Logistic Regression Project 2 Model Answer

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The project asks to determine the best fitted model for being out of work in Germany during 1988. Potential explanatory predictors are listed below, and are available in the rwm1yr data, which is abstracted from the German Health Reform Registry for the year 1988.

Data: rwm1yr

outwork	1=not working; 0=working	g binary female	e 1=femaie; 0=male	binary
married	Married=1; Single=0	binary kids	1=have children; 0=no ch	nildren binary
edlevel	Level of education	categorical docvis	MD visits/year	continuous
hospvis	Days in hospital/year	continuous age	Ages 25-64	continuous
hhninc	Household income (Marks,	OECD wgt) continuo	ous	

A summary profile of the response, *outwork*, and possible predictors is given as:

. su

Variable	I	Obs	Mean	Std. Dev.	Min	Max
	-+					
outwork	1	4483	.3276824	.4694207	0	1
female	1	4483	.4840509	.4998013	0	1
married	I	4483	.7521749	.4317979	0	1
kids	1	4483	.3794334	.4853001	0	1
edlevel	1	4483	1.491189	.9475775	1	4
	-+					
docvis	I	4483	2.871961	5.144336	0	90
hospvis	I	4483	.1490074	.8763926	0	35
age	1	4483	43.44011	11.28801	25	64
hhninc	I	4483	3.487401	1.641828	0	20

edlevel, a 4 level categorical variable is factored into 4 dummy or indicator variables. We will use the first level, 'not a high school graduate', as the reference. It has over three-fourths of the observations.

. tab edlevel, gen(educ)

Level of				
education	I	Freq.	Percent	Cum.
	+			
Not HS grad	I	3,401	75.86	75.86
HS grad		294	6.56	82.42
Coll/Univ		456	10.17	92.59
Grad School	I	332	7.41	100.00
	+			
Total	1	4,483	100.00	

A univariable logistic regression is used to determine of any binary or continuous predictor is clearly not associated with the response, *outwork*. A univariable logistic regression is also provided of outwork on the levels of *edlevel*, with level 1 as the reference. The levels, each binary indicator variables, have been given the names *educ2 – educ4*.

. logistic outwork female married kids docvis hospvis age hhninc

Logistic regre	ess	ion				Number	of obs	; =	448	33
						LR chi2	2(7)	=	1136.4	16
						Prob >	chi2	=	0.000	00
Log likelihood	d =	-2267.3785			Pseudo	R2	=	0.200) 4	
outwork	0	dds Ratio	Std. Err.	Z	P>	> z	[95%	Conf.	Interval	L]
	+									
female	I	6.033494	.4621664	23.46	0.	.000	5.192	383	7.01085	55
married	l	1.529322	.151078	4.30	0.	.000	1.260	117	1.85603	39
kids	I	1.274946	.1132263	2.74	0.	.006	1.071	.267	1.5173	35
docvis	I	1.016134	.0070402	2.31	0.	.021	1.002	2429	1.03002	27
hospvis	I	1.088353	.0509789	1.81	0.	.071	.9928	859	1.19	93
age	I	1.046549	.0040013	11.90	0.	.000	1.038	3736	1.05442	21
hhninc	I	.6413558	.0192654	-14.79	0.	.000	.6046	863	.68024	19
_cons	I	.0643173	.0136003	-12.98	0.	.000	.0424	1948	.097346	54

. glm outwork educ2-educ4, nolog fam(bin) nohead eform

	I	OIM				
	•				[95% Conf.	-
	+					
educ2	.9435484	.1215855	-0.45	0.652	.732957	1.214646
educ3	.9342676	.0988733	-0.64	0.521	.759257	1.149619
educ4	.2733037	.0461847	-7.68	0.000	.1962473	.3806162
_cons	.5299145	.0190971	-17.62	0.000	.4937763	.5686977

A model with all predictors except level 2 of edlevel appears to be a well fitted model.

. glm outwork female-kids docvis hospvis age hhninc educ3 educ4, fam(bin) eform

```
Iteration 0: log likelihood = -2269.6826
Iteration 1: log likelihood = -2246.2986
Iteration 2: log likelihood = -2246.2469
Iteration 3: log likelihood = -2246.2469
```

Generalized linear mo	odels	No. of obs	=	4483
Optimization : ML	L	Residual df	=	4473
		Scale parameter	=	1
Deviance = 4	4492.493702	(1/df) Deviance	=	1.004358
Pearson = 5	5121.343676	(1/df) Pearson	=	1.144946
Variance function: V((u) = u*(1-u)	[Bernoulli]		
Link function : g($(u) = \ln (u/(1-u))$	[Logit]		
		AIC	=	1.006579

Log likelihood = -2246.246851 BIC = -33116.7

(

[.] di e(11) -2796.9669

outwork		Odds Ratio	Std. Err.	Z	P> z	[95% Conf.	<pre>Interval]</pre>
	+-						
female		6.238166	.4856971	23.51	0.000	5.355293	7.266588
married		1.575058	.1593084	4.49	0.000	1.29182	1.920396
kids	1	1.323519	.1184544	3.13	0.002	1.110575	1.577293
docvis		1.017057	.0070992	2.42	0.015	1.003237	1.031066
hospvis	1	1.089815	.0514316	1.82	0.068	.9935324	1.195428
age	I	1.0501	.0040986	12.52	0.000	1.042097	1.058164
hhninc		.6391308	.0197298	-14.50	0.000	.6016076	.6789944
educ3	I	2.126172	.2689686	5.96	0.000	1.659275	2.724448
educ4		.6815386	.1282189	-2.04	0.042	.4713599	.9854359
_cons	I	.0498737	.0109012	-13.72	0.000	.0324951	.0765463

The differences in values of the standard errors when applying a robust variance estimator gives evidence that there is excess correlation in the data. We should use robust SEs then for our model. The *p*-values appear better then with model-based SEs.

. glm outwork female-kids docvis hospvis age hhninc educ3 educ4, fam(bin) eform robust

```
Iteration 0: log pseudolikelihood = -2269.6826
Iteration 1: log pseudolikelihood = -2246.2986
Iteration 2: log pseudolikelihood = -2246.2469
Iteration 3: log pseudolikelihood = -2246.2469
Generalized linear models
                                             No. of obs = 4483
Optimization : ML
                                             Residual df =
                                                                  4473
                                              Scale parameter =
Deviance
             = 4492.493702
                                             (1/df) Deviance = 1.004358
             = 5121.343676
Pearson
                                              (1/df) Pearson = 1.144946
Variance function: V(u) = u*(1-u)
                                             [Bernoulli]
Link function : g(u) = \ln(u/(1-u))
                                             [Logit]
                                             AIC
                                                           = 1.006579
Log pseudolikelihood = -2246.246851
                                             BIC
                                                            = -33116.7
```

I		Robust				
outwork	Odds Ratio	Std. Err.	Z	P> z	[95% Conf.	Interval]
+						
female	6.238166	.4838883	23.60	0.000	5.358337	7.26246
married	1.575058	.1726084	4.15	0.000	1.270616	1.952444
kids	1.323519	.1169449	3.17	0.002	1.113061	1.573771
docvis	1.017057	.007751	2.22	0.026	1.001978	1.032362
hospvis	1.089815	.0449568	2.08	0.037	1.005169	1.181589
age	1.0501	.0043535	11.79	0.000	1.041602	1.058667
hhninc	.6391308	.0248904	-11.49	0.000	.5921618	.6898253
educ3	2.126172	.294894	5.44	0.000	1.62009	2.790343
educ4	.6815386	.127023	-2.06	0.040	.4729837	.9820526
_cons	.0498737	.0126814	-11.79	0.000	.0302995	.0820931

The AIC and BIC values are lower with this model than any other.

```
. abic  
AIC Statistic = 1.006579  
AIC*n = 4512.4937  
BIC Statistic = 1.01239  
BIC(Stata) = 4576.5742
```

The fit of the model is accessed by using various post-estimation tests. We use a HosmerLemeshow Goodness-of-fit test and a Tukey-Pregibon linktest.

```
. qui logistic outwork female married kids docvis hospvis age hhninc educ3 educ4 . estat gof, table group(10)
```

Logistic model for outwork, goodness-of-fit test

```
6 | 0.3671 | 137 | 141.6 | 311 | 306.4 | 448 |
    7 | 0.4619 | 226 | 186.6 | 223 | 262.4 | 449 |
    8 | 0.5554 | 234 | 228.2 | 214 | 219.8 | 448 |
    9 | 0.6816 | 252 | 276.2 | 196 | 171.8 | 448 |
     10 | 0.9837 | 355 | 343.5 | 93 | 104.5 | 448 |
     number of observations =
                           10
         number of groups =
    Hosmer-Lemeshow chi2(8) = 70.92
             Prob > chi2 = 0.0000
. linktest
Iteration 0: \log likelihood = -2835.6103
Iteration 1: log likelihood = -2253.8784
Iteration 2: log likelihood = -2239.1808
Iteration 3: \log \text{ likelihood} = -2238.8469
Iteration 4: log likelihood = -2238.8453
Iteration 5: log likelihood = -2238.8453
Logistic regression
                                     Number of obs = 4483
                                     LR chi2(2) = 1193.53
                                                = 0.0000
                                     Prob > chi2
                                     Pseudo R2 = 0.2105
Log likelihood = -2238.8453
             Coef. Std. Err. z P>|z| [95% Conf. Interval]
______
     _hat | 1.130544 .0487535 23.19 0.000 1.034989 1.226099
    _hatsq | .0882216 .0207308 4.26 0.000 .04759 .1288533
```

In both circumstances, the test fail to confirm that the model properly fits the data. After attempting a variety of models, the following model apparently fits. The model below produces the near same results whether a robust variance estimator is used for standard errors.

. logistic outwork female hospvis educ4

Logistic regre	ssion			Number	of obs	=	4483
				LR chi	L2(3)	=	696.20
				Prob >	> chi2	=	0.0000
Log likelihood	= -2487.5081	L		Pseudo	R2	=	0.1228
outwork	Odds Ratio	Std. Err.	Z	P> z	[95%	Conf.	Interval]
female	5.348065	.3837571	23.37	0.000	4.646	412	6.155676
hospvis	1.091037	.0489109	1.94	0.052	.9992	638	1.191238
educ4	.3431769	.0603354	-6.08	0.000	.2431	446	.4843636
_cons	.1997761	.0116325	-27.66	0.000	.1782	297	.2239273

We first apply a Hosmer-Lemeshow goodness-of-fit test, collapsing on three levels. A TukeyPregibon *linktest* follows, indicating that the model fits as a logistic regression.

```
. estat gof, table group(3)
```

Logistic model for outwork, goodness-of-fit test

```
(Table collapsed on quantiles of estimated probabilities)
```

т.														. 1
I	Group		Prob		0bs_1	I	Exp_1	I	Obs_0	I	Exp_0	1	Total	I
1		+-		-+		-+-		-+-		-+-		-+		-
I	1		0.1665		315	1	333.2	I	1828	I	1809.8	-	2143	I
1	2		0.5165	I	1017		1008.2	I	1091	I	1099.8	I	2108	I
I	3		0.9575		137	1	127.6	I	95	I	104.4	-	232	I
+														+

```
number of observations = 4483
number of groups = 3
Hosmer-Lemeshow chi2(1) = 2.87
Prob > chi2 = 0.0905
```

. linktest

```
Iteration 0: \log likelihood = -2835.6103
Iteration 1: log likelihood = -2496.8493
Iteration 2: log likelihood = -2487.5291
Iteration 3: \log likelihood = -2487.4605
Iteration 4: \log likelihood = -2487.4605
Logistic regression
                                  Number of obs = 4483
                                   LR chi2(2) = 696.30
                                  Prob > chi2 = 0.0000
                                  Pseudo R2
Log likelihood = -2487.4605
                                               0.1228
   outwork |
            Coef. Std. Err.
                            z P>|z|
                                       [95% Conf. Interval]
-----
     _hat | 1.042692 .1442169 7.23 0.000 .7600317 1.325352
    hatsq | .0258423 .0834595 0.31 0.757 -.1377353
                                                 .18942
    . abic
AIC Statistic = 1.111536 AIC*n = 4983.0161
BIC Statistic = 1.112225
                         BIC(Stata) = 5008.6484
```

The failure of the square of the hat statistic to be significant indicates that the model fits as a logistic model; i.e. that the link has been correctly specified. The AIC and BIC values are also low. Note that the left hand side AIC and BIC are consistent, which indicates fit.

A classification test given a cutoff point at the mean of the model fitted values shows only a 69% correct classification rate. This is not particularly good, but the model does apparently fit as a logistic regression model.

```
. predict mu
(option pr assumed; Pr(outwork))
```

Correctly classified

	Obs				
	4483 .3				
. estat class,	cutoff(.3276823)			
Logistic model	for outwork				
-	True				
Classified		~D			
	1079				
	390				
	1469				
Classified + if	predicted Pr(D) >= .32	76823		
	as outwork != 0				
Sensitivity		Pr(+			
Specificity				67.02%	
Positive predic	tive value	Pr(D	+)	52.05%	
Negative predic	tive value	Pr(~D	-)	83.82%	
False + rate fo	r true ~D	Pr(+	~D)	32.98%	
False - rate fo	r true D	Pr(-	D)	26.55%	
False + rate fo	r classified +	Pr(~D	+)	47.95%	
	r classified -				

To determine the covariate profile that best predicts being out-of-work, we have

69.13%

```
. sort mu
```

. su mu

Variab				Std. Dev.	Max
				.1811158	.9575343
. l female	hospv:	is educ4 i	5 mu>.9575		
+			+		
fe	emale	hospvis	educ4		
4483.	1	35	0		

+----+

Therefore, a female patient without graduate level education who has been in the hospital 35 days during 1988 had a 96% chance of being unemployed during that year. The aim of the model is to extrapolate to future years. We can expect that females without post collegiate education who spend more than a month in the hospital during a calendar year will be unemployed.