HW8_Social_Media_Logistics_Regression_Yuefei_Chen

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Model development

Running the following code, we build a multiple regression model based on rent house data. Its independent variables "Instagram_value", "Linkedin_value", "Snapchat_value", "Twitter_value", "What-sapp_Wechat_value", "Youtube_value", "OTT_Netflix_Hulu_Prime_video_value", "Reddit_value", "job_interview_calls", "networking_done_with_coffee_chats", "learning_done_in_terms_of_items_created". The dependent variable is "Tired_waking_up_in_morning".

```
library(readr)
library(ggplot2)
library(pROC)
## Type 'citation("pROC")' for a citation.
## Attaching package: 'pROC'
## The following objects are masked from 'package:stats':
##
##
       cov, smooth, var
APP_data <- read_csv("Dataset/Social Media_cleaned.csv")
## New names:
## * 'Hours_spent' -> 'Hours_spent...3'
## * 'Hours spent' -> 'Hours spent...6'
## * 'Hours_spent' -> 'Hours_spent...9'
## * 'Hours_spent' -> 'Hours_spent...15'
## * 'Hours_spent' -> 'Hours_spent...18'
## * 'Hours_spent' -> 'Hours_spent...21'
## * 'Hours_spent' -> 'Hours_spent...24'
## Rows: 23 Columns: 33
## -- Column specification -
## Delimiter: ","
       (15): ID, Instagram, Linkedin, Snapchat, Twitter, Whatsapp_Wechat, Yout...
## dbl (12): Instagram_value, Linkedin_value, Snapchat_value, Twitter_value, W...
## time (6): Hours_spent...3, Hours_spent...6, Hours_spent...9, Hours spent, H...
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
```

```
str(APP_data)
## tibble [22 x 25] (S3: tbl_df/tbl/data.frame)
                                                : chr [1:22] "masinl" "peace" "Patty" "Bunny" ...
                                                : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
## $ Instagram
## $ Instagram_value
                                                : num [1:22] 3.5 7.73 3.77 5.38 0 2.33 5.37 7 8.65 0.17
## $ Linkedin
                                                : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
## $ Linkedin_value
                                                : num [1:22] 4 5.2 7 5.32 0.58 7 4 4 10 0 ...
                                                : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
## $ Snapchat
## $ Snapchat_value
                                                : num [1:22] 1 3.68 0.53 1.3 0 0.47 0 3 3.83 0 ...
## $ Twitter
                                                : chr [1:22] "Yes" "No" "No" "No" ...
## $ Twitter_value
                                                : num [1:22] 5 0 0 0 0.67 0 0 0 0 0 ...
                                                : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
## $ Whatsapp_Wechat
## $ Whatsapp_Wechat_value
                                                : num [1:22] 1 4.18 9.83 5.3 3 12 6 10 6.15 1 ...
                                               : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
## $ Youtube
## $ Youtube_value
                                                : num [1:22] 2.5 4.25 1.85 2 3.5 7 3 2 4 3 ...
## $ OTT_Netflix_Hulu_Prime video
                                                : chr [1:22] "Yes" "No" "Yes" "Yes" ...
## $ OTT_Netflix_Hulu_Prime_video_value
                                                : num [1:22] 14.5 0 2 2 2 3 0 3 3 0 ...
## $ Reddit
                                                : chr [1:22] "Yes" "No" "No" "No" ...
## $ Reddit_value
                                                : num [1:22] 2.5 0 0 0 1 0 0 0 0 0 ...
## $ Application_type_Social media_OTT_Learning: chr [1:22] "OTT" "Social Media" "Social Media" "Social Media"
## $ job_interview_calls
                                                : num [1:22] 0 0 0 2 0 0 0 0 1 0 ...
## $ networking_done_with_coffee_chats
                                                : num [1:22] 0 1 0 0 2 0 2 0 0 0 ...
## $ learning_done_in_terms_of_items_created : num [1:22] 3 3 4 4 4 4 3 2 6 2 ...
## $ Mood_Productivity
                                                : chr [1:22] "Yes" "Yes" "Yes" "Yes" ...
                                                : chr [1:22] "No" "No" "No" "No" ...
## $ Tired_waking_up_in_morning
## $ Trouble_falling_asleep
                                                : chr [1:22] "No" "Yes" "No" "No" ...
## $ felt_the_entire_week
                                                : num [1:22] 3 3 4 4 3 5 4 4 3 2 ...
APP_data$Tired_waking_up_in_morning <- as.factor(APP_data$Tired_waking_up_in_morning)
#reg_data$area <- as.factor(reg_data$area)</pre>
#reg_data$rooms <- as.factor(reg_data$rooms)</pre>
#reg_data$bathroom <- as.factor(reg_data$rooms)</pre>
#reg_data$rent_amount <- as.factor(reg_data$rent_amount)</pre>
logistic <- glm(Tired_waking_up_in_morning~Instagram_value + Linkedin_value + Snapchat_value + Twitter_
## Warning: glm.fit: algorithm did not converge
```

 $APP_{data} \leftarrow APP_{data}[c(1:22), c(1:2, 4:5, 7:8, 10:11, 13:14, 16:17, 19:20, 22:23, 25:33)]$

Model Acceptance and Residual Analysis

In the summary of the model, we focus on R squared value, coefficients, and P-value of each coefficient. The R-squared value is 1 and p value is 0.003830217. The Pseudo R-square shows there is an improvement and better than baseline model. The p-value based on Likelihood Ratio Test shows that the model improvement is significant. The AIC value is 25.

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

```
summary(logistic)
```

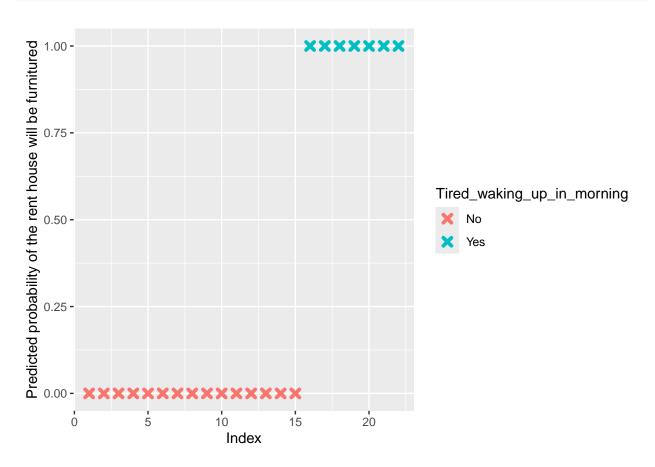
```
##
## Call:
## glm(formula = Tired_waking_up_in_morning ~ Instagram_value +
       Linkedin_value + Snapchat_value + Twitter_value + Whatsapp_Wechat_value +
##
##
       Youtube_value + OTT_Netflix_Hulu_Prime_video_value + Reddit_value +
       job interview calls + networking done with coffee chats +
##
       learning_done_in_terms_of_items_created, family = "binomial",
##
       data = APP data)
##
##
## Coefficients:
##
                                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)
                                                      224245.98
                                                                  0.001
                                                                            0.999
                                               149.87
## Instagram_value
                                               81.67
                                                        54138.45
                                                                   0.002
                                                                            0.999
                                                        37871.65 -0.002
## Linkedin_value
                                              -83.49
                                                                            0.998
## Snapchat_value
                                               -55.48
                                                        69825.80 -0.001
                                                                            0.999
## Twitter_value
                                              -733.98
                                                       249046.93 -0.003
                                                                            0.998
## Whatsapp_Wechat_value
                                                        39967.73 -0.001
                                              -44.65
                                                                            0.999
## Youtube value
                                             -170.27
                                                        75162.26 -0.002
                                                                            0.998
## OTT_Netflix_Hulu_Prime_video_value
                                               71.64
                                                        45451.68
                                                                  0.002
                                                                            0.999
## Reddit value
                                                32.48
                                                        22129.84
                                                                  0.001
                                                                            0.999
## job_interview_calls
                                              -201.82 105010.15 -0.002
                                                                            0.998
## networking_done_with_coffee_chats
                                               112.53
                                                        80398.13
                                                                  0.001
                                                                            0.999
## learning_done_in_terms_of_items_created
                                               185.57
                                                        69364.98
                                                                   0.003
                                                                            0.998
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 2.7522e+01 on 21 degrees of freedom
## Residual deviance: 1.7479e-08 on 10 degrees of freedom
## AIC: 24
##
## Number of Fisher Scoring iterations: 25
11.null <- logistic$null.deviance/-2</pre>
11.proposed <- logistic$deviance/-2</pre>
(ll.null - ll.proposed) / ll.null
## [1] 1
1 - pchisq(2*(11.proposed - 11.null), df=(length(logistic$coefficients)-1))
## [1] 0.003830217
```

Prediction

The data will be predicted in the model and the predicted probability of the rent house will be furnitured table is as follows.

```
predicted.data <- data.frame(probability.of.Tired_waking_up_in_morning=logistic$fitted.values,Tired_wak
predicted.data <- predicted.data[order(predicted.data$probability.of.Tired_waking_up_in_morning, decrea
predicted.data$rank <- 1:nrow(predicted.data)
ggplot(data=predicted.data, aes(x=rank, y=probability.of.Tired_waking_up_in_morning)) +
geom_point(aes(color=Tired_waking_up_in_morning), alpha=1, shape=4, stroke=2) +</pre>
```

```
xlab("Index") +
ylab("Predicted probability of the rent house will be furnitured")
```



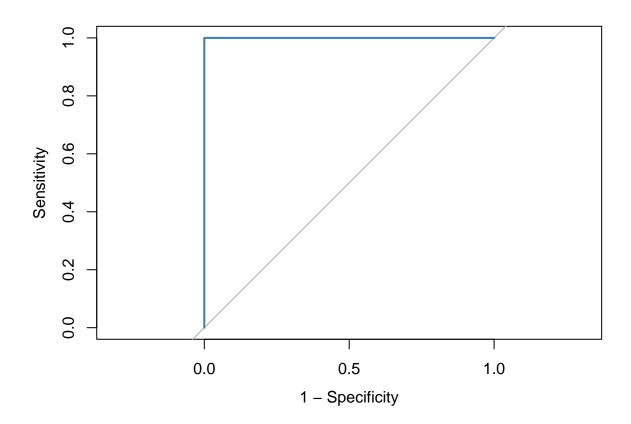
Model Accuracy

Receiver operating characteristic (ROC) curves is shown as follows. The area under the curve (AUC) is 1, which means the accuracy of the model is considered outstanding.

```
roc(APP_data$Tired_waking_up_in_morning,logistic$fitted.values,plot=TRUE, legacy.axes=TRUE, col="#377eb
```

Setting levels: control = No, case = Yes

Setting direction: controls < cases



```
##
## Call:
## roc.default(response = APP_data$Tired_waking_up_in_morning, predictor = logistic$fitted.values,
##
## Data: logistic$fitted.values in 15 controls (APP_data$Tired_waking_up_in_morning No) < 7 cases (APP_data*Tired_waking_up_in_morning No) < 7 cases (APP_data*Tired_waking_up_in_morning No)</pre>
```