lab-week6

Task 1

```r
#task1.r
input = as.data.frame(read.csv("./income.csv"))
input[1:10,]
```

```
##    ID Income Age Education Gender
## 1   1    113  69        12      1
## 2   2     91  52        18      0
## 3   3    121  65        14      0
## 4   4     81  58        12      0
## 5   5     68  31        16      1
## 6   6     92  51        15      1
## 7   7     75  53        15      0
## 8   8     76  56        13      0
## 9   9     56  42        15      1
## 10 10     53  33        11      1
```

```r
Model_A <- lm(Income ~ Age + Education + Gender, input)
summary(Model_A)
```

```
##
## Call:
## lm(formula = Income ~ Age + Education + Gender, data = input)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.340  -8.101   0.139   7.885  37.271
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.26299    1.95575   3.714 0.000212 ***
## Age          0.99520    0.02057  48.373  < 2e-16 ***
## Education    1.75788    0.11581  15.179  < 2e-16 ***
## Gender      -0.93433    0.62388  -1.498 0.134443
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.07 on 1496 degrees of freedom
## Multiple R-squared:  0.6364, Adjusted R-squared:  0.6357
## F-statistic:   873 on 3 and 1496 DF,  p-value: < 2.2e-16
```

```r
Model_B <- lm(Income ~ Age + Education, input)
summary(Model_B)
```

```
##
## Call:
## lm(formula = Income ~ Age + Education, data = input)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -36.889  -7.892   0.185   8.200  37.740
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.75822    1.92728   3.507 0.000467 ***
## Age          0.99603    0.02057  48.412  < 2e-16 ***
## Education    1.75860    0.11586  15.179  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.08 on 1497 degrees of freedom
## Multiple R-squared:  0.6359, Adjusted R-squared:  0.6354
## F-statistic:  1307 on 2 and 1497 DF,  p-value: < 2.2e-16
```

```r
Age <- 41
Education <- 12
new_pt <- data.frame(Age, Education)

conf_int <- predict(Model_B, new_pt, level = .95,interval = "confidence")
conf_int
```

```
##        fit      lwr      upr
## 1 68.69884 67.83102 69.56667
```

```r
pred_int <- predict(Model_B,new_pt,level=.95,interval="prediction")
pred_int
```

```
##        fit      lwr      upr
## 1 68.69884 44.98867 92.40902
```

A **Confidence Interval** is a range of values we are fairly sure our true value lies in.

A **Prediction Interval** is a range of values that is likely to contain the value of a single new observation given specified settings of the predictors.

The range of the prediction interval is always greater than the range of the confidence interval. That is, given an X, it is a little more accurate to estimate the mean average of the corresponding Y than to estimate an individual value.

Task 2

```r
#task2.r
churn = as.data.frame(read.csv("./churn.csv"))
head(churn)
```

```
##   ID Churned Age Married Cust_years Churned_contacts
## 1  1       0  61       1          3                1
## 2  2       0  50       1          3                2
## 3  3       0  47       1          2                0
## 4  4       0  50       1          3                3
## 5  5       0  29       1          1                3
## 6  6       0  43       1          4                3
```

```r
sum(churn$Churned)
```

```
## [1] 1743
```

```r
CModel_A <- glm (Churned~Age + Married + Cust_years + Churned_contacts,
                 data=churn, family=binomial(link="logit"))
summary(CModel_A)
```

```
##
## Call:
## glm(formula = Churned ~ Age + Married + Cust_years + Churned_contacts,
##     family = binomial(link = "logit"), data = churn)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4542  -0.5206  -0.1971  -0.0728   3.3786
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       3.415201   0.163734  20.858   <2e-16 ***
## Age              -0.156643   0.004088 -38.320   <2e-16 ***
## Married           0.066432   0.068302   0.973    0.331
## Cust_years        0.017857   0.030497   0.586    0.558
## Churned_contacts  0.382324   0.027313  13.998   <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: 8387.3  on 7999  degrees of freedom
## Residual deviance: 5357.9  on 7995  degrees of freedom
## AIC: 5367.9
##
## Number of Fisher Scoring iterations: 6
```

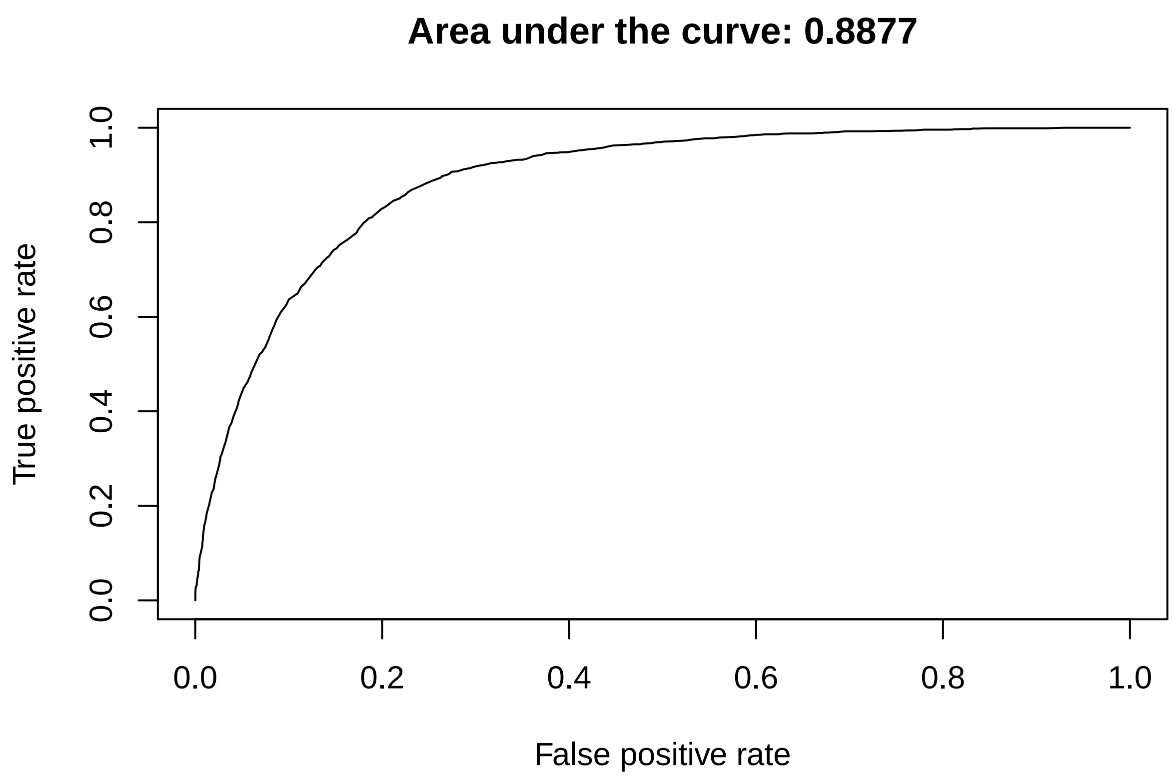
```r
CModel_B <- glm (Churned~Age + Married + Churned_contacts,
                 data=churn, family=binomial(link="logit"))
summary(CModel_B)
```

```
##
## Call:
## glm(formula = Churned ~ Age + Married + Churned_contacts, family = binomial(link = "logit"),
##     data = churn)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4476  -0.5178  -0.1972  -0.0723   3.3776
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       3.472062   0.132107  26.282   <2e-16 ***
## Age              -0.156635   0.004088 -38.318   <2e-16 ***
## Married           0.066430   0.068299   0.973    0.331
## Churned_contacts  0.381909   0.027302  13.988   <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: 8387.3  on 7999  degrees of freedom
## Residual deviance: 5358.3  on 7996  degrees of freedom
## AIC: 5366.3
##
## Number of Fisher Scoring iterations: 6
```

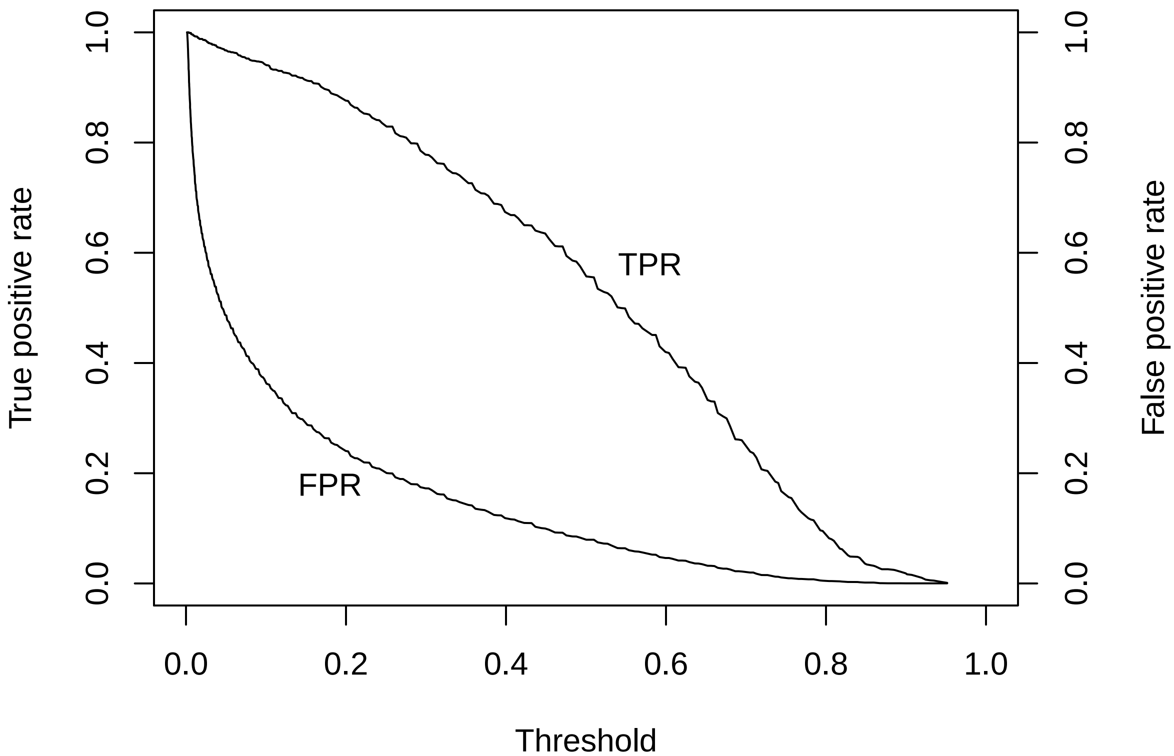
```r
CModel_C <- glm (Churned~Age + Churned_contacts,
                 data=churn, family=binomial(link="logit"))
summary(CModel_C)
```

```
##
## Call:
## glm(formula = Churned ~ Age + Churned_contacts, family = binomial(link = "logit"),
##     data = churn)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4599  -0.5214  -0.1960  -0.0736   3.3671
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       3.502716   0.128430   27.27   <2e-16 ***
## Age              -0.156551   0.004085  -38.32   <2e-16 ***
## Churned_contacts  0.381857   0.027297   13.99   <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: 8387.3  on 7999  degrees of freedom
## Residual deviance: 5359.2  on 7997  degrees of freedom
## AIC: 5365.2
##
## Number of Fisher Scoring iterations: 6
```

```r
library(ROCR)

pred = predict(CModel_C, type="response")
predObj = prediction(pred, churn$Churned )

rocObj = performance(predObj, measure="tpr", x.measure="fpr")
aucObj = performance(predObj, measure="auc")

plot(rocObj, main = paste("Area under the curve:", round(aucObj@y.values[[1]] ,4)))
```




```r
alpha <- round(as.numeric(unlist(rocObj@alpha.values)),4)
fpr <- round(as.numeric(unlist(rocObj@x.values)),4)
tpr <- round(as.numeric(unlist(rocObj@y.values)),4)


par(mar = c(5,5,2,5))
plot(alpha,tpr, xlab="Threshold", xlim=c(0,1), ylab="True positive rate", type="l")
par(new="True")


plot(alpha,fpr, xlab="", ylab="", axes=F, xlim=c(0,1), type="l" )
axis(side=4)
mtext(side=4, line=3, "False positive rate")
text(0.18,0.18,"FPR")
text(0.58,0.58,"TPR")
```




```r
i <- which(round(alpha,2) == .5)
paste("Threshold=" , (alpha[i]) , " TPR=" , tpr[i] , " FPR=" , fpr[i])
```

```
## [1] "Threshold= 0.5004  TPR= 0.5571  FPR= 0.0793"
```

```r
i <- which(round(alpha,2) == .15)
paste("Threshold=" , (alpha[i]) , " TPR=" , tpr[i] , " FPR=" , fpr[i])
```

```
## [1] "Threshold= 0.1543  TPR= 0.9116  FPR= 0.2869"
## [2] "Threshold= 0.1518  TPR= 0.9122  FPR= 0.2875"
## [3] "Threshold= 0.1479  TPR= 0.9145  FPR= 0.2942"
## [4] "Threshold= 0.1455  TPR= 0.9174  FPR= 0.2981"
```

AUC=0.8877

In Machine Learning, performance measurement is an essential task. So when it comes to a classification problem, we can count on an AUC - ROC Curve. When we need to check or visualize the performance of the multi - class classification problem, we use AUC (Area Under The Curve) ROC (Receiver Operating Characteristics) curve.

AUC - ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represents degree or measure of separability. It tells how much model is capable of distinguishing between classes. Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, Higher the AUC, better the model is at distinguishing between patients with disease and no disease.

The ROC curve is plotted with TPR against the FPR where TPR is on y-axis and FPR is on the x-axis.

In confusion matrix,

predicted class - actual class	Positive	Negative
Positive	TP	FP
Negative	FN	TN

TPR (True Positive Rate) / Recall /Sensitivity

$$TPR = \frac{TP}{RP + FN}$$

$$FPR = \frac{FP}{TN + FP}$$

When AUC is 0.8877, it means there is 88.8% chance that model will be able to distinguish between positive class and negative class.