kNN, Linear regression, and multilinear regression

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1.1 kNN, Linear regression, and multilinear regression

For the acquisition of our data, we will be using the Arduino micro controller with two sensors, an HC-SR04 ultrasonic sensor and the other an analog SHARP 0A41SK sensor.

The HC-SR04 ultrasonic sensor works by sending out high frequency sound waves and then measuring the time it takes for those sound waves to bounce back off of an object and return to the sensor. The sensor consists of two main components: a transmitter and a receiver.

Code Arduino for sensor Ultrasonic HC-SR04

```
# Pin digital 12 Trigger sensor
const int Trigger = 12;
# Pin Digital 11 Echo sensor
const int Echo = 11;

void setup() {
  # Begin comunication Serial
  Serial.begin(9600);
  # Set pin as Output
  pinMode(Trigger, OUTPUT);
  # Set pin as Input
  pinMode(Echo, INPUT);
  digitalWrite(Trigger, LOW);
}

void loop()
{
  # Variable for calculation time Echo
  long t;

  digitalWrite(Trigger, HIGH);
  delayMicroseconds(10);
   # Send Pulse 10uS
  digitalWrite(Trigger, LOW);

  t = pulseIn(Echo, HIGH);

  Serial.print("Time: ");
  Serial.print(t);
  Serial.println();
  delay(2000);
}
```

The Sharp GP2Y0A21 infrared sensor works by emitting an infrared (IR) beam and then measuring the distance to an object based on the reflection of that beam. The sensor consists of an IR emitter and a receiver.

Code Arduino for sensor SHARP GP2Y0A21

```
void setup() {
  // Comunicación seria a 9600 baudios
  Serial.begin(9600);
}

void loop() {
  // Leemos la entrada analógica 0 :
  int ADC_SHARP = analogRead(A0);
  Serial.println(ADC_SHARP);
  delay(10);
}
```

1.2 Predict Model

- 1.2.1 Pre-process your data (if required) and to perform an Exploratory Data Analysis.
- 1.2.2 Train a linear model per sensor to predict the distance detected by each sensor.

Analysis for the sensor ADC1 - ADC2

```r
# Import the librarys
library (tidyverse)
```

```
## Warning: package 'readr' was built under R version 4.2.3
```

```r
library (caret)
```

```
## Warning: package 'caret' was built under R version 4.2.3
```

```r
library(psych)
```

```
## Warning: package 'psych' was built under R version 4.2.3
```

```r
folder <- dirname(rstudioapi::getSourceEditorContext()$path)
parentFolder <- dirname(folder)

#Read CSV File
Sensors1 <- read_csv(file = paste0(parentFolder, "/Datasets/Sensor.csv")) %>% as.data.frame()
#Show our Dataset Sensors1
Sensors1
```

```
##    ADC1 ADC2 DISTANCE
## 1   636  471       10
## 2   642  472       10
## 3   635  471       10
## 4   642  471       10
## 5   636  472       10
## 6   874  341       15
## 7   873  342       15
## 8   873  345       15
## 9   874  345       15
## 10  874  340       15
```

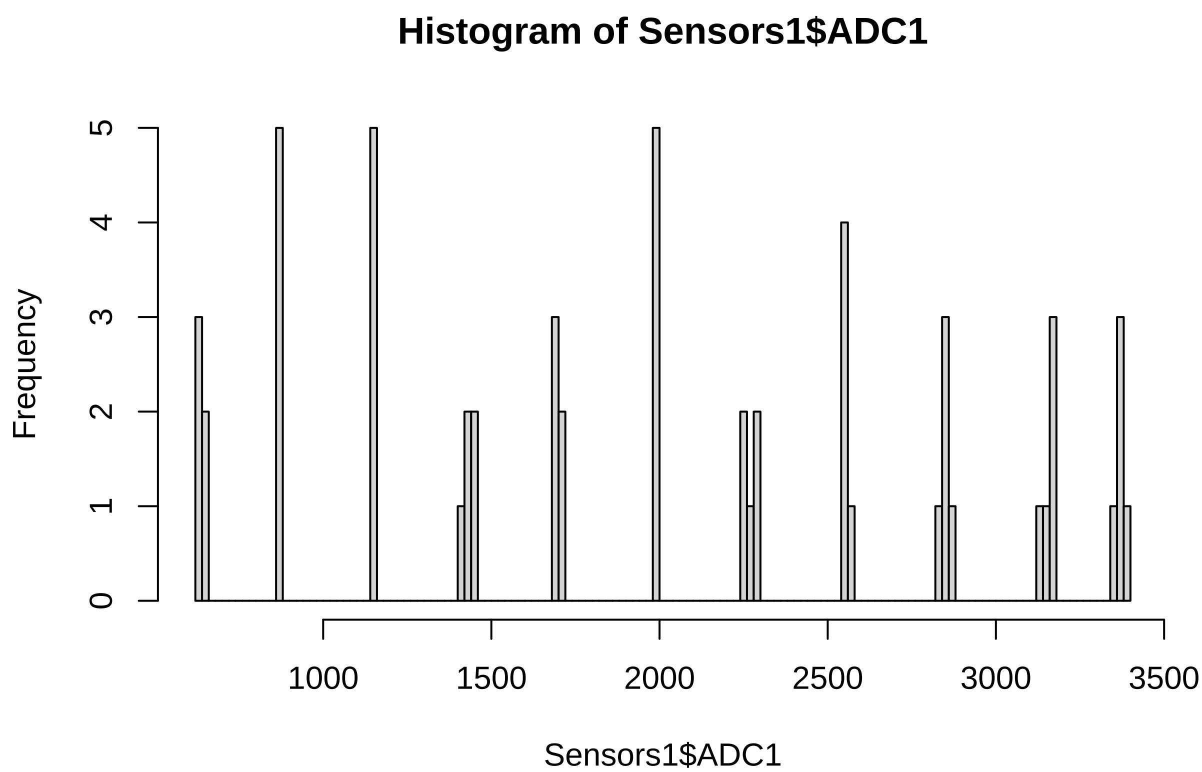
```
## 11 1153  271       20
## 12 1157  298       20
## 13 1157  270       20
## 14 1157  266       20
## 15 1156  276       20
## 16 1418  217       25
## 17 1424  218       25
## 18 1452  217       25
## 19 1451  217       25
## 20 1425  217       25
## 21 1699  176       30
## 22 1696  188       30
## 23 1702  188       30
## 24 1700  187       30
## 25 1701  189       30
## 26 1999  166       35
## 27 1999  166       35
## 28 2000  167       35
## 29 2000  166       35
## 30 1999  166       35
## 31 2259  145       40
## 32 2260  145       40
## 33 2265  145       40
## 34 2289  128       40
## 35 2283  145       40
## 36 2565  132       45
## 37 2542  132       45
## 38 2548  128       45
## 39 2541  133       45
## 40 2548  132       45
## 41 2841  120       50
## 42 2847  120       50
## 43 2840  119       50
## 44 2866  120       50
## 45 2841  119       50
## 46 3140  112       55
## 47 3168  111       55
## 48 3168  112       55
## 49 3160  111       55
## 50 3162  112       55
## 51 3365  103       60
## 52 3359  103       60
## 53 3392  103       60
## 54 3366  103       60
## 55 3361  103       60
```

```
# Give our a summary for variables ADC1 ADC2 And DISTANCE
summary(Sensors1)
```

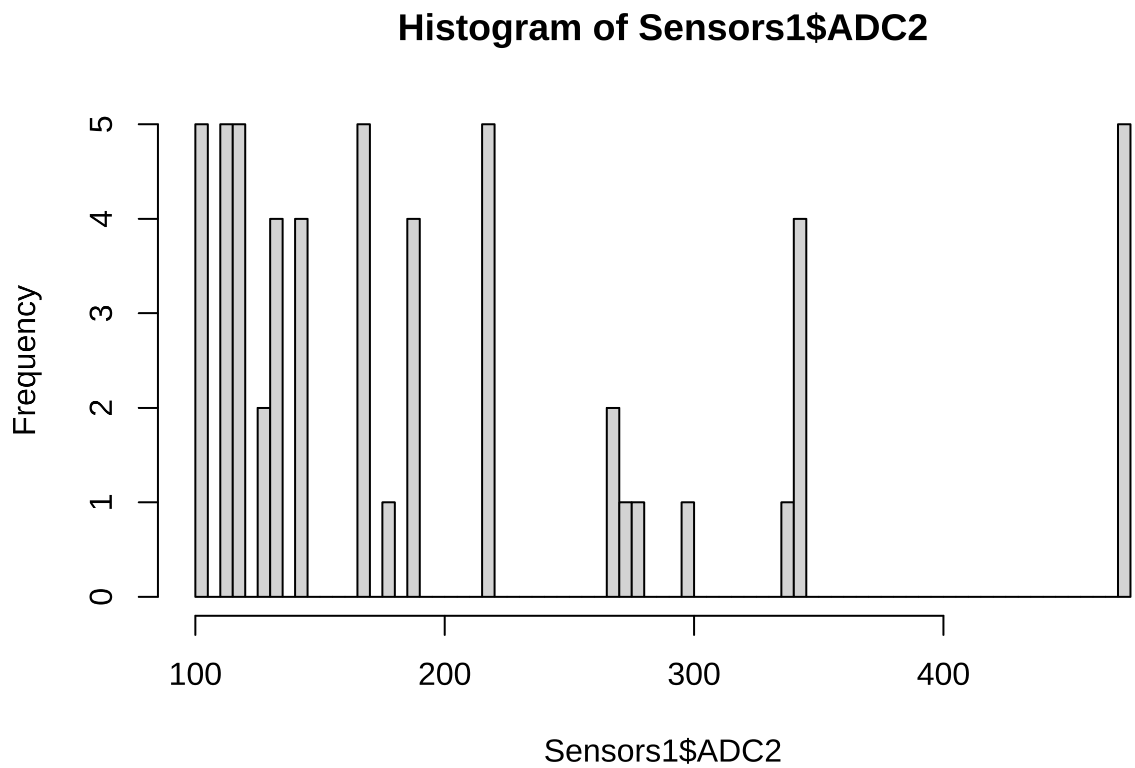
```
##       ADC1           ADC2         DISTANCE
##  Min.   : 635   Min.   :103   Min.   :10
##  1st Qu.:1157   1st Qu.:120   1st Qu.:20
##  Median :1999   Median :166   Median :35
##  Mean   :2000   Mean   :206   Mean   :35
##  3rd Qu.:2840   3rd Qu.:268   3rd Qu.:50
```

```
##  Max.   :3392   Max.   :472   Max.   :60
```

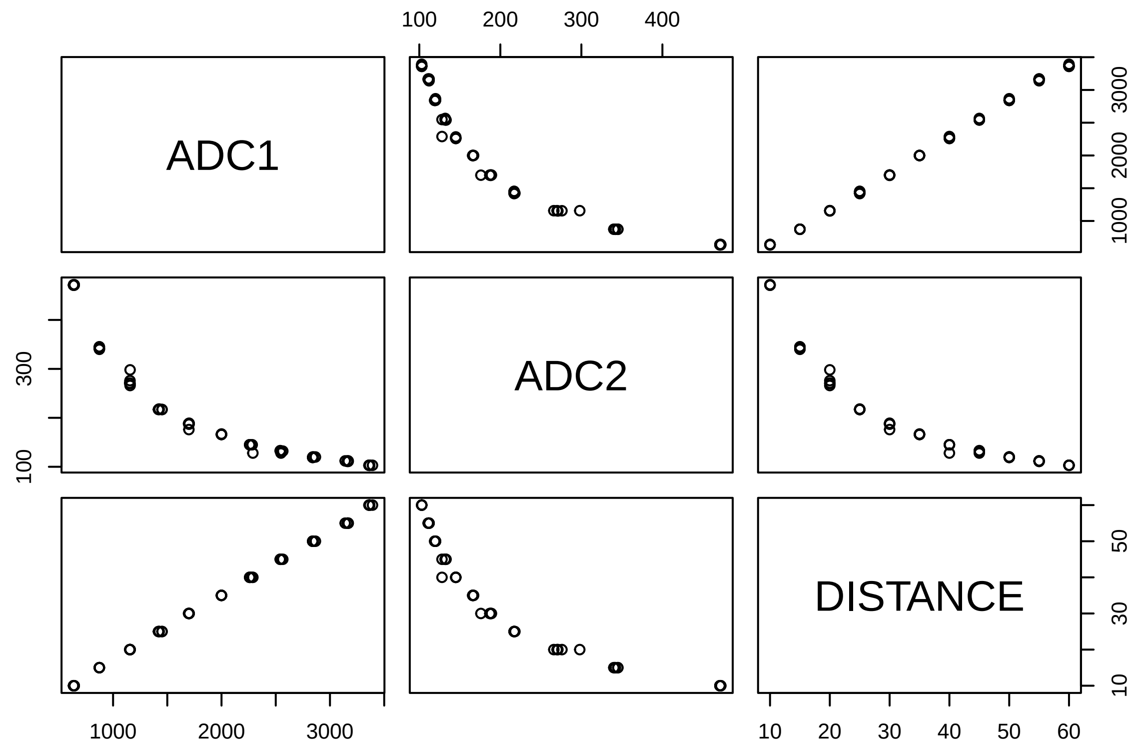
```r
# Histogram of the linear model ADC1
hist(Sensors1$ADC1,breaks = 100)
```




```r
# Histogram of the linear model ADC2
hist(Sensors1$ADC2,breaks = 100)
```




```
pairs(Sensors1[-c(7,8)], pch = 21
, bg = c("red", "green3", "blue")[unclass(Sensors1$DISTANCE)])
```




```r
# Select the corresponding columns
Data1 <- Sensors1[, c("DISTANCE", "ADC1")]
Data2 <- Sensors1[, c("DISTANCE", "ADC2")]
# Split data into training and test sets ADC1 - ADC2
set.seed(123)
trainIndex1 <- createDataPartition(Data1$DISTANCE, p = 0.8, list = FALSE)
trainData1 <- Data1[trainIndex1, ]
testData1 <- Data1[-trainIndex1, ]

trainIndex2 <- createDataPartition(Data2$DISTANCE, p = 0.8, list = FALSE)
trainData2 <- Data2[trainIndex2, ]
testData2 <- Data2[-trainIndex2, ]
# Train the linear model for distance and ADC1 - ADC2
Model1 <- lm(DISTANCE ~ ADC1, data = trainData1)
Model2 <- lm(DISTANCE ~ ADC2, data = trainData2)
# Evaluate model performance for distance and ADC1 - ADC2
predictions1 <- predict(Model1, newdata = testData1)
rmse1 <- sqrt(mean((predictions1 - testData1$DISTANCE)^2))
cat(sprintf("RMSE for DISTANCE y ADC1: %.2f\n", rmse1))
```

```
## RMSE for DISTANCE y ADC1: 0.35
```

```r
predictions2 <- predict(Model2, newdata = testData2)
rmse2 <- sqrt(mean((predictions2 - testData2$DISTANCE)^2))
cat(sprintf("RMSE for DISTANCE y ADC2: %.2f\n", rmse2))
```

```
## RMSE for DISTANCE y ADC2: 6.77
```

> [!NOTE]
>
> An analysis of our predictors will be that the ADC1 sensor will have a better response to implement the ADC1 sensor. The value of RMSE closer to 0 will indicate a greater precision in the prediction of the implemented model.

- 1.2.4 Train a multilinear regression using the data from the 2 sensors to predict the distance to the wall.

```
# Train multilinear regression model
AllModel <- lm(DISTANCE ~ ADC1 + ADC2, data = Sensors1)
# Predict using the trained model
predicted_values <- predict(AllModel, Sensors1)
# Evaluate model performance
rmse <- caret::RMSE(predicted_values, Sensors1$DISTANCE)
r_squared <- summary(AllModel)$r.squared
# Print model summary and evaluation metrics
print(summary(AllModel))
```

```
##
## Call:
## lm(formula = DISTANCE ~ ADC1 + ADC2, data = Sensors1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.78861 -0.17296  0.01641  0.20323  0.84470
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.9743746  0.4334817   2.248   0.0289 *
## ADC1         0.0174501  0.0001211 144.059  < 2e-16 ***
## ADC2        -0.0042143  0.0009714  -4.338 6.63e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3507 on 52 degrees of freedom
## Multiple R-squared:  0.9995, Adjusted R-squared:  0.9995
## F-statistic: 5.587e+04 on 2 and 52 DF,  p-value: < 2.2e-16
```

```
cat(paste0("RMSE: ", rmse, "\n"))
```

```
## RMSE: 0.341013403282297
```

```
cat(paste0("R-squared: ", r_squared, "\n"))
```

```
## R-squared: 0.999534839435127
```

- 1.2.5 Test the performance in your models by using cross-validation.

```
#Cross-validation for Model 1 ADC1
set.seed(123)
Model1 <- train(DISTANCE ~ ADC1, data = Sensors1, method = "lm", trControl = trainControl(method = "cv"
print(Model1)
```

```
## Linear Regression
##
## 55 samples
##  1 predictor
##
```

```
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 49, 48, 49, 50, 49, 51, ...
## Resampling results:
##
##   RMSE       Rsquared  MAE
##   0.4127814  0.99962   0.32821
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
#Cross-validation for Model 2 ADC2
set.seed(123)
Model2 <- train(DISTANCE ~ ADC2, data = Sensors1, method = "lm", trControl = trainControl(method = "cv"
print(Model2)
```

```
## Linear Regression
##
## 55 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 49, 48, 49, 50, 49, 51, ...
## Resampling results:
##
##   RMSE      Rsquared  MAE
##   6.971404  0.880278  6.138437
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

News prediction from the trainning Datasets

To predict the distance from a model we created the dataset PModel.CSV containing data from the ADC1 and ADC2 sensor and sampled every 100mm.

```
PModel <- read_csv(file = paste0(parentFolder, "/Datasets/PModel.csv")) %>% as.data.frame()
#The head() function is very useful for getting a quick idea of the data in an object, especially if th
head(PModel)
```

```
##   ADC1 ADC2
## 1  627  475
## 2  633  475
## 3  627  486
## 4  633  475
## 5  627  475
## 6 1169  309
```

```
#Summary of our Dataset
summary(PModel)
```

```
##       ADC1           ADC2
##  Min.   : 627   Min.   :107.0
##  1st Qu.:1035   1st Qu.:136.5
##  Median :1756   Median :214.5
##  Mean   :1889   Mean   :254.8
##  3rd Qu.:2612   3rd Qu.:350.5
```

```
## Max.   :3412   Max.   :486.0
```

```r
#create variable for predictions Firts Model
P1 <- predict(Model1,newdata=PModel)
print(P1)
```

```
##        1        2        3        4        5        6        7        8
## 10.40050 10.50802 10.40050 10.50802 10.40050 20.11387 20.49022 20.49022
##        9       10       11       12       13       14       15       16
## 20.49022 20.38269 41.27899 41.38652 40.79511 41.38652 41.38652 60.31147
##       17       18       19       20
## 59.75591 60.20394 59.86344 59.75591
```

```r
#Create variable for predictions Second Model
P2 <- predict(Model2,newdata =PModel)
print(P2)
```

```
##         1         2         3         4         5         6         7         8
##  0.115937  0.115937 -1.310742  0.115937  0.115937 21.645816 25.536758 25.666456
##         9        10        11        12        13        14        15        16
## 25.666456 25.017965 42.397506 42.397506 42.138110 42.916298 42.397506 47.844825
##        17        18        19        20
## 47.844825 47.844825 47.326032 47.844825
```

```r
#Create variable for predictions model multilinear
P3 <- predict(AllModel,newdata =PModel)
print(P3)
```

```
##         1         2         3         4         5         6         7         8
##  9.913829 10.018530  9.867472 10.018530  9.913829 20.071369 20.564250 20.568465
##         9        10        11        12        13        14        15        16
## 20.568465 20.442692 41.354258 41.458959 40.874676 41.475816 41.458959 60.063298
##        17        18        19        20
## 59.522343 59.958597 59.610187 59.522343
```