

Working with linear and logistics regression models

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Further remarks on logistic regression

Diagnostics: residuals and leverages

Test of fit: The Hosmer-Lemeshow test

Enough data?

General things for regression models:

The `lincom` command

Collinearity - correlated explanatory variables

What model should I use?

Automatic model selection

The consequences of model selection

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Linear and Logistic regression - Note 4.1

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Logistic regression models: Diagnostics

In the linear regression we saw some example of statistics:

residuals, standardized residuals and leverage

which can be used in the model checking and search for strange or influential data points.

Such statistics can also be defined for the logistic regression model.

But they are much more difficult to interpret and cannot in general be recommended.

Checking the validity of a logistic regression model will mostly be based on comparing it with other models.

We will return to this later!

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Logistic regression models: Test of fit

A common, and to some extend informative, test of fit is the **Hosmer-Lemeshow test**.

Consider the model for obesity from Monday

$$\text{logit}(\Pr(\text{obese})) = \beta_0 + \beta_1 \cdot \text{woman} + \beta_2 \cdot (\text{age} - 45)$$

Logit estimates

	Number of obs	=	4690			
LR chi2(2)	=	55.68				
Prob > chi2	=	0.0000				
Pseudo R2	=	0.0155				
<hr/>						
obese	coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_Isex_2	.2743977	.0903385	3.04	0.002	.0973375	.451458
age45	.0344723	.0051354	6.71	0.000	.0244072	.0445374
_cons	-2.147056	.0721981	-29.74	0.000	-2.288561	-2.00555

Significantly better than nothing - but is it good?

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Logistic regression models: Test of fit

What about comparing the **estimated prevalence** with the **observed prevalence**?

In the Hosmer-Lemeshow test the data is divided into groups (traditionally 10) according to the **estimated** probabilities and the **observed** and **expected** counts are compared in these groups by a chi-square test.

Most programs, that can fit a logistic regression model, can calculate this test.

In STATA it is done by (after fitting the model):

`1fit, group(10) table`

The data is divided into **deciles** after the estimated probabilities.

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Logistic regression models: Test of fit

OUTPUT

Logistic model for obese, goodness-of-fit test
(Table collapsed on quantiles of estimated probabilities)

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.0841	64	40.9	462	485.1	526
2	0.0953	43	45.5	453	450.5	496
3	0.1045	44	44.6	398	397.4	442
4	0.1112	42	50.3	422	413.7	464
5	0.1217	44	51.4	394	386.6	438
6	0.1332	52	63.0	441	430.0	493
7	0.1456	53	61.7	389	380.3	442
8	0.1592	62	69.8	392	381.2	454
9	0.1834	98	89.9	424	432.1	522
10	0.2407	99	83.8	314	329.2	413

number of observations = 4690
number of groups = 10
Hosmer-Lemeshow chi2(8) = 26.01
Prob > chi2 = 0.0010

Significant difference between observed and expected!

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One problem:
Too many in
the tails

Logistic regression models: Do you have enough data?

All inference in logistic regression models are based on asymptotics, i.e. **assuming that you have a lot of data!**

Rule of thumb:

You should have at least **10 events** per variable (parameter) in the model.

A large standard error typically indicates that you have to little information concerning the variable and that the **estimate and standard error are not valid**.

Lower your ambitions or get more data!

A exact methods exists, but only one (**expensive**) program can do it.

And it will give also wide confidence intervals.

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Logistic regression models: Test of fit

xi: logit obese i.sex*age45

1fit, group(10) table

Logistic model for obese, goodness-of-fit test

(Table collapsed on quantiles of estimated probabilities)

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.0796	36	35.9	466	466.1	502
2	0.1011	42	41.1	406	406.9	448
3	0.1053	49	49.6	429	428.4	478
4	0.1096	50	54.8	458	453.2	508
5	0.1124	52	54.2	436	433.8	488
6	0.1153	51	46.4	355	359.6	406
7	0.1182	52	53.9	410	408.1	462
8	0.1590	76	70.3	428	433.7	504
9	0.2133	96	91.8	391	395.2	487
10	0.3310	97	103.0	310	304.0	407

number of observations = 4690

number of groups = 10

Hosmer-Lemeshow chi2(8) = 2.43
Prob > chi2 = 0.9650

The model 'fits' - when we look at in this way !!!!!!!

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The lincom command after logit or regress

Consider the model:

$$\text{logit}(\Pr(\text{obese})) = \beta_0 + \beta_1 \cdot \text{woman} + \beta_2 \cdot (\text{age} - 45)$$

obese	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_Isex_2	.2743977	.0903385	3.04	0.002	.0973375 .451458
age45	.0344723	.0051354	6.71	0.000	.0244072 .0445374
_cons	-2.147056	.0721981	-29.74	0.000	-2.288561 -2.00555

Here men are reference.

If we want to find the log odds for a 45 year old women we can calculate by hand $-2.147 + 0.274 = -1.873$

But what about confidence interval?

We could change the reference to women and fit the model once more.

But.....

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The lincom command after logit or regress

$$\text{logit}(\text{Pr}(\text{obese})) = \beta_0 + \beta_1 \cdot \text{woman} + \beta_2 \cdot (\text{age} - 45)$$

STATA has a command that can be used for this: "lincom"

```
lincom _cons+_Isex
( 1) _Isex_2 + _cons = 0

obese | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+
(1) | -1.8726 .05813 -32.21 0.000 -1.986602 -1.758714
```

You can add ", or" to get odds/odds ratios.

```
lincom _cons+_Isex, or
( 1) _Isex_2 + _cons = 0

obese | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]
-----+
(1) | .1537145 .0088363 -32.21 0.000 .1371606 .172266
```

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The lincom command after logit or regress

$$\text{logit}(\text{Pr}(\text{obese})) = \beta_0 + \beta_1 \cdot \text{woman} + \beta_2 \cdot (\text{age} - 45)$$

Some examples:

Odds for a 42 year old woman:

```
lincom _cons+_Isex-age45*3, or
( 1) _Isex_2 - 3 age45 + _cons = 0
```

```
obese | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]
-----+
(1) | .1386122 .0088378 -30.89 0.000 .1222772 .1571295
```

Odds ratio for 4.5 age difference:

```
lincom age45*4.5, or
```

```
( 1) 4.5 age45 = 0
```

```
obese | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]
-----+
(1) | 1.167804 .069869 6.71 0.000 1.116091 1.221914
```

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Collinearity

Consider a subsample of the serum cholesterol data set and the **three** models:

model 0: regress logsc1 sex sbp dbp

model 1: regress logsc1 sex dbp

model 2: regress logsc1 sex sbp

variable	model0	model1	model2
sbp	.00126448 .00087992 0.1524	.0014988 .0005548 .00075	Estimate Se p
dbp	.00056517 .00164485 0.7315	.00239702 .0010424 0.0226	
sex	.02080574 .02636149 0.4310	.02446746 .02631111 0.3536	.0197773 .02613048 0.4501
_cons	5.1444085 .09912234 0.0000	5.1555212 .09909537 0.0000	5.1615877 .08539118 0.0000
N	194	194	194

Each BP-measure is statistical significant, when the other is removed!

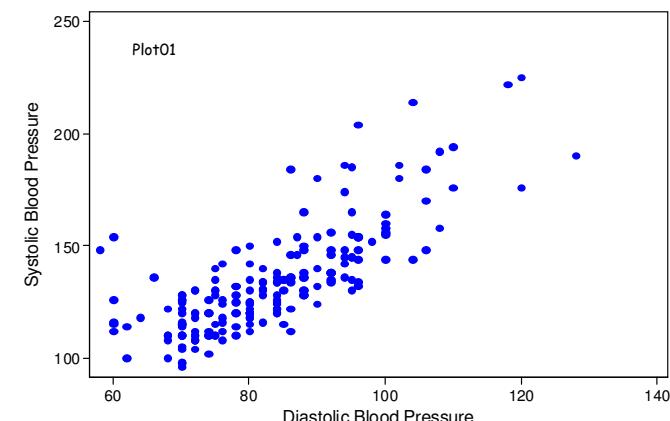
Legend: $b/\text{se}/p$

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Collinearity



SBP and DBP are highly **positively correlated** that will lead to highly **negatively correlated estimates!!!**

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Collinearity

This can be seen by listing the **correlation between the estimates**.

In STATA by the command: `vce, cor`

	sbp	dbp	sex	_cons
sbp	1.0000			
dbp	-0.7750	1.0000		
sex	-0.0967	0.1135	1.0000	
_cons	-0.0780	-0.5044	-0.4665	1.0000

If two estimates are highly correlated, it indicates that it is very difficult to estimate the "**independent effect**" of the each of the two variables.

Often it is even **nonsense** to try to do it!

Often it see better to try to **reformulate the problem**.

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Collinearity

One way to work around the problem of collinearity is to '**orthogonalize**' it:

Create two new variable:

one measures the **blood pressure**

and another that measure the **difference** in systolic and diastolic blood pressure.

Some **candidates**:

$(\text{sbp}+\text{dbp})/2$ and $(\text{sbp}-\text{dbp})$

$(\text{sbp}+\text{dbp})/2$ and (sbp/dbp)

$\ln(\text{sbp} \cdot \text{dbp})/2$ and $\ln(\text{sbp}/\text{dbp})$

We will here consider the second pair.

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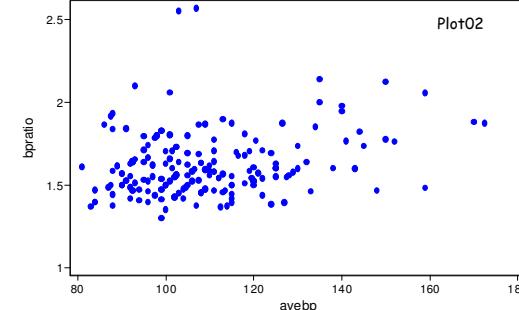
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Collinearity

$\text{avebp} = (\text{sbp} + \text{dbp})/2$ and $\text{bpratio} = (\text{sbp}/\text{dbp})$

Only weakly associated



`regress logsc1 avebp bpratio sex`

	avebp	bpratio	sex	_cons
avebp	1.0000			
bpratio	-0.2456	1.0000		
sex	0.0382	-0.1041	1.0000	
_cons	-0.4542	-0.6874	-0.2585	1.0000

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Collinearity

The serum cholesterol data set and the **three** models:

model 0: `regress logsc1 sex avebp bpratio`

model 1: `regress logsc1 sex avebp`

model 2: `regress logsc1 sex bpratio`

Variable	model0	model1	model2
avebp	.00198973 .0007887 0.0125	.00206564 .00076285 0.0074	
bpratio	.02769662 .07067134 0.6956		.07148118 .06946246 0.3048
sex	.02060675 .02632924 0.4348	.02168128 .026128 0.4077	.01806662 .02667689 0.4991
_cons	5.1003417 .12936418 0.0000	5.1351912 .09374803 0.0000	5.2485724 .11685799 0.0000
N	194	194	194

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Blood pressure seems to play a role,

The ratio between SBP and DBP might not.

Collinearity

Look out for it:

- systolic and diastolic blood pressure
- 24 hour blood pressure and 'clinical' blood pressure
- weight and height
- age and parity
- age and time since menopause
- BMI and skinfold measure
- age, birth cohort and calendar time
- volume and concentration
-

Remember you will need a **huge amount** of data to disentangle the effects of correlated explanatory variables

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Which model should I use?

This a hard question!

The first thing to remember is that all models are **approximations!**

The "true", the "best" or the "correct" model **does not exist!**

The **quality** of a model depends on what you want to use it for.

So the first thing to clarify is:

What is the **purpose** of your analysis - what is the **aim** of your data collection?

Different purposes - different models!!!!

When you have found out what you want you still have an **infinity** of models to chose between.

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Which model should I use?

The choice is always a choice between **complicated** and **less complicated** models.

Complicated models are often better models, in the sense that they are **better approximations** to the truth.

But complicated models can be:

Very hard to **estimate** - many parameters.

Very hard to **understand**.

Very hard to **communicate**.

So in these senses they are **not so good** models.

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Which model should I use?

Less complicated models are often not as good models, in the sense that they are **not so good approximations** to the truth.

But less complicated models can be:

Easy to **estimate** - few parameters.

Easy to **understand**

Easy to **communicate**

So in these senses they are **better** models.

The first thing to remember is that all models are **approximations!**

Statistical significance has nothing to do with the quality of the model!

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Which model should I use?

You can often divide the explanatory variables into groups:

- 1: Variables of **primary interest** - main exposure.
- 2: Variables of **less interest** - variables you want to **adjust** for.

A good model will try to introduce the **first** group in an **interpretable** way into model.

- You want to **know** "how they work".

E.g. if you specifically are interested on the "effect" of age you should model age in a **understandable** way.

Still you have to look out for collinearity.

Which model should I use?

The **second** type of variables can be introduced any way you like.

It can be very complicated - you do not care- as long as they do the job - that is, **adjust sufficiently**.

If you are not interested in age in itself - you just want to adjust - then age can be introduced in a complicated/weird way, e.g. a fourth order polynomial.

In **general**:

Models with many parameters need more data to obtain precise estimate.

Again few data - lower your ambition !

Automatic model selection

Some programs (even STATA) have programmed algorithms for **automatic model selection**!

That is, procedures that will find the "best" model to answer your question without knowing what **you want, know or anything else about the problem!**

It is very rarely of any interest, especially if you have **little data**.

There are in general three types of such algorithms:

Backward selection : You specify a **start model** and the procedure will reduce the model by **removing** variables from the model until nothing can be removed.

The **criteria** for removing variables are typically **high p-values**.

Automatic model selection

Forward selection : You specify a **start model** together with a list of variables that might be included in a model. The procedure will build the model by **adding variable** from the list to the model until nothing can be added.

The **criteria** for adding variables is typically **low p-values**.

Best subset selection: You specify a list of variables that might be included in a model and **number** of variables you want in the model. The procedure will then search among the possible models and find the "best".

The **criteria** is typically the **highest likelihood** or related statistics.

Automatic model selection

Some comments:

- These procedures **do not know anything about the subject**.
- They will not consider **transformation** of the variables.
- or **interaction**.
- They will chose **arbitrarily** between explanatory variables that are highly correlated.

Model selection and some implications

Even when you do not use an automatic model selection procedures : The **final model** is selected!

That is, you have spend some time **working** with the model you present!

You might choose only to include **statistical significant** variables in the model.

You might group **two levels** of a explanatory variable **into one level** if there is no statistical significant difference between the two levels.

The implications of this selection:

- The **estimates** tend to be too far **away from null**.
- The **standard errors** are too **small**.
- The **CI's** are to **narrow** and the **p-values** too **small**.