## Numeric Prediction

Blake Pappas

2023-12-17

#### Numeric Prediction in R

### Load the following packages:

```
library(caret)
library(class)
library(dplyr)
library(glmnet)
```

In this exercise, we use the "laptop.csv" file. The goal is to predict the "Price" of a laptop based on its attributes.

P1: Import the dataset. Split it to 80% training and 20% testing.

#### P2: Build a K-NN Model

Do you need to normalize the data?

Answer: Yes, the data needs to be normalized.

```
normalize = function(x) {
  return ((x - min(x)) / (max(x) - min(x)))
  }
laptop_normalized = laptop %>% mutate_at(2:8, normalize)
laptop_normalized_train = laptop_normalized[train_rows, ]
laptop_normalized_test = laptop_normalized[-train_rows, ]
```

Examine the normalized dataset. What went wrong? Why?

Answer: Because the only value for the field "Screen.Size" is 15, there is a divide by zero error and all the normalized values resulted in a value of NaN.

Write the code below to fix it:

```
# Don't include the "Screen.Size" field in the normalization function.
laptop_normalized = laptop %>% mutate_at(3:8, normalize)
laptop_normalized_train = laptop_normalized[train_rows, ]
laptop_normalized_test = laptop_normalized[-train_rows, ]
```

#### P3: Build a K-NN classifier with a k value of 50

# P4: Evaluate the performance of the K-NN model

```
actual = laptop_normalized_test$Price
error = pred_knn - actual
# Average Error
```

```
KNN_AE = mean(error)
KNN_AE
## [1] 1.926922
# Mean Absolute Error
KNN_MAE = mean(abs(error))
KNN_MAE
## [1] 12.90081
# Mean Absolute Percentage Error
KNN_MAPE = mean(abs(error / actual))
KNN_MAPE
## [1] 0.02721691
# Root Mean Squared Error
KNN_RMSE = sqrt(mean(error^2))
KNN_RMSE
## [1] 19.24014
# Total Sum of Squared Error
KNN_SSE = sum(error^2)
KNN_SSE
## [1] 588591
```

# P5: Now, repeat P3 and P4 with different k values (e.g., 50-60). Use a loop. Report the RMSE.

- ## [1] 18.1591
- ## [1] 19.76281
- ## [1] 20.16131
- ## [1] 18.73482
- ## [1] 19.40419
- ## [1] 18.71618
- ## [1] 21.80249
- ## [1] 19.71056
- ... [1] 10.11000
- ## [1] 17.45733
- ## [1] 18.4461
- ## [1] 18.94631
- ## [1] 19.14078
- ## [1] 18.35375
- ## [1] 17.23189
- ## [1] 18.89389
- ## [1] 19.35365
- ## [1] 18.42411
- ## [1] 10.42411
- ## [1] 19.32266
- ## [1] 18.90913
- ## [1] 20.6505
- ## [1] 19.36423
- ## [1] 16.96404
- ## [1] 21.47797
- ## [1] 18.0963
- ## [1] 19.91855
- ## [1] 16.94643
- ## [1] 10.94043
- ## [1] 18.77599
- ## [1] 20.36921
- ## [1] 19.0613 ## [1] 17.8734
- ## [1] 20.31572
- ## [1] 19.3392
- ## [1] 19.28582
- ## [1] 18.8486
- ## [1] 18.8965
- ## [1] 17.43267
- ## [1] 20.58754
- ## [1] 19.47707
- ## [1] 16.60578
- ## [1] 19.71162
- ## [1] 20.58979
- ## [1] 17.82
- ## [1] 16.59068
- ## [1] 19.95856
- ## [1] 18.96204
- ## [1] 19.8268
- ## [1] 16.92591
- ## [1] 20.99563
- ## [1] 20.74548
- ## [1] 20.63612
- ## [1] 20.9891
- ## [1] 19.88239 ## [1] 20.49446
- ## [1] 20.11526

```
## [1] 20.57336

## [1] 19.4961

## [1] 16.56597

## [1] 22.21314

## [1] 19.46517

## [1] 18.07051
```

P6: Build a linear regression model. Use cross-validation. Report the mean RMSE.

```
cv = createFolds(y = laptop$Price, k = 5)

rmse_cv = c()

for (test_row in cv) {

    laptop_train = laptop[-test_row, ]
    laptop_test = laptop[test_row, ]

    lm_model = lm(Price ~ ., data = laptop_train)

    pred_lm = predict(lm_model, laptop_test)

    rmse = sqrt(mean((pred_lm - laptop_test[, 1])^2))

    rmse_cv = c(rmse_cv, rmse)
}

# Mean RMSE

print(mean(rmse_cv))
```

## [1] 16.50833