adding a binary predictor variable, female, to the model.

------------------------------------------------------------------------------

hon | Coef. Std. Err. z P>|z| [95% Conf. Interval]

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

female | .5927822 .3414294 1.74 0.083 -.0764072 1.261972

intercept | -1.470852 .2689555 -5.47 0.000 -1.997995 -.9437087

------------------------------------------------------------------------------

The coefficient for female is the log of odds ratio between the female group and male group: log(1.809) = .593

The ratio of the odds for female to the odds for male is (32/77)/(17/74) = (32\*74)/(77\*17) = 1.809. So the odds for males are 17 to 74, the odds for females are 32 to 77, and the odds for female are about 81% higher than the odds for males.

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Logistic regression with a single continuous predictor variable

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hon | Coef. Std. Err. z P>|z| [95% Conf. Interval]

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

math | .1563404 .0256095 6.10 0.000 .1061467 .206534

intercept | -9.793942 1.481745 -6.61 0.000 -12.69811 -6.889775

------------------------------------------------------------------------------

coefficient for math is the difference in the log odds. In other words, for a one-unit increase in the math score, the expected change in log odds is .1563404.

exp(.1563404) = 1.1692241.

So we can say for a one-unit increase in math score, we expect to see about 17% increase in the odds of being in an honors class. This 17% of increase does not depend on the value that math is held at.

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Logistic regression with multiple predictor variables and no interaction terms

Applying such a model to our example dataset, each estimated coefficient is the expected change in the log odds of being in an honors class for a unit increase in the corresponding predictor variable holding the other predictor variables constant at certain value. Each exponentiated coefficient is the ratio of two odds, or the change in odds in the multiplicative scale for a unit increase in the corresponding predictor variable holding other variables at certain value. Here is an example.

------------------------------------------------------------------------------

hon | Coef. Std. Err. z P>|z| [95% Conf. Interval]

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

math | .1229589 .0312756 3.93 0.000 .0616599 .1842578

female | .979948 .4216264 2.32 0.020 .1535755 1.80632

read | .0590632 .0265528 2.22 0.026 .0070207 .1111058

intercept | -11.77025 1.710679 -6.88 0.000 -15.12311 -8.417376

------------------------------------------------------------------------------

This fitted model says that, holding math and reading at a fixed value, the odds of getting into an honors class for females (female = 1)over the odds of getting into an honors class for males (female = 0) is exp(.979948) = 2.66. In terms of percent change, we can say that the odds for females are 166% higher than the odds for males. The coefficient for math says that, holding female and reading at a fixed value, we will see 13% increase in the odds of getting into an honors class for a one-unit increase in math score since exp(.1229589) = 1.13.

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Odds ratios greater than 1 correspond to "positive effects" because they increase the odds. Those between 0 and 1 correspond to "negative effects" because they decrease the odds. Odds ratios of exactly 1 correspond to "no association." An odds ratio cannot be less than 0.

Accuracy = (Number of Correct Predictions) / (Total Number of Predictions) this can be represented as: Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives)