## Binomial GLM (Logistic Regression): Malformation example

In a small study data was collected on the presence of a sex organ malformation on a infant to study how the mother's alcohol consumption affected it. The information collected on each subject is

$$y = \begin{cases} 1 & \text{present} \\ 0 & \text{absent} \end{cases} \quad x = \text{mother's average drinks per day}$$

The data is tabulated as follows

Consumption	Consumption score $(x)$	Absent	Present
0	0.0	17066	48
< 1	0.5	14464	38
1-2	1.5	788	5
3-5	4.0	126	1
$\geq 6$	7	37	1

- > Alcohol=c(0,0.5,1.5,4,7)
- > Absent=c(17066,14464,788,126,37)
- > Present=c(48,38,5,1,1)
- > cbind(Alcohol, Absent, Present)

#### Alcohol Absent Present

[1,]	0.0	17066	48
[2,]	0.5	14464	38
[3,]	1.5	788	5
[4,]	4.0	126	1
[5,]	7.0	37	1

> malform.logit=glm(cbind(Present,Absent)~Alcohol,family=binomial(link=logit))
> summary(malform.logit)

#### Call:

glm(formula = cbind(Present, Absent) ~ Alcohol, family = binomial(link = logit))

# Deviance Residuals:

### Coefficients:

Signif. codes: 0 Ś\*\*\*Š 0.001 Ś\*\*Š 0.01 Ś\*Š 0.05 Ś.Š 0.1 Ś Š 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 6.2020 on 4 degrees of freedom Residual deviance: 1.9487 on 3 degrees of freedom

AIC: 24.576

Number of Fisher Scoring iterations: 4

The estimated regression is

$$\log\left(\frac{\hat{\pi}(x)}{1 - \hat{\pi}(x)}\right) = -5.961 + 0.3166x$$

with the  $\beta_1$  being significant and positive, implying that as alcohol consumption increases so does the probability of malformation. As  $x \uparrow 1$  unit the odds of malformation (to no malformation) increase multiplicative by  $e^{0.3166} = 1.3725$ . That is, for a mother consuming alcohol, there is about a 37% increase in a chance of malformation compared to a mother consuming 1 unit less (within the range of the data).

A 50-50 probability of malformation occurs at -(-5.961)/0.3166 = 18.82817 drinks which is outside the range of our data.

To test the significance of multiple  $\beta$ 's (however we only have one  $\beta$  corresponding to one predictor) we take the difference of the deviance of the reduced to the full model

> ts=malform.logit\$null.deviance-malform.logit\$deviance;ts

[1] 4.253277

> df=malform.logit\$df.null-malform.logit\$df.residual;df

[1] 1

> 1-pchisq(ts,df)

[1] 0.03917467

The observed and fitted probabilities are:

- > tab=round(cbind(fitted.values(malform.logit),Present/(Present+Absent)),3)
- > dimnames(tab)=list(c("0","0.5","1.5","4","7"),c("Fitted prob.","0bserved prob."))
- > tab

	Fitted	prob.	Observed prob
0		0.003	0.003
0.5		0.003	0.003
1.5		0.004	0.006
4		0.009	0.008
7		0 023	0.026

## Model for Binomial data

