



Visual metaphors

1198

557

Admit?: Yes

■ Quantitative data: magnitude ~ position along an axis

1493

1278

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O

m

∢

Admitted

Male

Admit?: No

■ Frequency data: count ~ area (Friendly, 1995)

Sex: Male

Sex: Female

overview

Model: (DeptGender)(Admit)

Rejected

Female





"Corrgrams: Exploratory displays for correlation matrices" (Friendly, 2002)

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overview

# Exploratory methods

- Minimal assumptions (like non-parametric methods)
- Show the *data*, not just *summaries*
- Help detect patterns, trends, anomalies, suggest hypotheses

# Plots for model-based methods

- Residual plots departures from model, omitted terms, ...
- Effect plots estimated probabilities of response or log odds
- Diagnostic plots influence, violation of assumptions

## Goals

- VCD and SSSG Make these methods available and accessible in SAS
- Practical power = Statistical power × Probability of Use
- Today's goal: take-home knowledge
- Tomorrow's goal: dynamic, interactive graphics for categorical data

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### Categorical Data Analysis with Graphics

# VCD Macros & SAS/IML programs

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Macros, datasets available at www.math.yorku.ca/SCS/vcd/

# Discrete distributions

Plots for discrete distributions DISTPLOT GOODFIT Goodness-of-fit for discrete distributions ORDPLOT Ord plot for discrete distributions POISPLOT Poissonness plot ROOTGRAM Hanging rootograms

#### Two-way and n-way tables

AGREE	Observer agreement chart
CORRESP	Plot PROC CORRESP results
FFOLD	Fourfold displays for $2  imes 2  imes k$ tables (macro)
FOURFOLD	Fourfold displays for $2 \times 2 \times k$ tables (SAS/IML)
SIEVEPLOT	Sieve diagrams
MOSAIC	Mosaic displays (macro)
MOSAICS	SAS/IML modules for mosaic displays
MOSMAT	Mosaic matrices (macro)
TABLE	Construct a grouped frequency table, with recoding
TRIPLOT	Trilinear plots for $n \times 3$ tables

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**Small multiples**— combine stratified graphs into coherent displays (Tufte, 1983)

e.g., scatterplot matrix for quantitative data: all pairwise scatterplots

vcdmacros

Model-based methods	
ADDVAR       Added variable plots for logistic regression         CATPLOT       Plot results from PROC CATMOD         HALFNORM       Half-normal plots for generalized linear models         INFLGLIM       Influence plots for generalized linear models         INFLOGIS       Influence plots for logistic regression         LOGODDS       Plot empirical logits and probabilities for binary data         POWERLOG       Power calculations for logistic regression         POWERRxC       Power calculations for two-way frequency table         POWER2x2       Power calculations for a 2 × 2 table         ROBUST       Robust fitting for linear models <b>Utility macros</b> DUMMY         Create dummy variables       LAGS         LAGS       Calculate lagged frequencies for sequential analysis         PANELS       Arrange multiple plots in a panelled display         SORT       Sort a dataset by the value of a statistic or formatted value         Utility       Graphics utility macros: BARS, EQUATE, GDISPLA, GENSYM, GSKIP, LABEL, POINTS, PSCALE         VCD Archive (vcdprog.zip) available to purchasers at:	R software and the vcd package         Model-based methods         glm       Fitting generalized linear models         loglm       MASS package: Fitting loglinear models         R Commander Menu-driven package for statistical analysis and graphics         car       Package for graphics and extensions of generalized linear models         effects       Effects plots for generalized linear models
<pre>support.sas.com/publishing/bbu/56571_sample.html</pre>	
SCS Short Course 12 © Michael Friendly	SCS Short Course 14 © Michael Friendly
Categorical Data Analysis with Graphics vcdpackage	Categorical Data Analysis with Graphics discrete
R software and the vcd package• R software and the vcd package, available at www.r-project.orgDiscrete distributionsdistplotdistplotPlots for discrete distributionsgoodfitGoodness-of-fit for discrete distributionsordplotOrd plot for discrete distributionspoisplotPoissonness plotrootgramHanging rootogramsTwo-way and n-way tablesagreementplotObserver agreement chartfourfoldFourfoldSeveplotSieve diagramsmosaicMosaic displayspairs.tableMatix of pairwise association displaysstructableManipulate high-dimensional contingency tablestriplotTrilinear plots for $n \times 3$ tables	<b>Discrete distributions</b> • Counts of occurrences: accidents, words in text, blood cells with some characteristic. • Data: Basic outcome value, $k$ , $k = 0, 1,,$ and number of observations, $n_k$ , with that value. • Example: distributions of key "marker" words: from, may, whilst, in Federalist Papers by James Madison, e.g., blocks of 200 words with may: $\overline{Occurrences(k)}$ 0 1 2 3 4 5 6 Blocks $(n_k)$ 156 63 29 8 4 1 1 • Example: Saxony families with 12 children having $k = 0, 1, 12$ sons. $\overline{k}$ 0 1 2 3 4 5 6 7 8 9 10 11 12 $\overline{n_k}$ 3 24 104 286 670 1033 1343 1112 829 478 181 45 7
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	Sidebar: Using SAS macros	
Discrete distributions	<ul> <li>SAS macros are high-level, general programs consisting of a series of DAT and PROC steps.</li> </ul>	A ste
Questions:	<ul> <li>Keyword arguments substitute your data names, variable names, and option the named macro parameters.</li> </ul>	ns fo
<ul> <li>Form of distribution: uniform, binomial, Poisson, negative binomial, geometric, etc. 2</li> </ul>	Use as: %macname(data=dataset, var=variables,);	
Estimate parameters	Most arguments have default values (e.g., data=_last_)	
<ul> <li>Visualize goodness of fit</li> <li>For example:</li> </ul>	All VCD macros have internal and online documentation, http://www.math/yorku.ca/SCS/vcd/	
Federalist Papers: might expect a Poisson( $\lambda$ ) distribution.	Use as:	
Parmines in Saxony: might expect a $Bin(n, p)$ distribution with $n = 12$ . Perhap $p = 0.5$ as well.	<pre>%macname(data=dataset, var=variables,);</pre>	
	<ul> <li>Macros can be installed in directories automatically searched by SAS. Put following options statement in your AUTOEXEC. SAS file:</li> </ul>	he
	options sasautos=('c:\sasuser\macros' sasautos):	
	$\mathbf{J} \mid \mathbf{U}$	
Short Course 16 ⓒ Michael Fr	ndly SCS Short Course 18 © M	chael I
Short Course     16     © Michael Fr       gorical Data Analysis with Graphics     dia	andly SCS Short Course 18 © M Categorical Data Analysis with Graphics	chael
Short Course       16       © Michael Fr         gorical Data Analysis with Graphics       dia         Fitting and graphing discrete distributions         CD methods to fit, visualize, and diagnose discrete distributions:         * Fitting: GOODFTT macro fits uniform, binomial, Poisson, negative binomial, geometric, logarithmic series distributions (or any specified multinomial)         * Hanging rootograms: Sensitively assess departure between Observed, Fitted counts (ROOTGRAM macro)	andly       SCS Short Course       18       © M         Categorical Data Analysis with Graphics       Sidebar: Using SAS macros         E.g., the GOODFIT macro is defined with the following arguments:       goodfit.sas         1       %macro goodfit(       */ analysis variable (basic court) */         2       data=_last_, /* name of the input data set       */         3       var=, /* frequency variable       */         4       freq=, /* frequency variable       */         4       garm=, /* required distribution to be fit       */         5       sumat=100000, /* sum probs. and fitted values here       */         6       format=, /* format for ungrouped analysis variable */       */         9       out=fit, /* output fit data set       */         9       outstat=stats); /* output statistics data set       */	chael I
Short Course       16       © Michael Fri         gorical Data Analysis with Graphics       dia         Fitting and graphing discrete distributions         CD methods to fit, visualize, and diagnose discrete distributions:         * Fitting: G00DF1T macro fits uniform, binomial, Poisson, negative binomial, geometric, logarithmic series distributions (or any specified multinomial)         * Hanging rootograms: Sensitively assess departure between Observed, Fitted counts (R00TGRAM macro)         * Ord plots: Diagnose form of a discrete distribution (ORDPLOT macro)	andly       SCS Short Course       18       © M         Categorical Data Analysis with Graphics       Categorical Data Analysis with Graphics         E.g., the GOODFIT macro is defined with the following arguments:       goodfit.sas         1       Xmacro goodfit(       goodfit.sas         2       Var=, /* analysis variable (basic count) */       */         4       freq=, /* frequency variable       */         5       dist=, /* name of distribution to be fit       */         6       format=, /* format for ungrouped analysis variable */       */         7       sumat=100000, /* sum probs. and fitted values here       */         9       out=fit, /* output fit data set       */         10       Treinclosed       */	chael
Short Course       16       © Michael Fri         gorical Data Analysis with Graphics       det         Fitting and graphing discrete distributions         CD methods to fit, visualize, and diagnose discrete distributions:         Fitting: GOODF1T macro fits uniform, binomial, Poisson, negative binomial, geometric, logarithmic series distributions (or any specified multinomial)         Hanging rootograms: Sensitively assess departure between Observed, Fitted counts (ROOTGRAM macro)         Ord plots: Diagnose form of a discrete distribution (ORDPLOT macro)         Poissonness plots: Robust fitting and diagnostic plots for Poisson (POISPLOT macro)	andly       SCS Short Course       18       © M         Categorical Data Analysis with Graphics       Categorical Data Analysis with Graphics         E.g., the GOODFIT macro is defined with the following arguments:       goodfit.sas         1       "macro goodfit(       goodfit.sas         2       data=last_, /* name of the input data set */       */         3       var=, /* frequency variable       */         4       fireq=, /* frequency variable       */         6       garm=, /* required distribution to be fit       */         6       jarm=, /* format for ungrouped analysis variable */       out=fit, /* output fit data set       */         10       outstat=stats); /* output statistics data set       */         11       Typical use:       1       %goodfit(data=madison,	ichael

discrete

#### Categorical Data Analysis with Graphics

Fitting discrete distributions



- Poisson,  $p(k) = e^{-\lambda} \lambda^k / k!$
- Binomial,  $p(k) = \binom{n}{k} p^k (1-p)^{n-k}$
- Negative binomial,  $p(k) = \binom{n+k-1}{k} p^n (1-p)^k$

Geometric, 
$$p(k) = p(1-p)^k$$

Logarithmic series,  $p(k) = \theta^k / [-k \log(1-\theta)]$ 

# Estimate parameter(s):

- Poisson,  $\hat{\lambda}=\sum kn_k/\sum n_k$  = mean Binomial,  $\hat{p}=\sum kn_k/(n\sum n_k)$  = mean / n
- Goodness of fit:

$$\chi^2 = \sum_{k=1}^{K} \frac{(n_k - N\hat{p}_k)^2}{N\hat{p}_k} \sim \chi^2(K-1)$$

where  $\hat{p}_k$  is the estimated probability of each basic count, under the hypothesis that the data follows the chosen distribution.

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Categorical Data Analysis with Graphics

discrete

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# GOODFIT macro: Fitting discrete distributions

- GOODFIT macro fits uniform, binomial, Poisson, negative binomial, geometric, logarithmic series distributions (or any specified multinomial)
- E.g., Try fitting Poisson model

dist=poisson);

madfit.sas title "Instances of 'may' in Federalist papers"; data madison: input count blocks; label count='Number of Occurrences' blocks='Blocks of Text'; datalines: 0 156 1 63 2 29 3 8 4 4 5 1 12 6 1 13 14 %goodfit(data=madison, var=count, freq=blocks, 15

Pearson chi-square = 88.92304707 Prob > chi-square = 0

Likelihood ratio G2 = 25.243121314 Prob > chi-square = 0.0001250511

Degrees of freedom = 5

The poisson model does not fit! Why?

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	assoc Categorical Data Analysis with G	Sraphics	8
Example: Cholesterol and Heart disease	Exact tests are v Exact test output:	alid and significant.	
fat sas		Pearson Chi-Square Te	ost
<pre>title 'Cholesterol diet and heart disease'; data fat; input diet \$ disease \$ count; datalines; LoChol No 6 LoChol Yes 2</pre>		Chi-Square DF Asymptotic Pr > ChiSq Exact Pr >= ChiSq	4.9597 1 0.0259 0.0393
7 HiChol No 4 8 HiChol Yes 11		Fisher's Exact Test	;
<pre>proc freq data=fat; weight count; toblog digt * diagona ( chicg poporcent pecel;</pre>		Cell (1,1) Frequency (F) Left-sided Pr <= F Right-sided Pr >= F	4 0.0367 0.9967
<pre>a tables diet * disease / chisq nopercent nocol; a exact pchi;</pre>		Table Probability (P) Two-sided Pr <= P	0.0334 0.0393
Standard output:			
Table of diet by disease			
diet disease		rdinal factors and Stratifie	ed analyses
Frequency  Row Pct  No  Yes   Total	- Mara nowarf		
	When either	the row (fector) or column (record	
HiChol       4       11       15 $26.67$ 73.33       1         LoChol       6       2       8 $$	specific (CMI account have proc freq; weight	d = Cochran - Mantel - Haentzel) greater power to detect ordered	nse) levels are ordered, more tests which take order into relations.
HiChol   4   11   15   26.67   73.33   LoChol   6   2   8   75.00   25.00   Total 10 13 23 Statistics for Table of diet by disease	specific (CMI account have proc freq; weight table f	de lockran - Mantel - Haentzel) greater power to detect ordered count; actor * response / chisq	nse) levels are ordered, more tests which take order into relations. cmh;
HiChol   4   11   15 	specific (CMI account have proc freq; weight table f • Control for o	<pre>ine Tow (factor) of column (respondent) if = Cochran - Mantel - Haentzel) greater power to detect ordered count; actor * response / chisq of ther background variables prior toget the accession background variables</pre>	nse) levels are ordered, more tests which take order into relations. cmh;
HiChol       4       11       15         26.67       73.33       15         LoChol       6       2       8         75.00       25.00       16         Total       10       13       23         Statistics for Table of diet by disease       10       13       23         Chi-Square       1       4.9597       0.0259         Likelihood Ratio Chi-Square       1       5.0975       0.0240         Continuity Adj. Chi-Square       1       3.1879       0.0742	specific (CMI account have proc freq; weight table f <b>Control for o</b> Stratified anly <i>within</i> levels o Can also test	the row (ractor) of column (respondent) greater power to detect ordered count; actor * response / chisq ther background variables rsis tests the association between of the control variable(s) for homogeneous association action	nse) levels are ordered, more tests which take order into relations. cmh; s n a main factor and response cross strata
HiChol41115 $26.67$ 73.3315LoChol62 $8$ 75.0025.00Total1013 $23$ Statistics for Table of diet by diseaseStatisticDFValueValueProbChi-Square14.9597 $0.0259$ Likelihood Ratio Chi-Square1 $0.0742$ Statistics for Table of the cells have expected counts less than 5. (Asymptotic) Chi-Square may not be a valid test.	specific (CMI account have proc freq; weight table f Control for o Stratified anly within levels o Can also test proc freq; weight table s	He row (factor) of column (respondent) greater power to detect ordered count; actor * response / chisq of ther background variables visis tests the association between of the control variable(s) for homogeneous association ac count; trata * factor * response	hse) levels are ordered, more tests which take order into relations. cmh; s a main factor and response cross strata / chisg cmh:
HiChol   4   11   15 26.67   73.33   LoChol   6   2   8 75.00   25.00   Total 10 13 23 Statistics for Table of diet by disease Statistic DF Value Prob Chi-Square 1 4.9597 0.0259 Likelihood Ratio Chi-Square 1 5.0975 0.0240 Continuity Adj. Chi-Square 1 3.1879 0.0742 WARNING: 50% of the cells have expected counts less than 5. (Asymptotic) Chi-Square may not be a valid test. The Pearson and LR $\chi^2$ tests are not valid The conservative continuity-adjusted test fails significance	specific (CMI account have proc freq; weight table f Control for o Stratified anly within levels o Can also test proc freq; weight table s	the row (factor) of column (respondent) greater power to detect ordered count; actor * response / chisq of ther background variables rsis tests the association between of the control variable(s) for homogeneous association ac count; trata * factor * response	nse) levels are ordered, more tests which take order into relations. cmh; 5 n a main factor and response pross strata / chisq cmh;

						Overal	ll analysis	<b>, ignoring sex</b> : Results (chi	sq option	ı)	
								STATISTICS FOR TABLE O	F TREAT	BY IMPROVE	
	Exa	ample: Ar	thritis tr	eatment			Statis <sup>.</sup>	tic	DF	Value	Prob
ta on treatmer	nt for rheum	atoid arthriti	s (Koch an	d Edwards, 19	988)		Chi-Sq	 uare	2	13.055	0.001
Ordinal re	sponse: r	none, some,	or marked	improvement			Likeli Mantel	hood Ratio Chi-Square -Haenszel Chi-Square	2	13.530 12.859	0.001
Factor: act	ive treatmer	nt vs. placeb	0				Phi Co	efficient		0.394	
Strata: Sex							Cramer	's V		0.394	
+		 -+	Outcome	+		Cochra	an-Mantel-	Haenszel tests: (cmb ontion)			
Treatment	Sex	None +	Some +	Marked	Total				TDEAT		
Active	Female Male	6   7			27 14		Cochran-l	Mantel-Haenszel Statist	ics (Ba	sed on Table	Scores)
Placebo	Female Male	19   10	7   0	6	32 11	Sta	atistic	Alternative Hypothesi	s DF	Value	Pr
+ Total		-+ 42	+14	-++ 28	- 84		1	Nonzero Correlation	1	12.859	0.0
							2	Row Mean Scores Diffe	r 1	12.859	0.0
nort Course rical Data Analysis v erall analysis	with Graphics	sex:	40		© Michael Friendly assoc	SCS Short C Categorical I	Course Data Analysis v	42 with Graphics			© Micha
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rical Data Analysis v rerall analysis ttle 'Arthrit ata arth; input sex do improve input cc output; end; atalines; male Active emale Placeb	with Graphics <b>5, ignoring</b> tis Treatment treat\$ @; = 'None punt @; <b>6</b> 5 50 19 7	<pre>sex: arthf ent: PROC f ', 'Some', 16 6</pre>	40 req.sas REQ Analy 'Marked';	/515'; ;	© Michael Friendly assoc	SCS Short C Categorical I	Data Analysis v	42 with Graphics CMH tests for ordi correlation: Use when <i>both</i>	nal vari	ables column variable	© Micha
rical Data Analysis v erall analysis ttle 'Arthrit tta arth; input sex\$ do improve input cc output; end; tallnes; emale Active imale Placeb le Placeb	with Graphics <b>c, ignoring</b> <b>treat</b> \$ @; = 'None punt @; <b>e</b> 6 5 po 19 7 <b>e</b> 7 2 po 10 0	<pre>sex: arthf ent: PROC f ', 'Some', 16 6 5 1</pre>	40 req.sas · 'REQ Analy 'Marked';	 /51s';	© Michael Friendly assoc	SCS Short C Categorical I	Course Data Analysis v Data Analysis v Data Analysis v CMH $\chi^2$ most pow	$\begin{tabular}{lllllllllllllllllllllllllllllllllll$	nal vari v row and res (1, 2,	<b>ables</b> column variable 3,)	© Micha
rical Data Analysis v erall analysis ttle 'Arthrit input sex\$ do improve input cc output; end; ttalines; emale Active male Placet ile Active ile Placet corfreq orde weight communications	<pre>with Graphics s, ignoring s sis Treatment treat\$ @; = 'None ount @; e 6 5 so 19 7 e 7 2 so 10 0 sex; pr=data; t;</pre>	<pre>sex:     arthf ent: PROC 1 ', 'Some',     16     6     5     1</pre>	40 req.sas ··· REQ Analy 'Marked';		© Michael Friendly assoc	SCS Short C Categorical I	Course Data Analysis v On-zero α CMH χ <sup>2</sup> most pow	the Graphics ${\bf CMH}$ tests for ordinates ${\bf CMH}$ tests for ordinates ${\bf COTRELATION}$ : Use when both $= (N-1)r^2$ , assigning scoreful for <i>linear</i> association a Scores Differ: Use when	nal vari row and res (1, 2, only colu	<b>ables</b> column variable 3,) mn variable is o	© Michae es are ordi ordinal
rical Data Analysis v rical Data Analysis v erall analysis title 'Arthrit tta arth; input sex\$ do improve input cc output; end; tallnes; emale Active male Active le Active le Placet Ignoring s coc freq orde weight coun tables trea run;	<pre>with Graphics s, ignoring s is Treatmed treat\$ @; = 'None ount @; e 6 5 oo 19 7 e 7 2 oo 10 0 sex; er=data; ht; at * improv</pre>	<pre>sex: arthf ent: PROC f ', 'Some', ' 16 6 5 1 ve / cmh ch</pre>	40 req.sas ·· rEQ Analy 'Marked'; aisq nocol		© Michael Friendly assoc	SCS Short C Categorical I No RC	Data Analysis v Data Analysis v Data Analysis v CMH $\chi^2$ most pow Dw Mean Analogou Ordinal va	with Graphics CMH tests for ordi Correlation: Use when bott $= (N-1)r^2$ , assigning sco erful for <i>linear</i> association <b>A Scores Differ</b> : Use when s to the Kruskal-Wallis non-pa ariable should be listed <i>last</i> in	nal vari o row and res (1, 2, only colu rametric t the TABL	ables column variable 3,) mn variable is o test (ANOVA on .ES statement	© Michae es are ordi ordinal rank score
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		assoc Categorical Data	analysis with Graphics		
Stratified analysis	MLI tooto poetrolling for or		Stratified te	sts	
* Stratified analysis, controlling for sex;		Individ	ual ( <i>partial</i> ) tests are followed by a <i>col</i>	nditional test, controlling	for strata
<pre>proc freq order=data; weight count; tables sex * treat * improve / cmh chisq noce run;</pre>	ol nopercent;	(SEX) These total s	tests <b>do not</b> require large sample size ample size.	e in the individual strata-	— just a lar
ightarrow separate table (partial tests) for Females and Males		■ They a	assume, but do not test that the associa	iation is the same for all	strata.
STATISTICS FOR TABLE 1 OF TREAT BY IN CONTROLLING FOR SEX=Female	IPROVE		SUMMARY STATISTICS FOR TR CONTROLLING FOR	REAT BY IMPROVE R SEX	
Statistic DF Value	Prob	Coch	ran-Mantel-Haenszel Statistics	s (Based on Table S	cores)
Chi-Square 2 11.296	0.004	Statis	tic Alternative Hypothesis	DF Value	Prob
Likelihood Ratio Chi-Square 2 11.731 Mantel-Haenszel Chi-Square 1 10.935	0.003 0.001		Nonzero Correlation Row Mean Scores Differ	1 14.632 1 14.632	0.000
Strong association between TREAT and IMPROVE for a strong association between TREAT and IMPROVE for a strong st	or females				
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		Friendly SCS Short Course	e 50		© Michael
egorical Data Analysis with Graphics		assoc Categorical Data	50 Analysis with Graphics		© Michael
Agorical Data Analysis with Graphics Males: STATISTICS FOR TABLE 2 OF TREAT BY IM CONTROLLING FOR SEX=Male	IPROVE	assoc Categorical Data /	analysis with Graphics Homogeneity of as association between the primary table tables: → Equal odds ratios across all DC FREQ: MEASURES option on TABI tables: Use PROC CATMOD to test for	ssociation variables is the same ov Il strata? LES statement → Bresk r no three-way associati	© Michael ver all strata ow-Day tes on = same
Agorical Data Analysis with Graphics Males: STATISTICS FOR TABLE 2 OF TREAT BY IM CONTROLLING FOR SEX=Male Statistic DF Value	IPROVE Prob	assoc Categorical Data /	Analysis with Graphics Homogeneity of as association between the primary table tables: → Equal odds ratios across all DC FREQ: MEASURES option on TABI tables: Use PROC CATMOD to test for ation for the primary factor & response	ssociation variables is the same ov Il strata? LES statement → Bresk or <i>no three-way associati</i> e variables.	© Michael ver all strata ow-Day tes on = same
Aales: STATISTICS FOR TABLE 2 OF TREAT BY IN CONTROLLING FOR SEX=Male Statistic DF Value 	PROVE Prob 0.086 0.054 0.054 ounts less valid test.	assoc Categorical Data / assoc Categorical Data / assoc assoc PR Larger associ Arthrit a = 1 a = 2 Zer rec 26 title2 ,	Analysis with Graphics Homogeneity of as association between the primary table tables: → Equal odds ratios across all DC FREQ: MEASURES option on TABI tables: Use PROC CATMOD to test for ation for the primary factor & response is data: homogeneity ↔ no 3-way sex oglinear model: [SexTreat] [SexOutcor Loglin sex   treat   improve@2 for o frequencies: PROC CATMOD treats a ode if necessary. Test homogeneity of treat*improve	variables is the same or Il strata? LES statement → Bresl r no three-way associati e variables. * treatment * outcome a me] [TreatOutcome] for PROC CATMOD as "structural zeros" by a sas association';	© Michael ver all strata ow-Day tes ion = same association default;
Aales: STATISTICS FOR TABLE 2 OF TREAT BY IN CONTROLLING FOR SEX=Male Statistic DF Value Chi-Square 2 4.907 Likelihood Ratio Chi-Square 2 5.855 Mantel-Haenszel Chi-Square 1 3.713  WARNING: 67% of the cells have expected co than 5. Chi-Square may not be a • Weak association between TREAT and IMPROVE fo • Sample size $N = 29$ for males is small	PROVE Prob 0.086 0.054 0.054 ounts less valid test. r males	assoc       Categorical Data /         assoc       Categorical Data /         assoc       is the i         2 × 2       PR         Larger       associ         Arthrit       = 1         assoc       Zer         rec       ?         data art       set a         2%       if co         10gli       logli         3       logli	Analysis with Graphics Homogeneity of as association between the primary table tables: → Equal odds ratios across all DC FREQ: MEASURES option on TABI tables: Use PROC CATMOD to test for ation for the primary factor & response is data: homogeneity ↔ no 3-way sex oglinear model: [SexTreat] [SexOutcor loglin sex   treat   improve@2 f of frequencies: PROC CATMOD treats a ode if necessary. Test homogeneity of treat*improve h; rth; unt=0 then count=1E-20; * san mod order=data; t count; sex * treat * improve = _response n sex treat improve / title='No	variables is the same or l strata? LES statement → Bresl r no three-way association e variables. * treatment * outcome a me] [TreatOutcome] for PROC CATMOD as "structural zeros" by or sas a association'; mpling zeros; se_ / ml; b 3-way associations';	© Michael

