# Fall Detection Model

*Samuel Matsiko*

*12/29/2019*

## Introduction

The dataset was obtained from Kaggle(https://www.kaggle.com/pitasr/falldata). As detailed on the website, this dataset was generated by wearable motion sensor units fit to the subjects' body at six different positions. Each unit comprises of three tri-axial devices (accelerometer, gyroscope, and magnetometer/compass). Fourteen volunteers performed a standardized set of movements including 20 voluntary falls and 16 activities of daily living (ADLs), resulting in a large dataset with 16382 trials. The dataset comprises of 7 variables, namely; ACTIVITY,TIME, SL, EEG, BP, HR and CIRCULATION. Find details on each column.

ACTIVITY - activity classification TIME - monitoring time SL - sugar level EEG - EEG monitoring rate BP - Blood pressure HR - Heart beat rate CIRCLUATION - Blood circulation

The aim is to build a model that detects falls for people in the fall risk groups. With this dataset, i have built a model using 6 predictors to differentiate 6 human movements(captured under the target label variable, ACTIVITY) of Standing, Walking, Sitting, Falling, Cramps and Running that are represented by values of 0,1,2,3,4,5 repectively.

As indicated in the method section below, the data has first been explored using the different technicques that have guided on the machine learning approaches to deploy.

## Method

Using different exploratory techniques detailed below, data is observed to be in tidy format with no null values. However, data has been observed to be of varying scales and has therfore been scaled. Further more, predictors are not correlated to the target label. It is also important to note that the variables are generally non-uniformly distributed. Given this nature of data, svm,knn and random forest machine learning approaches have been deployed

### Data Overview

#### Dimensions of the dataset

```
## [1] 16382     7
```

#### Column names of the dataset

```
## [1] "ACTIVITY"    "TIME"        "SL"          "EEG"         "BP"
## [6] "HR"          "CIRCLUATION"
```

#### Data Types of the dataset

```
##    ACTIVITY        TIME          SL         EEG          BP          HR
##    "factor"   "numeric"   "numeric"   "numeric"   "integer"   "integer"
## CIRCLUATION
##   "integer"
```

**Layout of the dataset**

```
##   ACTIVITY    TIME       SL      EEG BP  HR CIRCLUATION
## 1        3 4722.92  4019.64 -1600.00 13  79         317
## 2        2 4059.12  2191.03 -1146.08 20  54         165
## 3        2 4773.56  2787.99 -1263.38 46  67         224
## 4        4 8271.27  9545.98 -2848.93 26 138         554
## 5        4 7102.16 14148.80 -2381.15 85 120         809
## 6        5 7015.24  7336.79 -1699.80 22  95         427
```

**Checking for null values**

```
## [1] FALSE
```

**Summary of the dataset**

```
##  ACTIVITY      TIME             SL                 EEG
##  0:4608   Min.   : 1954   Min.   :     42.2   Min.   :-12626000
##  1: 502   1st Qu.: 7264   1st Qu.:   9941.2   1st Qu.:    -5630
##  2:2502   Median : 9769   Median :  31189.2   Median :    -3361
##  3:3588   Mean   :10937   Mean   :  75272.0   Mean   :    -5621
##  4:3494   3rd Qu.:13482   3rd Qu.:  80761.4   3rd Qu.:    -2150
##  5:1688   Max.   :50896   Max.   :2426140.0   Max.   :  1410000
##        BP               HR          CIRCLUATION
##  Min.   :  0.00   Min.   : 33.0   Min.   :    5
##  1st Qu.: 25.00   1st Qu.:119.0   1st Qu.:  587
##  Median : 44.00   Median :180.0   Median : 1581
##  Mean   : 58.25   Mean   :211.5   Mean   : 2894
##  3rd Qu.: 78.00   3rd Qu.:271.0   3rd Qu.: 3539
##  Max.   :533.00   Max.   :986.0   Max.   :52210
```

Seeing the different variables are of have varying scales(from above), all predictors have been scaled but not the target label variable, ACTIVITY. We also observe that the target label values are imbalanced as indicated below in percentage proportions.

**Summary after scaling**

```
##  ACTIVITY      TIME              SL                 EEG
##  0:4608   Min.   :-1.7072   Min.   :-0.59003   Min.   :-116.61681
##  1: 502   1st Qu.:-0.6981   1st Qu.:-0.51239   1st Qu.:  -0.00008
##  2:2502   Median :-0.2219   Median :-0.34574   Median :   0.02088
##  3:3588   Mean   : 0.0000   Mean   : 0.00000   Mean   :   0.00000
##  4:3494   3rd Qu.: 0.4837   3rd Qu.: 0.04305   3rd Qu.:   0.03207
##  5:1688   Max.   : 7.5946   Max.   :18.43786   Max.   :  13.08084
##        BP                HR            CIRCLUATION
##  Min.   :-1.2062   Min.   :-1.3739   Min.   :-0.7552
##  1st Qu.:-0.6885   1st Qu.:-0.7121   1st Qu.:-0.6031
##  Median :-0.2951   Median :-0.2427   Median :-0.3433
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.4089   3rd Qu.: 0.4576   3rd Qu.: 0.1685
##  Max.   : 9.8306   Max.   : 5.9597   Max.   :12.8899
```

**Target label proportion**

```
##    Count Percentage
## 0  4608       28.13
## 1   502        3.06
## 2  2502       15.27
## 3  3588       21.90
## 4  3494       21.33
## 5  1688       10.30
```

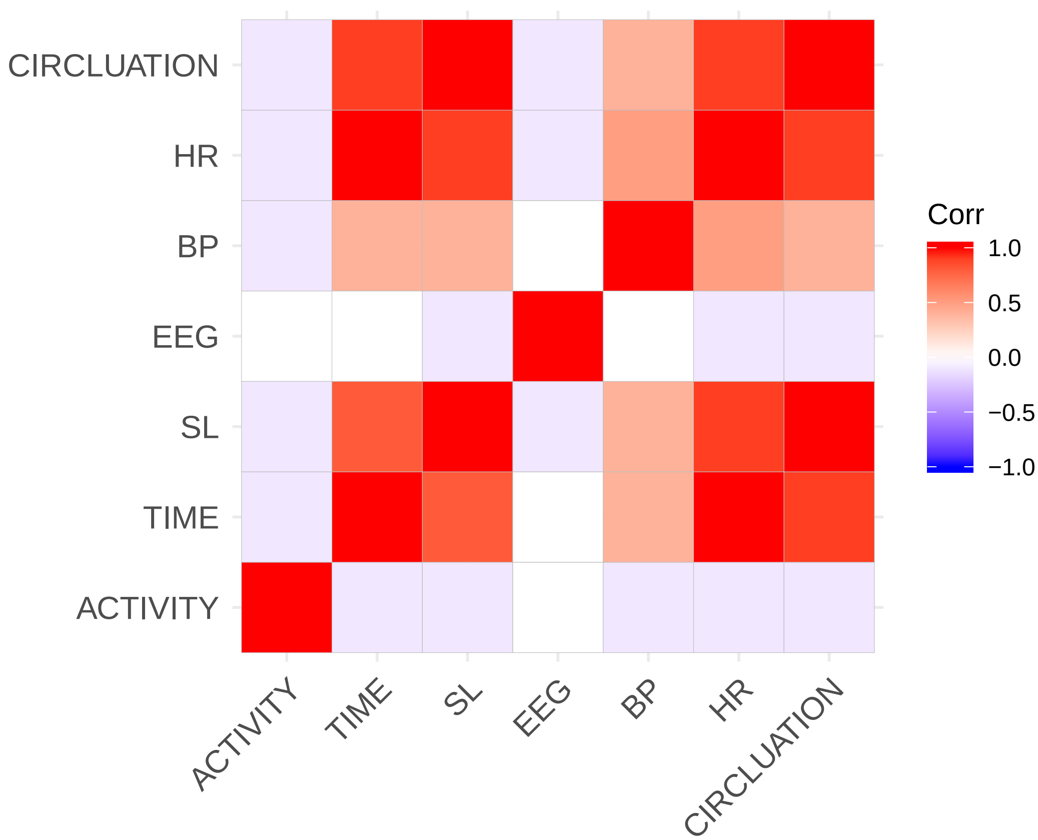
### Understanding Correlation between Variables

From the correlation matrix below and the corresponding plot, data is largely not correlated. Hence, SVM,KNN and random forests approaches have been considered in modelling the data.

**Correlation matrix**

```
##             ACTIVITY TIME   SL  EEG   BP   HR CIRCLUATION
## ACTIVITY         1.0 -0.1 -0.1  0.0 -0.1 -0.1        -0.1
## TIME            -0.1  1.0  0.8  0.0  0.4  1.0         0.9
## SL              -0.1  0.8  1.0 -0.1  0.4  0.9         1.0
## EEG              0.0  0.0 -0.1  1.0  0.0 -0.1        -0.1
## BP              -0.1  0.4  0.4  0.0  1.0  0.5         0.4
## HR              -0.1  1.0  0.9 -0.1  0.5  1.0         0.9
## CIRCLUATION     -0.1  0.9  1.0 -0.1  0.4  0.9         1.0
```

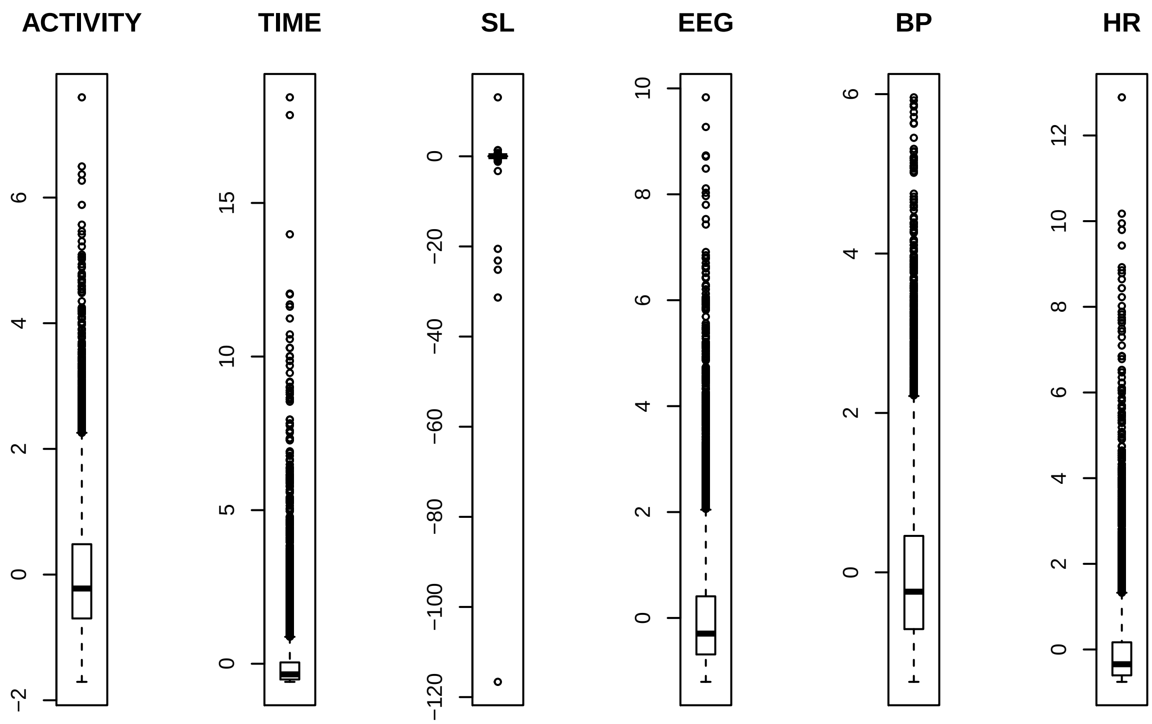
**A plot of the correlation matrix**

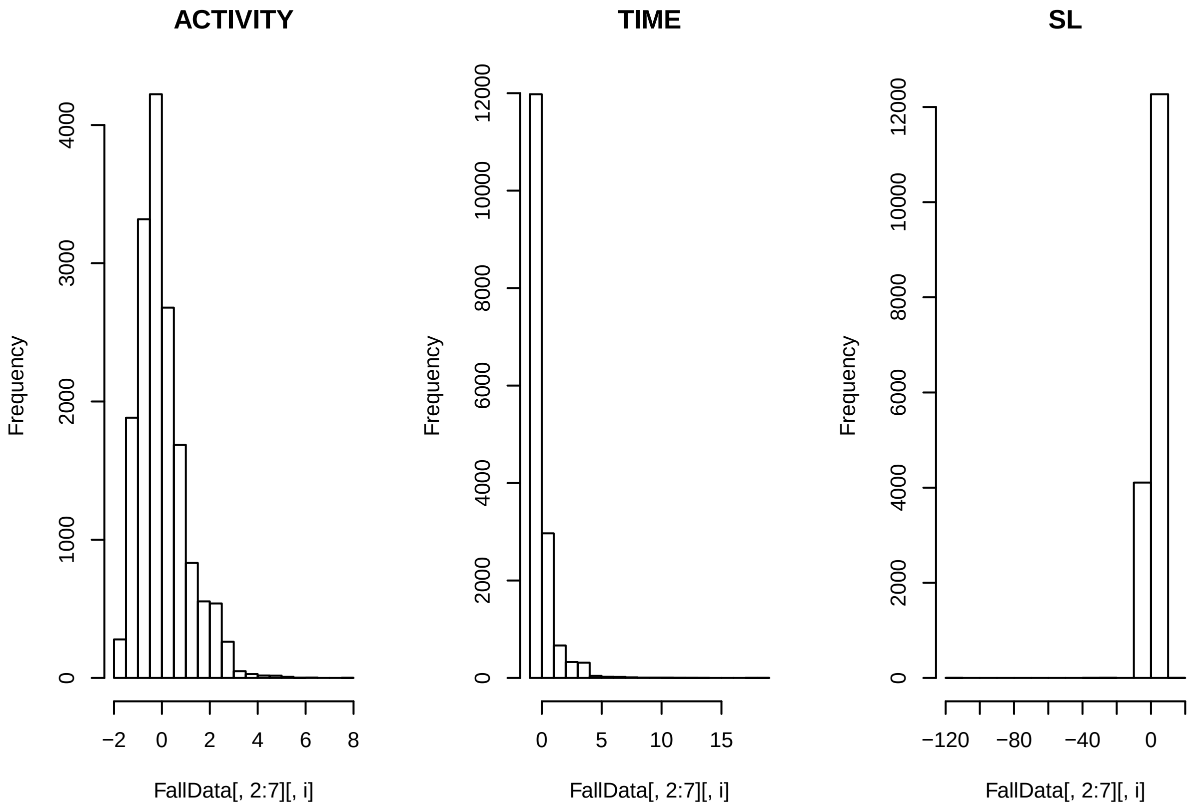


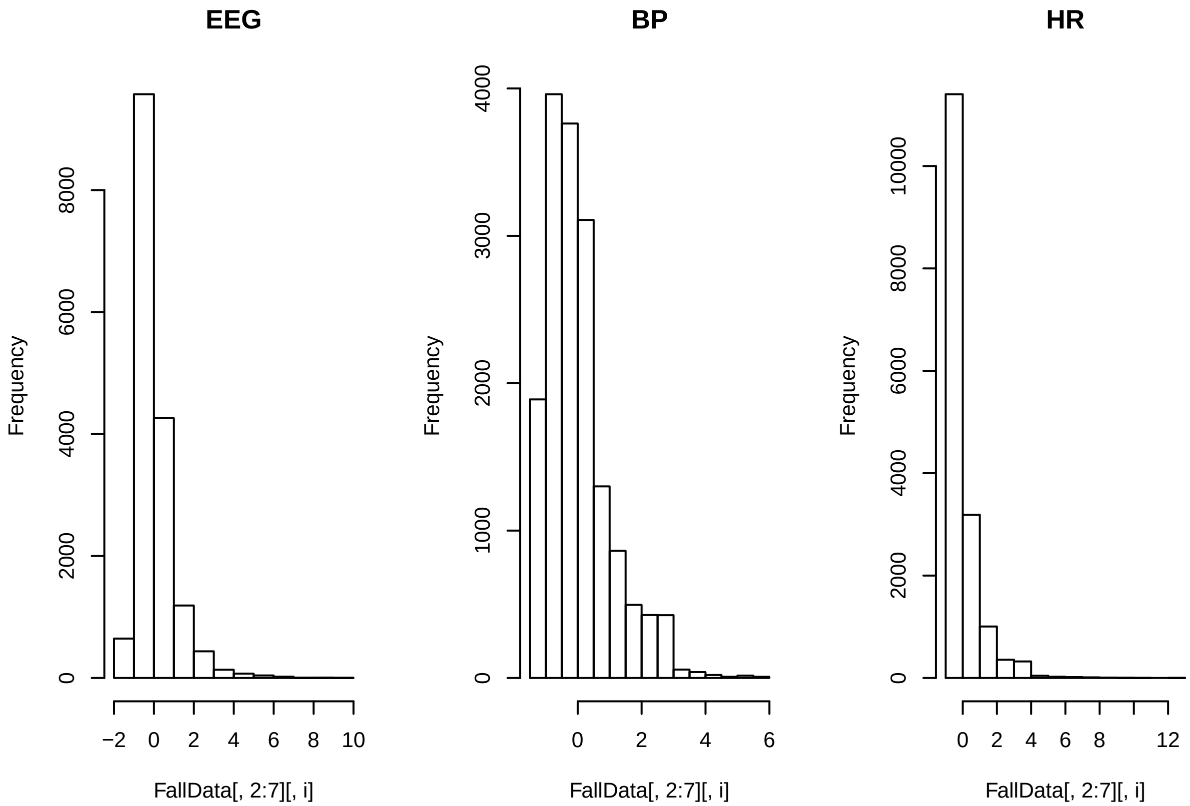
## Distribution of Data

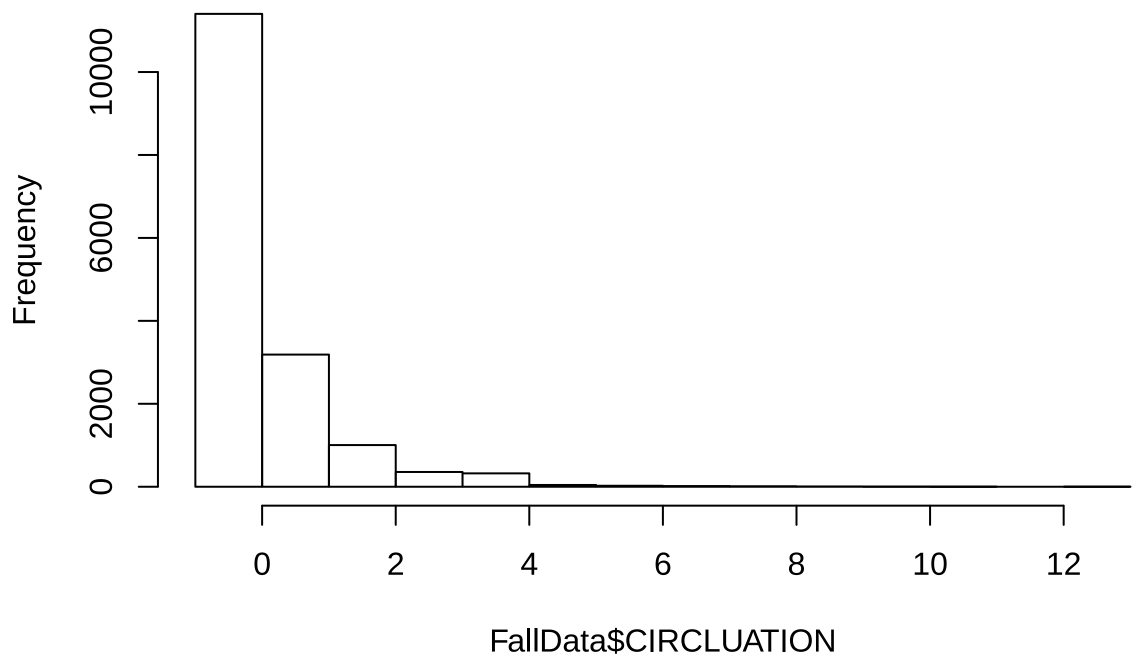
Exploring distribution of data by boxplot and histograms for each variable, and distribution of each variable for every target label, data is seen to be non-randomly distributed, even after scaling.

**Boxplots of individuals variables**

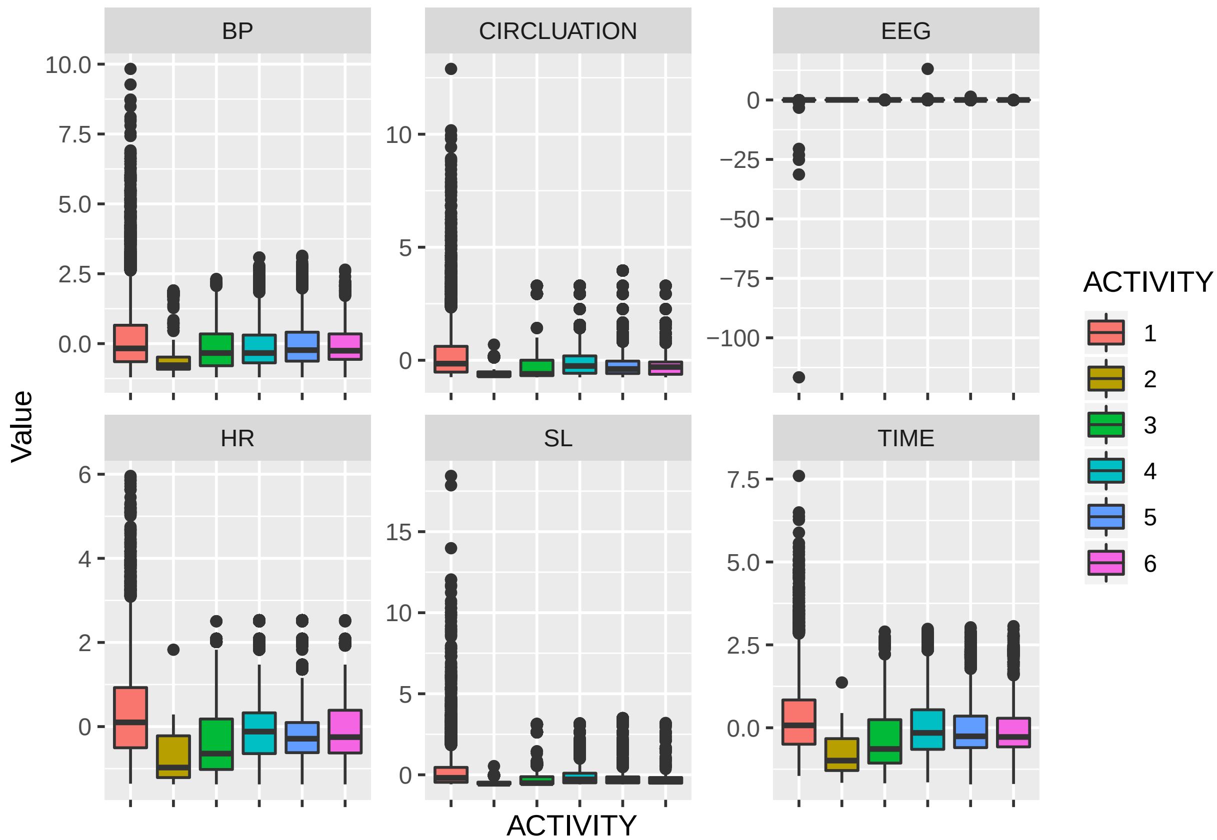



ACTIVITY
TIME
SL
Frequency
FallData[, 2:7][, i]
0
1000
2000
3000
4000
2000
4000
6000
8000
10000
12000
−2
2
4
6
8
5
10
15
−120
−80
−40


EEG
BP
HR
Frequency
FallData[, 2:7][, i]
0
2000
4000
6000
8000
−2
0
2
4
6
8
10
1000
3000
10000
12




**Distribution of target variables against each predictor**




## Results

The model has been trained with three machine learning approaches, Support Vector Machines(SVM),knn and random forest as the data is largely not correlated and non-uniformally distributed. For a model that distinguishes different human movements, the performance metric chosen is accuracy.Random forest produced the best results with accuracy at 77% for the final results and Sensitivity of 75% and Specificity of 89% for class 3, the falling category. During training, SVM had the lowest accuracy at 23% followed by knn at 59% and random forest had 75%.

## Conclusion

A fall detection system to detect falls from six other human movements has been built using a random forest machine learning approach with an overall accuracy of 77%. While the accuracy is still wanting, performance of the model can improved with more data as already observed in the accuracy difference when training with less and much more data. Performance of the model might also be improved if trained with real-world scenarios data. Future works will look at feature engineering, ensembling and PCA in a bid to improve performance.