

Example of Fitting Log-Linear Models

November 20, 2017

1 Fitting a Model to a 4-way Table

Our data consists of responses by 607 individuals on a survey about different categories of government spending. All responses have the values 1, 2, or 3, with 1 meaning "Too Low", 2 means "About Right", and 3 means "Too High." The 4 categories of government spending are labelled Environment (E), Health (H), Cities (C), and Law (L). There are $3^4 = 81$ possible outcomes which can be summarized in a $3 \times 3 \times 3 \times 3$ table. The data appear on the website for the book and are discussed in Exercise 9.5.

We fit 3 successive log-linear models starting with main effects only (`fit1`), main effects plus all 2-way interactions (`fit2`), and added in all 3 way interactions (`fit3`). Based on these results, we fit a model which includes all main effects and some second order interactions (`fit2.2`).

The results are given below with some discussion afterwards.

```
> data = scan("data.txt")
Read 405 items
> data=matrix(data,ncol=5,byrow=T)
> apply(data,2,range)
      [,1] [,2] [,3] [,4] [,5]
[1,]    1    1    1    1    0
[2,]    3    3    3    3   90
> colnames(data) = c("Environment","Health","Cities","Law","Count")
> data1 = data.frame(data)
> for(j in 1:4) data1[,j] = as.factor(data1[,j])
> # seems to be necessary to do the columns separately
> fit1 = glm(Count ~ Environment + Health + Cities + Law,family=poisson,data=data1)
> summary(fit1)
```

Call:

```
glm(formula = Count ~ Environment + Health + Cities + Law, family = poisson,
    data = data1)
```

Deviance Residuals:

	Min	1Q	Median	3Q	Max
	-2.5722	-0.9335	-0.2423	0.7653	4.3062

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.77602	0.09860	38.296	< 2e-16 ***
Environment2	-1.24379	0.10032	-12.398	< 2e-16 ***
Environment3	-2.54048	0.17556	-14.470	< 2e-16 ***
Health2	-1.14579	0.09773	-11.724	< 2e-16 ***
Health3	-2.51770	0.17570	-14.329	< 2e-16 ***
Cities2	0.58280	0.10784	5.404	6.50e-08 ***
Cities3	0.55320	0.10842	5.102	3.35e-07 ***
Law2	-0.69315	0.08909	-7.781	7.22e-15 ***
Law3	-2.24601	0.16627	-13.508	< 2e-16 ***

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

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 1370.46 on 80 degrees of freedom
Residual deviance: 124.34 on 72 degrees of freedom
AIC: 349.18

Number of Fisher Scoring iterations: 5

```
> fit2 = glm(Count ~ (Environment + Health + Cities + Law)^2,  
+ family=poisson,data=data1)  
> summary(fit2)
```

Call:

```
glm(formula = Count ~ (Environment + Health + Cities + Law)^2,  
family = poisson, data = data1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.62783	-0.47669	-0.07639	0.33622	1.49280

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	4.13581	0.11860	34.873	< 2e-16 ***
Environment2	-1.87605	0.25914	-7.240	4.50e-13 ***
Environment3	-3.35321	0.49608	-6.759	1.39e-11 ***

Health2	-1.71829	0.24541	-7.002	2.53e-12	***
Health3	-3.32730	0.43918	-7.576	3.56e-14	***
Cities2	0.35994	0.15091	2.385	0.017077	*
Cities3	0.18281	0.15530	1.177	0.239138	
Law2	-1.22106	0.21381	-5.711	1.12e-08	***
Law3	-2.82469	0.42119	-6.706	1.99e-11	***
Environment2:Health2	0.30916	0.24086	1.284	0.199289	
Environment3:Health2	0.72034	0.42138	1.709	0.087363	.
Environment2:Health3	1.41304	0.41061	3.441	0.000579	***
Environment3:Health3	2.14249	0.55665	3.849	0.000119	***
Environment2:Cities2	0.49541	0.29000	1.708	0.087576	.
Environment3:Cities2	-0.18961	0.62730	-0.302	0.762446	
Environment2:Cities3	0.50830	0.29291	1.735	0.082676	.
Environment3:Cities3	1.20002	0.51769	2.318	0.020448	*
Environment2:Law2	0.18129	0.22199	0.817	0.414120	
Environment3:Law2	-0.50679	0.43985	-1.152	0.249249	
Environment2:Law3	0.13019	0.41894	0.311	0.755978	
Environment3:Law3	-0.13285	0.63780	-0.208	0.835001	
Health2:Cities2	0.26396	0.27714	0.952	0.340864	
Health3:Cities2	-0.93284	0.53780	-1.735	0.082819	.
Health2:Cities3	0.28104	0.28199	0.997	0.318940	
Health3:Cities3	-0.18648	0.45472	-0.410	0.681730	
Health2:Law2	0.72344	0.20826	3.474	0.000513	***
Health3:Law2	0.83749	0.42130	1.988	0.046826	*
Health2:Law3	-0.06301	0.47762	-0.132	0.895044	
Health3:Law3	1.87407	0.50792	3.690	0.000225	***
Cities2:Law2	0.42931	0.24677	1.740	0.081907	.
Cities3:Law2	0.30279	0.25359	1.194	0.232469	
Cities2:Law3	-0.20576	0.54351	-0.379	0.705005	
Cities3:Law3	0.87351	0.46044	1.897	0.057811	.

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

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 1370.458 on 80 degrees of freedom
Residual deviance: 31.669 on 48 degrees of freedom
AIC: 304.5

Number of Fisher Scoring iterations: 5

```
> fit3 = glm(Count ~ (Environment + Health + Cities + Law)^3,
+ family=poisson,data=data1)
Warning message:
glm.fit: fitted rates numerically 0 occurred
> summary(fit3)
```

Call:

```
glm(formula = Count ~ (Environment + Health + Cities + Law)^3,
    family = poisson, data = data1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.08934	-0.11186	-0.00002	0.11730	0.73809

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	4.141e+00	1.254e-01	33.020	< 2e-16	***
Environment2	-1.827e+00	3.252e-01	-5.618	1.93e-08	***
Environment3	-3.043e+00	5.908e-01	-5.150	2.60e-07	***
Health2	-1.830e+00	3.283e-01	-5.573	2.50e-08	***
Health3	-3.436e+00	6.704e-01	-5.125	2.97e-07	***
Cities2	3.532e-01	1.631e-01	2.165	0.0304	*
Cities3	1.573e-01	1.701e-01	0.924	0.3553	
Law2	-1.327e+00	2.687e-01	-4.938	7.90e-07	***
Law3	-2.653e+00	4.839e-01	-5.482	4.21e-08	***
Environment2:Health2	1.625e-01	6.642e-01	0.245	0.8067	
Environment3:Health2	7.311e-01	1.200e+00	0.609	0.5425	
Environment2:Health3	1.097e+00	1.009e+00	1.087	0.2771	
Environment3:Health3	2.337e+00	1.335e+00	1.751	0.0800	.
Environment2:Cities2	3.913e-01	3.940e-01	0.993	0.3206	
Environment3:Cities2	-6.708e-01	8.783e-01	-0.764	0.4450	
Environment2:Cities3	5.534e-01	3.988e-01	1.388	0.1652	
Environment3:Cities3	9.207e-01	6.874e-01	1.340	0.1804	
Environment2:Law2	2.117e-01	5.773e-01	0.367	0.7139	
Environment3:Law2	-2.139e+01	1.453e+04	-0.001	0.9988	
Environment2:Law3	-2.256e-01	1.240e+00	-0.182	0.8557	
Environment3:Law3	-2.071e+01	7.635e+03	-0.003	0.9978	
Health2:Cities2	4.625e-01	3.944e-01	1.173	0.2410	
Health3:Cities2	-5.460e-01	9.565e-01	-0.571	0.5681	

Health2:Cities3	4.808e-01	4.067e-01	1.182	0.2372
Health3:Cities3	-5.957e-01	9.631e-01	-0.618	0.5363
Health2:Law2	1.083e+00	5.024e-01	2.156	0.0311 *
Health3:Law2	1.500e+00	8.974e-01	1.671	0.0947 .
Health2:Law3	-1.918e+01	9.446e+03	-0.002	0.9984
Health3:Law3	2.398e+00	1.071e+00	2.239	0.0252 *
Cities2:Law2	5.669e-01	3.226e-01	1.757	0.0789 .
Cities3:Law2	4.767e-01	3.364e-01	1.417	0.1565
Cities2:Law3	-5.572e-01	7.027e-01	-0.793	0.4278
Cities3:Law3	7.479e-01	5.766e-01	1.297	0.1946
Environment2:Health2:Cities2	-1.724e-01	7.193e-01	-0.240	0.8106
Environment3:Health2:Cities2	4.521e-01	1.504e+00	0.301	0.7637
Environment2:Health3:Cities2	6.724e-01	1.230e+00	0.547	0.5846
Environment3:Health3:Cities2	-1.949e+01	1.350e+04	-0.001	0.9988
Environment2:Health2:Cities3	-9.485e-02	7.403e-01	-0.128	0.8981
Environment3:Health2:Cities3	-1.276e-01	1.348e+00	-0.095	0.9246
Environment2:Health3:Cities3	1.217e+00	1.112e+00	1.094	0.2740
Environment3:Health3:Cities3	-4.823e-01	1.836e+00	-0.263	0.7928
Environment2:Health2:Law2	5.134e-01	5.082e-01	1.010	0.3124
Environment3:Health2:Law2	5.656e-02	1.015e+00	0.056	0.9556
Environment2:Health3:Law2	-8.817e-01	1.010e+00	-0.873	0.3828
Environment3:Health3:Law2	3.972e-01	1.674e+00	0.237	0.8125
Environment2:Health2:Law3	4.775e-01	1.099e+00	0.434	0.6641
Environment3:Health2:Law3	-1.805e+01	6.693e+03	-0.003	0.9978
Environment2:Health3:Law3	-3.357e-01	1.233e+00	-0.272	0.7853
Environment3:Health3:Law3	2.046e+00	1.977e+00	1.035	0.3008
Environment2:Cities2:Law2	7.886e-02	6.447e-01	0.122	0.9026
Environment3:Cities2:Law2	2.117e+01	1.453e+04	0.001	0.9988
Environment2:Cities3:Law2	-3.892e-01	6.658e-01	-0.585	0.5588
Environment3:Cities3:Law2	2.084e+01	1.453e+04	0.001	0.9989
Environment2:Cities2:Law3	7.037e-01	1.441e+00	0.488	0.6253
Environment3:Cities2:Law3	3.266e+00	1.466e+04	0.000	0.9998
Environment2:Cities3:Law3	2.190e-01	1.347e+00	0.163	0.8708
Environment3:Cities3:Law3	2.043e+01	7.635e+03	0.003	0.9979
Health2:Cities2:Law2	-5.844e-01	5.861e-01	-0.997	0.3187
Health3:Cities2:Law2	-1.825e+00	1.447e+00	-1.262	0.2071
Health2:Cities3:Law2	-5.786e-01	6.080e-01	-0.952	0.3413
Health3:Cities3:Law2	1.918e-01	1.150e+00	0.167	0.8675
Health2:Cities2:Law3	1.879e+01	9.446e+03	0.002	0.9984
Health3:Cities2:Law3	3.365e-02	1.506e+00	0.022	0.9822

Health2:Cities3:Law3	1.936e+01	9.446e+03	0.002	0.9984
Health3:Cities3:Law3	-1.168e+00	1.486e+00	-0.786	0.4318

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

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 1370.4575 on 80 degrees of freedom
 Residual deviance: 8.5237 on 16 degrees of freedom
 AIC: 345.36

Number of Fisher Scoring iterations: 19

```
> fit2.2 = glm(Count ~ Environment + Health + Cities + Law +
+ Environment*Health + Health*Law,family=poisson,data=data1)
> summary(fit2.2)
```

Call:

```
glm(formula = Count ~ Environment + Health + Cities + Law + Environment *
    Health + Health * Law, family = poisson, data = data1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9483	-0.7317	-0.2197	0.4454	2.0474

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.90715	0.09960	39.227	< 2e-16 ***
Environment2	-1.41968	0.12382	-11.466	< 2e-16 ***
Environment3	-2.92376	0.24195	-12.084	< 2e-16 ***
Health2	-1.51455	0.14586	-10.384	< 2e-16 ***
Health3	-3.69507	0.34408	-10.739	< 2e-16 ***
Cities2	0.58280	0.10784	5.404	6.51e-08 ***
Cities3	0.55320	0.10842	5.102	3.35e-07 ***
Law2	-0.91458	0.10942	-8.359	< 2e-16 ***
Law3	-2.45788	0.20839	-11.795	< 2e-16 ***
Environment2:Health2	0.36231	0.23698	1.529	0.126298
Environment3:Health2	0.67247	0.41118	1.635	0.101951
Environment2:Health3	1.41968	0.39773	3.569	0.000358 ***
Environment3:Health3	2.23061	0.52230	4.271	1.95e-05 ***

Health2:Law2	0.73226	0.20622	3.551	0.000384	***
Health3:Law2	0.76043	0.40832	1.862	0.062557	.
Health2:Law3	-0.02703	0.47326	-0.057	0.954457	
Health3:Law3	2.01605	0.47535	4.241	2.22e-05	***

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

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 1370.458 on 80 degrees of freedom
 Residual deviance: 71.422 on 64 degrees of freedom
 AIC: 312.26

Number of Fisher Scoring iterations: 5

We note the following items in the analysis:

1. Note that the first level of each factor is set as the baseline, so it is automatically 0 in all effects. That is why we see Law2 and Law3 terms but no Law1 terms.
2. In `fit1`, all terms are significant, suggesting we can reject a null hypothesis of independence. The LRT test for independence has a chi-squared value of $1370.46 - 124.34$ with $80 - 72 = 8$ degrees of freedom and clearly has a p-value of basically 0.
3. In `fit2`, the main effects of C “lose” significance, and most of the interaction terms of C with other variables are not “very” significant.
4. In `fit3`, we see most of the second order effects with are not significant, and all of the third order terms are not significant. Also, there was a warning “**fitted rates numerically 0 occurred**”, all of which suggests the third order model is unnecessary.

Based on these observations, we did the `fit2.2`, which includes all main effects and only the E*H and H*L interactions. Note that this model corresponds to independence of C with (E,H,L), and conditional independence of E,L given H. Clearly, this is a much simpler model than the full second order model, and would be easy to summarize as a simple graphical model (if you know what those are). Also, most of the terms are “very” significant.

I would hesitate to drop selective terms from different factor levels in second order interactions. So, based on the significance patterns, I conclude this is a pretty good model.

We perhaps should do a full, formal test of the null hypothesis that the fit2.2 model is valid vs. the more general fit2 model. The LRT chi-squared is $71.422 - 31.669 = 39.75$ with $64 - 48 = 16$ d.f. The p-value is .00085, so we can reject the null hypothesis if we want, but I like the model for being more parsimonious.

This analysis shows the power of log-linear models. We can quickly fit them and use the results to arrive at a parsimonious model, and often interpret the results in terms of independence or conditional independence.

2 Fitting Ordinal Predictors Using Linear Scores