# DATA ANALYSIS ON HUMAN ACTIVITY RECOGNITION USING SMARTPHONES DATASET

SOEN 691 - Big Data Analytics (Winter 2020)

NAME	STUDENT ID		
Girish Kumar Kadapa	40083533		
Naren Morabagal Somasekhar	40082567		
Adarsh Aravind	40082585		
Liangzhao Lin	40085480		

# **AGENDA**

- 1. INTRODUCTION
- 2. DATASET
- 3. TECHNOLOGIES
- 4. DATA PREPROCESSING
- 5. MODEL TRAINING
- 6. OUTCOME/EVALUATION METRICS
- 7. CONCLUSION AND FUTURE WORK

# INTRODUCTION

Dataset analysis project.

The goal of this project is to analyze the data, train the model, interpret and discuss the results of the data analysis with various metrics such as accuracy rate, F1 score, precision and recall.

The project is to predict the human activity labels such as "Walking, Walking\_Upstairs, Walking\_Downstairs, Sitting, Standing, Laying" from the data collected from the smartphone sensors.

# **DATASET**

The dataset has captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz, containing 561-feature vector with time and frequency domain variables and labels namely six activities (WALKING, WALKING\_UPSTAIRS, WALKING\_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone on the waist performed by a person.

Data Set Characteristics	Multivariate, Time-Series
Associated Tasks	Classification, Clustering
Number of Instances	10299
Number of Attributes	561

# DATASET (CONT...)

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 labels.
- An identifier of the subject who carried out the experiment.

The movement data recorded was the x, y, and z accelerometer data (linear acceleration) and gyroscopic data (angular velocity) from the smartphone.

# **TECHNOLOGIES**

- 1. Supervised Machine Learning Algorithms
  - 1.1. Random Forest
  - 1.2. K-nearest Neighbours
  - 1.3. Logistic Regression
- 2. Scikit-learn
- 3. Python Libraries Matplotlib, seaborn, and plotly for plotting, GridSearch, Numpy for array vectorization, Pandas dataframes, precision, recall, fl\_score, SimpleImputer, MinMaxScaler, confusion\_matrix

# DATA PRE-PROCESSING

- 1. Eliminate duplicate values
- 2. Remove/Impute null values
- 3. Scaling the features between the range [-1, 1]
- 4. Feature selection
- 5. Removing outliers
- 6. Data visualization
- 7. Class labels balance check

# DATA PRE-PROCESSING (CONT...)

#### Check if any duplicate rows are available

1.000000

1.000000

1.000000

```
In [214]: train_features[train_features.duplicated()].count().sum()
Out[214]: 0
           Check if any null values are present and impute them with column mean (if the count is insignificant)
In [215]: Imputer = SimpleImputer(missing_values=np.nan, strategy="mean")
In [216]: train_features = Imputer.fit_transform(train_features.values)
           train_features = pd.DataFrame(train_features)
In [217]: train_features.isnull().sum().sum()
Out[217]: 0
           Transform features by scaling each feature between [-1 1]
In [218]: scaler = MinMaxScaler(feature range=(-1,1))
In [219]: train features = pd.DataFrame(scaler.fit transform(train features.values))
In [220]: train features.describe()
Out[220]:
            count 7352.000000
                              7352.000000
                                           7352.000000
                                                        7352.000000
                                                                     7352.000000
                                                                                  7352.000000
                                                                                              7352.000000
                                                                                                           7352.000000 7352.00
                  0.274488
                               -0.017695
                                            -0.109141
                                                         -0.605438
                                                                      -0.489659
                                                                                  -0.604754
                                                                                               -0.630512
                                                                                                            -0.519133
                                                                                                                        -0.6061
            mean
            std
                  0.070261
                               0.040811
                                           0.056635
                                                        0.448734
                                                                     0.524651
                                                                                  0.418687
                                                                                               0.424073
                                                                                                           0.493927
                                                                                                                        0.4141;
                   -1.000000
                               -1.000000
                                            -1.000000
                                                         -1.000000
                                                                      -1.000000
                                                                                  -1.000000
                                                                                               -1.000000
                                                                                                            -1.000000
                                                                                                                        -1.0000
            min
                  0.262975
                               -0.024863
                                            -0.120993
                                                         -0.992754
                                                                     -0.977304
                                                                                  -0.980233
                                                                                               -0.993591
                                                                                                            -0.977803
                                                                                                                        -0.9802
                  0.277193
                               -0.017219
                                            -0.108676
                                                         -0.946196
                                                                     -0.845545
                                                                                  -0.859365
                                                                                               -0.950709
                                                                                                            -0.854984
                                                                                                                        -0.8571
                  0.288461
                               -0.010783
                                            -0.097794
                                                         -0.242813
                                                                     0.007919
                                                                                  -0.262415
                                                                                               -0.292680
                                                                                                            -0.051363
                                                                                                                        -0.2656
```

1.000000

1.000000

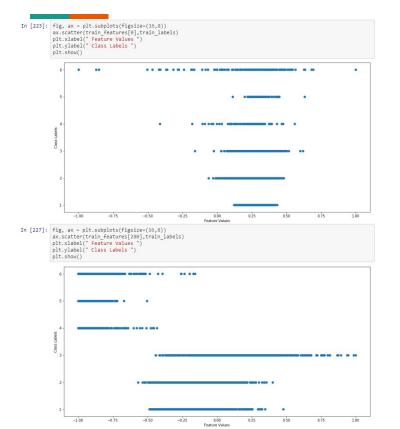
1.000000

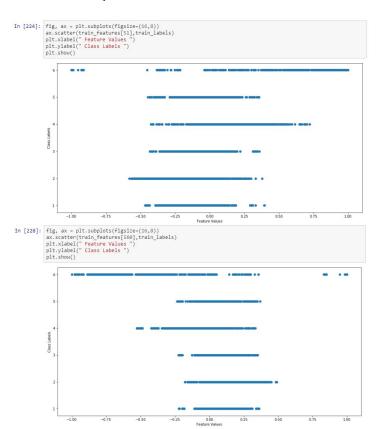
1.000000

1.000000

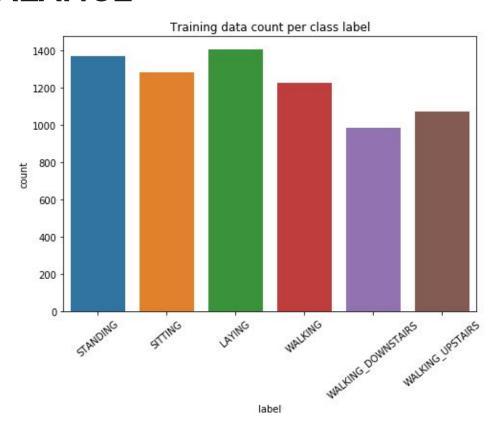
1.00001

# DATA PRE-PROCESSING (CONT...)





# **DATA BALANCE**



# **MODEL TRAINING - GRIDSEARCH**

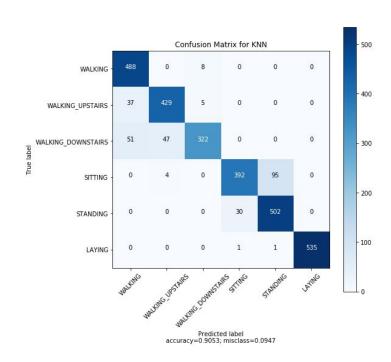
```
In [215]:
          knn params = {'n neighbors':np.array(range(9,18))}
          knn = KNeighborsClassifier()
           gridcv knn = GridSearchCV(knn, knn params, verbose=False, cv=3)
In [216]: gridcv knn.fit(train features,train labels['label'].ravel())
Out[216]: GridSearchCV(cv=3, error_score='raise-deprecating',
                       estimator=KNeighborsClassifier(algorithm='auto', leaf size=30,
                                                      metric='minkowski',
                                                      metric params=None, n jobs=None,
                                                      n neighbors=5, p=2.
                                                      weights='uniform'),
                       iid='warn', n jobs=None,
                       param grid={'n neighbors': array([ 9, 10, 11, 12, 13, 14, 15, 16, 17])},
                       pre dispatch='2*n jobs', refit=True, return train score=False,
                       scoring=None, verbose=False)
In [217]: gridcv knn.best params
Out[217]: {'n neighbors': 17}
```

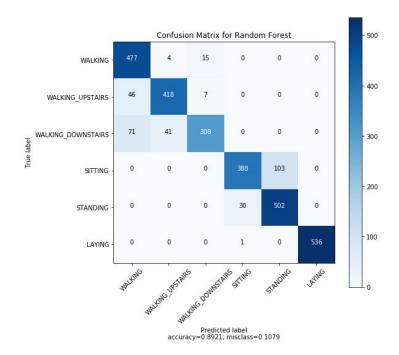
```
In [222]: rf params = {'n_estimators' : np.arange(10,30,10), 'max_depth' : np.arange(1,6,2)}
          rf = RandomForestClassifier(random state=0)
          gridcv rf = GridSearchCV(rf, rf params, verbose=False, cv=3)
In [223]: gridcv rf.fit(train features,train labels['label'].ravel())
Out[223]: GridSearchCV(cv=3, error score='raise-deprecating',
                       estimator=RandomForestClassifier(bootstrap=True, class_weight=None,
                                                        criterion='gini', max depth=None,
                                                         max features='auto'.
                                                         max leaf nodes=None,
                                                        min impurity_decrease=0.0,
                                                         min impurity split=None,
                                                        min samples leaf=1,
                                                        min samples split=2,
                                                        min weight fraction leaf=0.0,
                                                        n estimators='warn', n jobs=None,
                                                        oob score=False, random state=0,
                                                        verbose=0, warm start=False),
                       iid='warn', n jobs=None,
                       param grid={'max depth': array([1, 3, 5]),
                                    'n estimators': arrav([10, 20])},
                       pre dispatch='2*n jobs', refit=True, return train score=False,
                       scoring=None, verbose=False)
In [224]: gridcv rf.best params
Out[224]: {'max depth': 5, 'n estimators': 20}
```

KNN

Random Forest

# **OUTCOME/EVALUATION METRICS - CONFUSION MATRIX**





KNN

**Random Forest** 

# OUTCOME/EVALUATION METRICS (CONT...)

knn\_predictions = gridcv\_knn.predict(test\_features)

rf\_predictions = gridcv\_rf.predict(test\_features)

print(classification\_report(test\_labels,knn\_predictions))

print(classification\_report(test\_labels,rf\_predictions))

	precision	recall	f1-score	support		precision	recall	f1-score	support
1	0.85	0.98	0.91	496	1	0.80	0.96	0.88	496
2	0.89	0.91	0.90	471	2	0.90	0.89	0.90	471
3	0.96	0.77	0.85	420	3	0.93	0.73	0.82	420
4	0.93	0.80	0.86	491	4	0.93	0.79	0.85	491
5	0.84	0.94	0.89	532	5	0.83	0.94	0.88	532
6	1.00	1.00	1.00	537	6	1.00	1.00	1.00	537
accuracy			0.91	2947	accuracy			0.89	2947
macro avg	0.91	0.90	0.90	2947	macro avg	0.90	0.89	0.89	2947
weighted avg	0.91	0.91	0.90	2947	weighted avg	0.90	0.89	0.89	2947

**KNN** 

Random Forest

# **OUTCOME/EVALUATION METRICS (CONT...)**

We have analysed the accuracy, precision, recall, and F1 score using three machine learning algorithms which is shown in the below table.

		Train Accuracy	Test Accuracy	Precision	Recall	F1 score
1	KNN	0.967492	0.905327	0.910584	0.905327	0.904179
2	Logistic Regression	0.994423	0.961995	0.963746	0.961995	0.961805
3	Random Forest	0.937296	0.892094	0.898754	0.892094	0.890947

### **CONCLUSION AND FUTURE WORK**

## Takeaways/Learning from the project:

We got the opportunity to implement end to end machine learning models.

#### Future work:

We would like to integrate trained models into hardware systems and get the live results and see the model in action.

# **THANK YOU**