# k-Nearest Neighbor for Bearing Fault Classification

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k-Nearest Neighbor is one of the simplest classification algorithms that doesn't require any training. To determine the class of a test data point, we calculate its distance to $k$ nearest training points. As labels for training set are known, class of the test point is decided by majority vote among the $k$ training labels. The only hyper-parameter of this algorithm is the value of $k$. It decides the number of neighbors to choose to do classification. Appropriate value of $k$ can be chosen by trying out different values.

In R, kNN is implemented using 'class' library.

## Description of data

Detailed discussion of how to prepare the data and its souce can be found in this post. Here we will only mention about different classes of the data. There are 12 classes and data for each class are taken at a load of 1hp. The classes are:

- C1 : Ball defect (0.007 inch)
- C2 : Ball defect (0.014 inch)
- C3 : Ball defect (0.021 inch)
- C4 : Ball defect (0.028 inch)
- C5 : Inner race fault (0.007 inch)
- C6 : Inner race fault (0.014 inch)
- C7 : Inner race fault (0.021 inch)
- C8 : Inner race fault (0.028 inch)
- C9 : Normal
- C10 : Outer race fault (0.007 inch, data collected from 6 O'clock position)
- C11 : Outer race fault (0.014 inch, 6 O'clock)
- C12 : Outer race fault (0.021 inch, 6 O'clock)

**Important Note:** In the CWRU website, sampling frequency for the normal data is not mentioned. Most research paper take it as 48k. Some authors also consider it as being taken at a sampling frequency of 12k. Some other authors just use it without ever mentioning its sampling frequency. In our application we only need segment of normal data of length 1024. So we will use the normal data segments available at the website without going into the discussion of sampling frequency. Still, to be on the safer side, we will show results including the normal data as a class as well as excluding it.

When we exclude normal data, we won't consider "C9" class and study the rest 11 fault classes. At that time "C09", "C10", and "C11" will correspond to outer race faults of fault depth 0.007, 0.014, and 0.021 inch respectively.

## Codes

```
library(reticulate)
use_condaenv("r-reticulate")
```

First download the data from here. Save the data in a folder and read it from that folder.

```
library(class)
data_wav_energy = read.csv('feature_wav_energy8_12k_1024_load_1.csv',
                           header = T)
# Change the above line to include your folder that contains data
```

```r
set.seed(1)
index = c(sample(1:115,35),sample(116:230,35), sample(231:345,35),
          sample(346:460,35),sample(461:575,35),sample(576:690,35),
          sample(691:805,35),sample(806:920,35),sample(921:1035,35),
          sample(1036:1150,35),sample(1151:1265,35),sample(1266:1380,35))

train_data = data_wav_energy[-index,]
test_data = data_wav_energy[index,]

# Shuffle data
train_data = train_data[sample(nrow(train_data)),]
test_data = test_data[sample(nrow(test_data)),]
```

It should be noted that for some of the deterministic techniques, shuffling of data is not required. But some other techniques like deep learning require the data to be shuffled for better training. So as a recipe we always shuffle data whether the method is deterministic or not. This doesn't hurt either for a deterministic technique.

```r
set.seed(11)
pred_test_knn = knn(train_data[,-9], test_data[,-9], train_data[,9], k = 1)
# Confusion matrix
test_confu = table(test_data$fault, pred_test_knn)
```

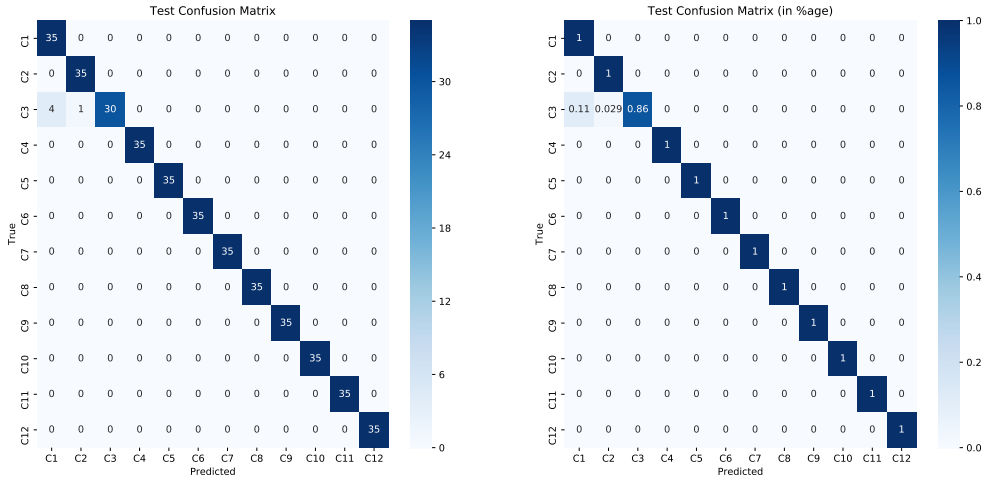
```r
import seaborn as sns
import matplotlib.pyplot as plt
fault_type = ['C1','C2','C3','C4','C5','C6','C7','C8','C9','C10','C11','C12']
plt.figure(1,figsize=(18,8))
plt.subplot(121)
sns.heatmap(r.test_confu, annot = True,
xticklabels=fault_type, yticklabels=fault_type, cmap = "Blues")
```

```
## <matplotlib.axes._subplots.AxesSubplot object at 0x000000001EEFB048>
```

```r
plt.title('Test Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.subplot(122)
sns.heatmap(r.test_confu/35, annot = True,
xticklabels=fault_type, yticklabels=fault_type, cmap = "Blues")
```

```
## <matplotlib.axes._subplots.AxesSubplot object at 0x0000000024A7FCC0>
```

```r
plt.title('Test Confusion Matrix (in %age)')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```




```
overall_test_accuracy = sum(diag(test_confu))/420
sprintf("Overall Test Accuracy: %.4f", overall_test_accuracy*100)
```

```
## [1] "Overall Test Accuracy: 98.8095"
```

This accuracy is overwhelming considering the fact that kNN is one of the simplest methods.

We will also show the results excluding the normal data. The results are as below.

```
data_without_normal = read.csv("feature_wav_energy8_12k_1024_load_1.csv",
                               header = T, nrows = 1265)
# Change the above line to include your folder that contains data
set.seed(1)
index = c(sample(1:115,35),sample(116:230,35), sample(231:345,35),
          sample(346:460,35),sample(461:575,35),sample(576:690,35),
          sample(691:805,35),sample(806:920,35),sample(921:1035,35),
          sample(1036:1150,35),sample(1151:1265,35))

train_new = data_without_normal[-index,]
test_new = data_without_normal[index,]

# Shuffle data
train_data_new = train_new[sample(nrow(train_new)),]
test_data_new = test_new[sample(nrow(test_new)),]
```

```
set.seed(11)
pred_test_knn_new = knn(train_data_new[,-9], test_data_new[,-9],
                        train_data_new[,9], k = 1)
# Confusion matrix
test_confu_new = table(test_data_new$fault, pred_test_knn_new)
```

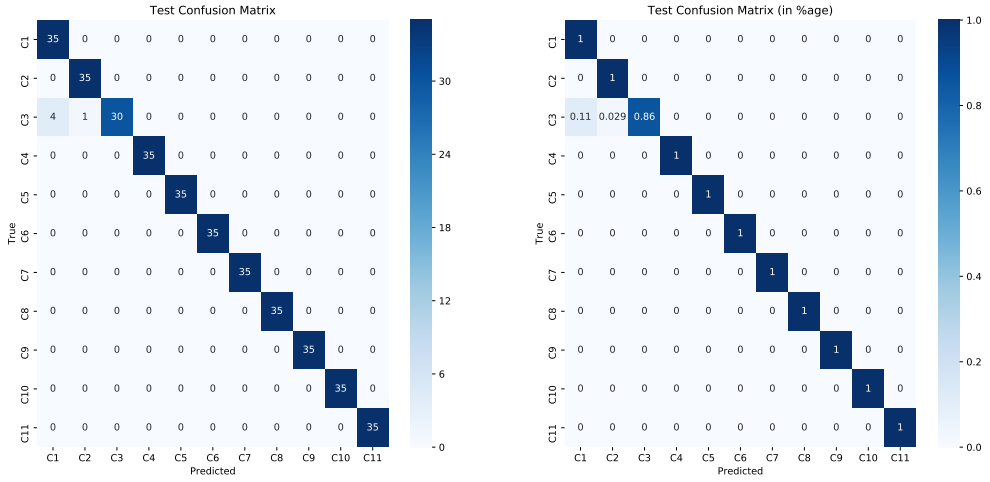
```
import seaborn as sns
import matplotlib.pyplot as plt
fault_type = ['C1','C2','C3','C4','C5','C6','C7','C8','C9','C10','C11']
plt.figure(1,figsize=(18,8))
plt.subplot(121)
sns.heatmap(r.test_confu_new, annot = True,
xticklabels=fault_type, yticklabels=fault_type, cmap = "Blues")
```

```
## <matplotlib.axes._subplots.AxesSubplot object at 0x000000001EEEA5F8>
```

```
plt.title('Test Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.subplot(122)
sns.heatmap(r.test_confu_new/35, annot = True,
xticklabels=fault_type, yticklabels=fault_type, cmap = "Blues")
```

```
## <matplotlib.axes._subplots.AxesSubplot object at 0x00000000243B18D0>
```

```
plt.title('Test Confusion Matrix (in %age)')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```




```
overall_test_accuracy_new = sum(diag(test_confu_new))/385
sprintf("New overall Test Accuracy: %.4f", overall_test_accuracy_new*100)
```

```
## [1] "New overall Test Accuracy: 98.7013"
```

To see results of other techniques applied to public condition monitoring datasets, visit this page.

Last updated: $7^{th}$ July, 2019