tRopical R Club

Data Mining #2: Logistic Regression

Martha Cooper, PhD

AITHM

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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?

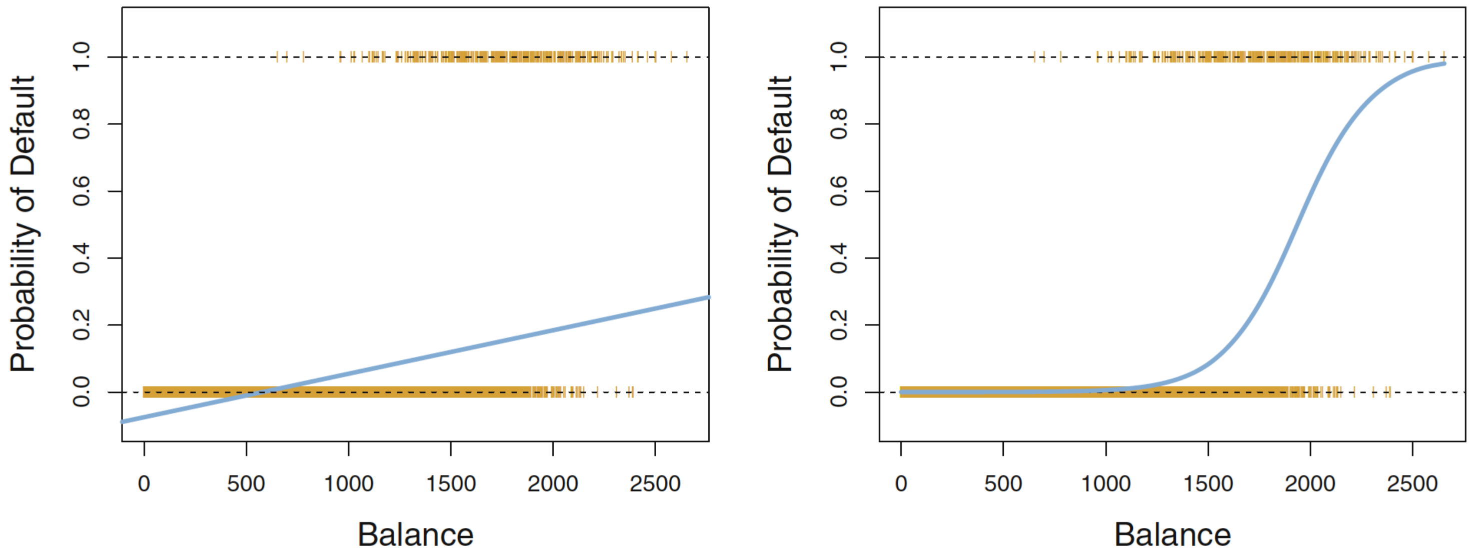
$$
\begin{aligned}
cancer &\in \{yes, no\} \\
credit\ card &\in \{defalt, not\ default\} \\
win\ &\in \{yes, no\} \\
drug\ &\in \{survived, not\ survived\}
\end{aligned}
$$

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

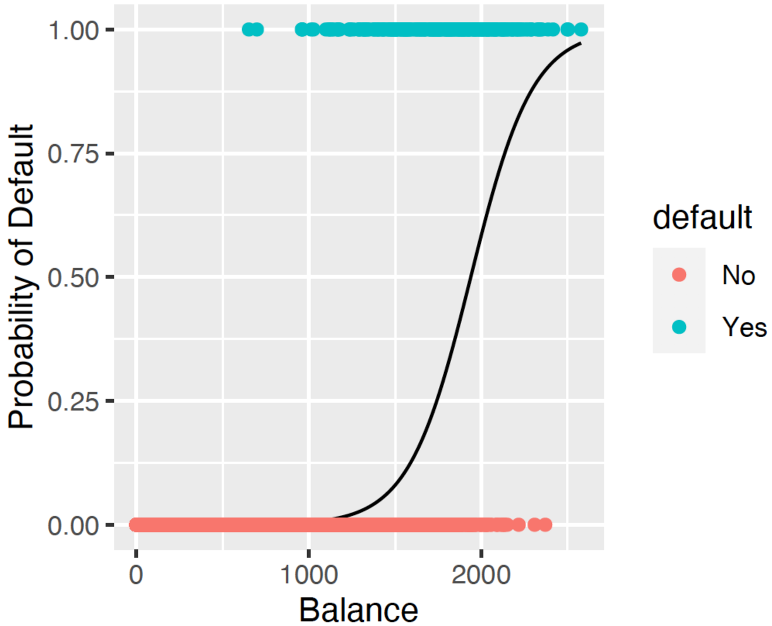


Problems with Linear Regression for Classification

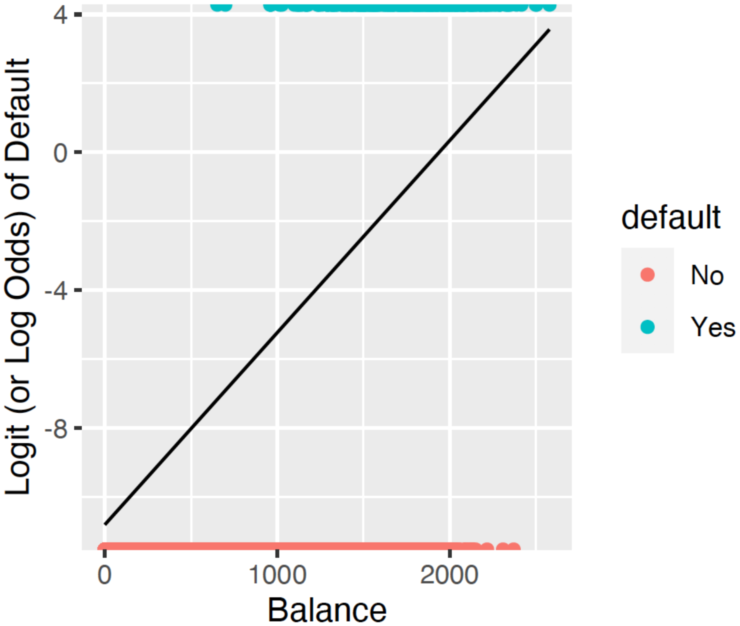
- Some values are outside [0,1]
- For multinomial classification, the order and interval between classes would be considered important and meaningful

The Logistic Model

Probability



Logit or Log Odds



The Logistic Model

Let $P(Y=1|X)$ be the probability that $Y=1$ given $X=(X_1,\ldots,X_k)$

Probability

$$P(Y=1|X_1,\ldots,X_k)=\frac{e^{\beta_0+\beta_1X_1+\ldots+\beta_kX_k}}{1+e^{\beta_0+\beta_1X_1+\ldots+\beta_kX_k}}$$

- where e is the Euler's number.
- This function means that $0\leq P(Y=1|X)\leq 1$

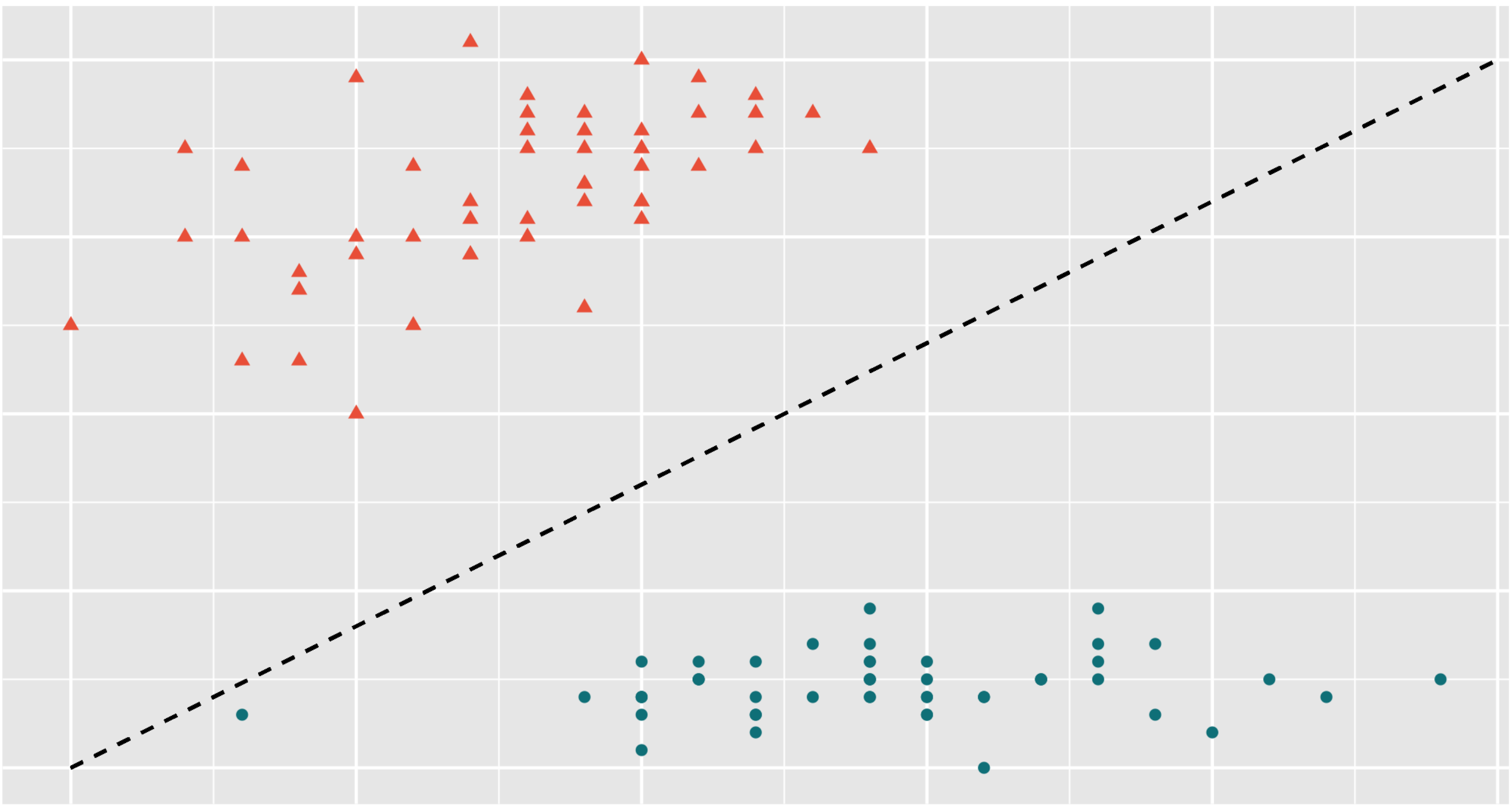
Logit (Log Odds)

$$\log(\frac{P(Y=1|X_1,\ldots,X_k)}{1-P(Y=1|X_1,\ldots,X_k)})=\beta_0+\beta_1X_1+\ldots+\beta_kX_k$$

- Where log is the natural log, $\log_e$
- Interpretation: β_1 represents the change in log odds of Y per 1 unit change in X_1 , holding other variables $(X_2,\ldots,X_k)$ constant

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) -10.529393049 0.3964461666 -26.55945 1.997400e-155
## balance       0.005422819 0.0002423825  22.37298 7.215171e-111
```

- β_0 : the log odds of a person defaulting if they have a credit card balance of 0 dollars = -10.535
- β_1 : For a one unit increase in balance, the log odds of a person defaulting increases by 0.0054 - Log odds ratio of a default probability for each one unit increase in balance**

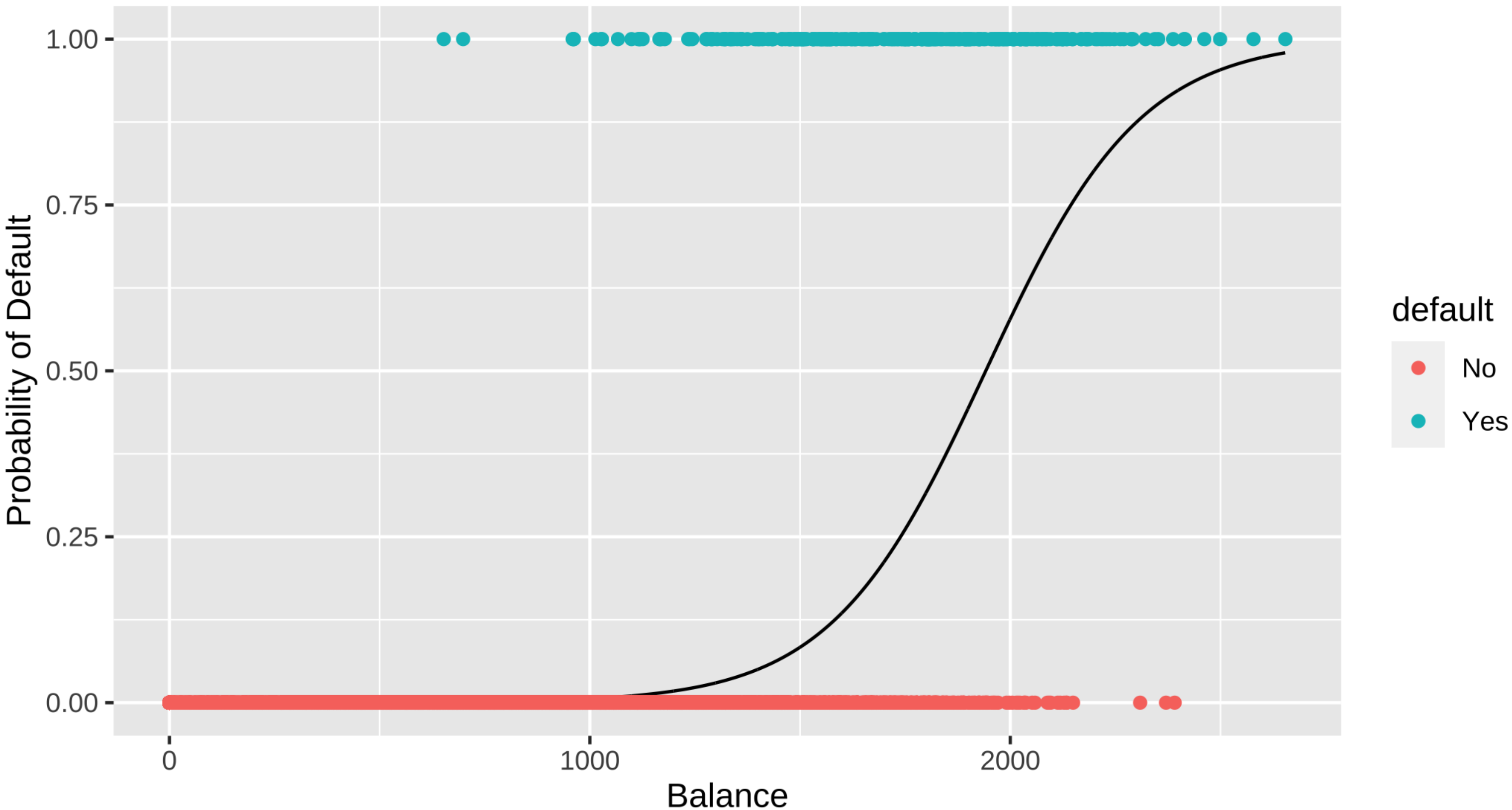
Making predictions in R

- make predictions based on training data

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

preds_lodds = ifelse(lodds > 0, "Yes", "No") #using log odds
preds_probs = ifelse(probs > 0.5, "Yes", "No") #using probabilities

all(preds_lodds == preds_probs) #prove to yourself these are the same th

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

Plot the model

- We are aiming for a plot like this:



Plot the model

```
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