

Stat 207 HW8

Cheng Luo 912466499
Fan Wu 912538518

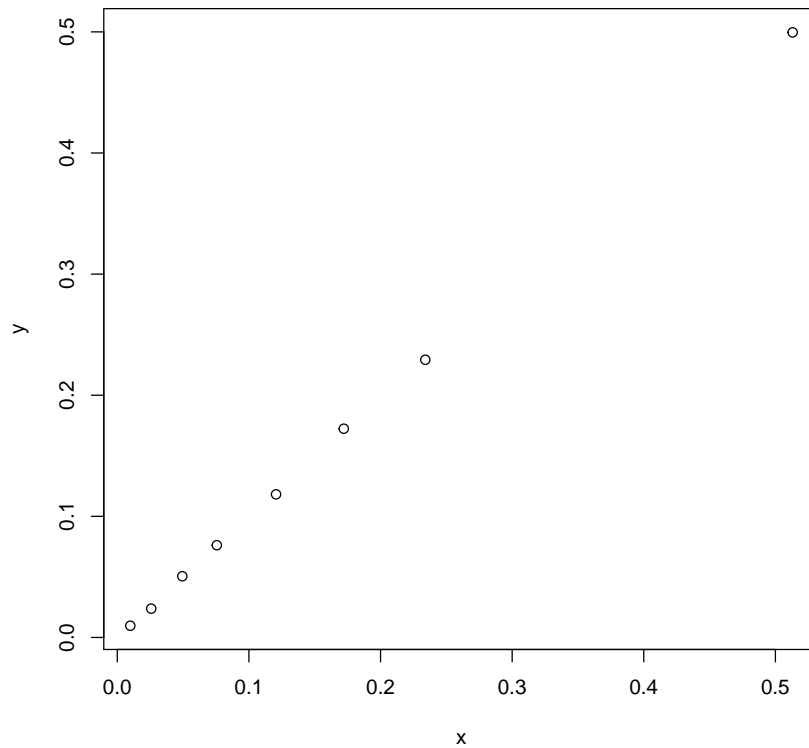
March 11, 2015

1 14.28

```
(a) dat = read.table("CH14PR14.txt")
names(dat) = c("Y", "X1", "X2", "X3")
logit = glm(Y ~ X1 + X2, data = dat, family = "binomial")
logitv = logit$fitted.values
dat = dat[order(logitv), ]
a = rep(1:8, each = 20)
a = a[-1]
b = split(dat, a)
Oj1 = sapply(b, function(x){sum(x[[1]])})
Ej1 = sapply(split(sort(logitv), a), sum)
Oj0 = sapply(b, function(x){length(x[[1]])-sum(x[[1]])})
Ej0 = sapply(b, function(x){length(x[[1]])})-Ej1
rbind(Oj1, Ej1, Oj0, Ej0)

##           1           2           3           4           5           6           7
## Oj1  0.000000  1.000000  0.000000  2.000000  1.000000  8.000000  2.000000
## Ej1  0.187472  0.5159059  0.9878718  1.512501  2.412695  3.44151  4.680125
## Oj0 19.000000 19.0000000 20.0000000 18.000000 19.000000 12.00000 18.000000
## Ej0 18.812528 19.4840941 19.0121282 18.487499 17.587305 16.55849 15.319875
##           8
## Oj1 10.000000
## Ej1 10.261919
## Oj0 10.000000
## Ej0  9.738081

y = sapply(split(sort(logitv), a), median)
x = Ej1/sapply(b, function(x){length(x[[1]])})
plot(x, y)
```



The plot seems to be linear, it's consistent with a response function of monotonic sigmoidal shape.

```
(b) X.squ = sum((rbind(0j1, 0j0)-rbind(Ej1, Ej0))^2/rbind(Ej1, Ej0));X.squ
## [1] 12.11578
```

$$H_0: E(Y) = [1 + \exp(-\beta_0 - \beta_1 X_1 - \beta_2 X_2)]^{-1}$$

$$\text{VS. } H_1: E(Y) \neq [1 + \exp(-\beta_0 - \beta_1 X_1 - \beta_2 X_2)]^{-1}$$

$$X^2 = \sum_j \sum_k \frac{(O_{jk} - E_{jk})^2}{E_{jk}} = 12.11578$$

we can reject H_0 if $X^2 > \chi^2(0.95, 8 - 2) = 12.5916$, otherwise reject H_1

so that reject H_1 because $X^2 < 12.5916$, Pvalue is 0.05943518.

```
(c) p = summary(logit)
     dr = p$deviance.resid;dr
```

##	1	2	3	4	5	6
##	-0.54602312	-0.51373259	1.15260237	-0.17517944	-0.18924467	-0.69185916
##	7	8	9	10	11	12
##	-0.18367445	-0.73777334	-0.47288089	-0.35855218	-0.62785882	-0.33244658
##	13	14	15	16	17	18
##	-0.49058859	-0.23345211	-0.11467682	-0.59485941	-0.85058862	-0.16214474
##	19	20	21	22	23	24
##	-0.22270681	-0.13939895	-0.34822874	-0.28168748	-0.24470112	-0.09084127
##	25	26	27	28	29	30
##	-0.50595282	-0.10798927	-0.69416101	-0.26781191	-0.83451488	-0.68109529
##	31	32	33	34	35	36
##	-0.32519247	-0.45851859	-0.92893094	-0.53211206	-0.33897782	-0.16073331
##	37	38	39	40	41	42
##	0.74365705	1.38971984	-0.61999873	-0.41310085	1.89079347	-0.35679774
##	43	44	45	46	47	48
##	1.71627562	-0.33244658	-0.72647043	-0.32961191	2.84304938	-0.69729005
##	49	50	51	52	53	54
##	-0.10990097	-0.18854516	-0.33530428	-0.21617318	-0.72171075	-0.59079687
##	55	56	57	58	59	60
##	2.23462510	-0.24806553	-0.42012390	-0.28029236	-1.30166964	2.00689554
##	61	62	63	64	65	66
##	1.10849910	-0.15933400	-0.68109529	-0.32124458	-0.10387671	-1.01249619
##	67	68	69	70	71	72
##	-0.12087236	-0.36424502	-0.62497861	1.86302691	-0.23960963	-0.48311783
##	73	74	75	76	77	78
##	-0.38006335	1.82187884	-1.44789883	-0.84697959	-0.83715068	-0.35248880
##	79	80	81	82	83	84
##	-0.58403320	-0.45631940	-0.35855218	1.94481807	-0.72970910	-0.53462959
##	85	86	87	88	89	90
##	-0.36293048	-1.15124676	-0.62286031	-0.65995923	2.34647993	-0.81345988
##	91	92	93	94	95	96
##	1.12311780	-0.17737218	1.27437628	-0.55762351	-0.49703364	-0.30029670
##	97	98	99	100	101	102
##	-1.06493877	-0.71059309	0.95982139	-0.33201751	-0.67802259	1.90510957
##	103	104	105	106	107	108
##	-0.45631940	-0.42162878	-0.12900059	-0.17648324	-0.19257415	-0.14876060
##	109	110	111	112	113	114
##	1.82969794	-0.32283373	-0.53091804	-0.13409993	-0.61013597	-0.72086770
##	115	116	117	118	119	120
##	-0.50887859	-0.61087534	-0.16356841	-0.16073331	-0.12675915	-0.49293406
##	121	122	123	124	125	126
##	-0.14931436	-0.21351074	1.84295971	-0.40421564	1.40875849	-0.30814469

```

##          127          128          129          130          131          132
## -0.40618549 -0.49528940 -0.51130056 -0.73777334 -0.28412789 -0.58877426
##          133          134          135          136          137          138
## -0.49703364 -1.22831729 -0.31850052  1.89079347 -0.29409388 -0.69416101
##          139          140          141          142          143          144
## -0.20982689 -0.48482421 -0.61925036 -0.28658859 -0.39176366 -0.48311783
##          145          146          147          148          149          150
## -1.11866815 -0.31307905 -0.35422338 -0.28065744 -0.72970910 -0.20982689
##          151          152          153          154          155          156
## -0.41110024 -0.42725579 -0.28554134 -0.38936035 -0.29263987 -0.25647527
##          157          158          159
##  0.42476809  0.86785144  1.67453806

  lows = lowess(logitv, dr, .7, 0);lows

## $x
## [1] 0.004117568 0.005380657 0.005813874 0.006020913 0.006553816
## [6] 0.007278447 0.008001755 0.008286057 0.008951093 0.009668986
## [11] 0.011003867 0.011085487 0.012613438 0.012834524 0.012834524
## [16] 0.013059435 0.013288233 0.015226801 0.015452533 0.015607367
## [21] 0.016726682 0.017571713 0.017617602 0.017747398 0.018371549
## [26] 0.021773129 0.021773129 0.022535610 0.023094563 0.024494189
## [31] 0.026882013 0.028298274 0.029495578 0.030299729 0.032354793
## [36] 0.035226199 0.038520373 0.038618820 0.038897215 0.039560541
## [41] 0.039947136 0.040234706 0.041915256 0.042323848 0.044087651
## [46] 0.046367188 0.047827674 0.049456440 0.050290414 0.050776320
## [51] 0.051501501 0.052872923 0.053626356 0.053761250 0.053761250
## [56] 0.054663641 0.055833717 0.058830122 0.060233817 0.060809646
## [61] 0.061668811 0.062257449 0.062257449 0.063737383 0.063737383
## [66] 0.064184764 0.069677590 0.072999098 0.073868811 0.078447141
## [71] 0.079182416 0.081029912 0.081787246 0.082350177 0.084469906
## [76] 0.085049591 0.087232199 0.098877166 0.098877166 0.099783195
## [81] 0.105784220 0.110149156 0.110149156 0.110883724 0.113379806
## [86] 0.114401854 0.115431916 0.116197114 0.116197114 0.120141456
## [91] 0.121446705 0.122531422 0.123624463 0.131455955 0.132006995
## [96] 0.133171735 0.133478501 0.138491730 0.143988948 0.150896868
## [101] 0.156796870 0.159137868 0.160140341 0.162160612 0.162883307
## [106] 0.167369727 0.167369727 0.169836784 0.170211426 0.174474811
## [111] 0.174857529 0.176323549 0.176323549 0.177411440 0.178894230
## [116] 0.183003454 0.187514843 0.190211007 0.195692078 0.205353025
## [121] 0.207010578 0.207010578 0.212848500 0.214103167 0.214103167
## [126] 0.215812168 0.223121468 0.228813560 0.229282366 0.229282366
## [131] 0.231934023 0.233743020 0.233743020 0.238263628 0.238263628
## [136] 0.246094701 0.281693191 0.294047656 0.295601219 0.301407172
## [141] 0.303543886 0.350437581 0.370722956 0.380731597 0.401048267

```

```
## [146] 0.432802264 0.443961491 0.465118050 0.484534317 0.514661378
## [151] 0.529698682 0.532220820 0.540973420 0.571374597 0.630886977
## [156] 0.649433730 0.686202121 0.758423830 0.913735656
##
## $y
## [1] -0.088172324 -0.091193892 -0.092230236 -0.092725513 -0.094000327
## [6] -0.095733792 -0.097464093 -0.098144200 -0.099735105 -0.101452449
## [11] -0.104645759 -0.104841011 -0.108496180 -0.109025064 -0.109025064
## [16] -0.109563096 -0.110097898 -0.114629173 -0.115156807 -0.115518722
## [21] -0.118135047 -0.120110252 -0.120217515 -0.120520906 -0.121979817
## [26] -0.129930790 -0.129930790 -0.131674467 -0.132952707 -0.136153436
## [31] -0.141614024 -0.144852796 -0.147590845 -0.149429815 -0.154063466
## [36] -0.160537759 -0.167965287 -0.168187260 -0.168814970 -0.170298321
## [41] -0.171162836 -0.171805908 -0.175564005 -0.176477711 -0.180421979
## [46] -0.185519548 -0.188785532 -0.192398644 -0.194248659 -0.195326551
## [51] -0.196935228 -0.199977472 -0.201648820 -0.201948059 -0.201948059
## [56] -0.203949843 -0.206545438 -0.213049988 -0.216097110 -0.217347109
## [61] -0.219212173 -0.220489979 -0.220489979 -0.223702599 -0.223702599
## [66] -0.224673765 -0.235828329 -0.242573485 -0.244070632 -0.251951891
## [71] -0.253217613 -0.256397943 -0.257701638 -0.258386084 -0.260963379
## [76] -0.261668196 -0.264321944 -0.225045104 -0.225045104 -0.219128032
## [81] -0.179936676 -0.154186042 -0.154186042 -0.149852507 -0.135127045
## [86] -0.129097542 -0.124673161 -0.121386438 -0.121386438 -0.104444471
## [91] -0.098838092 -0.094178954 -0.092681826 -0.081955110 -0.082230732
## [96] -0.082813318 -0.082966758 -0.085474301 -0.094606794 -0.103042914
## [101] -0.106432963 -0.107778064 -0.107963004 -0.108335712 -0.108469038
## [106] -0.109296710 -0.109296710 -0.112443596 -0.112921475 -0.118359689
## [111] -0.118847870 -0.120717870 -0.120717870 -0.122933578 -0.125953576
## [116] -0.134322830 -0.144160594 -0.150039986 -0.164525881 -0.191343995
## [121] -0.195401210 -0.195401210 -0.209690769 -0.212761835 -0.212761835
## [126] -0.214943573 -0.224274748 -0.224766647 -0.224807160 -0.224807160
## [131] -0.225036311 -0.225576792 -0.225576792 -0.226927430 -0.226927430
## [136] -0.228381345 -0.216959869 -0.223662497 -0.223545473 -0.223108129
## [141] -0.222011054 -0.180446860 -0.167914434 -0.163179048 -0.152280685
## [146] -0.128270882 -0.116634223 -0.092479525 -0.069813508 -0.033587453
## [151] -0.015034380 -0.011922648 -0.001158003 0.035380766 0.102419493
## [156] 0.122606667 0.162324533 0.242116112 0.426978094
```

It shows that the model is adequate, because the plot shows approximately a horizontal line with zero intercept.

2 14.39

```
(a) dat = read.table("CH14PR39.txt")
names(dat) = c("Y", "X1", "X2", "X3", "X4")
poi = glm(Y ~ ., data = dat, family = "poisson")
summary(poi)

##
## Call:
## glm(formula = Y ~ ., family = "poisson", data = dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1854  -0.7819  -0.2564   0.5449   2.3626
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.489467   0.336869   1.453  0.14623
## X1          -1.069403   0.133154  -8.031 9.64e-16 ***
## X2           -0.046606   0.119970  -0.388  0.69766
## X3            0.009470   0.002953   3.207  0.00134 **
## X4            0.008566   0.004312   1.986  0.04698 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 199.19  on 99  degrees of freedom
## Residual deviance: 108.79  on 95  degrees of freedom
## AIC: 377.29
##
## Number of Fisher Scoring iterations: 5
```

$$b_0 = 0.489467 \quad s(b_0) = 0.336869$$

$$b_1 = -1.069403 \quad s(b_1) = 0.133154$$

$$b_2 = -0.046606 \quad s(b_2) = 0.119970$$

$$b_3 = 0.009470 \quad s(b_3) = 0.002953$$

$$b_4 = 0.008566 \quad s(b_4) = 0.004312$$

$$\mu = \exp(0.489467165 - 1.069402551X_1 - 0.046606063X_2 + 0.009469987X_3 + 0.008565829X_4)$$

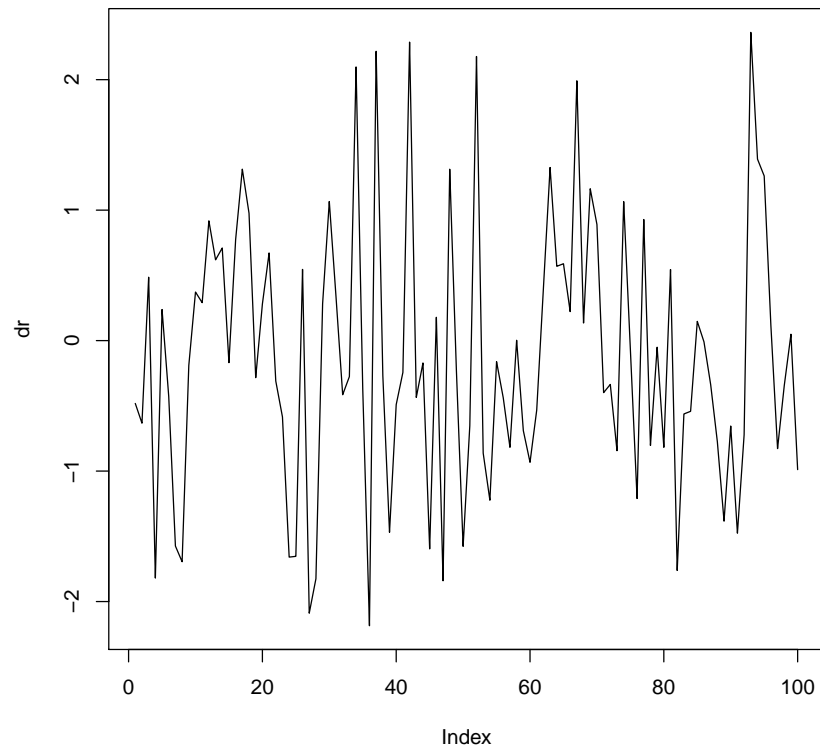
```
(b) p = summary(poi)
dr = p$deviance.resid;dr

##      1      2      3      4      5
```



```
## -0.481563003 -0.632820229 0.485684782 -1.819828480 0.238302497
##          6          7          8          9         10
## -0.427206484 -1.574566470 -1.694831446 -0.190494237 0.372414202
##          11         12         13         14         15
## 0.290568448 0.917894609 0.618945304 0.710218879 -0.169117683
##          16         17         18         19         20
## 0.774212615 1.313966589 0.976533023 -0.284161510 0.281078819
##          21         22         23         24         25
## 0.671826155 -0.309823439 -0.585274974 -1.659501048 -1.653549229
##          26         27         28         29         30
## 0.545695411 -2.089197070 -1.825162331 0.283158353 1.066089357
##          31         32         33         34         35
## 0.338495236 -0.414912576 -0.276062096 2.097482057 -0.373770021
##          36         37         38         39         40
## -2.185378873 2.217373787 -0.269196968 -1.468917177 -0.490568471
##          41         42         43         44         45
## -0.243689445 2.287659410 -0.435460637 -0.171363655 -1.596370920
##          46         47         48         49         50
## 0.178588604 -1.840819930 1.313615961 -0.233624875 -1.576829772
##          51         52         53         54         55
## -0.652282150 2.177759158 -0.862317963 -1.223172388 -0.161565009
##          56         57         58         59         60
## -0.438457085 -0.817656201 0.002451800 -0.690070466 -0.932653968
##          61         62         63         64         65
## -0.532725622 0.400431092 1.326821516 0.569505372 0.589162479
##          66         67         68         69         70
## 0.222202292 1.991163395 0.134986579 1.163783804 0.890153115
##          71         72         73         74         75
## -0.398888037 -0.335860573 -0.843868576 1.065308951 -0.068529260
##          76         77         78         79         80
## -1.210403791 0.928316209 -0.803424449 -0.050707876 -0.817762385
##          81         82         83         84         85
## 0.544674549 -1.761754891 -0.562223893 -0.541853422 0.147418906
##          86         87         88         89         90
## -0.009840529 -0.337422359 -0.774688780 -1.383658148 -0.654757856
##          91         92         93         94         95
## -1.475851025 -0.722343228 2.362545161 1.391144309 1.262066676
##          96         97         98         99         100
## 0.117099736 -0.827717570 -0.345172951 0.048822205 -0.988857456

plot(dr, type = "l")
```



```
(c) logLik(poi)

## 'log Lik.' -183.6439 (df=5)

poiR = glm(Y ~ .-X2 , data = dat, family = "poisson")
logLik(poiR)

## 'log Lik.' -183.7194 (df=4)

qchisq(1-0.05, 5-4)

## [1] 3.841459

pchisq(0.151, 1, lower.tail = FALSE)

## [1] 0.6975815
```

$H_0: \beta_2 = 0$
 VS. $H_1: \beta_2 \neq 0$
 The full model: $\mu = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4)$
 $\ln(L(F)) = -183.6439$
 The reduced model: $\mu = \exp(\beta_0 + \beta_1 X_1 + \beta_3 X_3 + \beta_4 X_4)$
 $\ln(L(R)) = -183.7194$
 $G^2 = -2(\ln(L(R)) - \ln(L(F))) = 0.151$
 we can reject H_0 if $G^2 > \chi^2(1 - 0.05, 5 - 4) = 3.8415$, otherwise reject H_1
 so that reject H_1 because $G^2 < 3.8415$,
 therefore, X_2 can be dropped from the regression model, and the P-value
 is 0.6975815. And the result is the same as the result we get in (b).

(d) `summary(poiR)`

```
##
## Call:
## glm(formula = Y ~ . - X2, family = "poisson", data = dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.2152  -0.7512  -0.2594   0.5830   2.2893
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.443890   0.317289   1.399  0.16181
## X1          -1.077770   0.131415  -8.201 2.38e-16 ***
## X3           0.009471   0.002957   3.203  0.00136 **
## X4           0.008979   0.004190   2.143  0.03209 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 199.19  on 99  degrees of freedom
## Residual deviance: 108.94  on 96  degrees of freedom
## AIC: 375.44
##
## Number of Fisher Scoring iterations: 5

b1 = -1.077770
s1 = 0.131415
z = qnorm(1-0.05/2)
c(b1-s1*z, b1+s1*z)
```

```
## [1] -1.3353387 -0.8202013
```

From `summary(poiR)`, we get $s(b_1) = 0.131415$, $b_1 = -1.077770$, based on $b_k \pm z(1 - \alpha/2)sb_k$, we conclude that we are 95 % confident that β_1 is between -1.3353387 and -0.8202013. Because the confidence interval is smaller than 0, aerobic exercise reduce the frequency of falls when controlling for balance and strength.

3 14.44

$$\begin{aligned} \ln L(\beta_0, \beta_1) &= \sum_{i=1}^n y_i(\beta_0 + \beta_1 X_i) - \sum_{i=1}^n (1 + \exp(\beta_0 + \beta_1 X_i)) \\ \frac{\partial \ln L}{\partial \beta_0} &= - \sum_{i=1}^n \left(Y_i - \frac{\exp(\beta_0 + \beta_1 X_i)}{[1 + \exp(\beta_0 + \beta_1 X_i)]^2} \right) \\ \frac{\partial \ln L}{\partial \beta_1} &= - \sum_{i=1}^n \left(Y_i X_i - \frac{\exp(\beta_0 + \beta_1 X_i)}{[1 + \exp(\beta_0 + \beta_1 X_i)]^2} \right) \\ \frac{\partial^2 \ln L}{\partial \beta_0^2} &= - \sum_{i=1}^n \frac{\exp(\beta_0 + \beta_1 X_i)}{[1 + \exp(\beta_0 + \beta_1 X_i)]^2} \\ \frac{\partial^2 \ln L}{\partial \beta_1^2} &= - \sum_{i=1}^n \frac{X_i^2 \exp(\beta_0 + \beta_1 X_i)}{[1 + \exp(\beta_0 + \beta_1 X_i)]^2} \\ \frac{\partial^2 \ln L}{\partial \beta_0 \partial \beta_1} &= - \sum_{i=1}^n \frac{X_i \exp(\beta_0 + \beta_1 X_i)}{[1 + \exp(\beta_0 + \beta_1 X_i)]^2} \end{aligned}$$

```
dat = read.table("CH14TA01.txt")
names(dat) = c("X", "Y", "pi")
b0 = -3.0597
b1 = 0.1615
t = exp(b0 + b1*dat$X)
t1 = sum(t/(1+t)^2);t1

## [1] 4.176239

t2 = sum((t * dat$X)/(1 + t)^2);t2

## [1] 74.57466

t3 = sum(((dat$X)^2*t)/(1 + t)^2);t3

## [1] 1568.482

H = matrix(c(t, t1, t2, t3), 2, 2);H
```

```

##          [,1]      [,2]
## [1,] 0.4499135 0.1236006
## [2,] 5.0723286 2.6586009

H_1 = solve(H);H_1

##          [,1]      [,2]
## [1,] 4.670787 -0.2171488
## [2,] -8.911367 0.7904346

sqrt(1.586)

## [1] 1.259365

sqrt(0.7904346)

## [1] 0.8890639

```

H^{-1} we get after rootsquare is the same as the estimated standard deviation in table 14.1(b)

4 14.45

$$\begin{aligned}
Y_i &= \frac{\gamma_0}{1 + \gamma_1 \exp(\gamma_2 X_i)} + \epsilon_i \\
E(Y_i) &= \frac{\gamma_0}{1 + \gamma_1 \exp(\gamma_2 X_i)} \\
\text{if } \gamma_0 &= 1 \\
E(Y_i) &= \frac{1}{1 + \gamma_1 \exp(\gamma_2 X_i)} \\
&= \frac{1}{1 + \exp(\ln \gamma_1 + \gamma_2 X_i)} \\
&= \frac{1}{1 + \exp(-\beta_0 - \beta_1 X_i)} \\
&= \frac{\exp(\beta_0 + \beta_1 X_i)}{1 + \exp(\beta_0 + \beta_1 X_i)} \\
\text{if } \gamma_1 &= \exp(-\beta_0), \gamma_2 = -\beta_1
\end{aligned}$$

5 14.46

$$E(Y) = [1 + \exp(-\beta_0 - \beta_1 X_1 - \beta_2 X_2 - \beta_3 X_1 X_2)]^{-1}$$

$$\pi'(X_1) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$$

$$\pi'(X_1 + 1) = \beta_0 + \beta_1(X_1 + 1) + \beta_2 X_2 + \beta_3(X_1 + 1)X_2$$

$$\pi'(X_1 + 1) - \pi'(X_1) = \ln(\text{oddsratio}) = \beta_1 X_1 + \beta_3 X_1 X_2$$

Hence the odds ratio for X_1 is $\exp(\beta_1 X_1 + \beta_3 X_1 X_2)$ therefore, they are different.

6 14.47

$$\pi = 1 - \exp[-\exp(\frac{X_i - \gamma_0}{\gamma_1})]$$

$$1 - \pi = \exp[-\exp(\frac{X_i - \gamma_0}{\gamma_1})]$$

$$\begin{aligned} \ln[-\ln(1 - \pi)] &= -\frac{\gamma_0}{\gamma_1} + \frac{1}{\gamma_1} X_i \\ &= \beta_0 + \beta_1 X_i \end{aligned}$$