Question 14.1

The breast cancer data set breast-cancer-wisconsin.data.txt from http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/ (http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/) (description at http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Original%29 (http://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Original%29)) has missing values.

1. Use the mean/mode imputation method to impute values for the missing data.
2. Use regression to impute values for the missing data.
3. Use regression with perturbation to impute values for the missing data.
4. (Optional) Compare the results and quality of classification models (e.g., SVM, KNN) build using (1) the data sets from questions 1,2,3; (2) the data that remains after data points with missing values are removed; and (3) the data set when a binary variable is introduced to indicate missing values.

In [ ]:
```
Approach Followed
```

In [4]:
```
#Clear environment

rm(list = ls())
# Setting the random number generator seed so that our results are reproducibl
e
set.seed(1)
```

In [117]:
```
##########LIBRARY##########
library("ggplot2")
#install.packages("devtools")
#install.packages("corrplot")
library("devtools")
library("corrplot") # to use Correlation plot
library(tidyr) # to get "gather" function
library(plyr) #to use arrange function
library(DAAG)# for cross validation
```

```
Loading required package: lattice


Attaching package: 'DAAG'


The following object is masked from 'package:plyr':

    ozone
```

In [29]:
```
data = read.table("breast-cancer-wisconsin.data.txt",header=FALSE,stringsAsFac
tors = FALSE,sep=",") %>% as_tibble()
head(data)
#summary(data)
```

A tibble: 6 × 11

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
<int>	<int>	<int>	<int>	<int>	<int>	<chr>	<int>	<int>	<int>	<int>
1000025	5	1	1	1	2	1	3	1	1	2
1002945	5	4	4	5	7	10	3	2	1	2
1015425	3	1	1	1	2	2	3	1	1	2
1016277	6	8	8	1	3	4	3	7	1	2
1017023	4	1	1	3	2	1	3	1	1	2
1017122	8	10	10	8	7	10	9	7	1	4

In [45]:
```r
# categorical tabulation of data with the variable and its frequency to find m
issing data is.
for (i in 2:11) {
  print(paste0("--------Field",i,'--------'))
  print(as.table(table(data[i])))
}
```

```
[1] "--------Field2--------"

  1   2   3   4   5   6   7   8   9  10 
145  50 108  80 130  34  23  46  14  69 
[1] "--------Field3--------"

  1   2   3   4   5   6   7   8   9  10 
384  45  52  40  30  27  19  29   6  67 
[1] "--------Field4--------"

  1   2   3   4   5   6   7   8   9  10 
353  59  56  44  34  30  30  28   7  58 
[1] "--------Field5--------"

  1   2   3   4   5   6   7   8   9  10 
407  58  58  33  23  22  13  25   5  55 
[1] "--------Field6--------"

  1   2   3   4   5   6   7   8   9  10 
 47 386  72  48  39  41  12  21   2  31 
[1] "--------Field7--------"

  ?   1  10   2   3   4   5   6   7   8   9 
 16 402 132  30  28  19  30   4   8  21   9 
[1] "--------Field8--------"

  1   2   3   4   5   6   7   8   9  10 
152 166 165  40  34  10  73  28  11  20 
[1] "--------Field9--------"

  1   2   3   4   5   6   7   8   9  10 
443  36  44  18  19  22  16  24  16  61 
[1] "--------Field10--------"

  1   2   3   4   5   6   7   8  10 
579  35  33  12   6   3   9   8  14 
[1] "--------Field11--------"

  2   4 
458 241 
```

In [46]:
```
#From above, Field 7 has "?" which denotes missing value
#Total:16 missing values

#table1 = as.table(table(data$X5,data$X2.1))
table1 = as.table(table(data[7]))
table1
```

```
  ?   1  10   2   3   4   5   6   7   8   9
 16 402 132  30  28  19  30   4   8  21   9
```

In [47]:
```
# show the missing 16 data points
data[which(data$V7 == "?"),]
```

A tibble: 16 × 11

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
<int>	<int>	<int>	<int>	<int>	<int>	<chr>	<int>	<int>	<int>	<int>
1057013	8	4	5	1	2	?	7	3	1	4
1096800	6	6	6	9	6	?	7	8	1	2
1183246	1	1	1	1	1	?	2	1	1	2
1184840	1	1	3	1	2	?	2	1	1	2
1193683	1	1	2	1	3	?	1	1	1	2
1197510	5	1	1	1	2	?	3	1	1	2
1241232	3	1	4	1	2	?	3	1	1	2
169356	3	1	1	1	2	?	3	1	1	2
432809	3	1	3	1	2	?	2	1	1	2
563649	8	8	8	1	2	?	6	10	1	4
606140	1	1	1	1	2	?	2	1	1	2
61634	5	4	3	1	2	?	2	3	1	2
704168	4	6	5	6	7	?	4	9	1	2
733639	3	1	1	1	2	?	3	1	1	2
1238464	1	1	1	1	1	?	2	1	1	2
1057067	1	1	1	1	1	?	1	1	1	2

In [51]:
```
# Find the percentage of observations with missing data.
print(paste0('Total rows:',nrow(data))) ##669
nrow(data[which(data$V7 == "?"),])/nrow(data) #16/669=0.023%
```

```
[1] "Total rows:699"
```

0.0228898426323319

In [66]:
```
#Since it is less than 5%, it complies with the Imputation rule to proceed wit
h the imputation
#Get the row# of missing entries
print(paste0("Row ID:",which(data$V7 == "?", arr.ind = TRUE)))
NeedImpute <-which(data$V7 == "?", arr.ind = TRUE)
```

```
 [1] "Row ID:24"  "Row ID:41"  "Row ID:140" "Row ID:146" "Row ID:159"
 [6] "Row ID:165" "Row ID:236" "Row ID:250" "Row ID:276" "Row ID:293"
[11] "Row ID:295" "Row ID:298" "Row ID:316" "Row ID:322" "Row ID:412"
[16] "Row ID:618"
```

Question 14.1.1

1. Use the mean/mode imputation method to impute values for the missing data.

In [ ]:
```
# I had a dilemma whether to treat Field 7 as the quantitative or categorical
 variable
#Though it had numbers, there are just 10 distinct values for this field (1 th
rough 10)
#making it look more like categorical field
#So, I am using mode
```

In [93]:
```
mode_1 <- mode(data[-NeedImpute,"V7"]) #mode return lists
```

In [94]:
```
distinct <-unique(data[-NeedImpute,"V7"]) #find unique values
distinct
```

A tibble: 10 × 1

V7
<chr>
1
10
2
4
3
9
7
5
8
6

In [104]:
```
mode_V7=which.max(tabulate(match(mode_1, distinct))) #find mode
mode_V7
#On manual check, 1 is present 400+ times out of 600+ records.
#so we have the correct mode
```

1

In [102]:
```
#######IMPUTE MODE of 1 #########
#Create a copy variable and Impute V7 with mode for V7

data_mode_imp <- data
```

In [108]:
```
data_mode_imp[NeedImpute,]$V7 <- as.character(mode_V7)
```

In [109]:
```
data_mode_imp$V7 <- as.integer(data_mode_imp$V7)
```

In [111]:
```
#######VALIDATION#########
#Check Imputed table
print(as.table(table(data_mode_imp[7])))
```

```
  1   2   3   4   5   6   7   8   9  10
418  30  28  19  30   4   8  21   9 132
```

In [ ]:
```
#From results above, No "?" found
```

END of Question 14.1.1

Question 14.1.2

1. Use regression to impute values for the missing data.

In [113]:
```
# Do not include the response variable in regression imputation

data_modified <- data[-NeedImpute,2:10] # exclude field7 with "?" values
data_modified$V7 <- as.integer(data_modified$V7)
```

In [114]:

```
# Generate linear model using all other factors as predictors

model <- lm(V7~V2+V3+V4+V5+V6+V8+V9+V10, data = data_modified)
summary(model)
```

```
Call:
lm(formula = V7 ~ V2 + V3 + V4 + V5 + V6 + V8 + V9 + V10, data = data_modifie
d)

Residuals:
    Min      1Q  Median      3Q     Max 
-9.7316 -0.9426 -0.3002  0.6725  8.6998 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.616652   0.194975  -3.163  0.00163 ** 
V2           0.230156   0.041691   5.521 4.83e-08 ***
V3          -0.067980   0.076170  -0.892  0.37246    
V4           0.340442   0.073420   4.637 4.25e-06 ***
V5           0.339705   0.045919   7.398 4.13e-13 ***
V6           0.090392   0.062541   1.445  0.14883    
V8           0.320577   0.059047   5.429 7.91e-08 ***
V9           0.007293   0.044486   0.164  0.86983    
V10         -0.075230   0.059331  -1.268  0.20524    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.274 on 674 degrees of freedom
Multiple R-squared:  0.615,	Adjusted R-squared:  0.6104 
F-statistic: 134.6 on 8 and 674 DF,  p-value: < 2.2e-16
```

In [115]:
```
#Variable selection using Step regression
step(model)
```

```
Start:  AIC=1131.43
V7 ~ V2 + V3 + V4 + V5 + V6 + V8 + V9 + V10

       Df Sum of Sq    RSS    AIC
- V9    1     0.139 3486.8 1129.5
- V3    1     4.120 3490.8 1130.2
- V10   1     8.317 3495.0 1131.0
<none>              3486.6 1131.4
- V6    1    10.806 3497.5 1131.5
- V4    1   111.227 3597.9 1150.9
- V8    1   152.482 3639.1 1158.7
- V2    1   157.657 3644.3 1159.6
- V5    1   283.119 3769.8 1182.8

Step:  AIC=1129.45
V7 ~ V2 + V3 + V4 + V5 + V6 + V8 + V10

       Df Sum of Sq    RSS    AIC
- V3    1     4.028 3490.8 1128.2
- V10   1     8.179 3495.0 1129.0
<none>              3486.8 1129.5
- V6    1    11.211 3498.0 1129.7
- V4    1   114.768 3601.6 1149.6
- V2    1   158.696 3645.5 1157.8
- V8    1   160.776 3647.6 1158.2
- V5    1   285.902 3772.7 1181.3

Step:  AIC=1128.24
V7 ~ V2 + V4 + V5 + V6 + V8 + V10

       Df Sum of Sq    RSS    AIC
- V6    1     8.606 3499.4 1127.9
- V10   1     8.889 3499.7 1128.0
<none>              3490.8 1128.2
- V4    1   153.078 3643.9 1155.6
- V2    1   155.308 3646.1 1156.0
- V8    1   157.123 3647.9 1156.3
- V5    1   282.133 3772.9 1179.3

Step:  AIC=1127.92
V7 ~ V2 + V4 + V5 + V8 + V10

       Df Sum of Sq    RSS    AIC
- V10   1     5.562 3505.0 1127.0
<none>              3499.4 1127.9
- V2    1   159.594 3659.0 1156.4
- V8    1   169.954 3669.4 1158.3
- V4    1   206.785 3706.2 1165.1
- V5    1   295.807 3795.2 1181.3

Step:  AIC=1127.01
V7 ~ V2 + V4 + V5 + V8

       Df Sum of Sq    RSS    AIC
<none>              3505.0 1127.0
- V2    1    155.70 3660.7 1154.7
- V8    1    172.42 3677.4 1157.8
```

```
- V4    1    201.22 3706.2 1163.1
- V5    1    290.68 3795.7 1179.4

Call:
lm(formula = V7 ~ V2 + V4 + V5 + V8, data = data_modified)

Coefficients:
(Intercept)           V2           V4           V5           V8
    -0.5360       0.2262       0.3173       0.3323       0.3238
```

In [116]:

```
#V2+V4+V5+V8  combination has lowest number of variables with better AIC 1127.
01
model2 <- lm(V7~V2+V4+V5+V8, data = data_modified)
summary(model2)
#R2 => 0.6107 (same R2 as all variables)
```

```
Call:
lm(formula = V7 ~ V2 + V4 + V5 + V8, data = data_modified)

Residuals:
    Min      1Q  Median      3Q     Max
-9.8115 -0.9531 -0.3111  0.6678  8.6889

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.53601    0.17514  -3.060   0.0023 **
V2           0.22617    0.04121   5.488 5.75e-08 ***
V4           0.31729    0.05086   6.239 7.76e-10 ***
V5           0.33227    0.04431   7.499 2.03e-13 ***
V8           0.32378    0.05606   5.775 1.17e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.274 on 678 degrees of freedom
Multiple R-squared:  0.6129,    Adjusted R-squared:  0.6107
F-statistic: 268.4 on 4 and 678 DF,  p-value: < 2.2e-16
```

In [122]:

```
# Use cross-validation to test how good this model really is.
model_cv <- cv.lm(data_modified, model2, m=5)
SST <- sum((as.numeric(data[-NeedImpute,]$V7) - mean(as.numeric(data[-NeedImpu
te,]$V7)))^2)
R2_cv <- 1 - attr(model_cv,"ms")*nrow(data[-NeedImpute,])/SST
R2_cv
#P values for all predictors are low
```

```
Analysis of Variance Table

Response: V7
           Df Sum Sq Mean Sq F value  Pr(>F)    
V2          1   3185    3185   616.2 < 2e-16 ***
V4          1   1683    1683   325.5 < 2e-16 ***
V5          1    510     510    98.6 < 2e-16 ***
V8          1    172     172    33.4 1.2e-08 ***
Residuals 678   3505       5                    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Warning message in cv.lm(data_modified, model2, m = 5):
"

 As there is >1 explanatory variable, cross-validation
 predicted values for a fold are not a linear function
 of corresponding overall predicted values.  Lines that
 are shown for the different folds are approximate
"
```

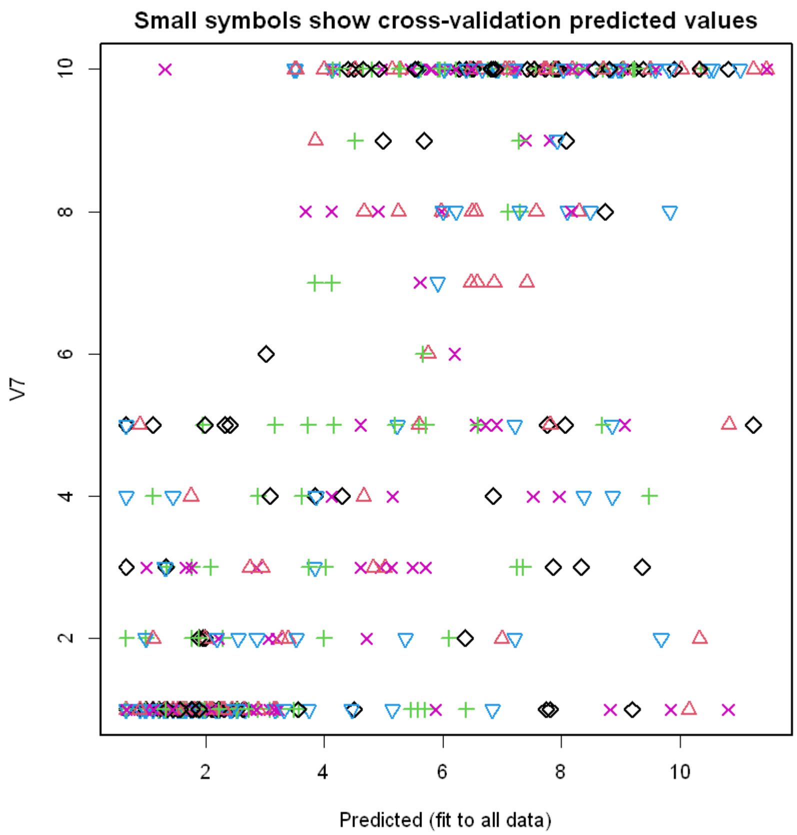
```
fold 1
Observations in test set: 136
               [,1]    [,2]   [,3]  [,4]  [,5]   [,6]   [,7]  [,8]  [,9] [,10]
Predicted     4.663 10.0184  1.213  6.62 6.575  1.213  1.213 10.15  5.02 7.572
cvpred        4.619 10.0582  1.255  6.52 6.465  1.255  1.255 10.07  4.82 7.447
V7            4.000 10.0000  1.000 10.00 7.000  1.000  1.000  1.00  3.00 8.000
CV residual -0.619 -0.0582 -0.255  3.48 0.535 -0.255 -0.255 -9.07 -1.82 0.553
              [,11] [,12] [,13] [,14]  [,15] [,16]  [,17] [,18]  [,19] [,20]
Predicted     5.598 5.750  3.50  3.39  1.990   7.7  1.213  3.15  1.998  4.67
cvpred        5.369 5.638  3.53  3.32  1.982   7.5  1.255  3.35  1.954  4.75
V7            5.000 6.000 10.00  2.00  1.000  10.0  1.000  1.00  1.000  8.00
CV residual -0.369 0.362  6.47 -1.32 -0.982   2.5 -0.255 -2.35 -0.954  3.25
              [,21]  [,22] [,23]   [,24] [,25] [,26]  [,27] [,28] [,29] [,30]
Predicted     1.990  1.311  4.82  0.9873  7.54  7.18  7.415  6.59  4.51 0.663
cvpred        1.982  1.425  4.79  1.0696  7.64  7.05  7.524  6.57  4.29 0.715
V7            1.000  1.000  3.00  1.0000 10.00 10.00  7.000 10.00 10.00 1.000
CV residual -0.982 -0.425 -1.79 -0.0696  2.36  2.95 -0.524  3.43  5.71 0.285
             [,31]   [,32]  [,33] [,34] [,35]  [,36]  [,37]   [,38]  [,39] [,4
0]
Predicted     2.53  1.1158  1.213  5.15  7.94 1.9896  1.763  0.9873  1.990  6.
49
cvpred        2.46  1.0861  1.255  5.10  7.90 1.9819  1.796  1.0696  1.982  6.
75
V7            1.00  1.0000  1.000 10.00 10.00 2.0000  1.000  1.0000  1.000  8.
00
CV residual -1.46 -0.0861 -0.255  4.90  2.10 0.0181 -0.796 -0.0696 -0.982  1.
25
              [,41]  [,42] [,43]  [,44] [,45] [,46] [,47]  [,48]   [,49] [,50]
Predicted     1.311  1.763 6.470  1.440  8.18  2.22 11.46  1.643  0.9873 6.864
cvpred        1.425  1.796 6.425  1.441  8.12  2.17 11.44  1.752  1.0696 6.883
V7            1.000  1.000 7.000  1.000 10.00  1.00 10.00  1.000  1.0000 7.000
CV residual -0.425 -0.796 0.575 -0.441  1.88 -1.17 -1.44 -0.752 -0.0696 0.117
             [,51] [,52] [,53]  [,54] [,55]  [,56]  [,57]  [,58]  [,59]  [,60]
Predicted     6.99  3.85  5.98  1.763  2.22  1.763  1.763  1.311  9.491  1.311
cvpred        6.84  3.70  5.82  1.796  2.17  1.796  1.796  1.425  9.392  1.425
V7            2.00  9.00  8.00  1.000  1.00  1.000  1.000  1.000 10.000  1.000
CV residual -4.84  5.30  2.18 -0.796 -1.17 -0.796 -0.796 -0.425  0.608 -0.425
              [,61] [,62] [,63] [,64] [,65] [,66] [,67]  [,68]  [,69] [,70]
Predicted     8.290  7.12  3.99  6.55  5.28  5.25  7.71  9.039 2.9499 0.663
cvpred        8.361  7.09  3.81  6.43  5.16  5.36  7.82  9.021 2.9251 0.715
V7            8.000 10.00 10.00  8.00 10.00  8.00 10.00 10.000 3.0000 1.000
CV residual -0.361  2.91  6.19  1.57  4.84  2.64  2.18  0.979 0.0749 0.285
               [,71]   [,72] [,73] [,74]  [,75] [,76]   [,77] [,78] [,79]
Predicted     0.9873  0.9873 0.663  3.18  1.763  2.53  0.9873  2.53  7.74
cvpred        1.0696  1.0696 0.715  3.14  1.796  2.46  1.0696  2.49  7.72
V7            1.0000  1.0000 1.000  1.00  1.000  1.00  1.0000  1.00 10.00
CV residual -0.0696 -0.0696 0.285 -2.14 -0.796 -1.46 -0.0696 -1.49  2.28
               [,80] [,81] [,82]   [,83] [,84] [,85]  [,86]  [,87]  [,88]  [,8
9]
Predicted     0.9873 2.745 11.23  0.9873  2.64 0.663 0.8897  1.885  1.794  1.6
59
cvpred        1.0696 2.774 11.25  1.0696  2.57 0.715 0.9004  1.781  1.643  1.5
96
V7            1.0000 3.000 10.00  1.0000  1.00 1.000 1.0000  1.000  1.000  1.0
00
CV residual -0.0696 0.226 -1.25 -0.0696 -1.57 0.285 0.0996 -0.781 -0.643 -0.5
96
```

```
             [,90] [,91]  [,92]  [,93] [,94]  [,95] [,96] [,97]  [,98]  [,99]
Predicted     2.88  7.05  1.342  1.666  2.44  1.666 0.663  7.89  1.990  1.311
cvpred        2.76  7.16  1.272  1.627  2.35  1.627 0.715  7.81  1.982  1.425
V7            1.00 10.00  1.000  1.000  1.00  1.000 1.000 10.00  1.000  1.000
CV residual  -1.76  2.84 -0.272 -0.627 -1.35 -0.627 0.285  2.19 -0.982 -0.425
             [,100] [,101] [,102] [,103] [,104] [,105] [,106] [,107] [,108]
Predicted      2.28   2.22  1.666  1.568  1.666  1.440  1.311   2.31  1.311
cvpred         2.40   2.17  1.627  1.458  1.627  1.441  1.425   2.34  1.425
V7             1.00   1.00  1.000  1.000  1.000  1.000  1.000   1.00  1.000
CV residual   -1.40  -1.17 -0.627 -0.458 -0.627 -0.441 -0.425  -1.34 -0.425
             [,109] [,110] [,111] [,112] [,113] [,114] [,115] [,116] [,117]
Predicted     10.33   2.08   3.52  10.82   6.46  1.311  1.568  1.983   2.30
cvpred        10.51   2.12   3.34  10.79   6.45  1.425  1.458  1.951   2.27
V7            10.00   1.00  10.00   5.00  10.00  1.000  1.000  1.000   1.00
CV residual   -0.51  -1.12   6.66  -5.79   3.55 -0.425 -0.458 -0.951  -1.27
             [,118] [,119] [,120] [,121] [,122] [,123] [,124] [,125] [,126]
Predicted     1.440   1.75   0.89   2.07   3.28  2.007  1.440  10.33  1.622
cvpred        1.441   1.73   0.90   2.06   3.25  1.926  1.441  10.51  1.717
V7            1.000   4.00   5.00   1.00   2.00  1.000  1.000   2.00  1.000
CV residual  -0.441   2.27   4.10  -1.06  -1.25 -0.926 -0.441  -8.51 -0.717
             [,127] [,128] [,129] [,130] [,131] [,132] [,133] [,134] [,135]
Predicted       2.1   1.54   2.29  1.305  0.663   8.71  1.440  1.116 0.8897
cvpred          2.1   1.61   2.24  1.393  0.715   8.74  1.441  1.086 0.9004
V7              1.0   1.00   1.00  1.000  1.000  10.00  1.000  2.000 1.0000
CV residual    -1.1  -0.61  -1.24 -0.393  0.285   1.26 -0.441  0.914 0.0996
             [,136]
Predicted      7.81
cvpred         8.04
V7             5.00
CV residual   -3.04

Sum of squares = 675    Mean square = 4.96    n = 136

Error in which.min(xval): 'list' object cannot be coerced to type 'double'
Traceback:

1. cv.lm(data_modified, model2, m = 5)
```



In [ ]:
```
#P values for all predictors are low
#SSE : 675
```

In [123]:
```
# Get predictions for missing V7 values.
V7_hat <- predict(model2, newdata = data[NeedImpute,])
```

In [126]:
```
#Create new variable and impute regression results
# Impute V7 for observations with missing data for V7 to predicted
# values with this linear model.

data_reg_imp <- data
```

In [128]:
```
data_reg_imp[NeedImpute,]$V7 <- as.character(V7_hat)
```

In [130]:
```
data_reg_imp$V7 <- as.numeric(data_reg_imp$V7)
```

In [132]:
```
# Round the V7_hat values since the originals are all integer

data_reg_imp[NeedImpute,]$V7 <- round(V7_hat)
data_reg_imp$V7 <- as.integer(data_reg_imp$V7)
```

1 · 10 · 2 · 4 · 1 · 10 · 10 · 1 · 1 · 1 · 1 · 1 · 3 · 3 · 9 · 1 · 1 ·
1 · 10 · 1 · 10 · 7 · 1 · 5 · 1 · 7 · 1 · 1 · 1 · 1 · 1 · 1 · 5 · 1 ·
1 · 1 · 1 · 1 · 10 · 7 · 8 · 3 · 10 · 1 · 1 · 1 · 9 · 1 · 1 · 8 · 3 ·
4 · 5 · 8 · 8 · 5 · 6 · 1 · 10 · 2 · 3 · 2 · 8 · 2 · 1 · 2 · 1 · 10 ·
9 · 1 · 1 · 2 · 1 · 10 · 4 · 2 · 1 · 1 · 3 · 1 · 1 · 1 · 1 · 2 · 9 · 4 ·
8 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 6 · 10 · 5 · 5 · 1 ·
3 · 1 · 3 · 10 · 10 · 1 · 9 · 2 · 9 · 10 · 8 · 3 · 5 · 2 · 10 · 3 · 2 ·
1 · 2 · 10 · 10 · 7 · 1 · 10 · 1 · 10 · 1 · 1 · 1 · 10 · 1 · 1 · 2 ·
1 · 1 · 1 · 1 · 1 · 1 · 5 · 5 · 1 · 2 · 8 · 2 · 1 · 10 · 1 · 10 · 5 ·
3 · 1 · 10 · 1 · 1 · 1 · 10 · 10 · 1 · 1 · 3 · 2 · 2 · 10 · 1 · 1 · 1 ·
1 · 1 · 1 · 10 · 10 · 10 · 1 · 1 · 1 · 10 · 1 · 1 · 1 · 10 · 10 · 1 ·
8 · 10 · 8 · 1 · 8 · 10 · 1 · 1 · 1 · 1 · 7 · 1 · 1 · 1 · … · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 5 · 4 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 10 · 1 · 1 ·
1 · 10 · 1 · 1 · 5 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 2 · 1 · 1 · 1 · 1 · 1 · 10 · 1 · 1 · 5 · 1 · 1 · 1 ·
5 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 1 · 3 · 10 · 5 ·
10 · 10 · 1 · 1 · 2 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 10 · 1 · 1 · 1 ·
10 · 1 · 3 · 1 · 1 · 10 · 10 · 1 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 10 · 8 · 1 · 1 · 10 · 1 · 10 · 2 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 2 · 1 · 1 · 1 · 4 · 6 · 5 · 1 · 1 · 1 · 1 · 1 · 3 · 1 · 1 · 1 · 2 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 2 · 1 · 4 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 5 · 8 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 10 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
5 · 1 · 1 · 2 · 1 · 3 · 4 · 5

In [133]:
```
# Make sure no V7 values are outside of the orignal range.

data_reg_imp$V7[data_reg_imp$V7 > 10] <- 10
data_reg_imp$V7[data_reg_imp$V7 < 1] <- 1
```

In [134]:
```
#######VALIDATION#########
#Check Imputed table using Regression
print(as.table(table(data_reg_imp$V7)))
```

```
  1   2   3   4   5   6   7   8   9  10
407  35  30  19  32   5   8  22   9 132
```

In [ ]:
```
#At this point, V7 is treated categorical and the earlier assumption of mode s
eems logical
######END OF 14.1.2 REGRESSION###
```

Question 14.1.3

1. Use regression with perturbation to impute values for the missing data.

In [135]:
```
V7_hat_pert <- rnorm(nrow(data[NeedImpute,]), V7_hat, sd(V7_hat))
V7_hat_pert
```

6.93560159884149 · 3.14378472827044 · 0.0857938353332633 · -0.78969862069257 · 0.957082750802076 · 3.31797604981644 · 0.791606077293643 · -0.577052435955559 · 6.79889283826345 · 7.76637878533918 · 2.78578227167521 · 2.98556237812507 · 6.48492560535614 · 3.8058246908451 · -0.730270274926497 · -1.57838968843703

In [142]:
```
# Notice that we get some negative values when we perturb the predicted value
s.

data_reg_pert_imp <- data
data_reg_pert_imp[NeedImpute,]$V7 <- as.character(V7_hat_pert)
data_reg_pert_imp$V7 <- as.numeric(data_reg_pert_imp$V7)
#data_reg_pert_imp$V7
```

1 · 10 · 2 · 4 · 1 · 10 · 10 · 1 · 1 · 1 · 1 · 1 · 3 · 3 · 9 · 1 · 1 ·
1 · 10 · 1 · 10 · 7 · 1 · 6.93560159884149 · 1 · 7 · 1 · 1 · 1 · 1 ·
1 · 1 · 5 · 1 · 1 · 1 · 1 · 1 · 10 · 7 · 3.14378472827044 · 3 · 10 ·
1 · 1 · 1 · 9 · 1 · 1 · 8 · 3 · 4 · 5 · 8 · 8 · 5 · 6 · 1 · 10 · 2 · 3 ·
2 · 8 · 2 · 1 · 2 · 1 · 10 · 9 · 1 · 1 · 2 · 1 · 10 · 4 · 2 · 1 · 1 ·
3 · 1 · 1 · 1 · 1 · 2 · 9 · 4 · 8 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 6 · 10 · 5 · 5 · 1 · 3 · 1 · 3 · 10 · 10 · 1 · 9 · 2 · 9 · 10 ·
8 · 3 · 5 · 2 · 10 · 3 · 2 · 1 · 2 · 10 · 10 · 7 · 1 · 10 · 1 · 10 ·
1 · 1 · 1 · 10 · 1 · 1 · 2 · 1 · 1 · 1 · 0.0857938353332633 · 1 · 1 ·
5 · 5 · 1 · -0.78969862069257 · 8 · 2 · 1 · 10 · 1 · 10 · 5 · 3 · 1 ·
10 · 1 · 1 · 0.957082750802076 · 10 · 10 · 1 · 1 · 3 ·
3.31797604981644 · 2 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 10 · 10 · 1 ·
1 · 1 · 10 · 1 · 1 · 1 · 10 · 10 · 1 · 8 · 10 · 8 · 1 · 8 · 10 · 1 ·
1 · 1 · 1 · 7 · 1 · 1 · 1 · ... · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 5 · 4 · 1 ·
1 · 1 · 1 · 1 · 1 · 10 · 10 · 1 · 1 · 1 · 10 · 1 · 1 · 5 · 10 · 1 · 1 ·
1 · 1 · 1 · 1 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 2 · 1 · 1 · 1 ·
1 · 1 · 10 · 1 · 1 · 5 · 1 · 1 · 1 · 5 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 10 · 1 · 3 · 10 · 5 · 10 · 10 · 1 · 1 · 2 · 1 · 1 · 1 · 1 ·
1 · 1 · 10 · 10 · 1 · 1 · 1 · 10 · 1 · 3 · 1 · 1 · 10 · 10 · 1 · 10 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 8 · 1 · 1 · 10 · 1 · 10 · 2 ·
10 · 1 · 1 · 1 · 1 · -1.57838968843703 · 1 · 1 · 1 · 2 · 1 · 1 · 1 · 4 ·
6 · 5 · 1 · 1 · 1 · 1 · 1 · 3 · 1 · 1 · 1 · 2 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 2 · 1 · 4 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 10 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 5 · 8 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
10 · 10 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 5 · 1 · 1 · 2 · 1 · 3 ·
4 · 5

In [143]:
```
# Round the V7_hat_pert values to integers.

data_reg_pert_imp[NeedImpute,]$V7 <- round(V7_hat_pert)
data_reg_pert_imp$V7 <- as.integer(data_reg_pert_imp$V7)
```

In [144]:
```
# Make sure no V7 values are outside of the orignal range.

data_reg_pert_imp$V7[data_reg_pert_imp$V7 > 10] <- 10
data_reg_pert_imp$V7[data_reg_pert_imp$V7 < 1] <- 1
```

In [145]:
```
#######VALIDATION#########
#Check Imputed table using Regression
print(as.table(table(data_reg_pert_imp$V7)))
```

```
  1   2   3   4   5   6   7   8   9  10
409  30  32  20  30   5  10  22   9 132
```

In [ ]:
```
######END OF 14.1.3 PERTURBATION###
```

Question 15.1

Describe a situation or problem from your job, everyday life, current events, etc., for which optimization would be appropriate. What data would you need?

Optimization in healthcare:

As the global healthcare industry is faced with the challenging situation of high demand, best quality for a better price, Prescriptive analytics can be used to not only what will happen, but also why it will happen, providing recommendations regarding actions that will take advantage of the predictions.

One of the scenario to utilize Optimization includes Best way to accommodate patient schedule taking into account of staffs availability, resource availability (facility, tests), patient's recent illness/procedure to accommodate this to establish schedules. Below model is setup for a single medical facility

Variables: x(i) : Open slots for patient Adhoc calls on day "i" y(i) : Open slots for previously scheduled appointment on day "i" z(i) : Total slots available for day "i" Constraint: x(i)+y(i) <= z(i) z(Mon) through z(fri) >0 z(sat)+z(Sun) =0

Objective: Minimize z(i)-[x(i)+y(i)] to efficiently use slots in the medical facility