

Multivariate Logistic Regression

As in univariate logistic regression, let $\pi(x)$ represent the probability of an event that depends on p covariates or independent variables. Then, using an inv.logit formulation for modeling the probability, we have:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}$$

So, the form is identical to univariate logistic regression, but now with more than one covariate. [Note: by “univariate” logistic regression, I mean logistic regression with one independent variable; really there are two variables involved, the independent variable and the dichotomous outcome, so it could also be termed bivariate.]

To obtain the corresponding logit function from this, we calculate (letting X represent the whole set of covariates X_1, X_2, \dots, X_p):

$$\begin{aligned} \text{logit}[\pi(X)] &= \ln \left[\frac{\pi(X)}{1 - \pi(X)} \right] \\ &= \ln \left[\frac{\frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}}{1 - \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}} \right] \\ &= \ln \left[\frac{\frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}}{\frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}} \right] \\ &= \ln \left[e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p} \right] \\ &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \end{aligned}$$

So, again, we see that the logit of the probability of an event given X is a simple linear function.

To summarize, the two basic equations of multivariate logistic regression are:

$$\pi(X) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p}}$$

which gives the probabilities of outcome events given the covariate values X_1, X_2, \dots, X_p , and

$$\text{logit}[\pi(X)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$$

which shows that logistic regression is really just a standard linear regression model, once we transform the dichotomous outcome by the logit transform. This transform changes the range of $\pi(X)$ from 0 to 1 to $-\infty$ to $+\infty$, as usual for linear regression.

Again analogously to univariate logistic regression, the above equations are for mean probabilities, and each data point will have an error term. Once again, we assume that this error has mean zero, and that it follows a binomial distribution with mean $\pi(X)$, and variance $\pi(X)(1 - \pi(X))$. Of course, now X is a vector, whereas before it was a scalar value.

Interpretation of the β coefficients in multiple logistic regression

Interpretation of the intercept, β_0 : Notice that regardless of the number of covariate values, if they are all set to zero, then we have

$$\pi(x) = \frac{e^{\beta_0}}{1 + e^{\beta_0}}$$

exactly the same as in the univariate case. So, the interpretation of β_0 remains the same as in the simpler case: β_0 sets the “baseline” event rate, through the above function, when all covariate values are set equal to zero.

For example, if $\beta_0 = 0$ then

$$\pi(x) = \frac{e^{\beta_0}}{1 + e^{\beta_0}} = \frac{e^0}{1 + e^0} = \frac{1}{1 + 1} = 0.5$$

and if $\beta_0 = 1$ then

$$\pi(x) = \frac{e^{\beta_0}}{1 + e^{\beta_0}} = \frac{e^1}{1 + e^1} = 0.73$$

and if $\beta_0 = -1$ then

$$\pi(x) = \frac{e^{\beta_0}}{1 + e^{\beta_0}} = \frac{e^{-1}}{1 + e^{-1}} = 0.27$$

and so on.

As before, positive values of β_0 give values greater than 0.5, while negative values of β_0 give probabilities less than 0.5, when all covariates are set to zero.

Interpretation of the slopes, $\beta_1, \beta_2, \dots, \beta_p$: Recall the effect on the probability of an event as X changes by one unit in the univariate case. There, we saw that the coefficient β_1 is such that e^{β_1} is the odds ratio for a unit change in X , and in general, for a change of z units, the $OR = e^{z\beta_1} = (e^{\beta_1})^z$.

Nothing much changes for the multivariate case, except:

- When there is more than one independent variable, if all variables are completely uncorrelated with each other, then the interpretations of all coefficients are simple, and follow the above pattern:

We have $OR = e^{z\beta_i}$ for any variable X_i , $i = 1, 2, \dots, p$, where the OR represents the odds ratio for a change of size z for that variable.

- When the variables are not uncorrelated, the interpretation is more difficult. It is common to say that $OR = e^{z\beta_i}$ represents the odds ratio for a change of size z for that variable *adjusted for the effects of the other variables*. While this is essentially correct, we must keep in mind that confounding and collinearity can change and obscure these estimated relationships. The way confounding operates is identical to what we saw for linear regression.

Estimating the β coefficients given a data set

As in the univariate case, the distribution associated with logistic regression is the binomial. For a single subject with covariate values $x_i = \{x_{1i}, x_{2i}, \dots, x_{pi}\}$, the likelihood function is:

$$\pi(x_i)^{y^i} (1 - \pi(x_i))^{1-y^i}$$

For n subjects, the likelihood function is:

$$\prod_{i=1}^n \pi(x_i)^{y^i} (1 - \pi(x_i))^{1-y^i}$$

To derive estimates of the unknown β parameters, as in the univariate case, we need to maximize this likelihood function. We follow the usual steps, including taking the logarithm of the likelihood function, taking $(p + 1)$ partial derivatives with respect to each β parameter and setting these $(p + 1)$ equations equal to zero, to form a set of $(p + 1)$ equations in $(p + 1)$ unknowns. Solving this system of equations gives the maximum likelihood equations.

We again omit the details here (as in the univariate case, no easy closed form formulae exists), and will rely on statistical software to find the maximum likelihood estimates for us.

Inferences typically rely on SE formulae for confidence intervals, and likelihood ratio testing for hypothesis tests. Again, we will omit the details, and rely on statistical software.

We next look at several examples.

Multiple Logistic Regression Examples

We will look at three examples:

- Logistic regression with dummy or indicator variables
- Logistic regression with many variables
- Logistic regression with interaction terms

In all cases, we will follow a similar procedure to that followed for multiple linear regression:

1. Look at various descriptive statistics to get a feel for the data. For logistic regression, this usually includes looking at descriptive statistics, for example within “outcome = yes = 1” versus “outcome = no = 0” subgroups.
2. The above “by outcome group” descriptive statistics are often sufficient for discrete covariates, but you may want to prepare some graphics for continuous variables. Recall that we did this for the age variable when looking at the CHD example.
3. For all continuous variables being considered, calculate a correlation matrix of each variable against each other variable. This allows one to begin to investigate possible confounding and collinearity.

4. Similarly, for each categorical/continuous independent variable pair, look at the values for the continuous variable in each category of the other variable.
5. Finally, create tables for all categorical/categorical independent variable pairs.
6. Perform a separate univariate logistic regression for each independent variable. This begins to investigate confounding (we will see in more detail next class), as well as providing an initial “unadjusted” view of the importance of each variable, by itself.
7. Think about any “interaction terms” that you may want to try in the model.
8. Perform some sort of model selection technique, or, often much better, think about avoiding any strict model selection by finding a set of models that seem to have something to contribute to overall conclusions.
9. Based on all work done, draw some inferences and conclusions. Carefully interpret each estimated parameter, perform “model criticism”, possibly repeating some of the above steps (for example, run further models), as needed.
10. Other inferences, such as predictions for future observations, and so on.

As with linear regression, the above should not be considered as “rules”, but rather as a rough guide as to how to proceed through a logistic regression analysis.

Logistic regression with dummy or indicator variables

Chapter 1 (section 1.6.1) of the Hosmer and Lemeshow book described a data set called ICU. Deleting the ID variable, there are 20 variables in this data set, which we describe in the table below:

Description	Coding	variable name
Vital Status (Main outcome)	0 = Lived 1 = Died	STA
Age	Years	AGE
Sex	0 = Male 1 = Female	SEX
Race	1 = White 2 = Black 3 = Other	RACE
Service at ICU Admission	0 = Medical 1 = Surgical	SER
Cancer Part of Present Problem	0 = No 1 = Yes	CAN
History of Chronic Renal Failure	0 = No 1 = Yes	CRN
Infection Probable at ICU Admission	0 = No 1 = Yes	INF
CPR Prior to ICU Admission	0 = No 1 = Yes	CPR
Systolic Blood Pressure at ICU Admission	mm Hg	SYS
Heart Rate at ICU Admission	Beats/min	HRA
Previous Admission to an ICU within 6 Months	0 = No 1 = Yes	PRE
Type of Admission	0 = Elective 1 = Emergency	TYP
Long Bone, Multiple, Neck, Single Area, or Hip Fracture	0 = No 1 = Yes	FRA
PO2 from Initial Blood Gases	0 > 60 1 ≤ 60	PO2
PH from Initial Blood Gases	0 ≥ 7.25 1 < 7.25	PH
PCO2 from initial Blood Gases	0 ≤ 45 1 > 45	PCO
Bicarbonate from Initial Blood Gases	0 ≥ 18 1 < 18	BIC
Creatinine from Initial Blood Gases	0 ≤ 2.0 1 > 2.0	CRE
Level of Consciousness at ICU Admission	0 = No Coma or Stupor 1 = Deep stupor 2 = Coma	LOC

The main outcome is vital status, alive or dead, coded as 0/1 respectively, under the variable name sta. For this illustrative example, we will investigate the effect of the dichotomous variables sex, ser, and loc. Later, we will look at more of the variables.

```
# read the data into R
```

```
> icu.dat <- read.table(file="g:\\icudat.txt", header = T)
```

```
# Take a quick look at the data
```

```
> summary(icu.dat)
```

sta	age	sex	race	ser
Min. :0.0	Min. :16.00	Min. :0.00	Min. :1.000	Min. :0.000
1st Qu.:0.0	1st Qu.:46.75	1st Qu.:0.00	1st Qu.:1.000	1st Qu.:0.000
Median :0.0	Median :63.00	Median :0.00	Median :1.000	Median :1.000
Mean :0.2	Mean :57.55	Mean :0.38	Mean :1.175	Mean :0.535
3rd Qu.:0.0	3rd Qu.:72.00	3rd Qu.:1.00	3rd Qu.:1.000	3rd Qu.:1.000
Max. :1.0	Max. :92.00	Max. :1.00	Max. :3.000	Max. :1.000
can	crn	inf	cpr	sys
Min. :0.0	Min. :0.000	Min. :0.00	Min. :0.000	Min. : 36.0
1st Qu.:0.0	1st Qu.:0.000	1st Qu.:0.00	1st Qu.:0.000	1st Qu.:110.0
Median :0.0	Median :0.000	Median :0.00	Median :0.000	Median :130.0
Mean :0.1	Mean :0.095	Mean :0.42	Mean :0.065	Mean :132.3
3rd Qu.:0.0	3rd Qu.:0.000	3rd Qu.:1.00	3rd Qu.:0.000	3rd Qu.:150.0
Max. :1.0	Max. :1.000	Max. :1.00	Max. :1.000	Max. :256.0
hra	pre	typ	fra	po2
Min. : 39.00	Min. :0.00	Min. :0.000	Min. :0.000	Min. :0.00
1st Qu.: 80.00	1st Qu.:0.00	1st Qu.:0.000	1st Qu.:0.000	1st Qu.:0.00
Median : 96.00	Median :0.00	Median :1.000	Median :0.000	Median :0.00
Mean : 98.92	Mean :0.15	Mean :0.735	Mean :0.075	Mean :0.08
3rd Qu.:118.25	3rd Qu.:0.00	3rd Qu.:1.000	3rd Qu.:0.000	3rd Qu.:0.00
Max. :192.00	Max. :1.00	Max. :1.000	Max. :1.000	Max. :1.00
ph	pco	bic	cre	loc
Min. :0.000	Min. :0.0	Min. :0.000	Min. :0.00	Min. :0.000
1st Qu.:0.000	1st Qu.:0.0	1st Qu.:0.000	1st Qu.:0.00	1st Qu.:0.000
Median :0.000	Median :0.0	Median :0.000	Median :0.00	Median :0.000
Mean :0.065	Mean :0.1	Mean :0.075	Mean :0.05	Mean :0.125
3rd Qu.:0.000	3rd Qu.:0.0	3rd Qu.:0.000	3rd Qu.:0.00	3rd Qu.:0.000
Max. :1.000	Max. :1.0	Max. :1.000	Max. :1.00	Max. :2.000

```
# Create the subset of variables we need
```

```
> icu1.dat <- data.frame(sta=icu.dat$sta, loc=icu.dat$loc,
```

```

sex=icu.dat$sex, ser=icu.dat$ser)

# Look at reduced data set

> summary(icu1.dat)
      sta      loc      sex      ser
Min.  :0.0   Min.  :0.000  Min.   :0.00  Min.   :0.000
1st Qu.:0.0   1st Qu.:0.000   1st Qu.:0.00  1st Qu.:0.000
Median :0.0   Median :0.000   Median :0.00  Median :1.000
Mean   :0.2   Mean   :0.125   Mean   :0.38  Mean   :0.535
3rd Qu.:0.0   3rd Qu.:0.000   3rd Qu.:1.00  3rd Qu.:1.000
Max.   :1.0   Max.   :2.000   Max.   :1.00  Max.   :1.000

# Notice that loc, sex, and ser need to be made into factor variables

icu1.dat <- data.frame(sta=icu.dat$sta, loc=as.factor(icu.dat$loc),
                      sex=as.factor(icu.dat$sex), ser=as.factor(icu.dat$ser))

# Look at reduced data set again, this time with factor variables

> summary(icu1.dat)
      sta      loc      sex      ser
Min.  :0.0   0:185   0:124   0: 93
1st Qu.:0.0   1: 5    1: 76   1:107
Median :0.0   2: 10
Mean   :0.2
3rd Qu.:0.0
Max.   :1.0

# Preliminary comments:
  - Not too many events, only 20% rate
  - loc may not be too useful, poor variability
  - sex and ser reasonably well balanced

# Create two by two tables of all variables, V1 = side, V2 = top

> table(icu1.dat$sta, icu1.dat$sex)

      0  1
0 100 60
1  24 16

# Not much difference observed
# (death rates: M 24/124= 0.19 ~ F 16/76 = 0.21)

```

```
> table(icu1.dat$sta, icu1.dat$ser)
```

```
  0  1
0 67 93
1 26 14
```

```
# Fewer deaths (sta=1) at the surgical unit (ser=1),
# OR = 67*14/(26*93) = 0.39
```

```
> table(icu1.dat$sta, icu1.dat$loc)
```

```
  0  1  2
0 158  0  2
1  27  5  8
```

```
# Probably very low accuracy here,
# but many more deaths in cats 1 and 2.
```

```
> table(icu1.dat$sex, icu1.dat$ser)
```

```
  0  1
0 54 70
1 39 37
```

```
# A bit, but not too much potential for confounding here,
# especially since effect of sex is not strong to begin with
```

```
> table(icu1.dat$sex, icu1.dat$loc)
```

```
  0  1  2
0 116  3  5
1  69  2  5
```

```
# Too few data points to say much, maybe females
# have higher values of loc
```

```
> table(icu1.dat$ser, icu1.dat$loc)
```

```
  0  1  2
0  84  2  7
1 101  3  3
```

```
# Again hard to say much
# Overall, loc does not look too useful, not much
# effect from any of these variables except maybe for ser.
```

```

# Simple logistic regression for each variable:

> output <- glm(sta ~ sex, data=icu1.dat, family=binomial)
> logistic.regression.or.ci(output)
$regression.table

Call:
glm(formula = sta ~ sex, family = binomial, data = icu1.dat)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6876  -0.6876  -0.6559  -0.6559   1.8123

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.4271      0.2273  -6.278 3.42e-10 ***
sex1           0.1054      0.3617   0.291  0.771
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 200.16  on 199  degrees of freedom
Residual deviance: 200.08  on 198  degrees of freedom
AIC: 204.08

Number of Fisher Scoring iterations: 4

$intercept.ci
[1] -1.8726220 -0.9816107

$slopes.ci
[1] -0.6035757  0.8142967

$OR
    sex1
1.111111

$OR.ci
[1] 0.5468528 2.2575874

# Very wide CI, result is inconclusive for sex covariate,
# as both endpoints of potential clinical interest.

```

```

> output <- glm(sta ~ ser, data=icu1.dat, family=binomial)
> logistic.regression.or.ci(output)
$regression.table

Call:
glm(formula = sta ~ ser, family = binomial, data = icu1.dat)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8098 -0.8098 -0.5296 -0.5296  2.0168

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.9466     0.2311  -4.097 4.19e-05 ***
ser1         -0.9469     0.3682  -2.572  0.0101 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 200.16  on 199  degrees of freedom
Residual deviance: 193.24  on 198  degrees of freedom
AIC: 197.24

Number of Fisher Scoring iterations: 4

$intercept.ci
[1] -1.3994574 -0.4937348

$slopes.ci
[1] -1.6685958 -0.2252964

$OR
      ser1
0.3879239

$OR.ci
[1] 0.1885116 0.7982796

# OR < 1, being in surgical unit may save lives,
# CI shows at least a 20% effect (approximately).

```

```

> output <- glm(sta ~ loc, data=icu1.dat, family=binomial)
> logistic.regression.or.ci(output)
$regression.table

Call:
glm(formula = sta ~ loc, family = binomial, data = icu1.dat)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7941  -0.5617  -0.5617  -0.5617   1.9619

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.7668     0.2082  -8.484 < 2e-16 ***
loc1          18.3328    1073.1090   0.017 0.986370
loc2           3.1531     0.8175   3.857 0.000115 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 200.16  on 199  degrees of freedom
Residual deviance: 163.78  on 197  degrees of freedom
AIC: 169.78

Number of Fisher Scoring iterations: 15

$intercept.ci
[1] -2.174912 -1.358605

$slopes.ci
          [,1]      [,2]
[1,] -2084.922247 2121.587900
[2,]   1.550710   4.755395

$OR
      loc1      loc2
9.158944e+07 2.340741e+01

$OR.ci
          [,1]      [,2]
[1,] 0.000000      Inf
[2,] 4.714817 116.2095

```

```

# As we suspected, too few data points to analyze this variable
# results are completely non-informative

# Drop loc from further analyses

# Multivariate logistic model for sex and ser

> output <- glm(sta ~ sex + ser, data=icu1.dat, family=binomial)
> logistic.regression.or.ci(output)
$regression.table

Call:
glm(formula = sta ~ sex + ser, family = binomial, data = icu1.dat)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8168  -0.8048  -0.5266  -0.5266   2.0221

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.96129    0.27885  -3.447 0.000566 ***
sex1         0.03488    0.36896   0.095 0.924688
ser1        -0.94442    0.36915  -2.558 0.010516 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 200.16  on 199  degrees of freedom
Residual deviance: 193.23  on 197  degrees of freedom
AIC: 199.23

Number of Fisher Scoring iterations: 4

$intercept.ci
[1] -1.5078281 -0.4147469

$slopes.ci
      [,1]      [,2]
[1,] -0.6882692  0.758025
[2,] -1.6679299 -0.220904

$OR
      sex1      ser1

```

```
1.0354933 0.3889063
```

```
$OR.ci
```

```
      [,1]      [,2]
[1,] 0.5024449 2.1340574
[2,] 0.1886372 0.8017936
```

```
# Almost identical results as for univariate model
# As we suspected, no confounding.
```

```
# Overall conclusion: Service at ICU Admission (ser)
# seems to be associated with a strong effect, the
# surgical unit being associated with fewer deaths
# (OR = 0.39, 95% CI = (.19, 0.80). Nothing much
# can be said about sex or loc, results are inconclusive.
```

```
# Can predict some death rates depending on sex/ser categories:
```

```
# Create a data set for all possible category combinations:
```

```
> newdata <- data.frame(sex=as.factor(c(0,0,1,1)), ser=as.factor(c(0,1,0,1)))
```

```
> newdata
```

```
  sex ser
1   0   0
2   0   1
3   1   0
4   1   1
```

```
# Predict outcome probabilities for these four categories:
```

```
> predict(output, newdata=newdata)
      1      2      3      4
-0.9612875 -1.9057045 -0.9264096 -1.8708266
```

```
# Above are on the logit scale, more useful to do this:
```

```
> predict(output, newdata=newdata, type="response")
      1      2      3      4
0.2766205 0.1294642 0.2836537 0.1334461
```

```
# Above are predictions on probability scale.
# Can see poor results when ser = 0, two sexes are similar in rate.
```

Logistic regression example with many variables

We will continue with the same example, but now consider many more variables, including both categorical and continuous variables.

Very shortly, we will see an excellent way to simultaneously select a model and to investigate confounding in data sets with a large number of variables. For now, we will take a quick look at logistic regression using four variables from the ICU data set: Age, sex, ser, and typ.

```
# Read in full data set

icu.dat <- read.table(file="g:\\icudat.txt", header = T)

# Create the reduced data set we will use:

> icu2.dat <- data.frame(sta=icu.dat$sta, sex=as.factor(icu.dat$sex),
  ser=as.factor(icu.dat$ser), age = icu.dat$age, typ=as.factor(icu.dat$typ))

# Check descriptive statistics

> summary(icu2.dat)
  sta      sex      ser      age      typ
Min.   :0.0    0:124    0: 93   Min.    :16.00   0: 53
1st Qu.:0.0    1: 76    1:107   1st Qu.:46.75   1:147
Median :0.0
Mean   :0.2
3rd Qu.:0.0
Max.   :1.0
      Median :63.00
      Mean   :57.55
      3rd Qu.:72.00
      Max.   :92.00

# Quick look at correlations

# Check effect of age and typ, two variables we did
# not look at before

> table(icu2.dat$sta, icu2.dat$typ)

  0  1
0 51 109
1  2  38

# Looks like a large effect: those presenting at
# emergency (typ=1) have a much higher death rate.
```

```

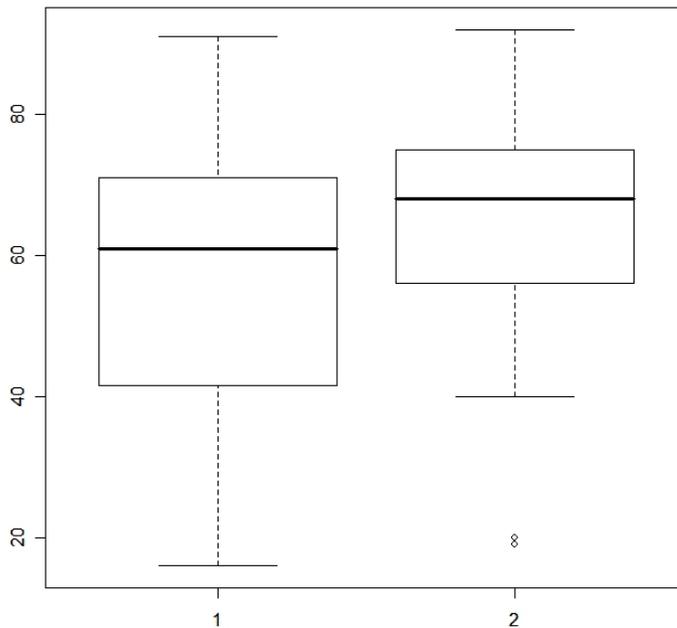
# Let's also look at a table between ser and typ:
> table(icu2.dat$ser, icu2.dat$typ)

  0  1
0  1 92
1 52 55

# Looks like there could be some confounding here,
# these are strongly related.

# Check the association between age and the outcome, sta
> boxplot(list(icu2.dat$age[icu2.dat$sta==0], icu2.dat$age[icu2.dat$sta==1]))

```



It looks like those with higher ages also have higher death rates.

Let's look at a regression with all five variables included:

```
> output <- glm(sta ~ sex + ser + age + typ, data=icu2.dat, family=binomial)
> logistic.regression.or.ci(output)
$regression.table
```

Call:

```
glm(formula = sta ~ sex + ser + age + typ, family = binomial,
     data = icu2.dat)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.2753	-0.7844	-0.3920	-0.2281	2.5072

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-5.26359	1.11678	-4.713	2.44e-06	***
sex1	-0.20092	0.39228	-0.512	0.60851	
ser1	-0.23891	0.41697	-0.573	0.56667	
age	0.03473	0.01098	3.162	0.00156	**
typ1	2.33065	0.80238	2.905	0.00368	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 200.16 on 199 degrees of freedom
 Residual deviance: 172.42 on 195 degrees of freedom
 AIC: 182.42

Number of Fisher Scoring iterations: 6

\$intercept.ci

[1] -7.452432 -3.074752

\$slopes.ci

	[,1]	[,2]
[1,]	-0.96976797	0.56792495
[2,]	-1.05615818	0.57834395
[3,]	0.01320442	0.05624833
[4,]	0.75801170	3.90328595

\$OR

sex1	ser1	age	typ1
0.8179766	0.7874880	1.0353364	10.2846123

```
$OR.ci
      [,1]      [,2]
[1,] 0.3791710 1.764602
[2,] 0.3477894 1.783083
[3,] 1.0132920 1.057860
[4,] 2.1340289 49.565050
```

As expected, age has a strong effect, with an odds ratio of 1.035 per year, or $1.035^{10} = 1.41$ per decade (95% CI per year of (1.013, 1.058), so (1.138, 1.757) per decade). Typ also has a very strong effect, with a CI of at least 2.

There does indeed seem to be some confounding between ser and typ, as the coefficient estimate for ser has changed drastically from when typ was not in the model. In fact, ser no longer looks “important”, it has been “replaced” by typ. Because of the high correlation between ser and typ, it is difficult to separate out the effects of these two variables.

We will return to this issue when we discuss model selection for logistic regression.

Logistic regression with interaction terms

Going back to the example where we had just sex and ser in the model, what if we wanted to investigate an interaction term between these two variables?

So far, we have seen that ser is associated with a strong effect, but the effect of sex was inconclusive. But, what if the effect of ser is different among males and females, i.e., what if we have an interaction (or sometimes called *effect modification*) between sex and ser?

Here is how to investigate this for logistic regression in R:

```
# Create the variable that will be used in the interaction:

# Create a blank vector to store new variable

> ser.sex <- rep(0, length(icu1.dat$ser))

# Change value to 1 when both ser and sex are one

> for (i in 1:length(icu1.dat$ser)) {if (icu1.dat$ser[i] == 1
    & icu1.dat$sex[i] == 1) ser.sex[i] <- 1 }

# Check new variable
```

```

> ser.sex
  [1] 0 0 0 0 1 0 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 1 1 1
 [36] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 1 0
 [71] 0 0 0 1 0 0 0 1 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0
[106] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1
[141] 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0
[176] 0 0 0 1 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

```

```

# Add new variable to data.frame,
# since all 0/1, do not bother with factors here

> icu3.dat <- data.frame(sta = icu1.dat$sta,
  ser = icu1.dat$ser, sex = icu1.dat$sex, ser.sex = ser.sex)

> summary(icu3.dat)
      sta      ser      sex      ser.sex
Min.   :0.0   Min.   :0.000  Min.   :0.00   Min.   :0.000
1st Qu.:0.0   1st Qu.:0.000   1st Qu.:0.00   1st Qu.:0.000
Median :0.0   Median :1.000   Median :0.00   Median :0.000
Mean   :0.2   Mean   :0.535   Mean   :0.38   Mean   :0.185
3rd Qu.:0.0   3rd Qu.:1.000   3rd Qu.:1.00   3rd Qu.:0.000
Max.   :1.0   Max.   :1.000   Max.   :1.00   Max.   :1.000

```

```

> Estimate the logistic regression model with interaction:

> output <- glm(sta ~ sex + ser + ser.sex, data=icu3.dat, family=binomial)

> logistic.regression.or.ci(output)
$regression.table

Call:
glm(formula = sta ~ sex + ser + ser.sex, family = binomial, data = icu3.dat)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8696  -0.7244  -0.4590  -0.4590   2.1460

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.7777     0.2930  -2.654  0.00795 **
sex           -0.4263     0.4799  -0.888  0.37440
ser          -1.4195     0.4945  -2.870  0.00410 **
ser.sex       1.1682     0.7518   1.554  0.12021
---

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 200.16 on 199 degrees of freedom
 Residual deviance: 190.81 on 196 degrees of freedom
 AIC: 198.81

Number of Fisher Scoring iterations: 4

\$intercept.ci

[1] -1.3519790 -0.2034301

\$slopes.ci

	[,1]	[,2]
[1,]	-1.366836	0.5142995
[2,]	-2.388770	-0.4502697
[3,]	-0.305277	2.6416881

\$OR

	sex	ser	ser.sex
	0.6529412	0.2418301	3.2162162

\$OR.ci

	[,1]	[,2]
[1,]	0.25491223	1.6724666
[2,]	0.09174244	0.6374562
[3,]	0.73691921	14.0368799

Looking at the confidence interval, the result is inconclusive,
 # but we can certainly not rule out an interaction term, OR = 3.22.

Possibly some confounding as well, so cannot conclude any strong result.

Note on ORs in presence of interactions

Note that one needs to be careful in interpreting the Odds Ratios from the above outputs, because of the interaction term.

The OR given above for the *sex* variable, 0.653, applies only within the medical service (coded as 0 in the *ser* variable), and the OR given above for *ser*, 0.242, applies only within males (coded 0 in the *sex* variable).

In order to obtain the OR for *sex* within the *ser* = 1 (surgical category), or to obtain the OR for *ser* within females (*sex* = 1), one needs to multiply by the OR from the interaction term. Hence, we have:

OR for *ser* within females = $0.242 * 3.22 = 0.779$.

OR for *sex* within surgical unit = $0.653 * 3.22 = 2.10$.