회귀분석 및 실습 HW14

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IRIS data

```
# data processing
iris_df <- iris</pre>
iris_df[,"Species"] <- as.factor(ifelse(iris_df[, "Species"] == "setosa", 1, 0))</pre>
#split train - test set
idx <- 1:150 %in% sample.int(150, 105) # 70:30
iris_train <- iris_df[idx, ]</pre>
iris_test <- iris_df[!idx, ]</pre>
# logistic regression
result <- glm(Species ~ ., data = iris_train, family = "binomial",</pre>
              control = glm.control(maxit = 30))
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
summary(result)
##
## Call:
## glm(formula = Species ~ ., family = "binomial", data = iris_train,
       control = glm.control(maxit = 30))
##
##
## Deviance Residuals:
##
         Min
                      1Q
                             Median
                                             ЗQ
                                                       Max
## -1.08e-05 -2.11e-08 -2.11e-08
                                     2.11e-08 9.43e-06
## Coefficients:
##
                  Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)
                    -45.564 973906.559
## Sepal.Length
                     20.536 355984.894
## Sepal.Width
                      6.034 229839.883
                                               0
                                                         1
## Petal.Length
                    -21.199 342109.766
                                               0
                                                         1
## Petal.Width
                    -31.115 528120.846
##
  (Dispersion parameter for binomial family taken to be 1)
##
       Null deviance: 1.3367e+02 on 104 degrees of freedom
##
## Residual deviance: 2.7413e-10 on 100 degrees of freedom
## AIC: 10
##
## Number of Fisher Scoring iterations: 27
# train accuracy with cutoff = 0.5
prob <- predict(result, iris_train, type = "response")</pre>
pred <- prediction(prob, iris_train$Species)</pre>
perf <- performance(pred, measure = "acc")</pre>
perf@y.values[[1]][max(which(perf@x.values[[1]] >= 0.5))]
## [1] 1
# train auc
perf <- performance(pred, measure = "tpr", x.measure = "fpr")</pre>
plot(perf)
      0.8
True positive rate
      9.0
      0.4
      0.2
      0.0
                           0.2
             0.0
                                          0.4
                                                        0.6
                                                                       8.0
                                                                                      1.0
                                         False positive rate
```

```
performance(pred, measure = "auc")@y.values[[1]]
## [1] 1
# test accuracy
prob <- predict(result, iris_test, type = "response")</pre>
pred <- prediction(prob, iris_test$Species)</pre>
perf <- performance(pred, measure = "acc")</pre>
perf@y.values[[1]][max(which(perf@x.values[[1]] >= 0.5))]
## [1] 1
# test auc
perf <- performance(pred, measure = "tpr", x.measure = "fpr")</pre>
plot(perf)
      0.8
True positive rate
       9.0
       0.4
      0.2
       0.0
              0.0
                             0.2
                                            0.4
                                                           0.6
                                                                          0.8
                                                                                         1.0
                                           False positive rate
performance(pred, measure = "auc")@y.values[[1]]
```

2. num of Awards

[1] 1

```
# data processing
p <- read.csv("https://stats.idre.ucla.edu/stat/data/poisson_sim.csv")
p <- within(p, {
   prog <- factor(prog, levels=1:3, labels=c("General", "Academic", "Vocational"))</pre>
```

```
id <- factor(id)</pre>
})
# split train - test set
idx <- 1:200 %in% sample.int(200, 140) # 70 : 30
p_train <- p[idx,]</pre>
p_test <- p[!idx,]</pre>
# poisson regression
m1 <- glm <- glm(num_awards ~ prog + math, family = "poisson", data = p_train)</pre>
summary(m1)
##
## Call:
## glm(formula = num_awards ~ prog + math, family = "poisson", data = p_train)
##
## Deviance Residuals:
       Min
                 1Q
                     Median
                                   3Q
                                            Max
## -2.1284 -0.8367 -0.5178 0.2979
                                        2.3711
##
## Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
##
## (Intercept)
                              0.75991 -6.415 1.41e-10 ***
                  -4.87485
## progAcademic
                                       3.241 0.00119 **
                   1.40623
                              0.43393
## progVocational 0.54371
                              0.54001 1.007 0.31401
                              0.01193 4.989 6.06e-07 ***
## math
                   0.05953
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
       Null deviance: 197.82 on 139 degrees of freedom
## Residual deviance: 128.06 on 136 degrees of freedom
## AIC: 270.32
##
## Number of Fisher Scoring iterations: 5
# train accuracy with cutoff = 0.5
prob <- predict(m1, p_train, type = "response")</pre>
sum(round(prob) == p_train$num_awards) / length(prob)
```

```
## [1] 0.5857143
# train MSE
sum((prob - p_train$num_awards)^2) / length(prob)
## [1] 0.7393426
# test accuracy with cutoff = 0.5
prob <- predict(m1, p_test, type = "response")</pre>
sum(round(prob) == p_test$num_awards) / length(prob)
## [1] 0.5833333
# test MSE
sum((prob - p_test$num_awards)^2) / length(prob)
## [1] 0.788173
#plot
p$phat <- predict(m1, p, type = "response")</pre>
ggplot(p, aes(x = math, y = phat, color = prog)) +
  geom_point(aes(y = num_awards), alpha = 0.5, position = position_jitter(h=.2))+
  geom_line(size = 1)+
  theme_bw()+
  labs(x = "Math score", y = "Expected number of awards")
```

