

Math 327

Section 9.2

Logistic Regression and Odds Ratios

Remember...

- Probability, p
 - Scale is 0 to 1
- Odds = $\frac{p}{1-p}$
 - Scale is 0 to ∞
- Log (Odds) = $\ln(Odds) = \ln\left(\frac{p}{1-p}\right)$
 - Scale is $-\infty$ to ∞

Odds Ratio

- In this section, we focus on a binary predictor variable
 - Remember, the response variable is also binary
- Odds Ratio
 - A way to compare two odds values
 - Remember: Odds is a ratio, so the Odds Ratio is a ratio of ratios
- Logit form of the model
 - $\log(odds) = \beta_0 + \beta_1 X$
 - So $odds = e^{\beta_0 + \beta_1 X}$
 - And $probability = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$ since $p = \frac{Odds}{1 + Odds}$

Example 9.6

- Explanatory variable: Treatment group, TMS or Placebo
- Response variable: Pain free after 2 hours, Yes or No
- Odds of Yes
 - Odds(Yes) for TMS: $39/61 = 0.639$
 - Odds(Yes) for Placebo: $22/78 = 0.282$
 - Odds Ratio, TMS vs. Placebo, $OR = \frac{0.639}{0.282} = 2.27$
 - Odds of being pain free after 2 hours is 2.27 times higher taking TMS vs. Placebo
- Odds of No
 - Odds(No) for TMS: $61/39 = 1.564$
 - Odds(No) for Placebo: $78/22 = 3.545$
 - Odds Ratio, Placebo vs. TMS, $OR = \frac{3.545}{1.564} = 2.27$
 - Odds of not being pain free after 2 hours is 2.27 times higher taking Placebo vs. TMS

	TMS	Placebo	Total
Pain-free 2 hrs later	39	22	61
Not pain-free 2 hrs. later	61	78	139
Total	100	100	200

Example 9.7

- Letrozole therapy
 - Treatment for post-menopausal women with breast cancer who have completed 5 years of tamoxifen therapy
 - 5000 women randomized to one of two groups: letrozole or placebo
 - Response variable: Disease-free survival (Yes or No)
 - Results
 - Letrozole: $Odds(DFS) = \frac{2390}{185} = 12.9$
 - Placebo: $Odds(DFS) = \frac{2241}{341} = 6.57$
 - Odds Ratio: $OR = \frac{12.9}{6.57} = 1.97$
 - Odds of disease-free survival is about twice as high for letrozole as for placebo

Disease-free survival	Letrozole	Placebo	Total
Yes	2390	2241	4631
No	185 (7.2%)	341 (13.2%)	566
Total	2575	2582	5157

Example 9.8

- Transition to marriage

- Does the chance of a single mother getting married depend on the gender of their child?

- If child is a boy:

- $Odds(married) = \frac{176}{134} = 1.31$

- If child is a girl:

- $Odds(married) = \frac{148}{142} = 1.04$

- Odds ratio:

- $OR = \frac{1.31}{1.04} = 1.26$

- The odds of getting married if the child is a boy is 26% higher (1.26 times higher) than if the child is a girl

Mother married	Boy	Girl	Total
Yes	176	148	324
No	134	142	276
Total	310	290	600

Odds Ratio and Slope

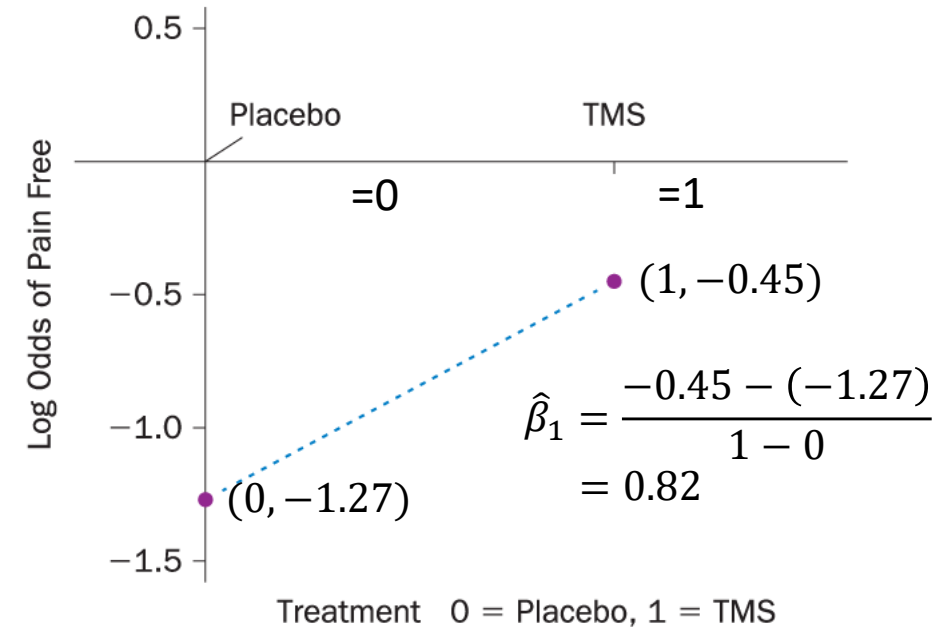
- In logistic regression, there is a constant slope on the logit scale
- Use empirical logits to help visualize the slope
 - Empirical logit = $\text{logit}(\hat{p}) = \log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \log\left(\frac{\#Yes}{\#No}\right)$
- Plot
 - Empirical logit vs. the 0, 1 predictor
 - Graphical summary of the 2x2 table

Example 9.9

- Migraines: TMS treatment vs Placebo

Pain-free?	TMS	Placebo	TMS vs. Placebo
Yes	39	22	
No	61	78	
Total	100	100	
Odds (Pain-free)	0.64	0.28	$OR = \frac{0.64}{0.28} = 2.27$
Log(Odds)	-0.45	-1.27	$Slope = -0.45 - (-1.27) = 0.82$

Note: $e^{Slope} = OR$
 $e^{0.82} = 2.27$



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Derivation:

$$e^{\hat{\beta}_1} = e^{Odds_2 - Odds_1} = \frac{e^{Odds_2}}{e^{Odds_1}} = \frac{Odds_2}{Odds_1} = OR$$

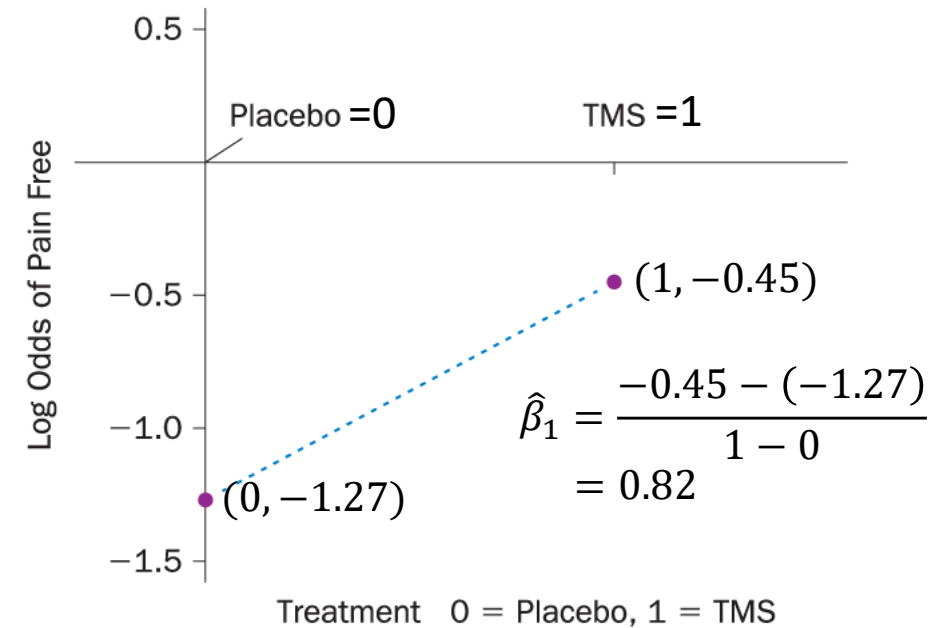
Fitted Slope and Odds Ratio

- In general the fitted slope is

- $$Slope = \frac{rise}{run} = \frac{change\ in\ log\ odds}{1-0} = \log(OR)$$

- Thus,

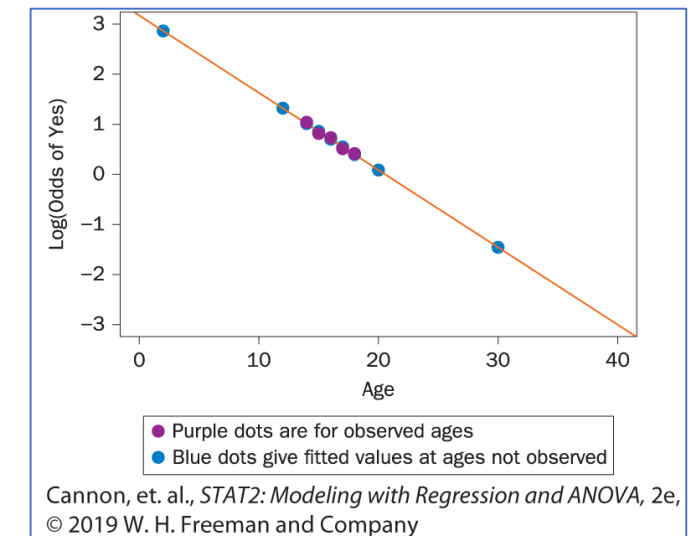
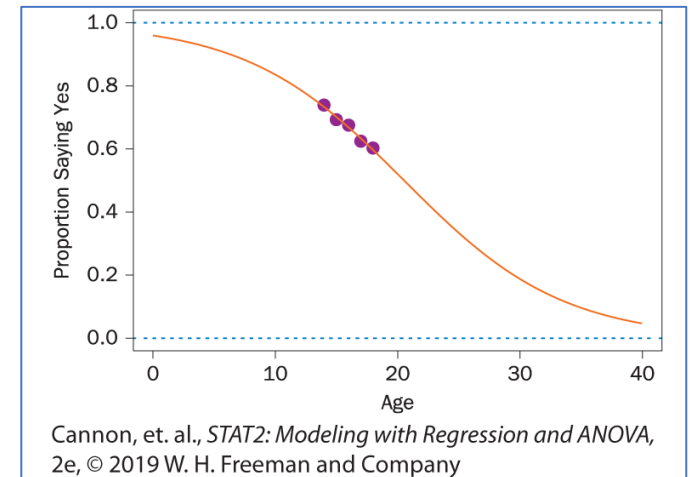
- $$OR = e^{slope} = e^{\hat{\beta}_1}$$



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Slope and Odds Ratio when Predictor is Quantitative

- Probability scale for the response
 - The slope changes with X (logistic curve)
- Log(Odds) scale for the response
 - The slope is constant, but it's “meaning keeps changing”
 - Explanation of “meaning keeps changing:” The impact of a one-unit change in X on the probability scale is different for different values of X . The impact is constant on the log(Odds) scale
 - The Odds Ratio is constant

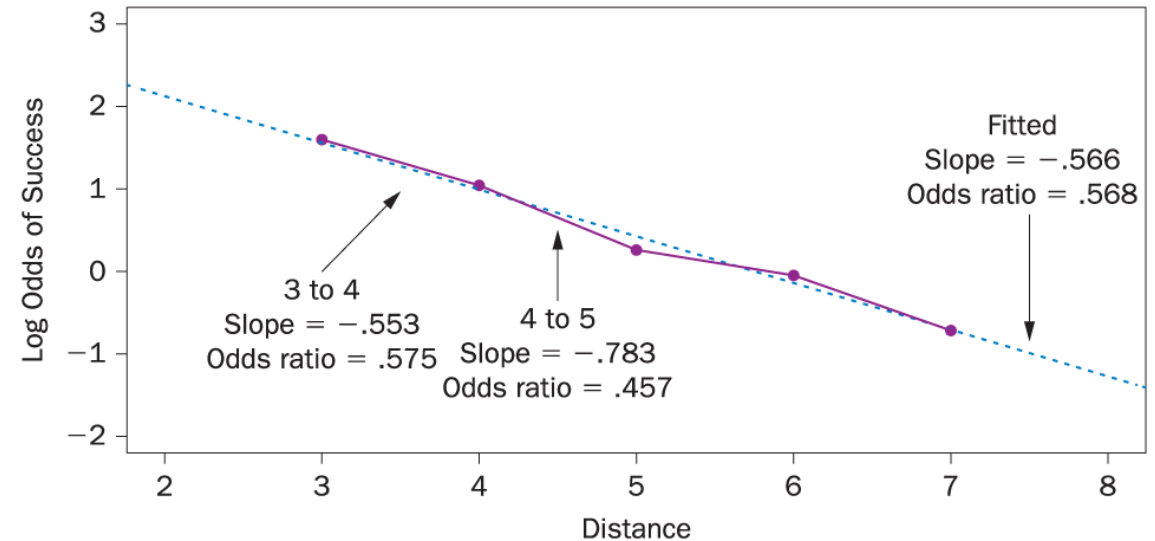


Example 9.10

- Putting success in golf
 - Response: Putt is successful
 - Predictor: Length of the putt (feet)

Length of putt (in feet)	3	4	5	6	7
Number of successes	84	88	61	61	44
Number of failures	17	31	47	64	90
Total number of putts	101	119	108	125	134
Proportion of successes	0.832	0.739	0.565	0.488	0.328
Odds of success	4.941	2.839	1.298	0.953	0.489
Empirical <u>logit</u>	1.60	1.04	0.26	-0.05	-0.72
Fitted logit value	1.558	0.992	0.426	-0.140	-0.706
Change in fitted logit value		-0.566	-0.566	-0.566	-0.566
Fitted probability	0.826	0.730	0.605	0.465	0.330
Change in fitted probability		-0.097	-0.125	-0.140	-0.135

per foot of putt length



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Length of putt (feet):	4 to 3	5 to 4	6 to 5	7 to 6
Empirical Odds Ratio	0.575	0.457	0.734	0.513
Fitted logistic Odds Ratio	0.568	0.568	0.568	0.568

Example 9.11

- Medical school admissions: Interpreting slope

```
> fit.med1 = glm (Acceptance ~ GPA, data=MedGPA, family=binomial)
> summary (fit.med1)
```

Call:
glm(formula = Acceptance ~ GPA, family = binomial, data = MedGPA)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.7805	-0.8522	0.4407	0.7819	2.0967

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-19.207	5.629	-3.412	0.000644	***
GPA	5.454	1.579	3.454	0.000553	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- $\hat{\beta}_1 = 5.45$ logit units per GPA unit
- $Odds_{GPA} = e^{-19.21+5.45 \cdot GPA}$
- $Odds_{GPA+1} = e^{-19.21+5.45(GPA+1)}$
- Describe one-unit increase in GPA in terms of the odds ratio:

$$\bullet \frac{Odds_{GPA+1}}{Odds_{GPA}} = \frac{e^{-19.21+5.45(GPA+1)}}{e^{-19.21+5.45 \cdot GPA}} = e^{5.45}$$

- A one-unit increase in GPA is associated with an $e^{5.45}$, or 233.7-fold, increase in the odds of acceptance
- Be aware of units: A 0.1-unit increase in GPA is associated with an $e^{0.545}$, or 1.72-fold, increase in the odds of acceptance, or not quite doubled
- Note: $1.72^{10} = 233.7$. If the odds of admission increases by a factor of 1.72 per 0.1 GPA units, then multiplying times 1.72 ten times is the same as multiplying by $1.72^{10} = 233.7$.

Example 9.11

- Confidence intervals for logistic regression parameters
 - We usually do not interpret the intercept, but $e^{\hat{\beta}_0}$ is the predicted odds of acceptance when $X = 0$ ($GPA = 0$)
 - In this case, it's nearly zero (4.557e-09)
 - With 95% confidence, the odds ratio for GPA is between 14.8 and 7,829
 - For every one unit increase in GPA, the odds of acceptance is between 14.8 and 7,829 times higher
 - With 95% confidence, the odds ratio for GPA/10 is between 1.31 and 2.45
 - For every one-tenth unit increase in GPA, the odds of acceptance increases between 1.31 and 2.45 times, or between 31% and 145% higher

```
> exp.betahat = exp (fit.med1$coefficients)
> ci.exp.beta = exp (confint (fit.med1))
Waiting for profiling to be done...
>
> cbind.data.frame (exp.betahat, ci.exp.beta)
              exp.betahat      2.5 %      97.5 %
(Intercept) 4.557449e-09 1.686955e-14 8.472476e-05
GPA          2.337298e+02 1.482501e+01 7.829246e+03
```

```
> exp.betahat0.1 = exp (fit.med1$coefficients/10)
> ci.exp.beta0.1 = exp (confint (fit.med1)/10)
Waiting for profiling to be done...
> cbind.data.frame (exp.betahat0.1, ci.exp.beta0.1)
              exp.betahat0.1      2.5 %      97.5 %
(Intercept) 0.1465117 0.04194791 0.3915624
GPA          1.7253270 1.30948191 2.4511619
```