Modelling Count Variables with R

Zero Truncated Poisson Distribution

Zero-Truncated Poisson Regression

► Zero-truncated Modelling is used to model count data for which the value zero cannot occur.

Example 1.

- A study of length of hospital stay, in days, as a function of age, kind of health insurance and whether or not the patient died while in the hospital.
- Length of hospital stay is recorded as a minimum of at least one day.

Example 2.

- ▶ A study of the number of journal articles published by tenured faculty as a function of discipline (fine arts, science, social science, humanities, medical, etc).
- ► To get tenure faculty must publish, therefore, there are no tenured faculty with zero publications.

Example 3.

- A study by the county traffic court on the number of tickets received by teenagers as predicted by school performance, amount of driver training and gender.
- ► Only individuals who have received at least one citation are in the traffic court files.

Example 4.

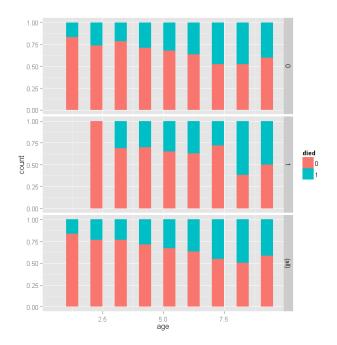
- Consider for example the random variable of the number of items in a shopper's basket at a supermarket checkout line.
- Presumably a shopper does not stand in line with nothing to buy (i.e. the minimum purchase is 1 item), so this phenomenon may follow a ZTP distribution

Data Set: hospitalstay

- We have a hypothetical data file, hospitalstay with 1,493 observations.
- The length of hospital stay variable is stay.
- ► The variable age gives the age group from 1 to 9 which will be treated as interval in this example.
- The variables hmo and died are binary indicator variables for HMO insured patients and patients who died while in the hospital, respectively.

Data Set: hospitalstay

```
died
##
       stay
                      age
                               hmo
                 Min.
                        :1.00
                               0:1254
##
   Min. : 1.00
                                       0:981
##
   1st Qu.: 4.00
                 1st Qu.:4.00
                               1: 239
                                       1:512
   Median: 8.00
                 Median:5.00
##
##
   Mean : 9.73
                 Mean :5.23
##
   3rd Qu.:13.00
                 3rd Qu.:6.00
##
   Max. :74.00
                 Max.
                        :9.00
```



Data Set: hospitalstay

- For the lowest ages, a smaller proportion of people in HMOs died, but for higher ages, there does not seem to be a huge difference, with a slightly higher proportion in HMOs dying if anything.
- Overall, as age group increases, the proportion of those dying increases, as expected.

- ► To fit the zero-truncated Poisson model, we use the vglm function in the VGAM package.
- This function fits a very flexible class of models called vector generalized linear models to a wide range of assumed distributions.
- ▶ In our case, we believe the data are Poisson, but without zeros.
- Thus the values are strictly positive Poisson, for which we use the positive Poisson family via the pospoisson function passed to vglm.

Fitting the Model with R

We will use the *hospitalstay* data.

```
m1 <- vglm(stay ~ age + hmo + died,
    family = pospoisson(),
    data = hospitalstay)
summary(m1)</pre>
```

Fitting the Model with R

Model Summary

```
## Coefficients:
```

```
## Estimate Std. Error z value

## (Intercept) 2.436 0.027 89.1

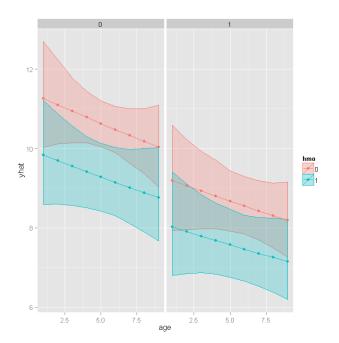
## age -0.014 0.005 -2.9

## hmo1 -0.136 0.024 -5.7

## died1 -0.204 0.018 -11.1
```

- ▶ The value of the coefficient for age, -0.0144 suggests that the log count of stay decreases by 0.0144 for each year increase in age.
- ► The coefficient for hmo, -0.1359 indicates that the log count of stay for HMO patient is 0.1359 less than for non-HMO patients.
- ► The log count of stay for patients who died while in the hospital was 0.2038 less than those patients who did not die.
- ► Finally, the value of the constant 2.4358 is the log count of the stay when all of the predictors equal zero.

- Can compute Cls using boot package
- Age does not have a significant effect, but hmo and died both do.



Zero-truncated negative binomial regression

Zero-truncated negative binomial regression is used to model count data for which the value zero cannot occur and for which over dispersion exists.

Zero-truncated negative binomial regression

- ➤ To fit the zero-truncated negative binomial model, we use the vglm function in the VGAM package.
- This function fits a very flexible class of models called vector generalized linear models to a wide range of assumed distributions.
- ▶ In our case, we believe the data come from the negative binomial distribution, but without zeros.
- Thus the values are strictly positive poisson, for which we use the positive negative binomial family via the posnegbinomial function passed to vglm.

Zero-truncated negative binomial regression

Fitting the Model with R

We will use the hospitalstay data again.

```
m1 <- vglm(stay ~ age + hmo + died,
  family = posnegbinomial(),
  data = hospitalstay)</pre>
```

```
summary(m1)
##
## Call:
## vglm(formula = stay ~ age + hmo + died,
      family = posnegbinomial(),
##
      data = hospitalstay)
##
##
## Pearson Residuals:
              Min 10 Median 30 Max
##
## log(munb) -1.4 -0.70 -0.23 0.45 9.8
## log(size) -14.1 -0.27 0.45 0.76 1.0
```

```
## Coefficients:
##
                Estimate Std. Error z value
   (Intercept):1
                  2.408
                             0.072
                                      33.6
## (Intercept):2
                   0.569
                             0.055
                                     10.4
                  -0.016
                             0.013 - 1.2
## age
                             0.059 - 2.5
## hmo1
                  -0.147
                  -0.218
                             0.046 - 4.7
## died1
```

- ▶ The first intercept is what we know as the typical intercept.
- ▶ The second is the **over dispersion parameter**, α .
- ▶ The number of linear predictors is two, one for the expected mean λ and one for the over dispersion.
- Next the dispersion parameter is printed, assumed to be one after accounting for overdispersion.

- ► The value of the coefficient for age, -0.0157 suggests that the log count of stay decreases by 0.0157 for each year increase in age.
- ► The coefficient for hmo, -0.1471 indicates that the log count of stay for HMO patient is 0.1471 less than for non-HMO patients.
- ▶ The log count of stay for patients who died while in the hospital was 0.2178 less than those patients who did not die.

- ▶ The value of the constant 2.4083 is the log count of the stay when all of the predictors equal zero.
- ▶ The value of the second intercept, the over dispersion parameter, α is 0.5686.
- To test whether we need to estimate over dispersion, we could fit a zero-truncated Poisson model and compare the two. (Not Covered).