Booklet of Code and Output for STAD29/STA 1007 Midterm Exam

## List of Figures in this document by page:

## List of Figures

1	NBA attendance data
2	Regression model for NBA attendances
3	Residual plots for NBA attendances
4	Ozone layer data
5	Ozone layer data processing part 1
6	Ozone layer data processing part 2
7	Ozone layer scatterplot
8	New Zealand bird data
9	Analysis 1 of NZ bird data
10	Analysis 2 of NZ bird data
11	Analysis 3 of NZ bird data
12	Space shuttle data (summary)
13	Space shuttle part 1
14	Space shuttle part 2
15	Space shuttle part 3
16	Predictions 1
17	Prediction 2
18	Primary biliary cirrhosis data
19	Survival analysis part 1
20	Survival analysis part 2
21	Survival analysis part 3
22	Survival analysis part 4

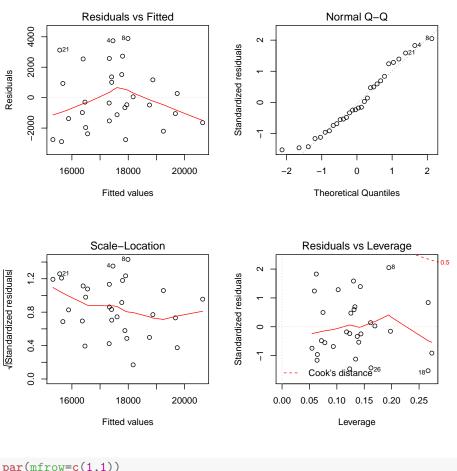
```
nba=read.table("nba-attendance.txt",header=T)
nba
##
               team wins market.share finals attendance
## 1
            Atlanta
                       47
                                  2.070
                                                      16478
## 2
             Boston
                       62
                                  2.105
                                                      18624
                                            yes
## 3
                                  0.981
         Charlotte
                       35
                                             no
                                                      14526
## 4
            Chicago
                       41
                                  3.052
                                                      21197
                                             no
## 5
         Cleveland
                       66
                                  1.332
                                            yes
                                                      20010
## 6
             Dallas
                       50
                                  2.175
                                            yes
                                                      20042
## 7
             Denver
                       54
                                  1.332
                                                      17223
                                             no
## 8
            Detroit
                       39
                                  1.684
                                                      21877
                                            yes
## 9
       GoldenState
                       29
                                  2.164
                                                      18942
                                             no
## 10
            Houston
                       53
                                  1.840
                                                      17482
                                             no
## 11
            Indiana
                                  0.974
                       36
                                             no
                                                      14182
## 12
        LAClippers
                       19
                                  4.940
                                                      16170
                                             no
## 13
           LALakers
                       65
                                  4.940
                                                      18997
                                            yes
## 14
            Memphis
                       24
                                  0.589
                                                      12745
                                             no
                                  1.352
## 15
              Miami
                       43
                                            yes
                                                      18229
## 16
         Milwaukee
                       34
                                  0.791
                                                      15389
                                             no
## 17
         {\tt Minnesota}
                       24
                                  1.512
                                             no
                                                      14505
## 18
         NewJersey
                                  6.495
                       34
                                             no
                                                      15147
## 19
        NewOrleans
                       49
                                  0.527
                                                      16968
                                             no
## 20
            NewYork
                       32
                                  6.495
                                             no
                                                      19287
## 21 OklahomaCity
                       23
                                  0.600
                                                      18693
                                             no
## 22
            Orlando
                       59
                                  1.281
                                            yes
                                                      17043
## 23 Philadelphia
                       41
                                  2.578
                                                      15802
                                             no
## 24
            Phoenix
                       46
                                  1.622
                                                      18422
                                             no
## 25
                                  1.027
           Portland
                       54
                                                      20524
                                             no
## 26
         Sacramento
                       17
                                  1.223
                                                      12571
                                             no
## 27
         SanAntonio
                       54
                                  0.715
                                            yes
                                                      18269
## 28
            Toronto
                       33
                                  4.900
                                             no
                                                      18773
## 29
               Utah
                       48
                                  0.803
                                             no
                                                      19903
## 30
         Washington
                       19
                                  2.028
                                                      16612
                                             no
```

Figure 1: NBA attendance data

```
nba.1=lm(attendance~wins+market.share+finals,data=nba)
summary(nba.1)
##
## Call:
## lm(formula = attendance ~ wins + market.share + finals, data = nba)
##
## Residuals:
             1Q Median
   Min
                              3Q
                                    Max
## -2888.4 -1490.0 -411.6 1315.2 3886.8
##
## Coefficients:
##
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13836.50 1473.50 9.390 7.73e-10 ***
                                  1.958 0.0611 .
                68.26
                          34.87
## market.share 269.36
                           232.72 1.157
                                           0.2576
## finalsyes 1037.88
                        1088.32 0.954
                                          0.3490
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 2113 on 26 degrees of freedom
## Multiple R-squared: 0.3049, Adjusted R-squared: 0.2247
## F-statistic: 3.802 on 3 and 26 DF, p-value: 0.02199
```

Figure 2: Regression model for NBA attendances

```
par(mfrow=c(2,2))
plot(nba.1)
```



```
par(mfrow=c(1,1))
```

Figure 3: Residual plots for NBA attendances

```
ozone=read.table("inhibit.txt",header=T)
ozone
      inhibit.deep uvb.deep inhibit.surface uvb.surface
##
## 1
              0.0
                      0.00
                                       7.0
                                                   0.01
                                        7.0
## 2
              1.0
                      0.00
                                                   0.02
## 3
              6.0
                      0.01
                                       7.0
                                                   0.03
## 4
              9.5
                      0.01
                                       9.0
                                                   0.04
## 5
             10.0
                      0.00
                                       11.0
                                                   0.03
## 6
             14.0
                      0.01
                                       12.5
                                                   0.03
                                                   0.04
## 7
              20.0
                      0.03
                                       21.0
## 8
              25.0
                      0.02
                                         NA
                                                     NA
              39.0
## 9
                      0.03
                                         NA
                                                     NA
## 10
              59.0
                      0.03
                                         NA
                                                     NA
suppressMessages(library(dplyr))
## Warning: package 'dplyr' was built under R version 3.5.2
```

Figure 4: Ozone layer data

```
ozone %>% mutate(inhibit=inhibit.deep,uvb=uvb.deep) %>%
    select(c(inhibit,uvb)) -> deep
ozone %>% mutate(inhibit=inhibit.surface,uvb=uvb.surface) %>%
    select(c(inhibit,uvb)) -> surface
```

Figure 5: Ozone layer data processing part 1

```
v=bind_rows(deep=deep,surface=surface,.id="depth")
V
##
       depth inhibit uvb
## 1
       deep
                 0.0 0.00
## 2
                 1.0 0.00
        deep
## 3
        deep
                 6.0 0.01
## 4
        deep
                9.5 0.01
## 5
              10.0 0.00
        deep
## 6
        deep
               14.0 0.01
## 7
                20.0 0.03
        deep
## 8
        deep
                25.0 0.02
## 9
        deep
                39.0 0.03
## 10
               59.0 0.03
        deep
               7.0 0.01
## 11 surface
## 12 surface
                7.0 0.02
## 13 surface
                7.0 0.03
               9.0 0.04
## 14 surface
## 15 surface
               11.0 0.03
## 16 surface
                12.5 0.03
## 17 surface
                21.0 0.04
## 18 surface
                  NA
                       NA
## 19 surface
                  NA
                       NA
## 20 surface
                  NA
                       NA
```

Figure 6: Ozone layer data processing part 2

```
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.5.3

ggplot(v,aes(x=uvb,y=inhibit,colour=depth))+
   geom_point()+geom_smooth(method="lm")

## Warning: Removed 3 rows containing non-finite values
(stat_smooth).

## Warning: Removed 3 rows containing missing values
(geom_point).
```

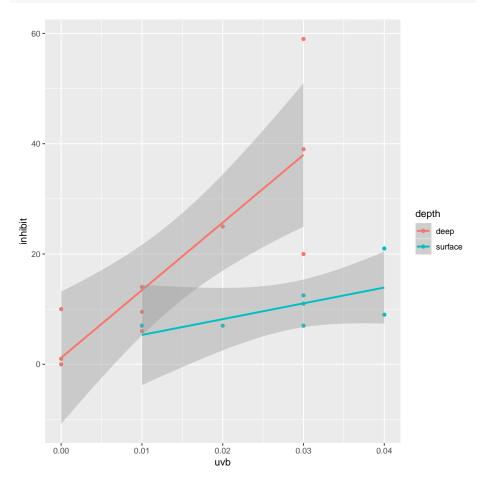


Figure 7: Ozone layer scatterplot

```
nzbirds=read.table("nzbird.txt",header=T)
str(nzbirds)
## 'data.frame': 67 obs. of 15 variables:
   $ Species: Factor w/ 67 levels "Aca_cann", "Aca_flam",...: 29 28 23 14 13 18 19 12 10 11
  $ Status : int 1 1 1 0 0 1 0 1 0 0 ...
## $ Length : int 1520 1250 870 720 820 770 50 570 580 480 ...
           : num 9600 5000 3360 2517 3170 ...
##
   $ Mass
##
   $ Range : num 1.21 0.56 0.07 1.1 3.45 2.96 0.01 9.01 7.9 4.33 ...
  $ Migr : int 1 1 1 3 3 2 1 2 3 3 ...
   $ Insect : int 12 0 0 12 0 0 0 6 6 0 ...
##
##
   $ Diet : int 2 1 1 2 1 1 1 2 2 1 ...
   $ Clutch : num 6 6 4 3.8 5.9 5.9 4 12.6 8.3 8.7 ...
##
## $ Broods : int 1 1 1 1 1 1 2 1 1 1 ...
## $ Wood : int 0 0 0 0 0 0 0 0 0 ...
## $ Upland : int 0 0 0 0 0 0 0 0 0 ...
## $ Water : int 1 1 1 1 1 1 0 1 1 1 ...
## $ Release: int 6 10 3 1 2 10 1 17 3 5 ...
## $ Indiv : int 29 85 8 10 7 60 2 1539 102 32 ...
```

Figure 8: New Zealand bird data

```
nzbirds.1=glm(Status~Length+Mass+Range+Migr+Insect+Diet+
 Clutch+Broods+Wood+Upland+Water+Release+Indiv,
 data=nzbirds,family="binomial")
summary(nzbirds.1)
##
## Call:
## glm(formula = Status ~ Length + Mass + Range + Migr + Insect +
      Diet + Clutch + Broods + Wood + Upland + Water + Release +
      Indiv, family = "binomial", data = nzbirds)
##
##
## Deviance Residuals:
      Min 1Q
                        Median
                                      30
                                              Max
## -1.56830 -0.25666 -0.04783
                                0.10892
                                           2.72372
##
## Coefficients:
##
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.338010 5.716762 -1.109
                                            0.2676
             -0.002815
                          0.005317
                                   -0.529
                                            0.5965
## Length
                                    1.594
## Mass
              0.002668
                         0.001674
                                            0.1110
## Range
              -0.131607
                        0.350234 -0.376
                                            0.7071
## Migr
              -2.043545
                        1.115824 -1.831
                                            0.0670 .
## Insect
              0.147992
                        0.212364
                                   0.697
                                            0.4859
## Diet
              2.028505
                          1.883201
                                    1.077
                                            0.2814
## Clutch
              0.079380
                        0.268305 0.296
                                            0.7673
## Broods
              0.021770
                          0.928327 0.023
                                            0.9813
## Wood
              2.490210
                          1.641601
                                   1.517
                                            0.1293
## Upland
              -4.713474
                          2.864827
                                   -1.645
                                            0.0999
## Water
              0.234944
                         2.670193
                                   0.088
                                            0.9299
## Release
              -0.012916
                          0.193211
                                   -0.067
                                            0.9467
              0.015926
                          0.008324
                                    1.913
## Indiv
                                            0.0557 .
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 90.343 on 66 degrees of freedom
## Residual deviance: 26.496 on 53 degrees of freedom
## AIC: 54.496
## Number of Fisher Scoring iterations: 8
```

Figure 9: Analysis 1 of NZ bird data

```
nzbirds.2=update(nzbirds.1,.~.-Length-Range-Insect-Clutch
 -Broods-Water-Release)
summary(nzbirds.2)
##
## Call:
## glm(formula = Status ~ Mass + Migr + Diet + Wood + Upland + Indiv,
      family = "binomial", data = nzbirds)
##
##
## Deviance Residuals:
##
      Min 1Q
                                     3Q
                        Median
                                              Max
## -1.62601 -0.32089 -0.07121
                               0.10296
                                          2.73035
##
## Coefficients:
##
                Estimate Std. Error z value Pr(>|z|)
## (Intercept) -5.1367680 2.7210950 -1.888 0.059058 .
        0.0019131 0.0007512 2.547 0.010876 *
## Mass
             -1.9596476 0.9658570 -2.029 0.042466 *
## Migr
## Diet
              1.8677300 0.9987152
                                    1.870 0.061465
                                    1.694 0.090286
## Wood
               2.3002854 1.3579902
## Upland
              -5.1221630 2.4552556 -2.086 0.036960 *
## Indiv
              0.0157164 0.0046631 3.370 0.000751 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
      Null deviance: 90.343 on 66 degrees of freedom
## Residual deviance: 28.052 on 60 degrees of freedom
## AIC: 42.052
##
## Number of Fisher Scoring iterations: 7
```

Figure 10: Analysis 2 of NZ bird data

```
anova(nzbirds.2,nzbirds.1,test="Chisq")

## Analysis of Deviance Table

##

## Model 1: Status ~ Mass + Migr + Diet + Wood + Upland + Indiv

## Model 2: Status ~ Length + Mass + Range + Migr + Insect + Diet + Clutch +

## Broods + Wood + Upland + Water + Release + Indiv

## Resid. Df Resid. Dev Df Deviance Pr(>Chi)

## 1 60 28.052

## 2 53 26.496 7 1.5554 0.9803
```

Figure 11: Analysis 3 of NZ bird data

```
space.shuttle=read.table("space-shuttle.txt",header=T)
str(space.shuttle)

## 'data.frame': 23 obs. of 5 variables:
## $ flight : int 1 2 3 5 6 7 8 9 10 11 ...
## $ distress : Factor w/ 3 levels "0","1-
2","3+": 1 2 1 1 2 1 1 1 2 3 ...
## $ temp : int 66 70 69 68 67 72 73 70 57 63 ...
## $ date : int 7772 7986 8116 8350 8494 8569 8642 8732 8799 8862 ...
## $ z.computed.: num 14.1 14.1 14.7 15.6 16.3 ...
```

Figure 12: Space shuttle data (summary)

```
##
## Attaching package: 'MASS'
## The following object is masked from 'package:dplyr':
##
## select

space.shuttle.1=polr(distress~temp+date,data=space.shuttle)
space.shuttle.2=polr(distress~date,data=space.shuttle)
space.shuttle.3=polr(distress~temp,data=space.shuttle)
```

Figure 13: Space shuttle part 1

```
anova(space.shuttle.2,space.shuttle.1)
## Likelihood ratio tests of ordinal regression models
##
## Response: distress
                                                                Pr(Chi)
##
          Model Resid. df Resid. Dev
                                        Test
                                                Df LR stat.
## 1
           date
                        20
                             43.71774
## 2 temp + date
                        19
                             37.59413 1 vs 2
                                                 1 6.123617 0.01333876
```

Figure 14: Space shuttle part 2

```
anova(space.shuttle.3,space.shuttle.1)
## Likelihood ratio tests of ordinal regression models
##
## Response: distress
##
          Model Resid. df Resid. Dev
                                                                Pr(Chi)
                                        Test
                                                Df LR stat.
## 1
           temp
                        20
                             47.92046
                             37.59413 1 vs 2
                                                 1 10.32633 0.001311456
## 2 temp + date
                        19
```

Figure 15: Space shuttle part 3

```
temps=c(67,75)
dates=c(8600,9300)
new=expand.grid(temp=temps,date=dates)
pp=predict(space.shuttle.1,new,type="p")
cbind(new,pp)
##
     temp date
                        0
                                1-2
## 1
       67 8600 0.44659249 0.3679833 0.1854242
## 2
       75 8600 0.76360667 0.1825854 0.0538079
## 3
       67 9300 0.07472014 0.2306452 0.6946346
## 4
       75 9300 0.24428243 0.3933556 0.3623620
```

Figure 16: Predictions 1

Figure 17: Prediction 2

```
pbc1=read.table("pbc.txt",header=T)
str(pbc1)
## 'data.frame': 312 obs. of 9 variables:
   $ id
            : int 1 2 3 4 5 6 7 8 9 10 ...
   $ days
##
             : int 400 4500 1012 1925 1504 2503 1832 2466 2400 51 ...
   $ status : int 2 0 2 2 1 2 0 2 2 2 ...
  $ drug
##
           : int 1 1 1 1 2 2 2 2 1 2 ...
## $ age
             : int 21464 20617 25594 19994 13918 24201 20284 19379 15526 25772 ...
   $ edema
##
            : num 1 0 0.5 0.5 0 0 0 0 0 1 ...
  $ bilirubi: num 14.5 1.1 1.4 1.8 3.4 0.8 1 0.3 3.2 12.6 ...
## $ albumin : num 2.6 4.14 3.48 2.54 3.53 3.98 4.09 4 3.08 2.74 ...
## $ prothom : num 12.2 10.6 12 10.3 10.9 11 9.7 11 11 11.5 ...
```

Figure 18: Primary biliary cirrhosis data

```
library(survival)
attach(pbc1)
y=Surv(days,status==2)
head(y,n=20)

## [1] 400 4500+ 1012 1925 1504+ 2503 1832+ 2466 2400 51 3762
## [12] 304 3577+ 1217 3584 3672+ 769 131 4232+ 1356
```

Figure 19: Survival analysis part 1

```
y.1=coxph(y~drug+age+edema+bilirubi+albumin+prothom)
summary(y.1)
## Call:
## coxph(formula = y ~ drug + age + edema + bilirubi + albumin +
##
      prothom)
##
##
   n= 312, number of events= 125
##
                 coef exp(coef)
                                 se(coef)
##
                                               z Pr(>|z|)
           -1.217e-02 9.879e-01 1.847e-01 -0.066 0.947446
## drug
## age
            9.036e-05 1.000e+00 2.569e-05 3.517 0.000436 ***
            8.198e-01 2.270e+00 3.104e-01 2.641 0.008262 **
## edema
## bilirubi 1.160e-01 1.123e+00 1.507e-02 7.699 1.37e-14 ***
## albumin -1.210e+00 2.981e-01 2.345e-01 -5.162 2.45e-07 ***
## prothom 2.658e-01 1.304e+00 7.403e-02 3.590 0.000330 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
##
           exp(coef) exp(-coef) lower .95 upper .95
             0.9879
                     1.0122
                                  0.6879
                                            1.419
## drug
## age
              1.0001
                        0.9999
                                  1.0000
                                             1.000
## edema
              2.2701
                        0.4405
                                1.2355
                                            4.171
## bilirubi 1.1230
                        0.8904
                                1.0903
                                            1.157
## albumin
             0.2981
                        3.3544
                                  0.1883
                                            0.472
              1.3045
                        0.7666
                                  1.1283
                                            1.508
## prothom
##
## Concordance= 0.827 (se = 0.02)
## Likelihood ratio test= 163.5 on 6 df,
                                          p=<2e-16
## Wald test
                      = 183.7 on 6 df,
                                          p=<2e-16
## Score (logrank) test = 284.7 on 6 df,
                                        p=<2e-16
```

Figure 20: Survival analysis part 2

```
drugs=c(1,2)
ages=c(15000,20000)
edemas=1
bilirubis=3
albumins=3.5
prothoms=10.5
new=expand.grid(drug=drugs,age=ages,edema=edemas,bilirubi=bilirubis,
 albumin=albumins,prothom=prothoms)
colours=c("red","blue","green","black")
cbind(new,colours)
##
           age edema bilirubi albumin prothom colours
    drug
## 1
     1 15000
                  1
                       3
                                 3.5 10.5
                                                red
## 2
       2 15000
                                 3.5
                                       10.5
                           3
                   1
                                               blue
                                              green
## 3
       1 20000
                   1
                           3
                                 3.5
                                       10.5
## 4
                           3 3.5 10.5 black
       2 20000
```

Figure 21: Survival analysis part 3

```
pp=survfit(y.1,new)
plot(pp,col=colours)
```

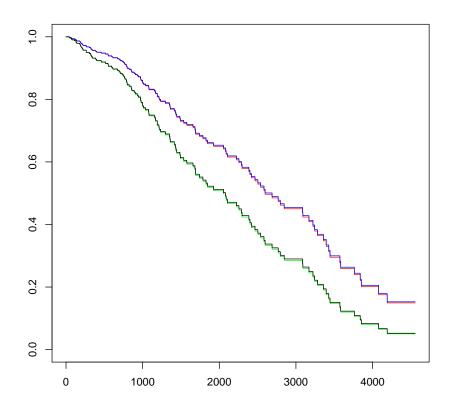


Figure 22: Survival analysis part 4