

## **36-720: Log-Linear Models: Three-Way Tables**

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- Aggregation and Association
- Modelling the Three-Way Table
- The Model of Complete Independence
- Models with One Factor Independent of the Others
- Conditional Independence Models
- The Model of No Three-Way Interaction

## Aggregation and Association

Consider two questions on a math test:

$Y_1$ : “What is the slope of  $y = 2x + 3$  at  $x = 0$ ?”

( $Y_1 = 0$  for wrong,  $Y_1 = 1$  for right).

$Y_2$ : “What is the slope of  $y = (x + 1)^2 + 5$  at  $x = 0$ ?”

( $Y_2 = 0$  for wrong,  $Y_2 = 1$  for right).

For 500 students a table cross-classifying responses to these two questions might be as follows:

OBS	$Y_2 = 0$	$Y_2 = 1$	Total	RESIDS	$Y_2 = 0$	$Y_2 = 1$
$Y_1 = 0$	88	52	140	$Y_1 = 0$	1.08	-1.22
$Y_1 = 1$	192	168	360	$Y_1 = 1$	-0.68	0.76
Total	280	220	500			

The odds ratio is 1.48, and the Wald test of  $H_0 : OR = 1$  yields  $z = 1.92$  ( $p \approx 0.05$ ).

For example,  $\hat{P}[Y_2 = 1 | Y_1 = 1] = \frac{168}{360} = 0.47 > 0.44 = \frac{220}{500} = \hat{P}[Y_2 = 1]$ .

On further investigation the students could be separated into a group of 200 students who had taken an algebra class (only) and 300 students who had taken a calculus class as well. Looking at the data separately for these two groups of students, we see

Algebra Students				Calculus Students			
	$Y_2 = 0$	$Y_2 = 1$	Total	RESIDS	$Y_2 = 0$	$Y_2 = 1$	Total
$Y_1 = 0$	64	16	80	$Y_1 = 0$	24	36	60
$Y_1 = 1$	96	24	120	$Y_1 = 1$	96	144	240
Total	160	40	200	Total	120	180	300

The odds ratios here are  $\frac{(64)(24)}{(16)(96)} = 1$  and  $\frac{(24)(144)}{(36)(96)} = 1$ . So,  $Y_1$  and  $Y_2$  are conditionally independent, given class:  $(Y_1 \perp\!\!\!\perp Y_2) | (\text{class})$ .

Note that

- $\hat{P}[Y_1 = 1 | \text{Algebra}] = 0.6 < \hat{P}[Y_1 = 1 | \text{Calculus}] = 0.8$ ;
- $\hat{P}[Y_2 = 1 | \text{Algebra}] = 0.2 < \hat{P}[Y_2 = 1 | \text{Calculus}] = 0.6$ ;

This co-monotonicity in probabilities is what increases the association in the combined table. See Esary, Proschan and Walkup (1967, *Ann. Math. Stat.*).

### Simpson's (Yule's) Paradox

Hospital A			Hospital B		
	Recovered	Died		Recovered	Died
Treatment	$n_{111}$	$n_{121}$	Treatment	$n_{112}$	$n_{122}$
Placebo	$n_{211}$	$n_{221}$	Placebo	$n_{212}$	$n_{222}$

Simpson's paradox occurs, e.g., when

$$OR_A = \frac{n_{111}n_{221}}{n_{211}n_{121}} \geq 1$$

$$OR_B = \frac{n_{112}n_{222}}{n_{212}n_{122}} \geq 1$$

$$OR_{A+B} = \frac{(n_{111} + n_{112})(n_{221} + n_{222})}{(n_{211} + n_{212})(n_{121} + n_{122})} < 1$$

(or reverse all inequalities, as in the math test example).

For example:

Hospital A			Hospital B		
	Recovered	Died		Recovered	Died
Treatment	81	6	Treatment	192	71
Placebo	234	36	Placebo	55	25

Here,  $OR_A = \frac{(81)(36)}{(6)(234)} = 2.08$ ;  $OR_B = \frac{(192)(25)}{(71)(55)} = 1.23$ ; and  $OR_{A+B} = \frac{(273)(61)}{(77)(289)} = 0.74$ .

Note that

- $\hat{P}[\text{Recov.} \mid \text{Hosp. A}] = 0.88 > \hat{P}[\text{Recov.} \mid \text{Hosp. B}] = 0.72$
- $\hat{P}[\text{Treat.} \mid \text{Hosp. A}] = 0.24 < \hat{P}[\text{Treat.} \mid \text{Hosp. B}] = 0.77$

This reversal of probabilities is what *reduces* the association in the combined table.

If the probabilities both increased (or both decreased) it would tend to *increase* the association in the combined table (as in the math test example).

Holland & Rosenbaum (1986, *Ann. Stat.*); Kadane, Meyer & Tukey (1999, *JASA*).

## Modelling the Three-Way Table

Phenomena like Simpson's Paradox make it clear that we cannot learn all there is to know about a three- (or higher-) way table by just looking at 2-way subtables or 2-way aggregates.

We now turn directly to models for  $m_{ijk}$  in a three-way table. We will develop, simultaneously,

- Direct models for  $m_{ijk}$ ; these show what (in-)dependence and conditional (in-)dependence assumptions are being made by the model;
- The corresponding log-linear models; these make a link between statistical (in-)dependence and terms in an ANOVA-like model.

In general we are looking at an  $I \times J \times K$  table. Here is a  $3 \times 2 \times 2$  example:

$k = 1$			$k = 2$		
	$j = 1$	$j = 2$		$j = 1$	$j = 2$
$i = 1$	$n_{111}$	$n_{121}$	$i = 1$	$n_{112}$	$n_{122}$
$i = 2$	$n_{211}$	$n_{221}$	$i = 2$	$n_{212}$	$n_{222}$
$i = 3$	$n_{311}$	$n_{321}$	$i = 3$	$n_{312}$	$n_{322}$

We consider mainly multinomial sampling, although the formalisms go through for the product multinomial model as well.

You can compute MLE's for most of these models by hand.

We will also show how to compute MLE's using R's `glm()` function.

## The Model of Complete Independence

The *model of complete independence* is

$$M^{(0)} : p_{ijk} = p_{i++}p_{+j+}p_{++k} \quad \text{or} \quad \perp\!\!\!\perp(\text{rows, columns, layers})$$

The MLE's are

$$\begin{aligned} \hat{p}_{ijk}^{(0)} &= \hat{p}_{i++}\hat{p}_{+j+}\hat{p}_{++k} \\ &= (n_{i++}/n_{+++})(n_{+j+}/n_{+++})(n_{++k}/n_{+++}) ; \\ \hat{m}_{ijk}^{(0)} &= n_{+++}\hat{p}_{ijk}^{(0)} \\ &= (n_{i++}n_{+j+}n_{++k})/n_{+++}^2 \\ &= (\hat{m}_{i++}\hat{m}_{+j+}\hat{m}_{++k})/\hat{m}_{+++}^2 \end{aligned}$$

where  $\hat{m}_{ijk}$  satisfy<sup>a</sup> the “marginal constraints”  $\hat{m}_{i++} = n_{i++}$ ,  $\hat{m}_{+j+} = n_{+j+}$ ,  $\hat{m}_{++k} = n_{++k}$ , and  $\hat{m}_{+++} = n_{+++}$ .

<sup>a</sup>This is so because  $n_{i++}$ , etc. are the sufficient statistics for the  $p$ 's when the multinomial model  $M^{(0)}$  is viewed as an exponential family model: The MLE in an exponential family model has to equate observed ( $n_{i++}$ , etc.) and expected ( $\hat{m}_{i++}$ , etc.) sufficient statistics.

The two test-statistics are

$$\begin{aligned} X^2 &= \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \frac{(n_{ijk} - \hat{m}_{ijk}^{(0)})^2}{\hat{m}_{ijk}^{(0)}} \\ G^2 &= 2 \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K n_{ijk} \log n_{ijk} / \hat{m}_{ijk}^{(0)} \end{aligned}$$

with df. for the  $\chi^2$  tests above are

$$(IJK - 1) - (I - 1) - (J - 1) - (K - 1) = IJK - I - J - K + 2.$$

The corresponding log-linear model is

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)}$$

which can be seen by log'ing  $m_{ijk}^{(0)} = n_{+++}p_{i++}p_{+j+}p_{++k}$  under  $M_0$ .

### Example

We consider the  $2 \times 2 \times 3$  table

		Adversity of school ( $k$ )						Total
		Low		Med		High		
		N	R	N	R	N	R	
Classroom Behavior ( $i$ )	Family Risk ( $j$ )	N	R	N	R	N	R	
	Nondeviant	16	7	15	34	5	3	80
	Deviant	1	1	3	8	1	3	17
Total		17	8	18	42	6	6	97

The model can be fitted directly or by using `glm()` in R. For example,

```
n <- scan(sep="&")
16 & 7 & 15 & 34 & 5 & 3
1 & 1 & 3 & 8 & 1 & 3
Beh <- c(rep("N",6),rep("D",6))
Risk <- rep(c("N","R"),3)
Schl <- rep(c(rep("L",2),rep("M",2),rep("H",2)),2)
summary(fit0 <- glm(n ~ Beh + Risk + Schl,family=poisson))
mhat <- fitted(fit0)
```

The table of fitted values is

	Low		Med		High		Total
	N	R	N	R	N	R	
Nondeviant	8.72	11.90	20.92	28.57	4.18	5.71	80
Deviant	1.85	2.53	4.44	6.07	0.89	1.21	17
Total	17	8	18	42	6	6	97

and it is easy to verify that this table has the same marginal totals as the original (as it must).

$X^2 = 17.30$  on  $df = (IJK - 1) - (I - 1) - (J - 1) - (K - 1) = 2 \cdot 2 \cdot 3 - 1 - 2 - 1 - 1 = 7$ ; with a  $p$ -value of 0.015.

$G^2 = 16.42$ ,  $df = 7$ ,  $p$ -value=0.02. Note that this is the same as the “residual deviance” in the `glm()` output.

The Pearson residuals for  $M^{(0)}$  are

	Low		Med		High	
	N	R	N	R	N	R
Nondeviant	2.47	-1.42	-1.29	1.02	0.40	-1.14
Deviant	-0.63	-0.96	-0.69	0.78	0.12	1.62

## Models with One Factor Independent of the Others

There are three such models:

$$M^{(1)} : \quad p_{ijk} = p_{i++}p_{+jk} \quad \text{or} \quad (\text{rows}) \perp (\text{columns}, \text{layers})$$

$$M^{(2)} : \quad p_{ijk} = p_{+j+}p_{i+k} \quad \text{or} \quad (\text{columns}) \perp (\text{rows}, \text{layers})$$

$$M^{(3)} : \quad p_{ijk} = p_{++k}p_{ij+} \quad \text{or} \quad (\text{layers}) \perp (\text{rows}, \text{columns})$$

The MLE's are straightforward again. For example under  $M^{(1)}$ ,

$$\hat{p}_{ijk}^{(1)} = \hat{p}_{i++}\hat{p}_{+jk} = n_{i++}n_{+jk}/n_{+++}^2$$

and

$$\hat{m}_{ijk}^{(1)} = \hat{m}_{i++}\hat{m}_{+jk}/\hat{m}_{+++}$$

subject to the same sorts of constraints, e.g.  $m_{+jk} = n_{+jk}$ , again due to equating expected and observed sufficient statistics for MLE's in the exponential family model.

The test-statistics are again

$$X^2 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \frac{(n_{ijk} - \hat{m}_{ijk}^{(s)})^2}{\hat{m}_{ijk}^{(s)}}$$

$$G^2 = 2 \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K n_{ijk} \log n_{ijk} / \hat{m}_{ijk}^{(s)},$$

depending on which model  $s = 1, 2$ , or  $3$  is in use; the df. for the  $\chi^2$  tests above are

$$(IJK - 1) - (I - 1) - (JK - 1) = (I - 1)(JK - 1) \text{ for } M^{(1)};$$

$$(IJK - 1) - (J - 1) - (IK - 1) = (J - 1)(IK - 1) \text{ for } M^{(2)};$$

$$(IJK - 1) - (K - 1) - (IJ - 1) = (K - 1)(IJ - 1) \text{ for } M^{(3)}.$$

The corresponding log-linear models are

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{23(jk)}$$

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{13(ik)}$$

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)}$$

which can be seen by log'ing the corresponding  $m_{ijk}$  under each  $M^{(s)}$ .

### Example, Continued

Returning to the school behavior data, we can fit all three models in R as

```
summary(fit1 <- glm(n ~ Beh + Risk*Schl,family=poisson))
summary(fit2 <- glm(n ~ Risk + Beh*Schl,family=poisson))
summary(fit3 <- glm(n ~ Schl + Beh*Risk,family=poisson))
```

and we discover

Resid Deviance	df	p-value	AIC
$G^2_{(1)} = 5.56$	5	0.35	60.39
$G^2_{(2)} = 12.76$	5	0.03	67.51
$G^2_{(3)} = 52.52$	8	0.00	101.27

It seems that  $M^{(1)}$  provides the best fit relative to the saturated model:  
(classroom behavior)  $\perp$  (school adversity, family risk)

The Pearson residuals for  $M^{(1)}$  are

	Low		Med		High	
	N	R	N	R	N	R
Nondeviant	0.53	0.16	0.04	-0.11	0.02	-0.88
Deviant	-1.15	-0.34	-0.09	0.24	-0.05	1.90

## Conditional Independence Models

For a model asserting (rows)  $\perp$  (columns) | (layers), we would have

$$P[ijk] = P[i|k]P[j|k]P[k] = \frac{P_{i+k}}{P_{++k}} \frac{P_{+jk}}{P_{++k}} P_{++k} = \frac{P_{i+k}P_{+jk}}{P_{++k}}$$

There are clearly three such models:

$$M^{(4)} : p_{ijk} = p_{i+k}p_{+jk}/p_{++k} \quad \text{or} \quad (\text{rows}) \perp (\text{columns}) | (\text{layers})$$

$$M^{(5)} : p_{ijk} = p_{ij+}p_{+jk}/p_{+j+} \quad \text{or} \quad (\text{rows}) \perp (\text{layers}) | (\text{columns})$$

$$M^{(6)} : p_{ijk} = p_{ij+}p_{i+k}/p_{i++} \quad \text{or} \quad (\text{columns}) \perp (\text{layers}) | (\text{rows})$$

The MLE's are straightforward again. For example under  $M^{(4)}$ ,

$$\hat{p}_{ijk}^{(4)} = \hat{p}_{i+k}\hat{p}_{+jk}/\hat{p}_{++k} = (n_{i+k}n_{+jk})/(n_{++k}n_{+++})$$

and

$$\hat{m}_{ijk}^{(4)} = \hat{m}_{i+k}\hat{m}_{+jk}/\hat{m}_{++k}$$

subject to the same sorts of constraints, e.g.  $m_{+jk} = n_{+jk}$ , again due to equating expected and observed sufficient statistics for MLE's in the exponential family model.



The test-statistics are again

$$X^2 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \frac{(n_{ijk} - \hat{m}_{ijk}^{(s)})^2}{\hat{m}_{ijk}^{(s)}}$$

$$G^2 = 2 \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K n_{ijk} \log n_{ijk} / \hat{m}_{ijk}^{(s)},$$

depending on which model  $s = 4, 5$ , or  $6$  is in use; the df. for the  $\chi^2$  tests above are

$$\begin{aligned} (I-1)(J-1)K & \quad \text{for } M^{(4)}; \\ (I-1)(K-1)J & \quad \text{for } M^{(5)}; \\ (J-1)(K-1)I & \quad \text{for } M^{(6)}. \end{aligned}$$

For example, the test for  $M^{(6)}$  clearly pools  $I$  tests for independence of the conditional  $J \times K$  subtable at each row, and each of these tests has  $(J-1)(K-1)$  df, so the total df is  $(J-1)(K-1)I$ .

The corresponding log-linear models are

$$\begin{aligned} \log m_{ijk} &= u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{13(ik)} + u_{23(jk)} \\ \log m_{ijk} &= u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{23(jk)} \\ \log m_{ijk} &= u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} \end{aligned}$$

For example, when the in the first model we fix  $k$ , we get an overparametrized version of the independence model  $\log m_{ij} = u + u_{1(i)} + u_{2(j)}$ .

### Example, Continued

Returning to the school behavior data, we can fit all three models in R as

```
summary(fit4 <- glm(n ~ Beh*Schl + Risk*Schl,family=poisson))
summary(fit5 <- glm(n ~ Schl*Risk + Beh*Risk,family=poisson))
summary(fit6 <- glm(n ~ Beh*Risk + Beh*Schl,family=poisson))
```

and we discover

Resid Deviance	df	p-value	AIC
$G_{(4)}^2 = 1.90$	3	0.60	60.65
$G_{(5)}^2 = 4.12$	4	0.39	60.87
$G_{(6)}^2 = 11.32$	4	0.02	68.07

Although two of these models fit well

(classroom behavior) $\perp\!\!\!\perp$ (family risk) | (school adversity)  
(classroom behavior) $\perp\!\!\!\perp$ (school adversity) | (family risk)

the best fitting of the previous three models is simpler, with a similar AIC (60.39):

(classroom behavior) $\perp\!\!\!\perp$ (school adversity, family risk).

## The Model of No Three-Way Interaction

Each of the models we have considered so far have involved the absence of one or more interaction in the log-linear model

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} + u_{23(jk)} + u_{123(ijk)}$$

or equivalently setting the corresponding odds-ratios equal to 1.

- The independence model sets  $u_{12(ij)} = u_{23(jk)} = u_{13(ik)} = u_{123(ijk)} = 0$   $\forall i, j, k$ .
- Independence of one factor from the other two sets the three-way interaction  $u_{123(ijk)} = 0$  and two of the three two-way interactions to zero (which two depends on the model).
- Conditional independence sets the three-way interaction  $u_{123(ijk)} = 0$  and sets one of the two-way interactions to zero (again, depending on the model).

There is one more model commonly considered, that sets only the three-way interaction  $u_{123(ijk)} = 0, \forall i, j, k$ . From this model,

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} + u_{23(jk)} \quad (*)$$

generically taking  $a = e^u$ , we see that the model for the cell means is

$$m_{ijk} = a \cdot a_{1(i)} \cdot a_{2(j)} \cdot a_{3(k)} \cdot a_{12(ij)} \cdot a_{13(ik)} \cdot a_{23(jk)}$$

Now consider an odds ratio in the  $I \times J$  table in any of the  $K$  layers:

$$\begin{aligned} OR(i, j, i', j' | k) &= \frac{p_{ijk} p_{i'j'k}}{p_{i'jk} p_{ij'k}} = \frac{m_{ijk} m_{i'j'k}}{m_{i'jk} m_{ij'k}} \\ &= \frac{[a a_{1(i)} a_{2(j)} a_{3(k)} a_{12(ij)} a_{13(ik)} a_{23(jk)}] [a a_{1(i')} a_{2(j')} a_{3(k)} a_{12(i'j')} a_{13(i'k)} a_{23(j'k)}]}{[a a_{1(i')} a_{2(j)} a_{3(k)} a_{12(i'j)} a_{13(i'k)} a_{23(jk)}] [a a_{1(i)} a_{2(j')} a_{3(k)} a_{12(ij')} a_{13(ik)} a_{23(j'k)}]} \\ &= \frac{[a_{12(ij)} a_{13(ik)} a_{23(jk)}] [a_{12(i'j')} a_{13(i'k)} a_{23(j'k)}]}{[a_{12(i'j)} a_{13(i'k)} a_{23(jk)}] [a_{12(ij')} a_{13(ik)} a_{23(j'k)}]} = \frac{a_{12(ij)} a_{12(i'j')}}{a_{12(i'j)} a_{12(ij')}}, \end{aligned}$$

which does not depend on  $k$ !

Therefore, the model of no three-way interaction

$$M^{(7)} : (*) \text{ holds}$$

is equivalent to the model in which the odds ratio is the same in every layer of the table.

For this model, there are not closed-form MLE's; they must be computed iteratively. However, the test statistics are as usual

$$X^2 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \frac{(n_{ijk} - \hat{m}_{ijk}^{(7)})^2}{\hat{m}_{ijk}^{(7)}}$$

$$G^2 = 2 \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K n_{ijk} \log n_{ijk} / \hat{m}_{ijk}^{(7)}$$

with df. for the  $\chi^2$  tests above are  $(I-1)(J-1)(K-1)$ .

The model is easy to fit with R

```
summary(fit7<-glm(n~Beh*Risk*Schl-Beh:Risk:Schl,family=poisson))
```

This yields a fit of  $G^2 = 0.94$  on 2 d.f. Clearly there is overfit here.

However, given that the model fits we can now estimate a common odds-ratio for (say) the interaction of classroom behavior and family risk, across all levels of school adversity:

```
n.mtx <- matrix(n,nrow=2,byrow=T)
```

```
mhat.mtx <- matrix(fitted(fit7),nrow=2,byrow=T)
```

```
OR(n.mtx[, (1:2)+0])$OR      # 2.29; CI is (0.12, 41.98)
```

```
OR(n.mtx[, (1:2)+2])$OR      # 1.18; CI is (0.27, 5.06)
```

```
OR(n.mtx[, (1:2)+4])$OR      # 5.00; CI is (0.34, 72.77)
```

```
OR(mhat.mtx[, (1:2)+0])$OR    # 1.80
```

```
OR(mhat.mtx[, (1:2)+2])$OR    # 1.80
```

```
OR(mhat.mtx[, (1:2)+4])$OR    # 1.80
```

When  $M^{(7)}$  holds, the common odds ratio is more stably estimated since it uses all the data in the table, instead of one layer of data at a time (see next slide).

Following our work above we know that under the model of no three-factor interaction, for all  $k$ ,

$$OR(i, j, i', j' | k) = \frac{a_{12(ij)}a_{12(i'j')}}{a_{12(i'j)}a_{12(ij')}} = \exp \left[ u_{12(ij)} + u_{12(i'j')} - u_{12(i'j)} - u_{12(ij')} \right]$$

Once we have fitted the model above we can access the estimated  $u$ -terms and their variance-covariance matrix as

```
print(U <- summary(fit7)$coefficients[,1])
# (Intercept)      BehN      RiskR      SchlL      SchlM
#  0.4765646    1.0026434    0.3945061   -0.3748634    0.3486696
# BehN:RiskR BehN:SchlL BehN:SchlM RiskR:SchlL RiskR:SchlM
# -0.5898590    1.6615308    0.9269025   -0.6094350    0.9456019
V <- summary(fit7)$cov.unscaled
```

Under the model of no three-way interaction,

$$\log(OR[Beh, Risk | Schl]) = BehN:RiskN + BehD:RiskR - BehN:RiskR - BehD:RiskN$$

but we can see above that R set all but one of these equal to zero to identify the model. For R's reduced model, then, we have that the log common odds ratio is

$$\log(OR[Beh, Risk]) = \log(OR[Beh, Risk | Schl]) = -BehN:RiskR = -U[6] = 0.59$$

with standard error  $\sqrt{V[6]} = 0.39$ .

Note also that  $\exp(-U[6]) = 1.80$ , the same as we calculated from the fitted subtables on the slide above.

An approximate 95% CI for the log common odds ratio is

$$-U[6] + (-2, 2) \sqrt{V[6]} = (-0.19, 1.37)$$

which we can exponentiate to get an approximate 95% interval for the common odds ratio itself

$$\exp(-0.19, 1.37) = (0.83, 3.93)$$

Note that

- The final CI contains 1, suggesting that we cannot reject either
  - \*  $\log(OR[Beh, Risk]) = 1$ , i.e. (behavior)  $\perp$  (family risk)
  - \*  $\log(OR[Beh, Risk | Schl]) = 1$ , i.e. (behavior)  $\perp$  (family risk) | (school);
- The CI here is much shorter than any of the CI's for OR's calculated from the 2x2 subtables above.

*Using all of the data really does sharpen the inference!*