

# hw1

## Libraries

```
library <- function(...) {suppressPackageStartupMessages(base::library(...))}  
if (!require(caret)) install.packages("caret"); library(caret)
```

Loading required package: caret

Loading required package: ggplot2

Loading required package: lattice

```
if (!require(dplyr)) install.packages("dplyr"); library(dplyr)
```

Loading required package: dplyr

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

filter, lag

The following objects are masked from 'package:base':

intersect, setdiff, setequal, union

## Starting point

We would like to use kNN method for recognizing the type of iris (class label *versicolor* or *virginica*). The predictors include:

- Sepal.Length
- Sepal.Width
- Petal.Length -Petal.Width

The objective of the analysis is to find a model that can be used to predict the type of the flower based on features. Also we will use extensive search approach to identify a good k for the task.

## Data management

```
dat <- read.csv('iris.csv') |> filter(Species %in% c("virginica", "versicolor"))
dat$Species <- as.factor(dat$Species)
dat |> head()
```

|   | Sepal.Length | Sepal.Width | Petal.Length | Petal.Width | Species    |
|---|--------------|-------------|--------------|-------------|------------|
| 1 | 7.0          | 3.2         | 4.7          | 1.4         | versicolor |
| 2 | 6.4          | 3.2         | 4.5          | 1.5         | versicolor |
| 3 | 6.9          | 3.1         | 4.9          | 1.5         | versicolor |
| 4 | 5.5          | 2.3         | 4.0          | 1.3         | versicolor |
| 5 | 6.5          | 2.8         | 4.6          | 1.5         | versicolor |
| 6 | 5.7          | 2.8         | 4.5          | 1.3         | versicolor |

## Summary statistics

```
summary(dat)
```

| Sepal.Length  | Sepal.Width   | Petal.Length  | Petal.Width   |
|---------------|---------------|---------------|---------------|
| Min. :4.900   | Min. :2.000   | Min. :3.000   | Min. :1.000   |
| 1st Qu.:5.800 | 1st Qu.:2.700 | 1st Qu.:4.375 | 1st Qu.:1.300 |
| Median :6.300 | Median :2.900 | Median :4.900 | Median :1.600 |
| Mean :6.262   | Mean :2.872   | Mean :4.906   | Mean :1.676   |
| 3rd Qu.:6.700 | 3rd Qu.:3.025 | 3rd Qu.:5.525 | 3rd Qu.:2.000 |

```
Max.      :7.900   Max.      :3.800   Max.      :6.900   Max.      :2.500
  Species
versicolor:50
virginica  :50
```

Both class labels includes 50 observations.

## Model creation and diagnostics

### Train-Test-Split

We will use 70% of the data as training part and 30% as testing part.

```
set.seed(1)
N = nrow(dat)
train_ind = sample(N, size = N * 70/100)
test_ind = setdiff(1:N, train_ind)
train_data = dat[train_ind,]
test_data = dat[test_ind,]
```

### Fit model

```
knn_model <- train(
  Species ~ .,
  data = train_data,
  method = "knn",
  tuneGrid = data.frame(k = 5)
)
```

### Make predictions

```
predictions <- predict(knn_model, newdata = test_data)
```

## Accuracy for N=5

```
# Calculate accuracy
confusion_matrix <- confusionMatrix(predictions, test_data$Species)
accuracy_r <- confusion_matrix$overall['Accuracy']
print(paste("kNN (5) Accuracy:", round(accuracy_r, 3)))
```

```
[1] "kNN (5) Accuracy: 0.967"
```

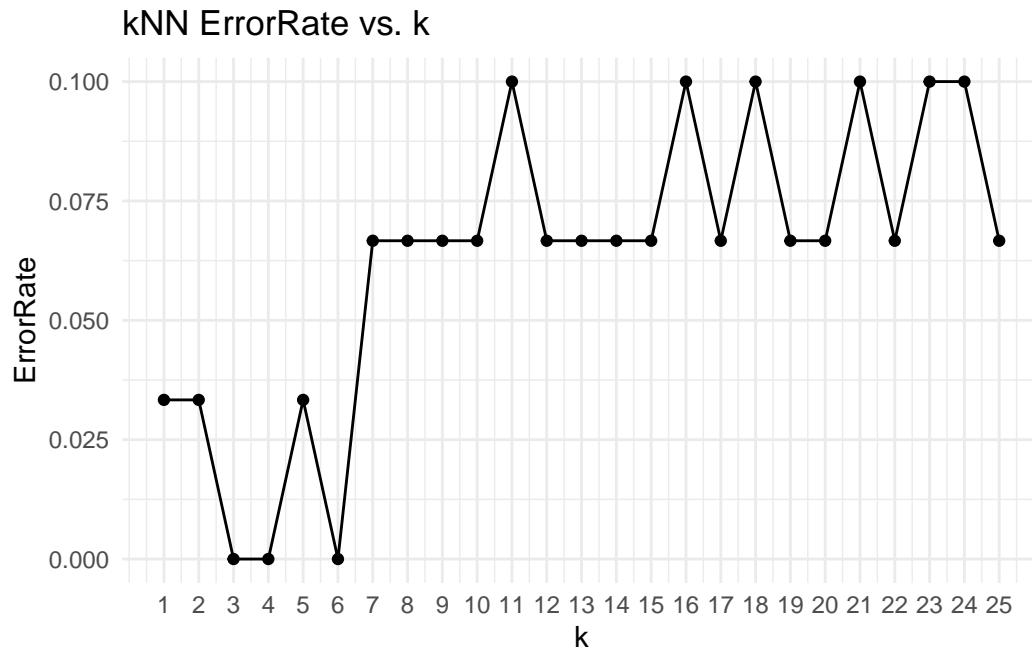
```
print(paste("kNN (5) Error rate:", round(1-accuracy_r, 3)))
```

```
[1] "kNN (5) Error rate: 0.033"
```

```
set.seed(1)
k_values <- 1:25
error_rate <- numeric(length(k_values))

for (i in k_values) {
  knn_model <- train(
    Species ~ .,
    data = train_data,
    method = "knn",
    tuneGrid = data.frame(k = k_values[i])
  )
  predictions <- predict(knn_model, newdata = test_data)
  confusion_matrix <- confusionMatrix(predictions, test_data$Species)
  error_rate[i] <- 1-confusion_matrix$overall['Accuracy']
}

# Plotting the accuracies
plot_data <- data.frame(k = k_values, ErrorRate = error_rate)
ggplot(plot_data, aes(x = k, y = ErrorRate)) +
  geom_line(aes(group = 1)) +
  geom_point() +
  scale_x_continuous(breaks = k_values) +
  labs(title = "kNN ErrorRate vs. k", x = "k", y = "ErrorRate") +
  theme_minimal()
```



We should consider odd numbers. It make sense to use 1 as good k because the error rate is very small (less then 4%), but the model achieve the absolute 0 error rate when  $k=3$ , so it is the best k for our purpose.