# Prediccion de KNN

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# Parte 1: Exploración de datos

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

parentFolder <- dirname (folder)
data_set_dia <-
    read.csv(paste0(parentFolder,"/diabetes_012_health_indicators_BRFSS2015.csv"))</pre>
```

Una vez que hayamos cargado nuestra colección de datos, es crucial examinar y evaluar la información que se encuentra en este archivo. En la ilustración siguiente, se presentan las variables junto con una breve descripción de su contenido.

Luego, empleando la función psych, podemos obtener un análisis estadístico de las 22 variables presentes en el conjunto de datos, abarcando medidas como la media, desviación estándar, rango mínimo y máximo, entre otros.

Por último, al emplear la función mutar, procederemos a modificar todos los datos que no sean "= 0" en la variable Diabetes\_012. Después, exhibiremos en una tabla concisa la cantidad de datos clasificados como "0" o "1" en esta variable de nuestro conjunto de datos.

```
test_diabetes<- data_set_dia %>% mutate(Diabetes_012 = ifelse(Diabetes_012!= "0", "1", Diabetes_012))

Conteo_Diabetes
```

```
## 0 1
## 213703 39977
```

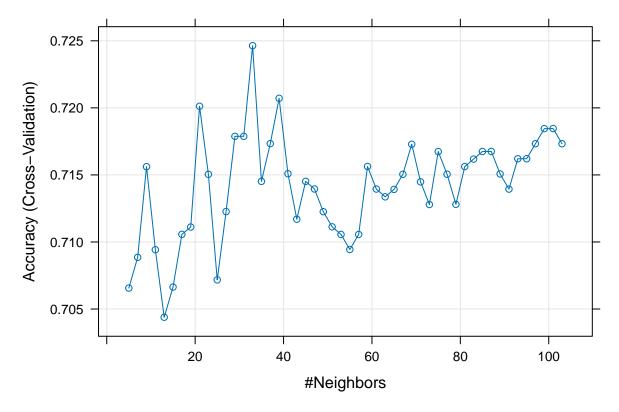
# Parte 2: KNN PREDICCIÓN DE DIABETES KNN

**Primera predicción** En esta sección del documento, implementaremos el método predictivo KNN. Para ello, emplearemos tres variables distintas para realizar las predicciones. Inicialmente, mediante un muestreo estratificado, seleccionaremos alrededor del 1% de los datos para el entrenamiento de nuestros modelos.

```
Sample_diabetes <- test_diabetes %>%
  group_by(Diabetes_012) %>%
  sample_n(1269, replace = TRUE) %>%
  ungroup()
```

```
Conteo_Sample_diabetes
```

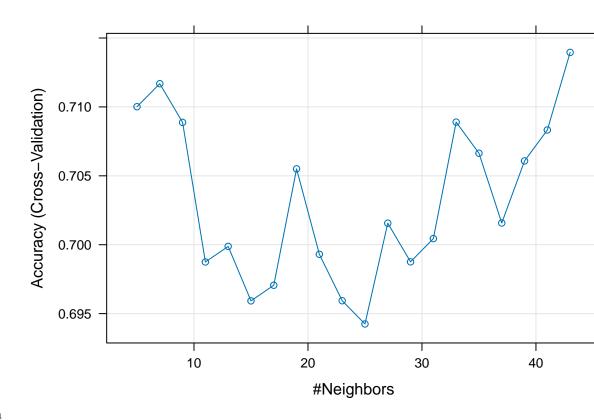
```
##
##
      0
## 1269 1269
set.seed(123)
Sample_diabetes_knn <- Sample_diabetes %>%
  group_by(Diabetes_012) %>%
  sample_n(1269, replace = TRUE) %>%
  ungroup()
S.index <- sample(1:nrow(Sample_diabetes_knn)</pre>
                        ,nrow(Sample_diabetes_knn)*0.7
                        ,replace = F)
predictors <- c("HighBP", "HighChol", "CholCheck", "BMI", "Smoker", "Stroke", "HeartDiseaseorAttack", "
TR.Data <- Sample_diabetes_knn[S.index, c(predictors, "Diabetes_012"), drop = FALSE]</pre>
TS.data <- Sample_diabetes_knn[-S.index, c(predictors, "Diabetes_012"), drop = FALSE]
TR.Data$Diabetes_012 <- factor(TR.Data$Diabetes_012)</pre>
TS.data$Diabetes_012 <- factor(TS.data$Diabetes_012)
ctrl <- trainControl(method = "cv", p = 0.7)</pre>
knnFit <- train(Diabetes_012 ~ .</pre>
                 , data = TR.Data
                 , method = "knn", trControl = ctrl
                 , preProcess = c("range") # c("center", "scale") for z-score
                 , tuneLength = 50)
plot(knnFit)
```



```
# Hacer predicciones
knnPredict <- predict(knnFit, newdata = TS.data)</pre>
# Crea la matriiz de confusion
confusionMatrix(data = knnPredict, reference = TS.data$Diabetes_012)
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction
                0
            0 243 82
##
##
            1 135 302
##
##
                  Accuracy : 0.7152
                    95% CI: (0.6817, 0.747)
##
##
       No Information Rate: 0.5039
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
                     Kappa: 0.4298
##
    Mcnemar's Test P-Value: 0.0004156
##
##
##
               Sensitivity: 0.6429
##
               Specificity: 0.7865
##
            Pos Pred Value: 0.7477
            Neg Pred Value: 0.6911
```

##

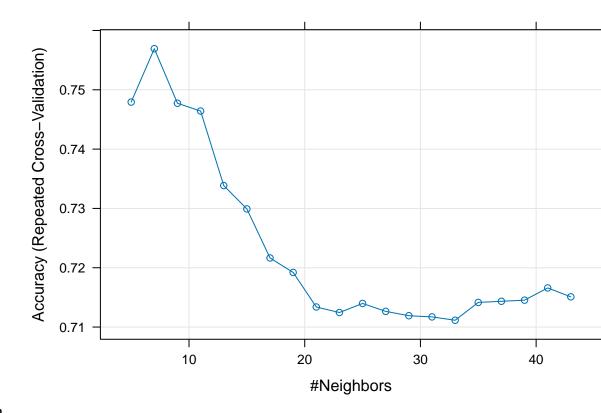
```
## Prevalence : 0.4961
## Detection Rate : 0.3189
## Detection Prevalence : 0.4265
## Balanced Accuracy : 0.7147
##
## 'Positive' Class : 0
##
```



Segunda prediccion

```
# crea predicciones
knnPredict2 <- predict(knnFit2, newdata = TS.data2)</pre>
# Crea la matriiz de confusion
confusionMatrix(data = knnPredict2, reference = TS.data2$Diabetes_012)
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction
               0 1
##
            0 239 78
            1 139 306
##
##
##
                  Accuracy : 0.7152
                    95% CI: (0.6817, 0.747)
##
##
       No Information Rate: 0.5039
       P-Value [Acc > NIR] : < 2.2e-16
##
##
##
                     Kappa: 0.4297
##
##
    Mcnemar's Test P-Value : 4.64e-05
##
##
               Sensitivity: 0.6323
##
               Specificity: 0.7969
##
            Pos Pred Value: 0.7539
##
            Neg Pred Value: 0.6876
##
                Prevalence: 0.4961
            Detection Rate: 0.3136
##
##
      Detection Prevalence: 0.4160
##
         Balanced Accuracy: 0.7146
##
##
          'Positive' Class: 0
##
predictors_to_remove2 <- c("ChoclCheck", "MentHlth", "PhysHlth", "Fruits", "Veggies")</pre>
TR.Data3 <- TR.Data2[, !(names(TR.Data2) %in% predictors_to_remove2)]</pre>
TS.data3 <- TS.data2[, !(names(TS.data2) %in% predictors_to_remove2)]
ctrl2 <- trainControl(method = "repeatedcv", number = 10, repeats = 3)</pre>
knnFit3 <- train(Diabetes_012 ~ .</pre>
                 , data = TR.Data3
                 , method = "knn", trControl = ctrl2
                 , preProcess = c("range") # c("center", "scale") for z-score
                  , tuneLength = 20)
```

plot(knnFit3)



# Tercera prediccion

```
knnPredict3 <- predict(knnFit3, newdata = TS.data3)

# Crea la matriiz de confusion
confusionMatrix(data = knnPredict3, reference = TS.data3$Diabetes_012)

## Confusion Matrix and Statistics</pre>
```

```
##
##
             Reference
## Prediction
                0
            0 256 66
##
            1 122 318
##
##
##
                  Accuracy : 0.7533
                    95% CI : (0.7211, 0.7835)
##
##
       No Information Rate: 0.5039
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
                     Kappa : 0.506
##
##
    Mcnemar's Test P-Value: 6.039e-05
##
##
               Sensitivity: 0.6772
               Specificity: 0.8281
##
            Pos Pred Value: 0.7950
##
            Neg Pred Value : 0.7227
##
```

```
## Prevalence : 0.4961
## Detection Rate : 0.3360
## Detection Prevalence : 0.4226
## Balanced Accuracy : 0.7527
##
## 'Positive' Class : 0
##
```

#### KNN HeartDiseaseorAttack Prediction

```
set.seed(123)
ss_heartDiseaseorAttack <- Sample_diabetes %>%
  group by(HeartDiseaseorAttack) %>%
  sample_n(1269, replace = TRUE) %>%
  ungroup()
predictors <- c("Diabetes 012", "HighBP", "HighChol", "CholCheck", "BMI", "Smoker", "Stroke", "PhysActi
# Datos originales
TR.Data <- ss_heartDiseaseorAttack[S.index, c(predictors, "HeartDiseaseorAttack"), drop = FALSE]
TS.data <- ss_heartDiseaseorAttack[-S.index, c(predictors, "HeartDiseaseorAttack"), drop = FALSE]
TR.Data$HeartDiseaseorAttack <- factor(TR.Data$HeartDiseaseorAttack)
TS.data$HeartDiseaseorAttack <- factor(TS.data$HeartDiseaseorAttack)
# Entrena el modelo KNN
ctrl <- trainControl(method = "cv", p = 0.7)</pre>
knnFit <- train(HeartDiseaseorAttack ~ .</pre>
                , data = TR.Data
                , method = "knn", trControl = ctrl
                , preProcess = c("range") # c("center", "scale") for z-score
                , tuneLength = 50)
# Crear predicciones
knnPredict <- predict(knnFit, newdata = TS.data)</pre>
# Crea la matriiz de confusion
# Datos originales
TR.Data <- ss_heartDiseaseorAttack[S.index, c(predictors, "HeartDiseaseorAttack"), drop = FALSE]
TS.data <- ss_heartDiseaseorAttack[-S.index, c(predictors, "HeartDiseaseorAttack"), drop = FALSE]
TR.Data$HeartDiseaseorAttack <- factor(TR.Data$HeartDiseaseorAttack)
TS.data$HeartDiseaseorAttack <- factor(TS.data$HeartDiseaseorAttack)
# Entrena el modelo KNN
ctrl <- trainControl(method = "cv", p = 0.7)</pre>
knnFit <- train(HeartDiseaseorAttack ~ .</pre>
                , data = TR.Data
                , method = "knn", trControl = ctrl
                , preProcess = c("range") # c("center", "scale") for z-score
                , tuneLength = 50)
```

```
# crear predicciones
knnPredict <- predict(knnFit, newdata = TS.data)

# Crea la matriiz de confusion
confusionMatrix(data = knnPredict, reference = TS.data$HeartDiseaseorAttack)</pre>
```

# Primera prediccion

#### Segunda prediccion

```
knnPredict3 <- predict(knnFit3, newdata = TS.data3)

# Crea la matriiz de confusion
confusionMatrix(data = knnPredict3, reference = TS.data3$HeartDiseaseorAttack)</pre>
```

Tercera prediccion

# KNN Encuentra predicción de sexo

```
## selección de 1500 muestras de cada factor del conjunto de datos#
set.seed(123)
ss_sex <- Sample_diabetes %>%
 group_by(Sex) %>%
  sample_n(1269, replace = TRUE) %>%
 ungroup()
predictors <- c("Diabetes_012", "HighBP", "HighChol", "CholCheck", "BMI", "Smoker", "Stroke", "HeartDise</pre>
# Datos Originales
TR.Data <- ss_sex[S.index, c(predictors, "Sex"), drop = FALSE]</pre>
TS.data <- ss_sex[-S.index, c(predictors, "Sex"), drop = FALSE]
TR.Data$Sex <- factor(TR.Data$Sex)</pre>
TS.data$Sex <- factor(TS.data$Sex)
# Entrena el modelo KNN
ctrl <- trainControl(method = "cv", p = 0.7)</pre>
knnFit <- train(Sex ~ .</pre>
               , data = TR.Data
               , method = "knn", trControl = ctrl
               , preProcess = c("range") # c("center", "scale") for z-score
               , tuneLength = 50)
# Crear predicciones
knnPredict <- predict(knnFit, newdata = TS.data)</pre>
#Crea la matriiz de confusion
confusionMatrix(data = knnPredict, reference = TS.data$Sex)
```

## Primera predicción

```
# Segundo modelo
```

#### Segunda predicción

Tercera predicción

Parte 3: Modelo de regresión lineal BM

# Primera predicción

```
##
## Call:
## lm(formula = BMI ~ ., data = TR.Data)
##
## Residuals:
      Min
              1Q Median
                             3Q
                                    Max
## -15.218 -3.753 -0.727
                          2.651 59.718
##
## Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
##
## (Intercept)
                      29.700892    1.248923    23.781    < 2e-16 ***
## Diabetes_012
                     2.282214  0.396631  5.754  1.00e-08 ***
## HighBP
                       2.821500 0.297689 9.478 < 2e-16 ***
## HighChol
                       1.269 0.204564
## CholCheck
                      0.859487 0.677266
## Smoker
                      -0.522257 0.272625 -1.916 0.055546 .
## Stroke
                      -0.813064
                                 0.708187 -1.148 0.251063
## HeartDiseaseorAttack -1.095276
                                 0.483551 -2.265 0.023611 *
## PhysActivity
                     -0.974136
                                 0.338502 -2.878 0.004046 **
## Fruits
                      -0.722677
                                 0.287499 -2.514 0.012023 *
## Veggies
                      -0.537476
                                 0.351942 -1.527 0.126870
## HvyAlcoholConsump
                      -0.945193
                                 0.597458 -1.582 0.113796
## AnyHealthcare
                                 0.612766 0.265 0.791329
                      0.162150
## NoDocbcCost
                      -0.528085
                                 0.505369 -1.045 0.296168
                      0.621751
## GenHlth
                                 0.163830
                                          3.795 0.000152 ***
## MentHlth
                      0.006135
                                 0.019977
                                          0.307 0.758794
## PhysHlth
                      -0.049331
                                 0.019188 -2.571 0.010210 *
## DiffWalk
                      2.097624
                                 0.436809 4.802 1.68e-06 ***
                                 0.274379 -0.085 0.932593
## Sex
                      -0.023210
```

```
0.048185 -8.601 < 2e-16 ***
## Age
                        -0.414443
## Education
                       0.065025
                                    0.152360 0.427 0.669579
## Income
                                    0.076249 -1.491 0.136132
                        -0.113682
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 5.968 on 2078 degrees of freedom
## Multiple R-squared: 0.157, Adjusted R-squared: 0.1485
## F-statistic: 18.43 on 21 and 2078 DF, p-value: < 2.2e-16
# Entrenar el modelo
train.control <- trainControl(method = "cv", number = 10 )</pre>
model <- train(BMI ~ ., data = TR.Data, method = "lm",</pre>
               trControl = train.control)
# Resumir los resultados
print(model)
## Linear Regression
##
## 2100 samples
##
   21 predictor
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1891, 1891, 1890, 1889, 1889, 1891, ...
## Resampling results:
##
##
    RMSE
               Rsquared
                          MAE
##
    5.984649 0.1486856 4.319634
## Tuning parameter 'intercept' was held constant at a value of TRUE
#### segunda
predictors_to_remove <- c("AnyHealthcare", "CholCheck", "MentHlth", "Education", "Sex")</pre>
TR.Data2 <- TR.Data[, !(names(TR.Data) %in% predictors_to_remove)]
TS.data2 <- TS.data[, !(names(TS.data) %in% predictors_to_remove)]
ins_model <- lm(BMI ~ ., data = TR.Data2)</pre>
summary(ins_model)
# Entrenar el modelo
train.control <- trainControl(method = "cv", number = 5)</pre>
model <- train(BMI ~ ., data = TR.Data2, method = "lm",</pre>
              trControl = train.control)
```

```
# Resumir los resultados
print(model)
```

#### Segunda predicción

Tercera predicción

# Modelo de regresión lineal MentHlth

```
set.seed(1)
data_estratificada2 <- data[sample(nrow(data), 3000), ]</pre>
predictors <- colnames(data_estratificada2)[-16]</pre>
S.index <- sample(1:nrow(data_estratificada2),</pre>
                     nrow(data_estratificada2) * 0.7,
                     replace = FALSE)
### ENTRENAMIENTO
TR.Data <- data_estratificada2[S.index, c(predictors, "MentHlth"), drop = FALSE]
TS.data <- data_estratificada2[-S.index, c(predictors, "MentHlth"), drop = FALSE]
ins_model <- lm(MentHlth ~ ., data = TR.Data)</pre>
summary(ins_model)
# Entrenar el modelo
train.control <- trainControl(method = "cv", number = 10 )</pre>
model <- train(MentHlth ~ ., data = TR.Data, method = "lm",</pre>
             trControl = train.control)
```

```
# Resumir los resultados
print(model)
```

# Primera predicción

#### Segunda predicción

## Tercera predicción

# Modelo de regresión lineal PhysHlth

```
data_estratificada3 <- data[sample(nrow(data), 3000), ]</pre>
predictors <- colnames(data_estratificada2)[-17]</pre>
S.index <- sample(1:nrow(data_estratificada3),</pre>
                     nrow(data_estratificada3) * 0.7,
                     replace = FALSE)
TR.Data <- data_estratificada2[S.index, c(predictors, "PhysHlth"), drop = FALSE]
TS.data <- data_estratificada2[-S.index, c(predictors, "PhysHlth"), drop = FALSE]
ins_model <- lm(PhysHlth ~ ., data = TR.Data)</pre>
summary(ins_model)
#Entrenar el modelo
train.control <- trainControl(method = "cv", number = 10 )</pre>
model <- train(PhysHlth ~ ., data = TR.Data, method = "lm",</pre>
             trControl = train.control)
# # Resumir los resultados
print(model)
```

## Primera predicción

# Segunda predicción

Tercera predicción