

Lab 8: Logistic Regression

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The Default Data Set

Consider the `Default` data set that comes in the R package "ISLR". We are interested in predicting whether an individual will default on his or her credit card payment, on the basis of annual income and monthly credit card balance.

```
# remember to load package ISLR!
```

```
names(Default)
```

```
## [1] "default" "student" "balance" "income"
```

```
dim(Default)
```

```
## [1] 10000      4
```

```
summary(Default)
```

```
## default      student      balance      income
## No :9667      No :7056      Min.   :  0.0      Min.   :  772
## Yes: 333      Yes:2944      1st Qu.: 481.7      1st Qu.:21340
##                                     Median : 823.6      Median :34553
##                                     Mean   : 835.4      Mean   :33517
##                                     3rd Qu.:1166.3      3rd Qu.:43808
##                                     Max.   :2654.3      Max.   :73554
```

```
summary(subset(Default, default == 'Yes'))
```

```
## default      student      balance      income
## No :  0      No :206      Min.   : 652.4      Min.   : 9664
## Yes:333      Yes:127      1st Qu.:1511.6      1st Qu.:19028
##                                     Median :1789.1      Median :31515
##                                     Mean   :1747.8      Mean   :32089
##                                     3rd Qu.:1988.9      3rd Qu.:43067
##                                     Max.   :2654.3      Max.   :66466
```

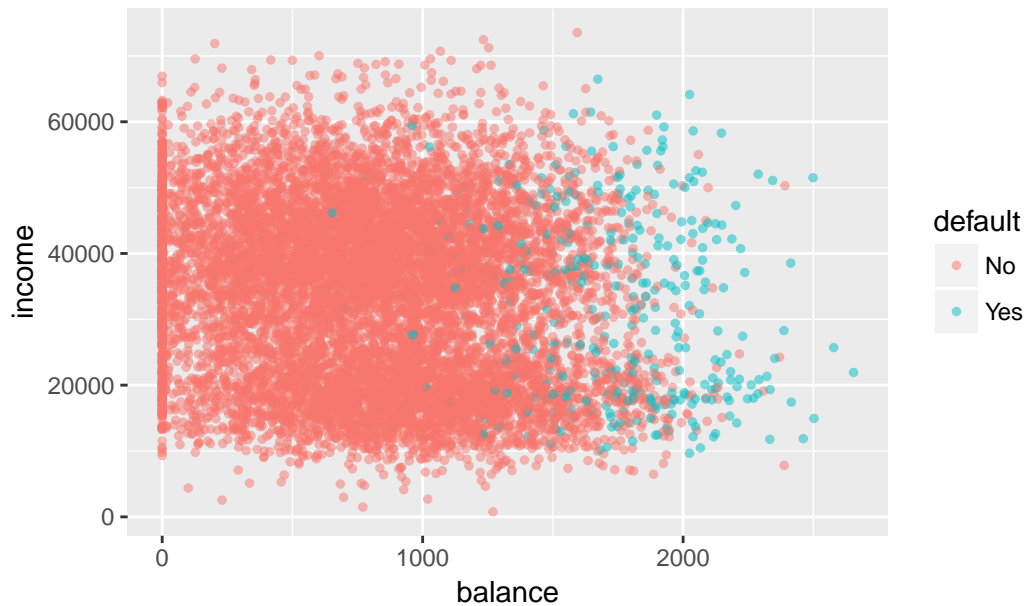
```
summary(subset(Default, default == 'No'))
```

```
## default      student      balance      income
## No :9667      No :6850      Min.   :  0.0      Min.   :  772
## Yes:  0      Yes:2817      1st Qu.: 465.7      1st Qu.:21405
##                                     Median : 802.9      Median :34589
```

```
##           Mean    : 803.9    Mean    :33566
##           3rd Qu.:1128.2    3rd Qu.:43824
##           Max.   :2391.0    Max.   :73554
```

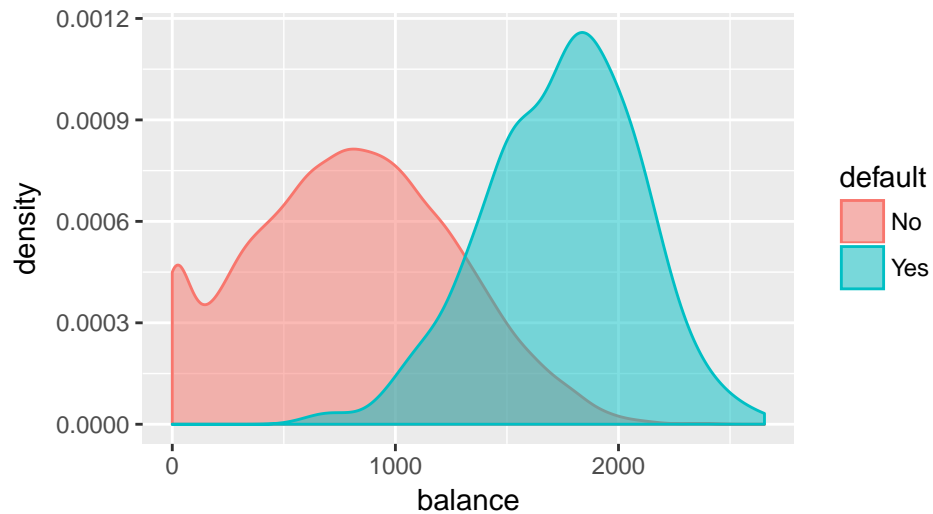
Begin with some exploratory displays of the data. You can start with a scatterplot of **balance** and **income**, distinguishing observations based on **default**, like in the image below

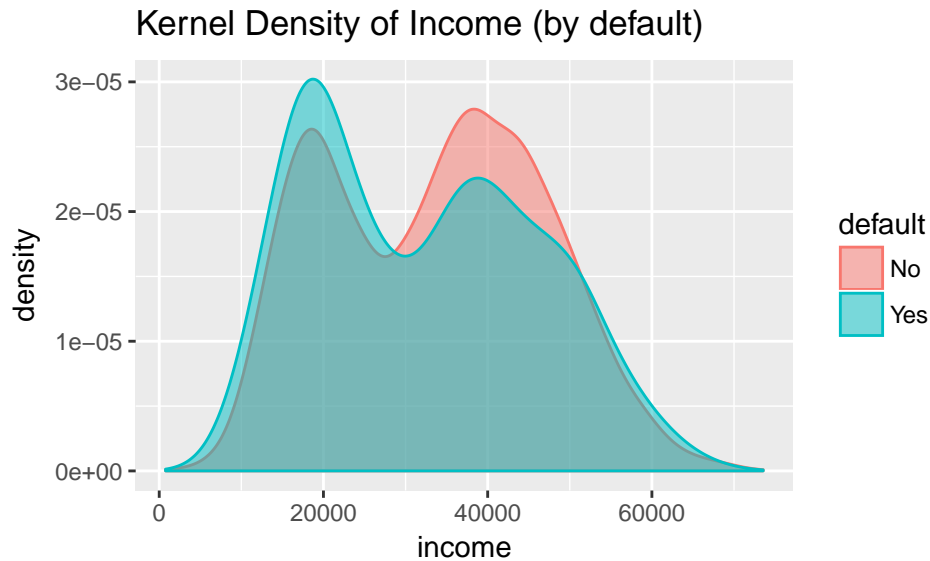
Scatterplot between Balance and Income



Make density plots of **balance** and **income**, for instance:

Kernel Density of Balance (by default)





OLS Regression

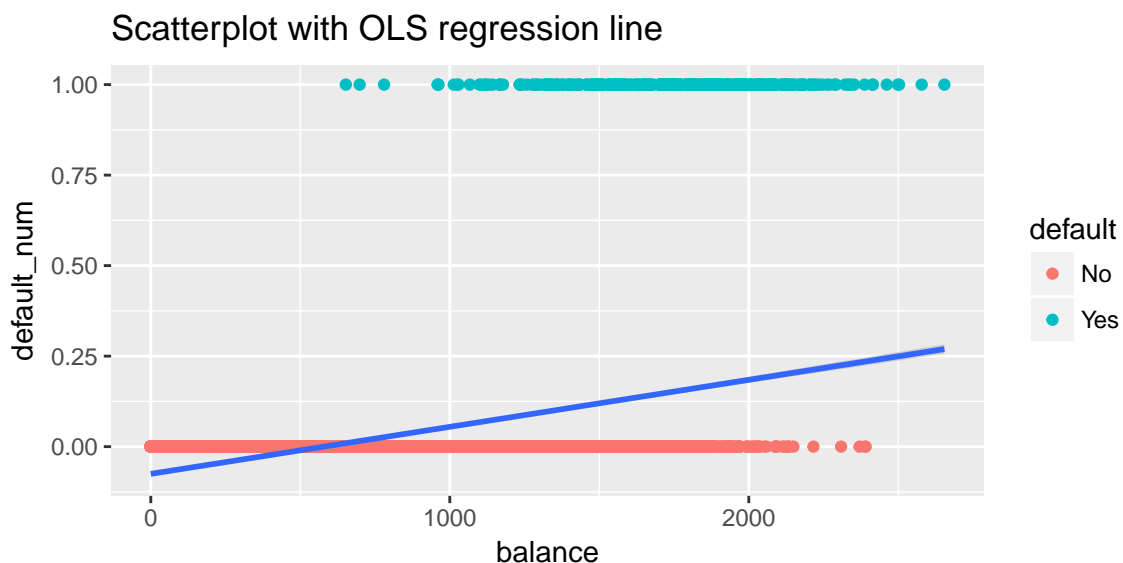
Out of curiosity, let's fit an OLS model by regressing `default` on `balance`. Because `default` is a factor, you should create a numeric `default` vector:

```
# code default as numeric
default_numeric <- rep(0, nrow(Default))
default_numeric[Default$default == 'Yes'] <- 1
Default$default_num <- default_numeric

ols_reg <- lm(default_num ~ balance, data = Default)
summary(ols_reg)
```

```
##
## Call:
## lm(formula = default_num ~ balance, data = Default)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.23533 -0.06939 -0.02628  0.02004  0.99046
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7.519e-02  3.354e-03  -22.42  <2e-16 ***
## balance      1.299e-04  3.475e-06   37.37  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1681 on 9998 degrees of freedom
```

```
## Multiple R-squared:  0.1226, Adjusted R-squared:  0.1225
## F-statistic: 1397 on 1 and 9998 DF,  p-value: < 2.2e-16
```



Logistic Regression

The response `default` falls into one of two categories: "Yes" or "No". Rather than modeling `default` directly, logistic regression models the probability that the response Y belongs to a particular category.

The probability of default given `balance` can be written as:

$$Pr(\text{default} = \text{Yes} | \text{balance})$$

To fit a logistic regression model you use the function `glm()`. The syntax of `glm()` is similar to that of `lm()`, except you must specify the argument `family = binomial` in order to tell R to run a logistic regression rather than some other type of generalized linear model.

Notice that `glm()` knows how to handle the response `default` which is a factor:

```
logreg_default <- glm(default ~ balance, family = binomial, data = Default)
summary(logreg_default)$coefficients
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -10.651330614 0.3611573721 -29.49221 3.623124e-191
## balance      0.005498917 0.0002203702  24.95309 1.976602e-137
```

How do we interpret the coefficients? A one-unit increase in `balance` is associated with an increase in the log odds of `default` by 0.005 units.

Many aspects of the logistic regression output shown in the `summary()` are similar to the `lm()` output. For example, you can measure the accuracy of the coefficient estimates by computing their standard errors.

To make predictions we can use the coefficient estimates. For instance, the predicted default probability for an individual with a `balance` of \$1,000 is:

$$\hat{p}(X) = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 X}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 X}} = \frac{e^{-10.6513 + 0.0055 \times 1000}}{1 + e^{-10.6513 + 0.0055 \times 1000}} = 0.00576$$

which is below 1%. In contrast, the predicted probability of default for an individual with a balance of \$2,000 is 0.586 or 58.6%.

Your turn

- Find out how to use `predict()` to obtain the probability of default for individuals with `balance` values of \$100, \$200, \$300, ..., \$2,000
- Fit another logistic regression model by regressing `default` on `student`. How would you interpret the coefficient estimate?
- Fit a third logistic regression by regressing `default` on `balance`, `student`, and `income`.
- Are all coefficient estimates significant?
- How would you explain the apparent contradiction between the opposite signs of the `student` coefficients (this regression versus the previous one)?
- Answer to these questions are in pages 134-137 of ISL.

The Stock Market Smarket Data

You will be working with the `Smarket` data, which is part of the "ISLR" package. This data consists of percentage returns from the S&P 500 stock index over 1,250 days, from the beginning of 2001 until the end of 2005. For each date, the percentage returns for each of the five previous tradings has been records, `Lag1` through `Lag5`. Other variables are:

- `Volume` = the number of shares traded on the previous day, in billions
- `Today` = the percentage return on the data in question
- `Direction` = whether the market was Up or Down on this date

```
# remember to load package ISLR
names(Smarket)
```

```
## [1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"
## [7] "Volume"    "Today"     "Direction"
```

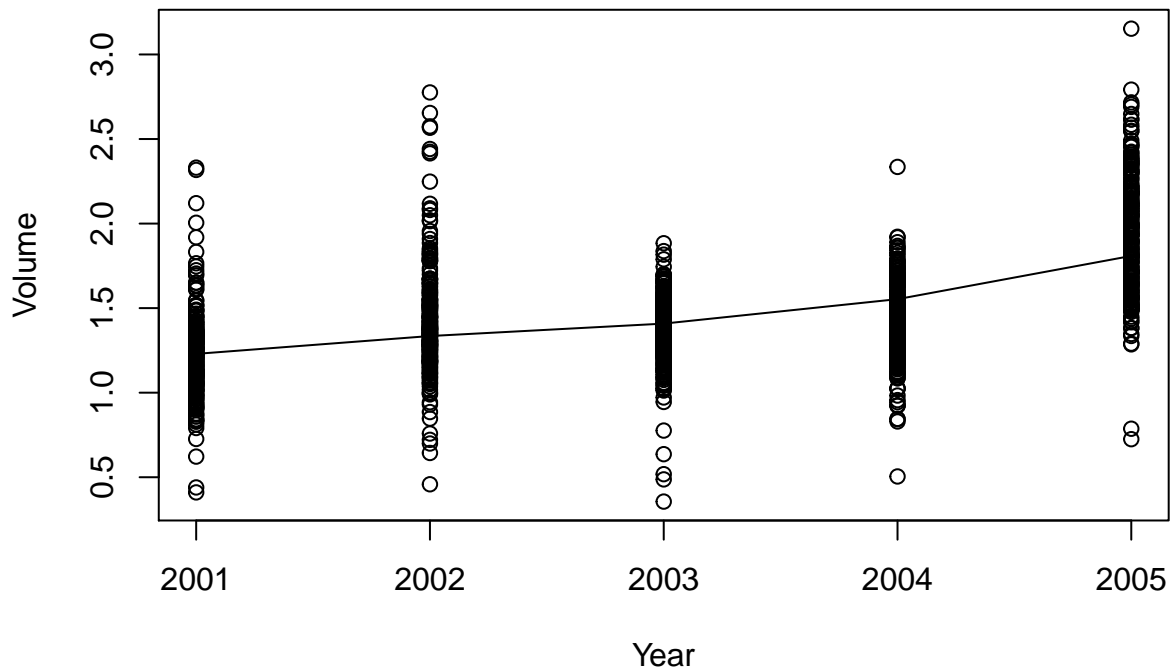
```
dim(Smarket)
```

```
## [1] 1250    9
```

```
summary(Smarket)
```

```
##      Year      Lag1      Lag2
## Min.   :2001  Min.   :-4.922000  Min.   :-4.922000
## 1st Qu.:2002  1st Qu.: -0.639500  1st Qu.: -0.639500
## Median :2003  Median : 0.039000  Median : 0.039000
## Mean   :2003  Mean   : 0.003834  Mean   : 0.003919
## 3rd Qu.:2004  3rd Qu.: 0.596750  3rd Qu.: 0.596750
## Max.   :2005  Max.   : 5.733000  Max.   : 5.733000
##      Lag3      Lag4      Lag5
## Min.   :-4.922000  Min.   :-4.922000  Min.   :-4.922000
## 1st Qu.: -0.640000  1st Qu.: -0.640000  1st Qu.: -0.640000
## Median : 0.038500  Median : 0.038500  Median : 0.038500
## Mean   : 0.001716  Mean   : 0.001636  Mean   : 0.00561
## 3rd Qu.: 0.596750  3rd Qu.: 0.596750  3rd Qu.: 0.59700
## Max.   : 5.733000  Max.   : 5.733000  Max.   : 5.73300
##      Volume      Today      Direction
## Min.   :0.3561  Min.   :-4.922000  Down:602
## 1st Qu.:1.2574  1st Qu.: -0.639500  Up  :648
## Median :1.4229  Median : 0.038500
## Mean   :1.4783  Mean   : 0.003138
## 3rd Qu.:1.6417  3rd Qu.: 0.596750
## Max.   :3.1525  Max.   : 5.733000
```

- Compute the matrix of correlations of the variables in `Smarket`, excluding the variable `Direction`
- Perform a PCA on `Smarket[, -9]` to get a visual display of the variables. You can accomplish this with the function `PCA()` from the "FactoMineR" package. By default, it plots a *circle of correlations*
- How correlated are the lag variables with today's returns? Are previous day's returns highly correlated with today's returns?
- Make a scatterplot of `Year` and `Volume`



Logistic Regression

Use the `glm()` function to fit a logistic regression model in order to predict `Direction` using `Lag1` through `Lag5` and `Volume`.

- Inspect the `summary()` of the "glm" object containing the output of the logistic regression.
- Looking at the p-values of the regression coefficients, which coefficient seems to be significant?
- What is the coefficient value of `Lag1`? How would you interpret the sign of this coefficient?
- Use the `predict()` function to predict the probability that the market will go up, given values of the predictors. Use the argument `type = "response"` which tells R to output probabilities of the form $P(Y = 1|X)$, as oppose to other information such as the logit. The first 10 probabilities look like this:

```
##           1           2           3           4           5           6           7
## 0.5070841 0.4814679 0.4811388 0.5152224 0.5107812 0.5069565 0.4926509
##           8           9          10
## 0.5092292 0.5176135 0.4888378
```

Estimation of Parameters

In this part of the lab, your mission is to implement code in R that allows you to estimate the logistic regression coefficients.

The estimation of the coefficients is carried out by Maximum Likelihood. Consider, for instance, a logistic model with one predictor and one response. We look for $\hat{\beta}_0$ and $\hat{\beta}_1$ that maximize the log-likelihood $l(\hat{\beta}_0, \hat{\beta}_1)$. To do so, we set the first order partial derivatives of $l(\beta)$ to zero.

$$\begin{aligned}\frac{\partial l(\beta)}{\partial \beta_0} &= \sum_{i=1}^n (y_i - p(x_i)) = 0 \\ \frac{\partial l(\beta)}{\partial \beta_1} &= \sum_{i=1}^n x_i (y_i - p(x_i)) = 0\end{aligned}$$

Unfortunately, there is no analytical solution to this problem. So how do you actually compute the estimates? Using the Newton-Raphson algorithm.

- Let \mathbf{y} be the column vector of response Y
- Let \mathbf{X} be the $n \times (p + 1)$ input (design) matrix
- Let \mathbf{p} be the n -vector of fitted probabilities with the i -th element $p(x_i; \beta^{old})$
- Let \mathbf{W} be an $n \times n$ diagonal matrix of weights with i -th element $p(x_i; \beta^{old})(1 - p(x_i; \beta^{old}))$

Then:

$$\begin{aligned}\frac{\partial l(\beta)}{\partial \beta} &= \mathbf{X}^\top (\mathbf{y} - \mathbf{p}) \\ \frac{\partial^2 l(\beta)}{\partial \beta \partial \beta^\top} &= -\mathbf{X}^\top \mathbf{W} \mathbf{X}\end{aligned}$$

Newton-Raphson algorithm

Here's the pseudo-code to obtain the estimate coefficients.

1. $\mathbf{b}^{old} \leftarrow \mathbf{0}$
2. Compute \mathbf{p} by setting its elements to:

$$p(x_i) = \frac{e^{\mathbf{x}_i^\top \mathbf{b}^{old}}}{1 + e^{\mathbf{x}_i^\top \mathbf{b}^{old}}}$$

3. Compute the diagonal matrix \mathbf{W} with the i -th diagonal element: $p(x_i)(1 - p(x_i))$, $i = 1, \dots, n$

4. $\mathbf{z} \leftarrow \mathbf{X}\mathbf{b}^{\text{old}} + \mathbf{W}^{-1}(\mathbf{y} - \mathbf{p})$
5. $\mathbf{b}^{\text{new}} \leftarrow (\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W} \mathbf{z}$
6. Check whether \mathbf{b}^{old} and \mathbf{b}^{new} are close “enough”, otherwise update $\mathbf{b}^{\text{old}} \leftarrow \mathbf{b}^{\text{new}}$, and go back to step 2.

Your turn: Write code in R for the algorithm described above. Use the `Lag` variables and `Volume` as predictors, and `Direction` as response. You will have to convert `Direction` into a numeric vector by converting 'Up' to 1 and 'Down' to 0.

Simplified Algorithm

Since \mathbf{W} is an $n \times n$ diagonal matrix, direct matrix operations with it may be very inefficient. A modified pseudo code is provided next.

1. $\mathbf{b}^{\text{old}} \leftarrow \mathbf{0}$
2. Compute \mathbf{p} by setting its elements to:

$$p(x_i) = \frac{e^{\mathbf{x}_i^T \mathbf{b}^{\text{old}}}}{1 + e^{\mathbf{x}_i^T \mathbf{b}^{\text{old}}}}$$

3. Compute the $n \times (p + 1)$ matrix $\tilde{\mathbf{X}}$ by multiplying the i -th row of matrix \mathbf{X} by $p(x_i)(1 - p(x_i))$, $i = 1, \dots, n$
4. $\mathbf{b}^{\text{new}} \leftarrow \mathbf{b}^{\text{old}} + (\mathbf{X}^T \tilde{\mathbf{X}})^{-1} \mathbf{X}^T (\mathbf{y} - \mathbf{p})$
5. Check whether \mathbf{b}^{old} and \mathbf{b}^{new} are close “enough”, otherwise update $\mathbf{b}^{\text{old}} \leftarrow \mathbf{b}^{\text{new}}$, and go back to step 2.

Your turn: Write code in R for the simplified algorithm described above. Use the `Lag` variables and `Volume` as predictors, and `Direction` as response. You will have to convert `Direction` into a numeric vector by converting 'Up' to 1 and 'Down' to 0.