

Modelling Count Variables with R

Zero-inflated Regression models - Summary

- ▶ Zero-inflated models attempt to account for excess zeros.
- ▶ In other words, two kinds of zeros are thought to exist in the data, "**true zeros**" and "**excess zeros**".

Zero-inflated Regression models

Two Distinct Processes

- ▶ The two parts of the a zero-inflated model are a binary model, usually a logit model to model which of the two processes the zero outcome is associated with and a count model, in this case, a negative binomial model, to model the count process.
- ▶ In other words, the excess zeros are generated by a separate process from the count values and that the excess zeros can be modelled independently.
- ▶ Zero-inflated models estimate two equations simultaneously, one for the count model and one for the excess zeros.
- ▶ The expected count is expressed as a combination of the two processes.

The `zeroinfl()` function

- ▶ In R, zero-inflated count data models can be fitted with the `zeroinfl()` function from the **pscl** package.
- ▶ Both the fitting function interface and the returned model objects of class “`zeroinfl()`” are modelled after the corresponding GLM functionality in R.

The `zeroinfl()` function

The arguments of `zeroinfl()` are given by

```
zeroinfl(formula, data, subset, na.action,  
          weights, offset,  
          dist = "poisson", link = "logit",  
          control = zeroinfl.control(...),  
          model = TRUE, y = TRUE, x = FALSE, ...)
```

Zero-inflated Regression models

Fishing Data Set

- ▶ We have data on 250 groups that went to a park.
- ▶ Each group was questioned about how many fish they caught (**count**), how many children were in the group (**child**), how many people were in the group (**persons**), and whether or not they brought a camper to the park (**camper**).
- ▶ In addition to predicting the number of fish caught, there is interest in predicting the existence of excess zeros, i.e., the probability that a group caught zero fish.
- ▶ We will use the variables child, persons, and camper in our model.

Zero-inflated Regression models

Fishing Data Set

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```
> head(fish)
```

	nofish	livebait	camper	persons	child	xb
1	1	0	0	1	0	-0.8963146
2	0	1	1	1	0	-0.5583450
3	0	1	0	1	0	-0.4017310
4	0	1	1	2	1	-0.9562981
5	0	1	0	1	0	0.4368910
6	0	1	1	4	2	1.3944855

```
zg count
```

1	3.0504048	0
2	1.7461489	0
3	0.2799389	0
4	-0.6015257	0
5	0.5277091	1
6	-0.7075348	0

What is a Zero-Inflated Model?

The Fishing Example

- ▶ A zero-inflated model assumes that zero outcome is due to two different processes.
- ▶ For instance, in the example of fishing presented here, the two processes are that a subject has gone 1. *fishing* vs. 2. *not fishing*.
- ▶ If not gone fishing, the only outcome possible is zero.
- ▶ If gone fishing, it is then a count process.

$$\begin{aligned} E(\text{no. fish caught} = k) \\ = P(\text{not fishing}) \times 0 + P(\text{fishing}) \times E(y = k | \text{fishing}) \end{aligned}$$

Zero-inflated Poisson regression

Though we can run a Poisson regression in R using the `glm` function in one of the core packages, we need another package to run the zero-inflated poisson model. We use the **pscl** package.

```
summary(m1 <- zeroinfl(count ~ child + camper |  
  persons, data = zinb))
```

Zero-inflated Poisson regression

```
##
```

```
## Call:
```

```
## zeroinfl(formula = count ~ child + camper | persons, data =
```

```
##
```

```
## Pearson residuals:
```

```
##      Min      1Q Median      3Q      Max
```

```
## -1.237 -0.754 -0.608 -0.192 24.085
```

Zero-inflated Poisson regression

```
## Count model coefficients (poisson with log link):  
##           Estimate Std. Error z value Pr(>|z|)  
## (Intercept)   1.5979    0.0855   18.68  <2e-16 ***  
## child        -1.0428    0.1000  -10.43  <2e-16 ***  
## camper1       0.8340    0.0936    8.91  <2e-16 ***
```

Zero-inflated Poisson regression

```
## Zero-inflation model coefficients (binomial with logit link)
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.297      0.374    3.47 0.00052 ***
## persons       -0.564      0.163   -3.46 0.00053 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Number of iterations in BFGS optimization: 12
## Log-likelihood: -1.03e+03 on 5 Df
```

Zero-inflated Poisson regression

- ▶ Below the model call, you will find a block of output containing Poisson regression coefficients for each of the variables along with standard errors, z-scores, and p-values for the coefficients.
- ▶ A second block follows that corresponds to the inflation model.
- ▶ This includes logit coefficients for predicting excess zeros along with their standard errors, z-scores, and p-values.

PART 4 :

Zero-Inflated Negative Binomial Regression

Zero-Inflated Negative Binomial regression

- ▶ Zero-inflated negative binomial regression is for modeling count variables with excessive zeros and it is usually for overdispersed count outcome variables.
- ▶ Furthermore, theory suggests that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently.

Zero-Inflated Negative Binomial regression

- ▶ We are going to use the variables: **child** and **camper** to model the count in the part of negative binomial model and the variable **persons** in the logit part of the model.
- ▶ We use the **pscl** to run a zero-inflated negative binomial regression.
- ▶ We begin by estimating the model (called `m1`) with the variables of interest.

Zero-Inflated Negative Binomial regression

```
m1 <- zeroinfl(count ~ child + camper | persons,  
  data = fishing, dist = "negbin",  
  EM = TRUE)
```

```
summary(m1)
```

```
## Call:
## zeroinfl(formula = count ~ child + camper | persons,
##          data = fishing,
##          dist = "negbin", EM = TRUE)
##
## Pearson residuals:
##      Min      1Q  Median      3Q      Max
## -0.586 -0.462 -0.389 -0.197 18.013
```

Zero-Inflated Negative Binomial regression

- ▶ Below the model call, you will find a block of output containing negative binomial regression coefficients for each of the variables along with standard errors, z-scores, and p-values for the coefficients.
- ▶ A second block follows that corresponds to the inflation model.
- ▶ This includes logit coefficients for predicting excess zeros along with their standard errors, z-scores, and p-values.

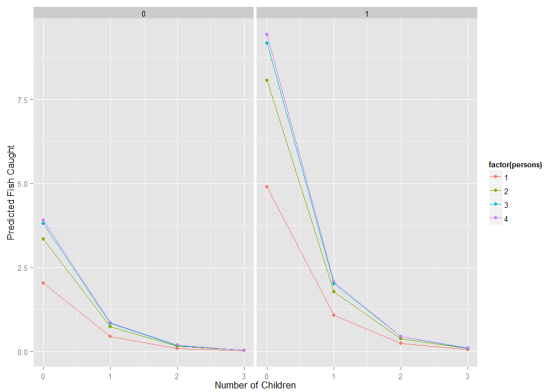
```
## Count model coefficients (negbin with log link):
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.371     0.256    5.35 8.6e-08 ***
## child         -1.515     0.196   -7.75 9.4e-15 ***
## camper1        0.879     0.269    3.26 0.0011 **
## Log(theta)    -0.985     0.176   -5.60 2.1e-08 ***
```

```
## Zero-inflation model coefficients (binomial with logit 1
##
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.603      0.836    1.92   0.055 .
## persons       -1.666      0.679   -2.45   0.014 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
##
## Theta = 0.373
## Number of iterations in BFGS optimization: 2
## Log-likelihood: -433 on 6 Df
```

- ▶ The predictors child and camper in the part of the negative binomial regression model predicting number of fish caught (count) are both significant predictors.
- ▶ The predictor person in the part of the logit model predicting excessive zeros is statistically significant.
- ▶ For these data, the expected change in $\log(\text{count})$ for a one-unit increase in child is -1.515255 holding other variables constant.
- ▶ A camper (camper = 1) has an expected $\log(\text{count})$ of 0.879051 higher than that of a non-camper (camper = 0) holding other variables constant.

Tests of Significance

- ▶ All of the predictors in both the count and inflation portions of the model are statistically significant.



- ▶ The log odds of being an excessive zero would decrease by 1.67 for every additional person in the group.
- ▶ In other words, the more people in the group the less likely that the zero would be due to not gone fishing.
- ▶ Put plainly, the larger the group the person was in, the more likely that the person went fishing.
- ▶ The Vuong test suggests that the zero-inflated negative binomial model is a significant improvement over a standard negative binomial model.

Vuong Testing

- ▶ Note that the model output above does not indicate in any way if our zero-inflated model is an improvement over a standard negative binomial regression.
- ▶ We can determine this by running the corresponding standard negative binomial model and then performing a Vuong test of the two models.
- ▶ We use the MASS package to run the standard negative binomial regression.

Vuong Testing

```
library(MASS)
summary(m2 <- glm.nb(count ~ child + camper, data = zinb))
.....
```

Vuong Testing

```
## Coefficients:
```

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.073     0.242    4.42 9.7e-06 ***
## child        -1.375     0.196   -7.03 2.1e-12 ***
## camper1       0.909     0.284    3.21 0.0013 **
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
```

Vuong Testing

```
vuong(m1, m2)
```

```
## Vuong Non-Nested Hypothesis Test-Statistic: 1.702  
## (test-statistic is asymptotically distributed  $N(0,1)$  under  
## null that the models are indistinguishable)  
## in this case:  
## model1 > model2, with p-value 0.0444
```

- ▶ The log odds of being an excessive zero would decrease by 1.67 for every additional person in the group.
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- ▶ The Vuong test suggests that the zero-inflated negative binomial model is a significant improvement over a standard negative binomial model.