SAS

Print

Interpreting the Odds Ratio

To help interpret the odds ratio output from the previous demonstration, let's see how to calculate the odds and the odds ratio from the logistic regression model.

$$\mathrm{logit}(p) = \log(\mathrm{odds}) = \beta_0 + \beta_1 * \mathrm{Basement\_Area}$$

For a continuous predictor variable, such as Basement_Area, the odds ratio measures the increase or decrease in odds associated with a one-unit difference of the predictor variable. Remember, the logit is the natural log of the odds. Because you can calculate an estimated logit from the logistic model, the odds can be calculated by simply exponentiating that value. An odds ratio for a one-unit difference is then the ratio of the exponentiated predicted logits that are one unit apart.

The odds ratio for Basement_Area indicates that the odds of being bonus eligible increase by 0.7% for each increase in one square foot of basement area. Because the 95% confidence interval, 1.005 to 1.010, does not include 1.000, the odds ratio is significant at the 0.05 alpha level, and therefore, the predictor Basement_Area is significantly different from 0. The profile likelihood confidence intervals are different from the Wald-based confidence intervals. This difference is because the Wald confidence intervals use a normal error approximation, whereas the profile likelihood confidence intervals are based on the value of the log-likelihood. These likelihood-ratio confidence intervals require a much greater number of computations, but are generally preferred to the Wald confidence intervals, especially for sample sizes less than 50.

The Odds Ratio plot displays the results of the Odds Ratio table graphically. This plot is obtained by applying the parameter estimates from the logistic model to values of the predictors, and then converting the predictions to the probability scale. A reference line shows the null hypothesis, an odds ratio equal to 1. When the confidence interval crosses the reference line, the effect of the variable is not significant.

Calculating and interpreting odds ratios for categorical variables is similar to that of continuous variables. Imagine now that we fit a logistic regression model with the predictor Lot_Shape_2 instead of Basement_Area. Lot_Shape_2 has only two levels, Regular and Irregular.

$$\mathrm{logit}(p) = \ln(\mathrm{odds}) = \beta_0 + \beta_1 * \mathrm{Lot\_Shape\_2}$$

The logit of p is also equal to the linear predictor for our model: $\beta_0 + \beta_1 * \mathrm{Lot\_Shape\_2}$. In this case, we use the level Regular to represent the redundant level. So, Regular lot shapes are coded as 0 and Irregular lot shapes are coded as 1. To obtain the odds for an Irregular lot shape, we exponentiate the linear predictor for the level.

$$\mathrm{odds}_{\mathrm{irregular}} = e^{\beta_0 + \beta_1}$$

First, we substitute 1 for Lot_Shape_2 to get $\beta_0 + \beta_1$ as the linear predictor. Then, we add the parameter estimates that we got for β_0 and β_1 and exponentiate the sum.

To obtain the odds for a Regular lot shape, we follow the same process.

$$\mathrm{odds}_{\mathrm{regular}} = e^{\beta_0}$$

First, we substitute 0 for Lot_Shape_2 to get β_0 as the linear predictor. Then we take the parameter estimate that we got for β_0 and exponentiate it. The odds ratio is then the odds for the Irregular lot shape divided by the odds for a Regular lot shape.

Loading [MathJax]/jax/output/CommonHTML/jax.js

$$\text{odds ratio} = \frac{e^{\beta_0+\beta_1}}{e^{\beta_0}} = e^{\beta_1}$$

Mathematically, this is equivalent to e^{β_1} , so we can divide the two values we just calculated, or we can simply take the parameter estimate that we got for β_1 and exponentiate it.

Copyright © 2019 SAS Institute Inc., Cary, NC, USA. All rights reserved.

Close

Loading [MathJax]/jax/output/CommonHTML/jax.js