## What to do today (Mar 20)?

- 1. Introduction and Preparation
- 2. Analysis with Binary Variables (Chp 1-2)
- 3. Analysis with Multicategory Variables (Chp 3)
- 4. Analysis with Count Variables (Chp 4)

# 5. Model Selection and Evaluation (Chp 5)

- ▶ 5.1 Variable selection (Chp 5.1.1-4)
- ▶ 5.2 Tools to assess model fit (Chp 5.2)
- 5.3 Examples

## To Return Marked Midterm 2 Papers

6. Additional Topics (Chp 6)

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# **5D. Model Selection and Evaluation: in loglinear** regression

e.g. loglinear model for three-way contingency tables:  $\ensuremath{\textbf{Recall}}$  that

▶ how to establish the association of the cell counts,  $N_{ijk} \sim Poisson(\mu_{ijk})$ , with X, Y, and Z, three categorical variables?

**Saturated Loglinear Model (XYZ)** (including all main effects, two factor interactions, three factor interactions: df=IJK)

$$\log \mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{jk}^{YZ} + \lambda_{ik}^{XZ} + \lambda_{ijk}^{XYZ}$$

Loglinear Model of Multual Independence (X,Y,Z) (including only main effects: df =I+J+K-2)

$$\log \mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z$$

**Loglinear Model of Homogeneous Association (XY,YZ,XZ)** (including all main effects, two factor interactions: assuming  $\lambda_{ijk}^{XYZ} = 0$ )

$$\log \mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{jk}^{YZ} + \lambda_{ik}^{XZ}$$

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Parameter Interpretation for Model (XY,YZ,XZ): when I=J=2, X-Y conditional odds ratio at Z = k for any k is

$$\log \theta_{XY(k)} = \log \left(\frac{\mu_{11k}\mu_{22k}}{\mu_{12k}\mu_{21k}}\right) = [\lambda_{11}^{XY} + \lambda_{22}^{XY}] - [\lambda_{12}^{XY} + \lambda_{21}^{XY}]$$

 $\implies$  Homogeneous Conditional Association of X-Y Further, if  $\lambda_{ij}^{XY} = 0$ ,

- ► ⇒ Model (YZ,XZ)
- $\log \theta_{XY(k)} = 0$ , for all  $k \Longrightarrow X \perp Y | Z$

**Statistical Inference** with (the loglinear (Poisson) regression with 3 categorical predictors):

- Be careful with coding X, Y, Z
- Choice of models: e.g. (X,Y,Z), (X,YZ), (YZ,XZ), (XY,YZ,XZ), (XYZ)
- Variouse inference procedures:
  - Estm model parameters; estm  $\mu_{ijk}$ ; estm OR
  - Model checking/comparison: Pearson's  $\chi^2$ -test, LRT-test

Example. Alcohol, Cigarette and Marijuana Use

Alcohol	Cigarette		Marijuana Use (M)
Use (A)	Use (C)	Yes	No
Yes	Yes	911	538
	No	44	456
No	Yes	3	43
	No	2	279

Source: a survey conducted in 1992 by the Wright State Univ. School of Medicine and the United Health Services in Dayton.

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Using *read.table* to read in data and *as.data.frame* to form it into R's data format, or

• counts < -c(911, 44, 3, 2, 538, 456, 43, 279)

Run R to fit different models with the data: for example,

For Model (ACM)

 $tmp.out < -glm(counts \sim A * C * M, family = poisson);$ 

For Model (AC,CM,AM)

 $tmp2.out < -glm(counts \sim A * C + C * M + A * M, family = poisson);$ 

For Model (CM,AM)

 $tmp3.out < -glm(counts \sim C * M + A * M, family = poisson);$ 

For Model (AC,M)

 $tmp4.out < -glm(counts \sim A * C + M, family = poisson);$ 

For Model (A,C,M)

 $tmp5.out < -glm(counts \sim A + C + M, family = poisson);$ 

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Step 1. Fitted Values for Loglinear Models:

- Plug in the estm for the parameters in the models to attain the fitted values, or
- Use "tmp.out\$fitted", for example

The fit for (AC,AM,CM) is close to the observed data, the same as the fitted values for (ACM).

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		Loglinear Model					
С	М	(A,C,M)	(AC,M)	(AM,CM)	(AC,AM,CM)	(ACM)	
Yes	Yes	540.0	611.2	909.24	910.4	911	
	No	740.2	837.8	438.84	538.6	538	
No	Yes	282.1	210.9	45.76	44.6	44	
	No	386.7	289.1	555.16	455.4	456	
Yes	Yes	90.6	19.4	4.76	3.6	3	
	No	124.2	26.6	142.16	42.4	43	
No	Yes	47.3	118.5	0.24	1.4	2	
	No	64.9	162.5	179.84	279.6	279	
	C Yes No Yes No	C M Yes Yes No No Yes No Yes Yes No No Yes No	C M (A,C,M)   Yes Yes 540.0   No 740.2   No Yes 282.1   No 386.7   Yes Yes 90.6   No 124.2   No Yes 47.3   No 64.9	C M (A,C,M) (AC,M)   Yes Yes 540.0 611.2   No 740.2 837.8   No Yes 282.1 210.9   No 386.7 289.1   Yes Yes 90.6 19.4   No 124.2 26.6   No Yes 47.3 118.5   No 64.9 162.5	C M (A,C,M) (AC,M) (AM,CM)   Yes Yes 540.0 611.2 909.24   No 740.2 837.8 438.84   No Yes 282.1 210.9 45.76   No 386.7 289.1 555.16   Yes Yes 90.6 19.4 4.76   No 124.2 26.6 142.16   No Yes 47.3 118.5 0.24   No 64.9 162.5 179.84	C M (A,C,M) (AC,M) (AM,CM) (AC,AM,CM)   Yes Yes 540.0 611.2 909.24 910.4   No 740.2 837.8 438.84 538.6   No Yes 282.1 210.9 45.76 44.6   No 386.7 289.1 555.16 455.4   Yes Yes 90.6 19.4 4.76 3.6   No 124.2 26.6 142.16 42.4   No Yes 47.3 118.5 0.24 1.4   No 64.9 162.5 179.84 279.6	

Fitted Values for Loglinear Models:

Step 2. To obtain estimates for what needed based on the analyses

- using the analysis outputs: the estms for the model parameters and their estimated standard errors
- using the fitted counts when applicable
- e.g. the OR of alcohol use (A yes vs not) between cigarette use or not (C yes vs not)

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- conditional on marijuana use (M=yes or not)
- marginal (regardless of M)

Step 3. Chi-Squared Goodness-of-Fit Tests: Loglinear Residuals •  $G^2[(AC, AM, CM)] = 2 \sum n_{ijk} \log(\frac{n_{ijk}}{\hat{\mu}_{ijk}})$ 

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$$X^{2}[(AM, CM)] = \sum \frac{(n_{ijk} - \hat{\mu}_{ijk})^{2}}{\hat{\mu}_{ijk}}$$

• e.g. the Pearson's residuals: 
$$e_{ijk} = \frac{n_{ijk} - \hat{\mu}_{ijk}}{\sqrt{\hat{\mu}_{ijk}}}$$

residual plots: e.g. scatter plot of eijk vs A

Step 4. Model Selection: (backward elimination)

Start: AIC=65.04 counts ~ ACM					
	Df	Deviance	AIC		
- A:C:M	1	0.37399	63.417		
< none $>$		0.00000	65.043		
Step: AIC=	=63.42	$2$ counts $\sim$	A + C + M + AC + AM + CM		
	Df	Deviance	AIC		
< none $>$		0.37	63.42		
- A:M	1	92.02	153.06		
- A:C	1	187.75	248.80		
- C:M	1	497.37	558.41		

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## Part V.2.2D for Three-Way Contingency Tables

Step 5. Tests about Partial Associations:

- The test statistic for testing  $\lambda^{AC} = 0$  in (AC,AM,CM) is
- $G^{2}[(AM, CM)|(AC, AM, CM)] = G^{2}(AM, CM) G^{2}(AC, AM, CM)$ = 187.8 - 0.04,

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df=2-1

 $\implies$  p < 0.001: strong evidence against the null hypothesis and in favor of an A-C partial association.

## What to study next?

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- 5. Model Selection and Evaluation (Chp 5)

## 6. Additional Topics (Chp 6)

- ▶ 6.1 Exact inference (Chp 6.2)
- 6.2 Revisit to Loglinear and Logistic Models for Contingency Tables: the Loglinear-Logit Connection (Supplementary)
- 6.3 Revisit II to GLM and Some Advanced Topics (Chp 5.3, Chp 6.5)