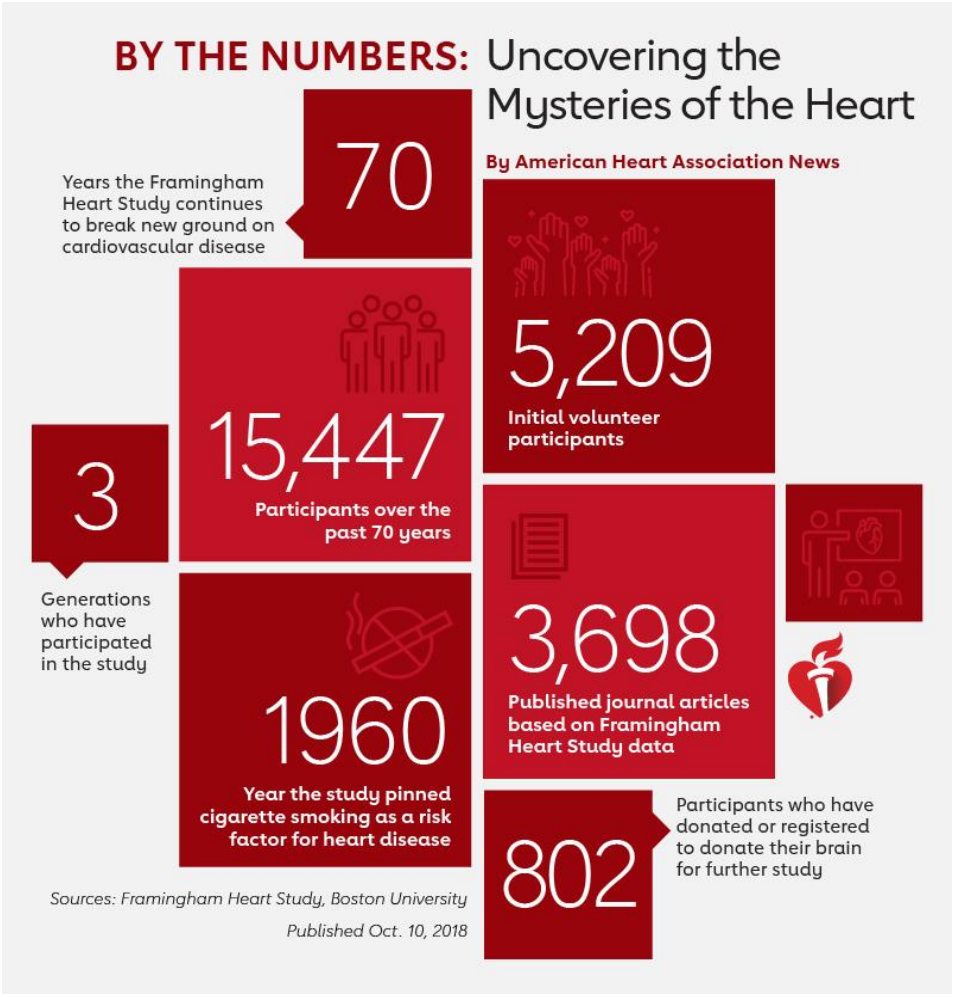
Lab 3

The Framingham Heart Study is a long term prospective study of cardiovascular disease among a population of subjects in the community of Framingham, Massachusetts. The Framingham Heart Study was a landmark study in epidemiology in that it was the first prospective study of cardiovascular disease and identified the concept of risk factors and their joint effects over the course of three generations. The study began in 1948 and 5,209 subjects were initially enrolled in the study. Participants have been examined biennially since the inception of the study and all subjects are continuously followed through regular surveillance for cardiovascular outcomes.

You will find the data file ***framinghamHeart.csv***, which you can load as **`dff`**. This is a subset of the data collected as part of the Framingham study. Participant clinic data was collected during three examination periods, approximately 6 years apart, from roughly 1956 to 1968. Each participant was followed for a total of 24 years for the outcome of a specified set of adverse health events. The dependent variable is **TenYearCHD**, specifying whether a subset of events associated with chronic heart disease occurred within 10 years of follow up. The variables are defined below. The purpose of the study is to determine the risk factors of heart disease.



Data Dictionary

Variable	Description	Coding
gender	Male or Female	0 = Female; 1 = Male
age	Age of the patient	
education	Highest level of education achieved	1 = High School; 2 = High School Diploma or GED; 3 = Some college or vocational School; 4 = College degree
currentSmoker	Indicates if the person is currently a smoker or not	0 = Not a smoker; 1 = Is a smoker
cigsPerDay	The number of cigarettes the person smoked on average in one day	
BPMeds	Whether the patient was on blood pressure medication	0 = Not on BP meds; 1 = On BP meds
prevalentStroke	Whether the patient previously had a stroke	0 = Free of disease; 1 = Stroke
prevalentHyp	Whether the patient has hypertension (high blood pressure)	0 = Free of disease; 1 = Hypertension
diabetes	Whether the patient has diabetes	0 = Free of disease; 1 = Diabetes
totChol	Total cholesterol level	mg/dL
sysBP	Systolic blood pressure	mmHg
diaBP	Diastolic blood pressure	mmHg
BMI	Body Mass Index	Weight (kg) / Height (meter-squared)
heartRate	Heart rate	Beats/Min (Ventricular)
glucose	Glucose level	mg/dL
TenYearCHD	Coronary heart disease	‘0' indicates the event did not occur during the 10-year follow

		up, and '1' indicates an event did occur during the follow up

Data Analysis

Before you start, **load the "caret" library** in addition to the usual four libraries we always load.

In addition, pay attention to what R reports after you load the dataset:

```
Parsed with column specification:
cols(
  gender = col_double(),
  age = col_double(),
  education = col_double(),
  currentSmoker = col_double(),
  cigsPerDay = col_double(),
  BPMeds = col_double(),
  prevalentStroke = col_double(),
  prevalentHyp = col_double(),
  diabetes = col_double(),
  totChol = col_double(),
  sysBP = col_double(),
  diaBP = col_double(),
  BMI = col_double(),
  heartRate = col_double(),
  glucose = col_double(),
  TenYearCHD = col_double()
)
```

Notice that R reads all the columns as numbers. You know from the data dictionary that some variables are supposed to be factors. You need to ask R to convert them into factors:

i. Create a list of columns that are supposed to be factors:

```
colsToFactor <- c('gender', 'education', 'currentSmoker', 'BPMeds',
'prevalentStroke', 'prevalentHyp', 'diabetes')
```

ii. Ask R to replace (overwrite) selected variables with their factor conversions:

```
dff <- dff %>%
  mutate_at(colsToFactor, ~factor(.))      => What do you think mutate_at does?
```

Now, if you run `str(dff)`, you will see that the variables in your data are correctly identified:

```
Classes 'spec_tbl_df', 'tbl_df', 'tbl' and 'data.frame':       3658 obs. of  16 variables:
 $ gender         : Factor w/ 2 levels "0","1": 2 1 2 1 1 1 1 1 2 2 ...
 $ age            : num  39 46 48 61 46 43 63 45 52 43 ...
 $ education      : Factor w/ 4 levels "1","2","3","4": 4 2 1 3 3 2 1 2 1 1 ...
 $ currentSmoker  : Factor w/ 2 levels "0","1": 1 1 2 2 2 1 1 2 1 2 ...
 $ cigsPerDay     : num  0 0 20 30 23 0 0 20 0 30 ...
 $ BPMeds         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ prevalentStroke: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ prevalentHyp   : Factor w/ 2 levels "0","1": 1 1 1 2 1 2 1 1 2 2 ...
 $ diabetes       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ totChol        : num  195 250 245 225 285 228 205 313 260 225 ...
 $ sysBP          : num  106 121 128 150 130 ...
 $ diaBP          : num  70 81 80 95 84 110 71 71 89 107 ...
 $ BMI            : num  27 28.7 25.3 28.6 23.1 ...
 $ heartRate      : num  80 95 75 65 85 77 60 79 76 93 ...
 $ glucose        : num  77 76 70 103 85 99 85 78 79 88 ...
 $ TenYearCHD     : num  0 0 0 1 0 0 1 0 0 0 ...
```

1. **Data exploration:** To explore visually whether blood pressure levels and total cholesterol levels are associated with heart disease, create boxplots of *sysBP*, *diaBP*, and *totChol*, broken up by the levels of *TenYearCHD*. [**Hint:** Dynamic plots may help understanding!]

2. **Data preprocessing:**

   (i) Read the data file into R. Set the seed to **123** and split the data into `dffTrain` and `dffTest`. Randomly sample 70% of the data for training and use the rest as test dataset.

   (ii) What are the proportions by gender in your training vs. test set? How does the distribution of age look? Looking at these, do you observe any signs of a sampling bias?

   Ans. After finding out the ratios of males(gender=1) vs females(gender=0) the training data gives the ratio as 55% and 45% and the test data is 56% and 44% i.e. they are nearly same which suggests that a **sampling bias does not exist**.

   Hints:

   [A] It's time to use R like a pro! You can pipe your *dffTrain* into the `group_by(variable)` function and then into **`tally()`** *-no arguments-* to get the counts across a group.

   - ❏ To add percentages, pipe one more step into `mutate(pct = 100*n/sum(n))`

   [B] For a continuous variable like age, there are so many groups, right? Each age is practically a different group. In such cases, you may want to create your own groups.

   - ❏ You can use *`ageGroup=cut_interval(age, length=10)`* in group_by()

   [C] You can also create a histogram for age, which probably makes more sense.

   - ❏ After creating the histogram, try adding `fill=gender` into aes() of ggplot(), and see what happens. In addition, define `color='black'` inside the histogram!

3. **Linear probability model:** Build a linear probability model `fitLPM` using all variables in `dffTrain`. Make sure to check for collinearity[1] by both thinking about the variables, and

[1] Likely multicollinearity. If "multicollinearity problem is extreme: any variable in the model can be written as a linear combination of all of the other variables in the model. Essentially, this means that we

using VIF values as guiding signals, and take necessary precautions. You know how to mitigate collinearity (if not, please ask during the lab!). After finalizing the model, which of the variables are statistically significant at the 95% level? What does this model tell you about the risk factors of heart disease? Do you have any reservations? Discuss.

Ans. A value greater than 2 in the VIF table suggests that a strong multicollinearity exists between some variables namely currentSmoker and cigsPerDay. The variable cigsPerDay can tell us if the person currently smokes or no and thus, we drop the variable currentSmoker. We also observe that the VIF values for sysBP and diaBP is high too, but we can't drop either of them because we do not know what relation exists between them.

After finalizing the new model, the variables significant at 95% level are **gender1, age, cigsPerDay, sysBP, glucose, prevalentStroke1, prevalentHyp1, and heartrate.** The model tells us that which variables influence chronic heart diseases. The model accounts for other non-significant variables as well which can be removed to improve the multiple R-square(variance) value of the model.

Hints:

[A] To include all the variables, use a full stop `.` To exclude a variable, use a negative `-`

[B] Run diagnostics to see whether this model violates the linear regression assumptions.

4. Speaking of using R like a pro, a better way to run a model and create a results table with predictions is as follows. Please run this code to make predictions using the LPM model and store them into *resultsLPM*[2]

```
resultsLPM <-
   lm( …fill in here… ) %>%
   predict( …fill in here… ) %>%    => Use the option type='response' for probabilities
   bind_cols(dffTest, predictedProb=.) %>%     => The dot marks where to pipe into
   mutate(predictedClass = …fill in here… )    => Use 50% as cutoff for classification
```

Inspect `resultsLPM`. Then, **copy and paste your code from Q2-ii** and check the prevalence of *TenYearCHD* in the *test dataset* this time. How many people have heart disease (in the

can never know exactly which variables (if any) truly are predictive of the outcome, and we can never identify the best coefficients for use in the regression. At most, we can hope to assign large regression coefficients to variables that are correlated with the variables that truly are predictive of the outcome." ISLR p. 243

[2] You can replicate this idea for any other model to make predictions -including the ones you did last week. When you are using this chunk of code for a linear regression, you don't need the last line because you don't need a conversion into classes. Instead, I would change *bind_cols(dffTest, **predictedProb**=.)* into *bind_cols(dffTest, **predictedValues**=.)* for a better understanding in a linear model.

test dataset)? Run the same code for *predictedClass* in the *resultsLPM*. How many people did the model predict having heart disease? Compare and report your observations.

Ans. The test dataset had 925 people who did not have any heart diseases. When the new model is created, the predictedClass there are 1087 cases which have heart diseases. The truth value is 172 while the predicted value is 10 which suggests that the new model is inefficient.

Before you continue:

You may have noticed that we did not convert TenYearCHD into a factor yet, even though it is a factor. This is because we wanted to use it in a linear model. It is time to make it a factor.

❑ Use `mutate()` to convert TenYearCHD to a factor both in *dffTrain* and *dffTest* datasets.

5. **Logistic regression:** Build a logistic regression using the predictor variables you decided to keep in the model you built in Q3. Which variables are statistically significant at the 95% level? Compare your results with the results you obtained from the model in Q3.

   Hint: See the appendix for an annotated logistic regression output in R with the definitions.

   Ans. In Q3, we removed the variable currentSmoker because it displayed high multicollinearity**.** The previous model had 95% significant variables as gender, age, cigsPerDay, sysBP, glucose, prevalentStroke, prevalentHyp, and heartrate.

   For the new model, at 95% significance level the variables are **cholesterol, gender, age, cigsPerDay, totchol, sysBP, glucose, prevalentHyp, and heartrate.**

   In the linear probability model, prevalentStroke was a significant variable in predicting heart disease while in the logistic model, it is not significant in determining heart disease. Simultaneously, in the logistic model, cholesterol level is a significant factor in determining heart disease and not in the linear model.

   A high residual deviance shows that the dependent variable is explained very well by our model using the predictor variables. The AIC of our logistic model is also very high, which means we have more independent variables than needed.

   Interpret the following variables: *age*, *gender*, and *diabetes* (whether significant or not):

   ❑ **Hint:** You can run **`exp(coef(fit))`** after a logistic model to exponentiate the coefficients of all variables at once and use them in your interpretations.
   ❑ **Type these interpretations AFTER completing the lab unless you have any questions.**

Age: 1.069

It means a 1-year increase in age is associated with an increase in odds of having heart disease by a factor of 1.06.

Gender: 1.525

It means that males have a probability of having heart disease by a factor of 1.52 over females.

Diabetes: 0.995

It means that a person who has diabetes has a lower chance by a factor of 0.995 of having heart disease.

6. Create a new results table ***resultsLog*** by using the logistic model. Let's continue like a pro.

   Hint: You will follow the same steps you took in Q4 but this time for logistic regression. This means, **your predictedClass will need to be defined as a factor** (you know how to do this!).

   How many people did the logistic model predict having heart disease? Report your observations and compare them with the actual values, and the predictions of the linear probability model from Q4. Do you think the logistic model is an improvement? Why?

   Ans. When we compare the results of the linear model with the logistic model, we see an improvement as the number of predicted cases went from 10 to 19. The logistic model is an improvement as interpretation of the predictedclass depends on the family (binomial) and the logistic loss function causes large errors to be penalized to a constant, and the outcome has only a limited number of possible values.

   Hint: For now, continue to use your code from Q2-ii to create the tables for comparison.

7. It is time to create a confusion matrix, a final step before evaluating performance (which we will cover next week). As you're using R like a pro, it is so easy to create a confusion matrix.

   - ❏ Pipe the *resultsLog* dataframe you created in **Q6** into the function `conf_mat(truth = ..., estimate = ...)`
   - ❏ **Optional:** Pipe one more step into `autoplot(type = 'heatmap')` to color code. This is useful when more than two classes are involved. For now, this is just a learning point.

   Explain what the matrix tells you in addition to what you learned from the tables in **Q6**.

   Ans. The different values that can be identified from the confusion matrix are:

   True Negative: 919 True Positive: 13

   False Negative: 159 False Positive: 6

The false negative value predicts whether a wrong value has been predicted for a person who has heart disease or no. It is important that the model does not predict this value wrong. This value should be low, but we observe that the value is very high. Also, the number of the true positives should have been high ideally for a good model, since we would want to identify correctly when a person has a coronary heart disease.

8. No analysis is complete without a visualization. Plot the relationship between the statistically significant variables (*age*, *cigsPerDay*, *totChol*, *glucose*) and the probability of heart disease:

   - ❏ Note that you stored the predicted probabilities as *predictedProb* in the *resultsLog* in Q6.
   - ❏ Use `geom_point()` and `geom_smooth()` after `ggplot()`, without adding any parameters
   - ❏ Be creative. For example, add `color=currentSmoker` (or `=gender`) into the `aes()`
   - ❏ Add a title for the plots, and label both axes [**Hint:** You can use the labs() function]

   Discuss your observations.

   Ans.

   Graph-1: Age vs. predictedClass

   The graphs increase in a steady manner for both male and females which suggests that the probability of getting a heart disease increase with age for both the sexes. The curve for males is higher than females which suggests that males have a higher chance of getting CHD as compared to females.

   Graph 2: No. of cigs per day versus predicted Probability

   Unlike the previous graph, the trends for males and females vary in this graph. For males, the trend increases slowly when the person smokes between 0 and 40 cigarettes a day. After the count of 40 cigarettes a day, the probability increases at a higher rate.

   For females, there is a very different and inconsistent trend. The probability of heart disease decreases when females smoke between 0 to 10 cigarettes a day, when the number of cigarettes smoked is between 10 to 20 cigarettes per day the probability of heart disease increases. After that between 20 to approximately 45 cigarettes per day the probability of heart disease remains almost the same.

   Graph 3: Total Cholesterol vs. predicted Probability

   In this graph, we see that the trend between males and females is the same. Both the trends are increasing but the rate of increase in the probability for females is higher than that for males. Another thing to note is that in the beginning the probability for heart disease in females is less than that of males.

Graph 4: Glucose vs. predicted Probability

The trends in this graph for males and females is the same, however the rate of increase in the probability for females is higher than that of males. Also, in the beginning the probability for heart disease in females is almost same than that of males, then there is a dip in the probability with females which increases the gap between the probabilities between males and females. However due to the higher rate of increase in females, the probability for risk for heart disease becomes greater than males after about 230 units of glucose.

Switching to a new framework "Caret" we will continue to use in this course from now on:

9. You already loaded the "caret" library at the beginning. If not, load it now. Replicate the analysis in Question 6, this time using the caret library. Use Appendix II[3] for guidance.

   - ❏ Name the results table resultsLogCaret and create it using the train function.
   - ❏ Inspect resultsLogCaret carefully, compare it with resultsLog from Q6 and discuss.
   - ❏ Create the confusion matrix using caret and compare it with the one in Q7. Discuss.
   - ❏ Don't worry about the rest of the output after the matrix. We will discuss it next week!

   Ans. The results of resultsLogCaret and resultsLog are similar. Both data frames have the same corresponding predictedClass values. This makes sense because both the models are logistic regressions performed on the same data set. The only difference is the different libraries used to create the model. Also, the values given by the caret model are same as that of the glm model.

10. Now that you have learned how to use logistic regression for classification, and how to do so **using the caret library**, you can solve another business problem for *Banco Portugal*. See Appendix III for the details of the dataset. The bank runs a telemarketing campaign for a savings account. Have you ever received one of those promotions by the way? "Open a savings account today and get XXX$ bonus!" See this month's promotions by clicking here.

    Banco Portugal hires you to predict whether a customer will open an account. The bank will use your model to develop promotional campaigns with higher conversion rates. Load the data, make conversions of variables as you see fit, and build logistic regression models using the caret library. Explore at least three alternative models[4], compare their performance, and pick a final model. Show your full work in the R Notebook. Below, discuss only your findings, your final decision, and explain how your final model helps Banco Portugal with its purpose.

    Now that we have discussed the performance measures, you can decide on a performance metric (or two) beyond just accuracy to compare the models and explain your reasoning.

[3] If you made it to this point, ask me for the handout that includes Appendix II and III.

[4] These models can all be logistic regressions with a different set of independent variables.

Because the caret library already reports the values of performance measures by default, you don't need to do any coding -This part is pretty much a thinking and reflecting exercise!

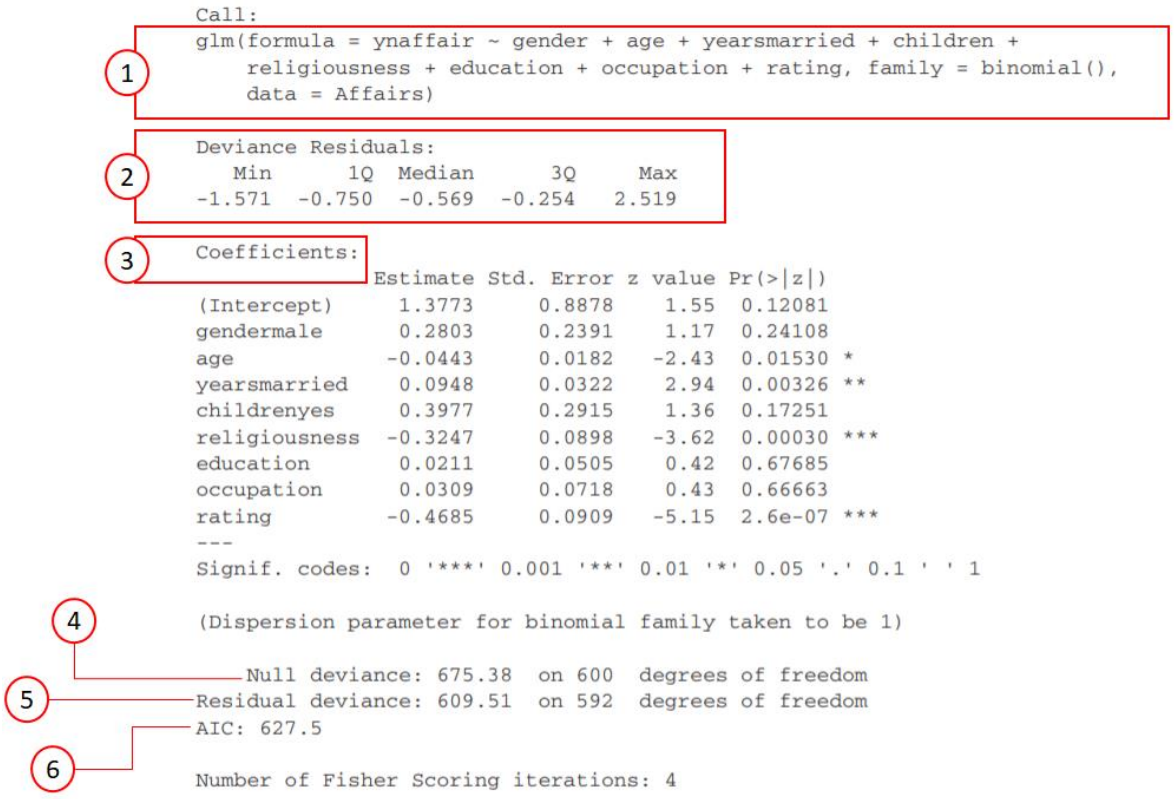
Ans. To first step was to explore data and understand the variables of the data frame. The first model that I created was using all the variables except duration since it did not help with the model. The false negative value was 871, the false positive is 302 balanced and the accuracy was 0.62.

To improve the model, some different predictor variables were considered while some were dropped. After doing that the new model's false negatives should have decreased, and true positives should have increased but we find out that the model is showing opposite results. The balanced accuracy decreases to 0.61.

In model 3, the **agegroup** variable was used to make the analysis. This variable does not have much dependence on the dependant variable but inspite of that it can be observed that the accuracy of the model is still high. This is strange because the number of true positives in the model results are 0, which is the most un-ideal situation and the number of false positives are 0, which is one of the ideal cases. This explains the high accuracy. What can be inferred from the results is that the data contains more 0 openedAccount values than 1 and this creates a bias. Hence, accuracy is a misleading factor of analysis.

Appendix I: How to run logistic regression in R and read the regression output

The output from summary() may seem overwhelming at first, so let's break it down one item at a time:



#	Item	Description
1	Formula	Like it was in the linear regression, the *glm()* formula describes the relationship between the dependent and independent variables. Note that you need to include *family = 'binomial'* as an argument.
2	Deviance Residuals	Because the difference between the observed and the fitted values are not very informative in a logistic regression, R reports the deviance residuals, which are the signed square roots of the ith observation to the overall deviance, calculated as follows: $$d_i = \text{sgn}(y_i - \hat{y}_i)\left\{2y_i \log\left(\frac{y_i}{\hat{y}_i}\right) + 2(n_i - y_i)\log\left(\frac{n_i - y_i}{n_i - \hat{y}_i}\right)\right\}^{(1/2)}$$

3	Coefficients	The regression coefficients show the change in log(odds) in the dependent variable for a unit change in the predictor variable, holding all other predictor variables constant. Because log(odds) are difficult to interpret, we usually exponentiate the coefficients and convert them into the odds scale: exp(the coefficient of yearsmarried) = exp(0.0948) = 1.10, which means a 1-year increase in the number of years married is associated with an increase in the odds of an affair by a factor of 1.10 (about a 10% increase), holding everything else constant. *What about a 10-year increase in the number of years married?* If you interpret a categorical variable like gendermale, exp(0.2803)=1.32 becomes the odds ratio. Therefore, the odds of a male having an affair are about 32% higher than the odds of a female doing so, holding everything else constant. You can exponentiate all coefficients by running `exp(coef(fit))`
4-5	Null Deviance, and Residual Deviance	The *null deviance* shows how well the dependent variable is explained by a model that includes only the intercept. The *residual deviance* shows how well the dependent variable is explained by a model that includes all the independent variables.
6	AIC	The Akaike Information Criterion (AIC) provides a method for assessing the quality of your model through comparison of related models. It's based on the Deviance measure, but includes a penalty for including additional independent variables. Much like adjusted R-squared, it intends to help you leave irrelevant predictors out. However, unlike adjusted R-squared, the reported number itself is not meaningful. When you compare nested models[5], you should select the model that has the smallest AIC. For BIC, run `BIC(fit)` after a regression, where *fit* is the model name, and R will report the BIC score. All of this also applies to BIC.
7	Fisher Scoring	This is just showing the number of iterations the model went through before it converged to this solution (not really useful).

[5] AIC can also be used in non-nested models, but using it requires caution. The data must be exactly the same.

Appendix II: Modeling using native way vs. the Caret way

Line by line comparison of making predictions using a logistic regression native way vs. caret way:

Note that the dependent variable is openedAccount in the example below:

```
1  ```{r}
2  resultsLog <-
3    glm(openedAccount ~ ., family='binomial', data=dfTrain) %>%
4    predict(dfTest, type='response') %>%
5    bind_cols(dfTest, predictedProb=.) %>%
6    mutate(predictedClass = as.factor(ifelse(predictedProb > 0.5, 1, 0)))
7
8  resultsLog %>%
9    conf_mat(truth=openedAccount, estimate=predictedClass)
10 ```
11
12 ```{r}
13 resultsLogCaret <-
14   train(openedAccount ~ ., family='binomial', data=dfTrain, method='glm') %>%
15   predict(dfTest, type='raw') %>%
16   bind_cols(dfTest, predictedClass=.)
17
18 resultsLogCaret %>%
19   xtabs(~predictedClass+openedAccount, .) %>%
20   confusionMatrix(positive = '1')
21 ```
```

Line 14 vs. Line 3: Use train() function instead of glm() and define the method in the method argument.
Line 15 vs. Line 4: Use predict() with type='raw' to get the predicted classes instead of probabilities.
Line 16 vs. Line 5: Name the column as predictedClass instead of predictedProb for this reason.
N/A vs. Line 6: No need to use a mutate() function to convert probabilities into classes.

Line 19 vs. N/A: Use the xtabs() function only because confusionMatrix() needs one.
Line 20 vs. Line 9: Use confusionMatrix() rather than conf_mat() and define the positive class.

Appendix III: Details of the Banco Portugal savings account dataset

Relevant Information:
The bank's customer-level data is extended by the addition of five social and economic features/predictors (at the end of data dictionary, national-wide indicators from Portugal), published by the Banco de Portugal and publicly available at bportugal.pt/estatisticasweb

Source:
Sérgio Moro (ISCTE-IUL), Paulo Cortez (Univ. Minho) and Paulo Rita (ISCTE-IUL) @ 2014

Past Usage:
The full dataset was described and analyzed in:
S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems (2014), doi:10.1016/j.dss.2014.03.001.

Objective:
The classification goal is to predict if a customer will open a savings account (*accountOpened*).

Data Summary:
Number of observations: 41188 Number of variables: 20+

Data Dictionary:
For more information, you can refer to Moro et al. (2014) cited above.

Variable	Data type	Description
openedAccount	categorical	Has the customer opened a savings account? ("yes","no")
newcustomer	categorical	If the customer is a new customer or not (yes = 1, no=0)
age	numeric	Age of the customer
agegroup	categorical	The age group that the customer belongs to ("Teenagers", "Young Adults", "Adults", "Senior Citizens")
job	categorical	Type of job ("admin", "blue-collar", "entrepreneur", "housemaid", "management", "retired", "self-employed", "services", "student", "technician", "unemployed", unknown)
marital	categorical	Marital status ("divorced", "married", "single", "unknown"; note: "divorced" means divorced or widowed)
education	categorical	Educational qualification ("basic.4y", "basic.6y", "basic.9y", "high.school", "illiterate", "professional.course",

		"university.degree", "unknown")
default	categorical	Has credit in default? ("no", "yes", "unknown")
housing	categorical	Has a housing loan? ("no", "yes", "unknown")
loan	categorical	Has a personal loan? ("no", "yes", "unknown")
contact	categorical	Contact communication type ("cellular", "telephone")
month	categorical	Last contact month of year ("jan", "feb", ..., "nov", "dec")
day_of_week	categorical	Last contact day of the week ("mon","tue","wed","thu","fri")
duration	numeric	Last contact duration, in seconds **Important**: This attribute highly affects the outcome (e.g., if duration=0 then y="no"). Yet, the duration is not known before a call is performed. Also, after the end of the call the outcome is obviously known. So, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.
campaign	numeric	Number of contacts performed during this campaign and for this client (includes the last contact)
pdays	numeric	Number of days passed by after the client was last contacted from a previous campaign **("999" means client was not previously contacted)**
previous	numeric	Number of contacts performed before this campaign
poutcome	categorical	Outcome of the previous marketing campaign ("failure", "nonexistent" ,"success")
emp.var.rate	numeric	Employment variation rate - quarterly indicator
cons.price.idx	numeric	Consumer price index - monthly indicator
cons.conf.idx	numeric	Consumer confidence index - monthly indicator
euribor3m	numeric	Euribor 3 month rate - daily indicator
nr.employed	numeric	Number of total employment - quarterly indicator