1. Prediction Task

1.1 Read and Explore the Data

First, load the data and packages.

In [1]:
```
#load packages
library(psych)
library(ggplot2)
library(GGally)
library(gridExtra)
library(cowplot)

#load data
train <- read.delim("ticdata2000.txt", header=FALSE)
predict <- read.delim("ticeval2000.txt", header=FALSE)
target <- read.delim("tictgts2000.txt", header=FALSE)
```

```
Attaching package: ‘ggplot2’

The following objects are masked from ‘package:psych’:

    %+%, alpha


Attaching package: ‘cowplot’

The following object is masked from ‘package:ggplot2’:

    ggsave
```

Inspect the data, omit the missing values if there is any.

In [2]:
```
# if there are missing values
train = na.omit(train)
predict = na.omit(predict)
target = na.omit(target)
```

In [3]:
```
#find dimensions of the data sets
dim(train)
dim(predict)
dim(target)
```

5822 86

4000 85

4000 1

In [4]:
```
head(train)
```

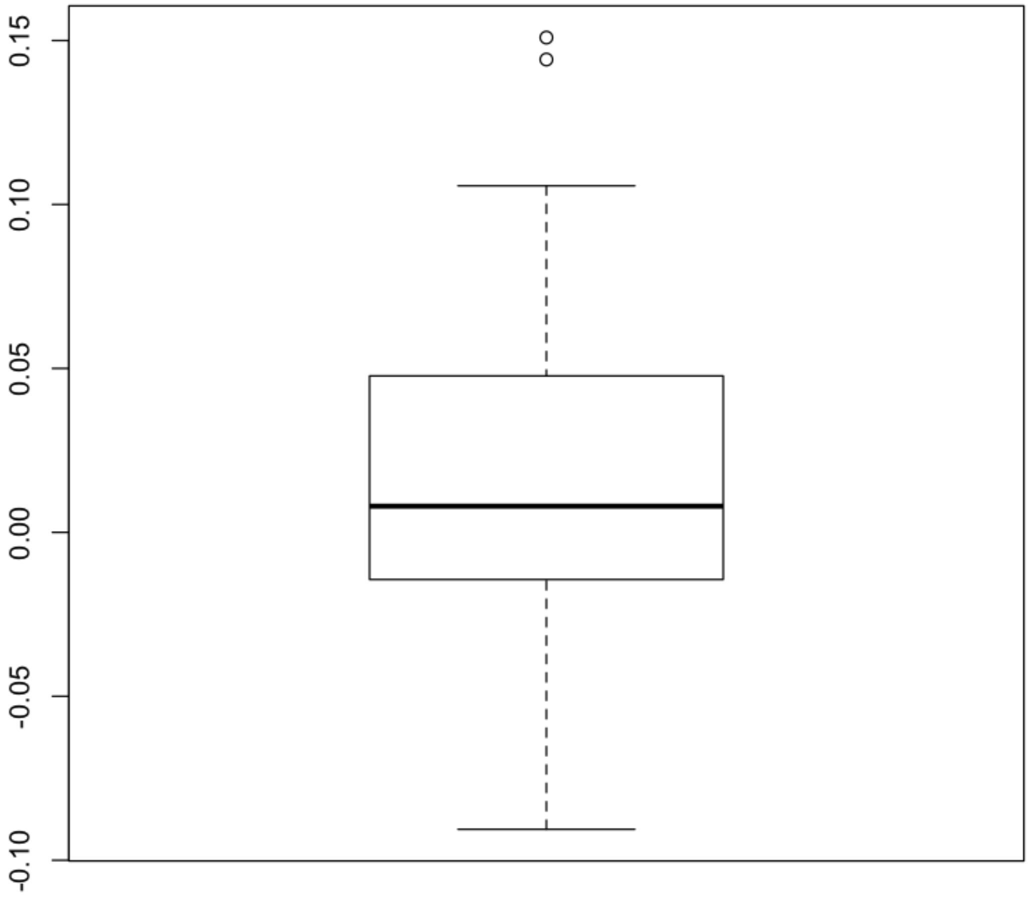
V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	⋯	V77	V78	V79	V80	V81	V82	V83	V84	V85
33	1	3	2	8	0	5	1	3	7	⋯	0	0	0	1	0	0	0	0	0
37	1	2	2	8	1	4	1	4	6	⋯	0	0	0	1	0	0	0	0	0
37	1	2	2	8	0	4	2	4	3	⋯	0	0	0	1	0	0	0	0	0
9	1	3	3	3	2	3	2	4	5	⋯	0	0	0	1	0	0	0	0	0
40	1	4	2	10	1	4	1	4	7	⋯	0	0	0	1	0	0	0	0	0
23	1	2	1	5	0	5	0	5	0	⋯	0	0	0	0	0	0	0	0	0

In [5]:
```
#Find the descriptive statistics of variables
round(describe(train),2)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	s
V1	1	5822	24.25	12.85	30	24.98	11.86	1	41	40	-0.43	-1.35	0.
V2	2	5822	1.11	0.41	1	1.00	0.00	1	10	9	7.42	99.99	0.
V3	3	5822	2.68	0.79	3	2.64	1.48	1	5	4	0.18	0.01	0.
V4	4	5822	2.99	0.81	3	2.95	0.00	1	6	5	0.47	0.62	0.
V5	5	5822	5.77	2.86	7	5.90	2.97	1	10	9	-0.33	-1.35	0.
V6	6	5822	0.70	1.00	0	0.52	0.00	0	9	9	2.24	8.62	0.
V7	7	5822	4.63	1.72	5	4.63	1.48	0	9	9	0.07	0.45	0.
V8	8	5822	1.07	1.02	1	0.96	1.48	0	5	5	0.90	0.79	0.
V9	9	5822	3.26	1.60	3	3.32	1.48	0	9	9	-0.13	-0.03	0.
V10	10	5822	6.18	1.91	6	6.33	1.48	0	9	9	-0.72	0.68	0.
V11	11	5822	0.88	0.97	1	0.76	1.48	0	7	7	1.32	2.76	0.
V12	12	5822	2.29	1.72	2	2.14	1.48	0	9	9	0.69	0.71	0.
V13	13	5822	1.89	1.80	2	1.66	1.48	0	9	9	0.97	0.82	0.
V14	14	5822	3.23	1.62	3	3.22	1.48	0	9	9	0.18	0.40	0.
V15	15	5822	4.30	2.01	4	4.25	1.48	0	9	9	0.18	-0.21	0.
V16	16	5822	1.46	1.62	1	1.20	1.48	0	9	9	1.36	1.99	0.
V17	17	5822	3.35	1.76	3	3.33	1.48	0	9	9	0.19	0.21	0.
V18	18	5822	4.57	2.30	5	4.58	2.97	0	9	9	-0.05	-0.61	0.
V19	19	5822	1.90	1.80	2	1.64	1.48	0	9	9	1.17	1.42	0.
V20	20	5822	0.40	0.78	0	0.23	0.00	0	5	5	2.84	11.09	0.
V21	21	5822	0.52	1.06	0	0.27	0.00	0	9	9	2.83	10.38	0.
V22	22	5822	2.90	1.84	3	2.80	1.48	0	9	9	0.66	0.80	0.
V23	23	5822	2.22	1.73	2	2.06	1.48	0	9	9	0.68	0.32	0.
V24	24	5822	2.31	1.69	2	2.18	1.48	0	9	9	0.67	0.57	0.
V25	25	5822	1.62	1.72	1	1.34	1.48	0	9	9	1.64	3.41	0.
V26	26	5822	1.61	1.33	2	1.49	1.48	0	9	9	1.11	3.03	0.
V27	27	5822	2.20	1.53	2	2.12	1.48	0	9	9	0.39	-0.19	0.
V28	28	5822	3.76	1.94	4	3.74	1.48	0	9	9	0.19	0.09	0.
V29	29	5822	1.07	1.30	1	0.84	1.48	0	9	9	1.42	1.98	0.
V30	30	5822	4.24	3.09	4	4.17	4.45	0	9	9	0.15	-1.31	0.
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	
V57	57	5822	0.02	0.19	0	0.00	0.00	0	3	3	13.03	174.68	0.
V58	58	5822	0.02	0.38	0	0.00	0.00	0	7	7	15.99	255.43	0.
V59	59	5822	1.83	1.88	2	1.68	2.97	0	8	8	0.39	-1.23	0.
V60	60	5822	0.00	0.04	0	0.00	0.00	0	3	3	60.61	3987.56	0.
V61	61	5822	0.02	0.27	0	0.00	0.00	0	6	6	15.91	269.40	0.
V62	62	5822	0.03	0.16	0	0.00	0.00	0	1	1	6.05	34.62	0.

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	s
V63	63	5822	0.02	0.20	0	0.00	0.00	0	6	6	16.65	330.21	0.(
V64	64	5822	0.05	0.41	0	0.00	0.00	0	5	5	8.82	78.19	0.(
V65	65	5822	0.40	0.49	0	0.38	0.00	0	2	2	0.42	-1.75	0.(
V66	66	5822	0.01	0.13	0	0.00	0.00	0	5	5	14.33	365.23	0.(
V67	67	5822	0.02	0.14	0	0.00	0.00	0	1	1	6.75	43.52	0.(
V68	68	5822	0.56	0.60	1	0.51	1.48	0	7	7	0.98	3.61	0.(
V69	69	5822	0.01	0.13	0	0.00	0.00	0	4	4	16.73	354.31	0.(
V70	70	5822	0.04	0.23	0	0.00	0.00	0	8	8	10.95	268.08	0.(
V71	71	5822	0.00	0.06	0	0.00	0.00	0	3	3	33.84	1304.72	0.(
V72	72	5822	0.01	0.13	0	0.00	0.00	0	3	3	12.22	187.68	0.(
V73	73	5822	0.03	0.24	0	0.00	0.00	0	4	4	9.45	111.64	0.(
V74	74	5822	0.01	0.12	0	0.00	0.00	0	6	6	29.44	1121.91	0.(
V75	75	5822	0.07	0.27	0	0.00	0.00	0	2	2	3.74	13.67	0.(
V76	76	5822	0.08	0.38	0	0.00	0.00	0	8	8	6.70	65.75	0.(
V77	77	5822	0.01	0.07	0	0.00	0.00	0	1	1	13.59	182.75	0.(
V78	78	5822	0.01	0.08	0	0.00	0.00	0	1	1	12.25	148.17	0.(
V79	79	5822	0.00	0.08	0	0.00	0.00	0	2	2	18.71	389.67	0.(
V80	80	5822	0.57	0.56	1	0.55	0.00	0	7	7	0.75	3.97	0.(
V81	81	5822	0.00	0.02	0	0.00	0.00	0	1	1	44.01	1935.00	0.(
V82	82	5822	0.01	0.08	0	0.00	0.00	0	2	2	14.62	236.35	0.(
V83	83	5822	0.03	0.21	0	0.00	0.00	0	3	3	7.54	63.14	0.(
V84	84	5822	0.01	0.09	0	0.00	0.00	0	2	2	11.80	146.72	0.(
V85	85	5822	0.01	0.12	0	0.00	0.00	0	2	2	8.49	73.24	0.(
V86	86	5822	0.06	0.24	0	0.00	0.00	0	1	1	3.71	11.79	0.(

In [6]:
```
#plot the correlation of the target with all predictors
cor <- as.data.frame(cor(train[-86], train$V86))
boxplot(cor)
```



In [7]:
```
#filter out the variables with relatively higher correlation.
rownames(cor)[cor$V1>=0.08 | cor$V1<=-0.08]
```

'V16' 'V18' 'V42' 'V43' 'V44' 'V47' 'V59' 'V61' 'V65' 'V68' 'V82'

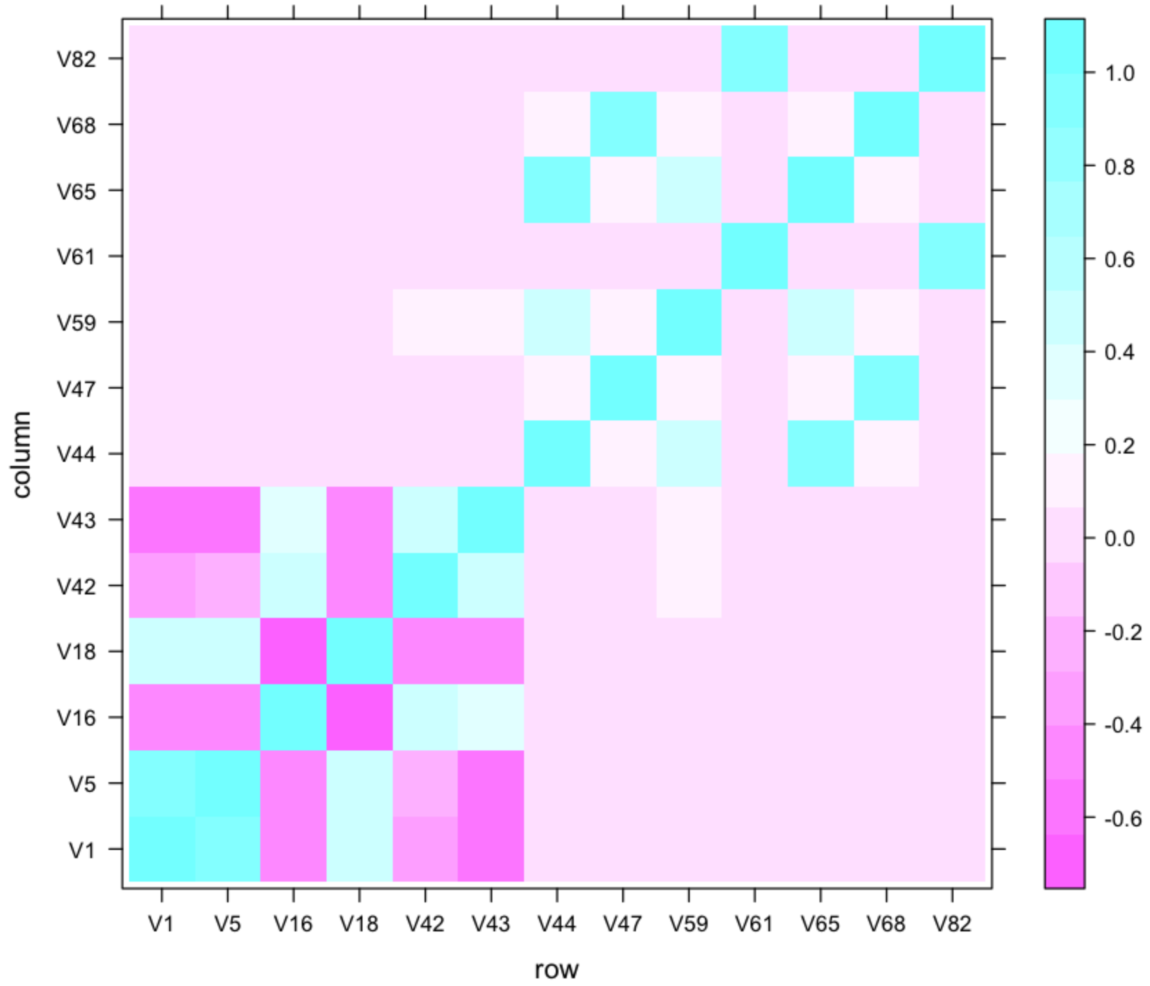
In [8]:
```
#include the high correlation variables and the categorical variables
sigcor <- c("V1","V5","V16","V18","V42","V43","V44","V47","V59","V61",
"V65","V68","V82","V86")
sigtrain <- train[sigcor]
head(sigtrain)
```

V1	V5	V16	V18	V42	V43	V44	V47	V59	V61	V65	V68	V82	V86
33	8	1	7	4	3	0	6	5	0	0	1	0	0
37	8	0	4	5	4	2	0	2	0	2	0	0	0
37	8	0	4	3	4	2	6	2	0	1	1	0	0
9	3	3	2	4	4	0	6	2	0	0	1	0	0
40	10	5	0	6	3	0	0	6	0	0	0	0	0
23	5	0	4	3	3	0	6	0	0	0	1	0	0

In [9]:
```
cor(sigtrain[-ncol(sigtrain)])
```

	V1	V5	V16	V18	V42	V43	
V1	1.000000000	0.9926718736	-0.4736063385	0.525678035	-0.300341320	-0.567807080	-0.
V5	0.992671874	1.0000000000	-0.4716200983	0.524061718	-0.282887733	-0.536337418	-0.
V16	-0.473606339	-0.4716200983	1.0000000000	-0.638593595	0.425444776	0.398037909	0.
V18	0.525678035	0.5240617183	-0.6385935955	1.000000000	-0.417082305	-0.447878781	-0.
V42	-0.300341320	-0.2828877334	0.4254447759	-0.417082305	1.000000000	0.452221075	0.
V43	-0.567807080	-0.5363374179	0.3980379085	-0.447878781	0.452221075	1.000000000	0.
V44	-0.040447498	-0.0492776598	0.0493646057	-0.044483581	0.020381246	0.012215097	1.
V47	-0.008458529	-0.0057226078	-0.0008229176	-0.003571270	0.024099514	0.022554549	0.
V59	-0.009754828	-0.0003219675	0.0269453362	-0.016937114	0.079690390	0.100062047	0.
V61	-0.018115529	-0.0205050911	0.0078658257	-0.018884358	0.009889381	0.019123180	0.
V65	-0.032936542	-0.0416142581	0.0441490043	-0.034907867	0.015006478	0.003220257	0.
V68	-0.008274480	-0.0055732945	0.0064960117	-0.009361827	0.027491218	0.033745754	0.
V82	-0.018161638	-0.0206830450	0.0076045933	-0.019264256	0.012048674	0.019636017	-0.

In [10]:
```
library(lattice)
levelplot(cor(sigtrain[-ncol(sigtrain)]))
```



The correlation matrix and the levelplot shows that the correlation between variables are not large, but sufficient to build model.

Note that there are two categorical (nominal) variables in the dataset, V1 (customer subtype) and V5 (customer main type).

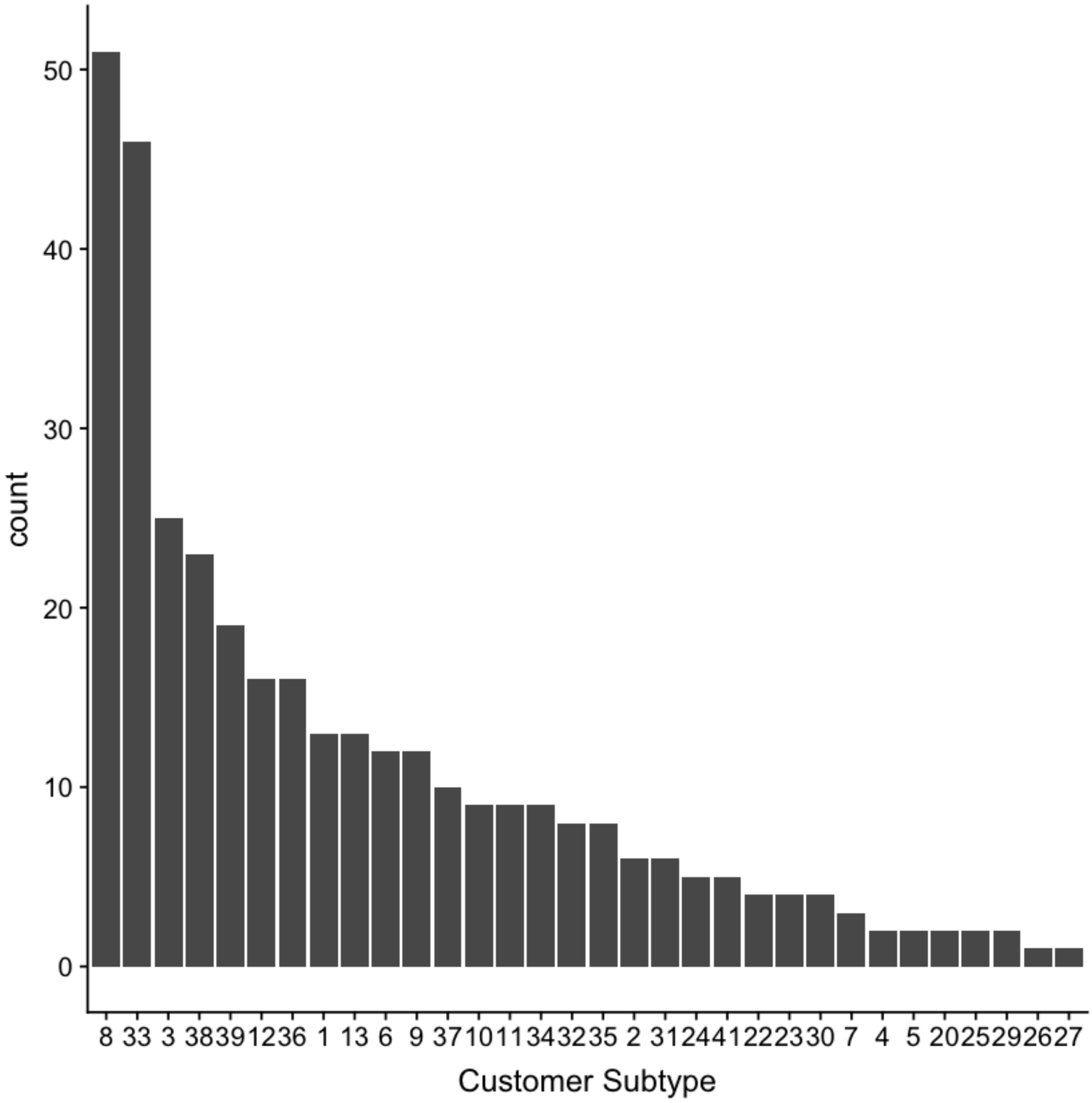
In [11]:
```
#dataframe for V1 & V86
cust.sub <- data.frame(train$V1, train$V86)
cust.sub$train.V1 <- as.factor(cust.sub$train.V1)
cust.sub$train.V86 <- as.factor(cust.sub$train.V86)

#dataframe for V5 & V86
cust.main <- data.frame(train$V5, train$V86)
cust.main$train.V5 <- as.factor(cust.main$train.V5)
cust.main$train.V86 <- as.factor(cust.main$train.V86)

#dataframe for those who have actually purchased
policy <- train[train$V86==1,]
policy$V1 <- as.factor(policy$V1)
policy$V5 <- as.factor(policy$V5)
```

Plot the distribution of the caravan policy customers of their subtype.

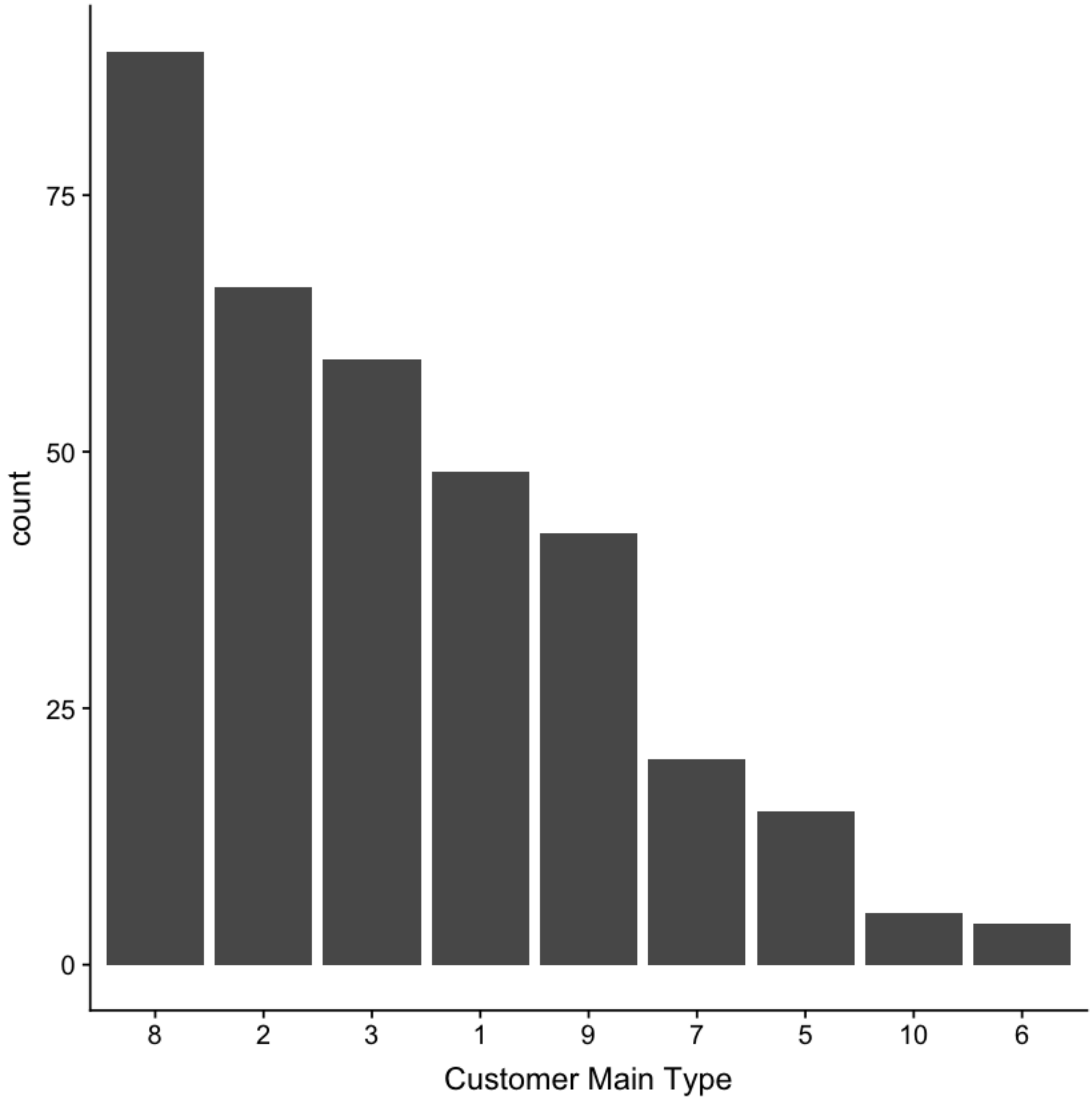
In [12]:
```
plot<-ggplot(policy, aes(x=reorder(V1,V1,function(x)-length(x))))
plot<-plot + geom_bar()
plot<-plot + labs(x="Customer Subtype")
plot
```



It is not hard to tell that customer subtype 8 and 33 has a lot more policy owners than other subtypes.

Plot the distribution of the caravan policy customers of their main type.

In [13]:
```
plot<-ggplot(policy,aes(x=reorder(V5,V5,function(x)-length(x))))
plot<-plot + geom_bar()
plot<-plot + labs(x="Customer Main Type")
plot
```



Customer main type 1, 2, 3, 8, 9 has a lot more policy owners than other main types.

In [14]:
```
library(fastDummies)
sigtrain <- dummy_cols(sigtrain, select_columns=c("V1","V5")) #create
 dummy variables
sigtrain <- sigtrain[, -c(1:2)] #drop V1 and V5
head(sigtrain)
```

V16	V18	V42	V43	V44	V47	V59	V61	V65	V68	⋯	V5_8	V5_3	V5_10	V5_5	V5_9	V5_7
1	7	4	3	0	6	5	0	0	1	⋯	1	0	0	0	0	0
0	4	5	4	2	0	2	0	2	0	⋯	1	0	0	0	0	0
0	4	3	4	2	6	2	0	1	1	⋯	1	0	0	0	0	0
3	2	4	4	0	6	2	0	0	1	⋯	0	1	0	0	0	0
5	0	6	3	0	0	6	0	0	0	⋯	0	0	1	0	0	0
0	4	3	3	0	6	0	0	0	1	⋯	0	0	0	1	0	0

In [15]:
```
dim(sigtrain)
```

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At this stage, the data frame has 60 columns, which is a lot, and there are a lot of dummy variables that are not significant enough to make a difference as discussed above, so they need to be dropped.

In [16]:
```
sigcor <- c("V1_8","V1_33","V5_1","V5_2","V5_3","V5_8","V5_9","V16","V
18","V42","V43","V44","V47","V59","V61","V65","V68","V82","V86")
sigtrain <- sigtrain[sigcor]
head(sigtrain)
```

V1_8	V1_33	V5_1	V5_2	V5_3	V5_8	V5_9	V16	V18	V42	V43	V44	V47	V59	V61	V65	V
0	1	0	0	0	1	0	1	7	4	3	0	6	5	0	0	
0	0	0	0	0	1	0	0	4	5	4	2	0	2	0	2	
0	0	0	0	0	1	0	0	4	3	4	2	6	2	0	1	
0	0	0	0	1	0	0	3	2	4	4	0	6	2	0	0	
0	0	0	0	0	0	0	5	0	6	3	0	0	6	0	0	
0	0	0	0	0	0	0	0	4	3	3	0	6	0	0	0	

In [17]:
```
dim(sigtrain)
```

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Create dummy variables for the "predict" dataframe for testing purposes later.

In [18]:
```
predict <- dummy_cols(predict, select_columns=c("V1","V5")) #create du
mmy variables
predict <- subset(predict, select=-c(V1,V5)) #drop V1 and V5
head(predict)
```

V2	V3	V4	V6	V7	V8	V9	V10	V11	V12	⋯	V5_8	V5_2	V5_9	V5_3	V5_7	V5_1	V5_10
1	4	2	0	6	0	3	5	0	4	⋯	1	0	0	0	0	0	0
1	3	2	0	5	0	4	5	2	2	⋯	0	1	0	0	0	0	0
1	3	3	1	4	2	3	5	2	3	⋯	0	0	1	0	0	0	0
1	2	3	2	3	2	4	5	4	1	⋯	0	0	0	1	0	0	0
1	2	4	0	2	0	7	9	0	0	⋯	0	0	0	0	1	0	0
1	2	4	1	4	2	3	5	0	4	⋯	0	0	0	0	1	0	0

1.2 Building Models

1.2.1 Model 1 - Multiple Logistic Regression Model

Use the full data set to perform a logistic regression with V86 as the response and V1:V85 as predictors, and use the summary function to print the results.

In [19]:
```
rough1 = glm(V86~., data = sigtrain, family = binomial)
summary(rough1)
```

```
Call:
glm(formula = V86 ~ ., family = binomial, data = sigtrain)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.6715  -0.3783  -0.2600  -0.1813   3.2205  

Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept) -4.585556   0.343508 -13.349  < 2e-16 ***
V1_8         0.494830   0.325042   1.522 0.127919    
V1_33       -0.091652   0.239698  -0.382 0.702192    
V5_1         0.982502   0.328871   2.988 0.002813 ** 
V5_2         1.045675   0.445651   2.346 0.018956 *  
V5_3         0.844231   0.305165   2.766 0.005667 ** 
V5_8         0.871727   0.258418   3.373 0.000743 ***
V5_9         0.993412   0.261135   3.804 0.000142 ***
V16          0.044170   0.043839   1.008 0.313663    
V18         -0.088001   0.036628  -2.403 0.016280 *  
V42          0.084743   0.049448   1.714 0.086571 .  
V43         -0.059975   0.060112  -0.998 0.318411    
V44          0.710084   0.383146   1.853 0.063840 .  
V47          0.224383   0.040454   5.547 2.91e-08 ***
V59          0.103722   0.036200   2.865 0.004166 ** 
V61         -0.089488   0.287665  -0.311 0.755737    
V65         -1.025152   0.761269  -1.347 0.178097    
V68         -0.001943   0.168248  -0.012 0.990784    
V82          2.255672   0.948089   2.379 0.017351 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2635.5  on 5821  degrees of freedom
Residual deviance: 2329.8  on 5803  degrees of freedom
AIC: 2367.8

Number of Fisher Scoring iterations: 6
```

Conduct ANOVA Test

From the summary of this model, it seems like variables named V5_1, V5_2, V5_3, V5_8, V5_9, V18, V47, V59 and V82 are significant, and we can drop some of the predictors, but we can first test that with the [anova() (https://stat.ethz.ch/R-manual/R-devel/library/stats/html/anova.glm.html)](https://stat.ethz.ch/R-manual/R-devel/library/stats/html/anova.glm.html) function to give an analysis of deviance table:

In [20]:
```
anova(rough1, test = "Chisq")
```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL	NA	NA	5821	2635.540	NA
V1_8	1	38.89891078	5820	2596.642	4.463296e-10
V1_33	1	0.12603450	5819	2596.516	7.225796e-01
V5_1	1	11.85132931	5818	2584.664	5.762020e-04
V5_2	1	5.39057458	5817	2579.274	2.024580e-02
V5_3	1	8.51731087	5816	2570.756	3.517839e-03
V5_8	1	5.30078457	5815	2565.456	2.131582e-02
V5_9	1	15.99783923	5814	2549.458	6.341482e-05
V16	1	10.49172579	5813	2538.966	1.199103e-03
V18	1	8.20789101	5812	2530.758	4.170860e-03
V42	1	3.47119800	5811	2527.287	6.244607e-02
V43	1	0.39515662	5810	2526.892	5.296012e-01
V44	1	50.27341849	5809	2476.618	1.337490e-12
V47	1	111.72261565	5808	2364.896	4.109679e-26
V59	1	8.04899685	5807	2356.847	4.552886e-03
V61	1	19.27155031	5806	2337.575	1.133833e-05
V65	1	2.09545318	5805	2335.480	1.477379e-01
V68	1	0.00241174	5804	2335.477	9.608321e-01
V82	1	5.62842507	5803	2329.849	1.767150e-02

From the table above, it can be observed that the residual deviance is gradually decreasing as the variables add up. The Pr(>Chi) column shows that variable V47 is the most relevant.

In [21]:
```
with(rough1, pchisq(null.deviance - deviance, df.null - df.residual, l
ower.tail = FALSE))
```

3.24787237347759e-54

If we choose α=0.05 , the p-value shown above indicate that rough1 fits significantly better than the null model.

Conduct Confusion Table

In [22]:
```
library(caret)
library(e1071)

probs <- predict(rough1, predict, type = "response")
pred.glm <- rep("0", length(probs))
pred.glm[probs > 0.5] <- "1"
CARAVAN = target$V1
confusionMatrix(table(pred.glm, CARAVAN), positive = "1")
```

```
Warning message:
“package ‘e1071’ was built under R version 3.5.2”

Confusion Matrix and Statistics

        CARAVAN
pred.glm    0    1
       0 3759  236
       1    3    2

               Accuracy : 0.9402
                 95% CI : (0.9325, 0.9474)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.5438

                  Kappa : 0.014

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.008403
            Specificity : 0.999203
         Pos Pred Value : 0.400000
         Neg Pred Value : 0.940926
             Prevalence : 0.059500
         Detection Rate : 0.000500
   Detection Prevalence : 0.001250
      Balanced Accuracy : 0.503803

       'Positive' Class : 1
```

The matrix shows that the fitted model predicted that a total of 5 (3+2) observed customer would purchase a caravan policy. Of these observations, 2 actually purchased and 3 did not. Hence 3 out of 3762 (0.08%) observed customers that actually did not purchase were incorrectly labeled. The error rate is very low. However, of 238 observed customers that actually purchased a caravan policy, 236 (99.16%) were missed by the logistic regression model.
There are two terms, sensitivity and specificity, which are used to characterize the performance of a classifier. The sensitivity is the percentage of customers that actually purchased a policy are correctly identified, which is computed as 2/(2+236) = 0.84%. The specificity is the percentage of those that actually did not purchase are correctly labeled, i.e., 1-0.08% = 99.92%. Therefore, it is clear that the sensitivity is very low, but the specificity is quite high.

The overall fraction of correct predictions on the training data is calculated using the following code:

The fitted model has correctly predicted 94.02% of the response in the data set, according to the result above. It is computed as (3759+2)/(3759+2+236+3) = 94.025%.

Now fit the logistic regression model using V5_1, V5_2, V5_3, V5_8, V5_9, V18, V47, V59 and V82 as the predictors.

In [23]:
```
model1 = glm(V86~V5_1+V5_2+V5_3+V5_8+V5_9+V18+V47+V59+V82, data = sigt
rain, family = binomial)
summary(model1)
```

```
Call:
glm(formula = V86 ~ V5_1 + V5_2 + V5_3 + V5_8 + V5_9 + V18 +
    V47 + V59 + V82, family = binomial, data = sigtrain)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6243  -0.3852  -0.2620  -0.1861   3.2188

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.19655    0.24485 -17.139  < 2e-16 ***
V5_1         0.83649    0.23171   3.610 0.000306 ***
V5_2         1.24757    0.22355   5.581 2.40e-08 ***
V5_3         0.70286    0.21513   3.267 0.001086 **
V5_8         0.77499    0.19148   4.047 5.18e-05 ***
V5_9         0.88955    0.22537   3.947 7.91e-05 ***
V18         -0.12226    0.03096  -3.950 7.83e-05 ***
V47          0.23484    0.02356   9.968  < 2e-16 ***
V59          0.15406    0.02982   5.166 2.40e-07 ***
V82          1.93180    0.37219   5.190 2.10e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2635.5  on 5821  degrees of freedom
Residual deviance: 2348.9  on 5812  degrees of freedom
AIC: 2368.9

Number of Fisher Scoring iterations: 6
```

In [24]:
```
with(model1, pchisq(null.deviance - deviance, df.null - df.residual, l
ower.tail = FALSE))
```

1.79019724389469e-56

In [25]:
```
probs1 <- predict(model1, predict, type = "response")
pred.glm1 <- rep("0", length(probs1))
pred.glm1[probs1 > 0.5] <- "1"
CARAVAN = target$V1
confusionMatrix(table(pred.glm1, CARAVAN), positive = "1")
```

```
Confusion Matrix and Statistics

         CARAVAN
pred.glm1    0    1
        0 3759  236
        1    3    2

               Accuracy : 0.9402
                 95% CI : (0.9325, 0.9474)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.5438

                  Kappa : 0.014

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.008403
            Specificity : 0.999203
         Pos Pred Value : 0.400000
         Neg Pred Value : 0.940926
             Prevalence : 0.059500
         Detection Rate : 0.000500
   Detection Prevalence : 0.001250
      Balanced Accuracy : 0.503803

       'Positive' Class : 1
```

When we use the new model (model1), we can predict the response in test data correctly by rate of 94.02%, the same as the rough fit.

Now use model 1 to generate a list of 800 customers in the test set that contains the most caravan polic owners.

In [26]:
```
probs1 <- as.data.frame(probs1)
rownames(probs1)<-c(1:4000)
model1probs <- cbind(number=rownames(probs1), probs1, row.names = NULL
)
head(model1probs)
```

number	probs1
1	0.028225748
2	0.284206469
3	0.145447125
4	0.087356106
5	0.005807055
6	0.013204875

In [27]:
```
target <- as.data.frame(target)
rownames(target) <- c(1:4000)
num.target <- cbind(number=rownames(target),target, row.names=NULL)
head(num.target)
```

number	V1
1	0
2	1
3	0
4	0
5	0
6	0

In [28]:
```
merge1 <- merge(x = model1probs, y = num.target, by = "number", all =
TRUE)
head(merge1)
```

number	probs1	V1
1	0.02822575	0
10	0.02963409	0
100	0.02653266	0
1000	0.07085008	0
1001	0.02085444	0
1002	0.02089732	0

In [29]:
```
sort.probs1 <- merge1[order(-merge1$probs1),]
row.names(sort.probs1) <- NULL
head(sort.probs1)
```

number	probs1	V1
576	0.9452900	1
3139	0.8648311	0
2863	0.7466873	0
1996	0.5844677	0
2622	0.5844677	1
3504	0.4731282	0

In [30]:
```
model1.top800 <- head(sort.probs1,800)

library(plyr)
count(model1.top800, 'V1')
count(target,"V1")
```

V1	freq
0	688
1	112

V1	freq
0	3762
1	238

Model 1 Result Conclusion
Therefore, in the set of 800 customers that model 1 finds, there are 112 caravan policy owners, 47.6% (112/238) of the owners were correctly identified.

1.2.2 Model 2 - Linear Discriminant Analysis

With V5_1, V5_2, V5_3, V5_8, V5_9, V18, V47, V59 and V82 being the predictors, develop another classification model using Linear Discriminant Analysis, MASS library is required.

In [31]:
```
library(MASS)
```

In [32]:
```
model2 = lda(V86~V5_1+V5_2+V5_3+V5_8+V5_9+V18+V47+V59+V82, data = sigt
rain)
model2
```

```
Call:
lda(V86 ~ V5_1 + V5_2 + V5_3 + V5_8 + V5_9 + V18 + V47 + V59 + 
    V82, data = sigtrain)

Prior probabilities of groups:
         0          1 
0.94022673 0.05977327 

Group means:
        V5_1       V5_2      V5_3      V5_8      V5_9      V18        V
47
0 0.09207161 0.07964925 0.1510778 0.2692729 0.1141761 4.624954 2.8593
35
1 0.13793103 0.18965517 0.1695402 0.2557471 0.1206897 3.747126 4.7183
91
       V59         V82
0 1.782974 0.003836317
1 2.531609 0.040229885

Coefficients of linear discriminants:
            LD1
V5_1  0.6652024
V5_2  1.4232172
V5_3  0.4636054
V5_8  0.5137090
V5_9  0.6401830
V18  -0.1169894
V47   0.2094012
V59   0.1713513
V82   5.2604728
```

In [33]:
```
pred.lda = predict(model2, predict, type= "response")
pred.target = pred.lda$class
CARAVAN = target$V1
confusionMatrix(table(pred.target, CARAVAN), positive = "1")
```

```
Confusion Matrix and Statistics

           CARAVAN
pred.target    0    1
          0 3753  235
          1    9    3

               Accuracy : 0.939
                 95% CI : (0.9311, 0.9462)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.6709

                  Kappa : 0.0184

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.01261
            Specificity : 0.99761
         Pos Pred Value : 0.25000
         Neg Pred Value : 0.94107
             Prevalence : 0.05950
         Detection Rate : 0.00075
   Detection Prevalence : 0.00300
      Balanced Accuracy : 0.50511

       'Positive' Class : 1
```

When we use the model 2, we can predict the response in test data correctly by rate of 93.9%.

In [34]:
```
probs2 <- as.data.frame(pred.lda)
rownames(probs2)<-c(1:4000)
model2probs <- cbind(number=rownames(probs2), probs2, row.names = NULL
)
head(model2probs)
```

number	class	posterior.0	posterior.1	LD1
1	0	0.9735053	0.026494747	-0.4023079
2	0	0.6732728	0.326727156	2.4655437
3	0	0.8786516	0.121348414	1.2145519
4	0	0.9268713	0.073128652	0.6572219
5	0	0.9932335	0.006766541	-1.7810387
6	0	0.9840153	0.015984712	-0.9160169

In [35]:
```
merge2 <- merge(x = model2probs, y = num.target, by = "number", all = TRUE)
head(merge2)
```

number	class	posterior.0	posterior.1	LD1	V1
1	0	0.9735053	0.02649475	-0.4023079	0
10	0	0.9717160	0.02828404	-0.3354221	0
100	0	0.9761813	0.02381872	-0.5110317	0
1000	0	0.9450927	0.05490731	0.3525693	0
1001	0	0.9802617	0.01973832	-0.7022408	0
1002	0	0.9810761	0.01892394	-0.7450104	0

In [36]:
```
sort.probs2 <- merge2[order(-merge2$posterior.1),]
row.names(sort.probs2) <- NULL
head(sort.probs2)
```

number	class	posterior.0	posterior.1	LD1	V1
576	1	0.0000563996	0.9999436	12.923862	1
3139	1	0.0002376120	0.9997624	11.492034	0
2863	1	0.0003980312	0.9996020	10.978325	0
1996	1	0.0298887532	0.9701112	6.649415	0
2622	1	0.0298887532	0.9701112	6.649415	1
3504	1	0.0471753672	0.9528246	6.177199	0

In [37]:
```
model2.top800 <- head(sort.probs2,800)

library(plyr)
count(model2.top800, 'V1')
count(target,"V1")
```

V1	freq
0	684
1	116

V1	freq
0	3762
1	238

Model 2 Result Conclusion
Therefore, in the set of 800 customers that model 1 finds, there are 116 caravan policy owners, 48.74% (116/238) of the owners were correctly identified.

1.2.3 Model 3 - K-Nearest Neighbor

With V5_1, V5_2, V5_3, V5_8, V5_9, V18, V47, V59 and V82 being the predictors, fit K-Nearest Neighbor classifier. class library is required.

In [38]:
```
library(class)
```

In [39]:
```
knn.var <- c("V5_1", "V5_2", "V5_3", "V5_8", "V5_9", "V18", "V47", "V5
9", "V82", "V86")
knn.train <- sigtrain[knn.var]
head(knn.train)
```

V5_1	V5_2	V5_3	V5_8	V5_9	V18	V47	V59	V82	V86
0	0	0	1	0	7	6	5	0	0
0	0	0	1	0	4	0	2	0	0
0	0	0	1	0	4	6	2	0	0
0	0	1	0	0	2	6	2	0	0
0	0	0	0	0	0	0	6	0	0
0	0	0	0	0	4	6	0	0	0

In [40]:
```
X.var <- c("V5_1", "V5_2", "V5_3", "V5_8", "V5_9", "V18", "V47", "V59"
, "V82")
knn.test <- predict[X.var]
head(knn.test)
```

V5_1	V5_2	V5_3	V5_8	V5_9	V18	V47	V59	V82
0	0	0	1	0	6	0	4	0
0	1	0	0	0	0	6	4	0
0	0	0	0	1	4	6	4	0
0	0	1	0	0	4	5	3	0
0	0	0	0	0	9	0	1	0
0	0	0	0	0	6	0	4	0

In [41]:
```
train.X <- knn.train[-ncol(knn.train)]
test.X <- knn.test
train.Y <- knn.train$V86
test.Y <- as.factor(target$V1)
```

In [42]:
```
## Let's use k values (no of NNs) as 1, 5 and 10 to see how they perfo
rm in terms of correct proportion of classification and success rate.
 The optimum k value can be chosen based on the outcomes as below...
set.seed(1)
knn.1 <- knn(train.X, test.X, train.Y, k=1)
knn.5 <- knn(train.X, test.X, train.Y, k=5)
knn.10 <- knn(train.X, test.X, train.Y, k=10)
```

Let's calculate the proportion of correct classification for k = 1, 5 and 10

In [43]:
```
confusionMatrix(knn.1, test.Y, positive="1") # k=1
```

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 3740  234
         1   22    4

               Accuracy : 0.936
                 95% CI : (0.928, 0.9434)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.891

                  Kappa : 0.0188

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.01681
            Specificity : 0.99415
         Pos Pred Value : 0.15385
         Neg Pred Value : 0.94112
             Prevalence : 0.05950
         Detection Rate : 0.00100
   Detection Prevalence : 0.00650
      Balanced Accuracy : 0.50548

       'Positive' Class : 1
```

In [44]:
```
confusionMatrix(knn.5, test.Y, positive="1") # k=5
```

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 3762  238
         1    0    0

               Accuracy : 0.9405
                 95% CI : (0.9327, 0.9476)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.5172

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.0000
            Specificity : 1.0000
         Pos Pred Value :    NaN
         Neg Pred Value : 0.9405
             Prevalence : 0.0595
         Detection Rate : 0.0000
   Detection Prevalence : 0.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 1
```

In [45]:
```
confusionMatrix(knn.10, test.Y, positive="1") # k=10
```

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 3762  238
         1    0    0

               Accuracy : 0.9405
                 95% CI : (0.9327, 0.9476)
    No Information Rate : 0.9405
    P-Value [Acc > NIR] : 0.5172

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.0000
            Specificity : 1.0000
         Pos Pred Value :    NaN
         Neg Pred Value : 0.9405
             Prevalence : 0.0595
         Detection Rate : 0.0000
   Detection Prevalence : 0.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 1
```

From the above 3 confusion matrices, it can be observed that even though the accuracy increases as k increases, the classifier with k = 1 still provides better predictions in terms of protential customers, AKA, the sensitivity (true positive rate) is higher.

However, since KNN is a classifier, the prediction itself is a factor, therefore, in this case, 1 or 0. It is unable to provide a list of customers with the highest possiblities to purchase caravan policies.

1.3 Conclusion

According to the results, Model 2 Linear Discriminant Analysis is the best choice as it identifies the most of the customers that actually purchased a caravan policy.

2. Description Task

Attributes V5_1, V5_2, V5_3, V5_8, V5_9, V18, V47, V59 and V82 have significant impact on the customer decision of buying a caravan policy, in which, V5_1, V5_2, V5_3, V5_8, V5_9 are the categories of customer main type.

The main customers are: successful hedonists, driven growers, average family, family with grown ups and conservative families.
Attribute V18 (Lower level education) has a negative influence on customers' decision in buying caravan policy.
Attributes V47 (Contribution car policies), V59 (Contribution fire policies) and V82 (Number of boat policies) all have positve influence on customers' decision in buying caravan policy.

Therefore, in terms of marketing, the company should focus on customers that:

- belong to the 5 types: successful hedonists, driven growers, average family, family with grown ups and conservative families;
- have high contribution in car policies and fire policies;
- have boat policies.

In [ ]: