What is Zero-Inflated Poisson Regression and how is it used in SAS data analysis?

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Zero-Inflated Poisson Regression is a statistical technique used in SAS data analysis to model count data with excessive zeros. It is an extension of the traditional Poisson regression model, which assumes that the count data follows a Poisson distribution. However, in real-world scenarios, there may be a large proportion of zero values in the data, which violates the assumption of the Poisson model. Zero-Inflated Poisson Regression addresses this issue by incorporating a two-part model, where the first part models the excess zeros and the second part models the non-zero counts. This allows for a more accurate and robust analysis of count data with excessive zeros. It is commonly used in fields such as healthcare, finance, and marketing to analyze data with a high number of zeros, such as insurance claims, financial transactions, and product sales. In SAS, this technique is implemented using the PROC GENMOD procedure, and it allows for the identification of significant predictors and the interpretation of their effects on both the zero and non-zero counts. Overall, Zero-Inflated Poisson Regression is a valuable tool in SAS data analysis for handling count data with excessive zeros and providing more accurate and reliable results.

Zero-InflatedPoisson Regression | SAS Data Analysis Examples

Version info: Code for this page was tested in SAS 9.3

Zero-inflated Poisson regression is used to model count data that has an excess of zero counts. Further, 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. Thus, the zip model has two parts, a Poisson count model and the logit model for predicting excess zeros. You may want to review these Data Analysis Example pages,

Poisson Regression and Logit Regression.

Please Note: The purpose of this page is to show how to use various data analysis commands. It does not cover all aspects of the research process which researchers are expected to do. In particular, it does not cover data cleaning and verification, verification of assumptions, model diagnostics and potential follow-up analyses.

Examples of zero-inflated Poisson regression

Example 1. School administrators study the attendance behavior of high school juniors over one semester at two schools. Attendance is measured by number of days of absent and is predicted by gender of the student and standardized test scores in math and language arts. Many students have no absences during the semester.

Example 2. The state wildlife biologists want to model how many fish are

being caught by fishermen at a state park. Visitors are asked whether or not they have a camper, how many people were in the group, were there children in the group and how many fish were caught. Some visitors do not fish, but there is no data on whether a person fished or not. Some visitors who did fish did not catch any fish so there are excess zeros in the data because of the people that did not fish.

Description of the data

Let's pursue Example 2 from above using the dataset fish.

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 zeroes that were not simply
a result of bad luck fishing. We will use the variables child, persons, and
camper in our model. Let's look at the data.

```
proc means data = fish mean std min max var;
var count child persons;
run;
```

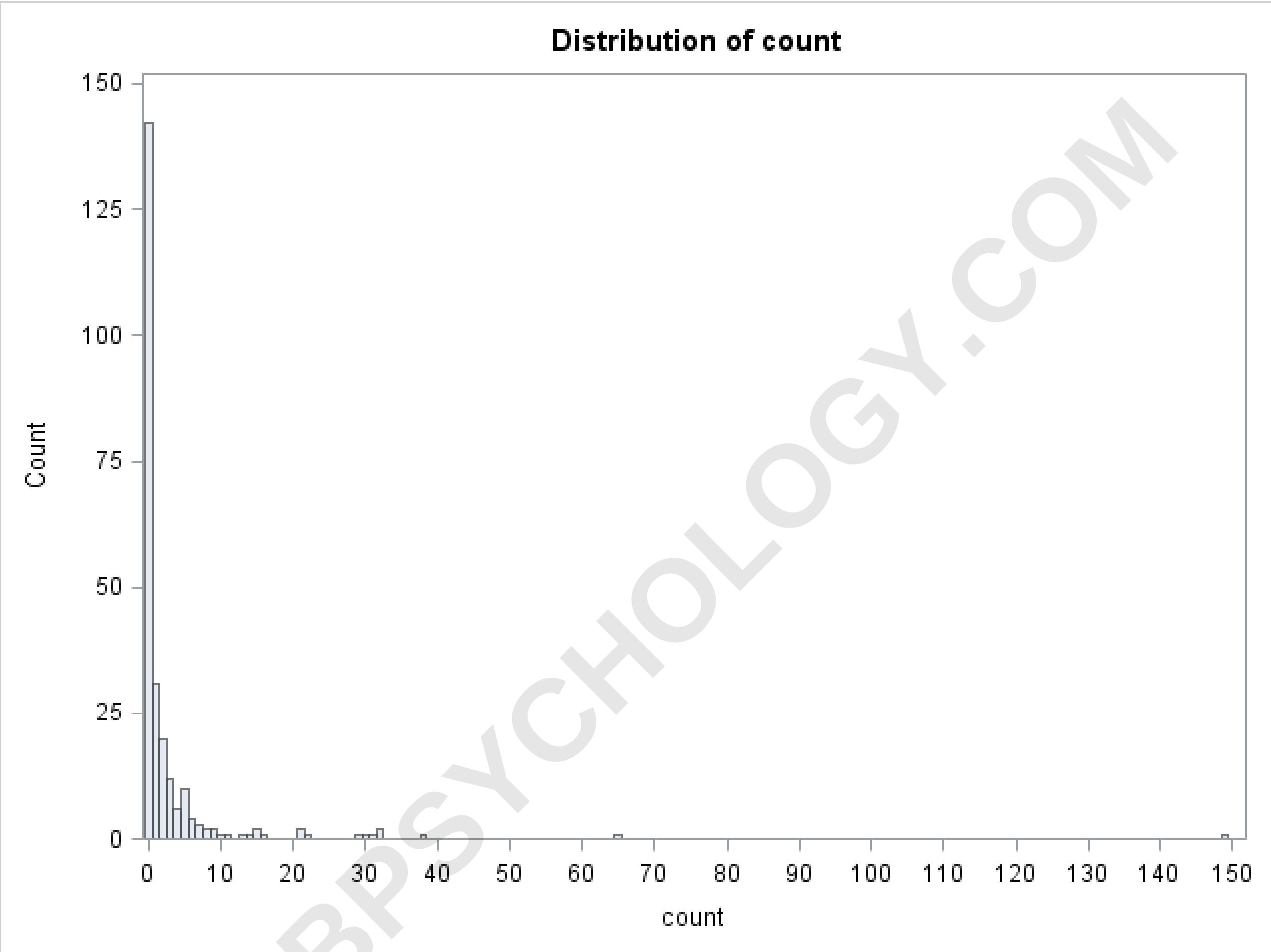
The MEANS Procedure

```
Variable Mean Std Dev Minimum Maximum Variance
--------------------------------------------------------------------------------
count 3.2960000 11.6350281 0 149.0000000 135.3738795
child 0.6840000 0.8503153 0 3.0000000 0.7230361
persons 2.5280000 1.1127303 1.0000000 4.0000000 1.2381687
--------------------------------------------------------------------------------
```

```
proc univariate data = fish noprint;
```

histogram count / midpoints = 0 to 50 by 1 vscale = count ;

run;



proc freq data = fish;

tables camper;

run;

The FREQ Procedure

Cumulative Cumulative

camper Frequency Percent Frequency Percent

----

0 103 41.20 103 41.20

1 147 58.80 250 100.00

Analysis methods you might consider

Below is a list of some analysis methods you may have encountered.
Some of the methods listed are quite reasonable while others have either fallen out of favor or
have limitations.

SAS zero-inflated Poisson regression analysis using proc genmod

If you are using SAS version 9.2 or higher, you can run a zero-inflated Poisson model using procgenmod.

```
proc genmod data = fish;
class camper;
model count = child camper /dist=zip;
zeromodel persons /link = logit;
run;
```

The GENMOD Procedure

Model Information

Data Set WORK.FISH Written by SAS

Distribution Zero Inflated Poisson
Link Function Log
Dependent Variable count

Number of Observations Read 250
Number of Observations Used 250

Class Level Information

Class Levels Values

camper 2 0 1

Criteria For Assessing Goodness Of Fit

Criterion DF Value Value/DF

Deviance 2063.2168
Scaled Deviance 2063.2168
Pearson Chi-Square 245 1543.4597 6.2998
Scaled Pearson X2 245 1543.4597 6.2998
Log Likelihood 774.8999
Full Log Likelihood -1031.6084

AIC (smaller is better) 2073.2168
AICC (smaller is better) 2073.4627
BIC (smaller is better) 2090.8241

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Standard Wald 95% Confidence Wald
Parameter DF Estimate Error Limits Chi-Square Pr > ChiSq

Intercept 1 2.4319 0.0413 2.3510 2.5128 3472.23 ChiSq

Intercept 1 1.2974 0.3739 0.5647 2.0302 12.04 0.0005
persons 1 -0.5643 0.1630 -0.8838 -0.2449 11.99 0.0005

The output begins with a summary of the model and the data.
This is followed by a list of goodness of fit statistics.

The next block of output includes parameter estimates from the count portion of
the model. It also includes the standard errors, Wald 95% confidence
intervals, Wald Chi-square statistics, and p-values for

the parameter estimates.

The last block of output corresponds to the zero-inflation portion of the model. This is a logistic model predicting the zeroes. The output includes parameter estimates for the inflation model predictors and their standard errors, Wald 95% confidence intervals, Wald Chi-square statistics, and p-values.

All of the predictors in both the count and inflation portions of the model are statistically significant. This model fits the data significantly better than the null model, i.e., the intercept-only model. To show that this is the case, we can run the null model (a model without any predictors) and compare the null model with the current model using chi-squared test on the difference of log likelihoods.

proc genmod data = fish;
model count = /dist=zip;

zeromodel / link = logit ;

run;

The GENMOD Procedure

Model Information

Data Set WORK.FISH Written by SAS

Distribution Zero Inflated Poisson

Link Function Log

Dependent Variable count

Number of Observations Read 250

Number of Observations Used 250

Criteria For Assessing Goodness Of Fit

Criterion DF Value Value/DF

Deviance 2254.0459

Scaled Deviance 2254.0459

Pearson Chi-Square 248 1918.7890 7.7371

Scaled Pearson X2 248 1918.7890 7.7371

Log Likelihood 679.4854

Full Log Likelihood -1127.0229

AIC (smaller is better) 2258.0459

AICC (smaller is better) 2258.0945
BIC (smaller is better) 2265.0888

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Standard Wald 95% Confidence Wald
Parameter DF Estimate Error Limits Chi-Square Pr > ChiSq

Intercept 1 2.0316 0.0349 1.9631 2.1000 3388.16 ChiSq

Intercept 1 0.2728 0.1277 0.0225 0.5232 4.56 0.0327

The log likelihoods for the full model and null mode are -1031.6084 and -1127.0229,
respectively. The chi-squared value is 2*(-1031.6084 - -1127.0229) = 190.829.
Since we have three predictor variables in the full model, the degrees of freedom
for the chi-squared test is 3. This yields a p-value <.0001. Thus, our
overall model is statistically significant.

We can use the estimate

statement to help understand our model. We will compute the expected counts for the categorical variable camper while holding the continuous variable child at its mean value using the atmeans option, as well as calculate the predicted probability that an observation came from the zero-generating process. In the estimate statement, we provide values at which to evaluate each coefficient for both the Poisson model and the zero-inflation model. The sets of coefficients of the two models are separated by the @ZERO keyword.

```
proc genmod data = fish;
class camper;
model count = child camper /dist=zip;
zeromodel persons /link = logit ;
estimate "camper = 0" intercept 1 child .684 camper 1 0
@ZERO intercept 1 persons 2.528;
estimate "camper = 1" intercept 1 child .684 camper 0 1
@ZERO intercept 1 persons 2.528;
run;
```

Contrast Estimate Results

Mean Mean L'Beta Standard
Label Estimate Confidence Limits Estimate Error Alpha

camper = 0 2.4220 1.9724 2.9741 0.8846 0.1048 0.05
camper = 0 (Zero Inflation) 0.4677 0.3838 0.5536 -0.1292 0.1756 0.05
camper = 1 5.5768 4.8823 6.3701 1.7186 0.0679 0.05
camper = 1 (Zero Inflation) 0.4677 0.3838 0.5536 -0.1292 0.1756 0.05

Contrast Estimate Results

L'Beta Chi-
Label Confidence Limits Square Pr > ChiSq

camper = 0 0.6792 1.0899 71.28 <.0001
camper = 0 (Zero Inflation) -0.4735 0.2150 0.54 0.4619
camper = 1 1.5856 1.8516 641.42 <.0001
camper = 1 (Zero Inflation) -0.4735 0.2150 0.54 0.4619

In the Mean Estimate column, we find predicted counts of fish from the
Poisson model, ignoring the zero-inflation model, for

both camper = 0 and camper = 1, as well as the predicted probability of belonging to the zero-generating process from the zero-inflation model. The zero-inflation model does not include camper as a predictor, so the probability of zero for both zero-inflation models is the same. To get the expected counts of fish from the mixture of the two models, simply multiply the expected counts from the Poisson model by the probability of getting a non-zero from the zero-inflation model (1 - p(zero)). Thus, the expected counts of fish for camper = 0 and camper = 1 including zero-inflation are 2.422*(1-0.4677) = 1.289 and 5.5768*(1-0.4677) = 2.968, respectively.

SAS zero-inflated Poisson analysis using proc countreg

Proc countreg is another option for running a zero-inflated Poisson regression in SAS (again, version 9.2 or higher). This

procedure allows
for a few more options
specific to count outcomes than proc genmod. The proc countreg
code for the original model run on this page appears below. We indicate
method = qn to specify the quasi-Newton optimization process that matches
the proc genmod results.

```
proc countreg data = fish method = qn;
class camper;
model count = child camper / dist= zip;
zeromodel count ~ persons;
run;
```

The COUNTREG Procedure

Class Level Information

Class Levels Values

camper 2 0 1

Model Fit Summary

Dependent Variable count

Number of Observations 250

Data Set MYLIB.FISH

Model ZIP

ZI Link Function Logistic

Log Likelihood -1032

Maximum Absolute Gradient 3.69075E-7

Number of Iterations 13

Optimization Method Quasi-Newton

AIC 2075

SBC 2096

Algorithm converged.

Parameter Estimates

Standard Approx

Parameter DF Estimate Error t Value Pr > |t|

Intercept 1 2.431911 0.041271 58.93 <.0001

child 1 -1.042838 0.099988 -10.43 <.0001

camper 0 1 -0.834022 0.093627 -8.91 <.0001

camper 1 0 0 . . .

Inf_Intercept 1 1.297439 0.373850 3.47 0.0005

Inf_persons 1 -0.564347 0.162962 -3.46 0.0005

SAS Zero-inflated Poisson analysis using proc nlmixed

For those using a version of SAS prior to 9.2, a zero-inflated negative binomial model is doable, though significantly more difficult. Please see this code fragment: Zero-inflated Poisson and Negative Binomial Using Proc Nlmixed.

Things to consider

See also

References