

Index of Lecture 4b

Page	Title
1	Practical information
2	Introduction to logistic model-building
3	Confounding in logistic models
4	Interaction in logistic models
5	Evaluating linearity by plots
6	Evaluating linearity by categorization
7	Evaluating linearity by polynomials
8	Model/variable selection
9	More about the AIC and BIC
10	Presentation of categorical predictor effects
11	Generalised linear models

PRACTICAL INFORMATION

Today's lecture:

- catch-up from previous lectures:
 - * prediction in logistic regression (L4a–11),
 - * presentation of categorical predictor effects (new slide),
 - * discussion of exercises: VER 14.3, VER 15,
- new material on logistic regression:
 - * model-building for logistic regression: principles and procedures (focusing mostly on differences to linear regression),
 - * model selection criteria,
 - * brief intro to generalised linear models.

News/Schedule:

- VHM 812 regression assignment posted, due February 18,
- VHM 802 (only) home assignment due today,
- lab session on Monday:
 - * linear regression model building,
 - * logistic regression, incl. VER 16.1,
- new VHM 812 quiz coming up (Monday).

INTRODUCTION TO LOGISTIC MODEL-BUILDING

Synthesis:

- similar to linear regression model-building,
- major principles and tools still apply, such as
 - * causal diagrams (confounding and intermediate effects),
 - * statistical testing to assess (significance of) effects, however different type of tests (Wald/likelihood-ratio tests),
 - * model fit statistics to compare (non-nested) models, however different type of statistics (AIC/BIC instead of R^2 -type statistics),
 - * exploration of form of effects (linearity, interaction),
 - * validation of model assumptions by residuals and diagnostics (next lecture).

List of topics covered in detail in this lecture:

- confounding and interaction,
- evaluation of linearity of continuous predictors (adaptation of tools from linear to logistic regression),
- model selection procedures,
- also brief discussion of pairwise comparisons (categorical predictors).

CONFOUNDING IN LOGISTIC MODELS

Same approach as in linear models:

- draw causal diagram to determine potential confounders,
- analyze with/without, and note “substantial” changes in estimates.

Illustration: confounding effects by `dcpct` on `dneo` or `dclox` in *Nocardia* data:

- `dcpct` not “causally later” than `dneo` and `dclox`,
- `dcpct` significant ($z = 3.15$, $P = 0.002$) in “full” model,
- check association between `dcpct` and `dneo/dclox`,
- comparison of estimates for `dneo` and `dclox` with/without `dcpct`:

Effect	Without <code>dcpct</code>	With <code>dcpct</code>
<code>dneo</code>	2.38 (SE = 0.55, $P < 0.0005$)	2.21 (SE = 0.58, $P < 0.0005$)
<code>dclox</code>	-1.01 (SE = 0.53, $P = 0.058$)	-1.41 (SE = 0.56, $P = 0.011$)

Conclusions:

- `dneo`: no serious confounding effect by `dcpct` (7 % change, strong significance in both models),
- `dclox`: substantial confounding effect by `dcpct` (40% change¹, change in significance).

¹ Calculated as $0.40/1.01 = 40\%$, using the guidelines from Section 13.5.2 of VER2; Example 16.4 uses $0.40/1.41 = 28\%$.

INTERACTION IN LOGISTIC MODELS

- same construction as in linear models using cross-product terms and/or dummy variables,
- similar statistical assessment using Wald/LR-tests,
- same interpretation on logit scale, but needs to be converted to odds-ratios.

Illustration: interaction between `dneo` and `dclox` in model for Nocardia data also including `dcpct`:

$$\begin{aligned} \text{logit}(\hat{p}) = & -3.777 + 0.023 \text{ dcpct} + 3.184 \text{ dneo} \\ & + 0.446 \text{ dclox} - 2.552 \text{ neoclox} \end{aligned}$$

Estimated logit(\hat{p}) for combinations of (`dneo`,`dclox`) and a fixed value of `dcpct` (using $a = -3.777 + 0.023 \text{ dcpct}$):

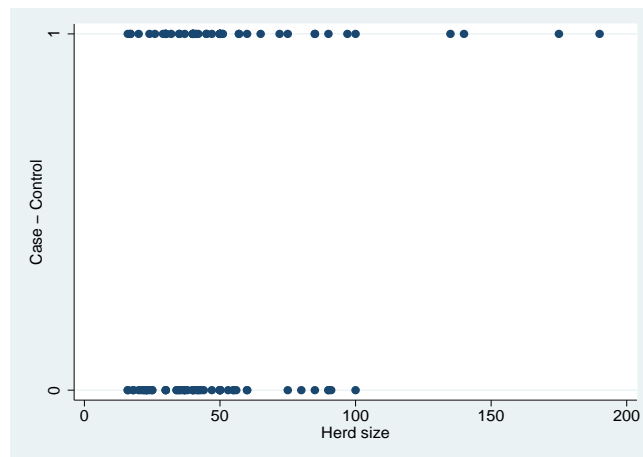
dneo	dclox	
	0	1
0	$a + 0 + 0 + 0$ $= a$	$a + 0 + 0.446 + 0$ $= a + 0.446$
1	$a + 3.184 + 0 + 0$ $= a + 3.184$	$a + 3.184 + 0.446 - 2.552$ $= a + 1.078$

- effect of `dclox` when `dneo` absent = 0.446 (OR = 1.56),
- effect of `dneo` when `dclox` absent = 3.184 (OR = 24.1),
- effect of `dclox` when `dneo` present = -2.106 (OR = 0.122),
- effect of `dneo` when `dclox` present = 0.632 (OR = 1.88),
- “added effect” of both products simultaneously = -2.552 .

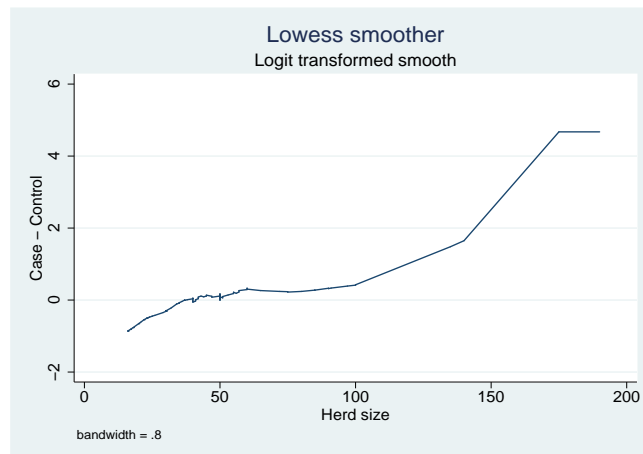
EVALUATING LINEARITY BY PLOTS

More difficult than in linear regression (!):

- less information in binary data
⇒ simple scatterplots often useless with continuous predictor; illustration for `numcow`:



- residuals of little use without replication/grouping (next lecture); `numcow` has almost no replication,
- new tool²: smoothed scatterplots on logit scale:



- * bandwidth=0.8 ~ 80% of points included in weighted average,
- * beware: smoother may be noisy towards ends of data range,
- * interpretation: linear up to ≈ 60 , then flat up to ≈ 100 .

² For simple associations only; no multivariable counterpart exists.

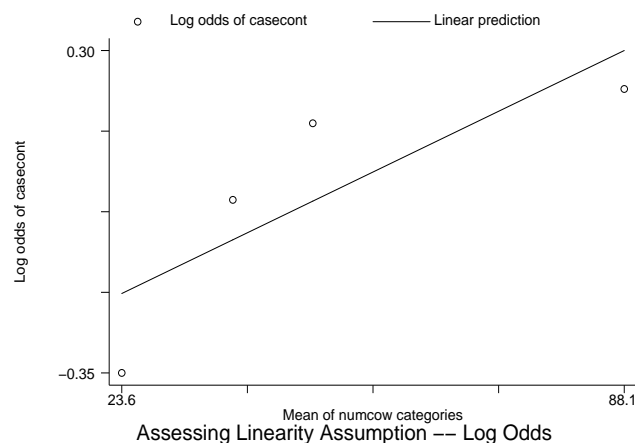
EVALUATING LINEARITY BY CATEGORIZATION

Same as in linear regression:

(but more important here because of less alternatives)³

- divide predictor's range into a few intervals based on cut-points with biological meaning or corresponding roughly to relevant percentiles,
- fit model with categorical (ordinal) predictor, and assess whether estimates follow a linear pattern.

Illustration with 4 intervals for numcow (univariate):



	Interval			Data			Estimates	
	min	max	mean	nobs	prop	logit	$\hat{\beta}$	SE
1	16	30	23.6	29	0.41	-0.35	0	—
2	32	41	37.9	26	0.50	0.00	0.348	0.54
3	42	53	48.2	26	0.54	0.15	0.502	0.54
4	55	190	88.1	27	0.56	0.22	0.571	0.54

- curve non-linear (but non-significant estimates),
- created with `lintrend` and `egen cut` commands.

³ Idea applies to both simple and multivariable logistic regression models.

EVALUATING LINEARITY BY POLYNOMIALS

- entirely same methods⁴ as for linear models, both for simple polynomials and advanced polynomials (see do-file),
 - construct predictors corresponding to desired model form, and assess their significance,
 - illustrated by quadratic term for `numcow` (univariate):

Coef.	Linear polynomial			Quadratic polynomial		
	Estim.	SE	<i>P</i>	Estim.	SE	<i>P</i>
interc.	-0.71	.41	–	-0.34	.76	–
<code>numcow</code>	0.015	.008	0.056	0.001	.026	0.97
<code>numcow</code> ²	–	–	–	0.000098	.00018	0.59

- * no significance for quadratic term,
- * note variable values for intercept and linear term,
- * centering of `numcow` reduces high collinearity (but not a serious problem here).

Summary of analyses for linearity of `numcow`:

- indications of non-linearity (categorized version, smoothed scatterplot),
 - no significance for non-linear model (though close with advanced methods, see do-file),
- ⇒ simple linear modelling seems preferable (any effect is weak, and `numcow` drops out quickly in multivariable models anyway).

⁴ Applicable to both simple and multivariable logistic regression models.

MODEL/VARIABLE SELECTION IN LOGISTIC MODELS

- Main tool: statistical tests of nested models (only),
- Supplementary tools: measures of model fit adjusted for no. of parameters,
 - * AIC statistic⁵: general for likelihood-based inference, and preferable to BIC^{6, 7}
 - * R²-type statistics exist for logistic regression but not recommended (difficult to interpret),
 - * used for overview and “informal” model choice; also maybe to compare non-nested models (if no nesting possible),
 - * should (in my view) not replace tests between nested models,
- Automated procedures (forward/backward/stepwise): as in linear models (same advantages/drawbacks), here based on Wald tests,
- Initial screening of (a large number of) predictors at liberal P ,
- Recommendation: manual selection among models built upon consideration of causal diagram and effects in data.

Illustration: dropping `dclox` from model (`dneo##dclox, dcpct, dbarn2`):

Model	$2 \ln L$	AIC	BIC	G^2	df	P
<code>dneo##dclox, dcpct, dbarn2</code>	-97.31	109.31	125.40	–	–	–
<code>dneo, dcpct, dbarn2</code>	-107.25	115.25	125.98	9.95	2	0.007

- quite strong significance of `dclox` (despite non-significant main effect and weakly significant interaction).

⁵ Akaike’s Information Criterion (AIC): computed as $-2 \ln L + 2 \cdot \# \text{param.}$

⁶ Bayesian Information Criterion (BIC): computed as $-2 \ln L + \ln(n) \cdot \# \text{param.}$, where $n = \text{no. of obs.}$; being developed within the Bayesian framework, its guidelines are less (little?) useful in classical statistics.

⁷ For both AIC and BIC, the sign is unimportant, but smaller/lower values correspond to “better” models, e.g. $1.2 < 3.5$, or $-5.3 < -2.5$.

MORE ABOUT THE AIC AND BIC

The “best” model selection statistic. . .

- people have very different opinions about this, sometimes tending to “semi-religious” convictions,
- preferences may depend on general statistical approach (Bayesian vs. classical/frequentist) and proposed use (e.g., as a guidance or as a definitive model selection tool),
- AIC and BIC are both based on the likelihood function with (different) penalties for the no. of observations,
 - * “best AIC” is more liberal (\Rightarrow larger models) than LR-tests for small df (up till df=7), more conservative (\Rightarrow smaller models) for large df,
 - * “best BIC” is very conservative (\Rightarrow small models),
 - * use only for models with comparable likelihoods (e.g., same data) – a very common source of errors.

Guidelines for interpreting AIC differences exist:⁸

(this is not an endorsement of their use for mechanical model selection!)

	AIC ₂ –AIC ₁	level of support for Model 2
Model 1 has	0 – 2	substantial
lower (better)	4 – 7	considerably less
AIC	> 10	essentially none

⁸ Burnham and Anderson 2002, *Model Selection and Multimodel Inference: a Practical Information-Theoretic Approach*, 2nd ed., p. 170.

PRESENTATION OF CATEGORICAL PREDICTOR EFFECTS

Things to consider in linear/logistic models when presenting results for a categorical (> 2 categories) predictor:

- unless pre-determined hypotheses exist, the overall P -value (for H_0 : equal effects across all categories) should be presented and used for discussion,
- for significant or “interesting” predictors, estimates with SE or CI should be shown in one of two possible layouts:
 - * differences to a “reference” (or “baseline”) category: the typical format of software packages when a particular parametrization has been selected (e.g., `regress` and `logit`),
 - * estimates for all categories with suitably defined (and reported) averaging across or values set for all other predictors,
- estimates should be backtransformed as needed (e.g., values may be given both as coefficients on logit scale and as ORs),
- unless pre-determined hypotheses exist, pairwise comparisons should be conducted between *all* category pairs⁹,
 - * adjusted for multiple comparisons if many categories are present and strict overall significance is required, otherwise unadjusted,
 - * many methods for adjustment for multiple comparisons exist¹⁰; the simplest and most flexible is the Bonferroni method: divide the significance level (0.05) by the number of comparisons (m) or multiply each P -value by m .
- results of pairwise comparisons may be reported (P -values) or indicated by letter coding¹¹.

⁹ Not only for comparisons with a reference category.

¹⁰ To be discussed in more detail in VHM 802.

¹¹ Most common system: two categories with the same letter indicated are not significantly different.

GENERALISED LINEAR MODELS (GLMS)

Main idea: extend scope of linear modelling by transforming, using the link function g , the parameter μ of principal interest (usually, the mean) to a more appropriate scale for linear modelling:

$$g(\mu) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k.$$

Components of a *generalised* (not general!) linear model:

- link function g ,
- set of explanatory variables (represented by x 's),
- distribution of outcome Y (usually one of few standard distrib.),
- assumption of independence between outcomes.

Examples:

- binary / binomial distribution – logistic regression (logit link),¹²
- multinomial distribution (ordinal data) – ordinal logistic regr.,
- Poisson distribution (count data) – Poisson regression (log link).

GLMs – a unified framework for many different models/analyses:

- similarities to linear models make analysis simpler/more intuitive,
- flexibility in modelling by choice of link function and distribution,
- common algorithms (software): maximum likelihood and quasi-likelihood¹³ estimation, inference (Wald type and likelihood-based) and model checking procedures.
- (link-)specific tools for interpretation, e.g. odds-ratio.

¹² Other links sometimes used for proportions: probit and complementary log-log.

¹³ Quasi-likelihoods were developed for specific situations where ordinary likelihood functions do not exist, e.g. overdispersed models (next lecture).