MCS-242: APPLIED STATISTICAL METHODS
COMPARISON OF SIMPLE AND MULTIPLE LOGISTIC REGRESSION

	Simple Logistic Regression	Multiple Logistic Regression
Response Variable type	Binary Categorical Numerical	Binary Categorical Numerical
Explanatory Variable(s) type	Binary Categorical Numerical	Binary Categorical Numerical
Model Equation: Logit form	$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x$	$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$
Model Equation: Probability form	$\pi = \frac{\exp(\beta_0 + \beta_1 x)}{1 + \exp(\beta_0 + \beta_1 x)}$	$\pi = \frac{\exp(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k)}{1 + \exp(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k)}$
Description of model terms	π = prob. of success β_0 = intercept of logit form β_1 = slope " "	β_i = slope of x_i
Model Assumptions	-linearity between logit (ln odds) + x -randomness of outcome -independence of outcomes	-linearity between logit + x_i for each x_i
Graphs used to test model assumptions	empirical logit plot: ln odds vs. x	empirical logit plots for each x_i
Estimated model equation	$\widehat{\text{logit}(\pi)} = \hat{\beta}_0 + \hat{\beta}_1 x$	$\widehat{\text{logit}(\pi)} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_k x_k$

	Simple Logistic Regression	**Multiple Logistic Regression**
Can you transform X? Why would you do so?	Yes No If x shows a non-linear relationship with the empirical logits (that could be fixed thru transform).	Yes No
Interpretation of slope coefficient	The odds of success for x+1 are $\exp(\beta_1)$ the odds of success for x.	The odds of success for x_i+1 are $\exp(\beta_i)$ the odds of success for x_i, holding other vars. constant.
	Wald test for individual coefficient (β_i):	
hypotheses	$H_0: \beta_1 = 0$ $H_a: \beta_1 \neq 0$	$H_0: \beta_i = 0$ $H_a: \beta_i \neq 0$
test statistic	$z = \hat{\beta}_1 / SE_{\hat{\beta}_1} \sim N(0,1)$	$z = \hat{\beta}_i / SE_{\hat{\beta}_i} \sim N(0,1)$
CI for individual coefficient (β_i)	$\hat{\beta}_1 \pm z^* SE_{\hat{\beta}_1}$	$\hat{\beta}_i \pm z^* \cdot SE_{\hat{\beta}_i}$
CI for odds ratio for 1-unit change in X	exp( )	exp( )
	G-test (drop-in-deviance test, LRT) for utility of the model:	
hypotheses	Ho: model is useless ($\beta_1=0$) Ha: model is useful ($\beta_1 \neq 0$)	Ho: model is useless (all $\beta_i=0$) Ha: model is useful (not all $\beta_i=0$)
test statistic (and how to find on R)	G = null deviance − residual deviance	same
distribution & degrees of freedom of test stat	$\sim \chi^2_1$	$\sim \chi^2_k$ (k = # vars. in model)
	Nested drop-in-deviance test (LRT):	
hypotheses		Ho: reduced model (k_1 vars). Ha: full model (k_1+k_2 vars.)
test statistic (and how to find on R)		G = resid. deviance reduced − resid. deviance full
distribution & degrees of freedom of test stat		$\sim \chi^2_{k_2}$