Multivariate Analysis for the Behavioral Sciences, Second Edition (Chapman and Hall/CRC, 2019)

Examples of Chapter 6: Applying Logistic Regression

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Examples

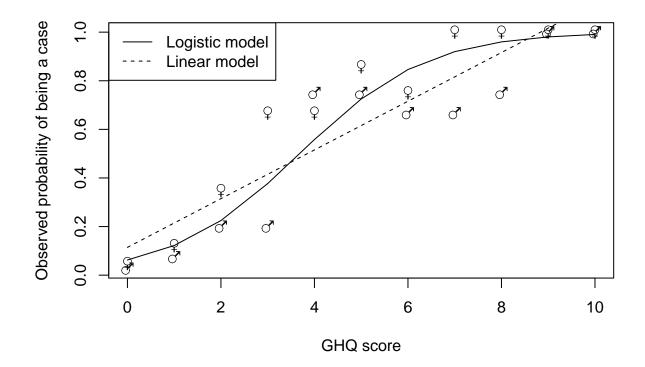
Table 6.1: Psychiatric Caseness Data

```
GHQ \leftarrow c(0:10, 0:10)
sex \leftarrow c(rep(0,11), rep(1,11))
ncases \leftarrow c(4, 4, 8, 6, 4, 6, 3, 2, 3, 2, 1, 1, 2, 2, 1, 3, 3, 2, 4, 3, 2, 2)
nnotcases <- c(80, 29, 15, 3, 2, 1, 1, 0, 0, 0, 0, 36, 25, 8, 4, 1, 1, 1, 2, 1, 0, 0)
cbind(sex, GHQ, ncases, nnotcases)
##
         sex GHQ ncases nnotcases
                       4
##
    [1,]
           0
               0
##
   [2,]
               1
                       4
                                29
           0
               2
                       8
                                15
##
   [3,]
           0
##
   [4,]
           0
               3
                       6
                                 3
   [5,]
           0
               4
                       4
                                 2
##
                       6
##
   [6,]
           0
               5
                                 1
   [7,]
               6
                       3
                                 1
##
## [8,]
               7
                       2
                                 0
           0
## [9,]
               8
                       3
                                 0
## [10,]
               9
                       2
                                 0
           0
                                 0
## [11,]
              10
                       1
## [12,]
                                36
               0
                       1
           1
                       2
## [13,]
           1
               1
                                25
               2
                       2
## [14,]
           1
                                 8
## [15,]
           1
               3
                       1
                                 4
## [16,]
           1
               4
                       3
                                 1
## [17,]
           1
               5
                       3
                                 1
                       2
                                 1
## [18,]
               6
           1
## [19,]
               7
                       4
                                 2
           1
## [20,]
           1
               8
                       3
                                 1
                       2
## [21,]
           1
               9
                                 0
                       2
                                 0
## [22,]
              10
sex <- factor(sex, levels = c(0, 1), labels = c("F", "M"))
```

Tables 6.2 and 6.3, Figure 6.1

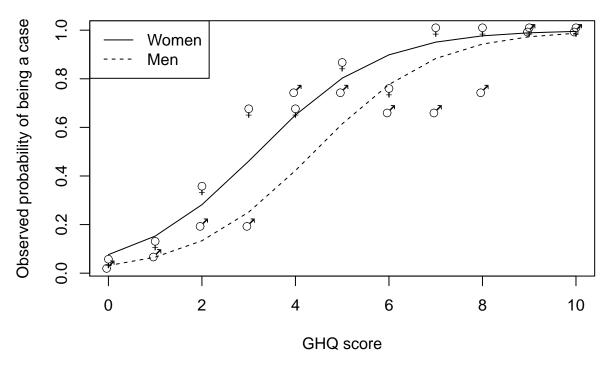
```
GHQ_reg <- glm(cbind(ncases,nnotcases) ~ sex, family = binomial)</pre>
summary(GHQ reg)
## Call:
## glm(formula = cbind(ncases, nnotcases) ~ sex, family = binomial)
## Deviance Residuals:
##
       Min
                 1Q
                      Median
                                    3Q
                                            Max
## -4.9434
             0.1076
                      2.1458
                                         3.4059
                                2.3646
##
## Coefficients:
##
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.11400
                           0.17575 -6.338 2.32e-10 ***
               -0.03657
                           0.28905 -0.127
                                               0.899
## sexM
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 130.31 on 21 degrees of freedom
## Residual deviance: 130.29 on 20 degrees of freedom
## AIC: 170.26
##
## Number of Fisher Scoring iterations: 5
predict(GHQ_reg, type = "response")
                     2
                                3
                                                                         7
##
                                          4
                                                     5
## 0.2471264 0.2471264 0.2471264 0.2471264 0.2471264 0.2471264 0.2471264 0.2471264
           8
                     9
                               10
                                         11
                                                    12
                                                              13
## 0.2471264 0.2471264 0.2471264 0.2471264 0.2403846 0.2403846 0.2403846
                               17
                                         18
                                                    19
## 0.2403846 0.2403846 0.2403846 0.2403846 0.2403846 0.2403846 0.2403846
##
          22
## 0.2403846
GHQ_reg1 <- glm(cbind(ncases,nnotcases) ~ GHQ, family = binomial)</pre>
fitted <- predict(GHQ_reg1, type = "response")</pre>
pobsv <- ncases / (ncases + nnotcases)</pre>
plot(GHQ, pobsy, type = "n", xlab = "GHQ score", ylab = "Observed probability of being a case")
text(GHQ, pobsv, ifelse(sex == "F", "\VE", "\MA"), vfont = c("serif", "plain"), cex = 1.25)
lines(0:10, fitted[1:11])
GHQ_lin <- lm(pobsv ~ GHQ)</pre>
summary(GHQ_lin)
##
## Call:
## lm(formula = pobsv ~ GHQ)
##
## Residuals:
        Min
                       Median
                  1Q
                                     30
                                             Max
## -0.21505 -0.11624 -0.03279 0.12180 0.25161
```

```
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 0.11434
                           0.05923
                                     1.931
                                            0.0678 .
                0.10024
                           0.01001 10.012 3.1e-09 ***
## GHQ
##
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.1485 on 20 degrees of freedom
## Multiple R-squared: 0.8337, Adjusted R-squared: 0.8254
## F-statistic: 100.2 on 1 and 20 DF, p-value: 3.099e-09
fitted <- predict(GHQ_lin)</pre>
lines(0:10, fitted[1:11], lty = 2)
legend("topleft", c("Logistic model", "Linear model"), lty = 1:2)
```



Tables 6.4 and 6.5, Figures 6.2 and 6.3

```
GHQ_reg2 <- glm(cbind(ncases,nnotcases) ~ sex + GHQ, family = binomial)</pre>
summary(GHQ_reg2)
## Call:
## glm(formula = cbind(ncases, nnotcases) ~ sex + GHQ, family = binomial)
## Deviance Residuals:
##
       Min
                 1Q
                      Median
                                   3Q
                                           Max
## -1.3955 -0.3939
                      0.1876
                               0.4315
                                        1.3306
##
## Coefficients:
##
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.49351
                           0.28164 -8.854 < 2e-16 ***
               -0.93609
                           0.43435 -2.155
                                             0.0311 *
## sexM
## GHQ
                0.77910
                           0.09903
                                     7.867 3.63e-15 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 130.306 on 21 degrees of freedom
## Residual deviance: 11.113 on 19 degrees of freedom
## AIC: 53.087
##
## Number of Fisher Scoring iterations: 5
fitted <- predict(GHQ_reg2, type = "response")</pre>
pobsv <- ncases / (ncases + nnotcases)</pre>
plot(GHQ, pobsv, type = "n", xlab = "GHQ score", ylab = "Observed probability of being a case")
text(GHQ, pobsv, ifelse(sex == "F", "\\VE", "\\MA"), vfont = c("serif", "plain"), cex = 1.25)
lines(0:10, fitted[1:11])
lines(0:10, fitted[12:22], lty = 2)
legend("topleft", c("Women", "Men"), lty = 1:2)
```



```
#interaction model
GHQ_reg3 <- glm(cbind(ncases,nnotcases) ~ sex * GHQ, family = binomial)</pre>
summary(GHQ_reg3)
##
## Call:
## glm(formula = cbind(ncases, nnotcases) ~ sex * GHQ, family = binomial)
##
## Deviance Residuals:
##
        Min
                   1Q
                         Median
                                        3Q
                                                 Max
##
  -1.29971 -0.32521
                      -0.03273
                                   0.39672
                                             1.45689
##
##
  Coefficients:
##
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.7732
                            0.3586 -7.732 1.06e-14 ***
##
  sexM
                -0.2253
                            0.6093
                                    -0.370
                                               0.712
                 0.9412
                            0.1569
## GHQ
                                      6.000 1.97e-09 ***
## sexM:GHQ
                -0.3020
                            0.1990
                                    -1.517
                                               0.129
##
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 130.3059
                                on 21 degrees of freedom
## Residual deviance:
                        8.7669 on 18 degrees of freedom
## AIC: 52.741
```

```
##
## Number of Fisher Scoring iterations: 5
fitted <- predict(GHQ_reg3, type = "response")
pobsv <- ncases / (ncases + nnotcases)
plot(GHQ, pobsv, type = "n", xlab = "GHQ score", ylab = "Observed probability of being a case")
text(GHQ, pobsv, ifelse(sex == "F", "\\VE", "\\MA"), vfont = c("serif", "plain"), cex = 1.25)
lines(0:10, fitted[1:11])
lines(0:10, fitted[12:22], lty = 2)
legend("topleft", c("Women", "Men"), lty = 1:2)</pre>
```

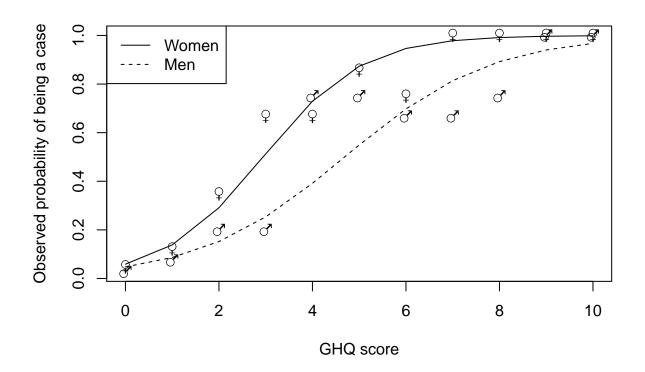


Table 6.6: Do-It-Yourself Data

```
work \leftarrow rep(c(1, 2, 3), c(12, 12, 12))
tenure \leftarrow \text{rep}(c(\text{rep}(1, 6), \text{rep}(2, 6)), 3)
type \leftarrow rep(c(rep(1, 3), rep(2, 3)), 6)
age \leftarrow rep(c(1, 2, 3), 12)
yes <- c(18, 15, 6, 34, 10, 2, 15, 13, 9, 28, 4, 6, 5, 3, 1, 56, 56, 35, 1, 1, 1, 12, 21,
         8, 17, 10, 15, 29, 3, 7, 34, 17, 19, 44, 13, 16, 2, 0, 3, 23, 52, 49, 3, 2, 0,
         9, 31, 51, 30, 23, 21, 22, 13, 11, 25, 19, 40, 25, 16, 12, 8, 5, 1, 54, 191,
         102, 4, 2, 2, 19, 76, 61)
no \leftarrow yes[c(7:12, 19:24, 31:36, 43:48, 55:60, 67:72)]
yes <- yes[c(1:6, 13:18, 25:30, 37:42, 49:54, 61:66)]
work <- factor(work, levels = c(1, 2, 3), labels = c("skilled", "unskilled", "office"))</pre>
tenure <- factor(tenure, levels = c(1, 2), labels = c("rent", "own"))
type <- factor(type, levels = c(1, 2), labels = c("apartment", "house"))</pre>
age <- factor(age, levels = c(1, 2, 3), labels = c("<30", "31-45", "46+"))
data.frame(work, tenure, type, age, yes, no)
##
           work tenure
                             type
                                    age yes no
## 1
        skilled
                  rent apartment
                                    <30
                                        18 15
## 2
        skilled
                  rent apartment 31-45
                                         15 13
## 3
        skilled
                  rent apartment
                                    46+
                                          6 9
## 4
                                    <30
                                         34 28
        skilled
                  rent
                            house
## 5
        skilled
                  rent
                            house 31-45
                                         10
## 6
        skilled
                  rent
                            house
                                    46+
## 7
        skilled
                   own apartment
                                    <30
                                         5 1
## 8
                   own apartment 31-45
        skilled
                                          3
                                             1
## 9
        skilled
                   own apartment
                                    46+
                                          1 1
## 10
        skilled
                   own
                            house
                                    <30
                                        56 12
## 11
        skilled
                            house 31-45 56 21
                   own
## 12
        skilled
                                    46+
                                         35 8
                   own
                            house
## 13 unskilled
                                    <30 17 34
                  rent apartment
## 14 unskilled
                  rent apartment 31-45
                                         10 17
## 15 unskilled
                  rent apartment
                                    46+
                                         15 19
## 16 unskilled
                  rent
                            house
                                    <30 29 44
## 17 unskilled
                            house 31-45
                  rent
                                         3 13
## 18 unskilled
                            house
                                    46+
                                          7 16
                  rent
## 19 unskilled
                   own apartment
                                    <30
                                          2
                                             3
## 20 unskilled
                   own apartment 31-45
                                          0
                                             2
## 21 unskilled
                   own apartment
                                    46+
                                          3 0
## 22 unskilled
                            house
                                    <30 23 9
                   own
## 23 unskilled
                            house 31-45 52 31
                   own
                                    46+ 49 51
## 24 unskilled
                   own
                            house
## 25
         office
                  rent apartment
                                    <30 30 25
## 26
         office
                  rent apartment 31-45 23 19
## 27
         office
                  rent apartment
                                    46+
                                         21 40
## 28
                                         22 25
         office
                            house
                                    <30
                  rent
## 29
         office
                            house 31-45
                                        13 16
                  rent
## 30
                                        11 12
         office
                  rent
                            house
                                    46+
## 31
         office
                   own apartment
                                    <30
```

## 33 office own apartment 46+ 1 2 ## 34 office own house <30 54 19 ## 35 office own house 31-45 191 76	## 33 office own apartment 46+ 1 2 ## 34 office own house <30 54 19								
## 34 office own house <30 54 19 ## 35 office own house 31-45 191 76	## 34 office own house <30 54 19 ## 35 office own house 31-45 191 76	##	32	office	own	apartment	31-45	5	2
## 35 office own house 31-45 191 76	## 35 office own house 31-45 191 76	##	33	office	own	apartment	46+	1	2
		##	34	office	own	house	<30	54	19
111 00 00 100	## 36 office own house 46+ 102 61	##	35	office	own	house	31-45	191	76
## 36 office own house 46+ 102 61		##	36	office	own	house	46+	102	61

Table 6.7

```
# R will create the dummy variables automatically when using factor variables:
reg <- glm(cbind(yes,no) ~ work + type + tenure + age, family = "binomial")</pre>
summary(reg)
##
## Call:
## glm(formula = cbind(yes, no) ~ work + type + tenure + age, family = "binomial")
## Deviance Residuals:
      Min 1Q Median
                                 3Q
                                         Max
## -1.9399 -0.6574 -0.1131 0.4123
                                      1.9501
##
## Coefficients:
                Estimate Std. Error z value Pr(>|z|)
##
## (Intercept)
                0.30606 0.15428 1.984
                                           0.0473 *
## workunskilled -0.76267
                           0.15197 -5.018 5.21e-07 ***
## workoffice -0.30535
                         0.14088 -2.167
                                           0.0302 *
                                            0.9865
## typehouse
              -0.00249 0.14717 -0.017
## tenureown
                1.01570
                         0.13787 7.367 1.74e-13 ***
                           0.13697 -0.825 0.4092
## age31-45
                -0.11304
## age46+
                -0.43661
                           0.14059 -3.106 0.0019 **
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 158.884 on 35 degrees of freedom
## Residual deviance: 29.671 on 29 degrees of freedom
## AIC: 167.87
##
## Number of Fisher Scoring iterations: 4
```

Table 6.8

```
reg <- glm(cbind(yes,no) ~ work + tenure + type + age, family = binomial)</pre>
step(reg, direction = "backward")
## Start: AIC=167.87
## cbind(yes, no) ~ work + tenure + type + age
##
##
           Df Deviance
                          AIC
            1 29.671 165.87
## - type
## <none>
                29.671 167.87
## - age
            2 40.559 174.76
            2 56.971 191.17
## - work
## - tenure 1 85.599 221.80
##
## Step: AIC=165.87
## cbind(yes, no) ~ work + tenure + age
           Df Deviance
##
                          AIC
## <none>
                29.671 165.87
            2 40.613 172.81
## - age
## - work
            2 56.985 189.19
## - tenure 1 110.781 244.98
## Call: glm(formula = cbind(yes, no) ~ work + tenure + age, family = binomial)
##
## Coefficients:
   (Intercept) workunskilled
                                   workoffice
                                                   tenureown
                                                                   age31-45
##
         0.3048
                       -0.7627
                                      -0.3053
                                                                   -0.1129
##
                                                      1.0144
         age46+
##
##
        -0.4364
##
## Degrees of Freedom: 35 Total (i.e. Null); 30 Residual
## Null Deviance:
                       158.9
## Residual Deviance: 29.67
                               AIC: 165.9
```

Tables 6.10 and 6.11: Low Back Pain Data

```
library(HSAUR3)
## Loading required package: tools
##
## Attaching package: 'HSAUR3'
## The following object is masked _by_ '.GlobalEnv':
##
##
       GHQ
data(backpain)
str(backpain)
## 'data.frame':
                   434 obs. of 4 variables:
             : Factor w/ 217 levels "1","2","3","4",...: 1 1 2 2 3 3 4 4 5 5 ...
## $ status : Factor w/ 2 levels "case", "control": 1 2 1 2 1 2 1 2 1 2 ...
## $ driver : Factor w/ 2 levels "no", "yes": 2 2 2 2 2 1 1 2 2 ...
## $ suburban: Factor w/ 2 levels "no", "yes": 2 1 2 2 1 2 1 1 1 2 ...
library(survival)
backpain_glm <- clogit(I(status == "case") ~ driver + suburban + strata(ID), data = backpain)
summary(backpain_glm)
## Call:
## coxph(formula = Surv(rep(1, 434L), I(status == "case")) ~ driver +
      suburban + strata(ID), data = backpain, method = "exact")
##
    n= 434, number of events= 217
##
##
##
                 coef exp(coef) se(coef)
                                            z Pr(>|z|)
                        1.9307
                                               0.0252 *
## driveryes
              0.6579
                                 0.2940 2.238
                                 0.2258 1.131
## suburbanyes 0.2555
                        1.2911
                                                 0.2580
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
              exp(coef) exp(-coef) lower .95 upper .95
##
## driveryes
                   1.931
                             0.5180
                                      1.0851
                                                  3.435
                   1.291
                                      0.8293
                                                  2.010
## suburbanyes
                             0.7746
## Rsquare= 0.022
                   (max possible= 0.5)
## Likelihood ratio test= 9.55 on 2 df,
                                          p=0.008457
## Wald test
                       = 8.85 on 2 df,
                                          p=0.01195
## Score (logrank) test = 9.31 on 2 df,
                                          p=0.0095
```