Home Work – 5
Machine Learning – CS633
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(a)
Motivation and Data:

Dataset - UCI Smartphone-Based Recognition of Human Activities and Postural Transitions
Number of samples – 10928
Number of features – 561
Machine Learning Task – Classification
Number of classes – 12

The potential applications of this classification problem are the major motivating factor to solve this problem.Human activity and posture recognition can be used in application like fitness monitoring. Smart phones are with everyone and carried around by the person where ever he goes. Hence, use of smart phones to monitor the activities of a person is a good idea to record almost all the physical activities of a person. We can give personalised feedback to the user regarding their daily activities, which includes lifestyle changes. This can help in improving the fitness and lifestyle of the person.
This technology can also be used to monitor old people with health issues. In case a person goes out and fall down due to some health issue, the smart phone can detect this and notify his family member. This ensure safety of old people.

Hence, this problem has massive potential to be used for different applications. This is one of the primary factor that motivates me to undertake this project.

This project seeks to be a building block of a complete software solution for a comprehensive health monitoring system using a smartphone.

(b)
Problem formulation:
This is a classification problem. Number of classes = 12.
The problem involves reading raw data from accelerometer and gyroscope, and then extracting features like mean, median, maximum frequency value, etc. during different activities. We use these features to predict the postural transitions of an individual.

Logistic Regression model –
A binary logistic regression model can be trained in a one-vs-rest fashion to achieve multiclass classification. Logistic regression is a simple linear model. Multiple logistic regressions can we trained to fit different straight lines and achieve multi-class classification.
Logistic Regression (One-vs-Rest) Performance –
Validation Accuracy: 96.7%
Test Accuracy: 96.7%

Neural Network model –
Number of layers = 3
Number of neurons in each layer = 50
Dropout probability = 0.3

Neural networks are the most versatile models, theoretically capable of learning any kind of dataset. One-hot encoding has to be done on the output values, so that a neural network can be trained.
Neural Network Performance –
Validation Accuracy: 93.6%
Test Accuracy: 93.3%
The logistic regression model gives better performance than the neural network (for this architecture) for this dataset.

(c)

Data pre-processing:

The dataset was tested for missing data, and it was found that this dataset contains no missing data.

The output values are categorical. The output values were converted to one-hot encoding.
One-hot encoding enables us to train neural networks, with each neuron associated with each output.

(d)

Data exploration:

Distribution of classes in train, test and validation sets-

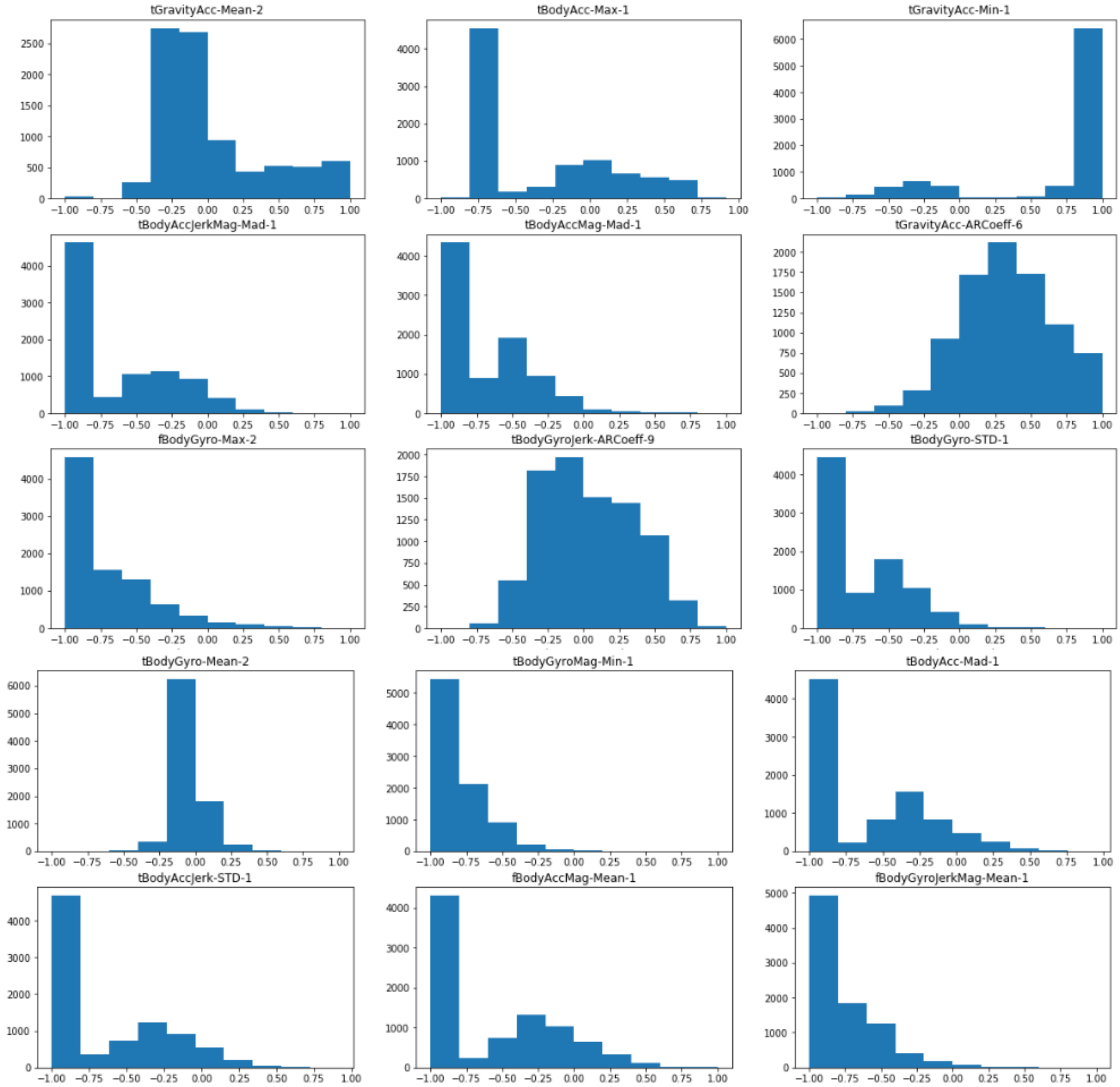
```
For the Train dataset
Class :  0  :  WALKING  :  1367
Class :  1  :  WALKING_UPSTAIRS  :  1232
Class :  2  :  WALKING_DOWNSTAIRS  :  1147
Class :  3  :  SITTING  :  1445
Class :  4  :  STANDING  :  1581
Class :  5  :  LAYING  :  1553
Class :  6  :  STAND_TO_SIT  :  53
Class :  7  :  SIT_TO_STAND  :  25
Class :  8  :  SIT_TO_LIE  :  84
Class :  9  :  LIE_TO_SIT  :  70
Class :  10  :  STAND_TO_LIE  :  114
Class :  11  :  LIE_TO_STAND  :  71

For the Test dataset
Class :  0  :  WALKING  :  198
Class :  1  :  WALKING_UPSTAIRS  :  152
Class :  2  :  WALKING_DOWNSTAIRS  :  125
Class :  3  :  SITTING  :  185
Class :  4  :  STANDING  :  194
Class :  5  :  LAYING  :  192
Class :  6  :  STAND_TO_SIT  :  9
Class :  7  :  SIT_TO_STAND  :  3
Class :  8  :  SIT_TO_LIE  :  9
Class :  9  :  LIE_TO_SIT  :  9
Class :  10  :  STAND_TO_LIE  :  11
Class :  11  :  LIE_TO_STAND  :  6

For the Validation dataset
Class :  0  :  WALKING  :  157
Class :  1  :  WALKING_UPSTAIRS  :  160
Class :  2  :  WALKING_DOWNSTAIRS  :  135
Class :  3  :  SITTING  :  171
Class :  4  :  STANDING  :  203
Class :  5  :  LAYING  :  213
Class :  6  :  STAND_TO_SIT  :  8
```

```
Class :  7  :  SIT_TO_STAND  :  5
Class :  8  :  SIT_TO_LIE  :  14
Class :  9  :  LIE_TO_SIT  :  6
Class :  10  :  STAND_TO_LIE  :  14
Class :  11  :  LIE_TO_STAND  :  7
```

Histogram of features selected by forward feature selection algorithm (15 important features):



Fishers' criterion can be used to determine the feature that most correlated to the output. Fishers' criterion uses inter class and intra class distances to find the feature that most correlates to the output. Fishers' value was calculated for all the 561 features. The results are listed in the code output of this report.

Pearson's correlation can be used to find correlations between features. Since the data set contains 561 features, I'll be calculating Pearson's correlation between few selected features (features selected by the greedy forward feature selection algorithm) Pearson's correlation was calculated between all the selected features.

Results of correlation analysis -

Highly correlated features - tBodyAccJerkMag-Mad-1 and tBodyAccJerk-STD-1
Least correlated features - tBodyAcc-Max-1 and tBodyGyro-Mean-2

(e)

Split data into train, test, and validation:

The data was split into train, test and validation set.
Number of samples in Train set – 8742 (80% of the dataset)
Number of samples in Test set – 1093 (10% of the dataset)
Number of samples in Validation set – 1093 (10% of the dataset)

(f)

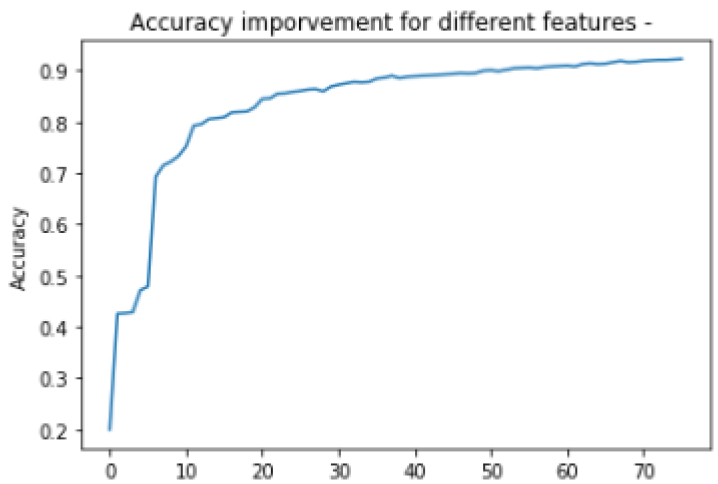
Feature selection:

Forward feature selection algorithm searched through all the features in a greedy fashion and generated a list of 15 best features that improves the performance of logistic regression model in the validation set.

List of top 15 selected features -

tGravityAcc-Mean-2
tBodyAcc-Max-1
tGravityAcc-Min-1
tBodyAccJerkMag-Mad-1
tBodyAccMag-Mad-1
tGravityAcc-ARCoeff-6
fBodyGyro-Max-2
tBodyGyroJerk-ARCoeff-9
tBodyGyro-STD-1
tBodyGyro-Mean-2
tBodyGyroMag-Min-1
tBodyAcc-Mad-1
tBodyAccJerk-STD-1
fBodyAccMag-Mean-1
fBodyGyroJerkMag-Mean-1

Test set accuracy achieved with only these 15 features = 87.2%

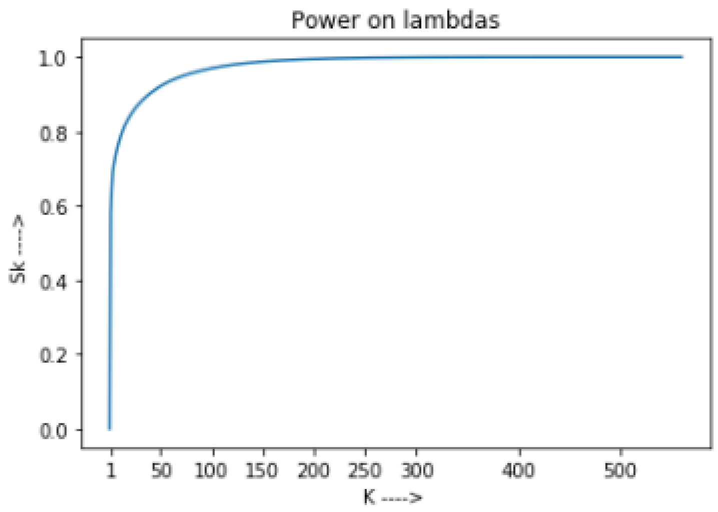


The graph above shows the improvement the accuracy as the number of features is increased.

(g)

Feature transformation:

PCA was implemented to reduce the dimensionality and select only the most important features (top 15) of data set.



Plot of sum of K eigenvalues by the sum of all the D eigenvalues reveals a lot of information regarding the features in the dataset.
Inference – Most of the variance (Close to 100%) in the data is captured using just 100 features, out of 561 total features.

Logistic regression model was trained for different PCA
Results of PCA for different K values –
K = 2
Accuracy Val = 0.5379688929551693
Accuracy Test = 0.5041171088746569
Accuracy Train = 0.5512468542667581

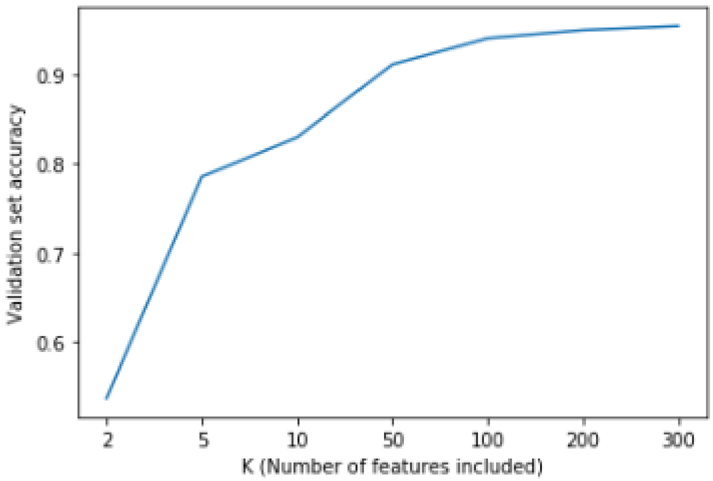
K = 5
Accuracy Val = 0.7859103385178408
Accuracy Test = 0.7301006404391582
Accuracy Train = 0.7862045298558682

K = 10
Accuracy Val = 0.8298261665141812
Accuracy Test = 0.848124428179323
Accuracy Train = 0.8523221230839625
K = 50
Accuracy Val = 0.9112534309240622
Accuracy Test = 0.9313815187557182
Accuracy Train = 0.945664607641272

K = 100
Accuracy Val = 0.9405306495882891
Accuracy Test = 0.958828911253431
Accuracy Train = 0.9735758407687028

K = 200
Accuracy Val = 0.94967978042086
Accuracy Test = 0.9624885635864593
Accuracy Train = 0.9871882864333105

K = 300
Accuracy Val = 0.9542543458371455
Accuracy Test = 0.9643183897529735
Accuracy Train = 0.9881034088309312



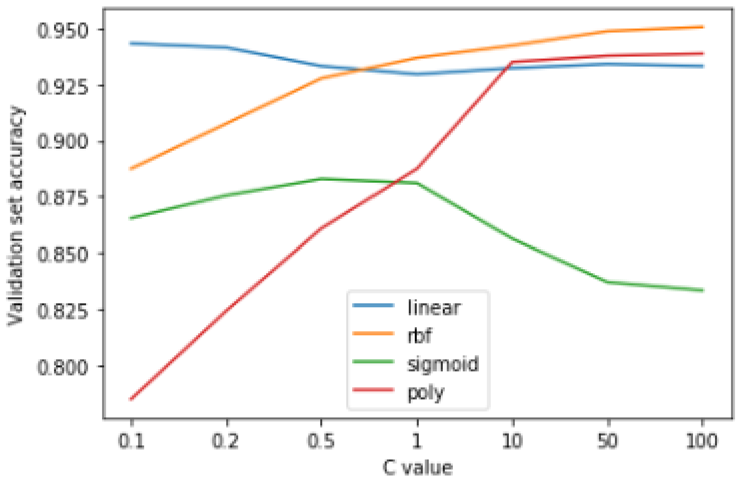
From the above data we can clearly see that the accuracy almost saturates after K=100. This clearly indicates that just having 100 features captures most of the variance in the dataset.

Neural network model was also trained (K=100):
Test accuracy obtained: 79.8%

(h)

Support vector machine:

PCA was performed on the dataset and top 100 features were used to train SVMs.
SVMs were trained for all combinations of inbuilt kernels and broad range of regularization values (C). C controls the regularization in the SVM model. The strength of the regularization is inversely proportional to C.



()

The above curve shows that ‘rbf’ kernel with C=100 achieves the highest accuracy.
The performance of linear kernel is almost unaffected for all regularization values and performs consistently good for all C values.

Highest accuracy reached with kernel = ‘rbf’ and C=100 : 95%

We can infer that we are able to get almost the same level of performance as that of using model trained with all the features, with just 100 features and SVM.

(i)

Ensemble learning:

Using Logistic regression estimator –
Number of estimators = 2 Val Accuracy = 0.7904849039341263 Test Accuracy = 0.8005489478499542
Number of estimators = 3 Val Accuracy = 0.7941445562671546 Test Accuracy = 0.8023787740164684
Number of estimators = 4 Val Accuracy = 0.8069533394327539 Test Accuracy = 0.8115279048490394
Number of estimators = 5 Val Accuracy = 0.8133577310155535 Test Accuracy = 0.8151875571820677
Number of estimators = 6 Val Accuracy = 0.7721866422689845 Test Accuracy = 0.7968892955169259
Number of estimators = 7 Val Accuracy = 0.7703568161024703 Test Accuracy = 0.7804208600182982
Number of estimators = 8 Val Accuracy = 0.747483989021043 Test Accuracy = 0.7822506861848124
Number of estimators = 9 Val Accuracy = 0.7749313815187557 Test Accuracy = 0.8042086001829826
Number of estimators = 10 Val Accuracy = 0.787740164684355 Test Accuracy = 0.807868252516011
Number of estimators = 11 Val Accuracy = 0.7346752058554438 Test Accuracy = 0.7749313815187557
Number of estimators = 12 Val Accuracy = 0.8051235132662397 Test Accuracy = 0.8161024702653248
Number of estimators = 13 Val Accuracy = 0.8014638609332113 Test Accuracy = 0.817932296431839
Number of estimators = 14 Val Accuracy = 0.7749313815187557 Test Accuracy = 0.8005489478499542
Number of estimators = 15 Val Accuracy = 0.797804208600183 Test Accuracy = 0.817932296431839
Number of estimators = 16 Val Accuracy = 0.8051235132662397 Test Accuracy = 0.8161024702653248
Number of estimators = 17 Val Accuracy = 0.7685269899359561 Test Accuracy = 0.8005489478499542
Number of estimators = 18 Val Accuracy = 0.797804208600183 Test Accuracy = 0.8124428179322964
Number of estimators = 19 Val Accuracy = 0.8087831655992681 Test Accuracy = 0.8133577310155535
With logistic regression model, best validation accuracy was obtained with 5 estimators – 81.3%

Using decision tree estimator –
Number of estimators = 1 Val Accuracy = 0.5233302836230558 Test Accuracy = 0.5297346752058555
Number of estimators = 2 Val Accuracy = 0.5800548947849954 Test Accuracy = 0.5507776761207686
Number of estimators = 3 Val Accuracy = 0.6550777676120768 Test Accuracy = 0.645928636779506
Number of estimators = 4 Val Accuracy = 0.6907593778591034 Test Accuracy = 0.6770356816102471
Number of estimators = 5 Val Accuracy = 0.6605672461116194 Test Accuracy = 0.6678865507776761
Number of estimators = 6 Val Accuracy = 0.6303751143641354 Test Accuracy = 0.6532479414455626
Number of estimators = 7 Val Accuracy = 0.6907593778591034 Test Accuracy = 0.6733760292772186
Number of estimators = 8 Val Accuracy = 0.7026532479414456 Test Accuracy = 0.6916742909423604
Number of estimators = 9 Val Accuracy = 0.6953339432753889 Test Accuracy = 0.6999085086916743
Number of estimators = 10 Val Accuracy = 0.7108874656907593 Test Accuracy = 0.6816102470265325
Number of estimators = 11 Val Accuracy = 0.7255260750228728 Test Accuracy = 0.7118023787740164
Number of estimators = 12 Val Accuracy = 0.7090576395242452 Test Accuracy = 0.7008234217749314
Number of estimators = 13 Val Accuracy = 0.7145471180237878 Test Accuracy = 0.7099725526075022
Number of estimators = 14 Val Accuracy = 0.737419945105215 Test Accuracy = 0.7145471180237878
Number of estimators = 15 Val Accuracy = 0.7282708142726441 Test Accuracy = 0.7053979871912168
Number of estimators = 16 Val Accuracy = 0.7255260750228728 Test Accuracy = 0.6971637694419031
Number of estimators = 17 Val Accuracy = 0.7136322049405307 Test Accuracy = 0.7108874656907593
Number of estimators = 18 Val Accuracy = 0.8133577310155535 Test Accuracy = 0.7904849039341263
Number of estimators = 19 Val Accuracy = 0.8032936870997255 Test Accuracy = 0.7795059469350412
With Decision tree model, best validation accuracy was obtained with 18 estimators – 81.3%

For this dataset, the performance of ada-boost is less compared to the model trained with selected features.

Final_Project

April 30, 2020

1 Machine Learning

2 Homework 5

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[1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from keras import models
from keras import layers
from keras.utils import to_categorical
```

```
Using TensorFlow backend.
```

[2]:
```
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
X = np.genfromtxt("Data_X.txt", delimiter=" ", skip_header=1)
y = np.genfromtxt("Data_y.txt", delimiter=" ", skip_header=1, dtype=int)
y = y - 1
print('X shape = ', X.shape)
print('y shape = ', y.shape)
```

```
X shape =  (10928, 561)
y shape =  (10928,)
```

[29]:

```
classes =␣
↪['WALKING','WALKING_UPSTAIRS','WALKING_DOWNSTAIRS','SITTING','STANDING','LAYING','STAND_TO_
```

5 (e) Split data into train, test, and validation.

[4]:
```
X_train, X_val_test, y_train, y_val_test = train_test_split(X, y, test_size=0.
↪2, random_state=1)
X_test, X_val, y_test, y_val = train_test_split(X_val_test, y_val_test,␣
↪test_size=0.5, random_state=3)

print('TrainX shape = ', X_train.shape)
print('TestX shape = ', X_test.shape)
print('ValX shape = ', X_val.shape)
```

```
TrainX shape =  (8742, 561)
TestX shape =  (1093, 561)
ValX shape =  (1093, 561)
```

6 (c) Data pre-processing.

[5]:
```
y_train_categorical = to_categorical(y_train)
y_test_categorical = to_categorical(y_test)
y_val_categorical = to_categorical(y_val)

print('Train y shape = ', y_train_categorical.shape)
print('Test y shape = ', y_test_categorical.shape)
print('Val y shape = ', y_val_categorical.shape)
```

```
Train y shape =  (8742, 12)
Test y shape =  (1093, 12)
Val y shape =  (1093, 12)
```

7 Check for missing data

[55]:
```
MissingMatrix = np.isnan(X_train)
MissingMatrix2 = np.isnan(y_train)
if np.sum(MissingMatrix) > 0 or np.sum(MissingMatrix2) > 0:
    print('Train set contains missing data !!')
else:
    print('No missing data in the train set :)')

MissingMatrix = np.isnan(X_test)
MissingMatrix2 = np.isnan(y_test)
if np.sum(MissingMatrix) > 0 or np.sum(MissingMatrix2) > 0:
    print('Test set contains missing data !!')
```

```
else:
    print('No missing data in the test set :)')

MissingMatrix = np.isnan(X_val)
MissingMatrix2 = np.isnan(y_val)
if np.sum(MissingMatrix) > 0 or np.sum(MissingMatrix2) > 0:
    print('Validation set contains missing data !!')
else:
    print('No missing data in the Validation set :)')
```

```
No missing data in the train set :)
No missing data in the test set :)
No missing data in the Validation set :)
```

8 (d) Data exploration.

9 Number of samples in each class output type

[143]:
```
print('For the Train dataset')
for i in range(len(classes)):
    print('Class : ', i , ' : ', classes[i] , ' : ', np.sum(y_train == i))

print('For the Test dataset')
for i in range(len(classes)):
    print('Class : ', i , ' : ', classes[i] , ' : ', np.sum(y_test == i))

print('For the Validation dataset')
for i in range(len(classes)):
    print('Class : ', i, ' : ' ,classes[i] , ' : ', np.sum(y_val == i))
```

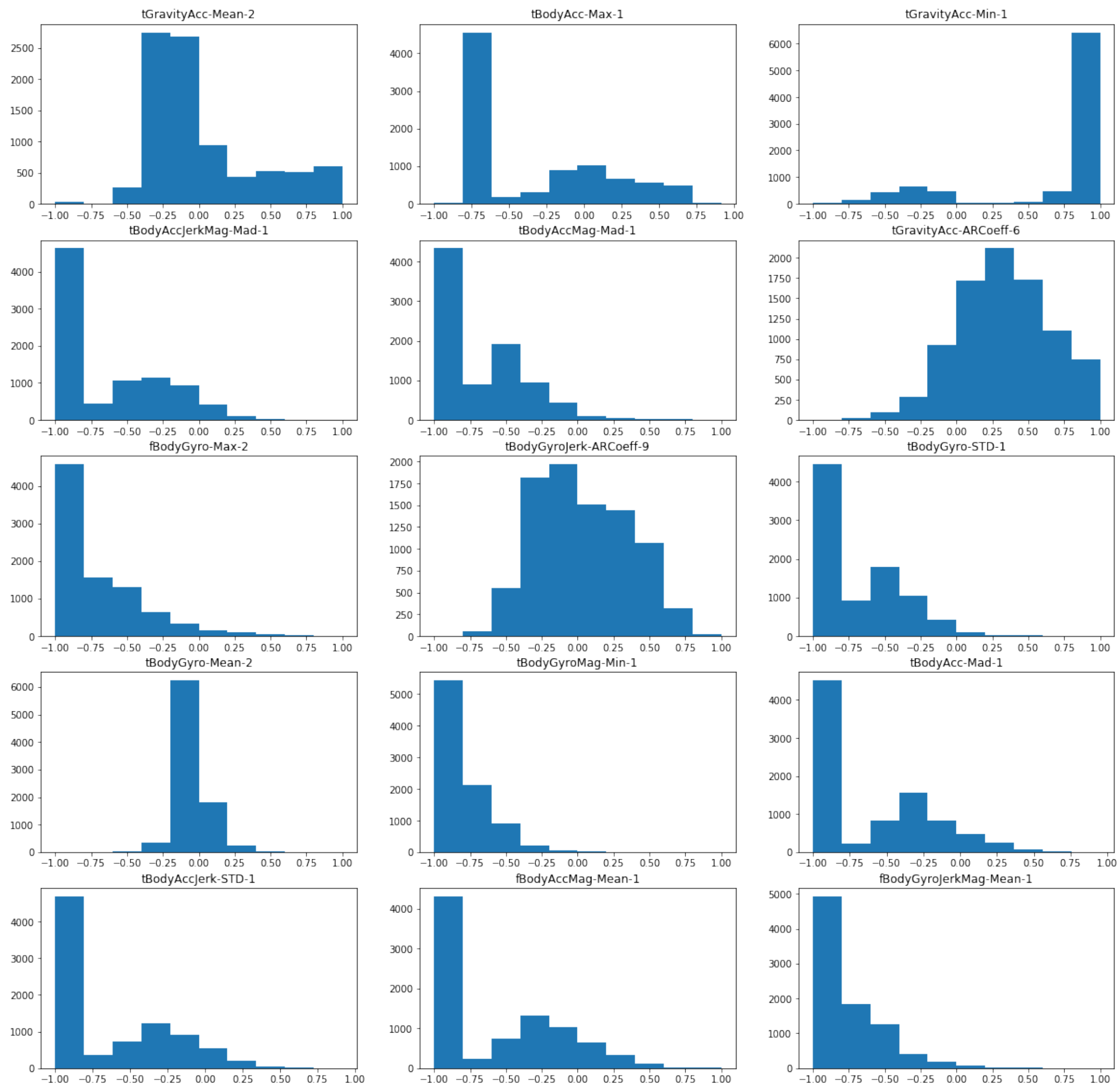
```
For the Train dataset
Class :  0  :  WALKING  :  1367
Class :  1  :  WALKING_UPSTAIRS  :  1232
Class :  2  :  WALKING_DOWNSTAIRS  :  1147
Class :  3  :  SITTING  :  1445
Class :  4  :  STANDING  :  1581
Class :  5  :  LAYING  :  1553
Class :  6  :  STAND_TO_SIT  :  53
Class :  7  :  SIT_TO_STAND  :  25
Class :  8  :  SIT_TO_LIE  :  84
Class :  9  :  LIE_TO_SIT  :  70
Class :  10  :  STAND_TO_LIE  :  114
Class :  11  :  LIE_TO_STAND  :  71
For the Test dataset
Class :  0  :  WALKING  :  198
Class :  1  :  WALKING_UPSTAIRS  :  152
```

```
Class :  2  :  WALKING_DOWNSTAIRS  :  125
Class :  3  :  SITTING  :  185
Class :  4  :  STANDING  :  194
Class :  5  :  LAYING  :  192
Class :  6  :  STAND_TO_SIT  :  9
Class :  7  :  SIT_TO_STAND  :  3
Class :  8  :  SIT_TO_LIE  :  9
Class :  9  :  LIE_TO_SIT  :  9
Class :  10  :  STAND_TO_LIE  :  11
Class :  11  :  LIE_TO_STAND  :  6
For the Validation dataset
Class :  0  :  WALKING  :  157
Class :  1  :  WALKING_UPSTAIRS  :  160
Class :  2  :  WALKING_DOWNSTAIRS  :  135
Class :  3  :  SITTING  :  171
Class :  4  :  STANDING  :  203
Class :  5  :  LAYING  :  213
Class :  6  :  STAND_TO_SIT  :  8
Class :  7  :  SIT_TO_STAND  :  5
Class :  8  :  SIT_TO_LIE  :  14
Class :  9  :  LIE_TO_SIT  :  6
Class :  10  :  STAND_TO_LIE  :  14
Class :  11  :  LIE_TO_STAND  :  7
```

10 Histogram

[149]:
```
selectedFeatures_index = [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6,
 ↪83, 502, 541]
```

[152]:
```
fig,axs = plt.subplots(5,3, figsize=(20,20))
for i,feat in enumerate(selectedFeatures_index):
    plt.subplot(5,3,i+1)
    plt.title(features[feat])
    plt.hist(X_train[:,feat])
```



11 Fishers_criterion

[41]:
```
def Fishers_criterion(X,y,classList, featureIndex):

    d = featureIndex

    mean_d = np.mean(X[:,d])
    mean_kd_List = []
    Numerator = 0
    for classX in classList:

        y_new = (y == classX)
        sample_index = 0
```

```
        mean_kd = 0
        for yCheck in y_new:
            if yCheck:
                mean_kd += X[sample_index, d]

            sample_index += 1

        mean_kd = mean_kd / np.sum(y_new)
        mean_kd_List.append(mean_kd)

        sample_index = 0
        for yCheck in y_new:
            if yCheck:
                Numerator += (X[sample_index,d] - mean_kd)**2

    denominator = 0
    index = 0
    for classX in classList:
        denominator += (mean_d - mean_kd_List[index])
        index += 1

    return Numerator / denominator
```

[43]:
```
for featureIndex in range(X.shape[1]):
    print(
            features[featureIndex],
            '    ',
            Fishers_criterion(X_train,y_train,[i for i in range(np.
 ↪max(y_train))], featureIndex)
         )
```

```
tBodyAcc-Mean-1      346.2946737127763
tBodyAcc-Mean-2      -1291.523857992131
tBodyAcc-Mean-3      -201.6430868433005
tBodyAcc-STD-1      -2027.6905052563761
tBodyAcc-STD-2      -518.2543566783183
tBodyAcc-STD-3      -307.4148314154306
tBodyAcc-Mad-1      -1881.8039471049865
tBodyAcc-Mad-2      -419.1340663207205
tBodyAcc-Mad-3      -232.24582131523792
tBodyAcc-Max-1      -4929.107662580646
tBodyAcc-Max-2      -375.21369800374674
tBodyAcc-Max-3      -352.08061423459964
tBodyAcc-Min-1      746.2626528052139
tBodyAcc-Min-2      1379.1816420338805
tBodyAcc-Min-3      527.1803835701816
tBodyAcc-SMA-1      -366.70343700650545
```

tBodyAcc-Energy-1	-615.3884824126255
tBodyAcc-Energy-2	-65.02657545768645
tBodyAcc-Energy-3	-52.5042777875331
tBodyAcc-IQR-1	-1460.3731755675592
tBodyAcc-IQR-2	-252.61864586924926
tBodyAcc-IQR-3	-153.8873772963894
tBodyAcc-ropy-1	-1705.0996781101687
tBodyAcc-ropy-1	-1932.0762961223443
tBodyAcc-ropy-1	-698.4205681984639
tBodyAcc-ARCoeff-1	671.6351304713354
tBodyAcc-ARCoeff-2	-614.2194799204639
tBodyAcc-ARCoeff-3	775.8568892291053
tBodyAcc-ARCoeff-4	874.8829528904765
tBodyAcc-ARCoeff-5	643.2014430771025
tBodyAcc-ARCoeff-6	-1954.141723315826
tBodyAcc-ARCoeff-7	2733.6868526042626
tBodyAcc-ARCoeff-8	-3588.1878323754036
tBodyAcc-ARCoeff-9	1212.3300095999673
tBodyAcc-ARCoeff-10	-1834.6552908835447
tBodyAcc-ARCoeff-11	239.97414995599735
tBodyAcc-ARCoeff-12	-250.2762198611411
tBodyAcc-Correlation-1	3204.9507751770047
tBodyAcc-Correlation-2	-2188.460548795115
tBodyAcc-Correlation-3	-421.92047771133304
tGravityAcc-Mean-1	-26957.364174532602
tGravityAcc-Mean-2	-2101.1277495002287
tGravityAcc-Mean-3	-11018.819217040469
tGravityAcc-STD-1	-58.87762550870549
tGravityAcc-STD-2	-59.560579565783506
tGravityAcc-STD-3	-45.685505536688055
tGravityAcc-Mad-1	-55.75148255817907
tGravityAcc-Mad-2	-57.37994307033903
tGravityAcc-Mad-3	-44.93708953535567
tGravityAcc-Max-1	-2784.1675740143546
tGravityAcc-Max-2	-773.8311122825874
tGravityAcc-Max-3	-1219.3344259760747
tGravityAcc-Min-1	3387.086294799823
tGravityAcc-Min-2	1778.2446511441267
tGravityAcc-Min-3	1657.2250589193134
tGravityAcc-SMA-1	-709.421814521286
tGravityAcc-Energy-1	15581.804411087905
tGravityAcc-Energy-2	-14799.579295411586
tGravityAcc-Energy-3	5152.503003278431
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fBodyGyro-Energy-3	-90.2044080436343
fBodyGyro-IQR-1	-4370.7439746376
fBodyGyro-IQR-2	-11716.6657262402
fBodyGyro-IQR-3	-5064.734798356074
fBodyGyro-ropy-1	-2624.0963755868506
fBodyGyro-ropy-1	-1691.0747729907034
fBodyGyro-ropy-1	-1971.8794975745345

```
fBodyGyro-MaxInds-1      95.71274810544858
fBodyGyro-MaxInds-2      417.90815727476445
fBodyGyro-MaxInds-3      151.91375348111987
fBodyGyro-MeanFreq-1      100.61243278505535
fBodyGyro-MeanFreq-2      78.88465237992774
fBodyGyro-MeanFreq-3      192.33637968155145
fBodyGyro-Skewness-1      -2276.445474345732
fBodyGyro-Kurtosis-1      -2969.6611429061745
fBodyGyro-Skewness-1      -562.1078424406046
fBodyGyro-Kurtosis-1      -280.6629867775174
fBodyGyro-Skewness-1      -104.536271761201
fBodyGyro-Kurtosis-1      -81.03842736962854
fBodyGyro-BandsEnergyOld-1      -197.5066098668359
fBodyGyro-BandsEnergyOld-2      2654.3729078274287
fBodyGyro-BandsEnergyOld-3      508.34818530459677
fBodyGyro-BandsEnergyOld-4      19489.596135648317
fBodyGyro-BandsEnergyOld-5      -5500.630661930682
fBodyGyro-BandsEnergyOld-6      -863.3682294261224
fBodyGyro-BandsEnergyOld-7      -215.0860733212317
fBodyGyro-BandsEnergyOld-8      -132.5171712590105
fBodyGyro-BandsEnergyOld-9      -325.44150579432676
fBodyGyro-BandsEnergyOld-10      646.1995342942887
fBodyGyro-BandsEnergyOld-11      -2142.0675947118093
fBodyGyro-BandsEnergyOld-12      -162.47086721334054
fBodyGyro-BandsEnergyOld-13      -339.9552445552855
fBodyGyro-BandsEnergyOld-14      -6417.135619295834
fBodyGyro-BandsEnergyOld-15      -144.40984707183426
fBodyGyro-BandsEnergyOld-16      514.9547374673974
fBodyGyro-BandsEnergyOld-17      266.98236311808375
fBodyGyro-BandsEnergyOld-18      306.063767254326
fBodyGyro-BandsEnergyOld-19      174.89714264715104
fBodyGyro-BandsEnergyOld-20      508.8384537503488
fBodyGyro-BandsEnergyOld-21      811.3755377085738
fBodyGyro-BandsEnergyOld-22      -174.3413991516826
fBodyGyro-BandsEnergyOld-23      -224.51310082778517
fBodyGyro-BandsEnergyOld-24      333.53259836618287
fBodyGyro-BandsEnergyOld-25      234.39587660573963
fBodyGyro-BandsEnergyOld-26      2124.5305546519876
fBodyGyro-BandsEnergyOld-27      -332.97546790857757
fBodyGyro-BandsEnergyOld-28      302.74393342290625
fBodyGyro-BandsEnergyOld-29      -57.67431853840122
fBodyGyro-BandsEnergyOld-30      590.8892585002591
fBodyGyro-BandsEnergyOld-31      456.02105754202887
fBodyGyro-BandsEnergyOld-32      613.9983809120955
fBodyGyro-BandsEnergyOld-33      4859.166168872157
fBodyGyro-BandsEnergyOld-34      -687.2391114917613
fBodyGyro-BandsEnergyOld-35      -264.8478016928956
fBodyGyro-BandsEnergyOld-36      -75.09527870571156
```

fBodyGyro-BandsEnergyOld-37 -76.02631738024274
fBodyGyro-BandsEnergyOld-38 636.0284364656416
fBodyGyro-BandsEnergyOld-39 -2630.2730929731006
fBodyGyro-BandsEnergyOld-40 -153.06525688256005
fBodyGyro-BandsEnergyOld-41 -85.98317940936617
fBodyGyro-BandsEnergyOld-42 915.4533485096505
fBodyAccMag-Mean-1 -874.301891550501
fBodyAccMag-STD-1 -210.62047934958076
fBodyAccMag-Mad-1 -573.9027132070845
fBodyAccMag-Max-1 -118.60149323951408
fBodyAccMag-Min-1 -105.73287149375513
fBodyAccMag-SMA-1 -874.301891550501
fBodyAccMag-Energy-1 -126.11464172472296
fBodyAccMag-IQR-1 -2629.098417980535
fBodyAccMag-ropy-1 -1912.6690245295547
fBodyAccMag-MaxInds-1 548.6795356893816
fBodyAccMag-MeanFreq-1 224.30343386287282
fBodyAccMag-Skewness-1 -79.29232817112496
fBodyAccMag-Kurtosis-1 -78.28059382904846
fBodyAccJerkMag-Mean-1 88816.03713869864
fBodyAccJerkMag-STD-1 37317.26422772581
fBodyAccJerkMag-Mad-1 -66347.4588864669
fBodyAccJerkMag-Max-1 8308.431989480534
fBodyAccJerkMag-Min-1 17628.694457059464
fBodyAccJerkMag-SMA-1 88816.03713869864
fBodyAccJerkMag-Energy-1 1103.7896543891547
fBodyAccJerkMag-IQR-1 130428.76171980033
fBodyAccJerkMag-ropy-1 -3007.386665462356
fBodyAccJerkMag-MaxInds-1 22.964717575150626
fBodyAccJerkMag-MeanFreq-1 467.66695650321446
fBodyAccJerkMag-Skewness-1 -39663.692904834534
fBodyAccJerkMag-Kurtosis-1 167258.23063528203
fBodyGyroMag-Mean-1 -830.8375165046043
fBodyGyroMag-STD-1 -387.4326273976131
fBodyGyroMag-Mad-1 -552.2702777150347
fBodyGyroMag-Max-1 -233.71955743889018
fBodyGyroMag-Min-1 -257.1173231461457
fBodyGyroMag-SMA-1 -830.8375165046043
fBodyGyroMag-Energy-1 -156.54683657887037
fBodyGyroMag-IQR-1 -1999.7005804673906
fBodyGyroMag-ropy-1 -2510.0111467520483
fBodyGyroMag-MaxInds-1 1889.8540799532482
fBodyGyroMag-MeanFreq-1 104.53173973330856
fBodyGyroMag-Skewness-1 -108.25175419920218
fBodyGyroMag-Kurtosis-1 -231.8572443500368
fBodyGyroJerkMag-Mean-1 -8017.2462080566265
fBodyGyroJerkMag-STD-1 -4992.158278216696
fBodyGyroJerkMag-Mad-1 -5069.190285151086

```
fBodyGyroJerkMag-Max-1      -5791.386679852823
fBodyGyroJerkMag-Min-1      -19712.7372617949
fBodyGyroJerkMag-SMA-1      -8017.2462080566265
fBodyGyroJerkMag-Energy-1      531.9859560099273
fBodyGyroJerkMag-IQR-1      -4301.684360390659
fBodyGyroJerkMag-ropy-1      -2231.230679521368
fBodyGyroJerkMag-MaxInds-1      17.161619750754426
fBodyGyroJerkMag-MeanFreq-1      85.99670325538354
fBodyGyroJerkMag-Skewness-1      -6083.2734712062465
fBodyGyroJerkMag-Kurtosis-1      -7167.424668325024
tBodyAcc-AngleWRTGravity-1      -1311.8698481587562
tBodyAccJerk-AngleWRTGravity-1      -1064.6343163304944
tBodyGyro-AngleWRTGravity-1      -25081.096544143064
tBodyGyroJerk-AngleWRTGravity-1      23254.443353950872
tXAxisAcc-AngleWRTGravity-1      12601.854756190784
tYAxisAcc-AngleWRTGravity-1      1777.836728337151
tZAxisAcc-AngleWRTGravity-1      7011.128404408679
```

12 Pearson's correlation

[43]:
```python
from scipy.stats import pearsonr
```

[44]:
```python
selectedFeatures_index = [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6,␣
↪83, 502, 541]
```

[60]:
```python
HighlyCorrelatedFeatures = None
HighCorr = float('-inf')
LeastCorrelatedFeatures = None
LeastCorr = float('inf')
for i in range(len(selectedFeatures_index)):
    for j in range(i+1,len(selectedFeatures_index)):
        corr = pearsonr(X_train[:,selectedFeatures_index[i]], X_train[:
↪,selectedFeatures_index[j]])[0]

        if HighCorr < np.abs(corr):
            HighCorr = np.abs(corr)
            HighlyCorrelatedFeatures = (features[selectedFeatures_index[i]],␣
↪features[selectedFeatures_index[j]], corr)

        if LeastCorr > np.abs(corr):
            LeastCorr = np.abs(corr)
            LeastCorrelatedFeatures = (features[selectedFeatures_index[i]],␣
↪features[selectedFeatures_index[j]], corr)

        print(features[selectedFeatures_index[i]], '    '␣
↪,features[selectedFeatures_index[j]], ' :   ', corr)
```

tGravityAcc-Mean-2 tBodyAcc-Max-1 : -0.4339063925060642
tGravityAcc-Mean-2 tGravityAcc-Min-1 : -0.7673838759819631
tGravityAcc-Mean-2 tBodyAccJerkMag-Mad-1 : -0.46242949843672077
tGravityAcc-Mean-2 tBodyAccMag-Mad-1 : -0.3146608120167613
tGravityAcc-Mean-2 tGravityAcc-ARCoeff-6 : -0.14394953210875003
tGravityAcc-Mean-2 fBodyGyro-Max-2 : -0.38334798517007795
tGravityAcc-Mean-2 tBodyGyroJerk-ARCoeff-9 : 0.4170869799924418
tGravityAcc-Mean-2 tBodyGyro-STD-1 : -0.42562833469359573
tGravityAcc-Mean-2 tBodyGyro-Mean-2 : -0.022768282353281204
tGravityAcc-Mean-2 tBodyGyroMag-Min-1 : -0.3189714567010238
tGravityAcc-Mean-2 tBodyAcc-Mad-1 : -0.4119864615889127
tGravityAcc-Mean-2 tBodyAccJerk-STD-1 : -0.47004043188283184
tGravityAcc-Mean-2 fBodyAccMag-Mean-1 : -0.4114576971618521
tGravityAcc-Mean-2 fBodyGyroJerkMag-Mean-1 : -0.41869788334286834
tBodyAcc-Max-1 tGravityAcc-Min-1 : 0.33016548378022403
tBodyAcc-Max-1 tBodyAccJerkMag-Mad-1 : 0.934334662223337
tBodyAcc-Max-1 tBodyAccMag-Mad-1 : 0.847373465986971
tBodyAcc-Max-1 tGravityAcc-ARCoeff-6 : -0.11152729714631202
tBodyAcc-Max-1 fBodyGyro-Max-2 : 0.692492076717723
tBodyAcc-Max-1 tBodyGyroJerk-ARCoeff-9 : -0.5734810560495016
tBodyAcc-Max-1 tBodyGyro-STD-1 : 0.8463957209982756
tBodyAcc-Max-1 tBodyGyro-Mean-2 : -0.00022302374161254973
tBodyAcc-Max-1 tBodyGyroMag-Min-1 : 0.6752647340098299
tBodyAcc-Max-1 tBodyAcc-Mad-1 : 0.9612319388514441
tBodyAcc-Max-1 tBodyAccJerk-STD-1 : 0.948806219726004
tBodyAcc-Max-1 fBodyAccMag-Mean-1 : 0.9463883098988615
tBodyAcc-Max-1 fBodyGyroJerkMag-Mean-1 : 0.8298290491281353
tGravityAcc-Min-1 tBodyAccJerkMag-Mad-1 : 0.3721461278590039
tGravityAcc-Min-1 tBodyAccMag-Mad-1 : 0.1983680166049218
tGravityAcc-Min-1 tGravityAcc-ARCoeff-6 : 0.058312941559624666
tGravityAcc-Min-1 fBodyGyro-Max-2 : 0.25295028301972283
tGravityAcc-Min-1 tBodyGyroJerk-ARCoeff-9 : -0.3372538725978167
tGravityAcc-Min-1 tBodyGyro-STD-1 : 0.31469308694858206
tGravityAcc-Min-1 tBodyGyro-Mean-2 : 0.08337292645285002
tGravityAcc-Min-1 tBodyGyroMag-Min-1 : 0.21249704340538816
tGravityAcc-Min-1 tBodyAcc-Mad-1 : 0.30518315779427896
tGravityAcc-Min-1 tBodyAccJerk-STD-1 : 0.3775151303991036
tGravityAcc-Min-1 fBodyAccMag-Mean-1 : 0.30121058888887575
tGravityAcc-Min-1 fBodyGyroJerkMag-Mean-1 : 0.31966253401505645
tBodyAccJerkMag-Mad-1 tBodyAccMag-Mad-1 : 0.798465783353562
tBodyAccJerkMag-Mad-1 tGravityAcc-ARCoeff-6 : -0.21951552062228694
tBodyAccJerkMag-Mad-1 fBodyGyro-Max-2 : 0.6834192571126508
tBodyAccJerkMag-Mad-1 tBodyGyroJerk-ARCoeff-9 : -0.55175860641473
tBodyAccJerkMag-Mad-1 tBodyGyro-STD-1 : 0.849216232540462
tBodyAccJerkMag-Mad-1 tBodyGyro-Mean-2 : 0.03202892622338806
tBodyAccJerkMag-Mad-1 tBodyGyroMag-Min-1 : 0.6661693976923173
tBodyAccJerkMag-Mad-1 tBodyAcc-Mad-1 : 0.9327245393008514
tBodyAccJerkMag-Mad-1 tBodyAccJerk-STD-1 : 0.9842726911010856

```
tBodyAccJerkMag-Mad-1     fBodyAccMag-Mean-1  :   0.940355954782806
tBodyAccJerkMag-Mad-1     fBodyGyroJerkMag-Mean-1  :   0.9196779723993647
tBodyAccMag-Mad-1     tGravityAcc-ARCoeff-6  :   0.09086569406882779
tBodyAccMag-Mad-1     fBodyGyro-Max-2  :   0.7104611718968642
tBodyAccMag-Mad-1     tBodyGyroJerk-ARCoeff-9  :   -0.5883207204408946
tBodyAccMag-Mad-1     tBodyGyro-STD-1  :   0.8173316426905883
tBodyAccMag-Mad-1     tBodyGyro-Mean-2  :   0.016699455756098727
tBodyAccMag-Mad-1     tBodyGyroMag-Min-1  :   0.7010301222497253
tBodyAccMag-Mad-1     tBodyAcc-Mad-1  :   0.8851860715579807
tBodyAccMag-Mad-1     tBodyAccJerk-STD-1  :   0.7914859582786847
tBodyAccMag-Mad-1     fBodyAccMag-Mean-1  :   0.9375188603773023
tBodyAccMag-Mad-1     fBodyGyroJerkMag-Mean-1  :   0.7377313834859738
tGravityAcc-ARCoeff-6     fBodyGyro-Max-2  :   0.040409840725956415
tGravityAcc-ARCoeff-6     tBodyGyroJerk-ARCoeff-9  :   -0.17699950558576885
tGravityAcc-ARCoeff-6     tBodyGyro-STD-1  :   -0.01958425603149138
tGravityAcc-ARCoeff-6     tBodyGyro-Mean-2  :   -0.007524135934941744
tGravityAcc-ARCoeff-6     tBodyGyroMag-Min-1  :   0.11315520298186373
tGravityAcc-ARCoeff-6     tBodyAcc-Mad-1  :   -0.0972447995510616
tGravityAcc-ARCoeff-6     tBodyAccJerk-STD-1  :   -0.1974903841607408
tGravityAcc-ARCoeff-6     fBodyAccMag-Mean-1  :   -0.04989556477364504
tGravityAcc-ARCoeff-6     fBodyGyroJerkMag-Mean-1  :   -0.20237226157587868
fBodyGyro-Max-2     tBodyGyroJerk-ARCoeff-9  :   -0.571484991352176
fBodyGyro-Max-2     tBodyGyro-STD-1  :   0.7263607703178482
fBodyGyro-Max-2     tBodyGyro-Mean-2  :   0.02003705779900134
fBodyGyro-Max-2     tBodyGyroMag-Min-1  :   0.6738728506079759
fBodyGyro-Max-2     tBodyAcc-Mad-1  :   0.6977618716608691
fBodyGyro-Max-2     tBodyAccJerk-STD-1  :   0.6857192222438688
fBodyGyro-Max-2     fBodyAccMag-Mean-1  :   0.7284115395841129
fBodyGyro-Max-2     fBodyGyroJerkMag-Mean-1  :   0.6929537739391008
tBodyGyroJerk-ARCoeff-9     tBodyGyro-STD-1  :   -0.6123740473187813
tBodyGyroJerk-ARCoeff-9     tBodyGyro-Mean-2  :   -0.025394345518728347
tBodyGyroJerk-ARCoeff-9     tBodyGyroMag-Min-1  :   -0.5379136662226554
tBodyGyroJerk-ARCoeff-9     tBodyAcc-Mad-1  :   -0.5774256529151484
tBodyGyroJerk-ARCoeff-9     tBodyAccJerk-STD-1  :   -0.5456528421337663
tBodyGyroJerk-ARCoeff-9     fBodyAccMag-Mean-1  :   -0.5941400383690237
tBodyGyroJerk-ARCoeff-9     fBodyGyroJerkMag-Mean-1  :   -0.5003842750556026
tBodyGyro-STD-1     tBodyGyro-Mean-2  :   0.04910958301103918
tBodyGyro-STD-1     tBodyGyroMag-Min-1  :   0.7178818730196939
tBodyGyro-STD-1     tBodyAcc-Mad-1  :   0.8613180534373523
tBodyGyro-STD-1     tBodyAccJerk-STD-1  :   0.8471310744764909
tBodyGyro-STD-1     fBodyAccMag-Mean-1  :   0.8766515783759751
tBodyGyro-STD-1     fBodyGyroJerkMag-Mean-1  :   0.7856355033306411
tBodyGyro-Mean-2     tBodyGyroMag-Min-1  :   0.11529655228948611
tBodyGyro-Mean-2     tBodyAcc-Mad-1  :   0.0146560540492784
tBodyGyro-Mean-2     tBodyAccJerk-STD-1  :   0.022857628356471246
tBodyGyro-Mean-2     fBodyAccMag-Mean-1  :   0.021315113858215568
tBodyGyro-Mean-2     fBodyGyroJerkMag-Mean-1  :   0.03224238110956783
tBodyGyroMag-Min-1     tBodyAcc-Mad-1  :   0.7050423465716047
```

```
tBodyGyroMag-Min-1     tBodyAccJerk-STD-1   :   0.6704952516197735
tBodyGyroMag-Min-1     fBodyAccMag-Mean-1   :   0.724513618483428
tBodyGyroMag-Min-1     fBodyGyroJerkMag-Mean-1   :   0.6236099865867623
tBodyAcc-Mad-1     tBodyAccJerk-STD-1   :   0.9485984947024525
tBodyAcc-Mad-1     fBodyAccMag-Mean-1   :   0.9575961857034766
tBodyAcc-Mad-1     fBodyGyroJerkMag-Mean-1   :   0.826473148320449
tBodyAccJerk-STD-1     fBodyAccMag-Mean-1   :   0.9344479751255199
tBodyAccJerk-STD-1     fBodyGyroJerkMag-Mean-1   :   0.8891614311511125
fBodyAccMag-Mean-1     fBodyGyroJerkMag-Mean-1   :   0.8700527161614238
```

[61]:
```
print('Highly Correlated features - ', HighlyCorrelatedFeatures)
print('Least Correlated features - ', LeastCorrelatedFeatures)
```

```
Highly Correlated features -  ('tBodyAccJerkMag-Mad-1', 'tBodyAccJerk-STD-1',
0.9842726911010856)
Least Correlated features -  ('tBodyAcc-Max-1', 'tBodyGyro-Mean-2',
-0.00022302374161254973)
```

13 Training Models

14 LogisticRegression

[17]:
```
from sklearn.linear_model import LogisticRegression
```

[52]:
```
clf = LogisticRegression()
clf.fit(X_train, y_train+1)

predictionsVal = clf.predict(X_val)
predictionsTest = clf.predict(X_test)

print('Accuracy Val = ', np.sum(predictionsVal == (y_val+1)) / y_val.shape[0] )
print('Accuracy Test = ', np.sum(predictionsTest == (y_test+1)) / y_test.
 ↪shape[0] )
```

```
Accuracy Val =  0.9679780420860018
Accuracy Test =  0.9679780420860018
```

15 Neural Network

[73]:
```
def Generate_Model_NN1():
    m = models.Sequential()
    m.add(layers.Dense( 50 , input_shape = (561,), activation='relu'))
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 50 , activation='relu'))
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 50 , activation='relu'))
```

```
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 12 , activation='sigmoid'))

    m.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
    return m
```

[85]:
```
model_1 = Generate_Model_NN1()
model_1.summary()
history = model_1.fit(X_train, y_train_categorical,
                      batch_size=100,
                      epochs=30,
                      validation_data=(X_val, y_val_categorical))
```

```
Model: "sequential_13"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_59 (Dense)             (None, 50)                28100

_________________________________________________________________
dropout_47 (Dropout)         (None, 50)                0

_________________________________________________________________
dense_60 (Dense)             (None, 50)                2550

_________________________________________________________________
dropout_48 (Dropout)         (None, 50)                0

_________________________________________________________________
dense_61 (Dense)             (None, 50)                2550

_________________________________________________________________
dropout_49 (Dropout)         (None, 50)                0

_________________________________________________________________
dense_62 (Dense)             (None, 12)                612
=================================================================
Total params: 33,812
Trainable params: 33,812
Non-trainable params: 0

_________________________________________________________________
Train on 8742 samples, validate on 1093 samples
Epoch 1/30
8742/8742 [==============================] - 0s 55us/step - loss: 1.6532 -
accuracy: 0.2880 - val_loss: 1.2092 - val_accuracy: 0.3458
Epoch 2/30
8742/8742 [==============================] - 0s 37us/step - loss: 1.2236 -
accuracy: 0.3334 - val_loss: 1.1773 - val_accuracy: 0.5425
Epoch 3/30
8742/8742 [==============================] - 0s 41us/step - loss: 1.1832 -
accuracy: 0.3423 - val_loss: 1.1513 - val_accuracy: 0.3477
Epoch 4/30
```

```
8742/8742 [==============================] - 0s 48us/step - loss: 1.1596 -
accuracy: 0.3593 - val_loss: 1.1216 - val_accuracy: 0.4163
Epoch 5/30
8742/8742 [==============================] - 0s 47us/step - loss: 1.1207 -
accuracy: 0.4085 - val_loss: 1.0215 - val_accuracy: 0.5242
Epoch 6/30
8742/8742 [==============================] - 0s 54us/step - loss: 1.0212 -
accuracy: 0.4484 - val_loss: 0.9136 - val_accuracy: 0.4309
Epoch 7/30
8742/8742 [==============================] - 0s 45us/step - loss: 0.9398 -
accuracy: 0.4986 - val_loss: 0.8666 - val_accuracy: 0.6185
Epoch 8/30
8742/8742 [==============================] - 0s 42us/step - loss: 0.8186 -
accuracy: 0.5668 - val_loss: 0.7191 - val_accuracy: 0.6359
Epoch 9/30
8742/8742 [==============================] - 0s 41us/step - loss: 0.7590 -
accuracy: 0.6004 - val_loss: 0.6914 - val_accuracy: 0.5773
Epoch 10/30
8742/8742 [==============================] - 0s 40us/step - loss: 0.7252 -
accuracy: 0.6080 - val_loss: 0.6760 - val_accuracy: 0.6542
Epoch 11/30
8742/8742 [==============================] - 0s 39us/step - loss: 0.7122 -
accuracy: 0.6201 - val_loss: 0.6824 - val_accuracy: 0.6267
Epoch 12/30
8742/8742 [==============================] - 0s 38us/step - loss: 0.6959 -
accuracy: 0.6227 - val_loss: 0.6652 - val_accuracy: 0.6304
Epoch 13/30
8742/8742 [==============================] - 0s 39us/step - loss: 0.6538 -
accuracy: 0.6627 - val_loss: 0.3798 - val_accuracy: 0.8289
Epoch 14/30
8742/8742 [==============================] - 0s 34us/step - loss: 0.4442 -
accuracy: 0.7813 - val_loss: 0.3210 - val_accuracy: 0.8161
Epoch 15/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.3960 -
accuracy: 0.8024 - val_loss: 0.3133 - val_accuracy: 0.8161
Epoch 16/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.3542 -
accuracy: 0.8253 - val_loss: 0.2910 - val_accuracy: 0.8545
Epoch 17/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.3470 -
accuracy: 0.8463 - val_loss: 0.2765 - val_accuracy: 0.8774
Epoch 18/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.2984 -
accuracy: 0.8735 - val_loss: 0.2342 - val_accuracy: 0.8975
Epoch 19/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.2813 -
accuracy: 0.8816 - val_loss: 0.2347 - val_accuracy: 0.8957
Epoch 20/30
```

```
8742/8742 [==============================] - 0s 33us/step - loss: 0.2642 -
accuracy: 0.8934 - val_loss: 0.1733 - val_accuracy: 0.9222
Epoch 21/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.2415 -
accuracy: 0.9038 - val_loss: 0.1840 - val_accuracy: 0.9222
Epoch 22/30
8742/8742 [==============================] - 0s 33us/step - loss: 0.2299 -
accuracy: 0.9068 - val_loss: 0.1711 - val_accuracy: 0.9259
Epoch 23/30
8742/8742 [==============================] - 0s 38us/step - loss: 0.2210 -
accuracy: 0.9156 - val_loss: 0.1627 - val_accuracy: 0.9286
Epoch 24/30
8742/8742 [==============================] - 0s 31us/step - loss: 0.2088 -
accuracy: 0.9198 - val_loss: 0.1563 - val_accuracy: 0.9305
Epoch 25/30
8742/8742 [==============================] - 0s 26us/step - loss: 0.1947 -
accuracy: 0.9238 - val_loss: 0.1578 - val_accuracy: 0.9323
Epoch 26/30
8742/8742 [==============================] - 0s 24us/step - loss: 0.1899 -
accuracy: 0.9282 - val_loss: 0.1562 - val_accuracy: 0.9387
Epoch 27/30
8742/8742 [==============================] - 0s 24us/step - loss: 0.1840 -
accuracy: 0.9251 - val_loss: 0.1492 - val_accuracy: 0.9369
Epoch 28/30
8742/8742 [==============================] - 0s 25us/step - loss: 0.1726 -
accuracy: 0.9329 - val_loss: 0.1372 - val_accuracy: 0.9424
Epoch 29/30
8742/8742 [==============================] - 0s 27us/step - loss: 0.1885 -
accuracy: 0.9256 - val_loss: 0.1474 - val_accuracy: 0.9396
Epoch 30/30
8742/8742 [==============================] - 0s 25us/step - loss: 0.1790 -
accuracy: 0.9295 - val_loss: 0.1391 - val_accuracy: 0.9369
```

[88]:

```
loss, test_acc = model_1.evaluate(X_test, y_test_categorical)
print('test_acc: ', test_acc)

loss, val_acc = model_1.evaluate(X_val, y_val_categorical)
print('val_acc: ', val_acc)

loss, train_acc = model_1.evaluate(X_train, y_train_categorical)
print('train_acc: ', train_acc)
```

```
1093/1093 [==============================] - 0s 30us/step
test_acc:  0.9332113265991211
1093/1093 [==============================] - 0s 31us/step
val_acc:  0.9368709921836853
8742/8742 [==============================] - 0s 22us/step
train_acc:  0.9604209661483765
```

[90]:
```
#model_1.save('model_1_Test_93_3.h5')
```

16 (f) Feature selection.

[18]:
```
def createDataSetWithSelectedFeatures(FullDataSet, FeaturesList):

    numFeatures = FullDataSet.shape[1]
    NewReducedDataSet = np.array( [ FullDataSet[:,FeaturesList[0]] ] ).T

    for i in range(len(FeaturesList)):

        if i == 0:
            continue

        if FeaturesList[i] < 0 or FeaturesList[i] > numFeatures-1:
            continue

        featureToSelect = FeaturesList[i]
        NewReducedDataSet = np.hstack( (NewReducedDataSet , np.array( [␣
↪FullDataSet[:,FeaturesList[i]] ] ).T) )

    return NewReducedDataSet
```

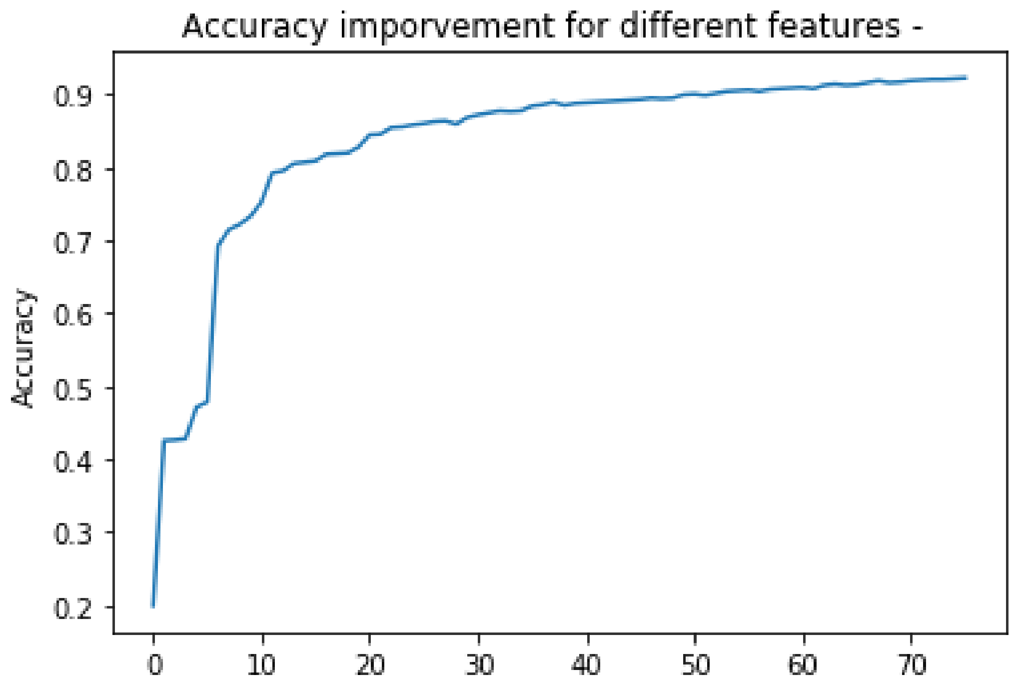
[21]:
```
NumFeaturesToSelect = 15
TotalNumFeatures = X_train.shape[1]
#TotalNumFeatures = 50
IncludedFeatures_X = np.zeros(shape=(X_train.shape[0], NumFeaturesToSelect))
IncludedFeatures_list = [-1 for i in range(NumFeaturesToSelect)]


PreviousBestValAcc = 0
EndSelection = False
Accuracies = []
for i in range(NumFeaturesToSelect):

    print('\nSelecting feature ', i+1)

    bestFeatureIndex = 0
    bestAccuracy = 0
    for feature_index in range(TotalNumFeatures):

        if feature_index in IncludedFeatures_list:
            continue

        featureX = np.array( [X_train[:,feature_index]] )
        IncludedFeatures_X[:,i] = featureX
```

```
        IncludedFeatures_list[i] = feature_index

        clfX = LogisticRegression()
        clfX.fit(IncludedFeatures_X[:,:i+1], (y_train+1))

        reducedValidationDataset = createDataSetWithSelectedFeatures(X_val,␣
↪IncludedFeatures_list)
        predictionsVal = clfX.predict(reducedValidationDataset)
        val_acc = np.sum(predictionsVal == (y_val+1)) / y_val.shape[0]

        #print(feature_index, ' Accuracy Val = ', val_acc )

        if val_acc > bestAccuracy:
            bestAccuracy = val_acc
            Accuracies.append(bestAccuracy)
            bestFeatureIndex = feature_index

    print('Best Validation accuracy:', bestAccuracy)
    if bestAccuracy > PreviousBestValAcc:
        PreviousBestValAcc = bestAccuracy
    else:
        break

    IncludedFeatures_list[i] = bestFeatureIndex
    IncludedFeatures_X[:,i] = np.array( [X_train[:,bestFeatureIndex]] )
    print('Selected Features - ', [x for x in IncludedFeatures_list if x != -1]␣
↪)


plt.figure()
plt.title('Accuracy imporvement for different features - ')
plt.ylabel('Accuracy')
plt.plot(Accuracies)
print(IncludedFeatures_list)
```

```
Selecting feature  1
Best Validation accuracy: 0.47118023787740165
Selected Features -  [41]

Selecting feature  2
Best Validation accuracy: 0.7145471180237878
Selected Features -  [41, 9]

Selecting feature  3
Best Validation accuracy: 0.7950594693504117
```

```
Selected Features -  [41, 9, 52]

Selecting feature  4
Best Validation accuracy: 0.8453796889295517
Selected Features -  [41, 9, 52, 228]

Selecting feature  5
Best Validation accuracy: 0.8636779505946935
Selected Features -  [41, 9, 52, 228, 202]

Selecting feature  6
Best Validation accuracy: 0.8774016468435498
Selected Features -  [41, 9, 52, 228, 202, 70]

Selecting feature  7
Best Validation accuracy: 0.889295516925892
Selected Features -  [41, 9, 52, 228, 202, 70, 433]

Selecting feature  8
Best Validation accuracy: 0.8947849954254345
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193]

Selecting feature  9
Best Validation accuracy: 0.9002744739249772
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123]

Selecting feature  10
Best Validation accuracy: 0.9057639524245197
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121]

Selecting feature  11
Best Validation accuracy: 0.909423604757548
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243]

Selecting feature  12
Best Validation accuracy: 0.9139981701738334
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6]

Selecting feature  13
Best Validation accuracy: 0.918572735590119
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6, 83]

Selecting feature  14
Best Validation accuracy: 0.9204025617566332
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6, 83,
502]

Selecting feature  15
```

```
Best Validation accuracy: 0.9222323879231473
Selected Features -  [41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6, 83,
502, 541]
[41, 9, 52, 228, 202, 70, 433, 193, 123, 121, 243, 6, 83, 502, 541]
```



[30]:
```python
print('List of selected features - \n')
for i in IncludedFeatures_list:
    print(features[i])
```

```
List of selected features -

tGravityAcc-Mean-2
tBodyAcc-Max-1
tGravityAcc-Min-1
tBodyAccJerkMag-Mad-1
tBodyAccMag-Mad-1
tGravityAcc-ARCoeff-6
fBodyGyro-Max-2
tBodyGyroJerk-ARCoeff-9
tBodyGyro-STD-1
tBodyGyro-Mean-2
tBodyGyroMag-Min-1
tBodyAcc-Mad-1
tBodyAccJerk-STD-1
fBodyAccMag-Mean-1
```

fBodyGyroJerkMag-Mean-1

[23]:
```
X_train_reduced_featuresSelected = createDataSetWithSelectedFeatures(X_train,␣
 ↪IncludedFeatures_list)
X_test_reduced_featuresSelected = createDataSetWithSelectedFeatures(X_test,␣
 ↪IncludedFeatures_list)
```

[24]:
```
clfX = LogisticRegression()
clfX.fit(X_train_reduced_featuresSelected, (y_train+1))
```

[24]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

[26]:
```
predictionsTest = clfX.predict(X_test_reduced_featuresSelected)
test_acc = np.sum(predictionsTest == (y_test+1)) / y_test.shape[0]
print('Accuracy on selected features Test dataset - ', test_acc)
```

```
Accuracy on selected features Test dataset -  0.8728270814272644
```

17 (g) Feature transformation (PCA).

[77]:
```
from numpy import linalg as LA
```

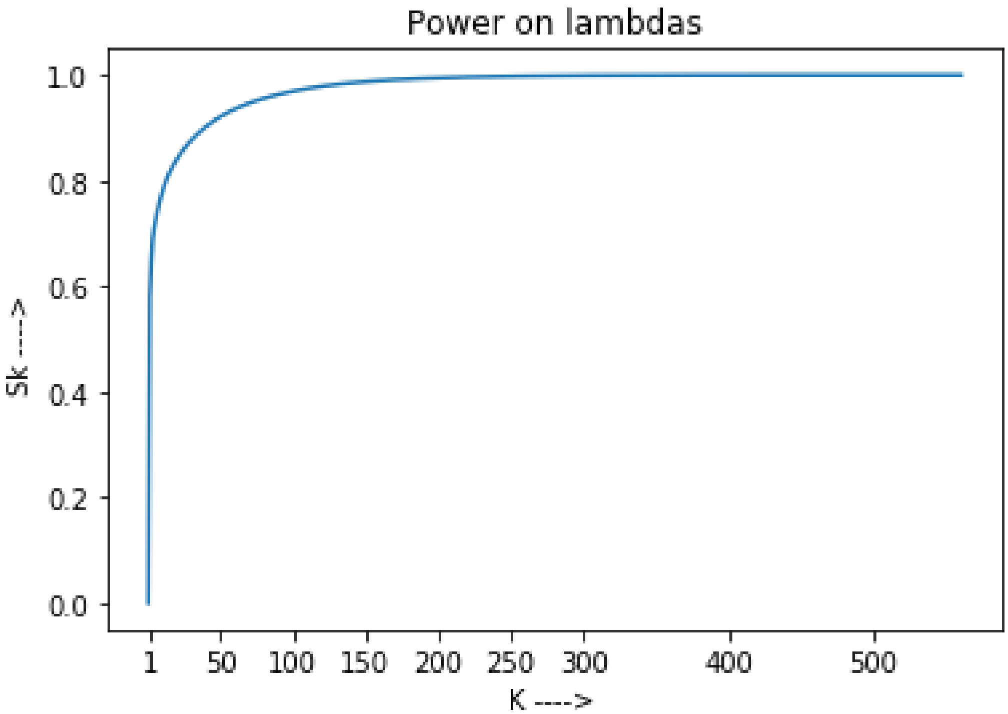
[127]:
```
def meanNormalize_features(Mat):

    NormalizedMat = np.array( [Mat[:,0] - np.mean(Mat[:,0])] ).T

    colsMax = Mat.shape[1]

    for i in range(colsMax):

        if i == 0:
            continue

        NormalizedMat = np.hstack( (NormalizedMat, np.array( [Mat[:,i] - np.
 ↪mean(Mat[:,i])] ).T ) )

    return NormalizedMat

def PCA_ML633(MatIn, K, plot='on'):

    Mat = meanNormalize_features(MatIn)
```

```
    CovMat = np.matmul(Mat.T , Mat)
    D = CovMat.shape[0]
    CovMat = CovMat / (D-1)

    Lambdas, vectors = LA.eigh(CovMat)

    if plot == 'on':

        lambda_sum = np.sum(Lambdas)
        plot_y = []
        for i in range(D):
            Vec_index = D - i
            First_i_lambda_sum = np.sum(Lambdas[D-i:D])
            plot_y.append(First_i_lambda_sum / lambda_sum)

        plt.title('Power on lambdas')
        plt.xlabel('K ----> ')
        plt.ylabel('Sk ----> ')
        plt.xticks([1,50,100,150,200,250,300,400,500])
        plt.plot(plot_y)

    if K > D:
        print('Error K > D')
        return

    U = np.array( [vectors[:,D-1]] ).T
    for i in range(K):

        if i == 0:
            continue

        Vec_index = D - i - 1
        U = np.hstack( (U, np.array( [vectors[:,Vec_index]] ).T) )

    return U , np.matmul(Mat, U)
```

[128]:
```
U , X_PCA = PCA_ML633(X , 100)
X_PCA_Train = X_PCA[:8742,:]
X_PCA_val = X_PCA[8742:9835,:]
X_PCA_test = X_PCA[9835:,:]

print('Shape of Train set ', X_PCA_Train.shape)
print('Shape of Test set ', X_PCA_test.shape)
print('Shape of Val set ', X_PCA_val.shape)
```

```
Shape of Train set  (8742, 100)
Shape of Test set  (1093, 100)
```

```
Shape of Val set  (1093, 100)
```



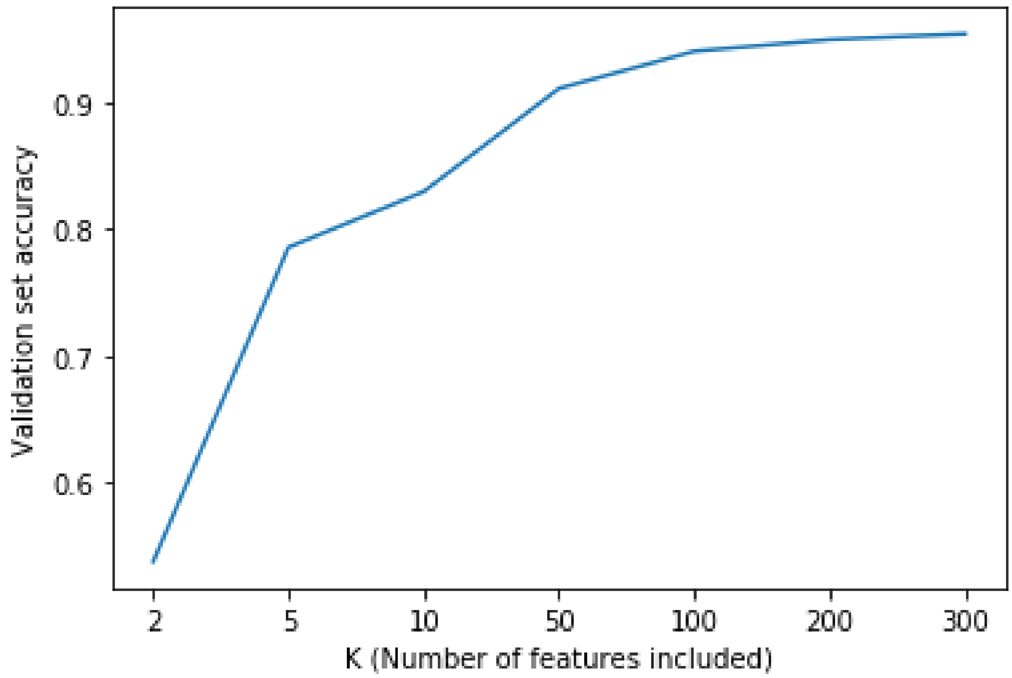
[96]:
```python
plotAcc = []
NumFeaturesInPCA = [2, 5, 10, 50, 100, 200, 300]
for NumFeaturesInPCA in NumFeaturesInPCA:
    print('K = ', NumFeaturesInPCA)
    U , X_PCA = PCA_ML633(X , NumFeaturesInPCA, plot='off')

    X_PCA_Train = X_PCA[:8742,:]
    y_PCA_Train = y[:8742]
    X_PCA_val = X_PCA[8742:9835,:]
    y_PCA_val = y[8742:9835]
    X_PCA_test = X_PCA[9835:,:]
    y_PCA_test = y[9835:]

    clf = LogisticRegression()
    clf.fit(X_PCA_Train, y_PCA_Train+1)

    predictionsTrain = clf.predict(X_PCA_Train)
    predictionsVal = clf.predict(X_PCA_val)
    predictionsTest = clf.predict(X_PCA_test)

    accVal = np.sum(predictionsVal == (y_PCA_val+1)) / y_PCA_val.shape[0]
    print('Accuracy Val = ', accVal )
```

```
    print('Accuracy Test = ', np.sum(predictionsTest == (y_PCA_test+1)) /
 ↪y_PCA_test.shape[0] )
    print('Accuracy Train = ', np.sum(predictionsTrain == (y_PCA_Train+1)) /
 ↪y_PCA_Train.shape[0] )
    plotAcc.append(accVal)
```

```
K =  2
Accuracy Val =  0.5379688929551693
Accuracy Test =  0.5041171088746569
Accuracy Train =  0.5512468542667581
K =  5
Accuracy Val =  0.7859103385178408
Accuracy Test =  0.7301006404391582
Accuracy Train =  0.7862045298558682
K =  10
Accuracy Val =  0.8298261665141812
Accuracy Test =  0.848124428179323
Accuracy Train =  0.8523221230839625
K =  50
Accuracy Val =  0.9112534309240622
Accuracy Test =  0.9313815187557182
Accuracy Train =  0.945664607641272
K =  100
Accuracy Val =  0.9405306495882891
Accuracy Test =  0.958828911253431
Accuracy Train =  0.9735758407687028
K =  200
Accuracy Val =  0.94967978042086
Accuracy Test =  0.9624885635864593
Accuracy Train =  0.9871882864333105
K =  300
Accuracy Val =  0.9542543458371455
Accuracy Test =  0.9643183897529735
Accuracy Train =  0.9881034088309312
```

[124]:
```
plt.figure()
plt.ylabel('Validation set accuracy')
plt.xlabel('K (Number of features included)')
locs, labels = plt.xticks()
NumFeaturesInPCA = [2, 5, 10, 50, 100, 200, 300]
plt.xticks(np.arange(len(NumFeaturesInPCA)), NumFeaturesInPCA)
plt.plot(plotAcc)
```

[124]:
```
[<matplotlib.lines.Line2D at 0x1ef8d73f0c8>]
```



[117]:
```
U , X_PCA = PCA_ML633(X , 100, plot='off')
X_PCA_Train = X_PCA[:8742,:]
X_PCA_val = X_PCA[8742:9835,:]
X_PCA_test = X_PCA[9835:,:]

y_cat = to_categorical(y)
y_cat_PCA_Train = y_cat[:8742,:]
y_cat_PCA_val = y_cat[8742:9835,:]
y_cat_PCA_test = y_cat[9835:,:]
```

[118]:
```
def Generate_Model_NN_PCA_DataSet():
    m = models.Sequential()
    m.add(layers.Dense( 30 , input_shape = (100,), activation='relu'))
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 30 , activation='relu'))
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 30 , activation='relu'))
    m.add(layers.Dropout(0.3))
    m.add(layers.Dense( 12 , activation='sigmoid'))

    m.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
    return m
```

[119]:
```
model_1_PCA_Trained = Generate_Model_NN_PCA_DataSet()
model_1_PCA_Trained.summary()
history = model_1_PCA_Trained.fit(X_PCA_Train, y_cat_PCA_Train,
                    batch_size=100,
                    epochs=20,
                    validation_data=(X_PCA_val, y_cat_PCA_val))
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_5 (Dense)              (None, 30)                3030
_________________________________________________________________
dropout_4 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_6 (Dense)              (None, 30)                930
_________________________________________________________________
dropout_5 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_7 (Dense)              (None, 30)                930
_________________________________________________________________
dropout_6 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_8 (Dense)              (None, 12)                372
=================================================================
Total params: 5,262
Trainable params: 5,262
Non-trainable params: 0
_________________________________________________________________
Train on 8742 samples, validate on 1093 samples
Epoch 1/20
8742/8742 [==============================] - 0s 39us/step - loss: 1.9908 -
accuracy: 0.2741 - val_loss: 1.3790 - val_accuracy: 0.4437
Epoch 2/20
8742/8742 [==============================] - 0s 18us/step - loss: 1.2402 -
accuracy: 0.4307 - val_loss: 0.8685 - val_accuracy: 0.5087
Epoch 3/20
8742/8742 [==============================] - 0s 22us/step - loss: 0.9587 -
accuracy: 0.5189 - val_loss: 0.8247 - val_accuracy: 0.5023
Epoch 4/20
8742/8742 [==============================] - 0s 24us/step - loss: 0.8762 -
accuracy: 0.5320 - val_loss: 0.7723 - val_accuracy: 0.5361
Epoch 5/20
8742/8742 [==============================] - 0s 22us/step - loss: 0.7827 -
accuracy: 0.5854 - val_loss: 0.6618 - val_accuracy: 0.6340
Epoch 6/20
8742/8742 [==============================] - 0s 22us/step - loss: 0.6736 -
```

```
accuracy: 0.6576 - val_loss: 0.5769 - val_accuracy: 0.7612
Epoch 7/20
8742/8742 [==============================] - 0s 21us/step - loss: 0.5986 -
accuracy: 0.6939 - val_loss: 0.5017 - val_accuracy: 0.7338
Epoch 8/20
8742/8742 [==============================] - 0s 22us/step - loss: 0.5367 -
accuracy: 0.7210 - val_loss: 0.4532 - val_accuracy: 0.7539
Epoch 9/20
8742/8742 [==============================] - 0s 21us/step - loss: 0.4904 -
accuracy: 0.7407 - val_loss: 0.4313 - val_accuracy: 0.7658
Epoch 10/20
8742/8742 [==============================] - 0s 21us/step - loss: 0.4533 -
accuracy: 0.7552 - val_loss: 0.4120 - val_accuracy: 0.7649
Epoch 11/20
8742/8742 [==============================] - 0s 21us/step - loss: 0.4280 -
accuracy: 0.7679 - val_loss: 0.4087 - val_accuracy: 0.7521
Epoch 12/20
8742/8742 [==============================] - 0s 18us/step - loss: 0.4127 -
accuracy: 0.7674 - val_loss: 0.4046 - val_accuracy: 0.7575
Epoch 13/20
8742/8742 [==============================] - 0s 20us/step - loss: 0.3986 -
accuracy: 0.7726 - val_loss: 0.3975 - val_accuracy: 0.7548
Epoch 14/20
8742/8742 [==============================] - 0s 19us/step - loss: 0.3798 -
accuracy: 0.7773 - val_loss: 0.3939 - val_accuracy: 0.8152
Epoch 15/20
8742/8742 [==============================] - 0s 18us/step - loss: 0.3771 -
accuracy: 0.7837 - val_loss: 0.3973 - val_accuracy: 0.7850
Epoch 16/20
8742/8742 [==============================] - 0s 17us/step - loss: 0.3631 -
accuracy: 0.7844 - val_loss: 0.3981 - val_accuracy: 0.8070
Epoch 17/20
8742/8742 [==============================] - 0s 18us/step - loss: 0.3662 -
accuracy: 0.7812 - val_loss: 0.3995 - val_accuracy: 0.7585
Epoch 18/20
8742/8742 [==============================] - 0s 17us/step - loss: 0.3604 -
accuracy: 0.7869 - val_loss: 0.3926 - val_accuracy: 0.7713
Epoch 19/20
8742/8742 [==============================] - 0s 17us/step - loss: 0.3496 -
accuracy: 0.7915 - val_loss: 0.3930 - val_accuracy: 0.7722
Epoch 20/20
8742/8742 [==============================] - 0s 17us/step - loss: 0.3417 -
accuracy: 0.7939 - val_loss: 0.3896 - val_accuracy: 0.7768
```

[121]:
```
loss, test_acc = model_1_PCA_Trained.evaluate(X_PCA_test, y_cat_PCA_test)
print('test_acc: ', test_acc)
```

```
loss, val_acc = model_1_PCA_Trained.evaluate(X_PCA_val, y_cat_PCA_val)
print('val_acc: ', val_acc)

loss, train_acc = model_1_PCA_Trained.evaluate(X_PCA_Train, y_cat_PCA_Train)
print('train_acc: ', train_acc)
```

```
1093/1093 [==============================] - 0s 22us/step
test_acc:  0.7987191081047058
1093/1093 [==============================] - 0s 26us/step
val_acc:  0.7767612338066101
8742/8742 [==============================] - 0s 20us/step
train_acc:  0.812743067741394
```

18 (h) Support vector machine.

[56]:
```
from sklearn import svm
```

[132]:
```
U , X_PCA = PCA_ML633(X , 100, plot='off')

X_PCA_Train = X_PCA[:8742,:]
y_PCA_Train = y[:8742]
X_PCA_val = X_PCA[8742:9835,:]
y_PCA_val = y[8742:9835]
X_PCA_test = X_PCA[9835:,:]
y_PCA_test = y[9835:]
```

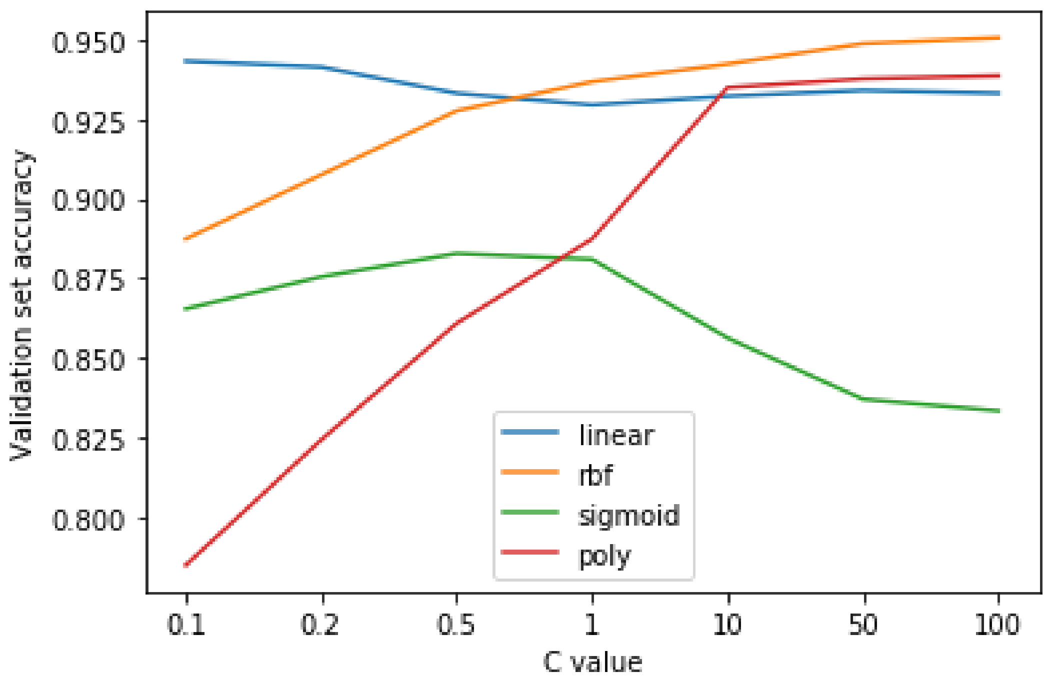
[137]:
```
accuracyDict = dict()
accuracyDict['linear'] = []
accuracyDict['rbf'] = []
accuracyDict['sigmoid'] = []
accuracyDict['poly'] = []
Reg_values = [0.1, 0.2, 0.5, 1, 10, 50, 100]
for kernelX in ['linear', 'rbf', 'sigmoid', 'poly']:
    for reg in Reg_values:
        print('Kernel: ', kernelX, '  C=', reg)
        SVM_clf = svm.SVC(C=reg, kernel=kernelX)
        SVM_clf.fit(X_PCA_Train, y_PCA_Train+1)
        predictions_val = SVM_clf.predict(X_PCA_val)
        predictions_test = SVM_clf.predict(X_PCA_test)
        acc1 = np.sum(np.equal(predictions_val, y_PCA_val+1)) / y_PCA_val.
 ↪shape[0]
        acc2 = np.sum(np.equal(predictions_test, y_PCA_test+1)) / y_PCA_test.
 ↪shape[0]
        print('Val Accuracy = ', acc1, 'Test Accuracy = ', acc2)
        accuracyDict[kernelX].append(acc1)
```

```
Kernel:  linear   C= 0.1
```

```
Val Accuracy =  0.9432753888380604 Test Accuracy =  0.9432753888380604
Kernel:  linear   C= 0.2
Val Accuracy =  0.9414455626715462 Test Accuracy =  0.9451052150045746
Kernel:  linear   C= 0.5
Val Accuracy =  0.9332113449222323 Test Accuracy =  0.9487648673376029
Kernel:  linear   C= 1
Val Accuracy =  0.929551692589204 Test Accuracy =  0.9505946935041171
Kernel:  linear   C= 10
Val Accuracy =  0.9322964318389753 Test Accuracy =  0.9560841720036597
Kernel:  linear   C= 50
Val Accuracy =  0.9341262580054894 Test Accuracy =  0.9560841720036597
Kernel:  linear   C= 100
Val Accuracy =  0.9332113449222323 Test Accuracy =  0.9560841720036597
Kernel:  rbf   C= 0.1
Val Accuracy =  0.8874656907593779 Test Accuracy =  0.8819762122598354
Kernel:  rbf   C= 0.2
Val Accuracy =  0.9075937785910339 Test Accuracy =  0.9204025617566332
Kernel:  rbf   C= 0.5
Val Accuracy =  0.9277218664226898 Test Accuracy =  0.9277218664226898
Kernel:  rbf   C= 1
Val Accuracy =  0.9368709972552608 Test Accuracy =  0.929551692589204
Kernel:  rbf   C= 10
Val Accuracy =  0.9423604757548033 Test Accuracy =  0.9432753888380604
Kernel:  rbf   C= 50
Val Accuracy =  0.9487648673376029 Test Accuracy =  0.9423604757548033
Kernel:  rbf   C= 100
Val Accuracy =  0.9505946935041171 Test Accuracy =  0.9432753888380604
Kernel:  sigmoid   C= 0.1
Val Accuracy =  0.8655077767612077 Test Accuracy =  0.8636779505946935
Kernel:  sigmoid   C= 0.2
Val Accuracy =  0.8755718206770357 Test Accuracy =  0.8774016468435498
Kernel:  sigmoid   C= 0.5
Val Accuracy =  0.8828911253430924 Test Accuracy =  0.889295516925892
Kernel:  sigmoid   C= 1
Val Accuracy =  0.8810612991765783 Test Accuracy =  0.888380603842635
Kernel:  sigmoid   C= 10
Val Accuracy =  0.8563586459286368 Test Accuracy =  0.8508691674290942
Kernel:  sigmoid   C= 50
Val Accuracy =  0.8371454711802379 Test Accuracy =  0.8536139066788655
Kernel:  sigmoid   C= 100
Val Accuracy =  0.8334858188472095 Test Accuracy =  0.8517840805123513
Kernel:  poly   C= 0.1
Val Accuracy =  0.7849954254345837 Test Accuracy =  0.7035681610247027
Kernel:  poly   C= 0.2
Val Accuracy =  0.8243366880146387 Test Accuracy =  0.777676120768527
Kernel:  poly   C= 0.5
Val Accuracy =  0.8609332113449222 Test Accuracy =  0.8298261665141812
Kernel:  poly   C= 1
```

```
Val Accuracy =  0.8874656907593779 Test Accuracy =  0.8655077767612077
Kernel:  poly  C= 10
Val Accuracy =  0.9350411710887465 Test Accuracy =  0.9121683440073193
Kernel:  poly  C= 50
Val Accuracy =  0.9377859103385179 Test Accuracy =  0.929551692589204
Kernel:  poly  C= 100
Val Accuracy =  0.938700823421775 Test Accuracy =  0.9313815187557182
```

[139]:
```python
for kernelX in accuracyDict:
    plt.plot(accuracyDict[kernelX], label=kernelX)

plt.legend()
plt.xlabel('C value')
plt.ylabel('Validation set accuracy')
plt.xticks(np.arange(len(Reg_values)), Reg_values)
plt.show()
```



19 (i) Ensemble learning

[62]:
```python
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
```

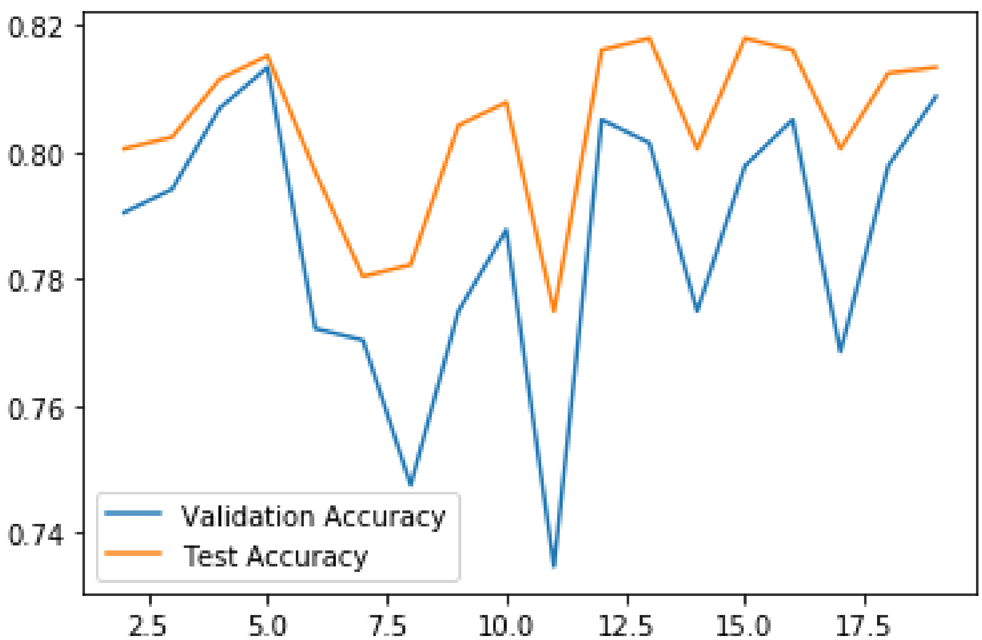
[63]:
```
Val_accuracy = []
Test_accuracy = []
num_estims = []

for n_est in range(2,20):
    estimator = LogisticRegression(multi_class='ovr')
    clf = AdaBoostClassifier(estimator, n_estimators=n_est, algorithm='SAMME')
    clf.fit(X_train, y_train+1)
    predictions_val = clf.predict(X_val)
    predictions_test = clf.predict(X_test)
    acc1 = np.sum(np.equal(predictions_val, y_val+1)) / y_val.shape[0]
    acc2 = np.sum(np.equal(predictions_test, y_test+1)) / y_test.shape[0]
    Val_accuracy.append(acc1)
    Test_accuracy.append(acc2)
    num_estims.append(n_est)
    print('Number of estimators = ', n_est, 'Val Accuracy = ', acc1, 'Test␣
↪Accuracy = ', acc2)
```

```
Number of estimators =  2 Val Accuracy =  0.7904849039341263 Test Accuracy =
0.8005489478499542
Number of estimators =  3 Val Accuracy =  0.7941445562671546 Test Accuracy =
0.8023787740164684
Number of estimators =  4 Val Accuracy =  0.8069533394327539 Test Accuracy =
0.8115279048490394
Number of estimators =  5 Val Accuracy =  0.8133577310155535 Test Accuracy =
0.8151875571820677
Number of estimators =  6 Val Accuracy =  0.7721866422689845 Test Accuracy =
0.7968892955169259
Number of estimators =  7 Val Accuracy =  0.7703568161024703 Test Accuracy =
0.7804208600182982
Number of estimators =  8 Val Accuracy =  0.747483989021043 Test Accuracy =
0.7822506861848124
Number of estimators =  9 Val Accuracy =  0.7749313815187557 Test Accuracy =
0.8042086001829826
Number of estimators =  10 Val Accuracy =  0.787740164684355 Test Accuracy =
0.807868252516011
Number of estimators =  11 Val Accuracy =  0.7346752058554438 Test Accuracy =
0.7749313815187557
Number of estimators =  12 Val Accuracy =  0.8051235132662397 Test Accuracy =
0.8161024702653248
Number of estimators =  13 Val Accuracy =  0.8014638609332113 Test Accuracy =
0.817932296431839
Number of estimators =  14 Val Accuracy =  0.7749313815187557 Test Accuracy =
0.8005489478499542
Number of estimators =  15 Val Accuracy =  0.797804208600183 Test Accuracy =
0.817932296431839
Number of estimators =  16 Val Accuracy =  0.8051235132662397 Test Accuracy =
```

```
0.8161024702653248
Number of estimators =  17 Val Accuracy =  0.7685269899359561 Test Accuracy =
0.8005489478499542
Number of estimators =  18 Val Accuracy =  0.797804208600183 Test Accuracy =
0.8124428179322964
Number of estimators =  19 Val Accuracy =  0.8087831655992681 Test Accuracy =
0.8133577310155535
```

[71]:
```python
plt.figure()
plt.plot(num_estims, Val_accuracy, label='Validation Accuracy')
plt.plot(num_estims, Test_accuracy, label='Test Accuracy')
plt.legend()
```

[71]: <matplotlib.legend.Legend at 0x1effe3c2b48>



[72]:
```python
Val_accuracy = []
Test_accuracy = []
num_estims = []

for n_est in range(1,20):
    estimator = DecisionTreeClassifier(max_depth=2)
    clf = AdaBoostClassifier(estimator, n_estimators=n_est, algorithm='SAMME')
    clf.fit(X_train, y_train+1)
    predictions_val = clf.predict(X_val)
    predictions_test = clf.predict(X_test)
    acc1 = np.sum(np.equal(predictions_val, y_val+1)) / y_val.shape[0]
```

```
    acc2 = np.sum(np.equal(predictions_test, y_test+1)) / y_test.shape[0]
    Val_accuracy.append(acc1)
    Test_accuracy.append(acc2)
    num_estims.append(n_est)
    print('Number of estimators = ', n_est, 'Val Accuracy = ', acc1, 'Test␣
↪Accuracy = ', acc2)
```

```
Number of estimators =  1 Val Accuracy =  0.5233302836230558 Test Accuracy =
0.5297346752058555
Number of estimators =  2 Val Accuracy =  0.5800548947849954 Test Accuracy =
0.5507776761207686
Number of estimators =  3 Val Accuracy =  0.6550777676120768 Test Accuracy =
0.645928636779506
Number of estimators =  4 Val Accuracy =  0.6907593778591034 Test Accuracy =
0.6770356816102471
Number of estimators =  5 Val Accuracy =  0.6605672461116194 Test Accuracy =
0.6678865507776761
Number of estimators =  6 Val Accuracy =  0.6303751143641354 Test Accuracy =
0.6532479414455626
Number of estimators =  7 Val Accuracy =  0.6907593778591034 Test Accuracy =
0.6733760292772186
Number of estimators =  8 Val Accuracy =  0.7026532479414456 Test Accuracy =
0.6916742909423604
Number of estimators =  9 Val Accuracy =  0.6953339432753889 Test Accuracy =
0.6999085086916743
Number of estimators =  10 Val Accuracy =  0.7108874656907593 Test Accuracy =
0.6816102470265325
Number of estimators =  11 Val Accuracy =  0.7255260750228728 Test Accuracy =
0.7118023787740164
Number of estimators =  12 Val Accuracy =  0.7090576395242452 Test Accuracy =
0.7008234217749314
Number of estimators =  13 Val Accuracy =  0.7145471180237878 Test Accuracy =
0.7099725526075022
Number of estimators =  14 Val Accuracy =  0.737419945105215 Test Accuracy =
0.7145471180237878
Number of estimators =  15 Val Accuracy =  0.7282708142726441 Test Accuracy =
0.7053979871912168
Number of estimators =  16 Val Accuracy =  0.7255260750228728 Test Accuracy =
0.6971637694419031
Number of estimators =  17 Val Accuracy =  0.7136322049405307 Test Accuracy =
0.7108874656907593
Number of estimators =  18 Val Accuracy =  0.8133577310155535 Test Accuracy =
0.7904849039341263
Number of estimators =  19 Val Accuracy =  0.8032936870997255 Test Accuracy =
0.7795059469350412
```