Poisson Regression

A Short Course on Data Analysis Using R Software (2017)

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Contents

1 Introduction

Multiple Poisson Regression for count is given as

$$ln\, E(Y|\mathbf{X}) = ln\, \mu = \beta_0 + \beta_1 X_1 + \cdots + \beta_{p-1} X_{p-1} = \beta_0 + \sum \beta_{p-1} X_{p-1}$$

where the **X** (in bold) denotes a collection of Xs. p is the number of estimated parameters.

Multiple Poisson Regression for rate with offset[1] is given as

$$ln\, E(Y|\mathbf{X}) = ln\, a(\mathbf{X}) + \beta_0 + \sum \beta_{p-1} X_{p-1}$$

The rate ratio, RR is

$$RR = e^{\beta_{p-1}}$$

[1] the ln of the denominator/person-years, a(X)

2 Preliminaries

2.1 Load libraries

```
library(epiDisplay)
library(car)
```

3 Simple Poisson regression models

3.1 Count data

3.1.1 X categorical

```
# - UKaccident.csv is modified from builtin data Seatbelts
acc = read.csv("UKaccident.csv")
#- driverskilled: number of death
#- law: before seatbelt law = 0, after law = 1
str(acc)
```

```
## 'data.frame':    122 obs. of  2 variables:
##  $ driverskilled: int  107 97 102 87 119 106 110 106 107 125 ...
##  $ law          : int  0 0 0 0 0 0 0 0 0 0 ...
```

```
head(acc)
```

```
##   driverskilled law
## 1           107   0
## 2            97   0
## 3           102   0
## 4            87   0
## 5           119   0
## 6           106   0
```

```
tail(acc)
```

```
##     driverskilled law
## 117            81   1
## 118            84   1
## 119            87   1
## 120            90   1
## 121            79   1
## 122            96   1
```

```
# - some descriptives
tapply(acc$driverskilled, acc$law, sum)  # total death before vs after
```

```
##     0     1
## 11826  1294
```

```
table(acc$law)  # num of observations before vs after
```

```
##
##   0   1
## 107  15
```

```r
# - mean count, manually
11826/107  # 110.5234, count before law
```

```
## [1] 110.5234
```

```r
1294/15  # 86.26667, count after law
```

```
## [1] 86.26667
```

```r
model.acc = glm(driverskilled ~ law, data = acc, family = poisson)
summary(model.acc)  # significant p based on Wald test
```

```
##
## Call:
## glm(formula = driverskilled ~ law, family = poisson, data = acc)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -3.16127  -0.72398   0.04531   0.77308   1.89182
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.705227   0.009196 511.681   <2e-16 ***
## law         -0.247784   0.029281  -8.462   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 219.17  on 121  degrees of freedom
## Residual deviance: 142.64  on 120  degrees of freedom
## AIC: 940.7
##
## Number of Fisher Scoring iterations: 4
```

```r
# - to get CI
cbind(coef(model.acc), confint(model.acc))
```

```
## Waiting for profiling to be done...
```

```
##                              2.5 %     97.5 %
## (Intercept)  4.7052269  4.6871495  4.7231960
## law         -0.2477837 -0.3056189 -0.1908312
```

```r
# - ln(count) = 4.71 - 0.25*LAW
4.71 - 0.25   # = 4.46
```

```
## [1] 4.46
```

```r
exp(4.71)  # 111.0522, count before law
```

```
## [1] 111.0522
```

```r
exp(4.46)  # 86.48751, count after law
```

```
## [1] 86.48751
```

```r
# - Model fit
poisgof(model.acc)  # fit well, based on chi-square test on the residual deviance
```

```
## $results
## [1] "Goodness-of-fit test for Poisson assumption"
##
## $chisq
## [1] 142.6436
##
## $df
## [1] 120
##
## $p.value
## [1] 0.07764771
```

```r
# - Diagnostics - standardized residuals
sr = rstandard(model.acc)
sr[abs(sr) > 1.96]
```

```
##         4        54        55        91       113
## -2.335861 -3.176147 -2.857937 -2.647896 -3.098644
```

```r
# - predicted count vs fitted values
fitted.acc = model.acc$fitted
data.frame(acc, fitted.acc)[names(sr[abs(sr) > 1.96]), ]  # look at the discrepancies
```

```
##     driverskilled law fitted.acc
## 4              87   0  110.52336
## 54             79   0  110.52336
## 55             82   0  110.52336
## 91             84   0  110.52336
## 113            60   1   86.26667
```

```r
# Summary with RR
idr.display(model.acc)  # easier, also view LR test
```

```
##
## Poisson regression predicting driverskilled
##
##                IDR(95%CI)        P(Wald's test) P(LR-test)
## law: 1 vs 0  0.78 (0.74,0.83)  < 0.001         < 0.001
##
## Log-likelihood = -468.3481
## No. of observations = 122
## AIC value = 940.6963
```

3.1.2 X numerical

```r
# - Data from https://stats.idre.ucla.edu/stat/data/poisson_sim.csv
aw = read.csv("poisson_sim.csv")
head(aw)
```

```
##    id num_awards prog math
## 1  45          0    3   41
## 2 108          0    1   41
## 3  15          0    3   44
## 4  67          0    3   42
## 5 153          0    3   40
## 6  51          0    1   42
```

```r
tail(aw)
```

```
##      id num_awards prog math
## 195  61          1    2   60
## 196 100          2    2   71
## 197 143          2    3   75
## 198  68          1    2   71
## 199  57          0    2   72
## 200 132          3    2   73
```

```r
str(aw)
```

```
## 'data.frame':    200 obs. of  4 variables:
##  $ id        : int  45 108 15 67 153 51 164 133 2 53 ...
##  $ num_awards: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ prog      : int  3 1 3 3 3 1 3 3 3 3 ...
##  $ math      : int  41 41 44 42 40 42 46 40 33 46 ...
```

```r
#- num_awards: The number of awards earned by students at one high school.
#- math: the score on their final exam in math.
model.aw = glm(num_awards ~ math, data = aw, family = poisson)
summary(model.aw)  # math sig.
```

```
##
## Call:
## glm(formula = num_awards ~ math, family = poisson, data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1853  -0.9070  -0.6001   0.3246   2.9529
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -5.333532   0.591261  -9.021   <2e-16 ***
## math         0.086166   0.009679   8.902   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 204.02  on 198  degrees of freedom
## AIC: 384.08
##
## Number of Fisher Scoring iterations: 6
```

```r
cbind(coef(model.aw), confint(model.aw))
```

```
## Waiting for profiling to be done...

##                               2.5 %    97.5 %
## (Intercept) -5.3335321 -6.52038334 -4.200322
## math         0.0861656  0.06737466  0.105356
```

```r
poisgof(model.aw)  # fit well
```

```
## $results
```

```
## [1] "Goodness-of-fit test for Poisson assumption"
##
## $chisq
## [1] 204.0213
##
## $df
## [1] 198
##
## $p.value
## [1] 0.3695697
```

```r
sr = rstandard(model.aw)
sr[abs(sr) > 1.96]
```

```
##        54       120       122       150       157       164       172       181       199
##  2.740294  1.975409  2.015236  2.112331  2.963862  2.253872  2.112331  2.451774 -2.241058
```

```r
aw_ = data.frame(aw[c(4, 2)], predicted = model.aw$fitted)
head(aw_)
```

```
##   math num_awards predicted
## 1   41          0 0.1651762
## 2   41          0 0.1651762
## 3   44          0 0.2139002
## 4   42          0 0.1800399
## 5   40          0 0.1515396
## 6   42          0 0.1800399
```

```r
tail(aw_)
```

```
##     math num_awards predicted
## 195   60          1 0.8490848
## 196   71          2 2.1907094
## 197   75          2 3.0922155
## 198   71          1 2.1907094
## 199   72          0 2.3878444
## 200   73          3 2.6027189
```

```r
aw_[names(sr[abs(sr) > 1.96]), ]  # look at the discrepancies
```

```
##     math num_awards predicted
## 54    50          3 0.3587060
## 120   49          2 0.3290921
## 122   58          3 0.7146750
## 150   57          3 0.6556731
## 157   61          5 0.9254913
## 164   62          4 1.0087733
## 172   57          3 0.6556731
## 181   69          6 1.8439209
## 199   72          0 2.3878444
```

```r
# 1 unit increase in math score
idr.display(model.aw)
```

```
##
## Poisson regression predicting num_awards
##
##                    IDR(95%CI)        P(Wald's test) P(LR-test)
```

```
## math (cont. var.) 1.09 (1.07,1.11)  < 0.001        < 0.001
##
## Log-likelihood = -190.0381
## No. of observations = 200
## AIC value = 384.0762
```

```
# 10 unit increase in math score? Manually...
b1 = coef(model.aw)[[2]] * 10
b1.ll = confint(model.aw)[[2]] * 10
```

```
## Waiting for profiling to be done...
```

```
b1.ul = confint(model.aw)[[4]] * 10
```

```
## Waiting for profiling to be done...
```

```
exp(cbind(`Math RR` = b1, `95% LL` = b1.ll, `95% UL` = b1.ul))
```

```
##       Math RR   95% LL   95% UL
## [1,] 2.367077 1.961573 2.867842
```

3.2 Rate data

```
# - data in Fleiss et al 2003
" Table 12.1
  cigar.day person.yrs cases        rate        pred
1       0.0       1421     0 0.000000000 0.000793326
2       5.2        927     0 0.000000000 0.001170787
3      11.2        988     2 0.002024291 0.001834458
4      15.9        849     2 0.002355713 0.002607843
5      20.4       1567     9 0.005743459 0.003652195
6      27.4       1409    10 0.007097232 0.006167215
7      40.8        556     7 0.012589928 0.016813428
"
```

```
## [1] " Table 12.1\n  cigar.day person.yrs cases        rate        pred\n1       0.0       1421      0
```

```
cigar.day = c(0, 5.2, 11.2, 15.9, 20.4, 27.4, 40.8)
person.yrs = c(1421, 927, 988, 849, 1567, 1409, 556)
cases = c(0, 0, 2, 2, 9, 10, 7)
cig = data.frame(cigar.day, person.yrs, cases)
cig
```

```
##   cigar.day person.yrs cases
## 1       0.0       1421     0
## 2       5.2        927     0
## 3      11.2        988     2
## 4      15.9        849     2
## 5      20.4       1567     9
## 6      27.4       1409    10
## 7      40.8        556     7
```

```
cig$rate = cig$cases/cig$person.yrs
cig
```

```
##   cigar.day person.yrs cases        rate
## 1       0.0       1421     0 0.000000000
```

```
## 2       5.2        927     0 0.000000000
## 3      11.2        988     2 0.002024291
## 4      15.9        849     2 0.002355713
## 5      20.4       1567     9 0.005743459
## 6      27.4       1409    10 0.007097232
## 7      40.8        556     7 0.012589928
```

```
model.cig = glm(cases ~ cigar.day, offset = log(person.yrs), data = cig, family = "poisson")
# - it includes offset variable
summary(model.cig)
```

```
##
## Call:
## glm(formula = cases ~ cigar.day, family = "poisson", data = cig,
##     offset = log(person.yrs))
##
## Deviance Residuals:
##       1        2        3        4        5        6        7
## -1.5015  -1.4733   0.1370  -0.1463   1.2630   0.4340  -0.8041
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.13928    0.45402 -15.725  < 2e-16 ***
## cigar.day    0.07485    0.01564   4.786  1.7e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 30.9017  on 6  degrees of freedom
## Residual deviance:  6.8956  on 5  degrees of freedom
## AIC: 28.141
##
## Number of Fisher Scoring iterations: 5
```

```
poisgof(model.cig)
```

```
## $results
## [1] "Goodness-of-fit test for Poisson assumption"
##
## $chisq
## [1] 6.895581
##
## $df
## [1] 5
##
## $p.value
## [1] 0.2285227
```

```
cig$pred = model.cig$fitted/cig$person.yrs
cig
```

```
##   cigar.day person.yrs cases        rate        pred
## 1       0.0       1421     0 0.000000000 0.000793326
## 2       5.2        927     0 0.000000000 0.001170787
## 3      11.2        988     2 0.002024291 0.001834458
```

```
## 4      15.9        849      2 0.002355713 0.002607843
## 5      20.4       1567      9 0.005743459 0.003652195
## 6      27.4       1409     10 0.007097232 0.006167215
## 7      40.8        556      7 0.012589928 0.016813428
```

```r
idr.display(model.cig)  # interpret?
```

```
##
## Poisson regression predicting cases with offset = log(person.yrs)
##
##                          IDR(95%CI)        P(Wald's test) P(LR-test)
## cigar.day (cont. var.) 1.08 (1.05,1.11)  < 0.001         < 0.001
##
## Log-likelihood = -12.0707
## No. of observations = 7
## AIC value = 28.1413
```

```r
# - 5 cigar/day
exp(coef(model.cig)[[2]] * 5)  # interpret?
```

```
## [1] 1.453868
```

```r
# - 10 cigar/day
exp(coef(model.cig)[[2]] * 10)  # interpret?
```

```
## [1] 2.113733
```

4 Multiple Poisson regression model

```r
# - Again, data from https://stats.idre.ucla.edu/stat/data/poisson_sim.csv
aw = read.csv("poisson_sim.csv")
str(aw)
```

```
## 'data.frame':    200 obs. of  4 variables:
##  $ id        : int  45 108 15 67 153 51 164 133 2 53 ...
##  $ num_awards: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ prog      : int  3 1 3 3 3 1 3 3 3 3 ...
##  $ math      : int  41 41 44 42 40 42 46 40 33 46 ...
```

```r
head(aw)
```

```
##    id num_awards prog math
## 1  45          0    3   41
## 2 108          0    1   41
## 3  15          0    3   44
## 4  67          0    3   42
## 5 153          0    3   40
## 6  51          0    1   42
```

```r
tail(aw)
```

```
##      id num_awards prog math
## 195  61          1    2   60
## 196 100          2    2   71
## 197 143          2    3   75
## 198  68          1    2   71
```

```
## 199  57          0    2   72
## 200 132          3    2   73
```

```r
#- num_awards: The number of awards earned by students at one high school.
#- prog: 1 = General, 2 = Academic, 3 = Vocational
#- math: the score on their final exam in math.
#- factor prog & save as a new variable prog1
aw$prog1 = factor(aw$prog, levels = 1:3, labels = c("General", "Academic", "Vocational"))
str(aw)
```

```
## 'data.frame':    200 obs. of  5 variables:
##  $ id        : int  45 108 15 67 153 51 164 133 2 53 ...
##  $ num_awards: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ prog      : int  3 1 3 3 3 1 3 3 3 3 ...
##  $ math      : int  41 41 44 42 40 42 46 40 33 46 ...
##  $ prog1     : Factor w/ 3 levels "General","Academic",..: 3 1 3 3 3 1 3 3 3 3 ...
```

```r
head(aw)
```

```
##    id num_awards prog math      prog1
## 1  45          0    3   41 Vocational
## 2 108          0    1   41    General
## 3  15          0    3   44 Vocational
## 4  67          0    3   42 Vocational
## 5 153          0    3   40 Vocational
## 6  51          0    1   42    General
```

```r
tail(aw)
```

```
##      id num_awards prog math      prog1
## 195  61          1    2   60   Academic
## 196 100          2    2   71   Academic
## 197 143          2    3   75 Vocational
## 198  68          1    2   71   Academic
## 199  57          0    2   72   Academic
## 200 132          3    2   73   Academic
```

4.1 Univariable

```r
# - Math
model.aw.u1 = glm(num_awards ~ math, data = aw, family = poisson)
summary(model.aw.u1)  # Math sig.
```

```
##
## Call:
## glm(formula = num_awards ~ math, family = poisson, data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1853  -0.9070  -0.6001   0.3246   2.9529
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -5.333532   0.591261  -9.021   <2e-16 ***
## math         0.086166   0.009679   8.902   <2e-16 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 204.02  on 198  degrees of freedom
## AIC: 384.08
##
## Number of Fisher Scoring iterations: 6
```

```r
# - Prog
model.aw.u2 = glm(num_awards ~ prog1, data = aw, family = poisson)
summary(model.aw.u2)  # Vocational vs General not sig. -> Combine
```

```
##
## Call:
## glm(formula = num_awards ~ prog1, family = poisson, data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4142  -0.6928  -0.6325   0.0000   3.3913
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -1.6094     0.3333  -4.828 1.38e-06 ***
## prog1Academic     1.6094     0.3473   4.634 3.59e-06 ***
## prog1Vocational   0.1823     0.4410   0.413    0.679
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 234.46  on 197  degrees of freedom
## AIC: 416.51
##
## Number of Fisher Scoring iterations: 6
```

```r
aw$prog2 = recode(aw$prog1, "c('General', 'Vocational') = 'General & Vocational'")
levels(aw$prog2)
```

```
## [1] "Academic"             "General & Vocational"
```

```r
# - Prog2: General & Vocational vs Academic
model.aw.u2a = glm(num_awards ~ prog2, data = aw, family = poisson)
summary(model.aw.u2a)
```

```
##
## Call:
## glm(formula = num_awards ~ prog2, family = poisson, data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4142  -0.6649  -0.6649   0.0000   3.3913
##
## Coefficients:
```

```
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 4.352e-16  9.759e-02   0.000        1
## prog2General & Vocational -1.509e+00  2.390e-01  -6.314 2.72e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 234.63  on 198  degrees of freedom
## AIC: 414.69
##
## Number of Fisher Scoring iterations: 6
```

```r
table(No_Award = aw$num_awards, aw$prog2)
```

```
##
## No_Award Academic General & Vocational
##        0       48                   76
##        1       32                   17
##        2       11                    2
##        3        9                    0
##        4        2                    0
##        5        2                    0
##        6        1                    0
```

```r
tapply(aw$num_awards, aw$prog2, sum)
```

```
##              Academic General & Vocational
##                   105                    21
```

4.2 Multivariable

```r
model.aw.m1 = glm(num_awards ~ math + prog2, data = aw, family = poisson)
summary(model.aw.m1)  # both vars sig.
```

```
##
## Call:
## glm(formula = num_awards ~ math + prog2, family = poisson, data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2020  -0.8346  -0.5115   0.2589   2.6793
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -4.15050    0.66781  -6.215 5.13e-10 ***
## math                        0.06995    0.01068   6.548 5.83e-11 ***
## prog2General & Vocational -0.89129    0.25662  -3.473 0.000514 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
```

```
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 190.16  on 197  degrees of freedom
## AIC: 372.22
##
## Number of Fisher Scoring iterations: 6
```

```r
poisgof(model.aw.m1)  # good fit
```

```
## $results
## [1] "Goodness-of-fit test for Poisson assumption"
##
## $chisq
## [1] 190.1611
##
## $df
## [1] 197
##
## $p.value
## [1] 0.6235879
```

```r
idr.display(model.aw.m1)
```

```
##
## Poisson regression predicting num_awards
##
##                                           crude IDR(95%CI)  adj. IDR(95%CI)
## math (cont. var.)                         1.09 (1.07,1.11)  1.07 (1.05,1.1)
##
## prog2: General & Vocational vs Academic 0.22 (0.14,0.35)  0.41 (0.25,0.68)
##
##                                           P(Wald's test) P(LR-test)
## math (cont. var.)                         < 0.001        < 0.001
##
## prog2: General & Vocational vs Academic < 0.001        < 0.001
##
## Log-likelihood = -183.108
## No. of observations = 200
## AIC value = 372.216
```

```r
AIC(model.aw.u1, model.aw.u2a, model.aw.m1)
```

```
##              df      AIC
## model.aw.u1   2 384.0762
## model.aw.u2a  2 414.6871
## model.aw.m1   3 372.2160
```

```r
# - diagnostics
sr = rstandard(model.aw.m1)
sr[abs(sr) > 1.96]
```

```
##        54       154       157       164       181       191       199
##  2.372000  1.996023  2.693894  2.014175  2.342797 -2.013339 -2.261164
```

```r
aw$pred = model.aw.m1$fitted
aw_diag = data.frame(num_of_awards = aw$num_awards, pred_awards = round(aw$pred, 1))
aw_diag[names(sr[abs(sr) > 1.96]), ]  # look at the discrepancies
```

```
##     num_of_awards pred_awards
```

```
## 54               3         0.5
## 154              2         0.3
## 157              5         1.1
## 164              4         1.2
## 181              6         2.0
## 191              0         2.0
## 199              0         2.4
```

```
# - model fit: scaled Pearson chi-square statistic
quasi = summary(glm(num_awards ~ math + prog2, data = aw, family = quasipoisson))
quasi$dispersion  # dispersion parameter = scaled Pearson chi-square statistic
```

```
## [1] 1.08969
```

```
# - closer to 1, better.
```

4.3 Interaction

```
model.aw.i1 = glm(num_awards ~ math + prog2 + math * prog2, data = aw, family = poisson)
summary(model.aw.i1)  # interaction term not sig.
```

```
##
## Call:
## glm(formula = num_awards ~ math + prog2 + math * prog2, family = poisson,
##     data = aw)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2295  -0.8162  -0.5377   0.2528   2.6826
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -4.30286    0.74810  -5.752 8.83e-09 ***
## math                              0.07241    0.01196   6.053 1.42e-09 ***
## prog2General & Vocational        -0.19552    1.50706  -0.130    0.897
## math:prog2General & Vocational -0.01277    0.02742  -0.466    0.641
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 287.67  on 199  degrees of freedom
## Residual deviance: 189.94  on 196  degrees of freedom
## AIC: 374
##
## Number of Fisher Scoring iterations: 6
```

```
AIC(model.aw.m1, model.aw.i1)  # increase in AIC, M1 is better
```

```
##             df      AIC
## model.aw.m1  3 372.2160
## model.aw.i1  4 373.9965
```

4.4 Final model

```r
# - Accept model.aw.m1
idr.display(model.aw.m1)
```

```
##
## Poisson regression predicting num_awards
##
##                                           crude IDR(95%CI)  adj. IDR(95%CI)
## math (cont. var.)                         1.09 (1.07,1.11)  1.07 (1.05,1.1)
##
## prog2: General & Vocational vs Academic 0.22 (0.14,0.35)  0.41 (0.25,0.68)
##
##                                           P(Wald's test) P(LR-test)
## math (cont. var.)                         < 0.001        < 0.001
##
## prog2: General & Vocational vs Academic < 0.001        < 0.001
##
## Log-likelihood = -183.108
## No. of observations = 200
## AIC value = 372.216
```

```r
b1 = coef(model.aw.m1)[[2]] * 10
b1.ll = confint(model.aw.m1)[[2]] * 10
```

```
## Waiting for profiling to be done...
```

```r
b1.ul = confint(model.aw.m1)[[5]] * 10
```

```
## Waiting for profiling to be done...
```

```r
exp(cbind(`Math RR` = b1, `95% LL` = b1.ll, `95% UL` = b1.ul))
```

```
##       Math RR  95% LL   95% UL
## [1,] 2.012665 1.63494 2.485884
```

References

Chongsuvivatwong, V. (2015). *EpiDisplay: Epidemiological data display package*. Retrieved from https://CRAN.R-project.org/package=epiDisplay

Fox, J., & Weisberg, S. (2017). *Car: Companion to applied regression*. Retrieved from https://CRAN.R-project.org/package=car

Kutner, M. H., Nachtscheim, C. J., Neter, J., & Li, W. (2005). *Applied linear statistical model (*5th ed. Singapore: McGraw-Hill.