Human Activity Recognition Using Smartphones Data Set

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.

More information about the features is available on the website above.

Plan for data exploration

1. Exploring data
   - Examine the data types and value_counts
2. feature engineering
   - see the data distribution
   - removing unimportant data if found
   - dealing with missing (NaN) values if found
   - feature scalling for continuous variables if needed
3. encoding
   - encoding for categorical variables if found as to Encode the activity label as an integer
4. Spliting the Data
   - StratifiedShuffleSplit
5. Applying classification models
   - Logistic Regression
   - K-Nearest Neighbors (KNeighbors)
   - Decision Trees
   - Ensemble Methods (Gradient Boosting)
6. Selecting the best model
7. Next steps

Exploring and feature engineering

In [ ]:

```

```

```python
# importing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import KFold, cross_val_predict, GridSearchCV, train_te
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.pipeline import Pipeline

%matplotlib inline
```

In [ ]:

```python
filepath = 'data/Human_Activity_Recognition_Using_Smartphones_Data.csv'
data = pd.read_csv(filepath, sep=',')
data.head()
```

Out[ ]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBo m
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0

5 rows × 562 columns

In [ ]:

```python
data.dtypes.value_counts()
```

Out[ ]:

```
float64    561
object       1
dtype: int64
```

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

In [ ]:

```python
# see the min and max of data excluding the target
print('min = ',data.iloc[:, :-1].min().value_counts())
print('max = ',data.iloc[:, :-1].max().value_counts())
```

```
min =  -1.0    561
dtype: int64
max =  1.0    561
dtype: int64
```

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

In [ ]:

```python
# Examine the breakdown of activities-- to see if balanced or not
data.Activity.value_counts(normalize=True)
```

Out[ ]:

```
LAYING                0.188756
STANDING              0.185067
SITTING               0.172541
WALKING               0.167201
WALKING_UPSTAIRS      0.149917
WALKING_DOWNSTAIRS    0.136518
Name: Activity, dtype: float64
```

In [ ]:
```
data.isnull().sum().all()
```

Out[ ]:
```
False
```

encoding

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, or if `DictVectorizer` is used, the resulting matrix must be converted to a non-sparse array.

we will use `LabelEncoder` to fit_transform the "Activity" column, and look at 5 random values.

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

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

Out[ ]:
```
1015    2
4858    5
7820    2
727     1
9480    0
Name: Activity, dtype: int32
```

looking at correlation

- 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 [ ]:
```
# 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
for coord in zip(*tril_index):
    corr_values.iloc[coord[0], coord[1]] = np.NaN

# Stack the data and convert to a data frame
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()
corr_values
```

Out[ ]:

	feature1	feature2	correlation	abs_correlation
0	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	0.128037	0.128037
1	tBodyAcc-mean()-X	tBodyAcc-mean()-Z	-0.230302	0.230302
2	tBodyAcc-mean()-X	tBodyAcc-std()-X	0.004590	0.004590
3	tBodyAcc-mean()-X	tBodyAcc-std()-Y	-0.016785	0.016785
4	tBodyAcc-mean()-X	tBodyAcc-std()-Z	-0.036071	0.036071
...	...	...	...	...
157075	angle(tBodyGyroJerkMean,gravityMean)	angle(Y,gravityMean)	-0.004582	0.004582
157076	angle(tBodyGyroJerkMean,gravityMean)	angle(Z,gravityMean)	-0.012549	0.012549
157077	angle(X,gravityMean)	angle(Y,gravityMean)	-0.748249	0.748249
157078	angle(X,gravityMean)	angle(Z,gravityMean)	-0.635231	0.635231
157079	angle(Y,gravityMean)	angle(Z,gravityMean)	0.545614	0.545614

157080 rows × 4 columns

In [ ]:

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

Out[ ]:

	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

Data split

- This can be done using any method, but consider using Scikit-learn's `StratifiedShuffleSplit` to maintain the same ratio of predictor classes.

In [ ]:

```
from sklearn.model_selection import StratifiedShuffleSplit
X = data[feature_cols]
y = data['Activity']
```

```
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.3,
                                          random_state=42)

train_idx, test_idx = next(strat_shuf_split.split(X, y))
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 [ ]:

```
y_train.value_counts(normalize=True)
```

Out[ ]:

```
0    0.188792
2    0.185046
1    0.172562
3    0.167152
5    0.149951
4    0.136496
Name: Activity, dtype: float64
```

In [ ]:

```
y_test.value_counts(normalize=True)
```

Out[ ]:

```
0    0.188673
2    0.185113
1    0.172492
3    0.167314
5    0.149838
4    0.136570
Name: Activity, dtype: float64
```

we maintained the distribution of the target class seccussfuly

Applying classification models

- Logistic Regression
- K-Nearest Neighbors (KNeighbors)
- Decision Trees
- Ensemble Methods (Gradient Boosting)

1.Logistic Regression

In [ ]:

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

In [ ]:

```
from sklearn.linear_model import LogisticRegressionCV
# L1 regularized logistic regression
lr_l1 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear').fit(X_tr
# L2 regularized logistic regression
lr_l2 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2', solver='liblinear').fit(X_tr
```

- Predict and store the class for each model.
- Store the probability for the predicted class for each model.

In [ ]:

```python
# Predict the class and the probability for each
y_pred = list()
y_prob = list()

coeff_labels = ['lr', 'l1', 'l2']
coeff_models = [lr, lr_l1, lr_l2]

for lab,mod in zip(coeff_labels, coeff_models):
    y_pred.append(pd.Series(mod.predict(X_test), name=lab))
    y_prob.append(pd.Series(mod.predict_proba(X_test).max(axis=1), name=lab))

y_pred = pd.concat(y_pred, axis=1)
y_prob = pd.concat(y_prob, axis=1)
y_pred.head()
```

Out[ ]:

	lr	l1	l2
0	3	3	3
1	5	5	5
2	3	3	3
3	1	1	1
4	0	0	0

In [ ]:

```python
y_prob.head()
```

Out[ ]:

	lr	l1	l2
0	0.998939	0.998948	0.999998
1	0.988165	0.999674	0.999477
2	0.987592	0.996099	0.999697
3	0.981381	0.999179	0.999865
4	0.998277	0.999920	0.999997

error metrics

For each model, calculate the following error metrics:

- Accuracy
- Precision
- Recall
- F-score
- Confusion Matrix

In [ ]:

```python
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
from sklearn.preprocessing import label_binarize

metrics = list()
cm = dict()

for lab in coeff_labels:
```

```python
    precision, recall, fscore, _ = score(y_test, y_pred[lab], average='weighted')

    accuracy = accuracy_score(y_test, y_pred[lab])

    # ROC-AUC scores can be calculated by binarizing the data
    auc = roc_auc_score(label_binarize(y_test, classes=[0,1,2,3,4,5]),
              label_binarize(y_pred[lab], classes=[0,1,2,3,4,5]),
              average='weighted')

    cm[lab] = confusion_matrix(y_test, y_pred[lab])

    metrics.append(pd.Series({'precision':precision, 'recall':recall,
                             'fscore':fscore, 'accuracy':accuracy,
                             'auc':auc},
                            name=lab))

metrics = pd.concat(metrics, axis=1)
```

In [ ]:

```python
metrics
```

Out[ ]:

	lr	l1	l2
precision	0.984144	0.983514	0.984477
recall	0.984142	0.983495	0.984466
fscore	0.984143	0.983492	0.984464
accuracy	0.984142	0.983495	0.984466
auc	0.990384	0.989949	0.990553

In [ ]:

```python
from sklearn.metrics import f1_score

lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
f1_lr = f1_score(y_pred, y_test, average='weighted')
f1_lr
```

Out[ ]:

```
0.9841419612283467
```

In [ ]:

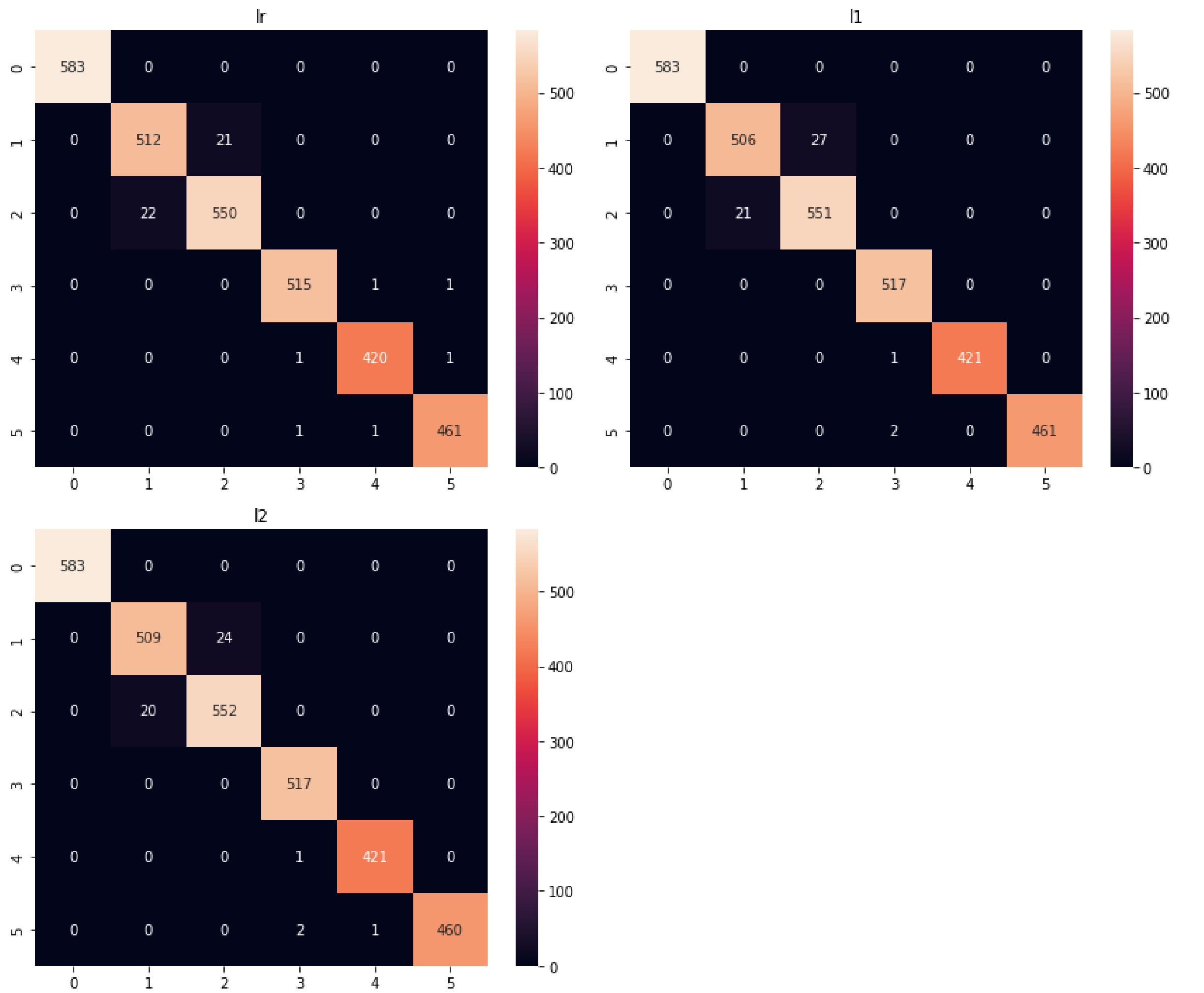
```python
### Display or plot the confusion matrix for each model.

fig, axList = plt.subplots(nrows=2, ncols=2)
axList = axList.flatten()
fig.set_size_inches(12, 10)

axList[-1].axis('off')

for ax,lab in zip(axList[:-1], coeff_labels):
    sns.heatmap(cm[lab], ax=ax, annot=True, fmt='d');
    ax.set(title=lab);

plt.tight_layout()
```



2.K-Nearest Neighbors (KNeighbors)

In [ ]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import f1_score

knn = KNeighborsClassifier(n_neighbors=3, weights='distance')
knn = knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
f1_knn = f1_score(y_pred, y_test, average='weighted')
f1_knn
```

Out[ ]:

```
0.9679843882037947
```

3.Decision Trees

In [ ]:

```
from sklearn.metrics import f1_score, make_scorer
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
import warnings
warnings.filterwarnings("ignore")

tuning_parameters = {'max_depth':[2,4,6,8,10],
                     'min_samples_leaf':[2,4,6,8,10],
                     'min_samples_split':[2,4,6,8,10]}

scorer = make_scorer(f1_score, average = 'weighted')
GR = GridSearchCV(DecisionTreeClassifier(random_state=42), tuning_parameters, scorin
GR = GR.fit(X_train, y_train)
```

```
print('GR.best_estimator_: ', GR.best_estimator_)
print('GR.best_score_: ', GR.best_score_)
print('GR.best_params_: ', GR.best_params_)
```

```
GR.best_estimator_:  DecisionTreeClassifier(max_depth=10, min_samples_leaf=4, min_sa
mples_split=10,
                       random_state=42)
GR.best_score_:  0.9266884691991407
GR.best_params_:  {'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 10}
```

In [ ]:

```
GR.best_score_, GR.best_params_
```

Out[ ]:

```
(0.9266884691991407,
 {'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 10})
```

In [ ]:

```
y_pred = GR.predict(X_test)
f1_dt = f1_score(y_pred, y_test, average='weighted')
f1_dt
```

Out[ ]:

```
0.9276476807305897
```

4.GradientBoosting

In [ ]:

```
from sklearn.ensemble import GradientBoostingClassifier
GBC = GradientBoostingClassifier(max_features=5, n_estimators=100, random_state=42)
GBC.fit(X_train.values, y_train.values)
y_pred = GBC.predict(X_test)
f1_GBC = f1_score(y_pred, y_test, average='weighted')
f1_GBC
```

Out[ ]:

```
0.9805798565748332
```

Selecting best model

In [ ]:

```
pd.DataFrame({'Logistic Regression':f1_lr, 'KNN':f1_knn,
                              'Decision Trees':f1_dt, 'Gradient Boosting':f1_GBC},in
```

Out[ ]:

	Logistic Regression	KNN	Decision Trees	Gradient Boosting
F1_SCORE	0.984142	0.967984	0.927648	0.98058

so we will chooce `GradientBoostingClassifier` or `logistic regression`

key findings

logistic regression without regularization got us the highest F1_Score so we will choose it and Decision Trees took too long and got the worst score

Next steps

we can use another encoding method like `LabelBinarizer` and we can try another ensemble method like `Random forest`