbers for K avoids the need to break ties within the classification algorithm. The min value of CE is .240 for K = 32. The minimum LR+

(d)

```
norm_feat <- apply(pima1[-6], 2, function(x) {
  return((x - mean(x))/sd(x))
})

k.list = seq(1, 125, 2)
cv.tab = knn.function(k.list, norm_feat, pima1[, 6])
cat("Min C.E.: ", min(cv.tab[, 1]), "\n")

## Min C.E.: 0.22
cat("Min LR+: ", min(cv.tab[, 2]), "\n")

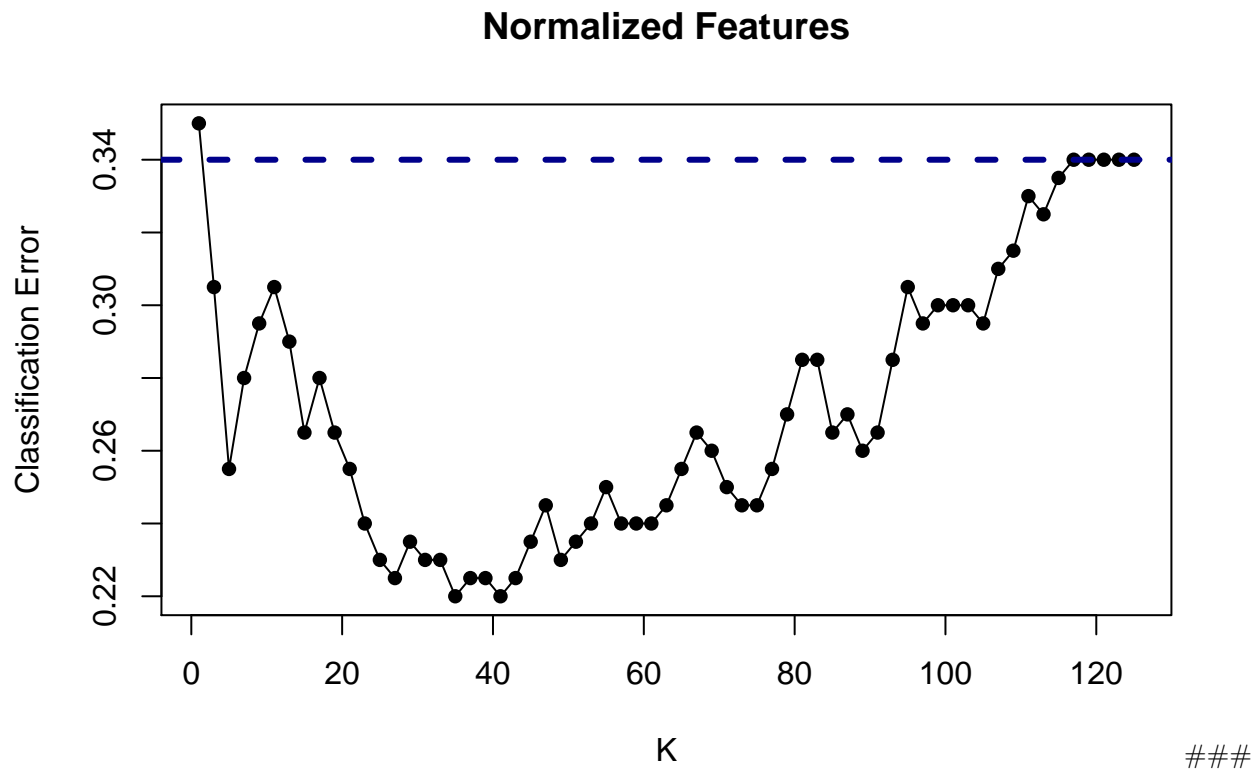
## Min LR+: 1
cat("Max LR+: ", max(cv.tab[, 2]), "\n")

## Max LR+: 1.906061
cat("Min LR-: ", min(cv.tab[, 3], na.rm = TRUE), "\n")

## Min LR-: 0.09366391
cat("Max LR-: ", max(cv.tab[, 3], na.rm = TRUE), "\n")

## Max LR-: 0.5454545

knn_mat <- knn.function(k.list, norm_feat, pima1[, 6])
plot(seq(1, 125, 2), knn_mat[, 1], pch = 16, ylab = "Classification Error",
     xlab = "K", main = "Normalized Features")
lines(seq(1, 125, 2), knn_mat[, 1], lty = 1)
abline(h = 0.34, lty = 2, lwd = 3, col = "dark blue")
```



Normalize reduces the scale of the variables resulting in reduced error.

Q5

(a)

```
lambda_bim <- function(lam, X, m = 10, t = 15/3600) {
  return(log(choose(m, X) * (1 - exp((-lam * t)/m))^(X) * (exp((-lam * t)/m)^(m -
    X))))
}

probs <- c()
ind <- seq(500, 700, 1)
for (i in ind) {
  probs <- c(probs, lambda_bim(i, X = 6))
}

plot(ind, probs)
```

Q5:

mCx

$$\log(\log(\frac{M}{x}) - x)$$

$$0 = x \cdot \frac{T}{M} \cdot \frac{1}{e^z - 1} + (M-x) \left(\frac{-T}{M} \right) \left(\frac{M}{x^2} \right) = \frac{1}{e^z - 1}$$

$$T \left(1 - \frac{x}{M} \right) \left(\frac{M}{Tx} \right) = \frac{1}{e^z - 1}$$

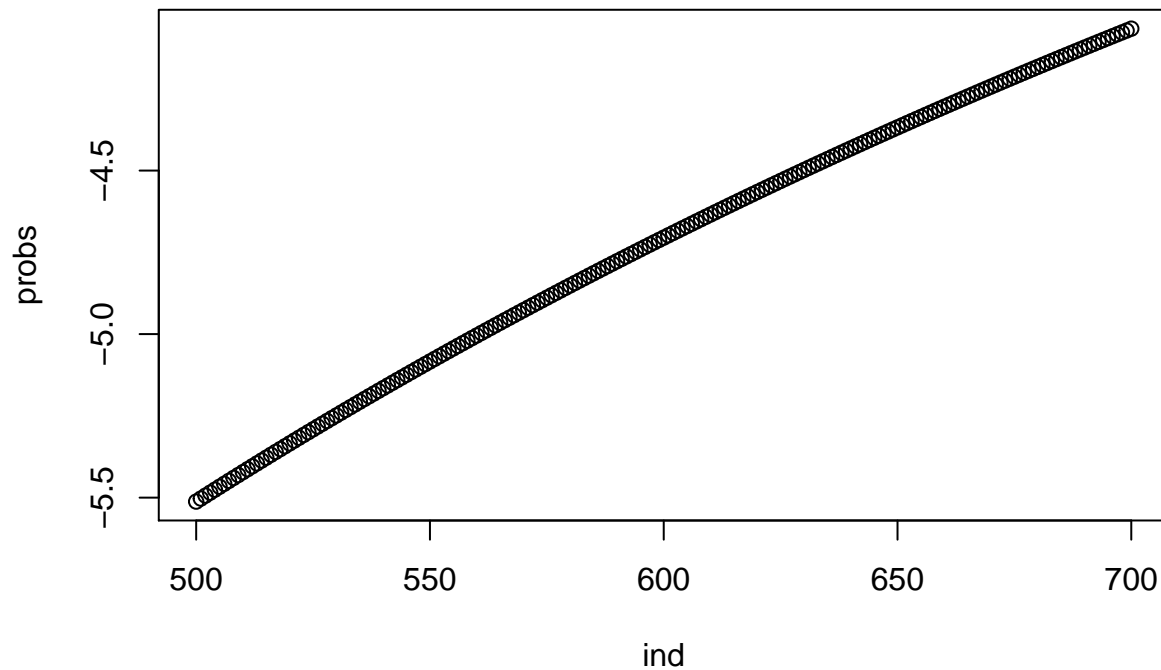
$$\frac{M-x}{x} \rightarrow \frac{M}{x} - 1$$

$$\frac{M}{T} \log\left(\frac{M}{M-x}\right)$$

$$\lambda = 0.5226$$

$$5.526$$

$$\begin{aligned} \frac{M}{M-x} &= \left(\frac{M}{x} - 1 \right)^{-1} + 1 \\ &= \frac{x}{M-x} + \frac{M-x}{M-x} \\ &= \frac{M}{M-x} \end{aligned}$$



(b)

```
lam_mle <- function(x, M = 10, t = (15/3600)) {
  (M/t) * log(M/(M - x))
}

for (i in 0:9) {
  sprintf("MLE for x=%s: %s", i, round(lam_mle(i), 3)) %>% print(.)
}
```

```
## [1] "MLE for x=0: 0"
## [1] "MLE for x=1: 252.865"
## [1] "MLE for x=2: 535.545"
## [1] "MLE for x=3: 856.02"
## [1] "MLE for x=4: 1225.981"
## [1] "MLE for x=5: 1663.553"
## [1] "MLE for x=6: 2199.098"
## [1] "MLE for x=7: 2889.535"
## [1] "MLE for x=8: 3862.651"
## [1] "MLE for x=9: 5526.204"
```

(c)

```
for (i in 0:10) {
  sprintf("MLE for x=%s: %s", i, round(lam_mle(i), 3)) %>% print(.)
}
```

```
## [1] "MLE for x=0: 0"
## [1] "MLE for x=1: 252.865"
## [1] "MLE for x=2: 535.545"
## [1] "MLE for x=3: 856.02"
## [1] "MLE for x=4: 1225.981"
```

```
## [1] "MLE for x=5: 1663.553"  
## [1] "MLE for x=6: 2199.098"  
## [1] "MLE for x=7: 2889.535"  
## [1] "MLE for x=8: 3862.651"  
## [1] "MLE for x=9: 5526.204"  
## [1] "MLE for x=10: Inf"
```

Can't divide by 0 so can't give all estimates