In [28]:
```
library(MASS)
library(pROC)
library(ggplot2)
library(caret)
options(warn=-1)
options(scipen = 999)
```

The dataset is from the UC Irvine Machine Learning Repository

Link to the dataset: https://archive.ics.uci.edu/dataset/222/bank+marketing

Moro,S., Rita,P., and Cortez,P.. (2012). Bank Marketing. UCI Machine Learning Repository. https://doi.org/10.24432/C5K306.

The data is from a direct marketing campaign of a Portuguese banking institution. The goal is to predict if the client will subscribe a term deposit. Often more than one contact to the same client was required.

In [2]:
```
df = read.csv('bank-full.csv',sep = ';')
```

In [3]:
```
head(df,10)
```

A data.frame: 10 × 17

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome
	<int>	<chr>	<chr>	<chr>	<chr>	<int>	<chr>	<chr>	<chr>	<int>	<chr>	<int>	<int>	<int>	<int>	<chr>
1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown
2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown
3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown
4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown
5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown
6	35	management	married	tertiary	no	231	yes	no	unknown	5	may	139	1	-1	0	unknown
7	28	management	single	tertiary	no	447	yes	yes	unknown	5	may	217	1	-1	0	unknown
8	42	entrepreneur	divorced	tertiary	yes	2	yes	no	unknown	5	may	380	1	-1	0	unknown
9	58	retired	married	primary	no	121	yes	no	unknown	5	may	50	1	-1	0	unknown
10	43	technician	single	secondary	no	593	yes	no	unknown	5	may	55	1	-1	0	unknown

In [4]:
```
sum(is.na(df))
```

0

- default: whether the customer has credit in default.
- balance: average yearly balance.
- houssing: whether they have housing loan or not.
- loan: whether they have personal loan or not.
- contact: contact communication type (cellular / telephone).
- day_of_week: last contact day of the week.
- month: last contact month of the year.
- duration: last contact duration.
- campaign: number of contacts performed during this campaign.
- pdays: number of days that passed by after the client was last contacted from a pervious campaign.
- previous: number of contacts performed before this campaign for this client.
- poutcome: outcome of previous marketing campaign.
- y: whether the client subscribed to a term deposit or not.

In [5]:

```
table(df$job)
```

```
       admin.   blue-collar  entrepreneur     housemaid    management 
         5171          9732          1487          1240          9458 
      retired self-employed      services       student    technician 
         2264          1579          4154           938          7597 
   unemployed       unknown 
         1303           288 
```

In [6]:

```
fact_names = c('job','marital','education','contact','month','poutcome','y')
for (i in fact_names)
    {
    df[,i] = as.factor(df[,i])
}
```

In [7]:

```
summary(df)
```

```
      age                       job             marital           education
 Min.   :18.00   blue-collar:9732   divorced: 5207   primary  : 6851
 1st Qu.:33.00   management :9458   married :27214   secondary:23202
 Median :39.00   technician :7597   single  :12790   tertiary :13301
 Mean   :40.94   admin.     :5171                    unknown  : 1857
 3rd Qu.:48.00   services   :4154
 Max.   :95.00   retired    :2264
                 (Other)    :6835
   default                balance          housing               loan
 Length:45211       Min.   : -8019   Length:45211       Length:45211
 Class :character   1st Qu.:    72   Class :character   Class :character
 Mode  :character   Median :   448   Mode  :character   Mode  :character
                    Mean   :  1362
                    3rd Qu.:  1428
                    Max.   :102127

     contact             day            month          duration
 cellular :29285   Min.   : 1.00   may    :13766   Min.   :   0.0
 telephone: 2906   1st Qu.: 8.00   jul    : 6895   1st Qu.: 103.0
 unknown  :13020   Median :16.00   aug    : 6247   Median : 180.0
                   Mean   :15.81   jun    : 5341   Mean   : 258.2
                   3rd Qu.:21.00   nov    : 3970   3rd Qu.: 319.0
                   Max.   :31.00   apr    : 2932   Max.   :4918.0
                                   (Other): 6060
    campaign          pdays          previous            poutcome
 Min.   : 1.000   Min.   : -1.0   Min.   :  0.0000   failure: 4901
 1st Qu.: 1.000   1st Qu.: -1.0   1st Qu.:  0.0000   other  : 1840
 Median : 2.000   Median : -1.0   Median :  0.0000   success: 1511
 Mean   : 2.764   Mean   : 40.2   Mean   :  0.5803   unknown:36959
 3rd Qu.: 3.000   3rd Qu.: -1.0   3rd Qu.:  0.0000
 Max.   :63.000   Max.   :871.0   Max.   :275.0000

   y
 no :39922
 yes: 5289
```

In [8]:
```
nrow(df)
```

45211

In [9]:
```
df = df[,!(names(df) %in% c('duration'))]
```

In [10]:
```
set.seed(42)
train_ind = sample(seq_len(nrow(df)),size=floor(0.75*nrow(df)))
train_df = df[train_ind,]
test_df = df[-train_ind,]
```

In [11]:
```
mod_0 = glm('y ~ 1',data=train_df,family=binomial)
```

In [12]:
```
mod_all = glm('y ~ .',data=train_df,family=binomial)
```

In [13]:
```
step_select = step(mod_0,direction='both',scope=formula(mod_all),trace=0)
```

In [14]:
```
step_select$anova
```

A data.frame: 11 × 6

Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
<I<chr>>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
	NA	NA	33907	24385.09	24387.09
+ poutcome	-3	1973.53171	33904	22411.56	22419.56
+ month	-11	1083.11592	33893	21328.44	21358.44
+ contact	-2	393.47478	33891	20934.97	20968.97
+ housing	-1	207.83385	33890	20727.14	20763.14
+ campaign	-1	92.26003	33889	20634.88	20672.88
+ job	-11	100.07382	33878	20534.80	20594.80
+ loan	-1	60.69899	33877	20474.10	20536.10
+ marital	-2	52.35172	33875	20421.75	20487.75
+ education	-3	23.54437	33872	20398.21	20470.21
+ balance	-1	14.25863	33871	20383.95	20457.95

In [15]:
```
unique(train_df$education)
```

secondary · primary · unknown · tertiary

▸ **Levels**:

In [16]:
```
summary(step_select)
```

```
Call:
glm(formula = y ~ poutcome + month + contact + housing + campaign +
    job + loan + marital + education + balance, family = binomial,
    data = train_df)

Coefficients:
                      Estimate   Std. Error z value              Pr(>|z|)
(Intercept)        -1.180687061  0.124557975  -9.479 < 0.0000000000000002 ***
poutcomeother       0.271787288  0.093357323   2.911              0.00360 **
poutcomesuccess     2.277489476  0.084980480  26.800 < 0.0000000000000002 ***
poutcomeunknown     0.062975376  0.059865960   1.052              0.29283
monthaug           -0.847241346  0.080229252 -10.560 < 0.0000000000000002 ***
monthdec            0.559970301  0.182014912   3.077              0.00209 **
monthfeb           -0.379871270  0.086590157  -4.387 0.000011492324600703 ***
monthjan           -1.134870476  0.124284835  -9.131 < 0.0000000000000002 ***
monthjul           -0.653821032  0.078274620  -8.353 < 0.0000000000000002 ***
monthjun            0.073079291  0.093953364   0.778              0.43667
monthmar            1.030498999  0.128279425   8.033 0.000000000000000949 ***
monthmay           -0.543281422  0.073810978  -7.360 0.000000000000183302 ***
monthnov           -0.847986662  0.085460043  -9.923 < 0.0000000000000002 ***
monthoct            0.614360060  0.111247983   5.522 0.000000033432824714 ***
monthsep            0.681163152  0.125037462   5.448 0.000000051033191758 ***
contacttelephone   -0.195799113  0.074275920  -2.636              0.00839 **
contactunknown     -1.212126279  0.072333643 -16.757 < 0.0000000000000002 ***
housingyes         -0.499003558  0.043994746 -11.342 < 0.0000000000000002 ***
campaign           -0.080528814  0.009692875  -8.308 < 0.0000000000000002 ***
jobblue-collar     -0.111287651  0.074279618  -1.498              0.13407
jobentrepreneur    -0.378454431  0.135305080  -2.797              0.00516 **
jobhousemaid       -0.233163702  0.134888048  -1.729              0.08389 .
jobmanagement      -0.059603425  0.075813936  -0.786              0.43176
jobretired          0.419249979  0.090260844   4.645 0.000003402889930066 ***
jobself-employed   -0.058123863  0.113150923  -0.514              0.60747
jobservices        -0.146308989  0.086756186  -1.686              0.09171 .
jobstudent          0.297406294  0.112862601   2.635              0.00841 **
jobtechnician      -0.105120391  0.071439235  -1.471              0.14117
jobunemployed       0.146486277  0.111752431   1.311              0.18992
jobunknown         -0.135460489  0.237739524  -0.570              0.56882
loanyes            -0.434720025  0.061542247  -7.064 0.000000000001620497 ***
maritalmarried     -0.236832632  0.059139523  -4.005 0.000062111403777477 ***
maritalsingle       0.040753363  0.063815846   0.639              0.52308
educationsecondary  0.220694856  0.065689247   3.360              0.00078 ***
educationtertiary   0.359296489  0.076376212   4.704 0.000002547405010813 ***
educationunknown    0.272604050  0.106618400   2.557              0.01056 *
balance             0.000019720  0.000005062   3.896 0.000097820700777982 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 24385  on 33907  degrees of freedom
Residual deviance: 20384  on 33871  degrees of freedom
AIC: 20458

Number of Fisher Scoring iterations: 6
```

$$g(x) = 0.271787288 * poutcomeother + 2.277489476 * poutcomesuccess + 0.062975376 * poutcomeunknown - 0.847241346 * montha$$
$$+ 0.073079291 * monthjun + 1.030498999 * monthmar - 0.543281422 * monthmay - 0.847986662 * monthnov + 0.614360060 *$$
$$- 0.499003558 * housingyes - 0.111287651 * jobblue - collar - 0.378454431 * jobentrepreneur - 0.233163702 * jobhousemaid - 0.$$
$$* jobservices + 0.297406294 * jobstudent - 0.105120391 * jobtechnician + 0.146486277 * jobunemployed - 0.135460489 * jobunk$$
$$* maritalsingle + 0.220694856 * educationsecondary + 0.359296489 * educationtertiary + 0.2$$

$$\pi(x) = \frac{\exp 0.271787288 * poutcomeother + 2.277489476 * poutcomesuccess + 0.062975376 * poutcomeunknown - 0.847241346 * mon \\ + 0.073079291 * monthjun + 1.030498999 * monthmar - 0.543281422 * monthmay - 0.847986662 * monthnov + 0.61436 \\ - 0.499003558 * housingyes - 0.111287651 * jobblue - collar - 0.378454431 * jobentrepreneur - 0.233163702 * jobhouse \\ * jobservices + 0.297406294 * jobstudent - 0.105120391 * jobtechnician + 0.146486277 * jobunemployed - 0.135460489 * \\ * maritalsingle + 0.220694856 * educationsecondary + 0.359296489 * educationtertiary + 0.272604050 * educationunkn}{1 + \exp 0.271787288 * poutcomeother + 2.277489476 * poutcomesuccess + 0.062975376 * poutcomeunknown - 0.847241346 * \\ + 0.073079291 * monthjun + 1.030498999 * monthmar - 0.543281422 * monthmay - 0.847986662 * monthnov + 0.61 \\ - 0.499003558 * housingyes - 0.111287651 * jobblue - collar - 0.378454431 * jobentrepreneur - 0.233163702 * jobho \\ * jobservices + 0.297406294 * jobstudent - 0.105120391 * jobtechnician + 0.146486277 * jobunemployed - 0.135460 \\ * maritalsingle + 0.220694856 * educationsecondary + 0.359296489 * educationtertiary + 0.272604050 * educationu}$$

In [17]:
```
print(exp(step_select$coefficients))
```

(Intercept)	poutcomeother	poutcomesuccess	poutcomeunknown
0.3070677	1.3123078	9.7521666	1.0650006
monthaug	monthdec	monthfeb	monthjan
0.4285956	1.7506205	0.6839494	0.3214638
monthjul	monthjun	monthmar	monthmay
0.5200548	1.0758158	2.8024639	0.5808391
monthnov	monthoct	monthsep	contacttelephone
0.4282763	1.8484733	1.9761750	0.8221774
contactunknown	housingyes	campaign	jobblue-collar
0.2975639	0.6071353	0.9226283	0.8946814
jobentrepreneur	jobhousemaid	jobmanagement	jobretired
0.6849192	0.7920239	0.9421381	1.5208205
jobself-employed	jobservices	jobstudent	jobtechnician
0.9435331	0.8638907	1.3463622	0.9002161
jobunemployed	jobunknown	loanyes	maritalmarried
1.1577590	0.8733137	0.6474459	0.7891234
maritalsingle	educationsecondary	educationtertiary	educationunknown
1.0415952	1.2469429	1.4323214	1.3133801
balance			
1.0000197			

- The log of odds of the client subscribing to a term deposit increases by 2.277489476 if the outcome of a previous campaign was success instead of failure.
    - The chances of a client subscribing to a term deposit is 75.21% more if the client's outcome of the previous campaign was success instead of failure.
- The log of odds of the client subscribing to a term deposit decreases by 1.134870476 if the last contact month of the year changes from april to january.
    - The chances of a client subscribing to a term deposit has 32.14% lesser chances if the last contact month of the year to the client changes from april.
- The log of odds of the client subscribing to a term deposit decreases by 0.195799113 if the client is contacted via telephone instead of cellular.
    - The chances of a client subscribing to a term deposit has 82.21% lesser chances if the client is contacted via telephone instead of cellular.
- The log of odds of the client subscribing to a term deposit decreases by 0.499003558 if the client already has a housing loan.
    - The chances of client subscribing to a term deposit has 60.71% lesser chances if the client has a housing loan.
- The log of odds of the client subscribing to a term deposit decreases by 0.080528814 with unit increase in the number of contacts made during the campaign.
    - The chances of a client subscribing to a term deposit is 92.26% lesser chances for every unit increase in the number of contacts made during the campaign.
- The log of odds of the client subscribing to a term deposit increases by 0.419249979 if the client is retired instead of having an admin job.
    - The chances of a client subscribing to a term deposit is 52.07% more if they are retired instead of having an admin job.
- The log of odds of the client subscribing to a term deposit decreases by 0.434720025 if the client has a personal loan.
    - The chances of a client subscribing to a term deposit decreases by 64.74% if the client has a personal loan.
- The log of odds of the client subscribing to a term deposit increases by 0.040753363 if the client is single instead of divorced / widowed.
    - The chances of a client subscribing to a term deposit is 4.15% more if the client is signle instead of being divorced / widowed.
- The log of odds of the client subscribing to a term deposit increases by 0.359296489 if the client has tertiary education instead of just primary.
    - The chances of a client subscribing to a term deposit is 43.23% more if the client has tertiary education as well instead of just primary.
- The log of odds of the client subscribing to a term deposit increases by 0.000019720 if the average yearly balance increases by 1 unit.
    - The chances of a client subscribing to a term deposit increases by 0.00197% per unit increase is average yearly balance.

In [18]:
```
pred_train = ifelse(predict(step_select,type='response')>=0.5,1,0)
```

In [19]:
```
length(pred_train)
```

33908

In [20]:
```
as.factor(train_df$y)
```

no · no · no · no · no · no · yes · yes · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · yes · no · no · yes · no · no · no · no · no · yes · no · no · no · no · no · no · yes · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · yes · no · no · no · yes · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · ··· · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · yes · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · yes · no · no · no · no · yes · no · no · no · no · yes · no · no · no · no · no · no · no · yes · no · no · no · yes · no · no · no · no · no · yes · no · no · yes · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes · no · yes · no · no · no · no · no · no · no · no · no · no · no · yes · yes · no · no · no · no · yes · yes · no · no · no · no · no · no · no · no · no · no · no · no · no · no · yes

- **Levels**:

In [21]:

```
confusionMatrix(as.factor(pred_train),as.factor(ifelse(train_df$y=='no',0,1)),mode='everything')
```

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 29583  3233
         1   380   712

               Accuracy : 0.8934
                 95% CI : (0.8901, 0.8967)
    No Information Rate : 0.8837
    P-Value [Acc > NIR] : 0.000000006606

                  Kappa : 0.2446

 Mcnemar's Test P-Value : < 0.0000000000000002

            Sensitivity : 0.9873
            Specificity : 0.1805
         Pos Pred Value : 0.9015
         Neg Pred Value : 0.6520
              Precision : 0.9015
                 Recall : 0.9873
                     F1 : 0.9424
             Prevalence : 0.8837
         Detection Rate : 0.8724
   Detection Prevalence : 0.9678
      Balanced Accuracy : 0.5839

       'Positive' Class : 0
```

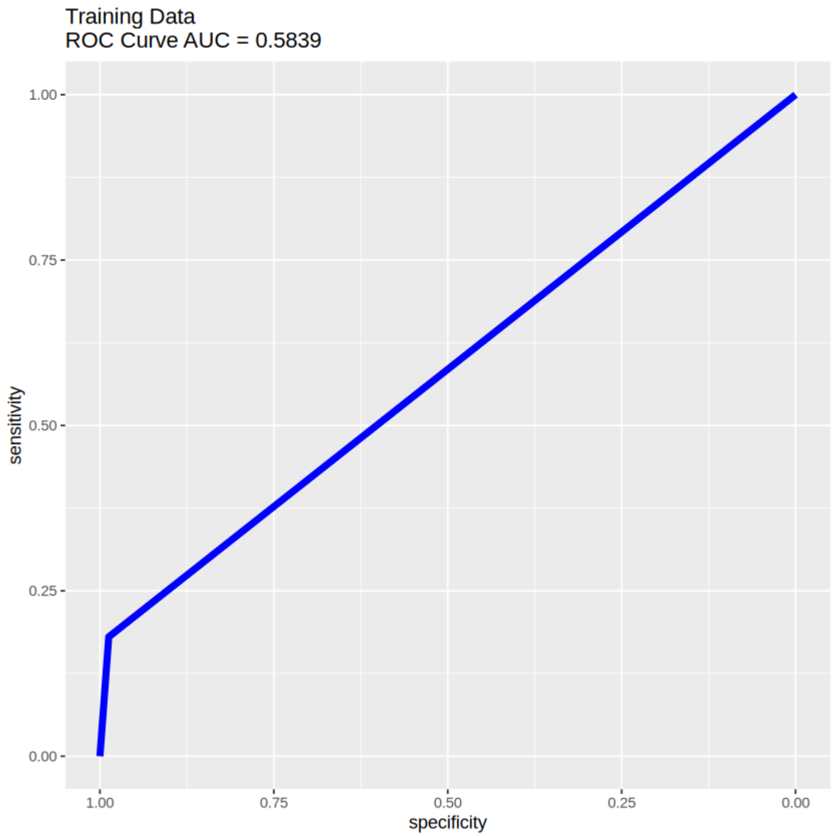
In [22]:

```r
objroc = roc(ifelse(train_df$y=='no',0,1),pred_train)
objauc = round(auc(ifelse(train_df$y=='no',0,1),pred_train),4)
```

```
Setting levels: control = 0, case = 1

Setting direction: controls < cases

Setting levels: control = 0, case = 1

Setting direction: controls < cases
```

In [23]:

```r
ggroc(objroc,colour='blue',size=2) + ggtitle(paste0('Training Data\n','ROC Curve ','AUC = ',objauc))
```



In [24]:
```
pred_test = ifelse(predict(step_select,test_df[,!(names(test_df) %in% c('y'))],type='response')>=0.5,1,0)
```

In [25]:
```
confusionMatrix(as.factor(pred_test),as.factor(ifelse(test_df$y=='no',0,1)),mode='everything')
```

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 9833 1111
         1  126  233

               Accuracy : 0.8906
                 95% CI : (0.8847, 0.8963)
    No Information Rate : 0.8811
    P-Value [Acc > NIR] : 0.0008808

                  Kappa : 0.2353

 Mcnemar's Test P-Value : < 0.0000000000000022

            Sensitivity : 0.9873
            Specificity : 0.1734
         Pos Pred Value : 0.8985
         Neg Pred Value : 0.6490
              Precision : 0.8985
                 Recall : 0.9873
                     F1 : 0.9408
             Prevalence : 0.8811
         Detection Rate : 0.8699
   Detection Prevalence : 0.9682
      Balanced Accuracy : 0.5804

       'Positive' Class : 0
```

In [26]:

```
objroc = roc(ifelse(test_df$y=='no',0,1),pred_test)
objauc = round(auc(ifelse(test_df$y=='no',0,1),pred_test),4)
```

```
Setting levels: control = 0, case = 1

Setting direction: controls < cases

Setting levels: control = 0, case = 1

Setting direction: controls < cases
```

In [27]:

```
ggroc(objroc,colour='blue',size=2) + ggtitle(paste0('Test Data\n','ROC Curve ','AUC = ',objauc))
```

Test Data
ROC Curve AUC = 0.5804