What is the process for conducting Exact Logistic Regression in SAS for data analysis?

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Exact Logistic Regression is a statistical method used for analyzing categorical data in SAS. This process involves several steps, including data preparation, model building, and interpretation of results.

First, the data must be organized and formatted correctly in SAS, with the response variable and explanatory variables clearly defined. This may involve converting categorical variables into binary variables using dummy coding.

Next, the model is built by specifying the dependent variable and independent variables in the logistic regression procedure. The EXACT option is then added to ensure that the analysis is conducted using exact methods rather than asymptotic approximations.

Once the model is run, the results are interpreted by examining the significance of the coefficients, odds ratios, and confidence intervals. This allows for the identification of significant predictors and their impact on the response variable.

In addition, diagnostics such as goodness-of-fit tests and residual analysis can be performed to assess the adequacy of the model.

Overall, the process of conducting Exact Logistic Regression in SAS involves careful data preparation, model building, and thorough interpretation of results to provide valuable insights into categorical data.

Exact Logistic Regression | SAS Data Analysis Examples

Versioninfo: Code for this page was tested in SAS 9.3.

Exact logistic regression is used to model binary outcome variables in which the log odds of the outcome is modeled as a linear combination of the predictor variables. It is used when the sample size is too small for a regular

logistic regression (which uses the standard maximum-likelihood-based estimator) and/or when some of the cells formed by the outcome and categorical predictor variable have no observations. The estimates given by exact logistic regression do not depend on asymptotic results.

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 checking, verification of assumptions, model diagnostics or potential follow-up analyses.

Example

Suppose that we are interested in the factors that influence whether or not a high school senior is admitted into a very competitive engineering school. The

outcome variable is binary (0/1): admit or not admit. The predictor variables of interest include student gender and whether or not the student took Advanced Placement calculus in high school. Because the response variable is binary, we need to use a model that handles 0/1 outcome variables correctly. Also, because of the number of students involved is small, we will need a procedure that can perform the estimation with a small sample size.

Description of the data

The data for this exact logistic data analysis include the number of students admitted, the total number of applicants broken down by gender (the variable female), and whether or not they had taken AP calculus (the variable apcalc). Since the dataset is so small, we will read it in directly.

```
options nocenter;

data exlogit;
```

```
input female apcalc admit num;
datalines;
0 0 0 7
0 0 1 1
0 1 0 3
0 1 1 7
1 0 0 5
1 0 1 1
1 1 0 0
1 1 1 6
;
run;
```

Let's look at some frequency tables. We will specify the variable num
as the frequency weight.

```
proc freq data = exlogit;
tables female*(apcalc admit);
tables apcalc*admit;
weight num;
run;
```

Table of female by apcalc

female apcalc

Frequency|
Percent |
Row Pct |
Col Pct | 0| 1| Total
---------+--------+--------+
0 | 8 | 10 | 18
| 26.67 | 33.33 | 60.00
| 44.44 | 55.56 |
| 57.14 | 62.50 |
---------+--------+--------+
1 | 6 | 6 | 12
| 20.00 | 20.00 | 40.00
| 50.00 | 50.00 |
| 42.86 | 37.50 |
---------+--------+--------+
Total 14 16 30
46.67 53.33 100.00

Table of female by admit

female admit

Frequency|

Percent |
Row Pct |
Col Pct | 0| 1| Total
---------+--------+--------+
0 | 10 | 8 | 18
| 33.33 | 26.67 | 60.00
| 55.56 | 44.44 |
| 66.67 | 53.33 |
---------+--------+--------+
1 | 5 | 7 | 12
| 16.67 | 23.33 | 40.00
| 41.67 | 58.33 |
| 33.33 | 46.67 |
---------+--------+--------+
Total 15 15 30
50.00 50.00 100.00

Table of apcalc by admit

apcalc admit

Frequency|
Percent |
Row Pct |
Col Pct | 0| 1| Total

---------+--------+--------+

0 | 12 | 2 | 14

| 40.00 | 6.67 | 46.67

| 85.71 | 14.29 |

| 80.00 | 13.33 |

---------+--------+--------+

1 | 3 | 13 | 16

| 10.00 | 43.33 | 53.33

| 18.75 | 81.25 |

| 20.00 | 86.67 |

---------+--------+--------+

Total 15 15 30

50.00 50.00 100.00

```
proc tabulate data = exlogit;
class female apcalc admit;
tables female='female', admit*apcalc='AP calculus'*F=6.
/ rts=13.;
freq num;
run;
```

--

| | admit |

| |------------------------|

	0	1
	AP calculus	AP calculus
	0	1	0	1
	N	N	N	N
female				
0	7	3	1	7
1	5	.	1	6

The tables reveal that 30 students applied for the Engineering program. Of those, 15 were admitted and 15 were denied admission. There were 18 male and 12 female applicants. Sixteen of the applicants had taken AP calculus and 14 had not. Note that all of the females who took AP calculus were admitted, versus only

about half the males.

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.

Using the exact logistic model

Let's run the exact logistic analysis using proc logistic with the
exact statement.
We will include the option estimate = both on the exact statement
so that we obtain both the point estimates and the odds ratios in the output.
We will also need to use the freq statement, for which we will specify the
frequency weight variable num.

```
proc logistic data = exlogit desc;
freq num;
model admit = female apcalc;
exact female apcalc / estimate = both;
```

run;

The LOGISTIC Procedure

Model Information

Data Set WORK.EXLOGIT
Response Variable admit
Number of Response Levels 2
Frequency Variable num
Model binary logit
Optimization Technique Fisher's scoring

Number of Observations Read 8
Number of Observations Used 7
Sum of Frequencies Read 30
Sum of Frequencies Used 30

Response Profile

Ordered Total
Value admit Frequency

1 1 15
2 0 15

Probability modeled is admit=1.

NOTE: 1 observation having nonpositive frequency or weight was excluded since it does not contribute to the analysis.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Intercept
Intercept and
Criterion Only Covariates

AIC 43.589 31.194
SC 44.990 35.398
-2 Log L 41.589 25.194

Testing Global Null Hypothesis: BETA=0

Test Chi-Square DF Pr > ChiSq

Likelihood Ratio 16.3947 2 0.0003
Score 14.2886 2 0.0008

Wald 9.6706 2 0.0079

Analysis of Maximum Likelihood Estimates

Standard Wald

Parameter DF Estimate Error Chi-Square Pr > ChiSq

Intercept 1 -2.5984 1.1361 5.2310 0.0222

female 1 1.4513 1.2037 1.4537 0.2279

apcalc 1 3.6685 1.1904 9.4973 0.0021

Odds Ratio Estimates

Point 95% Wald

Effect Estimate Confidence Limits

female 4.269 0.403 45.179

apcalc 39.193 3.801 404.075

Association of Predicted Probabilities and Observed Responses

Percent Concordant 80.4 Somers' D 0.756

Percent Discordant 4.9 Gamma 0.885

Percent Tied 14.7 Tau-a 0.391

Pairs 225 c 0.878

Exact Conditional Analysis

Conditional Exact Tests

--- p-Value ---

Effect Test Statistic Exact Mid

female Score 1.5143 0.3401 0.2438

Probability 0.1925 0.3401 0.2438

apcalc Score 13.0574 0.0003 0.0002

Probability 0.000283 0.0003 0.0002

Exact Parameter Estimates

Standard 95% Confidence

Parameter Estimate Error Limits p-Value

female 1.3605 1.1698 -1.1290 5.3680 0.4557

apcalc 3.3387 1.1251 1.1017 7.2659 0.0006

Exact Odds Ratios

95% Confidence

Parameter Estimate Limits p-Value

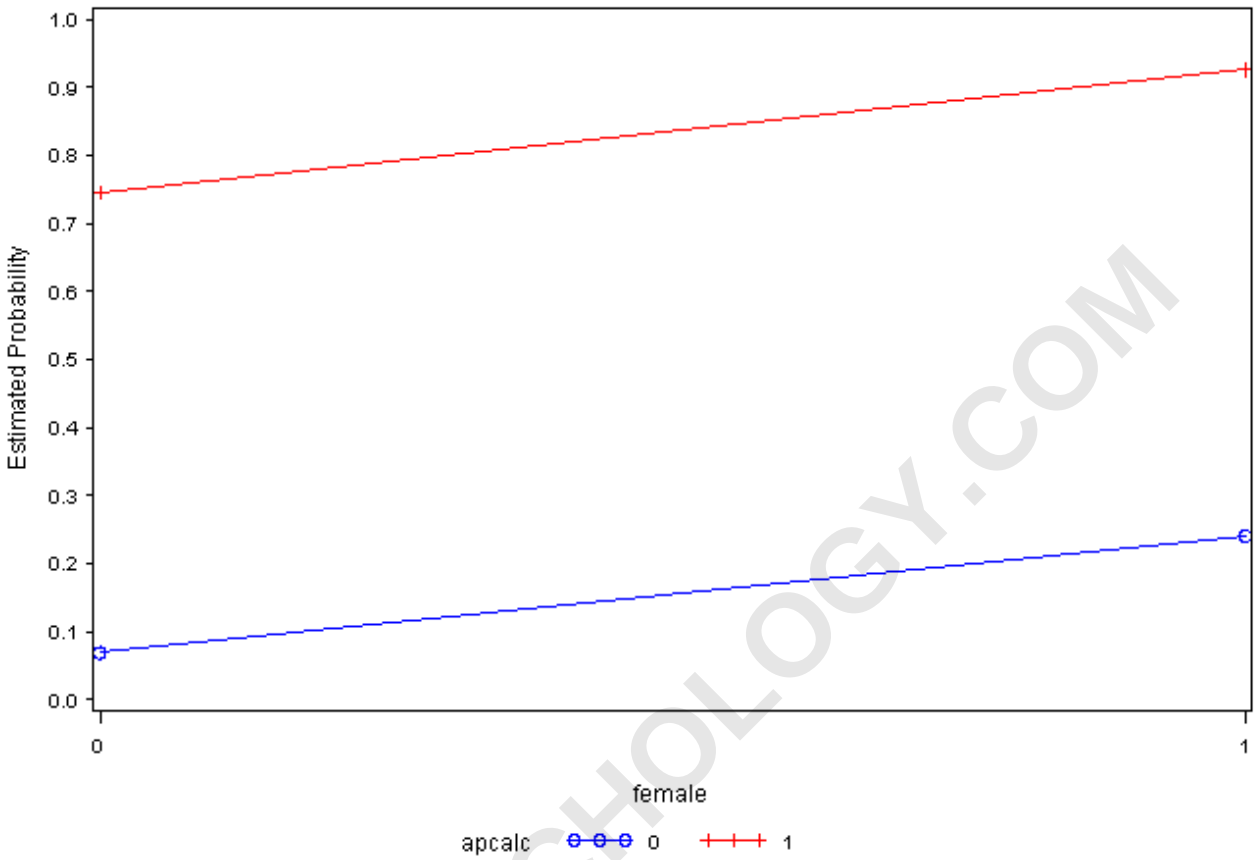
female 3.898 0.323 214.433 0.4557

apcalc 28.182 3.009 >999.999 0.0006

We can also graph the predicted probabilities. To do this, we will create a new variable called p using the output statement. Then we will use proc gplot to graph p.

```
proc logistic data = exlogit desc;
freq num;
model admit = female apcalc;
exact female apcalc / estimate = both;
output out = pred predicted = p;
run;

symbol1 c=blue v=circle i=join;
symbol2 c=red v=plus i=join;
symbol3 c=black v=square i=join;
axis1 label=(r=0 a=90) minor=none;
axis2 minor=none order=(0 1);
proc gplot data= pred;
plot p*female=apcalc / vaxis=axis1 haxis=axis2;
run;
quit;
```



Things to consider

See also

References