

# 09 - Classification

Logistic Regression, Discriminant Analysis, and Naive Bayes

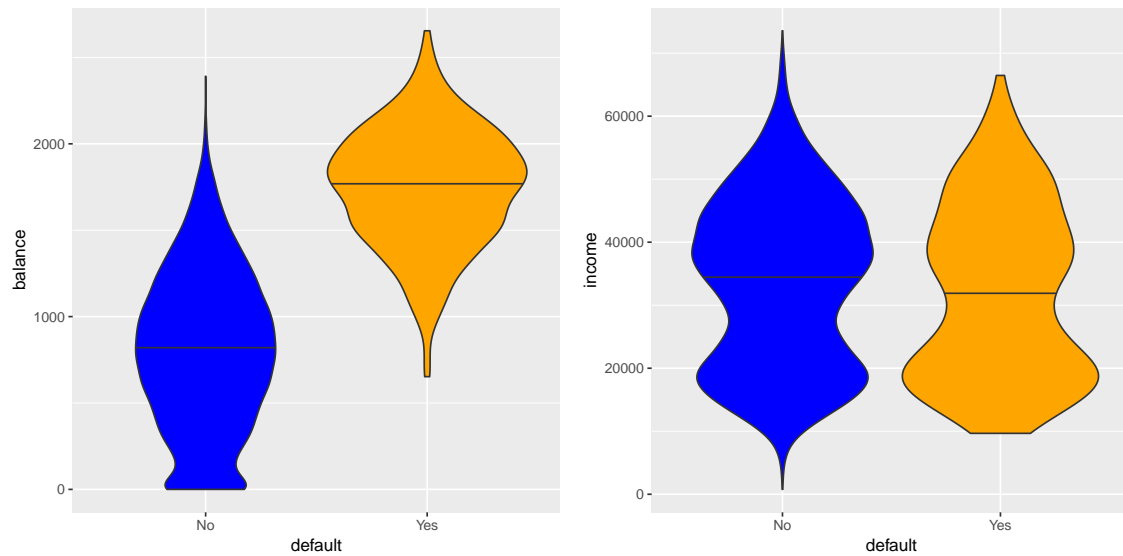
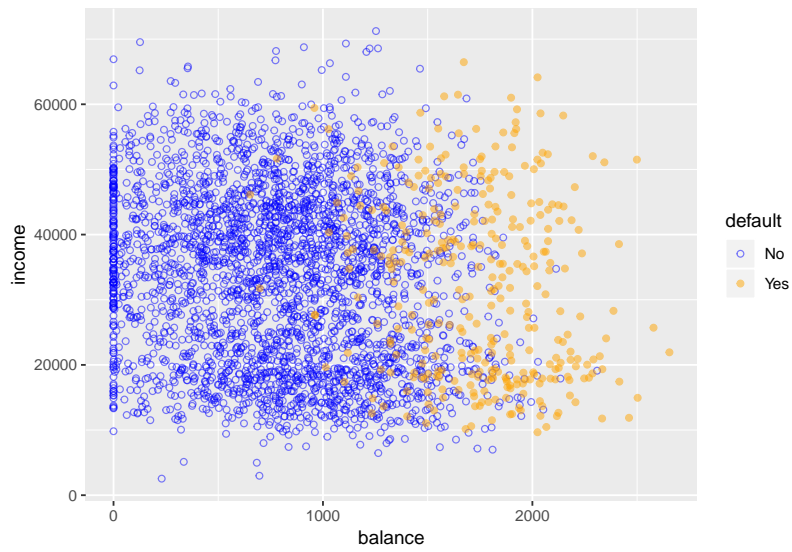
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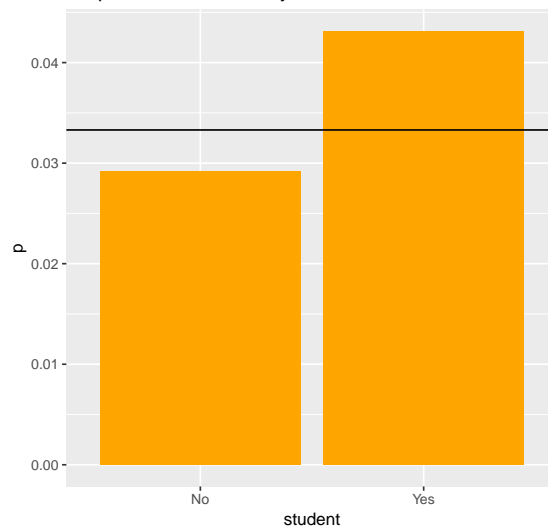
## Contents

<b>1</b>	<b>Classification Intro</b>	<b>2</b>
1.1	Required R Packages . . . . .	2
1.2	Credit Card Default data (Default) . . . . .	2
<b>2</b>	<b>Classification and Pattern Recognition</b>	<b>5</b>
2.1	Binary Classification . . . . .	6
<b>3</b>	<b>Logistic Regression</b>	<b>8</b>
3.1	Basics . . . . .	8
3.2	Estimation . . . . .	9
3.3	Logistic Regression in Action . . . . .	11
<b>4</b>	<b>Linear Discriminant Analysis (LDA)</b>	<b>13</b>
<b>5</b>	<b>Evaluation of Binary Classification Models</b>	<b>13</b>
<b>6</b>	<b>Naive Bayes</b>	<b>13</b>





Proportion of Defaults by Student status



**Your Turn #1 : Credit Card Default Modeling**

How would you construct a model to predict defaults?

## 2 Classification and Pattern Recognition

- The response variable is categorical and denoted  $G \in \mathcal{G}$ 
  - Default Credit Card Example:  $\mathcal{G} = \{\text{"Yes"}, \text{"No"}\}$
  - Medical Diagnosis Example:  $\mathcal{G} = \{\text{"stroke"}, \text{"heart attack"}, \text{"drug overdose"}, \text{"vertigo"}\}$
- The training data is  $D = \{(X_1, G_1), (X_2, G_2), \dots, (X_n, G_n)\}$
- Let  $f_g(\mathbf{x}) = \Pr(\mathbf{X} = \mathbf{x} \mid G = g)$  be the *class conditional density* function

### Your Turn #2

Think of two *models* (i.e., PDFs) to estimate  $f_{\text{Yes}}(\text{balance} = 1500)$  in the credit default example.



- The optimal decision/classification is based on the posterior probability  $\Pr(G = g \mid \mathbf{X} = \mathbf{x})$ 
  - We will discuss some optimal decisions in the binary case

### Your Turn #3

Write out the equation for  $\Pr(G = g \mid \mathbf{X} = \mathbf{x})$  using  $f_g(\mathbf{x})$  and  $\pi_g = \Pr(G = g), g \in \mathcal{G}$ .

- In real life, all of this is complicated because we have to estimate everything.
  - This is not easy in general, and is made more difficult in high dimensions (e.g., when  $\mathbf{x}$  is a long vector).

## 2.1 Binary Classification

- Classification is simplified when there are only 2 classes.
- It is often convenient to *code* the response variable to a binary  $\{0, 1\}$  variable:

$$Y_i = \begin{cases} 1 & G_i = \mathcal{G}_1 \\ 0 & G_i = \mathcal{G}_2 \end{cases} \quad (\text{outcome of interest})$$

- In the `Default` data, it would be natural to set `default=Yes` to 1 and `default=No` to 0.
- Now we can use the more general descriptions:
  - $f_1(\mathbf{x}) = \Pr(X = x \mid Y = 1)$ ,  $f_0(\mathbf{x}) = \Pr(X = x \mid Y = 0)$
  - $p(x) = \Pr(Y = 1 \mid \mathbf{X} = \mathbf{x})$
  - $\pi = \Pr(Y = 1)$

### 2.1.1 Linear Regression

- In this set-up we can run linear regression

$$\hat{y}(\mathbf{x}) = \hat{\beta}_0 + \sum_{j=1}^p \hat{\beta}_j x_j$$

```
##-- Create binary column (y)
Default = Default %>% mutate(y = ifelse(default == "Yes", 1L, 0L))

##-- Fit Linear Regression Model
fit.lm = lm(y~student + balance + income, data=Default)
```

term	estimate	std.error	statistic	p.value
(Intercept)	-0.0812	0.0084	-9.685	0.0000
studentYes	-0.0103	0.0057	-1.824	0.0682
balance	0.0001	0.0000	37.412	0.0000
income	0.0000	0.0000	1.039	0.2990

### Your Turn #4 : OLS for Binary Responses

1. For the binary  $Y$ , what is linear regression estimating?
2. What is the *loss function* that linear regression is using?
3. How could you create a *hard classification* from the linear model?
4. Does it make sense to use linear regression for binary classification?

### 2.1.2 $k$ -nearest neighbor (kNN)

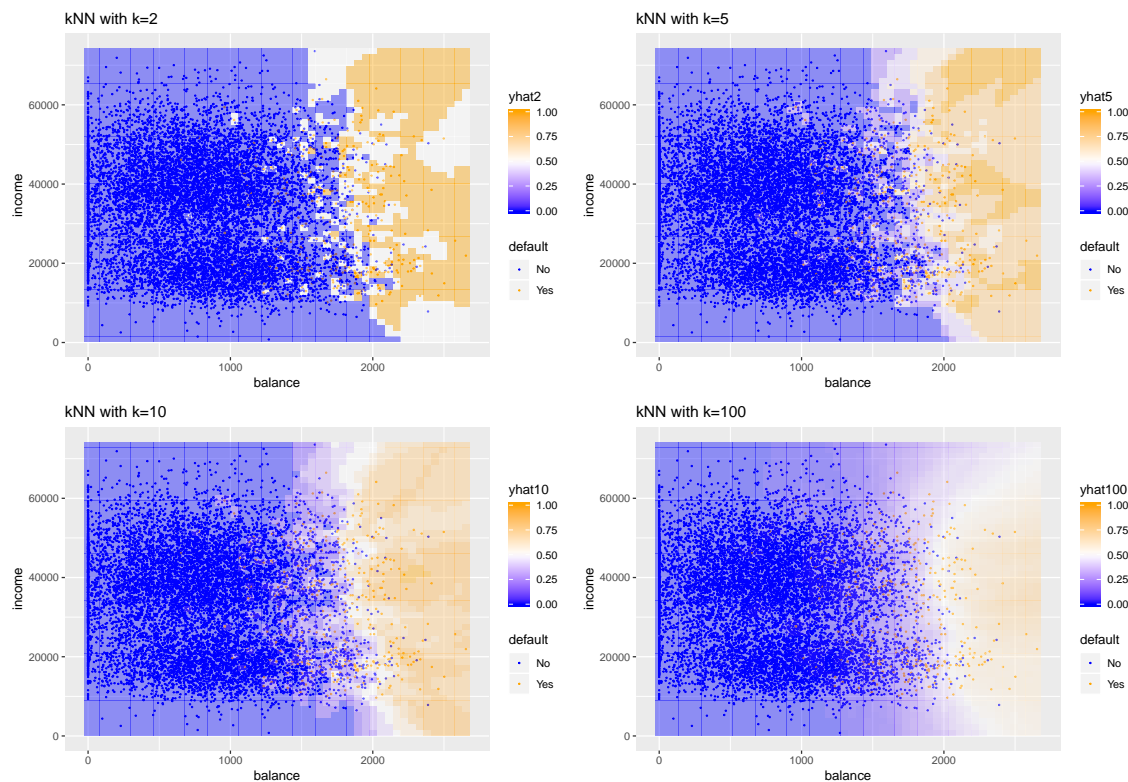
- The  $k$ -NN method is a non-parametric *local* method, meaning that to make a prediction  $\hat{y}|x$ , it only uses the training data in the *vicinity* of  $x$ .
  - contrast with OLS linear regression, which uses all  $X$ 's to get prediction.
- The model is simple to describe

$$f_{\text{knn}}(x; k) = \frac{1}{k} \sum_{i: x_i \in N_k(x)} y_i$$

$$= \text{Avg}(y_i \mid x_i \in N_k(x))$$

- $N_k(x)$  are the set of  $k$  nearest neighbors
  - only the  $k$  closest  $y$ 's are used to generate a prediction
  - it is a *simple mean* of the  $k$  nearest observations
- When  $y$  is binary (i.e.,  $y \in \{0, 1\}$ ), the kNN model estimates

$$f_{\text{knn}}(x; k) \approx p(x) = \Pr(Y = 1 | X = x)$$



#### Your Turn #5 : Thoughts about kNN

The above plots show a kNN model using the *continuous* predictors of *balance* and *income*.

- How can you use kNN with the categorical *student* predictor?

## 3 Logistic Regression

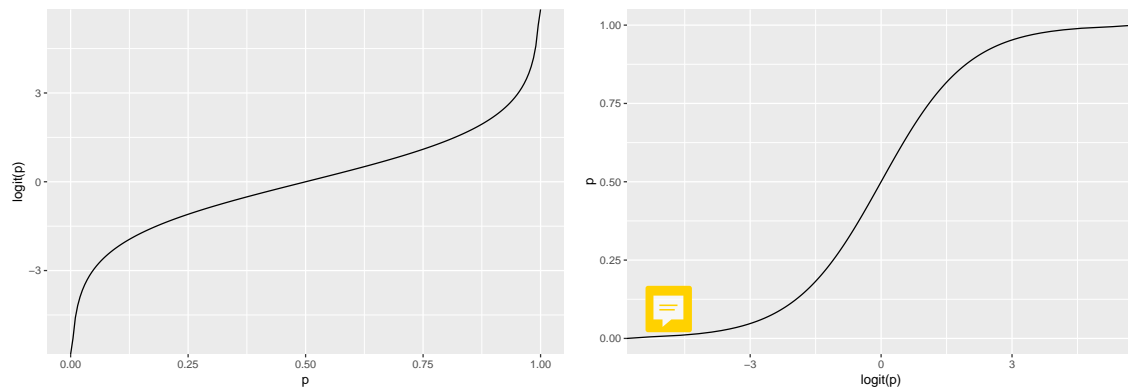
### 3.1 Basics

- Let  $0 \leq p \leq 1$  be a probability.
- The log-odds of  $p$  is called the *logit*

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

- The inverse logit is the *logistic function*. Let  $f = \text{logit}(p)$ , then

$$\begin{aligned} p &= \frac{e^f}{1 + e^f} \\ &= \frac{1}{1 + e^{-f}} \end{aligned}$$





**Logistic Regression Details****3.2 Estimation****3.2.1 Bernoulli Likelihood Function**

**Bernoulli Likelihood****3.2.2 MLE for Logistic Regression**

## MLE for Logistic Regression

## 3.3 Logistic Regression in Action

- In R , logistic regression can be implemented with the `glm()` since it is a type of *Generalized Linear Model*.
- Because logistic regression is a special case of *Binomial* regression, use the `family=binomial()` argument

```
#-- Fit logistic regression model
fit.lr = glm(y~student + balance + income, data=Default,
             family="binomial")
```

term	estimate	std.error	statistic	p.value
(Intercept)	-10.8690	0.4923	-22.0801	0.0000
studentYes	-0.6468	0.2363	-2.7376	0.0062
balance	0.0057	0.0002	24.7376	0.0000
income	0.0000	0.0000	0.3698	0.7115

## Your Turn #6 : Interpreting Logistic Regression

1. What is the estimated probability of default for a Student with a balance of \$1000?
2. What is the estimated probability of default for a *Non-Student* with a balance of \$1000?
3. Why does student=Yes appear to lower risk of default, when plot of student status

vs. default appears to increase risk?

**4 Linear Discriminant Analysis (LDA)****5 Evaluation of Binary Classification Models****6 Naive Bayes**