Homework 6

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Link to repository:

```
# Load libraries and dataset
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------------------------- tidyverse 1.2.1 --
```

```
## v ggplot2 2.2.1     v purrr   0.2.4
## v tibble  1.4.2     v dplyr   0.7.4
## v tidyr   0.8.0     v stringr 1.3.0
## v readr   1.1.1     v forcats 0.3.0
```

```
## -- Conflicts ------------------------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(haven)
library(car)
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
## The following object is masked from 'package:purrr':
##
##     some
```

```
library(ROCR)
```

```
## Warning: package 'ROCR' was built under R version 3.4.4
```

```
## Loading required package: gplots
```

```
## Warning: package 'gplots' was built under R version 3.4.4
```

```
##
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':
##
##     lowess
```

```
helpdata <- haven::read_spss("helpmkh.sav")

# choose variable
h1 <- helpdata %>%
  select(age, female, pss_fr, homeless,
         pcs, mcs, cesd)

# add dichotomous variable to indicate depression for people with CESD scores >= 16
h1 <- h1 %>%
  mutate(cesd_gte16 = cesd >= 16)

# change cesd_gte16 LOGIC variable type to numeric coded 1=TRUE and 0=FALSE
h1$cesd_gte16 <- as.numeric(h1$cesd_gte16)

# check final data subset h1
summary(h1)
```

```
##       age            female           pss_fr          homeless     
##  Min.   :19.00   Min.   :0.0000   Min.   : 0.000   Min.   :0.0000  
##  1st Qu.:30.00   1st Qu.:0.0000   1st Qu.: 3.000   1st Qu.:0.0000  
##  Median :35.00   Median :0.0000   Median : 7.000   Median :0.0000  
##  Mean   :35.65   Mean   :0.2362   Mean   : 6.706   Mean   :0.4614  
##  3rd Qu.:40.00   3rd Qu.:0.0000   3rd Qu.:10.000   3rd Qu.:1.0000  
##  Max.   :60.00   Max.   :1.0000   Max.   :14.000   Max.   :1.0000  
##       pcs             mcs              cesd         cesd_gte16    
##  Min.   :14.07   Min.   : 6.763   Min.   : 1.00   Min.   :0.0000  
##  1st Qu.:40.38   1st Qu.:21.676   1st Qu.:25.00   1st Qu.:1.0000  
##  Median :48.88   Median :28.602   Median :34.00   Median :1.0000  
##  Mean   :48.05   Mean   :31.677   Mean   :32.85   Mean   :0.8985  
##  3rd Qu.:56.95   3rd Qu.:40.941   3rd Qu.:41.00   3rd Qu.:1.0000  
##  Max.   :74.81   Max.   :62.175   Max.   :60.00   Max.   :1.0000
```

1. [Model 1] Run a simple linear regression (`lm()`) for `cesd` using the `mcs` variable, which is the mental component quality of life score from the SF36.

```
slr<-lm(cesd~mcs, data=h1)
slr
```

```
## 
## Call:
## lm(formula = cesd ~ mcs, data = h1)
## 
## Coefficients:
## (Intercept)          mcs  
##     53.9022      -0.6647
```

2. Write the equation of the final fitted model (i.e. what is the intercept and the slope)? Write a sentence describing the model results (interpret the intercept and slope).

NOTE: The `mcs` values range form 0 to 100 where the population norm for "normal mental health quality of life" is considered to be a 50. If you score higher than 50 on the `mcs` you have mental health better than the population and visa versa - if your `mcs` scores are less than 50 then your mental health is considered to be worse than the population norm.

```
cesd=53.9022-0.6647*mcs
```

For every 1 point increase in MCS score, the CEDS score decreases by 0.6647. Generally, better mental health is associated with lower depression score. Those with an MCS score of 0 will have a CESD of 53.9022.

3. How much variability in the `cesd` does the `mcs` explain? (what is the R^2?) Write a sentence describing how well the `mcs` does in predicting the `cesd`.

The adjusted R^2 is 0.4638, which indicates that `cesd` accounts for 46.38% of the variability in `mcs`, which is fairly good for a simple linear regression model.

4. [Model 2] Run a second linear regression model (`lm()`) for the `cesd` putting in all of the other variables:

```
mlr<-lm(cesd~age +female +pss_fr +homeless +pcs +mcs, data=h1)
summary(mlr)
```

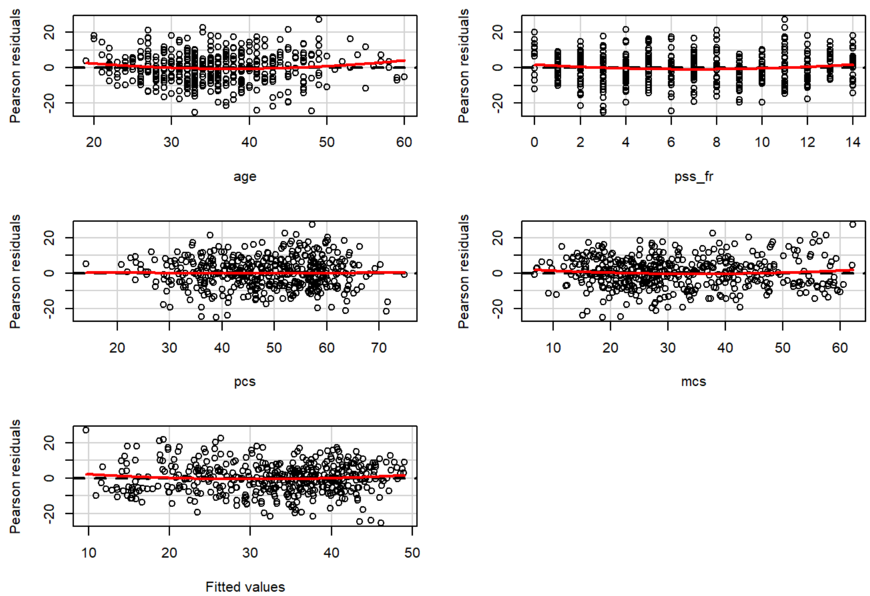
```
##
## Call:
## lm(formula = cesd ~ age + female + pss_fr + homeless + pcs +
##     mcs, data = h1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25.1711  -5.9894  -0.2077   5.5706  27.3137
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 65.30046    3.18670  20.492  < 2e-16 ***
## age         -0.01348    0.05501  -0.245   0.8065
## female       2.35028    0.98810   2.379   0.0178 *
## pss_fr      -0.25569    0.10567  -2.420   0.0159 *
## homeless     0.46545    0.84261   0.552   0.5810
## pcs         -0.23639    0.03987  -5.929  6.1e-09 ***
## mcs         -0.62093    0.03261 -19.042  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.683 on 446 degrees of freedom
## Multiple R-squared:  0.5249, Adjusted R-squared:  0.5185
## F-statistic: 82.14 on 6 and 446 DF,  p-value: < 2.2e-16
```

5. Which variables are significant in the model? Write a sentence or two describing the impact of these variables for predicting depression scores (HINT: interpret the coefficient terms).

When adjusting for the other variables in the model, the following variables are significant in the model: `female` , `pss_fr` , `pcs` , and `mcs` . When adjusting for the other variables, a 1 unit increase in `female` results in a 2.35028 increase in `cesd` , and a 1 unit increase in `pss_fr` , `pcs` , or `mcs` results in a 0.25569, 0.23639, or 0.62093 decrease in `cesd` respectively.

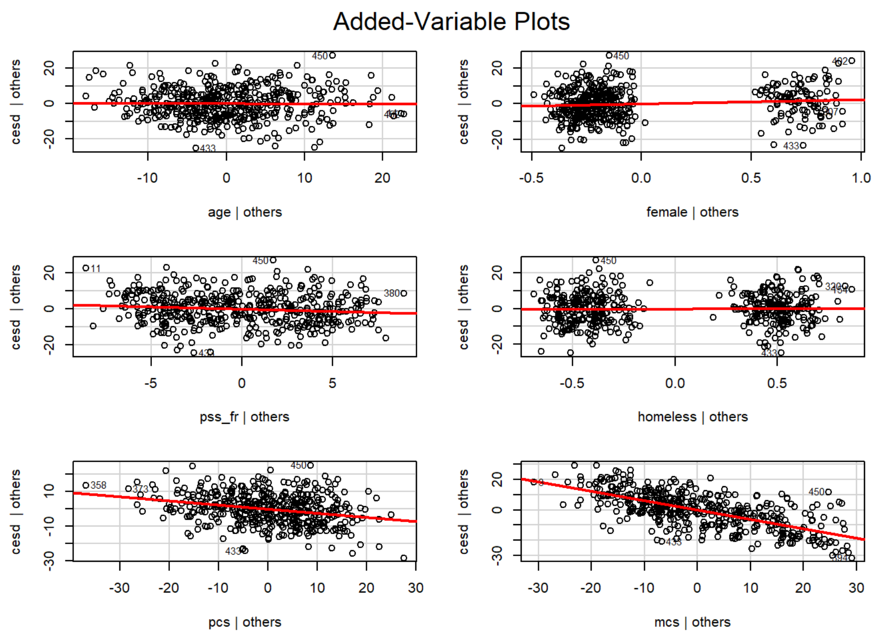
6. Following the example we did in class for the Prestige dataset https://cdn.rawgit.com/vhertzb/2018week9/2f2ea142/2018week9.html?raw=true (https://cdn.rawgit.com/vhertzb/2018week9/2f2ea142/2018week9.html?raw=true), generate the diagnostic plots for this model with these 6 predictors (e.g. get the residual plot by variables, the added-variable plots, the Q-Q plot, diagnostic plots). Also run the VIFs to check for multicollinearity issues.

```
residualPlots(mlr)
```

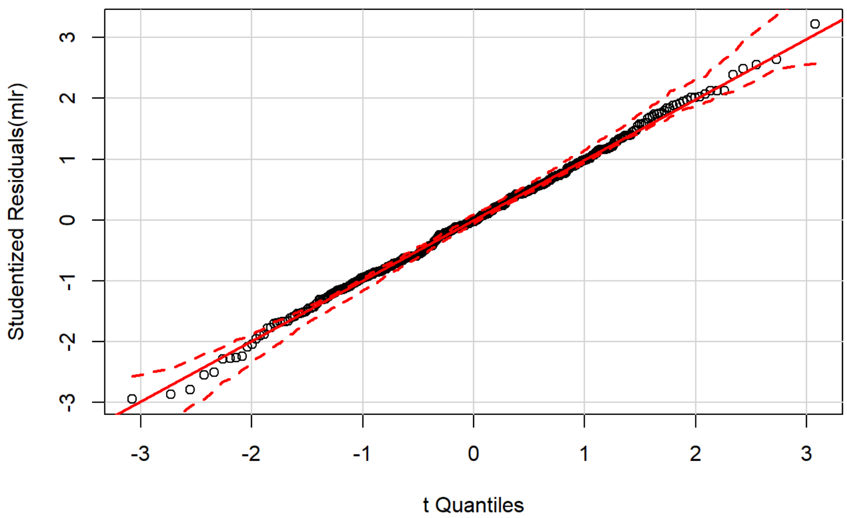



```
##            Test stat Pr(>|t|)
## age            1.941    0.053
## pss_fr         1.964    0.050
## pcs            0.081    0.936
## mcs            1.260    0.208
## Tukey test     1.434    0.152
```

```
avPlots(mlr, id.n=2, id.cex=0.7)
```



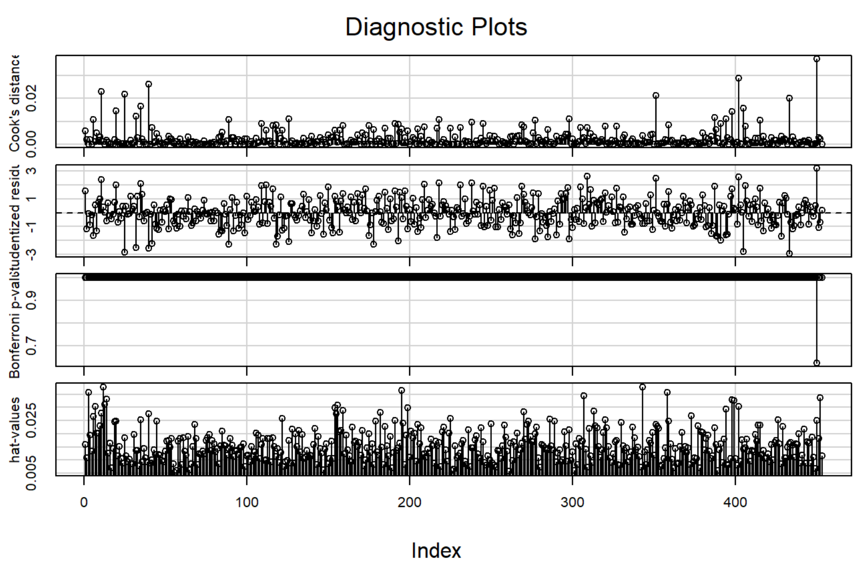

```
qqPlot(mlr)
```



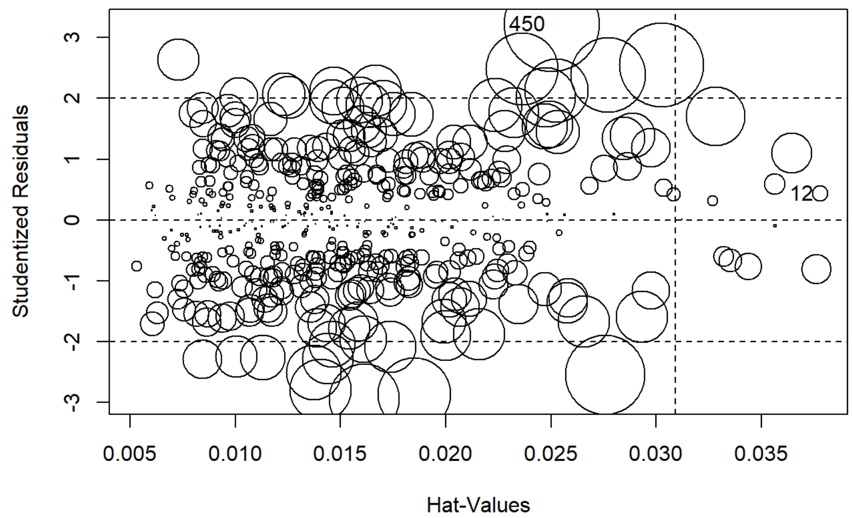

```
outlierTest(mlr)
```

```
##
## No Studentized residuals with Bonferonni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferonni p
## 450 3.218868          0.0013811      0.62564
```

```
influenceIndexPlot(mlr)
```




```
influencePlot(mlr)
```




```
##       StudRes        Hat       CookD
## 12  0.4313265 0.03779399 0.001045833
## 450 3.2188680 0.02502996 0.037218269
```

```
vif(mlr)
```

```
##      age   female   pss_fr homeless      pcs      mcs
## 1.078264 1.058232 1.068213 1.060007 1.108172 1.050768
```

7. [Model 3] Repeat Model 1 above, except this time run a logistic regression (`glm()`) to predict CESD scores => 16 (using the `cesd_gte16` as the outcome) as a function of `mcs` scores. Show a summary of the final fitted model and explain the coefficients. [**REMEMBER** to compute the Odds Ratios after you get the raw coefficient (betas)].

```
library(Rcmdr)

glm <- glm(cesd_gte16 ~ age + female + homeless + mcs + pcs + pss_fr,
  family=binomial(logit), data=h1)
summary(glm)
```

```
##
## Call:
## glm(formula = cesd_gte16 ~ age + female + homeless + mcs + pcs +
##     pss_fr, family = binomial(logit), data = h1)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.85998   0.05842   0.11550   0.25922   1.98715
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 12.613583   1.943130   6.491 8.51e-11 ***
## age         -0.009384   0.026395  -0.356   0.7222
## female      -0.292533   0.512991  -0.570   0.5685
## homeless     0.025789   0.422105   0.061   0.9513
## mcs         -0.165266   0.022569  -7.323 2.43e-13 ***
## pcs         -0.057856   0.023500  -2.462   0.0138 *
## pss_fr      -0.035518   0.049629  -0.716   0.4742
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 297.59  on 452  degrees of freedom
## Residual deviance: 166.90  on 446  degrees of freedom
## AIC: 180.9
##
## Number of Fisher Scoring iterations: 7
```

```
exp(coef(glm))  # Exponentiated coefficients ("odds ratios")
```

```
##  (Intercept)          age       female     homeless          mcs
## 3.006143e+05 9.906595e-01 7.463708e-01 1.026125e+00 8.476682e-01
##          pcs       pss_fr
## 9.437861e-01 9.651054e-01
```

The coeficients indicate the probability that a variable will increase or decrease the probability of an event when adjusting for all the other variables. For instance, when adjusting for sex, homelessness, MCS, PCS, and PSS, an increase in age is associated with a 0.009384 decrease in probability of CESD greater than 16.

8. Use the `predict()` function like we did in class to predict CESD => 16 and compare it back to the original data. For now, use a cutoff probability of 0.5 - if the probability is > 0.5 consider this to be true and false otherwise. Like we did in class. **REMEMBER** See the R code for the class example at https://github.com/melindahiggins2000/N741_lecture11_27March20 (https://github.com/melindahiggins2000/N741_lecture11_27March2

```
+ How well did the model correctly predict CESD scores => 16 (indicating depression)? (make the "confusion matrix" and look
at the true positives and true negatives versus the false positives and false negatives).
```

```
glm.predict <- predict(glm, newdata=h1,
                      type="response")
table(h1$cesd_gte16, glm.predict > 0.5)
```

```
##
##     FALSE TRUE
##   0    24   22
##   1    14  393
```

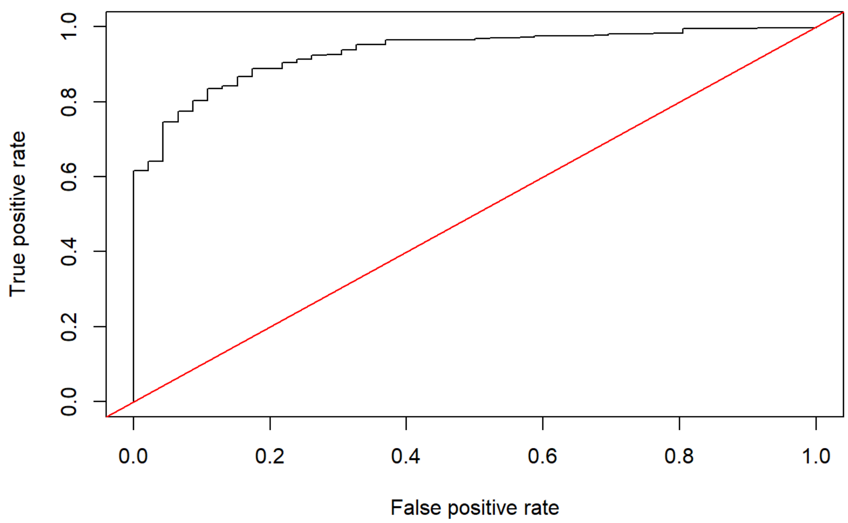
```
t1 <- table(glm.predict > 0.5, h1$cesd_gte16)
t1
```

```
##
##          0   1
##   FALSE  24  14
##   TRUE   22 393
```

The model was able to predict 393 of the 415 true cases CESD scores =>6.

9. Make an ROC curve plot and compute the AUC and explain if this is a good model for predicting depression or not

```
p <- predict(glm, newdata=h1,
             type="response")
pr <- prediction(p, as.numeric(h1$cesd_gte16))
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
abline(a=0, b=1, col="red")
```



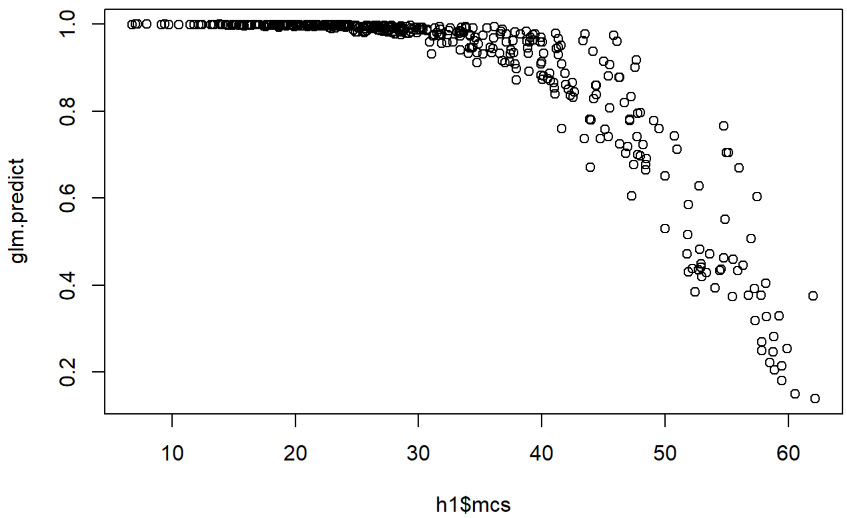

```
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
auc
```

```
## [1] 0.931471
```

AUC of 0.93 is great, so this is a good model to predict depression.

10. Make a plot showing the probability curve - put the `mcs` values on the X-axis and the probability of depression on the Y-axis. Based on this plot, do you think the `mcs` is a good predictor of depression? [**FYI** This plot is also called an "effect plot" is you're using `Rcmdr` to do these analyses.]

```
plot(h1$mcs, glm.predict)
```



HOW DO YOU INTERPRET?? MCS less than 30 seems to indicate 1.0 for prediction, then negative slope.