Medical Care - Zero-Inflated and Zero-Hurdle-Model

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First the medcare data are loaded:

```
> library(catdata)
> data(medcare)
> attach(medcare)
```

The dependent variable "ofp" (numbers of physician visits) is a count variable, so a poisson-family glm seems to be a good choice.

```
> med1=glm(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school,
+          family=poisson,data=medcare[male==1 & ofp<=30,])
> summary(med1)

Call:
glm(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school, family = poisson, data = medcare[male ==
    1 & ofp <= 30, ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.3338  -1.9118  -0.6178   0.8085   7.5113

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.289181   0.140378   2.060   0.0394 *
hosp             0.161705   0.010324  15.663  < 2e-16 ***
healthpoor       0.131090   0.031910   4.108 3.99e-05 ***
healthexcellent -0.269974   0.047458  -5.689 1.28e-08 ***
numchron         0.153347   0.007691  19.939  < 2e-16 ***
age              0.076527   0.017635   4.340 1.43e-05 ***
married          0.145469   0.027905   5.213 1.86e-07 ***
school           0.029470   0.002858  10.311  < 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: 8830.3  on 1760  degrees of freedom
```

```
Residual deviance: 7655.9  on 1753  degrees of freedom
AIC: 12502

Number of Fisher Scoring iterations: 5
```

In many real-world datasets the variance of count-data is higher than predicted by the Poisson distribution, so we fit a quasi-Poisson model with dispersion parameter.

```
> med2=glm(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school,
+          family=quasipoisson,data=medcare[male==1 & ofp<=30,])
> summary(med2)

Call:
glm(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school, family = quasipoisson, data = medcare[male ==
    1 & ofp <= 30, ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.3338  -1.9118  -0.6178   0.8085   7.5113

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.289181   0.304171   0.951  0.34188
hosp             0.161705   0.022371   7.228 7.26e-13 ***
healthpoor       0.131090   0.069142   1.896  0.05813 .
healthexcellent -0.269974   0.102833  -2.625  0.00873 **
numchron         0.153347   0.016664   9.202  < 2e-16 ***
age              0.076527   0.038211   2.003  0.04536 *
married          0.145469   0.060465   2.406  0.01624 *
school           0.029470   0.006193   4.759 2.11e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 4.695025)

    Null deviance: 8830.3  on 1760  degrees of freedom
Residual deviance: 7655.9  on 1753  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 5
```

With an estimated dispersion parameter of 4.69 the standard errors are much bigger now. An alternative to a quasi-poisson model is to use the negative binomial distribution.

```
> library(MASS)
> med3=glm.nb(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school,
+             data=medcare[male==1 & ofp<=30,])
> summary(med3)
```

```
Call:
glm.nb(formula = ofp ~ hosp + healthpoor + healthexcellent +
    numchron + age + married + school, data = medcare[male ==
    1 & ofp <= 30, ], init.theta = 1.235593605, link = log)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4084  -0.9827  -0.2823   0.3482   3.0269

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.201812   0.317908   0.635  0.52555
hosp             0.226922   0.032299   7.026 2.13e-12 ***
healthpoor       0.198313   0.079353   2.499  0.01245 *
healthexcellent -0.290092   0.093235  -3.111  0.00186 **
numchron         0.171727   0.018834   9.118  < 2e-16 ***
age              0.075012   0.040340   1.859  0.06296 .
married          0.166799   0.060681   2.749  0.00598 **
school           0.030996   0.006335   4.893 9.92e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(1.2356) family taken to be 1)

    Null deviance: 2293.3  on 1760  degrees of freedom
Residual deviance: 2040.5  on 1753  degrees of freedom
AIC: 9291.5

Number of Fisher Scoring iterations: 1


              Theta:  1.2356
          Std. Err.:  0.0581

 2 x log-likelihood:  -9273.4800
```

In this model the standard errors are slightly lower with the result that "healthexcellent" and "married" are now significant. (level=0.05) In count data there are often much more zeros than expected. Therefore one can fit a "zero-inflated" model using the pscl package. In the first "zero-inflated" model one assumes that the occurence of zeros does depend on covariates:

```
> library(pscl)

> med4=zeroinfl(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school|1,
+               data=medcare[male==1 & ofp<=30,])
> summary(med4)

Call:
zeroinfl(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school | 1, data = medcare[male == 1 & ofp <= 30,
```

```
    ])

Pearson residuals:
    Min      1Q  Median      3Q     Max
-1.7341 -1.1258 -0.3746  0.6335  7.4442

Count model coefficients (poisson with log link):
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.185461   0.145168   8.166 3.18e-16 ***
hosp             0.135716   0.010674  12.715  < 2e-16 ***
healthpoor       0.152397   0.031970   4.767 1.87e-06 ***
healthexcellent -0.220640   0.050046  -4.409 1.04e-05 ***
numchron         0.102397   0.007998  12.803  < 2e-16 ***
age              0.024986   0.018062   1.383    0.167
married          0.023912   0.028614   0.836    0.403
school           0.015762   0.002950   5.343 9.15e-08 ***

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.51681    0.06359  -23.85   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 14
Log-likelihood: -5577 on 9 Df
```

In the second "zero-inflated" model the occurence of zeros can depend on covariates:

```
> med5=zeroinfl(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school,
+                data=medcare[male==1 & ofp<=30,])
> summary(med5)

Call:
zeroinfl(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school, data = medcare[male == 1 & ofp <= 30, ])

Pearson residuals:
    Min      1Q  Median      3Q     Max
-3.5146 -1.0496 -0.4430  0.6023  7.9454

Count model coefficients (poisson with log link):
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.22709    0.14415   8.513  < 2e-16 ***
hosp             0.13549    0.01069  12.676  < 2e-16 ***
healthpoor       0.15193    0.03195   4.755 1.98e-06 ***
healthexcellent -0.20314    0.04859  -4.181 2.90e-05 ***
numchron         0.10045    0.00797  12.604  < 2e-16 ***
age              0.02212    0.01800   1.229    0.219
married          0.01771    0.02825   0.627    0.531
school           0.01485    0.00292   5.087 3.64e-07 ***
```

```
Zero-inflation model coefficients (binomial with logit link):
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)       3.13374    0.88944   3.523 0.000426 ***
hosp             -0.60179    0.15686  -3.836 0.000125 ***
healthpoor        0.21235    0.24601   0.863 0.388050
healthexcellent   0.26134    0.21546   1.213 0.225149
numchron         -0.47280    0.06538  -7.231 4.78e-13 ***
age              -0.34563    0.11432  -3.023 0.002500 **
married          -0.69907    0.14796  -4.725 2.31e-06 ***
school           -0.09232    0.01674  -5.515 3.50e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 21
Log-likelihood: -5491 on 16 Df
```

An alternative to "zero-inflation" is the "zero-hurdle" model. In the following similar models as above are fitted.

```
> med6=hurdle(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school|1
+             ,data=medcare[male==1 & ofp<=30,])
> summary(med6)

Call:
hurdle(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school | 1, data = medcare[male == 1 & ofp <= 30,
    ])

Pearson residuals:
    Min      1Q  Median      3Q     Max
-1.7065 -1.1225 -0.3671  0.6301  7.4080

Count model coefficients (truncated poisson with log link):
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.228410   0.144000   8.531  < 2e-16 ***
hosp             0.135443   0.010691  12.669  < 2e-16 ***
healthpoor       0.152058   0.031945   4.760 1.94e-06 ***
healthexcellent -0.204398   0.048755  -4.192 2.76e-05 ***
numchron         0.100331   0.007964  12.599  < 2e-16 ***
age              0.022058   0.017985   1.226    0.220
married          0.017420   0.028232   0.617    0.537
school           0.014812   0.002919   5.075 3.88e-07 ***
Zero hurdle model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.47077    0.06114   24.06   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 14
Log-likelihood: -5582 on 9 Df
```

```
> med7=hurdle(ofp ~ hosp+healthpoor+healthexcellent+numchron+age+married+school,
+              data=medcare[male==1 & ofp<=30,])
> summary(med7)

Call:
hurdle(formula = ofp ~ hosp + healthpoor + healthexcellent + numchron +
    age + married + school, data = medcare[male == 1 & ofp <= 30, ])

Pearson residuals:
    Min      1Q  Median      3Q     Max
-3.5123 -1.0503 -0.4421  0.6023  7.9503

Count model coefficients (truncated poisson with log link):
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.228410   0.144000   8.531  < 2e-16 ***
hosp             0.135443   0.010691  12.669  < 2e-16 ***
healthpoor       0.152058   0.031945   4.760 1.94e-06 ***
healthexcellent -0.204398   0.048755  -4.192 2.76e-05 ***
numchron         0.100331   0.007964  12.599  < 2e-16 ***
age              0.022058   0.017985   1.226    0.220
married          0.017420   0.028232   0.617    0.537
school           0.014812   0.002919   5.075 3.88e-07 ***
Zero hurdle model coefficients (binomial with logit link):
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -3.14201    0.87104  -3.607  0.00031 ***
hosp             0.60986    0.15535   3.926 8.65e-05 ***
healthpoor      -0.20092    0.24410  -0.823  0.41043
healthexcellent -0.28448    0.20846  -1.365  0.17236
numchron         0.47781    0.06438   7.422 1.15e-13 ***
age              0.34266    0.11187   3.063  0.00219 **
married          0.69079    0.14560   4.745 2.09e-06 ***
school           0.09278    0.01642   5.651 1.60e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 14
Log-likelihood: -5491 on 16 Df
```