Logistic Regression with Credit data Set

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```
## Project
#To Build a Logistic Regression Model to predict default10yr a categorical
variable in creditset using the predictors age,income and loan using the
creditset.csv
##Solution:

#In this project We need to predict default10yr using the other predictor
variables given in the dataset using Logstic Regression as our #response
variable is a categorical variable .We will train our model and then test our
model by splitting the  crediset into 2 datasets .

# Importing the dataset

# creditset<-read.csv(file.choose())  OR
#we can use this to upload/import our creditset csv file from computer too
creditset<- read.csv("G:/Business Analytics_R_Acad glid/creditset.csv")
dim(creditset)

## [1] 2000    6

names(creditset)

## [1] "clientid"    "income"      "age"          "loan"         "LTI"
## [6] "default10yr"

#We can see that  creditset has 2000 observations with 6 variables/columns .
We need to predict  response Variable "default10yr" which is categorical
variable ,so we have to make a Logistic Regression Model

library(caTools)

## Warning: package 'caTools' was built under R version 3.4.3

# Splitting creditset into training and testing DATASET

# Splitting creditset into training and testing DATASET

table(creditset$default10yr)

##
##    0    1
## 1717  283
```

```
set.seed(2)
split<-sample.split(creditset,SplitRatio = 0.75)
split

## [1]  TRUE  TRUE  TRUE  TRUE FALSE FALSE

training<-subset(creditset,split=="TRUE")
dim(training)

## [1] 1334    6

testing<-subset(creditset,split== "FALSE")
dim(testing)

## [1] 666   6

names(creditset)

## [1] "clientid"    "income"      "age"          "loan"         "LTI"
## [6] "default10yr"

####Checking Actual 0's & 1's of default10yr in creditset,trainingset,testing
set . O -> Non-defaulter , 1-> defaulter

table(creditset$default10yr) #tells us how many defaulters & non defualters
are there in the creditset

##
##    0    1
## 1717  283

table(training$default10yr)   #tells us how many defaulters & non defualters
are there in the training set

##
##    0    1
## 1133  201

table(testing$default10yr)    #tells us how many defaulters & non defualters
are there in the testing set

##
##   0   1
## 584  82

#we need to predict default10yr from the data given.As default10yr is a
categorial 1 being defaulter 0 being non -defaulter.We need to use logistic
regression for predicting our dependent variable default10yr.In above we have
divided our data set into 2 parts  training and testing. We are going to
build our model /train our model with training dataset and will test the same
model on our testing dataset. training & testing are the subsets of
creditset.For building our  Logistic Regression model clientid  and LTI are
not the predictors of default10yr we will not use these variables while
```

```
building our model . Our predictor variables are age,income and loan .We need
to decide and optimize our model in such a way that the accuracy is more and
the threshold cutoff probability is such that the model is not dangerous like
we predict defaulters as non-defaulters as such an info will be dangerous for
bank meaning  False-Negative should be minimum but  not much accuracy of the
model is lost

#Building Logistic Regression Model

model<-glm(default10yr~income+age+loan,data=training,family= binomial)
model

## 
## Call:  glm(formula = default10yr ~ income + age + loan, family = binomial, 
##     data = training)
## 
## Coefficients:
## (Intercept)       income          age         loan  
##   9.8166458   -0.0002367   -0.3465840    0.0017076  
## 
## Degrees of Freedom: 1333 Total (i.e. Null);  1330 Residual
## Null Deviance:       1131 
## Residual Deviance: 316.7     AIC: 324.7

#Hence our logit function predictors are as below

    # Constant term  is 9.8166458
    #Coefficient for  Income is  -0.0002367
    #  Coefficient for  age  is  -0.3465840
    #  Coefficient for  loan is  0.0017076
# Our Logit function becomes

    # logit(odds) = Logit(default10yr) =  9.8166458 + ((-0.0002367) * Income)
+ ((-0.3465840) * age) + ((0.0017076) *loan)

    # p(default10yr) = e^(9.8166458 + ((-0.0002367) * Income) + ((-0.3465840)
* age) + ((0.0017076) *loan)) / ( 1+ e^(9.8166458 + ((-0.0002367) * Income) +
((-0.3465840) * age) + ((0.0017076) *loan))

#Optimizing Our Model
# Building others models trying to optimize "model" by trying combinations of
predictors

model1<-glm(default10yr~income,data=training,family= binomial)
summary(model1)

## 
## Call:
## glm(formula = default10yr ~ income, family = binomial, data = training)
## 
## Deviance Residuals: 
```

```
##     Min       1Q   Median       3Q      Max  
## -0.5958  -0.5813  -0.5674  -0.5523   1.9862  
## 
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -1.897e+00  2.536e-01  -7.480 7.44e-14 ***
## income       3.687e-06  5.292e-06   0.697    0.486    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 1130.9  on 1333  degrees of freedom
## Residual deviance: 1130.4  on 1332  degrees of freedom
## AIC: 1134.4
## 
## Number of Fisher Scoring iterations: 4
```

```
model2<-glm(default10yr~age,data=training,family= binomial)
summary(model2)
```

```
## 
## Call:
## glm(formula = default10yr ~ age, family = binomial, data = training)
## 
## Deviance Residuals: 
##      Min        1Q    Median        3Q       Max  
## -1.39150  -0.48762  -0.21609  -0.09672   2.02203  
## 
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)    
## (Intercept)  3.06921    0.32098   9.562   <2e-16 ***
## age         -0.14283    0.01076 -13.278   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 1130.91  on 1333  degrees of freedom
## Residual deviance:  809.99  on 1332  degrees of freedom
## AIC: 813.99
## 
## Number of Fisher Scoring iterations: 6
```

```
model3<-glm(default10yr~loan,data=training,family= binomial)
summary(model3)
```

```
## 
## Call:
## glm(formula = default10yr ~ loan, family = binomial, data = training)
## 
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6076  -0.5434  -0.3574  -0.2567   2.3937
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.667e+00  1.981e-01  -18.51   <2e-16 ***
## loan         3.450e-04  2.748e-05   12.56   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1130.91  on 1333  degrees of freedom
## Residual deviance:  941.76  on 1332  degrees of freedom
## AIC: 945.76
##
## Number of Fisher Scoring iterations: 5
```

```
model4<-glm(default10yr~age+income,data=training,family= binomial)
summary(model4)
```

```
##
## Call:
## glm(formula = default10yr ~ age + income, family = binomial,
##     data = training)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.39233  -0.48738  -0.21597  -0.09667   2.02211
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.065e+00  4.347e-01   7.050 1.79e-12 ***
## age         -1.428e-01  1.077e-02 -13.266  < 2e-16 ***
## income       8.987e-08  6.139e-06   0.015    0.988
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1130.91  on 1333  degrees of freedom
## Residual deviance:  809.99  on 1331  degrees of freedom
## AIC: 815.99
##
## Number of Fisher Scoring iterations: 6
```

```
model5<-glm(default10yr~age+loan,data=training,family= binomial)
summary(model5)
```

```
##
## Call:
## glm(formula = default10yr ~ age + loan, family = binomial, data =
training)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.22066  -0.28396  -0.08938  -0.01918   2.60955
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.904e+00  3.987e-01   4.776 1.79e-06 ***
## age         -2.147e-01  1.654e-02 -12.986  < 2e-16 ***
## loan         6.128e-04  4.831e-05  12.686  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1130.91  on 1333  degrees of freedom
## Residual deviance:  521.43  on 1331  degrees of freedom
## AIC: 527.43
##
## Number of Fisher Scoring iterations: 7
```

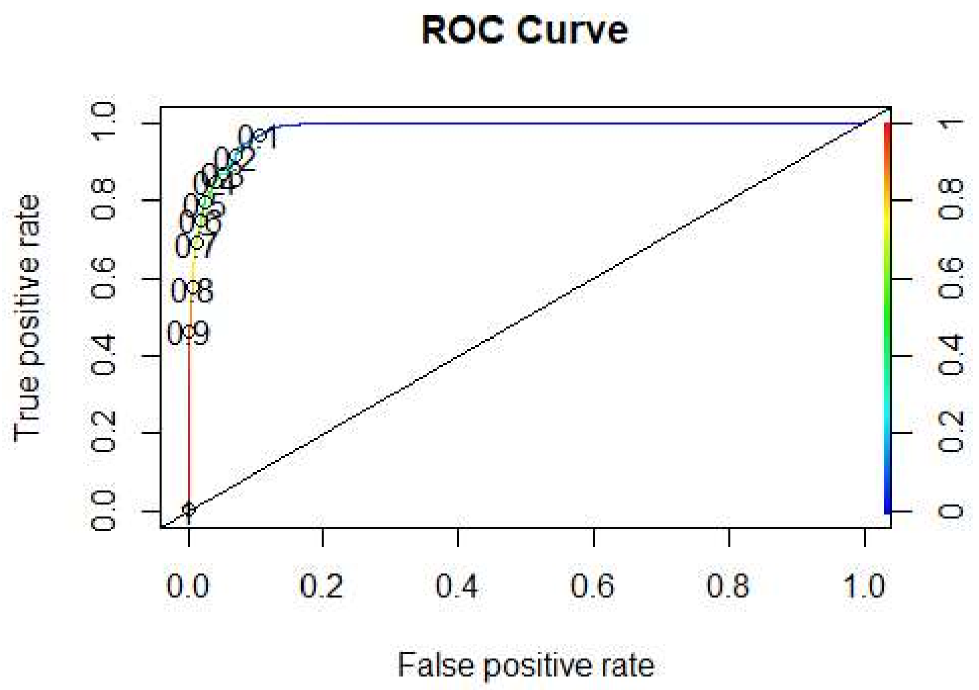
```
model6<-glm(default10yr~income+loan,data=training,family= binomial)
summary(model6)
```

```
##
## Call:
## glm(formula = default10yr ~ income + loan, family = binomial,
##     data = training)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6818  -0.5102  -0.2789  -0.1034   2.2054
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.429e+00  2.842e-01  -5.028 4.97e-07 ***
## income      -9.240e-05  1.074e-05  -8.607  < 2e-16 ***
## loan         6.568e-04  5.181e-05  12.677  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1130.91  on 1333  degrees of freedom
## Residual deviance:  842.77  on 1331  degrees of freedom
## AIC: 848.77
```

```
##
## Number of Fisher Scoring iterations: 6

# In all the above models from model1 to model6 the AIC value has not
decreased hence we cannot remove any of the predictors from Logistic
Regression model named "model" . So we can say all the three predictors
age,income & loan are good predictors of default10yr.  Our Final model for
predicting default10yr is model which is optimized.

#Predicting Probabilities for training dataset

# now we will find the predicted probabilties associated with our model for
training dataset
library(CARS)

## Warning: package 'CARS' was built under R version 3.4.3

res<-predict(model,training,type="response")
head(res,n=5)

##            1            2            3            4            7
## 3.909786e-06 2.198782e-02 6.628029e-06 3.250508e-03 2.377538e-01

# Confusion Matrix for our results when compared with predicted values for
training dataset
# we have threshold prob of 0.5 in this case which is taken by default

tabtraining0.5<-
table(ActualValue=training$default10yr,PredictedValue=res>=0.5) #checked with
probability cutoff = 0.5
tabtraining0.5

##            PredictedValue
## ActualValue FALSE TRUE
##           0  1105   28
##           1    42  159

accuracytraining0.5<-sum(diag(tabtraining0.5)/sum(tabtraining0.5))
accuracytraining0.5

## [1] 0.9475262

#our model built is accurate to upto 95%  meaning it predicted defaulter as
defaulter & non-defaulter as non-defaulter in the training dataset from
creditset with almost 95% accuracy
# Predicting Probabilties for testing dataset

# now checking our model for accuracy with testing dataset
# Finding the predicted probabilties associated with observations using our
model for testing dataset
res1<-predict(model,testing,type="response")
head(res1)
```

```
##             5            6           11           12           17
## 9.245496e-01 1.160065e-07 1.078035e-03 8.220100e-05 5.608433e-04
##           18
## 1.193050e-07

# Confusion Matrix for our results when compared with predicted values for
testing dataset
tabtesting0.5<-
table(ActualValue=testing$default10yr,PredictedValue=res1>=0.5) #with
probability cutoff= 0.5
tabtesting0.5

##            PredictedValue
## ActualValue FALSE TRUE
##           0   562   22
##           1    14   68

accuracytesting0.5<-sum(diag(tabtesting0.5)/sum(tabtesting0.5))
accuracytesting0.5 #accuracy at 0.5 cutoff prob

## [1] 0.9459459

#our model built is accurate to upto 95%  meaning after verifying ith testing
dataset from creditset.As it predicted & we verified defaulter as defaulter &
non-defaulter as non-defaulter in the testing dataset from creditset with
almost 95% accuracy

# ROC curve

# now we will try to check using ROCR package whether our cutoff Probability
is with less False-Negative or not .
# We can also check using ROC Curve whether our cutoff probablity is most
closest to NW corner of the graph or not meaning it has least distance with
NW corner of graph .

library(ROCR)

## Warning: package 'ROCR' was built under R version 3.4.3

## Loading required package: gplots

## Warning: package 'gplots' was built under R version 3.4.3

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

ROCRPred<-prediction(res,training$default10yr)
ROCRPref<-performance(ROCRPred,"tpr","fpr")
```

```r
plot(ROCRPref,colorize=TRUE,main="ROC
Curve",print.cutoffs.at=seq(0.1,by=0.1))
abline(a=0,b=1)
```



```r
# We can see that  the distance between the 0.4 probabilty and the Northwest
corner is  less as compared to  0.5
# so we can decide to take our cutoff probabilty as 0.4
# this probability will also decrese number of false-Negatives which were
dangerous to our model

#### Trying different Probabilty values as cutoff to check diffrent Confusion
matrices
# checking confusion Matrix for diffrent Probabilities for our training
dataset
table(ActualValue=training$default10yr,PredictedValue=res>=0.3) #checked with
probability cutoff = 0.3

##            PredictedValue
## ActualValue FALSE TRUE
##           0  1073   60
##           1    26  175

table(ActualValue=training$default10yr,PredictedValue=res>=0.4) #checked with
probability cutoff = 0.4

##            PredictedValue
## ActualValue FALSE TRUE
##           0  1088   45
##           1    30  171

table(ActualValue=training$default10yr,PredictedValue=res>=0.5) #checked with
probability cutoff = 0.5

##            PredictedValue
## ActualValue FALSE TRUE
##           0  1105   28
##           1    42  159

# so finally As per the model our probability cutoff is  0.4 as it gives me a
good accuracy along with less false negatives
# Thus giving the Confusion matrix as

tabtraining0.4<-
table(ActualValue=training$default10yr,PredictedValue=res>=0.4) #checked with
probability cutoff = 0.4
tabtraining0.4

##            PredictedValue
## ActualValue FALSE TRUE
##           0  1088   45
##           1    30  171

# checking actual 0's & 1's in training dataset
table(training$default10yr)

##
##    0    1
## 1133  201

accuracytraining0.4<-sum(diag(tabtraining0.4))/sum(tabtraining0.4)
accuracytraining0.4

## [1] 0.9437781

#Sensitivity & Specificity & Accuracy for training dataset

#calculating Sensitivity & Specificity for dataset training for  p=0.4
sensitivitytraining0.4<-
tabtraining0.4[4]/(tabtraining0.4[2]+tabtraining0.4[4])
sensitivitytraining0.4

## [1] 0.8507463

specificitytraining0.4<-tabtraining0.4[1]/(tabtraining0.4[1] +
tabtraining0.4[3])
specificitytraining0.4

## [1] 0.9602824
```

```
# Classification Accuracy for group 0 for training dataset is equal to
"specificitytraining0.4" calculated as shown in output

# Classification Accuracy for group 1 is equal to  calculated as
"sensitivitytraining0.4" shown in  output

# Classification Accuracy of our model for training dataset is given by
equal to
classification_accuracy_training0.4<-
(sensitivitytraining0.4+specificitytraining0.4)/2
classification_accuracy_training0.4

## [1] 0.9055144

#Overall accuracy  found by using the table meaning true predictions out of
actuals is given by
# (TruePositive + TrueNegative ) / (TP+TN+FP+FN)
accuracy_tabtraining0.4<-sum(diag(tabtraining0.4))/sum(tabtraining0.4)
accuracy_tabtraining0.4

## [1] 0.9437781

#Verifying our Model on Testing dataset

# checking actual 0's & 1's in testing dataset
table(testing$default10yr)

##
##   0   1
## 584  82

# We have below Confusion matrix as for testing
tabtesting0.4<-
table(ActualValue=testing$default10yr,PredictedValue=res1>=0.4) #checked with
probability cutoff = 0.4
tabtesting0.4

##              PredictedValue
## ActualValue FALSE TRUE
##           0   559   25
##           1    10   72

## Verifying our Model with Probability 0.4 for the testing dataset

# Verifying our Model with Probability 0.4 for the testing dataset

#calculating Sensitivity & Specificity for dataset testing for  p=0.4
sensitivitytesting0.4<-tabtesting0.4[4]/(tabtesting0.4[2]+tabtesting0.4[4])
sensitivitytesting0.4

## [1] 0.8780488
```

```
specificitytesting0.4<-tabtesting0.4[1]/(tabtesting0.4[1] + tabtesting0.4[3])
specificitytesting0.4

## [1] 0.9571918

# Classification Accuracy for group 0 for testing dataset is equal to
"specificitytesting0.4" calculated as shown in output

# Classification Accuracy for group 1 is equal to  calculated as
"sensitivitytesting0.4" shown in  output

# Classification Accuracy of our model for testing dataset is given by  equal
to
classification_accuracy_testing0.4<-
(sensitivitytesting0.4+specificitytesting0.4)/2
classification_accuracy_testing0.4

## [1] 0.9176203

#Overall accuracy  found by using the table,meaning true total predictions
out of total actuals is given by
# (TruePositive + TrueNegative ) / (TP+TN+FP+FN)
accuracy_tabtesting0.4<-sum(diag(tabtesting0.4))/sum(tabtesting0.4)
accuracy_tabtesting0.4

## [1] 0.9474474

#Our Logistic Regression model "model" is a good model which is able to
predict  the data which was even not supplied to it i.e. testing dataset. As
model was trained with training dataset. We get good  Overall Accuracy and
also model is less risky .

# Calculating Area under ROC curve
# install.packages("verification")
library(verification)

## Warning: package 'verification' was built under R version 3.4.3

## Loading required package: fields

## Warning: package 'fields' was built under R version 3.4.3

## Loading required package: spam

## Warning: package 'spam' was built under R version 3.4.3

## Loading required package: dotCall64

## Warning: package 'dotCall64' was built under R version 3.4.3

## Loading required package: grid
## Spam version 2.1-2 (2017-12-21) is loaded.
## Type 'help( Spam)' or 'demo( spam)' for a short introduction
## and overview of this package.
## Help for individual functions is also obtained by adding the
## suffix '.spam' to the function name, e.g. 'help( chol.spam)'.

##
## Attaching package: 'spam'

## The following objects are masked from 'package:base':
##
##     backsolve, forwardsolve

## Loading required package: maps

## Warning: package 'maps' was built under R version 3.4.3

## Loading required package: boot

## Loading required package: CircStats

## Warning: package 'CircStats' was built under R version 3.4.3

## Loading required package: MASS

## Loading required package: dtw

## Warning: package 'dtw' was built under R version 3.4.3

## Loading required package: proxy

## Warning: package 'proxy' was built under R version 3.4.3

##
## Attaching package: 'proxy'

## The following object is masked from 'package:spam':
##
##     as.matrix

## The following objects are masked from 'package:stats':
##
##     as.dist, dist

## The following object is masked from 'package:base':
##
##     as.matrix

## Loaded dtw v1.18-1. See ?dtw for help, citation("dtw") for use in
publication.

roc.area(training$default10yr,res)
```

```
## $A
## [1] 0.9826288
##
## $n.total
## [1] 1334
##
## $n.events
## [1] 201
##
## $n.noevents
## [1] 1133
##
## $p.value
## [1] 5.273768e-106
```

```
# Area unde ROC curve is equal to as shown below

# Calculating Nagelkerke R square
# install.packages("fmsb")
library(fmsb)
NagelkerkeR2(model)
```

```
## $N
## [1] 1334
##
## $R2
## [1] 0.7992079
```

```
# our Nagelkerke R square is calculated as shownabove .

logLik(model)
```

```
## 'log Lik.' -158.3399 (df=4)
```

```
# The probability of the observed results given the parameter estimates is
known as the Likelihood. Since the likelihood is a small number less than 1,
it is customary to use -2 times the log likelihood (-2LL) as an estimate of
how well the model fits the data. A good model is one that results in a high
likelihood of the observed results. This translates into a small value for -
2LL (if a model fits perfectly, the likelihood=1 and -2LL=0)

#This is far from zero, however because there is no upper boundary for -2LL
it is difficult to make a statement about the meaning of the score.
 # It is more often used to see whether adding additional variables to the
model leads to a significant reduction in the -2LL.
```

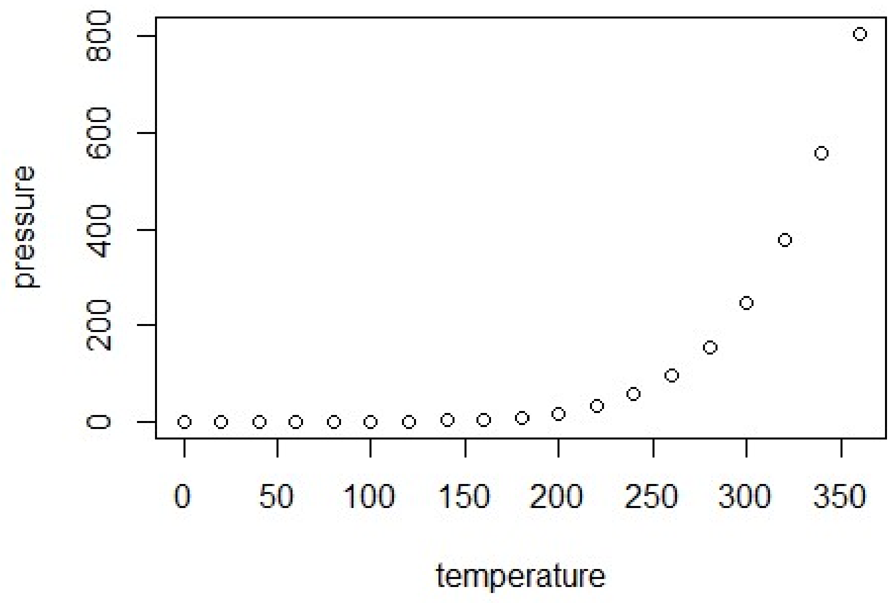
R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

Including Plots

You can also embed plots, for example:



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.