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
library(ggplot2)

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
```

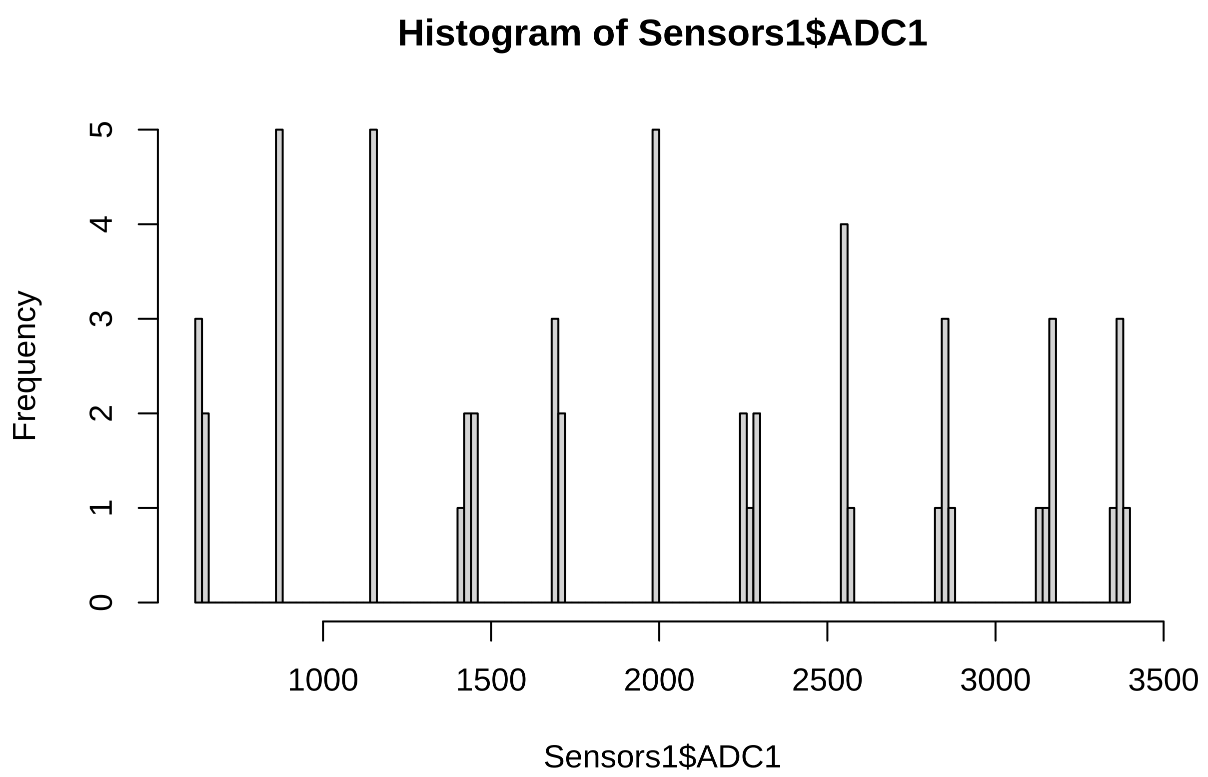
```
## 9   874  345        15
## 10  874  340        15
## 11 1153  271        20
## 12 1157  298        20
## 13 1157  270        20
## 14 1157  266        20
## 15 1156  276        20
## 16 1418  217        25
## 17 1424  218        25
## 18 1452  217        25
## 19 1451  217        25
## 20 1425  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)
```

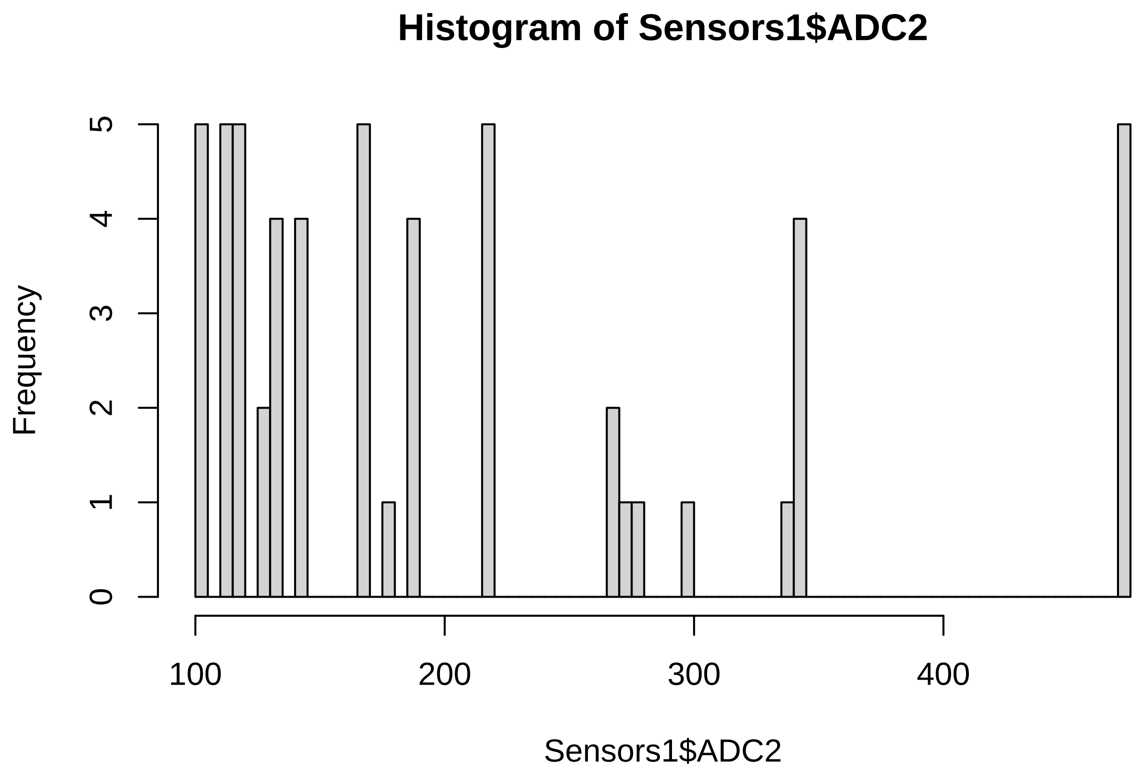
```
##       ADC1            ADC2         DISTANCE
##  Min.   : 635   Min.   :103   Min.   :10
##  1st Qu.:1157   1st Qu.:120   1st Qu.:20
##  Median :1999   Median :166   Median :35
```

```
##  Mean   :2000   Mean   :206   Mean   :35
##  3rd Qu.:2840   3rd Qu.:268   3rd Qu.:50
##  Max.   :3392   Max.   :472   Max.   :60
```

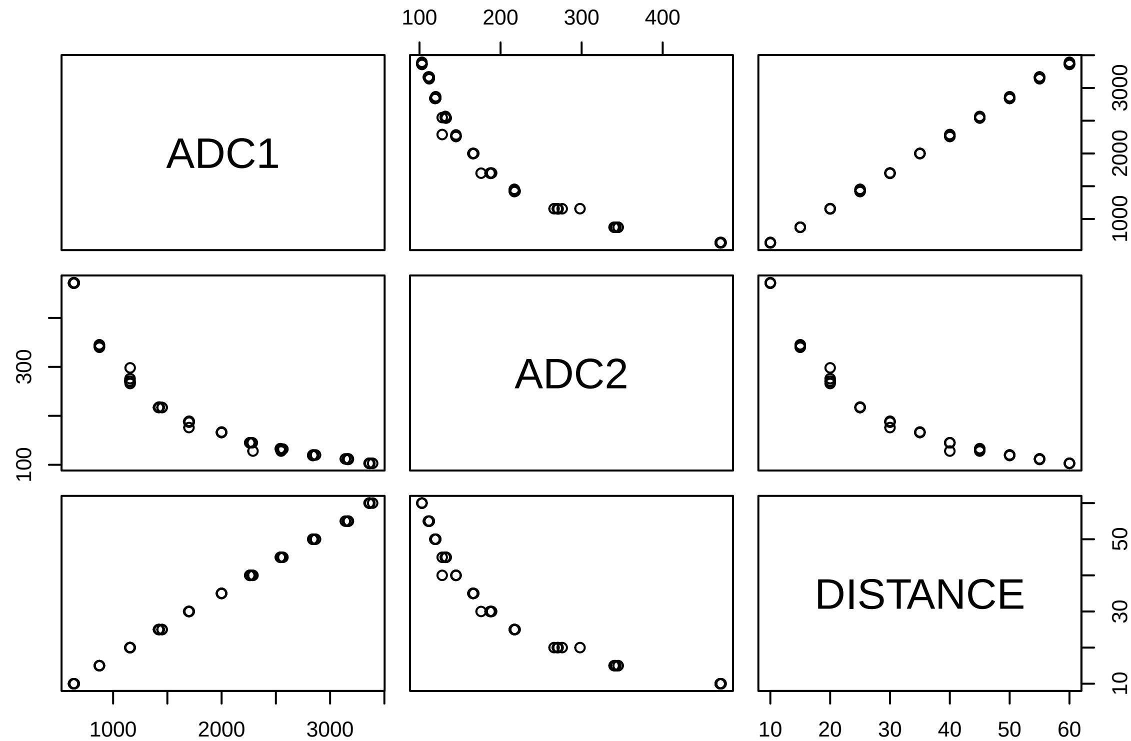
```r
# Histogram of the linear model ADC1
hist(Sensors1$ADC1,breaks = 100)
```




```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)])
```




```
# 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
```

```
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)
```

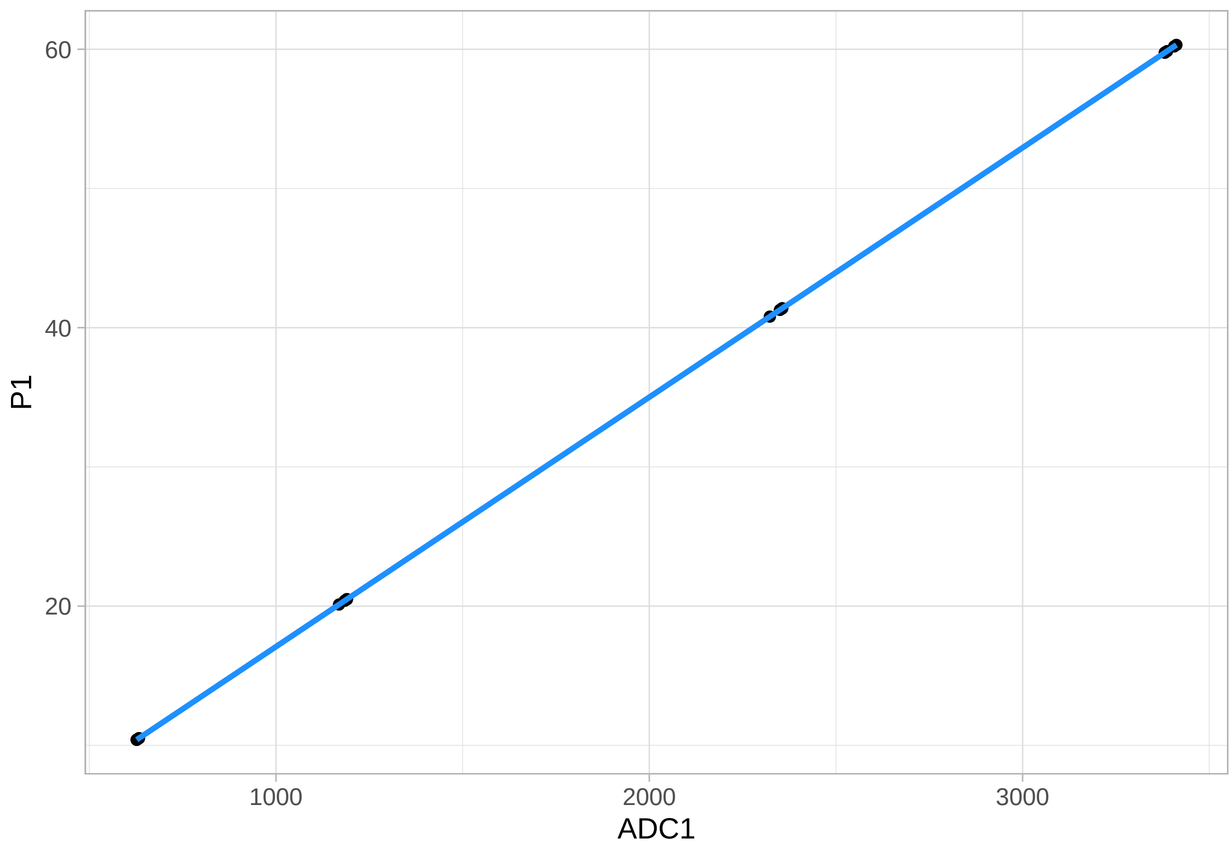
```
##       ADC1           ADC2
##  Min.   : 627   Min.   :107.0
##  1st Qu.:1035   1st Qu.:136.5
##  Median :1756   Median :214.5
##  Mean   :1889   Mean   :254.8
##  3rd Qu.:2612   3rd Qu.:350.5
```

```
## 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
#We plot the graph that relates the distance that is the predictor and the value of the ADC1 sensor.
ggplot(PModel, aes(x=ADC1, y=P1)) +
geom_point() +
geom_smooth(method='lm', formula=y~x, se=FALSE, col='dodgerblue1') +
theme_light()
```

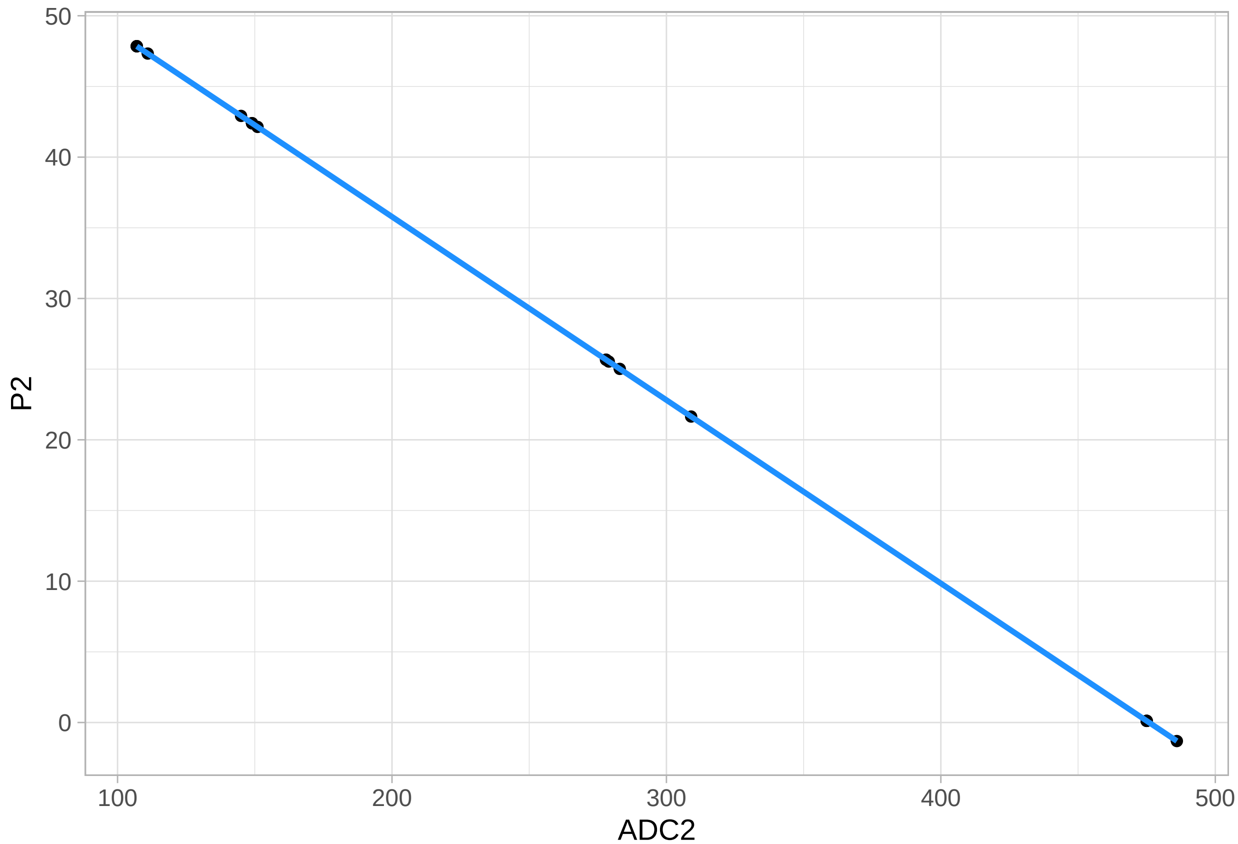



```r
#Create variable for predictions Second Model
P2 <- predict(Model2,newdata =PModel)
print(P2)
```

```
##         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
```

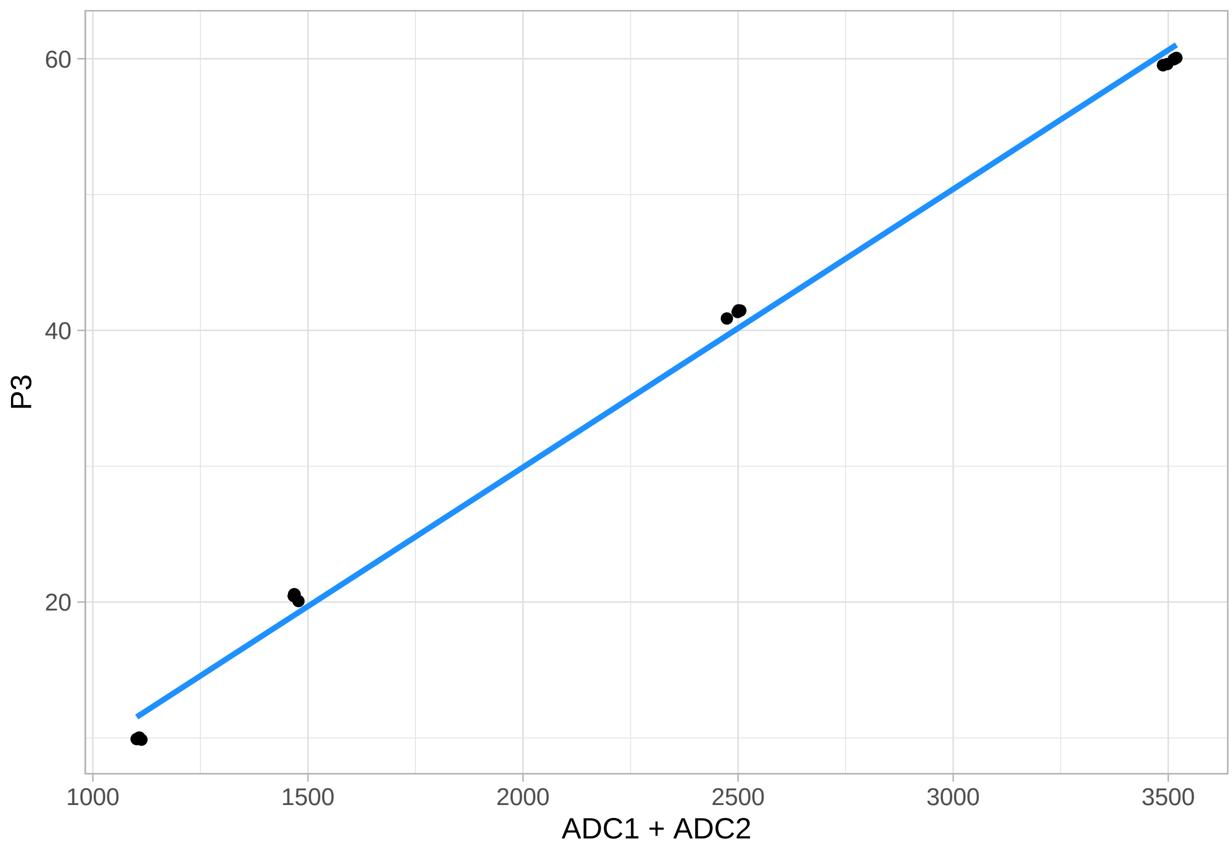
```r
#We plot the graph that relates the distance that is the predictor and the value of the ADC2 sensor.
ggplot(PModel, aes(x=ADC2, y=P2)) +
geom_point() +
geom_smooth(method='lm', formula=y~x, se=FALSE, col='dodgerblue1') +
theme_light()
```




```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
```

```r
#We plot the graph that relates the distance that is the predictor between the multi-linear model ADC1+
ggplot(PModel, aes(x=ADC1+ADC2, y=P3)) +
geom_point() +
geom_smooth(method='lm', formula=y~x, se=FALSE, col='dodgerblue1') +
theme_light()
```



- 1.2.7 Discuss all your codes and results.
- The sensor 1 ADC1 has a linear behavior, this is an ultrasonic sensor that works by mechanical waves, training our model we obtain that this is the best response to use it as a prediction model for our distance variable.
- The sensor 2 ADC2 is a SHARP sensor of analog infrared operation, where its behavior is not linear, another characteristic of this sensor is the closer the object of detection, its variable will increase, it is inversely proportional to the distance.
- We have two Datasets the first one called Sensors1 which contains values for the training for the 3 models, the first model obtained a better response obtaining a RMSE value of 0.4127814 , which is an efficient predictor value to implement models for distance detection,
- The second model obtained a non-optimal response with an RMSE value of 6.9711404, however by performing a better data analysis we can improve the efficiency of our model.
- The third model is a multilinear model where we take into account both ADC1 and ADC2 sensors to make a distance prediction, the combination of these data gives us an RMSE of 0.34101 which tells us that the effectiveness of this combined model is good for predictions.
- After analyzing the graphs and values obtained from our models, Model 1 is the most optimal after training to predict our variable which in this case is distance.
- RMSE is a measure of the average distance between the predicted and actual values, and it is calculated as the square root of the mean of the squared differences between the predicted and actual values.
- MAE is a measure of the average absolute difference between the predicted and actual values, and it is calculated as the mean of the absolute differences between the predicted and actual values.

- R-squared (R^2) is a statistical measure that represents the proportion of the variance in the dependent variable,ranges from 0 to 1, where 0 means that the model explains none of the variance and 1 means that the model explains all the variance.

Predictions of a categorical variable

Develop a system (hardware and software) that includes the 2 sensors used in part 1. The system needs to let you capture data that is useful to determine if a wall in front of the system is flat, convex, or concave.

- 2.1 Data Acquisition

For data acquisition we will use the above sensors to make measurements on different surfaces, and we will take 5 samples per 100mm for each surface.

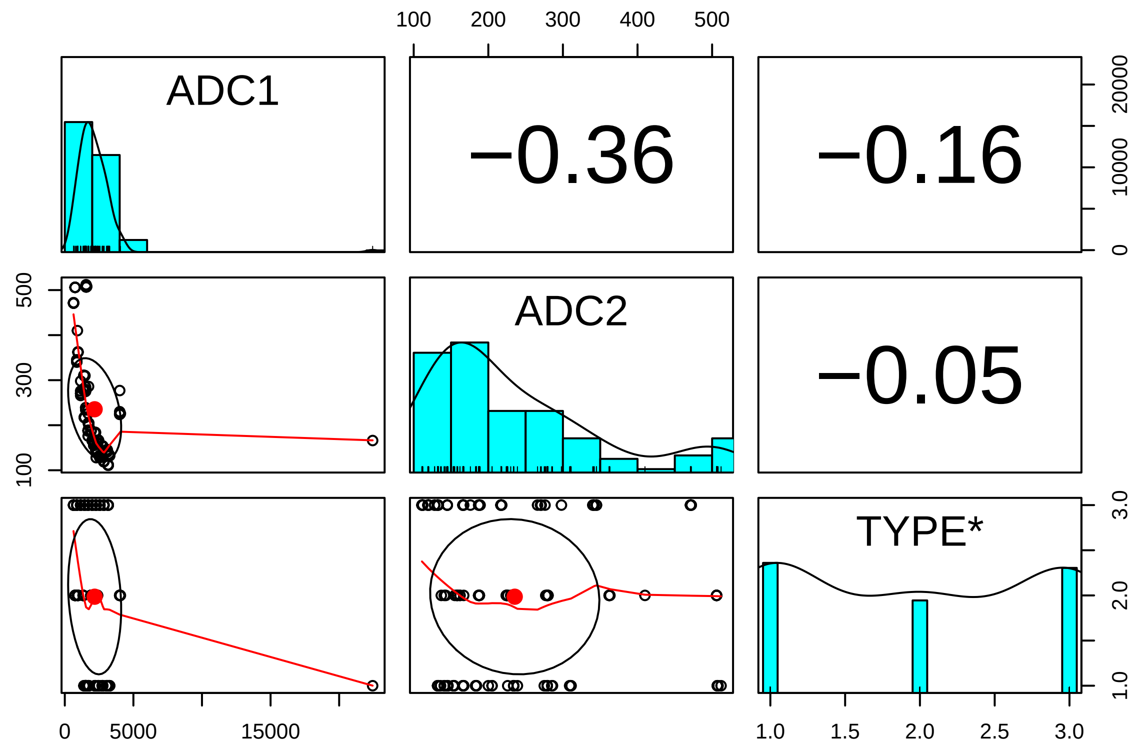
```
Shapes <- read_csv(file = paste0(parentFolder, "/Datasets/WallShapes.csv")) %>% as.data.frame()

head(Shapes)
```

```
##   ADC1 ADC2 TYPE
## 1  636  471 FLAT
## 2  642  472 FLAT
## 3  635  471 FLAT
## 4  642  471 FLAT
## 5  636  472 FLAT
## 6  874  341 FLAT
```

```
summary(Shapes)
```

```
##       ADC1            ADC2           TYPE
##  Min.   :  635   Min.   :111.0   Length:139
##  1st Qu.: 1446   1st Qu.:149.5   Class :character
##  Median : 1923   Median :188.0   Mode  :character
##  Mean   : 2176   Mean   :235.4
##  3rd Qu.: 2643   3rd Qu.:279.5
##  Max.   :22443   Max.   :512.0
```

```
pairs.panels(Shapes[c("ADC1",
"ADC2",
"TYPE")]
,pch=21, bg=c("red","green3","blue", "orange")[unclass(Shapes$TYPE)])
```



- 2.2 Predictive Model

```
# Convert the 'TYPE' column to factor
Shapes$TYPE <- as.factor(Shapes$TYPE)

# Split the dataset into training and testing sets
set.seed(123)
trainIndex3 <- createDataPartition(Shapes$TYPE, p = 0.7, list = FALSE)
train_datashapes <- Shapes[trainIndex3, ]
test_datashapes <- Shapes[-trainIndex3, ]

# Train the kNN model
knn_model <- train(TYPE ~ ADC1 + ADC2, data = train_datashapes, method = "knn", trControl = trainControl

# Predict the shape of the wall on the test set
Model1k <- predict(knn_model, newdata = test_datashapes)

# Evaluate the model
confusionMatrix(Model1k, test_datashapes$TYPE)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction CONCAVE CONVEX FLAT
##    CONCAVE       9      3    0
##    CONVEX        0      8    3
##    FLAT          6      0   12
```

```
##
## Overall Statistics
##
##                Accuracy : 0.7073
##                  95% CI : (0.5446, 0.8387)
##     No Information Rate : 0.3659
##     P-Value [Acc > NIR] : 9.326e-06
##
##                   Kappa : 0.5568
##
##  Mcnemar's Test P-Value : 0.007383
##
## Statistics by Class:
##
##                      Class: CONCAVE Class: CONVEX Class: FLAT
## Sensitivity                  0.6000        0.7273      0.8000
## Specificity                  0.8846        0.9000      0.7692
## Pos Pred Value               0.7500        0.7273      0.6667
## Neg Pred Value               0.7931        0.9000      0.8696
## Prevalence                   0.3659        0.2683      0.3659
## Detection Rate               0.2195        0.1951      0.2927
## Detection Prevalence         0.2927        0.2683      0.4390
## Balanced Accuracy            0.7423        0.8136      0.7846
```

```
# Train the kNN model on the full dataset
Model2k <- train(TYPE ~ ., data = Shapes, method = "knn", trControl = trainControl(method = "cv"), tuneL

# Print the model's results
print(Model2k)
```

```
## k-Nearest Neighbors
##
## 139 samples
##   2 predictor
##   3 classes: 'CONCAVE', 'CONVEX', 'FLAT'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 125, 125, 124, 125, 125, 125, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    5  0.9406593  9.109333e-01
##    7  0.7526007  6.292905e-01
##    9  0.4280586  1.351066e-01
##   11  0.4362271  1.422365e-01
##   13  0.3499634  1.752850e-03
##   15  0.3510623  7.693213e-03
##   17  0.3520879  3.559569e-05
##   19  0.3873260  4.770307e-02
##   21  0.4450183  1.361139e-01
##   23  0.4819048  1.926935e-01
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 5.
```

- 2.2.3 Test Model

```
PWallShapes1 <- read_csv(file = paste0(parentFolder, "/Datasets/PWallShapes.csv")) %>%
as.data.frame()
head(PWallShapes1)
```

```
##   ADC1 ADC2
## 1  815  506
## 2  816  506
## 3  815  506
## 4  822  506
## 5  839  506
## 6 1089  299
```

```
summary(PWallShapes1)
```

```
##       ADC1              ADC2
##  Min.   : 751.0   Min.   :271.0
##  1st Qu.: 817.5   1st Qu.:276.5
##  Median :1192.5   Median :402.5
##  Mean   :2340.5   Mean   :396.6
##  3rd Qu.:1392.8   3rd Qu.:507.0
##  Max.   :9613.0   Max.   :561.0
```