Coding

6.

Here we have that "x1_covariate1" is just the intercept term, so we don't need to include it since we already add intercept in our algorithm. We use least square estimator of beta to initialize our algorithm.

```
myLR <- function(Y, X, it_max=25, eps=1e-8){
    D = cbind(1, X)
    p = dim(D)[2]
    beta = solve(t(D) %*% D) %*% t(D) %*% Y
    prob = exp(D %*% beta) / (1 + exp(D %*% beta))
    for(i in 1:it_max){
        WAUX = diag(array(prob * (1-prob)))
        W = solve(t(D) %*% WAUX %*% D)
        dbeta = W %*% t(D) %*% (Y - prob)
        if(norm(dbeta,"2") <= eps)
            break
        beta = beta + dbeta
        prob = exp(D %*% beta) / (1 + exp(D %*% beta))
    }
    std = sqrt(diag(W))
    result = list(beta = beta, std = std)
    return(result)
}

data = read.csv("Ex0107.txt", sep=" ")
Y = data$y_response
X2 = data$x2_covariate2

fit = glm(Y ~ X2, family = binomial)
result = myLR(Y,X2)

summary(fit)
```

```
##
## Call:
## glm(formula = Y ~ X2, family = binomial)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0372  -0.7635   0.3422   0.8527   1.3705
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.6172     0.5711   1.081   0.2798
## X2            1.5091     0.7773   1.941   0.0522 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 27.526  on 19  degrees of freedom
## Residual deviance: 21.390  on 18  degrees of freedom
## AIC: 25.39
##
## Number of Fisher Scoring iterations: 5
```

```r
print(result)
```

```
## $beta
##        [,1]
##   0.6172003
## X 1.5090921
##
## $std
##                   X
## 0.5710882 0.7772833
```

And we can see here my estimator consists with R function.

7.

```r
library(magrittr)
library(dplyr)

data2 = read.csv("Ex0109.csv")
counts = aggregate(cbind(Pro05,Anti05,Pro06,Anti06,Pro07,Anti07) ~ Party, data = data2, sum)
print(counts)
```

```
##   Party Pro05 Anti05 Pro06 Anti06 Pro07 Anti07
## 1     D  2825    551  1905    332  3242    554
## 2     R   346   2957   366   1840   671   3105
```

```r
X = rbind(c(5,0),
          c(6,0),
          c(7,0),
          c(5,1),
          c(6,1),
          c(7,1))
colnames(X) = c("Year","Party")
Pro = c(2825,1905,3242,346,366,671)
Anti = c(551,332,554,2957,1840,3105)
fit = glm(cbind(Pro,Anti) ~ X, family=binomial)
summary(fit)
```

```
##
## Call:
## glm(formula = cbind(Pro, Anti) ~ X, family = binomial)
##
## Deviance Residuals:
##       1        2        3        4        5        6
##  2.0658   0.5652  -2.5970  -3.8257   2.4914   1.2503
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)  0.66794    0.14341   4.658 3.20e-06 ***
## XYear        0.17428    0.02360   7.384 1.54e-13 ***
## XParty      -3.47344    0.04118 -84.339  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 10145.221  on 5  degrees of freedom
## Residual deviance:    33.738  on 3  degrees of freedom
## AIC: 86.475
##
## Number of Fisher Scoring iterations: 4
```

We can see here the p value for Party is extremely small, so the behavior of two parties towards pro-environment voting is significant different regardless of year effect.