MA5810: Introduction to Data Mining

Week 3; Collaborate Session 1: Logistic Regression

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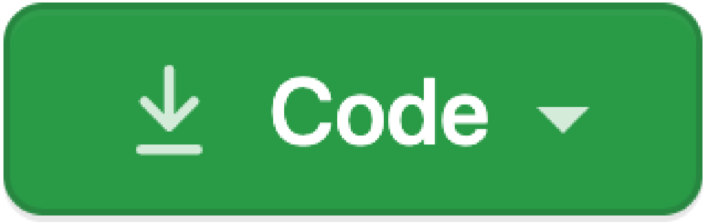
2019-21-9 (updated: 2020-11-05)

Housekeeping

- Collaborate 1 = Wednesdays 6-7pm (Martha)
- Collaborate 2 = Thursdays 7-8pm (Hongbin)

For my Collaborate Sessions, you can get the slides & R code for each week here:

https://github.com/MarthaCooper/MA5810



Subject: MA5810 Intro to Data Mining

MA5810 Learning Outcomes

1. Overview of Data Mining and Examples
2. Unsupervised data mining methods e.g. clustering and outlier detection;
3. Unsupervised and supervised techniques for dimensionality reduction;
4. Supervised data mining methods for pattern classification (Today = Logistic Regression);
5. Apply these concepts to real data sets using R (Today).

Today's Goals

- Understand the background behind Logistic Regression
- Apply Logistic Regressions to real datasets using R
- Understand the pros and cons of Logistic Regression

Linear Regression Review

- The simple linear regression model is:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Where

- Y is the dependent variable
- $beta_0$ is the intercept (Y when $X = 0$)
- $beta_1$ is the slope of the regression line
- $epsilon$ is the error term

Multiple Linear Regression Review

- Multiple regression with k independent variables

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon$$

- When interpreting one of the slopes in multiple regression model, we should take into account the effect of the other variables

- For instance, β_1 represents the change in Y per 1 unit change in X_1 , holding other variables $(X_2, \ldots, X_k)$ constant

Generalised Linear Models & Classification

- GLM: Appropriate when Y isn't normally distributed but is in the exponential family of distributions

- In classification where Y is binomial (or multinomial)

- Given these features, does this sample belong to class A or B?

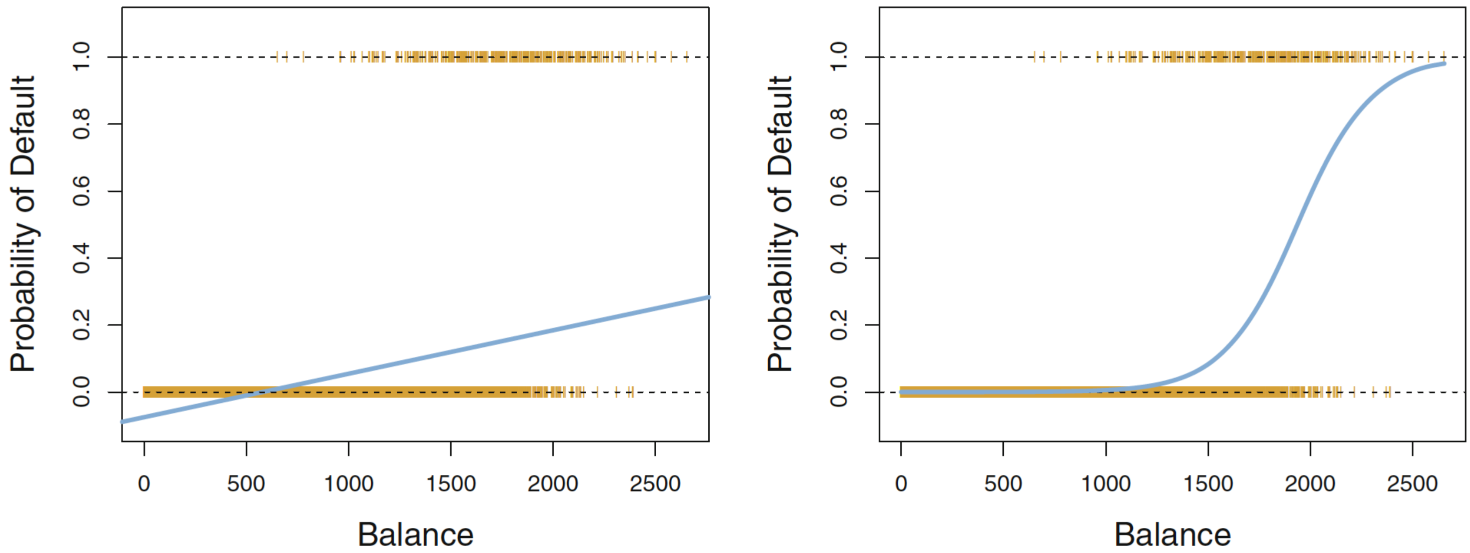
$$
\begin{aligned}
cancer &\in \{yes, no\} \\
credit\ card &\in \{defalt, not\ default\} \\
win\ &\in \{yes, no\} \\
drug\ &\in \{survived, not\ survived\}
\end{aligned}
$$

Logistic Regression

- Binomial family Generalised Linear Model
- Models the probability that Y belongs to a particular category

Logistic Regression

- Binomial family Generalised Linear Model
- Models the probability that a subject belongs to a particular category

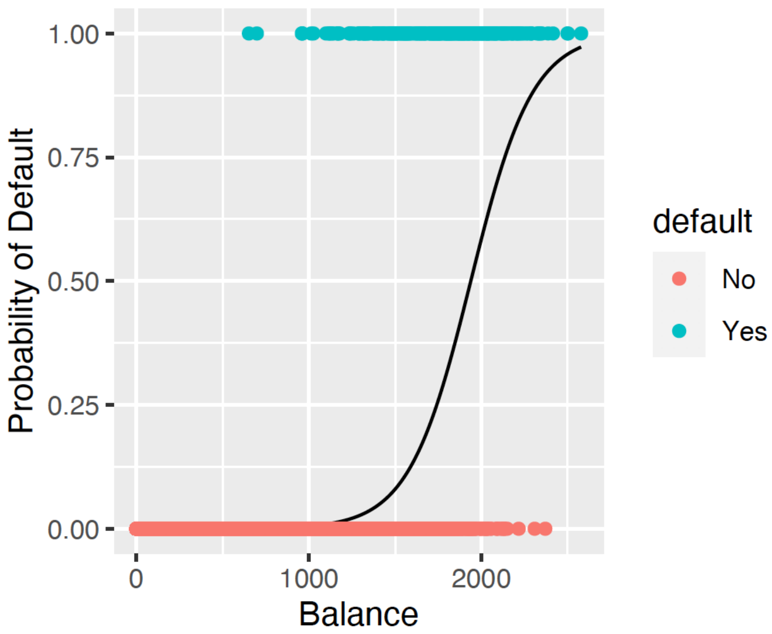


Problems with Linear Regression for Classification

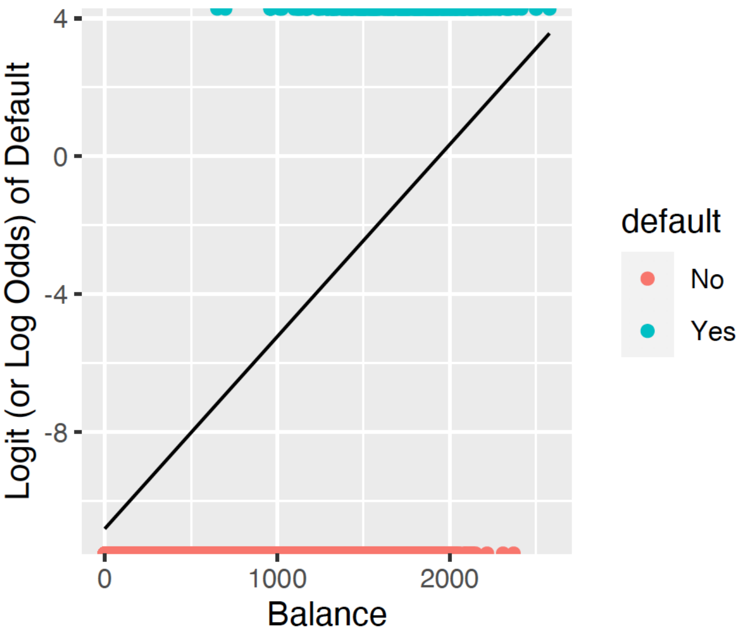
- Some values are outside [0,1]
- For multinomial classification, the order and interval between classes would be considered important and meaningful

The Logistic Model

Probability

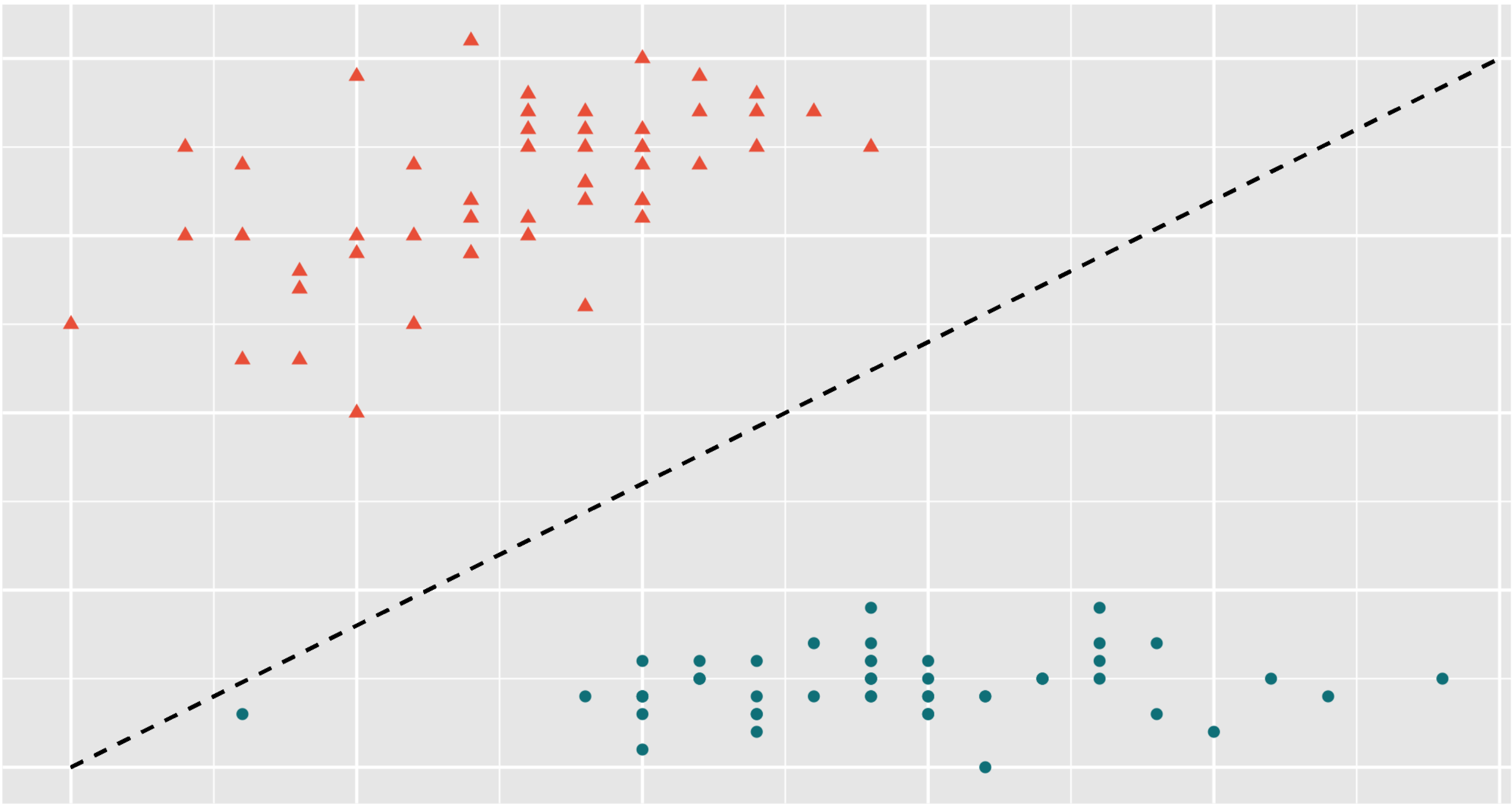


Logit or Log Odds



Estimating the coefficients

Maximum Likelihood



Logistic Regression Pros and Cons

Pros

- Identify which features are important for classification
- Interpret how important each feature is for classification

Cons

- Doesn't perform well if the decision boundary isn't linear
- Two groups (although extensions make more possible)

Logistic Regression in R

```
#load data
library(ISLR, warn.conflicts = F, quietly = T) #for data
library(caret, warn.conflicts = F, quietly = T) #for splitting the data
library(dplyr, warn.conflicts = F, quietly = T) #for piping

data("Default") #credit card default data from ISLR
str(Default)

#split into training (80%) and test
split <- createDataPartition(Default$default, p = 0.8, list = F)

train <- Default[split, ]
test <- Default[-split, ]

c(nrow(train), nrow(test)) # print number of observations in test vs. t

table(train$default) %>% prop.table() # Proportions of people that defa

#Train the model to predict the likelihood of default status based on c
def_logmod1 <- glm(default ~ balance, data = train, family = "binomial")
```

Interpretting the coefficients

```
summary(def_logmod1)$coef #interpret the coefficients
```

```
##                  Estimate    Std. Error   z value      Pr(>|z|)
## (Intercept) -10.667896998 0.4047941470 -26.35388 4.632708e-153
## balance       0.005524981 0.0002477719  22.29866 3.807597e-110
```

- β_0 : Log odds
- β_1 : Log odds ratio

Making predictions in R

- make predictions based on training data

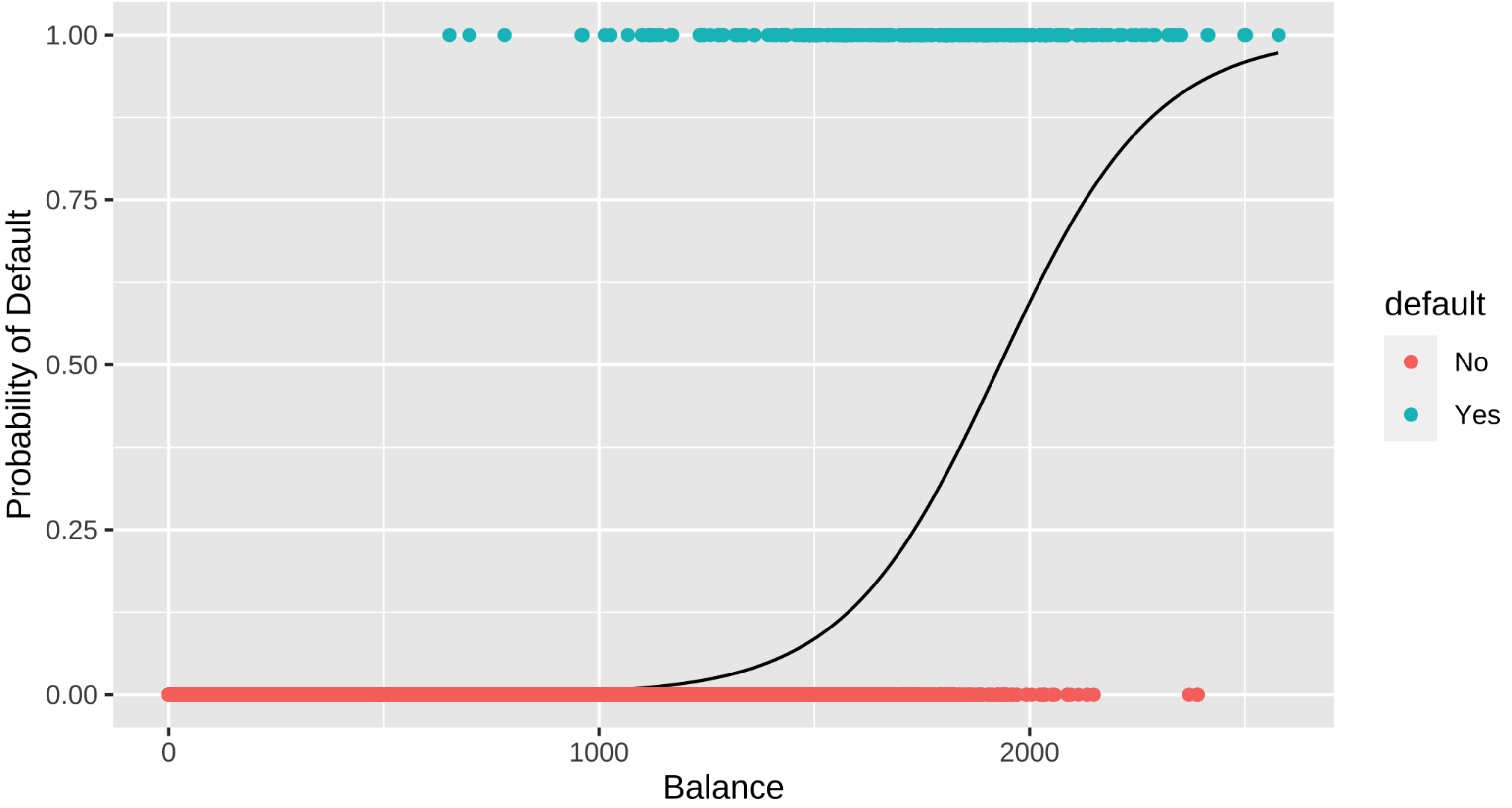
```
lodds <- predict(def_logmod1, type = "link")#log odds

preds_lodds = ifelse(lodds > 0, "Yes", "No") #using log odds

confusionMatrix(as.factor(preds_lodds), train$default) #confusion matri
```

Plot the model

- We are aiming for a plot like this:



Plot the model

- Coding the plot:

```
def_logmod1$coef #look at coefs
#save coefficients
b0 <- def_logmod1$coef[1] #beta0
b1 <- def_logmod1$coef[2] #beta1

#calculate probabilities
x_range <- seq(from = min(train$balance), to = max(train$balance))#range
#calculate the logits
default_logits <- b0 + b1*x_range

#calculate probabilities to plot
default_probabilities <- exp(balance_logits)/(1 + exp(balance_logits))

probabilities_to_plot <- data.frame("balance" = x_range,
                                    "probabilitiy_of_default" =  default

ggplot(probabilities_to_plot, aes(x = balance, y = probabilitiy_of_defau
  geom_line()+ #plot model
  geom_point(data = train, aes(x = balance,
                               y = ifelse(default == "Yes", 1, 0),
                               colour = default))+#add training data
  xlab("Balance")
```

Making predictions in R

- make predictions based on test data

```
test_lodds <- predict(def_logmod1, newdata = test, type = "link") #logi
test_preds_lodds = ifelse(test_lodds > 0, "Yes", "No") #using logits
confusionMatrix(as.factor(test_preds_lodds), test$default) #confusion ma
```

Extra reading

- Chapter 4 of James *et al.*, ISLR
- Chapter 10 of David Dalpiaz, R for Statistical Learning

References

- James *et al.*, ISLR
- David Dalpiaz, R for Statistical Learning

Slides

- xaringhan, xaringanthemer, remark.js, knitr, R Markdown