





The screenshot shows the Results Browser window for 'Live Recaptures (CJS)'. It contains a table with the following data:

Model	AICc	Delta AICc	AICc Weight	Model Likelihood	No. Par.	Deviance
{Phi(.) p(.) PIM}	322.55	0.00	0.96003	1.0000	2	41.8150
{Phi(t) p(.) PIM}	330.06	7.50	0.02253	0.0235	7	38.8150
{Phi(.) p(t) PIM}	330.68	8.13	0.01651	0.0172	7	39.4370
{Phi(t) p(t) PIM}	336.43	13.88	0.00093	0.0010	11	36.4010

Deviance plays the role of residual sum of squares in linear regression. To assess the significance of a factor(s), we compare the Deviance for models with and without the factor in question. You'll see how to calculate the deviance for this model type on the next page.

Likelihood Ratio Tests: Deviance_Reduced Model – Deviance_General Model ~chi-squared

European Dippers - males only

Reduced Model	General Model	Chi-sq.	df	Prob.
{Phi(.) p(.) PIM}	{Phi(t) p(.) PIM}	3.000	5	0.7000
{Phi(.) p(.) PIM}	{Phi(.) p(t) PIM}	2.378	5	0.7947
{Phi(.) p(.) PIM}	{Phi(t) p(t) PIM}	5.414	9	0.7968
{Phi(t) p(.) PIM}	{Phi(.) p(t) PIM}	-0.622	0	*****
{Phi(t) p(.) PIM}	{Phi(t) p(t) PIM}	2.414	4	0.6601
{Phi(.) p(t) PIM}	{Phi(t) p(t) PIM}	3.036	4	0.5518

NOTE: the LRT works only for nested models, i.e., comparison #4 is not conceptually valid even if the test were possible mathematically.

Another role of Deviance is in testing for GOF – this will be the next major topic that we tackle. Here’s a table that we’ll use to gain understanding of how the saturated model’s deviance and deviance *df* are calculated. A saturated model fits perfectly and is sometimes a model in the model set (e.g., S(week) in lab 1) and sometimes not (like in Lab 3 where we can’t run such a model but can calculate the deviance as below).

EH	n_i	R_i	Contribution to DEV ($n_i \cdot \ln(n_i/R_i)$)	Releases & Re-releases prior to occ. 7	Pieces of Information (rows-1)
1111110	1	12	-2.4849066	6	4
1111000	1		-2.4849066	4	
1100000	4		-4.3944492	8	
1010000	1		-2.4849066	2	
1000000	5		-4.3773437	5	
0111100	1	20	-2.9957323	4	3
0111000	1		-2.9957323	3	
0110000	7		-7.3487549	14	
0100000	11		-6.576207	11	
0011110	1	25	-3.2188758	4	4
0011100	4		-7.3303259	12	
0011000	8		-9.1154743	16	
0010110	1		-3.2188758	3	
0010000	11		-9.0307861	11	
0001111	6	22	-7.7956979	18	4
0001110	3		-5.9772905	9	
0001100	6		-7.7956979	12	
0001001	1		-3.0910425	1	
0001000	6		-7.7956979	6	
0000111	10	22	-7.8845736	20	2
0000110	3		-5.9772905	6	
0000100	9		-8.0443609	9	
0000011	12	23	-7.8070508	12	1
0000010	11		-8.1135884	11	
0000001	17	17	0		
/* SUM	141	141	lnL	207	18
			-2lnL		
			276.679136		

The -2lnL value of 276.679, effective sample size of 207, and d.f. of 18 can now be used in comparisons and tests for fitted models. E.g., model $\Phi(\cdot)$, $p(\cdot)$, has 2 parameters and $-2\ln L = 318.494$, the deviance is $318.494 - 276.679 = 41.815$, and deviance d.f. = 16 (18 – 2).

Discussion of Questions that some students have struggled with in past years.

1. 5 $\hat{\phi}$'s, 5 \hat{p} 's, & 1 combo. = $\hat{\phi}_1, \hat{\phi}_2, \dots, \hat{\phi}_5, \hat{p}_2, \hat{p}_3, \dots, \hat{p}_6$, and $\hat{\phi}_6 \cdot \hat{p}_7$
2. Sine link gets it right: $k=11$. Logit link gets it wrong: $k=10$.
3. Students typically do pretty well with this one but ... some forget to check the # of parameters in all of the models. For part *b*, you could do model averaging as

long as you were paying attention to the problem with ϕ_i in the $\phi(t), p(t)$ model. For example, if you just do model averaging, for this parameter, you'll see the following:

Model	Weight	Estimate	Standard Error
{Phi(.) p(.) PIM}	0.96003	0.5658226	0.0355404
{Phi(t) p(.) PIM}	0.02253	0.6319703	0.0796463
{Phi(.) p(t) PIM}	0.01650	0.5560768	0.0342813
{Phi(t) p(t) PIM}	0.00093	0.7637583	514.1293800
Weighted Average		0.5673361	0.5140185
Unconditional SE		15.6690091	
95% CI for Wgt. Ave. Est. (logit trans.) is 0.0000000 to 1.0000000			
Percent of Variation Attributable to Model Variation is 99.89%			

You don't have much model-selection uncertainty here and so you could just use the best model to make inferences if you wanted to.

Parameter	Estimate	Standard Error	Lower	Upper
1:Phi	0.5658226	0.0355404	0.4953193	0.6337593
2:p	0.9231757	0.0363182	0.8149669	0.9704014

- Here's how to calculate the probability of getting a 1000000 encounter history (see text on this topic on page 420 of Williams et al.). Be sure you understand.

$$\begin{aligned} \chi_7 &= 1 \\ \chi_6 &= (1 - \phi_6) + \phi_6 \cdot (1 - p_7) \cdot \chi_7 \\ \chi_5 &= (1 - \phi_5) + \phi_5 \cdot (1 - p_6) \cdot \chi_6 \\ \chi_4 &= (1 - \phi_4) + \phi_4 \cdot (1 - p_5) \cdot \chi_5 \\ \chi_3 &= (1 - \phi_3) + \phi_3 \cdot (1 - p_4) \cdot \chi_4 \\ \chi_2 &= (1 - \phi_2) + \phi_2 \cdot (1 - p_3) \cdot \chi_3 \\ \chi_1 &= (1 - \phi_1) + \phi_1 \cdot (1 - p_2) \cdot \chi_2 \end{aligned}$$

So, for model $\phi(\cdot), p(\cdot)$ with MLE's of $\phi=0.5658226$ & $p=0.9231757$, the probability of an individual having a 1000000 for its encounter history is 0.4539083.

In R, you'd simply type:

```
phi=.5658226
p=.9231757
x7=1
x6=(1-phi)+phi*(1-p)*x7
x5=(1-phi)+phi*(1-p)*x6
x4=(1-phi)+phi*(1-p)*x5
x3=(1-phi)+phi*(1-p)*x4
x2=(1-phi)+phi*(1-p)*x3
x1=(1-phi)+phi*(1-p)*x2
x1 # = 0.4539083
```