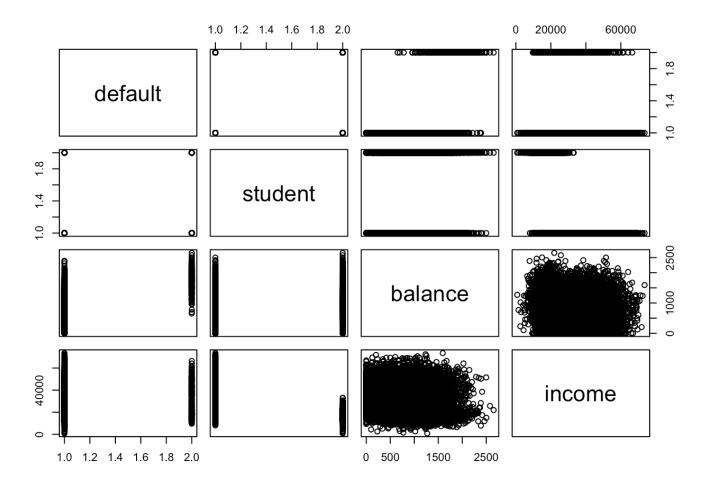
# **Problem 1**

Chapter 5, Exercise 5 (Sec. 5.4, p. 198).

#### Part A



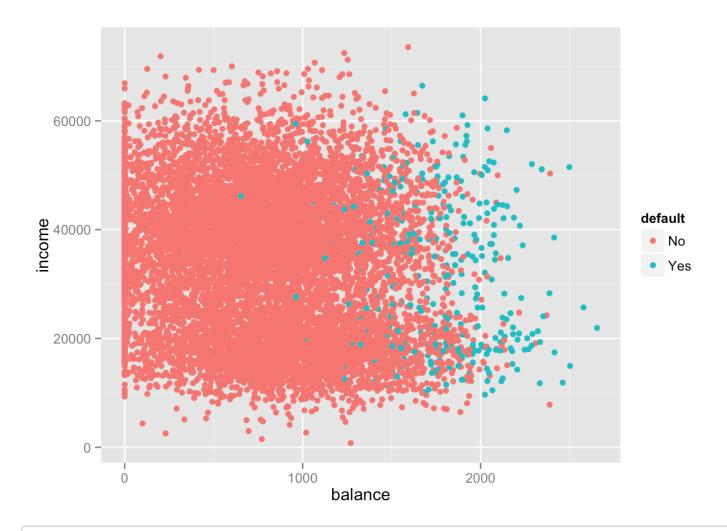
```
fit = glm(default ~ income + balance, family = 'binomial')
coef(fit)
```

```
## (Intercept) income balance
## -1.154047e+01 2.080898e-05 5.647103e-03
```

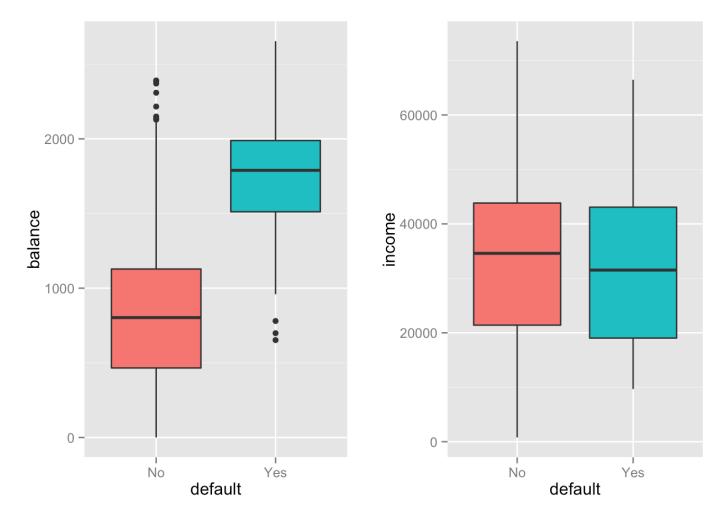
```
tmp = table(Default$default)
percent_defaults = (tmp[[2]]/tmp[[1]])*100
cat(percent_defaults, "percent of people default")
```

```
## 3.444709 percent of people default
```

```
# The following code is inspired by: rpubs.com/ryankelly/21379
x = qplot(x = balance, y = income, color = default, geom = 'point') + scale_shap
e(solid = FALSE)
y = qplot(x = default, y = balance, fill = default, geom = 'boxplot') + guides(fil
l = FALSE)
z = qplot(x = default, y = income, fill = default, geom = 'boxplot') + guides(fill
= FALSE)
x
```



grid.arrange(y, z, nrow=1)



### Part B

```
set.seed(1)

total = nrow(Default)
num = floor(0.9 * total)

sampled = Default[sample(total), ]
Default.train = sampled[1:num, ]
Default.test = sampled[(num + 1):total, ]
fit = multinom(default ~ income + balance, data = Default.train, family = 'binomia 1')
```

```
## # weights: 4 (3 variable)
## initial value 6238.324625
## iter 10 value 716.944726
## final value 716.865607
## converged
```

```
print(summary(fit))
```

```
## Call:
## multinom(formula = default ~ income + balance, data = Default.train,
##
       family = "binomial")
##
## Coefficients:
##
                      Values
                                Std. Err.
## (Intercept) -1.152515e+01 4.576857e-08
                2.027518e-05 4.415690e-06
## balance
                5.668073e-03 9.492261e-05
##
## Residual Deviance: 1433.731
## AIC: 1439.731
```

```
pred = predict(fit, Default.test)
print(confusionMatrix(pred, Default.test$default)$table)
```

```
## Reference
## Prediction No Yes
## No 965 19
## Yes 6 10
```

## Part C

```
##
## ===== Cross validation run # 2 ==============
## # weights: 4 (3 variable)
## initial value 6238.324625
## iter 10 value 685.892190
## final value 685.885544
## converged
##
            Reference
## Prediction No Yes
##
         No 956
                 29
##
         Yes
               2 13
\#\# MSE = 0.0475
## ===== Cross validation run # 3 ==============
## # weights: 4 (3 variable)
## initial value 6238.324625
## iter 10 value 702.235743
## final value 702.233405
## converged
##
            Reference
## Prediction No Yes
                  22
##
         No 966
##
         Yes
               4
## MSE = 0.0443
## ===== Cross validation run # 4 ==============
## # weights: 4 (3 variable)
## initial value 6238.324625
## iter 10 value 691.160350
## final value 691.157602
## converged
##
            Reference
## Prediction No Yes
##
         No 960
                  29
##
         Yes
## MSE = 0.0433
```

Each of the 4 runs gave in similar results with just a little bit of variation:

- The 0-1 loss for each run was 25/1000, 31/1000, 26/1000, and 33/1000 respectively.
- Of these errors, the respective ratios of false positives to false negatives were 6:19, 2:29, 4:22, and 4:29.

```
• We missed 10/(10 + 19) = .35, 13/(29 + 13) = .31, 8/(8 + 22) = .27, and 7/(7 + 29) = .19 of defaults.
```

```
• We missed 6/(6 + 965) = .0062, 2/(2 + 956) = .0021, 4/(4 + 966) = .0041, and 4/(960 + 4) = .0041 of non-defaults.
```

Our model does a pretty good job at categorizing non-defaults correctly (missing < 1%), but it fails miserably on actual defaults (missing upwards of 20% and as bad as 35%).

#### Part D

```
##
## ===== Cross validation run # 1 ============
## # weights: 5 (4 variable)
## initial value 6238.324625
## iter 10 value 712.052175
## final value 711.984415
## converged
## MSE = 0.0465
## ===== Cross validation run # 2 ============
## # weights: 5 (4 variable)
## initial value 6238.324625
## iter 10 value 683.842024
## final value 683.604493
## converged
## MSE = 0.0467
## ===== Cross validation run # 3 =============
## # weights: 5 (4 variable)
## initial value 6238.324625
## iter 10 value 697.797874
## final value 697.507099
## converged
## MSE = 0.0443
## ===== Cross validation run # 4 =================
## # weights: 5 (4 variable)
## initial value 6238.324625
## iter 10 value 687.959598
## final value 687.757482
## converged
## MSE = 0.0433
```

Including the student variable didn't affect our MSE significantly. Since it has no notable effect on our results, it's best to just remove the student variable from our analysis entirely.