Supervised Machine Learning: Classification

Introduction

We will be using the Human Activity Recognition with Smartphones database, which was built from the recordings of study participants performing activities of daily living (ADL) while carrying a smartphone with an embedded inertial sensors. The objective is to classify activities into one of the six activities (walking, walking upstairs, walking downstairs, sitting, standing, and laying) performed.

For each record in the dataset it is provided:

Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration. Triaxial Angular velocity from the gyroscope. A 561-feature vector with time and frequency domain variables. Its activity label.

In [1]:
```
# Import the necessary libraries
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns, os, sys
```

```
C:\Users\raman\AppData\Local\Programs\Python\Python37\lib\site-packages\numpy\_distributor_in
it.py:32: UserWarning: loaded more than 1 DLL from .libs:
C:\Users\raman\AppData\Local\Programs\Python\Python37\lib\site-packages\numpy\.libs\libopenbl
as.TXA6YQSD3GCQQC22GEQ54J2UDCXDXHWN.gfortran-win_amd64.dll
C:\Users\raman\AppData\Local\Programs\Python\Python37\lib\site-packages\numpy\.libs\libopenbl
as.WCDJNK7YVMPZQ2ME2ZZHJJRJ3JIKNDB7.gfortran-win_amd64.dll
  stacklevel=1)
```

In [2]:
```
# Read the file
filepath = 'Final Project\\Human_Activity_Recognition_Using_Smartphones_Data.csv'
data = pd.read_csv(filepath, sep=',')
```

In [3]:
```
data.head()
```

Out[3]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fB
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527	-0.934724	...	
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686	-0.943068	...	
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469	-0.938692	...	
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0.989302	-0.938692	...	
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0.990441	-0.942469	...	

5 rows × 562 columns

Data Exploration

In [4]:
```
data.shape
```

Out[4]:
```
(10299, 562)
```

The data columns are all floats except for the activity label.

In [5]:
```
data.dtypes.value_counts()
```

Out[5]:
```
float64    561
object       1
dtype: int64
```

In [6]:
```
data.dtypes.tail()
```

Out[6]:
```
angle(tBodyGyroJerkMean,gravityMean)    float64
angle(X,gravityMean)                    float64
angle(Y,gravityMean)                    float64
angle(Z,gravityMean)                    float64
Activity                                 object
dtype: object
```

The data are all scaled from -1 (minimum) to 1.0 (maximum).

In [7]:
```
data.iloc[:, :-1].min().value_counts()
```

Out[7]:
```
-1.0    561
dtype: int64
```

In [8]:
```
data.iloc[:, :-1].max().value_counts()
```

Out[8]:
```
1.0    561
dtype: int64
```

Examine the breakdown of activities--they are relatively balanced.

In [9]:
```
data.Activity.value_counts()
```

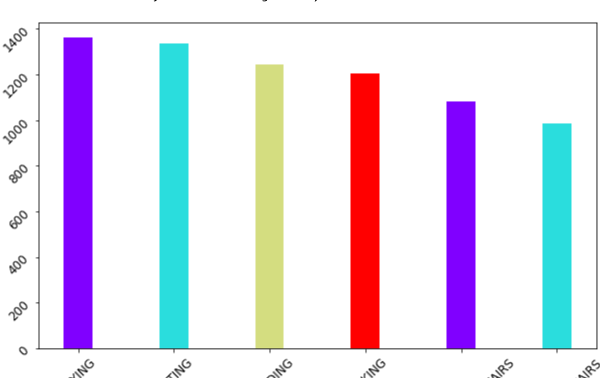
Out[9]:
```
LAYING                1944
STANDING              1906
SITTING               1777
WALKING               1722
WALKING_UPSTAIRS      1544
WALKING_DOWNSTAIRS    1406
Name: Activity, dtype: int64
```

In [10]:
```
# Calculate the correlation values
feature_cols = data.columns[:-1]
corr_values = data[feature_cols].corr()

# Simplify by emptying all the data below the diagonal
tril_index = np.tril_indices_from(corr_values)

# Make the unused values NaNs
corr_array = np.array(corr_values)
corr_array[np.tril_indices_from(corr_values)] = np.nan

# recreate correlation pandas dataframe
corr_values = pd.DataFrame(corr_array,columns = corr_values.columns, index = corr_values.ind
ex)

# Stack the data and convert to a dataframe
corr_values = (corr_values
               .stack()
               .to_frame()
               .reset_index()
               .rename(columns={'level_0':'feature1',
                                'level_1':'feature2',
                                0:'correlation'}))

# Get the absolute values for sorting
corr_values['abs_correlation'] = corr_values.correlation.abs()
```

In [11]:
```
from sklearn.model_selection import StratifiedShuffleSplit

# Get the split indexes
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.3,
                                          random_state=42)

train_idx, test_idx = next(strat_shuf_split.split(data[feature_cols], data.Activity))

# Create the dataframes
X_train = data.loc[train_idx, feature_cols]
y_train = data.loc[train_idx, 'Activity']

X_test  = data.loc[test_idx, feature_cols]
y_test  = data.loc[test_idx, 'Activity']
```

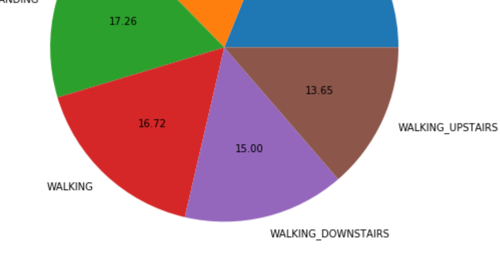
In [12]:
```
# Data Visualization
import matplotlib.cm as cm
count_of_each_activity = np.array(y_train.value_counts())
activities = sorted(y_train.unique())
colors = cm.rainbow(np.linspace(0, 1, 4))
plt.figure(figsize=(10,6))
plt.bar(activities,count_of_each_activity,width=0.3,color=colors)
plt.xticks(rotation=45,fontsize=12)
plt.yticks(rotation=45,fontsize=12)
```

Out[12]:
```
(array([   0.,  200.,  400.,  600.,  800., 1000., 1200., 1400., 1600.]),
 <a list of 9 Text yticklabel objects>)
```



In [13]:
```
plt.figure(figsize=(16,8))
plt.pie(count_of_each_activity, labels = activities, autopct = '%0.2f')
```

Out[13]:
```
([<matplotlib.patches.Wedge at 0x1e0bac5bf60>,
  <matplotlib.patches.Wedge at 0x1e0bac686a0>,
  <matplotlib.patches.Wedge at 0x1e0bac68d68>,
  <matplotlib.patches.Wedge at 0x1e0bac73470>,
  <matplotlib.patches.Wedge at 0x1e0bac73b38>,
  <matplotlib.patches.Wedge at 0x1e0bac83240>],
 [Text(0.9121289404751981, 0.6148339580306154, 'LAYING'),
  Text(-0.21504004519819878, 1.0787760559824995, 'SITTING'),
  Text(-1.0656462070182775, 0.27276026372541656, 'STANDING'),
  Text(-0.7531206776833063, -0.8017538555229015, 'WALKING'),
  Text(0.26369462766475305, -1.0679256263152164, 'WALKING_DOWNSTAIRS'),
  Text(1.0004049732078233, -0.457372812463809, 'WALKING_UPSTAIRS')],
 [Text(0.4975248766228353, 0.33536397710760835, '18.88'),
  Text(-0.11729457010810841, 0.5884233032631815, '18.50'),
  Text(-0.5812615674645149, 0.148778325668409, '17.26'),
  Text(-0.410793096918167, -0.4373202848306735, '16.72'),
  Text(0.14383343327168346, -0.5825048870810271, '15.00'),
  Text(0.5456754399315399, -0.249476079525714, '13.65')])
```



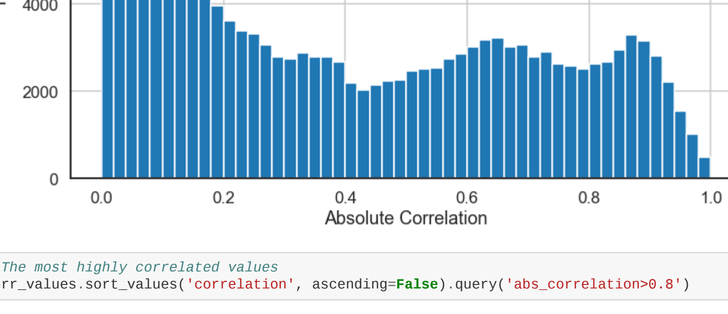
Scikit learn classifiers won't accept a sparse matrix for the prediction column. Thus, either 'LabelEncoder' needs to be used to convert the activity labels to integers. Use 'LabelEncoder' to fit_transform the "Activity" column, and look at 5 random values.

In [14]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
data['Activity'] = le.fit_transform(data.Activity)
data['Activity'].sample(5)
```

Out[14]:
```
8936    0
9617    1
2956    0
6765    4
6627    2
Name: Activity, dtype: int32
```

Calculate the correlations between the dependent variables. Create a histogram of the correlation values. Identify those that are most correlated (either positively or negatively).

In [15]:
```
sns.set_context('talk')
sns.set_style('white')

ax = corr_values.abs_correlation.hist(bins=50, figsize=(12, 8))
ax.set(xlabel='Absolute Correlation', ylabel='Frequency');
```



In [16]:
```
# The most highly correlated values
corr_values.sort_values('correlation', ascending=False).query('abs_correlation>0.8')
```

Out[16]:

	feature1	feature2	correlation	abs_correlation
156894	fBodyBodyGyroJerkMag-mean()	fBodyBodyGyroJerkMag-sma()	1.000000	1.000000
93902	tBodyAccMag-sma()	tGravityAccMag-sma()	1.000000	1.000000
101139	tBodyAccJerkMag-mean()	tBodyAccJerkMag-sma()	1.000000	1.000000
96706	tGravityAccMag-mean()	tGravityAccMag-sma()	1.000000	1.000000
94257	tBodyAccMag-energy()	tGravityAccMag-energy()	1.000000	1.000000
...	...	...	...	...
22657	tGravityAcc-mean()-Y	angle(Y,gravityMean)	-0.993425	0.993425
39225	tGravityAcc-arCoeff()-Z,3	tGravityAcc-arCoeff()-Z,4	-0.994267	0.994267
38739	tGravityAcc-arCoeff()-Z,2	tGravityAcc-arCoeff()-Z,3	-0.994628	0.994628
23176	tGravityAcc-mean()-Z	angle(Z,gravityMean)	-0.994764	0.994764
38252	tGravityAcc-arCoeff()-Z,1	tGravityAcc-arCoeff()-Z,2	-0.995195	0.995195

22815 rows × 4 columns

In [17]:
```
y_train.value_counts(normalize=True)
```

Out[17]:
```
LAYING                0.188792
STANDING              0.185046
SITTING               0.172562
WALKING               0.167152
WALKING_UPSTAIRS      0.149951
WALKING_DOWNSTAIRS    0.136496
Name: Activity, dtype: float64
```

In [18]:
```
y_test.value_counts(normalize=True)
```

Out[18]:
```
LAYING                0.188673
STANDING              0.185113
SITTING               0.172492
WALKING               0.167314
WALKING_UPSTAIRS      0.149838
WALKING_DOWNSTAIRS    0.136570
Name: Activity, dtype: float64
```

Summary of training at least three different classifier models

In [19]:
```
from sklearn.linear_model import LogisticRegression

# Standard logistic regression
lr = LogisticRegression(solver='liblinear').fit(X_train, y_train)
```

In [20]:
```
y_pred = lr.predict(X_test)
```

In [21]:
```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score
cm = confusion_matrix(y_test, y_pred)
accuracy_score=accuracy_score(y_test,y_pred)
recall_score=recall_score(y_test,y_pred,average='weighted')
f1_score=f1_score(y_test,y_pred,average='weighted')
print(y_pred)
print(cm)
print(accuracy_score)
print(recall_score)
print(f1_score)
```

```
['WALKING' 'WALKING_UPSTAIRS' 'WALKING' ... 'SITTING' 'SITTING'
 'WALKING_UPSTAIRS']
[[583   0   0   0   0   0]
 [  0 512  21   0   0   0]
 [  0  22 550   0   0   0]
 [  0   0   0 515   1   1]
 [  0   0   0   1 420   1]
 [  0   0   0   1   1 461]]
0.9841423948220065
0.9841423948220065
0.984142828415666
```

In [22]:
```
accuracy_scores = np.zeros(4)
```

In [23]:
```
from sklearn.metrics import accuracy_score
accuracy_scores[0] = accuracy_score(y_test, y_pred)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[0]))
```

```
Logistic Regression accuracy: 98.41423948220066%
```

In [24]:
```
# K Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier
clf = KNeighborsClassifier().fit(X_train, y_train)
```

In [25]:
```
prediction = clf.predict(X_test)
```

In [26]:
```
accuracy_scores[1] = accuracy_score(y_test, prediction)*100
print('K Nearest Neighbors Classifier accuracy: {}%'.format(accuracy_scores[1]))
```

```
K Nearest Neighbors Classifier accuracy: 96.44012944983818%
```

In [27]:
```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score
cm = confusion_matrix(y_test, prediction)
accuracy_score=accuracy_score(y_test,prediction)
recall_score=recall_score(y_test,prediction,average='weighted')
f1_score=f1_score(y_test,prediction,average='weighted')
print(prediction)
print(cm)
print(accuracy_score)
print(recall_score)
print(f1_score)
```

```
['WALKING' 'WALKING_UPSTAIRS' 'WALKING' ... 'SITTING' 'SITTING'
 'WALKING_UPSTAIRS']
[[582   1   0   0   0   0]
 [  1 479  52   0   0   1]
 [  0  44 528   0   0   0]
 [  0   0   0 517   0   0]
 [  0   0   0   6 413   3]
 [  0   0   0   0   2 461]]
0.9644012944983819
0.9644012944983819
0.9643655770411813
```

In [28]:
```
# Support Vector Classifier
from sklearn.svm import SVC
svc = SVC().fit(X_train, y_train)
```

In [29]:
```
prediction = svc.predict(X_test)
```

In [30]:
```
from sklearn.metrics import accuracy_score
accuracy_scores[2] = accuracy_score(y_test, prediction)*100
print('Support Vector Classifier accuracy: {}%'.format(accuracy_scores[2]))
```

```
Support Vector Classifier accuracy: 97.47572815533981%
```

In [31]:
```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score
cm = confusion_matrix(y_test, prediction)
accuracy_score=accuracy_score(y_test,prediction)
recall_score=recall_score(y_test,prediction,average='weighted')
f1_score=f1_score(y_test,prediction,average='weighted')
print(prediction)
print(cm)
print(accuracy_score)
print(recall_score)
print(f1_score)
```

```
['WALKING' 'WALKING_UPSTAIRS' 'WALKING' ... 'SITTING' 'SITTING'
 'WALKING_UPSTAIRS']
[[583   0   0   0   0   0]
 [  1 501  30   0   0   1]
 [  0  37 535   0   0   0]
 [  0   0   0 516   0   1]
 [  0   0   0   1 418   3]
 [  0   0   0   1   3 459]]
0.974757281553398
0.974757281553398
0.9747434952030193
```

In [32]:
```
# Random Forest
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier().fit(X_train, y_train)
```

In [33]:
```
y_pred = rfc.predict(X_test)
```

In [34]:
```
from sklearn.metrics import accuracy_score
accuracy_scores[3] = accuracy_score(y_test, y_pred)*100
print('Random Forest Classifier accuracy: {}%'.format(accuracy_scores[3]))
```

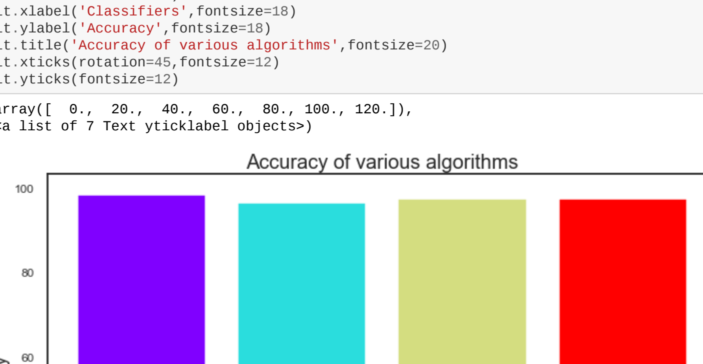
```
Random Forest Classifier accuracy: 97.57281553398059%
```

In [35]:
```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score
cm = confusion_matrix(y_test, y_pred)
accuracy_score=accuracy_score(y_test,y_pred)
recall_score=recall_score(y_test,y_pred,average='weighted')
f1_score=f1_score(y_test,y_pred,average='weighted')
print(y_pred)
print(cm)
print(accuracy_score)
print(recall_score)
print(f1_score)
```

```
['WALKING' 'WALKING_UPSTAIRS' 'WALKING' ... 'SITTING' 'SITTING'
 'WALKING_UPSTAIRS']
[[582   0   0   0   0   1]
 [  0 511  21   0   0   1]
 [  0  20 552   0   0   0]
 [  0   0   0 506   4   7]
 [  0   0   0   2 409  11]
 [  0   0   0   0   8 455]]
0.9757281553398058
0.9757281553398058
0.975755729570549
```

In [36]:
```
# Performance of different classifiers
import matplotlib.cm as cm
plt.figure(figsize=(12,8))
colors = cm.rainbow(np.linspace(0, 1, 4))
labels = ['Logsitic Regression', 'K Nearest Neighbors', 'Support Vector Classifier', 'Random
Forest']
plt.bar(labels,
        accuracy_scores,
        color = colors)
plt.xlabel('Classifiers',fontsize=18)
plt.ylabel('Accuracy',fontsize=18)
plt.title('Accuracy of various algorithms',fontsize=20)
plt.xticks(rotation=45,fontsize=12)
plt.yticks(fontsize=12)
```

Out[36]:
```
(array([  0.,  20.,  40.,  60.,  80., 100., 120.]),
 <a list of 7 Text yticklabel objects>)
```



Final Classifier Model

We can clearly see that the Logistic Regression model performs the best for the task of Human Activity Recognition with Machine Learning.

Summary Key Findings and Insights

By inspecting the dataset, we can see that there are a lot of features. It is easy to identify that there is an accelerometer, gyroscope, and other values in the data set. We can check everyone's share by plotting a bar graph of each type. Accelerometer values have Acc in them, Gyroscope values have Gyro, and rest can be considered like others:

In [40]:
```
Acc = 0
Gyro = 0
other = 0

for value in X_train.columns:
    if "Acc" in str(value):
        Acc += 1
    elif "Gyro" in str(value):
        Gyro += 1
    else:
        other += 1

plt.figure(figsize=(12,8))
plt.bar(['Accelerometer', 'Gyroscope', 'Others'],[Acc,Gyro,other],color=('r','g','b'))
```

Out[40]:
```
<BarContainer object of 3 artists>
```

The accelerometer provides the maximum functionality, followed by the gyroscope. The other features are much less so.

Suggestions for next steps in analyzing this data

- More data can be helpful.
- More data exploration and feature engineering can also be good.
- Using different models like LSTM, neural networks, to see the performance of the data on other models.