

Bagging for Bearing Fault Classification

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Bagging (Bootstrap aggregating) is the process of combining results of several trees to come up with a classifier. Bootstrapping is used to generate several samples from the original training set. Trees are grown on each bootstrap sample. Finally the results of all trees are averaged to obtain final classifier. If several random variables are uncorrelated, averaging those reduces variance. Similarly if individual trees are not correlated to each other, bagging produces a result with low variance. In this post, we will apply bagging to classify different bearing faults.

Description of data

Detailed discussion of how to prepare the data and its source can be found in this post. Here we will only mention about different classes of the data. There are 10 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 : Inner race fault (0.007 inch)
- C5 : Inner race fault (0.014 inch)
- C6 : Inner race fault (0.021 inch)
- C7 : Normal
- C8 : Outer race fault (0.007 inch, data collected from 6 O'clock position)
- C9 : Outer race fault (0.014 inch, 6 O'clock)
- C10 : Outer race fault (0.021 inch, 6 O'clock)

Codes

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

How to get data?

Readers can download the .csv file used in this notebook from here. Another convenient way is to download the whole repository and run the downloaded notebooks.

```
data_wav_energy = read.csv('./data/feature_wav_energy8_48k_2048_load_1.csv',
                           header = T)
# Change the above line to include your folder that contains data
set.seed(1)
index = c(sample(1:230,75),sample(231:460,75), sample(461:690,75),
          sample(691:920,75),sample(921:1150,75),sample(1151:1380,75),
          sample(1381:1610,75),sample(1611:1840,75),sample(1841:2070,75),
          sample(2071:2300,75))
```

```

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.

For bagging we will use 'randomForest' package. As the name suggests, the package is also used for random forest classification. As we will see in another post, bagging and random forest are very similar to each other. For the time being, we will use that package for bagging.

```
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```

bagging_fit = randomForest(fault~., train_data, mtry = 8)
pred_bagging = predict(bagging_fit, test_data)
# Confusion matrix
test_confu = table(test_data$fault, pred_bagging)

```

```

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 0x000000001A89CD08>
```

```

plt.title('Test Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.subplot(122)
sns.heatmap(r.test_confu/75, annot = True,
xticklabels=fault_type, yticklabels=fault_type, cmap = "Blues")

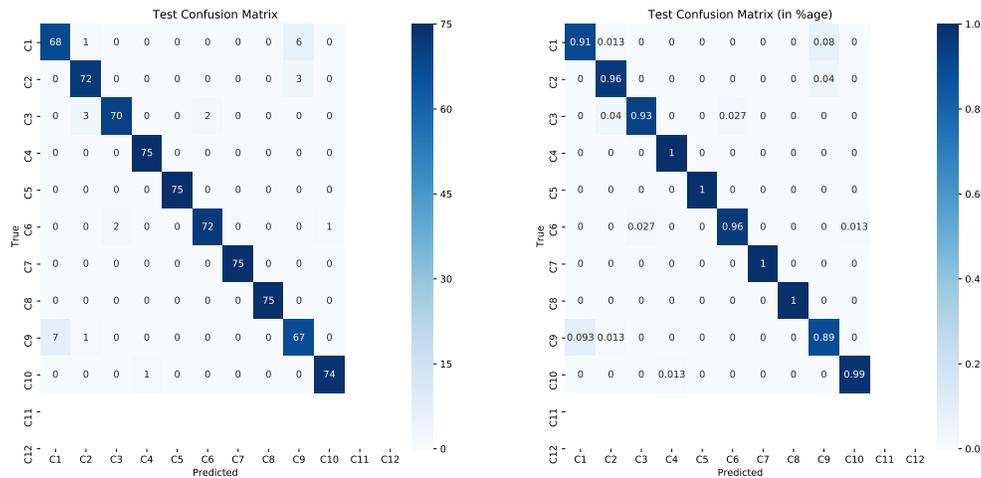
```

```
## <matplotlib.axes._subplots.AxesSubplot object at 0x0000000015AA00C8>
```

```

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

```



```
overall_test_accuracy = sum(diag(test_confu))/750
sprintf("Overall Test Accuracy: %.4f", overall_test_accuracy*100)
```

```
## [1] "Overall Test Accuracy: 96.4000"
```

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

```
sessionInfo()
```

```
## R version 3.6.2 (2019-12-12)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 7 x64 (build 7601) Service Pack 1
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_United States.1252
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods    base
##
## other attached packages:
## [1] randomForest_4.6-14 reticulate_1.14
##
## loaded via a namespace (and not attached):
## [1] Rcpp_1.0.3      digest_0.6.23  rappdirs_0.3.1 jsonlite_1.6.1
## [5] magrittr_1.5    evaluate_0.14  rlang_0.4.4    stringi_1.4.5
## [9] rmarkdown_2.1  tools_3.6.2   stringr_1.4.0  xfun_0.12
## [13] yaml_2.2.0     compiler_3.6.2 htmltools_0.4.0 knitr_1.27
```

Last updated: 15th February, 2020