CS 199

HW2 - Predicting Crime Rates

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Contents

1 Removing variables with missing values

1.1 Implementation

```r
# Read the data.
data <- read.csv('communitiesH.data', h=T) # Headers = True.

# Remove non-predictive attributes (including state number).
clean_data <- data[, -c(1:5)]

# Remove the attributes with question marks (unknowns) of them.
unkw <- clean_data == '?'
unkw_per_attr <- apply(unkw, 2, sum) # Sum the columns (2).
attr_with_unkw <- which(unkw_per_attr > 0) # Equivalent to find in Matlab.
no_unkw_data <- clean_data[, -attr_with_unkw]
```

2 Basics - Linear regression

2.1 Implementation

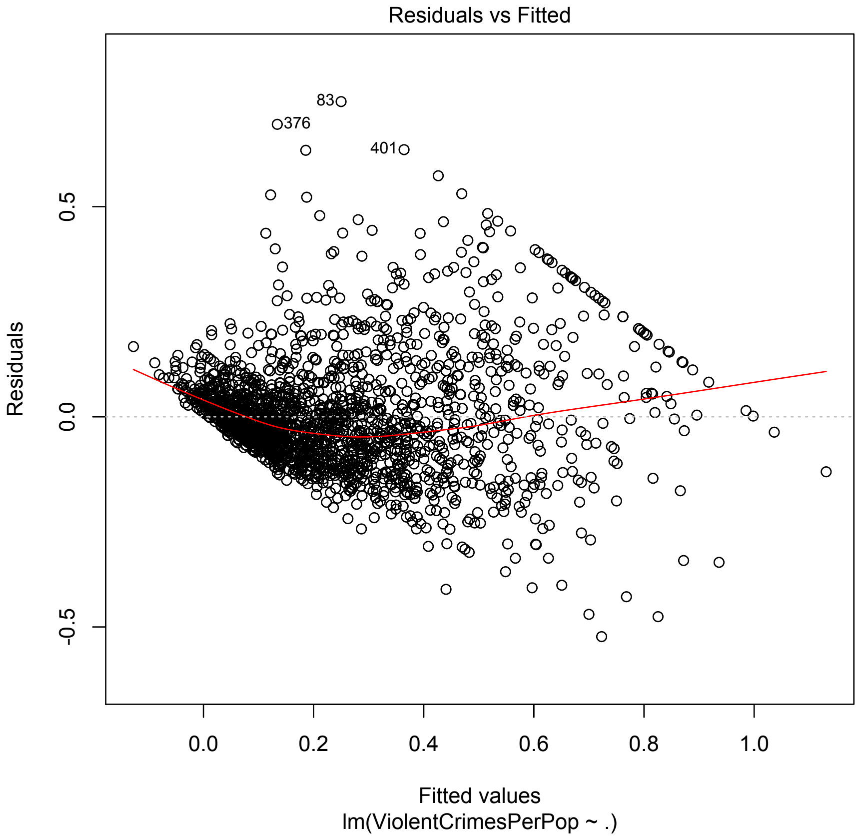
```r
# Compute the regression with the data free of unknowns.
linear_regr <- lm(ViolentCrimesPerPop ~ ., data=no_unkw_data)

# Evaluate the regression looking at the mean-squared error on the training data.
residuals <- resid(linear_regr)  # Function to get the residuals.
mse_residuals <- sum((residuals - mean(residuals)) ^ 2) / length(residuals)
printf(" - Mean-squared error on the whole data: %.2e", mse_residuals)

# Split off some test data and compute a new regression on the rest of the data
# (train data).
folds <- cvFolds(nrow(no_unkw_data), K=5)
train_data <- no_unkw_data[folds$subsets[folds$which != 1], ]
test_data  <- no_unkw_data[folds$subsets[folds$which == 1], ]

linear_regr_test <- lm(ViolentCrimesPerPop ~ ., data=train_data)

# Evaluate the regression looking at the mean-squared error on that test data.
residuals_test <- test_data$ViolentCrimesPerPop - predict(linear_regr_test, test_data)
plot(test_data$ViolentCrimesPerPop, residuals_test)

mse_residuals_test <- sum((residuals_test - mean(residuals_test)) ^ 2) / length(residuals_test)
printf(" - Mean-squared error on the test data (20%%): %.2e", mse_residuals_test)

# Prepare the data for the Box-Cox tranformation substituting zero values by
```

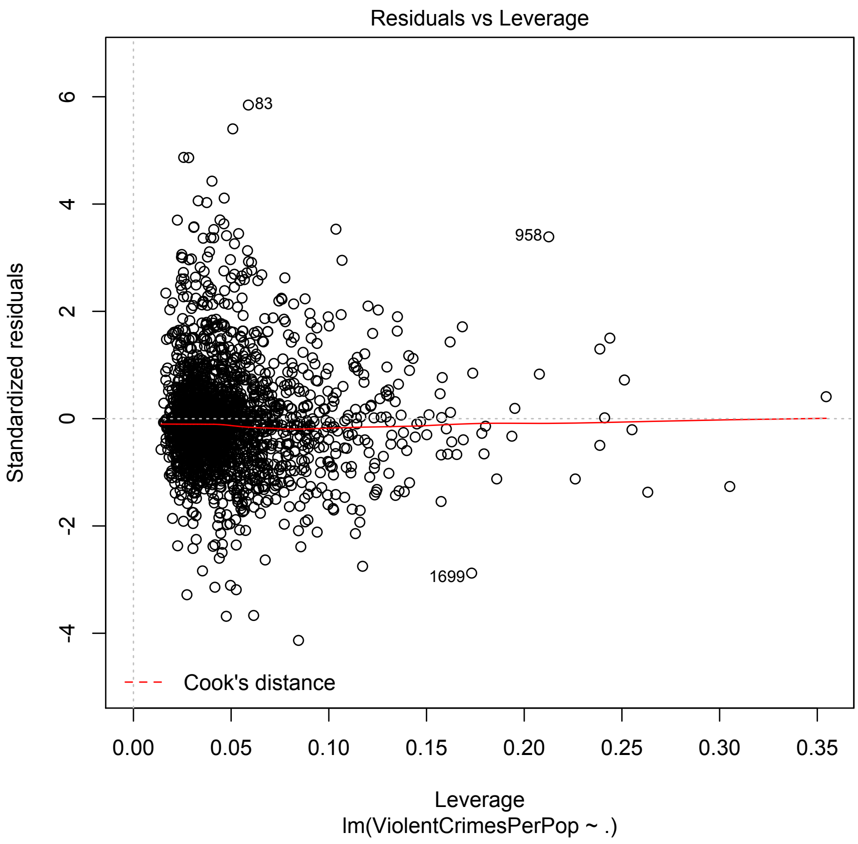
```
# a very small number.
boxcox_data <- no_unkw_data
boxcox_data$ViolentCrimesPerPop[ which(boxcox_data$ViolentCrimesPerPop == 0) ] <- 1e-100

# Apply Box-Cox and get a list of the lamdbas and their log likelihood and obtain
# the value with the highest likelihood.
linear_regr_mod <- lm(ViolentCrimesPerPop ~ ., data=boxcox_data)
lambdas <- boxcox(linear_regr_mod, plotit=F)
max_lambda <- lambdas$x[ which(lambdas$y == max(lambdas$y)) ]

# Change the very low values to zero again.
boxcox_data$ViolentCrimesPerPop[which(boxcox_data$ViolentCrimesPerPop == 1e-100)] <- 0

# Transform the data with the given value of lambda.
if (max_lambda == 0) {
  boxcox_data$ViolentCrimesPerPop <- log(boxcox_data$ViolentCrimesPerPop)
} else {
  boxcox_data$ViolentCrimesPerPop <- (boxcox_data$ViolentCrimesPerPop^max_lambda - 1)/max_lambda
}

# Compute the linear regression again and plot it.
boxcox_regr <- lm(ViolentCrimesPerPop ~ ., data=boxcox_data)
plot(boxcox_regr)
```

2.2 Results

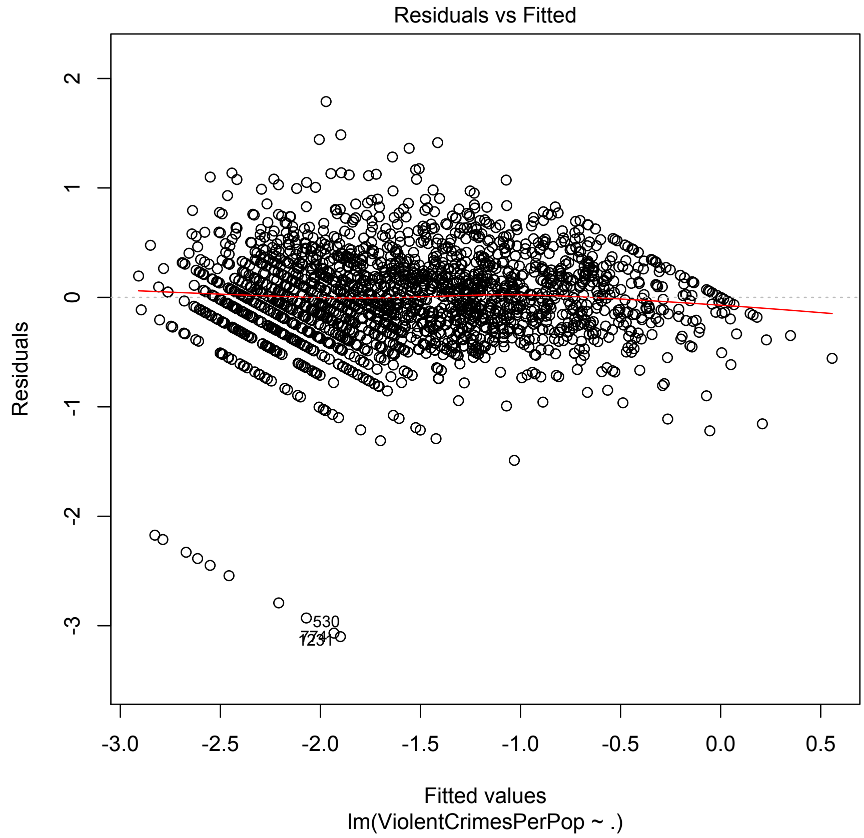
- Mean-squared error on the whole data: 1.66e-02
- Mean-squared error on the test data (20%): 1.88e-02

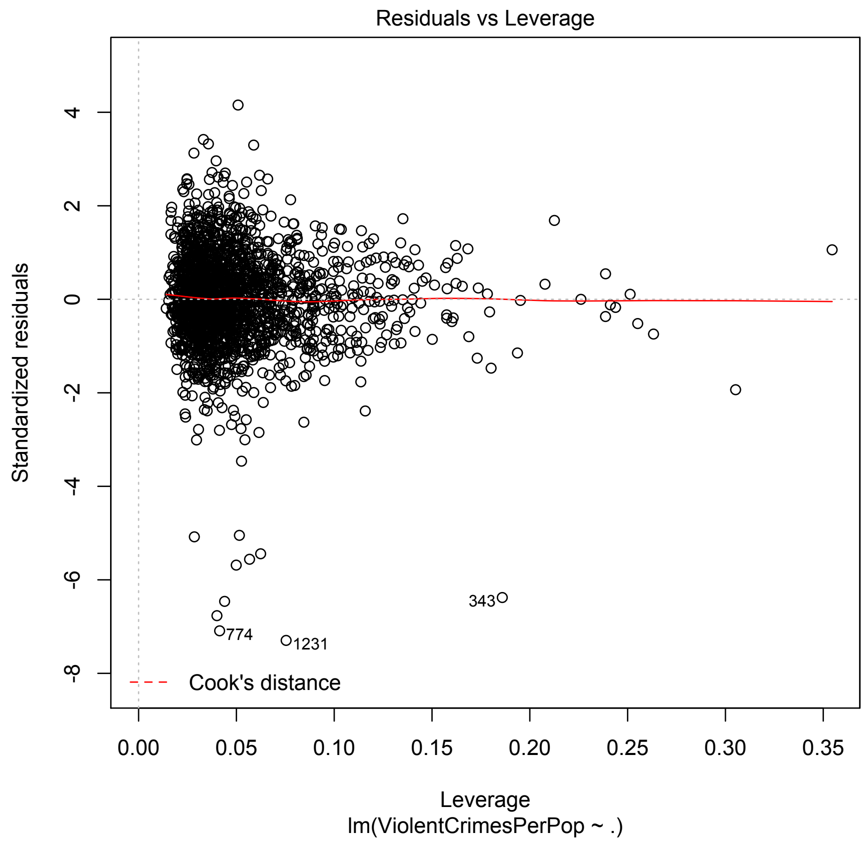
2.2.1 Standard data





2.2.2 Box-Cox transformed data





2.3 Conclusions

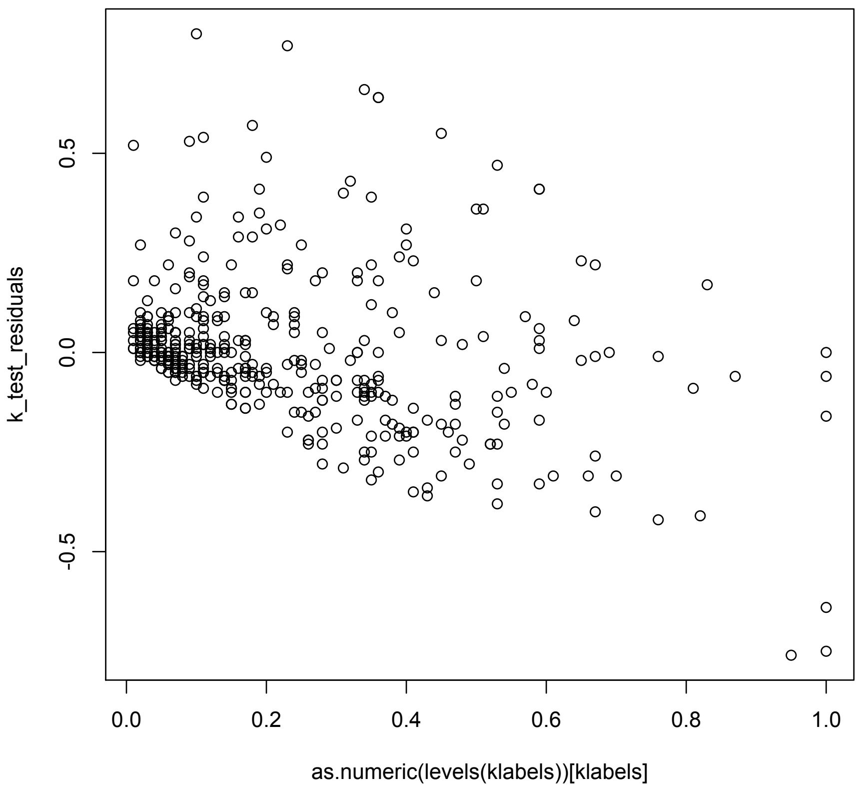
3 Basics - Nearest Neighbour regression

3.1 Implementation

```
# Compute the regression and plot it.
nn_regr <- knn.reg(train_data[!(names(train_data)) %in% c("ViolentCrimesPerPop")],
                     test = NULL,
                     train_data$ViolentCrimesPerPop, k = 1,
                     algorithm = c("kd_tree"))
plot(nn_regr$pred, nn_regr$residuals)

# Evaluate the regression on the above training data with mean-squared error.
mse_residuals_knn <- sum((nn_regr$residuals - mean(nn_regr$residuals)) ^ 2) /
    length(nn_regr$residuals)
printf(" - Mean-squared error on the training data (80%%): %.2e", mse_residuals_knn)

# Compute the regression on the above test data.
klabels <- knn(train_data[!(names(train_data)) %in% c("ViolentCrimesPerPop")],
               test_data [!(names(test_data))  %in% c("ViolentCrimesPerPop")],
               train_data$ViolentCrimesPerPop, k = 1,
               prob = FALSE, algorithm = c("kd_tree"))
k_test_residuals <- test_data$ViolentCrimesPerPop - as.numeric(levels(klabels))[klabels]
plot(as.numeric(levels(klabels))[klabels], k_test_residuals)

# Evaluate the previous regression with mean-squared error and print the result.
mse_residuals_knn_test <- sum((k_test_residuals - mean(k_test_residuals)) ^ 2) /
    length(k_test_residuals)
printf(" - Mean-squared error on the test data (20%%): %.2e", mse_residuals_knn_test)
```

3.2 Results

- Mean-squared error on the test data (20%): 3.64e-02



3.3 Conclusions

4 Dealing with missing values

4.1 Implementation

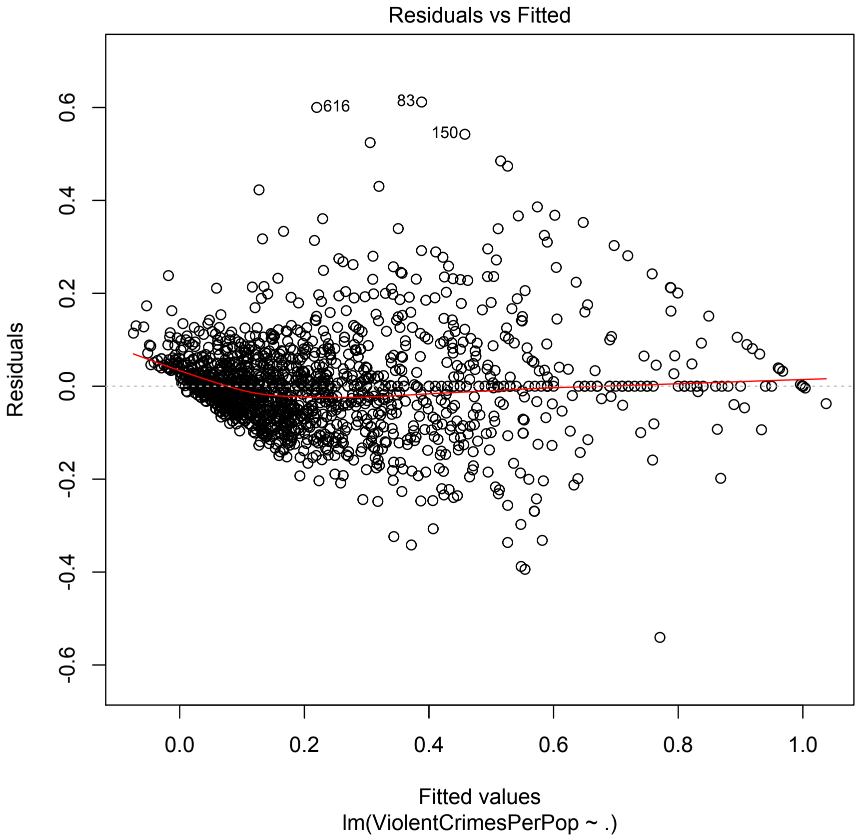
```
# Impute unknown values by covering all the columns with unknowns.
interpolated_data <- clean_data
for(i in attr_with_unkw) {
    # Divide data by rows in two sets: one with the samples that
        contain a question
    # mark in that column and one with the rest.
    unk_indices <- which(clean_data[,i] == '?')
    i_unk_data <- no_unkw_data[unk_indices, ]
    i_no_unk_data <- no_unkw_data[-unk_indices, ]

    # Compute the nearest neighbours in the set of elements with
        question mark of
    # the elements with a question mark in that column.
    i_klabels <- knn(i_no_unk_data,
                     i_unk_data,
                     i_no_unk_data$ViolentCrimesPerPop, k = 1,
                     prob = FALSE, algorithm=c("kd_tree"))
    indices <- attr(i_klabels, "nn.index")
    nn_subs <- clean_data[-unk_indices, ][indices,]

```

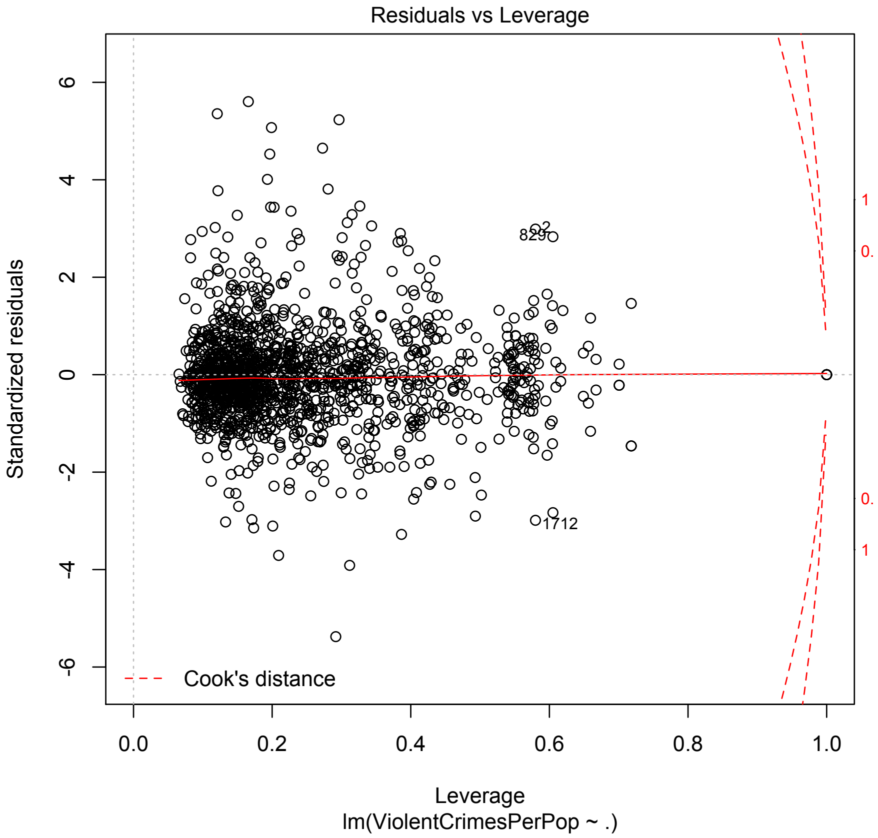
```
    # Substitute the question mark values by the value of the nearest neighbour.
    interpolated_data[unk_indices, i] <- nn_subs[,i]
}

# Split off new test data.
folds <- cvFolds(nrow(interpolated_data), K=5)
train_data <- interpolated_data[folds$subsets[folds$which != 1], ]
test_data  <- interpolated_data[folds$subsets[folds$which == 1], ]

# Compute a linear regression again and evaluate it with mean-squares.
printf("Linear Regression (imputed missing values):")
linear_regr_test <- lm(ViolentCrimesPerPop ~ ., data=train_data)

residuals_test <- test_data$ViolentCrimesPerPop - predict(linear_regr_test, test_data)
plot(test_data$ViolentCrimesPerPop, residuals_test)

mse_residuals_test <- sum((residuals_test - mean(residuals_test)) ^ 2) / length(residuals_test)
printf(" - Mean-squared error on the test data (20%%): %.2e", mse_residuals_test)

# Also, compute a nearest neighbour regression and evaluate it.
printf("Nearest Neighbours (imputed missing values):")
klabels <- knn(train_data[!(names(train_data)) %in% c("ViolentCrimesPerPop")],
               test_data [!(names(test_data))  %in% c("ViolentCrimesPerPop")],
               train_data$ViolentCrimesPerPop, k = 1,
               prob = FALSE, algorithm = c("kd_tree"))
k_test_residuals <- test_data$ViolentCrimesPerPop - as.numeric(levels(klabels))[klabels]
plot(as.numeric(levels(klabels))[klabels], k_test_residuals)

# Compute the mean-squared error and print the result.
mse_residuals_knn_test <- sum((k_test_residuals - mean(k_test_residuals)) ^ 2) /
    length(k_test_residuals)
printf(" - Mean-squared error on the test data (20%%): %.2e", mse_residuals_knn_test)
```

4.2 Results

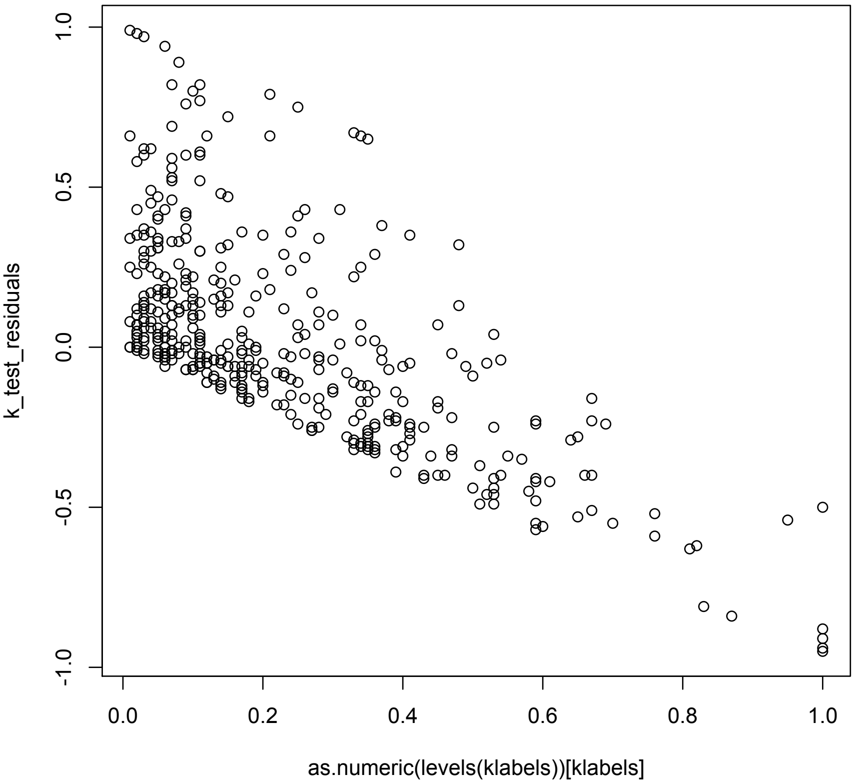
Linear Regression (imputed missing values): - Mean-squared error on the test data (20%): 1.88e-02 Nearest Neighbours (imputed missing values): - Mean-squared error on the test data (20%): 1.00e-01

4.2.1 Linear regression





4.2.2 Nearest Neighbours



4.3 Conclusions

5 Modified Nearest Neighbours

5.1 Implementation

```
# Compute the euclidean distance between two vectors that may contain question
# mark elements in a vectorized way.
distance_vec <- function(v1, v2){
  # Change question mark elements of each vector by the same position elements
  # in the other vector, so that they get cancelled when computing the distance.
  unk_indices_1 <- which(v1 == '?')
  unk_indices_2 <- which(v2 == '?')

  v1[unk_indices_1] = v2[unk_indices_1]
  v2[unk_indices_2] = v1[unk_indices_2]

  # Change question marks elements with same position in both vectors by 0.
  unk_indices <- which(v1 == '?')
  v1[unk_indices] <- 0
```

```
  v2[unk_indices] <- 0

  # Ensure vectors type is numeric.
  v1 <- as.numeric(v1)
  v2 <- as.numeric(v2)

  # Return the euclidian distance.
  return(sqrt(sum((v1 - v2) ^ 2)))
}

# Compute the euclidean distance between two vectors that may contain
   question
# mark elements in a linear way.
distance_lin <- function(v1, v2){
  s <- 0
  for(i in 1:length(v1)){
    if(v1[i] != '?' & v2[i] != '?'){
      # Only elements that are not question marks contribute to the
         distance.
      s <- s + ((as.numeric(v1[i]) - as.numeric(v2[i])) ^ 2)
    }
  }
  return(sqrt(s))
}


# Compute the modified nearest neighbour of every element in the
   dataset.
nn_data <- clean_data
for(i in 1:nrow(clean_data)){
  min_distance <- -1
  min_index <- -1

  for(j in 1:nrow(clean_data)){
    if(i != j){
      d <- distance(clean_data[i,], clean_data[j,])
      if(min_distance == -1 | d < min_distance){
        min_distance <- d
        min_index <- j
      }
    }
  }

  nn_data[i,] <- clean_data[min_index,]
}
```

5.2 Conclusions

Two different implementations have been tried for this exercise, one that computes the distance between two vectors with some question mark elements in a linear way (`distance_lin`) and other that does the same but with vectorial operations (`distance_vec`).

Unfortunately, the linear code that uses this distance functions and other R specific instructions to apply the function to matrix columns, like `outer`, were so slow during the execution that it was impossible to obtain results.