

Logistic regression with multiple predictor variables and no interaction terms

In general, we can have multiple predictor variables in a logistic regression model.

$$\text{logit}(p) = \log(p/(1-p)) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$

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.

$$\text{logit}(p) = \log(p/(1-p)) = \beta_0 + \beta_1 \text{math} + \beta_2 \text{female} + \beta_3 \text{read}$$

Logistic regression	Number of obs	=	200
	LR chi2(3)	=	66.54
	Prob > chi2	=	0.0000
Log likelihood = -78.084776	Pseudo R2	=	0.2988

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 $\exp(.1229589) = 1.13$.