human-activity-recognition-using-neural-networks

January 5, 2021

[1]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

```
/kaggle/input/human-activity-recognition-with-smartphones/train.csv
/kaggle/input/human-activity-recognition-with-smartphones/test.csv
```

Import Libraries

[2]:
```
# To store data
import pandas as pd

# To do linear algebra
import numpy as np
from numpy import pi

# To create plots
from matplotlib.colors import rgb2hex
from matplotlib.cm import get_cmap
```

```python
import matplotlib.pyplot as plt

# To create nicer plots
import seaborn as sns

# To create interactive plots
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
init_notebook_mode(connected=True)

# To get new datatypes and functions
from collections import Counter
from cycler import cycler

# To investigate distributions
from scipy.stats import norm, skew, probplot
from scipy.optimize import curve_fit

# To build models
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

# To gbm light
from lightgbm import LGBMClassifier

# To measure time
from time import time
```

```
<IPython.core.display.HTML object>
```

Load Data

[3]:
```python
# Load datasets
train_df = pd.read_csv('../input/human-activity-recognition-with-smartphones/
↪train.csv')
test_df = pd.read_csv('../input/human-activity-recognition-with-smartphones/
↪test.csv')

# Combine boths dataframes
train_df['Data'] = 'Train'
test_df['Data'] = 'Test'
both_df = pd.concat([train_df, test_df], axis=0).reset_index(drop=True)
both_df['subject'] = '#' + both_df['subject'].astype(str)
```

```python
# Create label
label = both_df.pop('Activity')

print('Shape Train:\t{}'.format(train_df.shape))
print('Shape Test:\t{}\n'.format(test_df.shape))

train_df.head()
```

```
Shape Train:    (7352, 564)
Shape Test:     (2947, 564)
```

[3]:

```
   tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  tBodyAcc-std()-X  \
0           0.288585          -0.020294          -0.132905         -0.995279
1           0.278419          -0.016411          -0.123520         -0.998245
2           0.279653          -0.019467          -0.113462         -0.995380
3           0.279174          -0.026201          -0.123283         -0.996091
4           0.276629          -0.016570          -0.115362         -0.998139

   tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  tBodyAcc-mad()-Y  \
0         -0.983111         -0.913526         -0.995112         -0.983185
1         -0.975300         -0.960322         -0.998807         -0.974914
2         -0.967187         -0.978944         -0.996520         -0.963668
3         -0.983403         -0.990675         -0.997099         -0.982750
4         -0.980817         -0.990482         -0.998321         -0.979672

   tBodyAcc-mad()-Z  tBodyAcc-max()-X  …  angle(tBodyAccMean,gravity)  \
0         -0.923527         -0.934724  …                    -0.112754
1         -0.957686         -0.943068  …                     0.053477
2         -0.977469         -0.938692  …                    -0.118559
3         -0.989302         -0.938692  …                    -0.036788
4         -0.990441         -0.942469  …                     0.123320

   angle(tBodyAccJerkMean),gravityMean)  angle(tBodyGyroMean,gravityMean)  \
0                              0.030400                         -0.464761
1                             -0.007435                         -0.732626
2                              0.177899                          0.100699
3                             -0.012892                          0.640011
4                              0.122542                          0.693578

   angle(tBodyGyroJerkMean,gravityMean)  angle(X,gravityMean)  \
0                             -0.018446             -0.841247
1                              0.703511             -0.844788
2                              0.808529             -0.848933
3                             -0.485366             -0.848649
4                             -0.615971             -0.847865
```

```
   angle(Y,gravityMean)  angle(Z,gravityMean)  subject  Activity   Data
0              0.179941             -0.058627        1  STANDING  Train
1              0.180289             -0.054317        1  STANDING  Train
2              0.180637             -0.049118        1  STANDING  Train
3              0.181935             -0.047663        1  STANDING  Train
4              0.185151             -0.043892        1  STANDING  Train

[5 rows x 564 columns]
```

Dataset Exploration

[4]:
```python
# Group and count main names of columns
pd.DataFrame.from_dict(Counter([col.split('-')[0].split('(')[0] for col in␣
↪both_df.columns]), orient='index').rename(columns={0:'count'}).
↪sort_values('count', ascending=False)
```

[4]:
```
                      count
fBodyAcc                 79
fBodyGyro                79
fBodyAccJerk             79
tGravityAcc              40
tBodyAcc                 40
tBodyGyroJerk            40
tBodyGyro                40
tBodyAccJerk             40
tBodyAccMag              13
tGravityAccMag           13
tBodyAccJerkMag          13
tBodyGyroMag             13
tBodyGyroJerkMag         13
fBodyAccMag              13
fBodyBodyAccJerkMag      13
fBodyBodyGyroMag         13
fBodyBodyGyroJerkMag     13
angle                     7
subject                   1
Data                      1
```

Mainly there are 'acceleration' and 'gyroscope' features. A few 'gravity' features are there as well.

Impressive how many features there are in regard of the limited number of sensors used.

[5]:
```python
# Get null values and dataframe information
print('Null Values In DataFrame: {}\n'.format(both_df.isna().sum().sum()))
both_df.info()
```

```
Null Values In DataFrame: 0

<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10299 entries, 0 to 10298
Columns: 563 entries, tBodyAcc-mean()-X to Data
dtypes: float64(561), object(2)
memory usage: 44.2+ MB
```

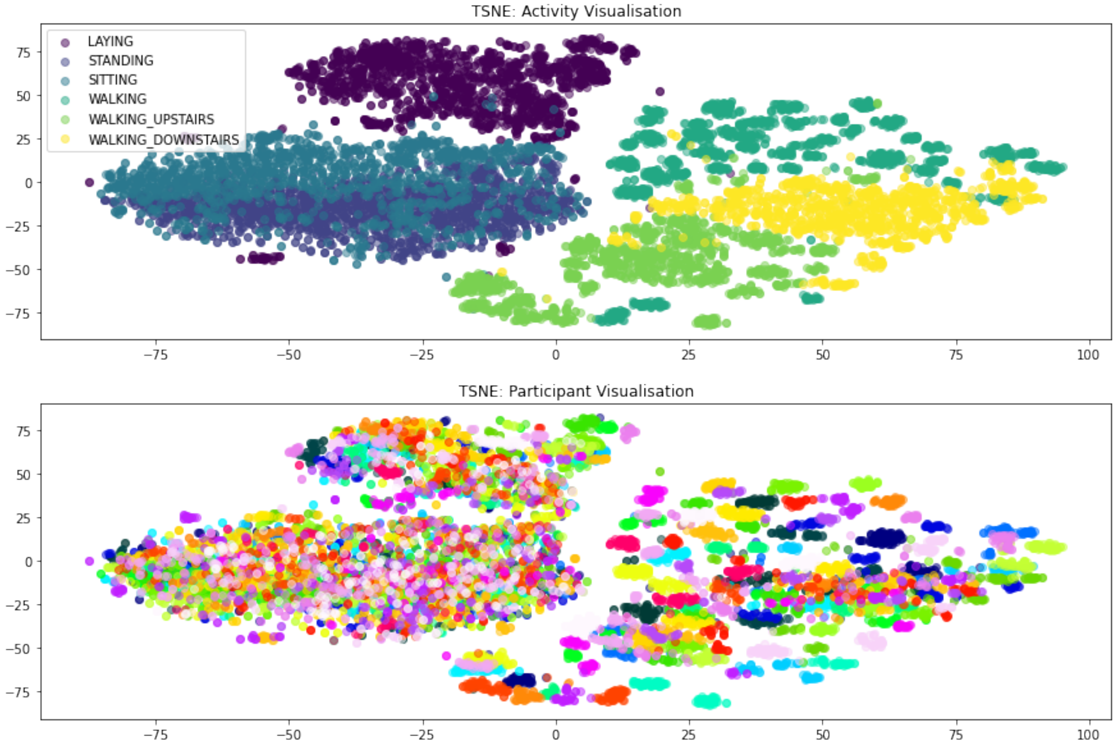
Distribution of Labels

[6]:
```
# Plotting data
label_counts = label.value_counts()

# Get colors
n = label_counts.shape[0]
colormap = get_cmap('viridis')
colors = [rgb2hex(colormap(col)) for col in np.arange(0, 1.01, 1/(n-1))]

# Create plot
data = go.Bar(x = label_counts.index,
              y = label_counts,
              marker = dict(color = colors))

layout = go.Layout(title = 'Smartphone Activity Label Distribution',
                   xaxis = dict(title = 'Activity'),
                   yaxis = dict(title = 'Count'))

fig = go.Figure(data=[data], layout=layout)
iplot(fig)
```

Disregarding the possibility of flawed data, the participants seem to walk roughly 10% faster downwards.

[7]:
```
# Create datasets
tsne_data = both_df.copy()
data_data = tsne_data.pop('Data')
subject_data = tsne_data.pop('subject')

# Scale data
scl = StandardScaler()
tsne_data = scl.fit_transform(tsne_data)

# Reduce dimensions (speed up)
pca = PCA(n_components=0.9, random_state=3)
tsne_data = pca.fit_transform(tsne_data)

# Transform data
tsne = TSNE(random_state=3)
tsne_transformed = tsne.fit_transform(tsne_data)
```

```
# Create subplots
fig, axarr = plt.subplots(2, 1, figsize=(15,10))

### Plot Activities
# Get colors
n = label.unique().shape[0]
colormap = get_cmap('viridis')
colors = [rgb2hex(colormap(col)) for col in np.arange(0, 1.01, 1/(n-1))]

# Plot each activity
for i, group in enumerate(label_counts.index):
    # Mask to separate sets
    mask = (label==group).values
    axarr[0].scatter(x=tsne_transformed[mask][:,0], y=tsne_transformed[mask][:
 ↪,1], c=colors[i], alpha=0.5, label=group)
axarr[0].set_title('TSNE: Activity Visualisation')
axarr[0].legend()


### Plot Subjects
# Get colors
n = subject_data.unique().shape[0]
colormap = get_cmap('gist_ncar')
colors = [rgb2hex(colormap(col)) for col in np.arange(0, 1.01, 1/(n-1))]

# Plot each participant
for i, group in enumerate(subject_data.unique()):
    # Mask to separate sets
    mask = (subject_data==group).values
    axarr[1].scatter(x=tsne_transformed[mask][:,0], y=tsne_transformed[mask][:
 ↪,1], c=colors[i], alpha=0.5, label=group)

axarr[1].set_title('TSNE: Participant Visualisation')
plt.show()
```



Plot-1: Activities are mostly separable.

Plot-2: Personal Information of the participants are visualised.

[8]:
```
# Split training testing data
enc = LabelEncoder()
label_encoded = enc.fit_transform(label)
X_train, X_test, y_train, y_test = train_test_split(tsne_data, label_encoded,␣
↪random_state=3)

# Create the model
lgbm = LGBMClassifier(n_estimators=500, random_state=3)
lgbm = lgbm.fit(X_train, y_train)

# Test the model
score = accuracy_score(y_true=y_test, y_pred=lgbm.predict(X_test))
print('Accuracy on testset:\t{:.4f}\n'.format(score))
```

```
Accuracy on testset:    0.9553
```

The separability of the participants seems to dissent concerning their activity in second t-SNE plots.

[9]:
```python
# Store the data
data = []
# Iterate over each activity
for activity in label_counts.index:
    # Create dataset
    act_data = both_df[label==activity].copy()
    act_data_data = act_data.pop('Data')
    act_subject_data = act_data.pop('subject')

    # Scale data
    scl = StandardScaler()
    act_data = scl.fit_transform(act_data)

    # Reduce dimensions
    pca = PCA(n_components=0.9, random_state=3)
    act_data = pca.fit_transform(act_data)


    # Split training testing data
    enc = LabelEncoder()
    label_encoded = enc.fit_transform(act_subject_data)
    X_train, X_test, y_train, y_test = train_test_split(act_data,␣
 ↪label_encoded, random_state=3)


    # Fit basic model
    print('Activity: {}'.format(activity))
    lgbm = LGBMClassifier(n_estimators=500, random_state=3)
    lgbm = lgbm.fit(X_train, y_train)

    score = accuracy_score(y_true=y_test, y_pred=lgbm.predict(X_test))
    print('Accuracy on testset:\t{:.4f}\n'.format(score))
    data.append([activity, score])
```

```
Activity: LAYING
Accuracy on testset:    0.6481

Activity: STANDING
Accuracy on testset:    0.5493

Activity: SITTING
Accuracy on testset:    0.5303

Activity: WALKING
Accuracy on testset:    0.9513

Activity: WALKING_UPSTAIRS
Accuracy on testset:    0.9249
```

```
Activity: WALKING_DOWNSTAIRS
Accuracy on testset:    0.9091
```

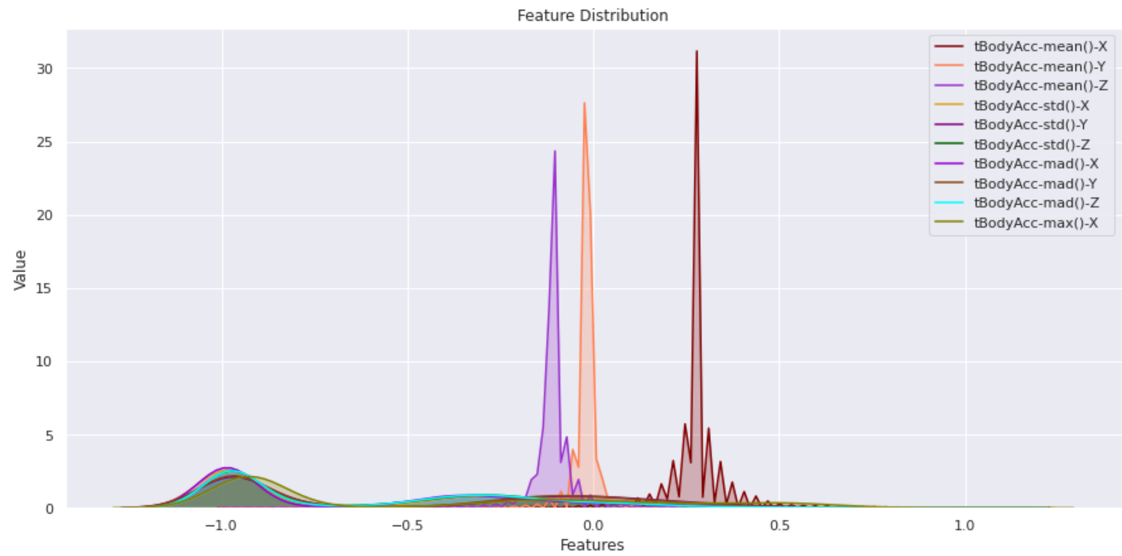
[10]:
```
# Create duration datafrae
duration_df = (both_df.groupby([label, subject_data])['Data'].count().
 ↪reset_index().groupby('Activity').agg({'Data':'mean'}) * 1.28).
 ↪rename(columns={'Data':'Seconds'})
activity_df = pd.DataFrame(data, columns=['Activity', 'Accuracy']).
 ↪set_index('Activity')
activity_df.join(duration_df)
```

[10]:

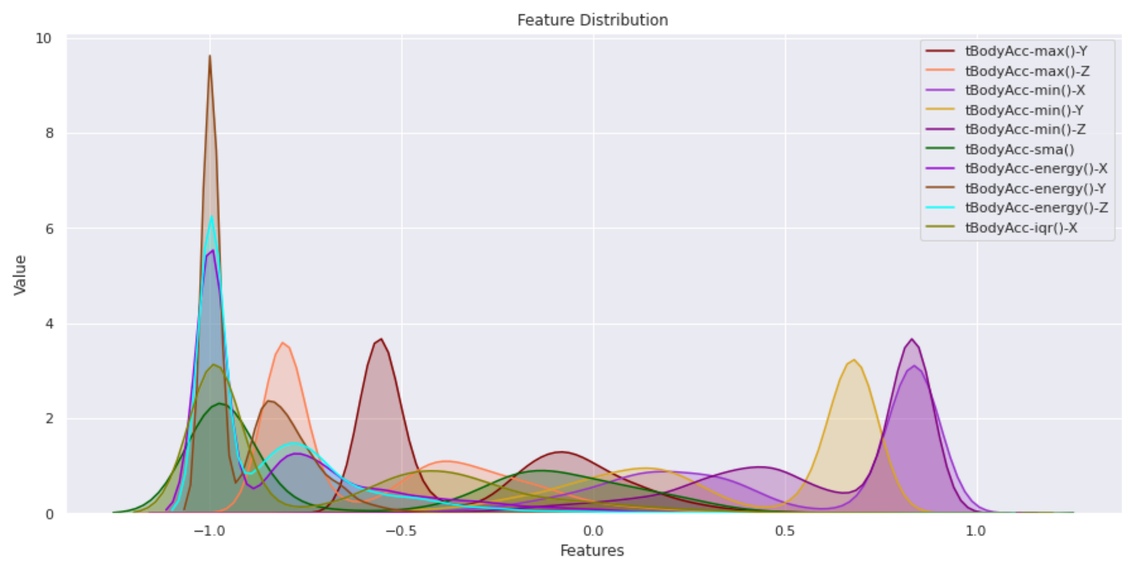
	Accuracy	Seconds
Activity		
LAYING	0.648148	82.944000
STANDING	0.549266	81.322667
SITTING	0.530337	75.818667
WALKING	0.951276	73.472000
WALKING_UPSTAIRS	0.924870	65.877333
WALKING_DOWNSTAIRS	0.909091	59.989333

Visualizations for feature distributions

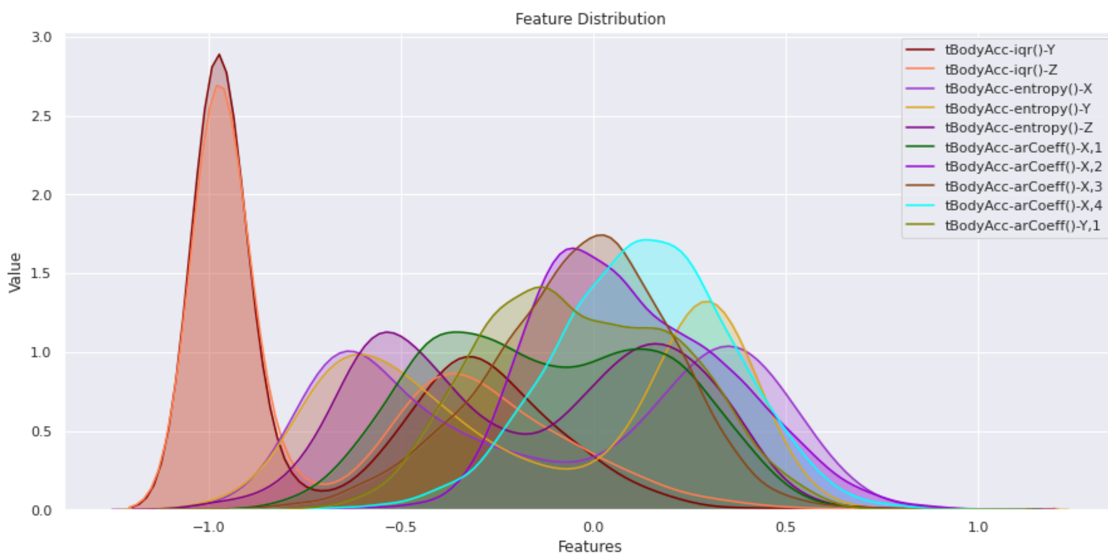
[11]:
```
sns.set(rc={'figure.figsize':(15,7)})
colours =␣
 ↪["maroon","coral","darkorchid","goldenrod","purple","darkgreen","darkviolet","saddlebrown",
index = -1
for i in train_df.columns[0:10]:
    index = index + 1
    fig = sns.kdeplot(train_df[i] , shade=True, color=colours[index])
plt.xlabel("Features")
plt.ylabel("Value")
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig)
```



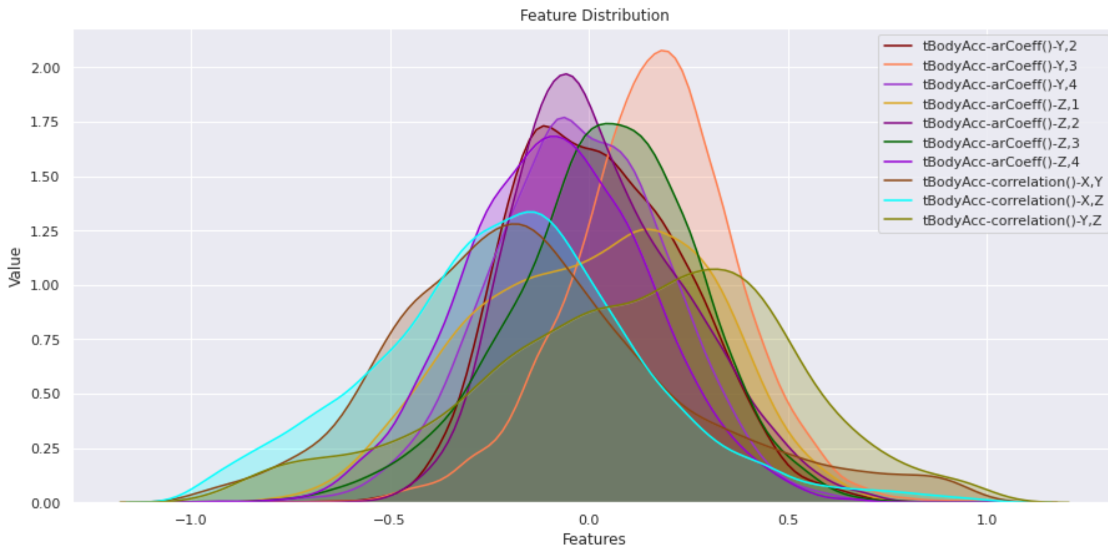
[12]:
```
sns.set(rc={'figure.figsize':(15,7)})
colours =␣
↪["maroon","coral","darkorchid","goldenrod","purple","darkgreen","darkviolet","saddlebrown",
index = -1
for i in train_df.columns[10:20]:
    index = index + 1
    ax1 = sns.kdeplot(train_df[i] , shade=True, color=colours[index])
plt.xlabel("Features")
plt.ylabel("Value")
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig)
```



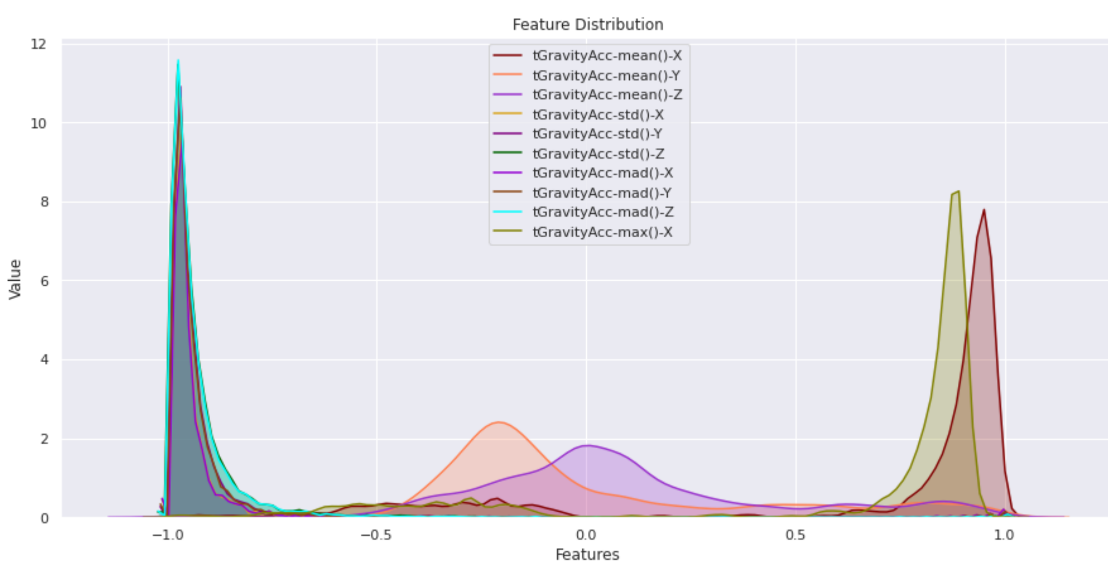
[13]:
```
sns.set(rc={'figure.figsize':(15,7)})
colours =␣
↪["maroon","coral","darkorchid","goldenrod","purple","darkgreen","darkviolet","saddlebrown",
index = -1
for i in train_df.columns[20:30]:
    index = index + 1
    ax1 = sns.kdeplot(train_df[i] , shade=True, color=colours[index])
plt.xlabel("Features")
plt.ylabel("Value")
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig)
```



[14]:
```
sns.set(rc={'figure.figsize':(15,7)})
colours =␣
↪["maroon","coral","darkorchid","goldenrod","purple","darkgreen","darkviolet","saddlebrown",
index = -1
for i in train_df.columns[30:40]:
    index = index + 1
    ax1 = sns.kdeplot(train_df[i] , shade=True, color=colours[index])
plt.xlabel("Features")
plt.ylabel("Value")
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig)
```

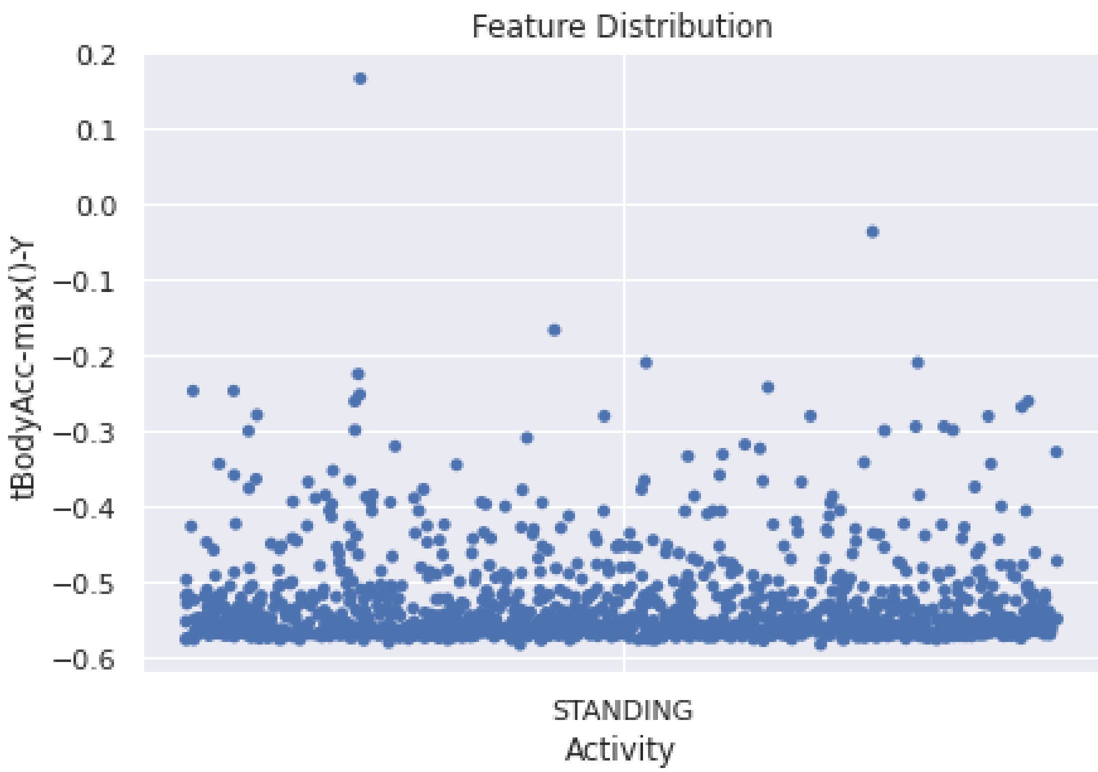


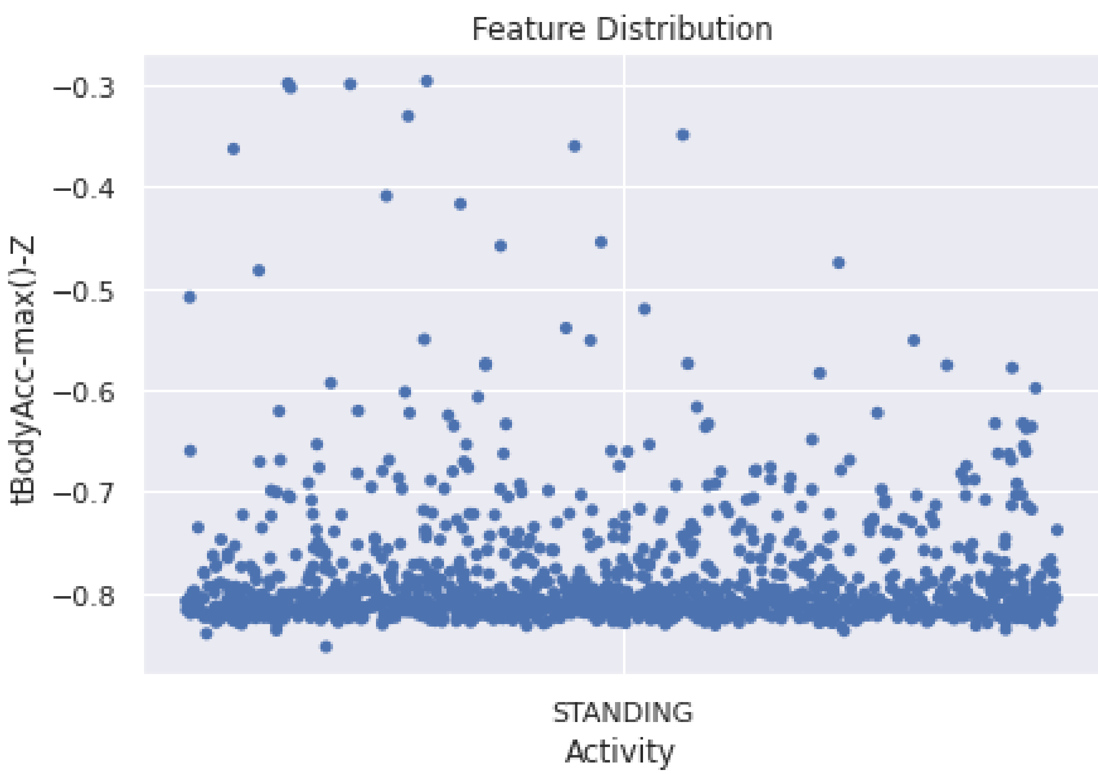
[15]:
```
sns.set(rc={'figure.figsize':(15,7)})
colours =␣
↪["maroon","coral","darkorchid","goldenrod","purple","darkgreen","darkviolet","saddlebrown",
index = -1
for i in train_df.columns[40:50]:
    index = index + 1
    ax1 = sns.kdeplot(train_df[i] , shade=True, color=colours[index])
plt.xlabel("Features")
plt.ylabel("Value")
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig)
```

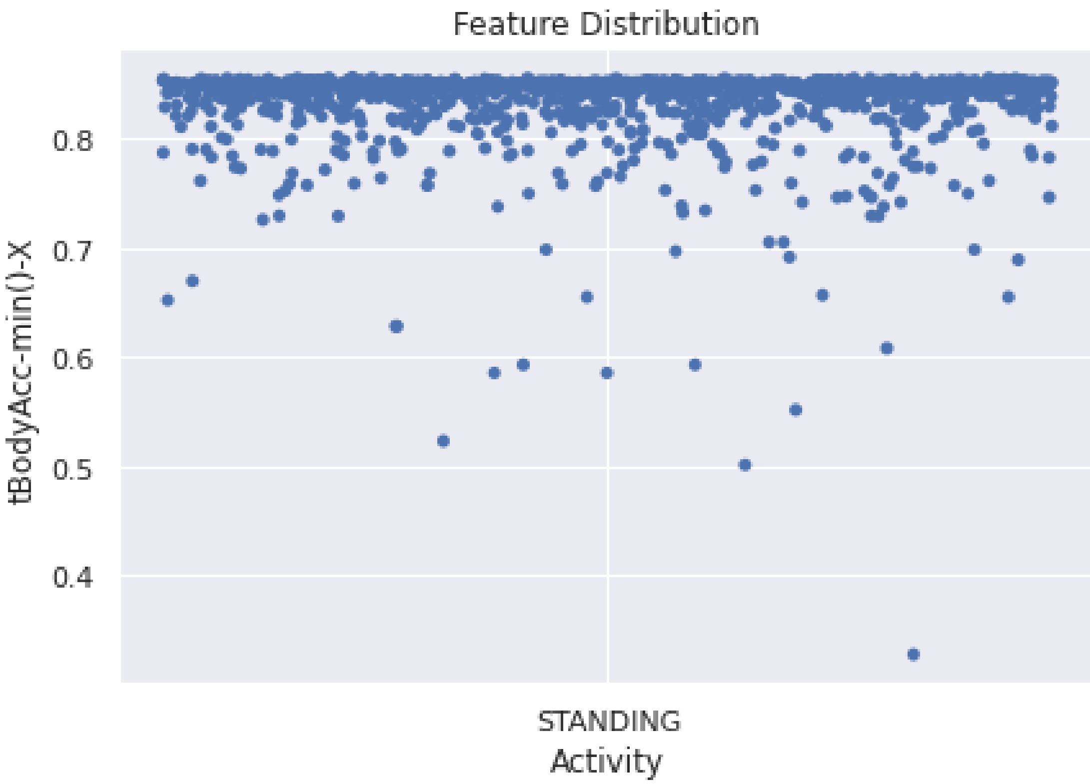


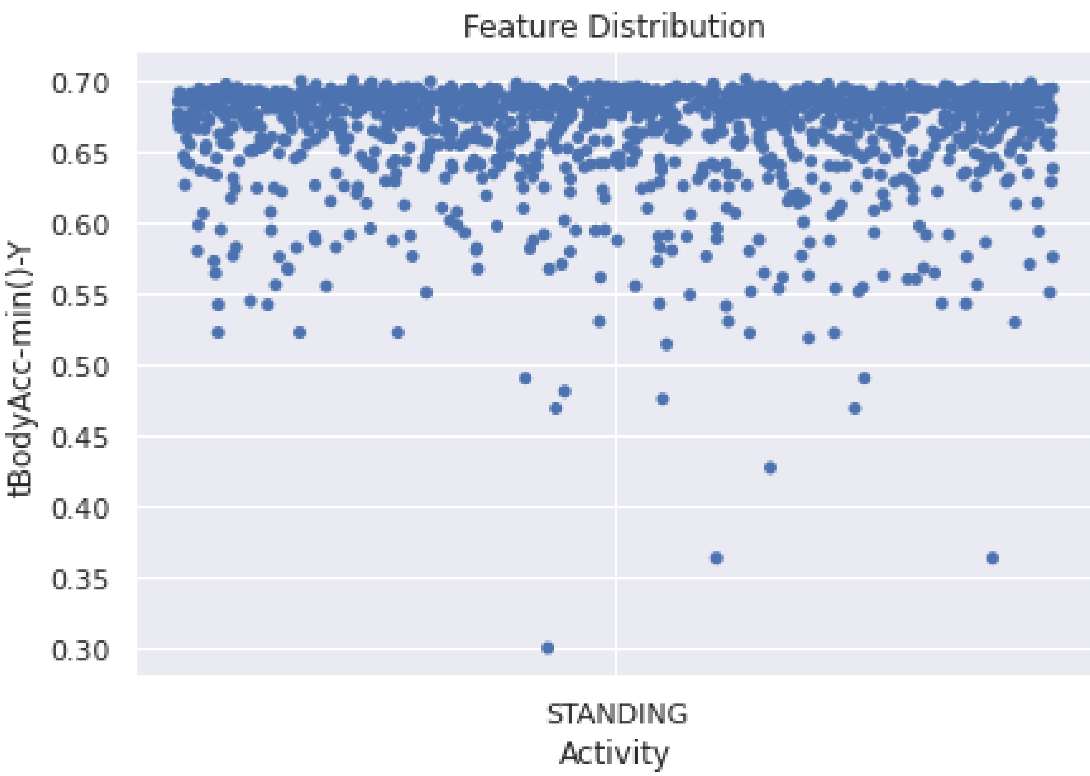
[16]:

```
sns.set(rc={'figure.figsize':(15,10)})
plt.subplot(221)
fig1 = sns.stripplot(x='Activity', y= train_df.
 ↪loc[train_df['Activity']=="STANDING"].iloc[:,10], data= train_df.
 ↪loc[train_df['Activity']=="STANDING"], jitter=True)
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig1)
plt.subplot(224)
fig2 = sns.stripplot(x='Activity', y= train_df.
 ↪loc[train_df['Activity']=="STANDING"].iloc[:,11], data= train_df.
 ↪loc[train_df['Activity']=="STANDING"], jitter=True)
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig2)
plt.subplot(223)
fig2 = sns.stripplot(x='Activity', y= train_df.
 ↪loc[train_df['Activity']=="STANDING"].iloc[:,12], data= train_df.
 ↪loc[train_df['Activity']=="STANDING"], jitter=True)
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig2)
plt.subplot(222)
fig2 = sns.stripplot(x='Activity', y= train_df.
 ↪loc[train_df['Activity']=="STANDING"].iloc[:,13], data= train_df.
 ↪loc[train_df['Activity']=="STANDING"], jitter=True)
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig2)
```

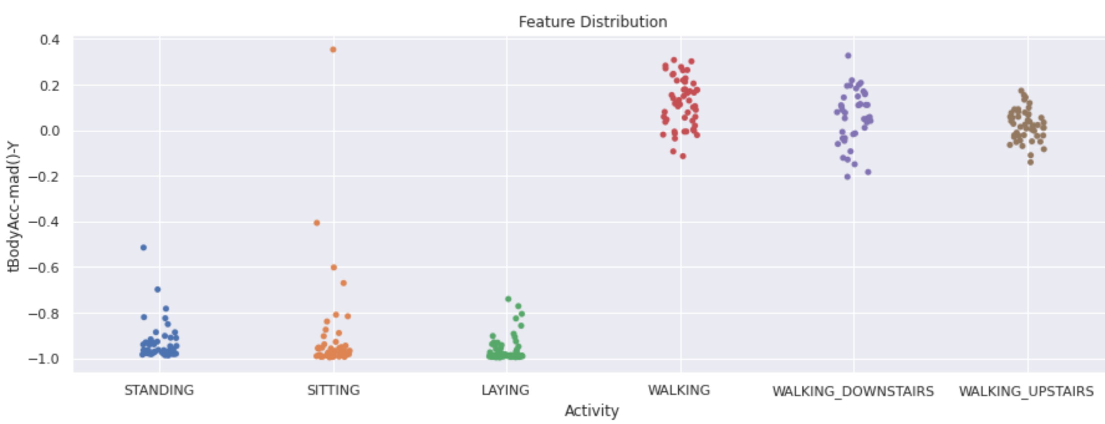

Feature Distribution
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
tBodyAcc-max()-Y
STANDING
Activity


Feature Distribution
−0.3
−0.4
−0.5
−0.6
−0.7
−0.8
tBodyAcc-max()-Z
STANDING
Activity


Feature Distribution
tBodyAcc-min()-X
0.8
0.7
0.6
0.5
0.4
STANDING
Activity

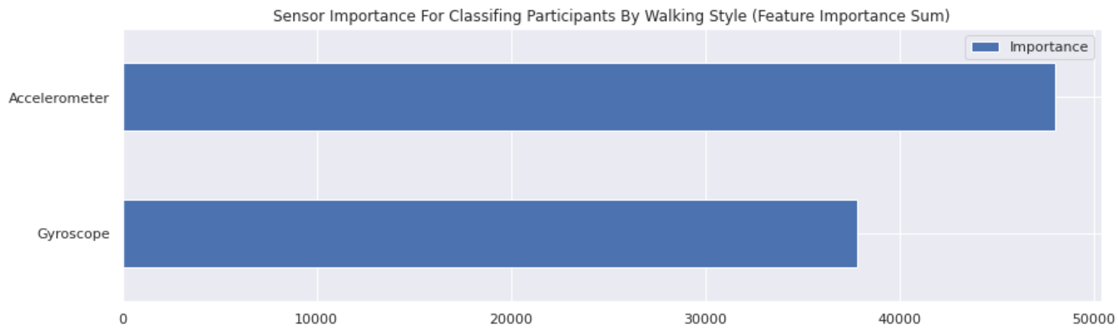


[17]:
```
sns.set(rc={'figure.figsize':(15,5)})
fig1 = sns.stripplot(x='Activity', y= train_df.loc[train_df['subject']==15].
 ↪iloc[:,7], data= train_df.loc[train_df['subject']==15], jitter=True)
plt.title("Feature Distribution")
plt.grid(True)
plt.show(fig1)
```

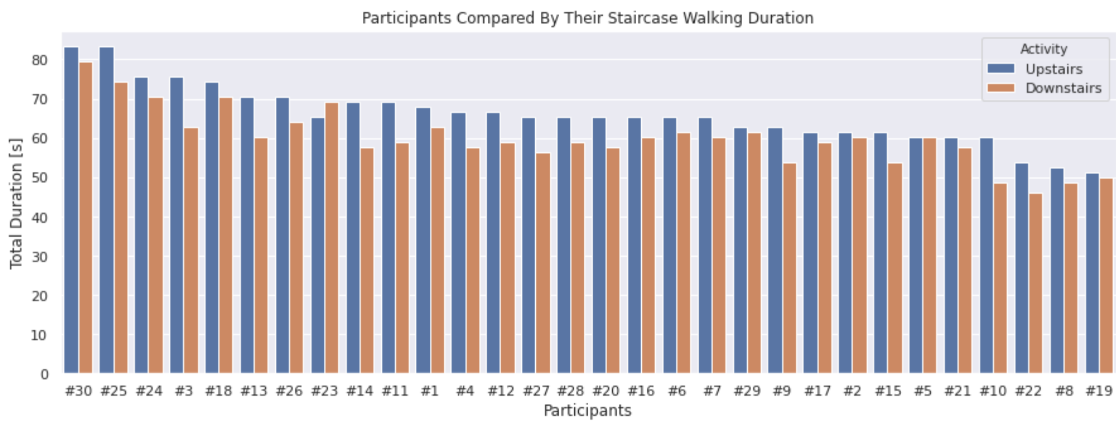


[18]:

```
# Create dataset
tsne_data = both_df[label=='WALKING'].copy()
data_data = tsne_data.pop('Data')
subject_data = tsne_data.pop('subject')

# Scale data
scl = StandardScaler()
tsne_data = scl.fit_transform(tsne_data)

# Split training testing data
enc = LabelEncoder()
label_encoded = enc.fit_transform(subject_data)
X_train, X_test, y_train, y_test = train_test_split(tsne_data, label_encoded,␣
↪random_state=3)


# Create model
lgbm = LGBMClassifier(n_estimators=500, random_state=3)
lgbm = lgbm.fit(X_train, y_train)

# Get importances
features = both_df.drop(['Data', 'subject'], axis=1).columns
importances = lgbm.feature_importances_

# Sum importances
data = {'Gyroscope':0, 'Accelerometer':0}
for importance, feature in zip(importances, features):
    if 'Gyro' in feature:
        data['Gyroscope'] += importance
    if 'Acc' in feature:
        data['Accelerometer'] += importance

# Create dataframe and plot
sensor_df = pd.DataFrame.from_dict(data, orient='index').rename(columns={0:
↪'Importance'})
sensor_df.plot(kind='barh', figsize=(14,4), title='Sensor Importance For␣
↪Classifing Participants By Walking Style (Feature Importance Sum)')
plt.show()
```

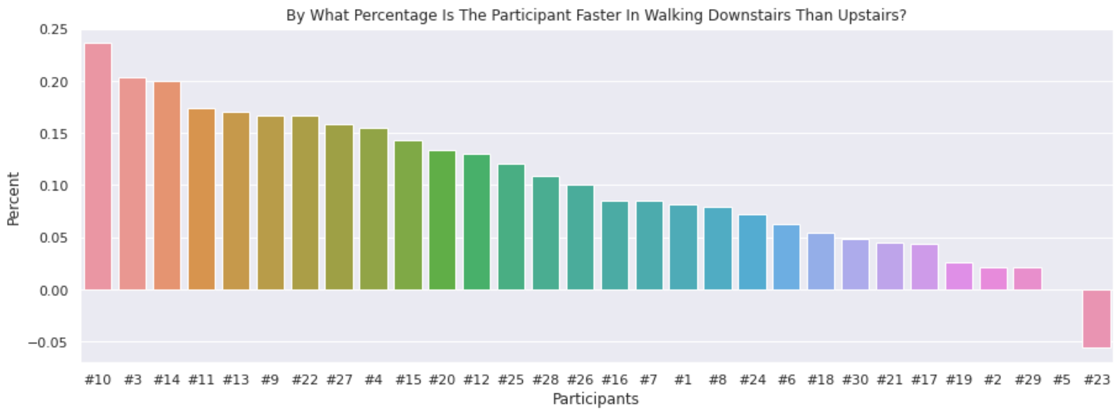


[19]:
```
# Group the data by participant and compute total duration of staircase walking
mask = label.isin(['WALKING_UPSTAIRS', 'WALKING_DOWNSTAIRS'])
duration_df = (both_df[mask].groupby([label[mask], 'subject'])['Data'].count()␣
 ↪* 1.28)

# Create plot
plot_data = duration_df.reset_index().sort_values('Data', ascending=False)
plot_data['Activity'] = plot_data['Activity'].map({'WALKING_UPSTAIRS':
 ↪'Upstairs', 'WALKING_DOWNSTAIRS':'Downstairs'})

plt.figure(figsize=(15,5))
sns.barplot(data=plot_data, x='subject', y='Data', hue='Activity')
plt.title('Participants Compared By Their Staircase Walking Duration')
plt.xlabel('Participants')
plt.ylabel('Total Duration [s]')
plt.show()
```

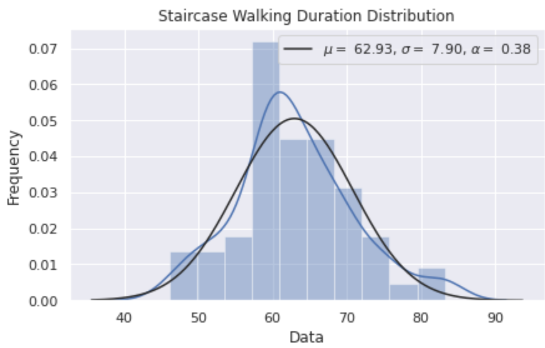


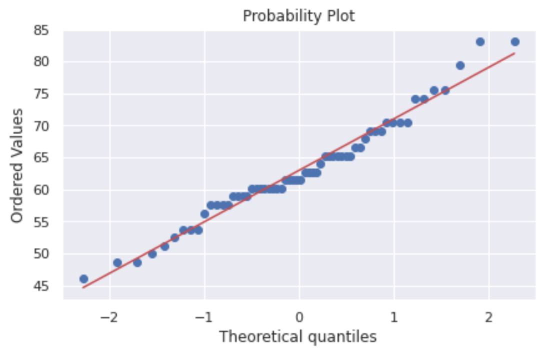
[20]:
```
# Create data and plot
plt.figure(figsize=(15,5))
```

```
plot_data = ((duration_df.loc['WALKING_UPSTAIRS'] / duration_df.
↪loc['WALKING_DOWNSTAIRS']) -1).sort_values(ascending=False)
sns.barplot(x=plot_data.index, y=plot_data)
plt.title('By What Percentage Is The Participant Faster In Walking Downstairs␣
↪Than Upstairs?')
plt.xlabel('Participants')
plt.ylabel('Percent')
plt.show()
```

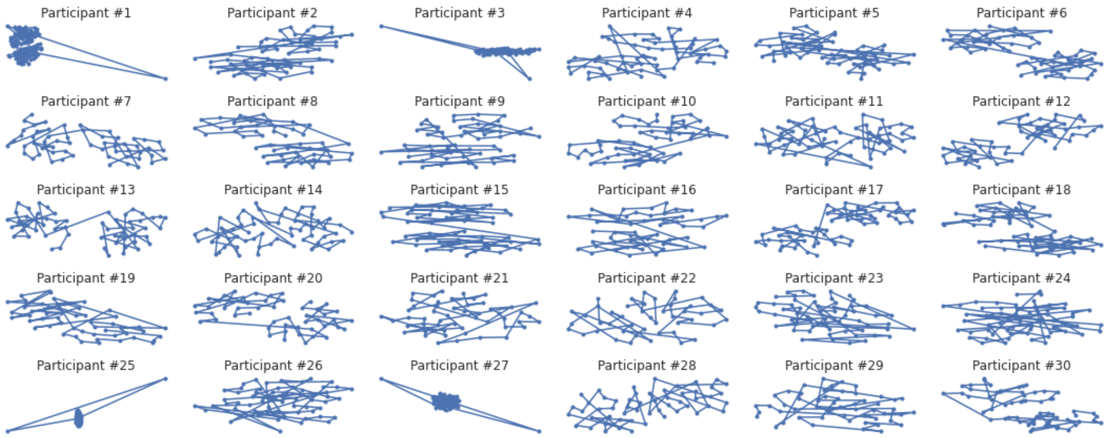


[21]:
```
def plotSkew(x):
    # Fit label to norm
    (mu, sigma) = norm.fit(x)
    alpha = skew(x)

    fig, axarr = plt.subplots(1, 2, figsize=(15,4))

    # Plot label and fit
    sns.distplot(x , fit=norm, ax=axarr[0])
    axarr[0].legend(['$\mu=$ {:.2f}, $\sigma=$ {:.2f}, $\\alpha=$ {:.2f}'.
↪format(mu, sigma, alpha)], loc='best')
    axarr[0].set_title('Staircase Walking Duration Distribution')
    axarr[0].set_ylabel('Frequency')

    # Plot probability plot
    res = probplot(x, plot=axarr[1])
    plt.show()


plotSkew(duration_df)
```

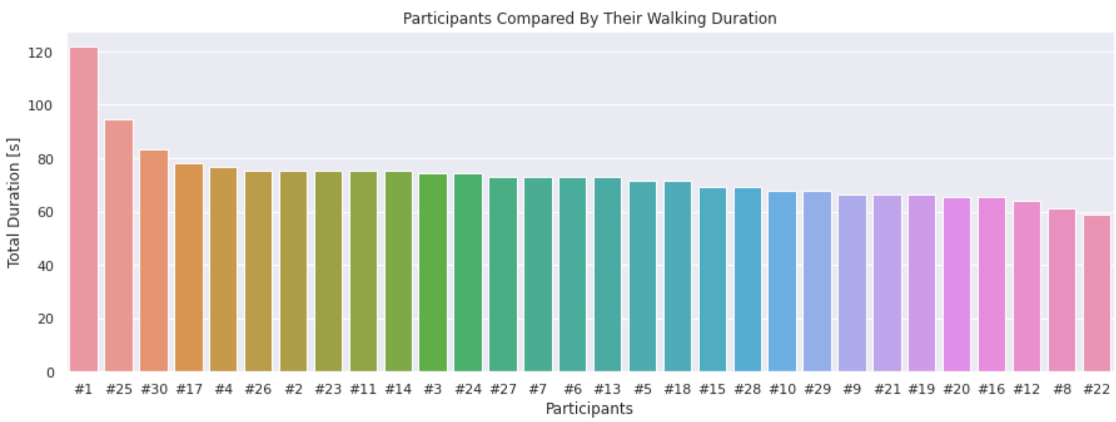




[22]:
```
fig, axarr = plt.subplots(5, 6, figsize=(15,6))

for person in range(0, 30):
    # Get data
    single_person = both_df[(label=='WALKING') & (both_df['subject']=='#{}'.
↪format(person+1))].drop(['subject', 'Data'], axis=1)
    # Scale data
    scl = StandardScaler()
    tsne_data = scl.fit_transform(single_person)
    # Reduce dimensions
    pca = PCA(n_components=0.9, random_state=3)
    tsne_data = pca.fit_transform(tsne_data)
    # Transform data
    tsne = TSNE(random_state=3)
    tsne_transformed = tsne.fit_transform(tsne_data)

    # Create plot
    axarr[person//6][person%6].plot(tsne_transformed[:,0], tsne_transformed[:
↪,1], '.-')
    axarr[person//6][person%6].set_title('Participant #{}'.format(person+1))
    axarr[person//6][person%6].axis('off')

plt.tight_layout()
plt.show()
```

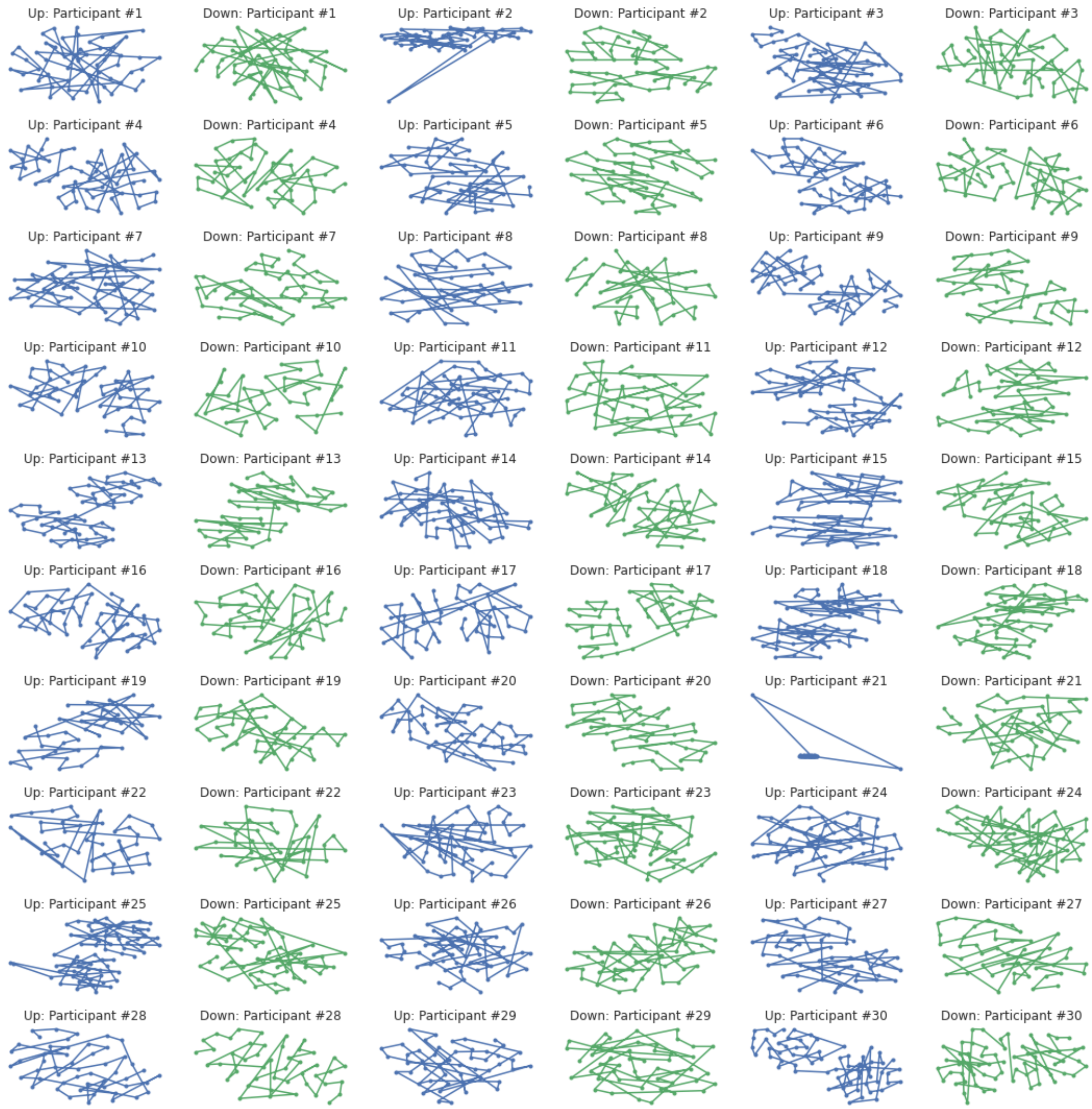


[23]:
```
# Group the data by participant and compute total duration of walking
mask = label=='WALKING'
duration_df = (both_df[mask].groupby('subject')['Data'].count() * 1.28)

# Create plot
plot_data = duration_df.reset_index().sort_values('Data', ascending=False)

plt.figure(figsize=(15,5))
sns.barplot(data=plot_data, x='subject', y='Data')
plt.title('Participants Compared By Their Walking Duration')
plt.xlabel('Participants')
plt.ylabel('Total Duration [s]')
plt.show()
```



[24]:
```
# Create subplots
fig, axarr = plt.subplots(10, 6, figsize=(15,15))
```

```
# Iterate over each participant
for person in range(0, 30):
    # Get data
    single_person_up = both_df[(label=='WALKING_UPSTAIRS') &␣
↪(both_df['subject']=='#{}'.format(person+1))].drop(['subject', 'Data'],␣
↪axis=1)
    single_person_down = both_df[(label=='WALKING_DOWNSTAIRS') &␣
↪(both_df['subject']=='#{}'.format(person+1))].drop(['subject', 'Data'],␣
↪axis=1)
    # Scale data
    scl = StandardScaler()
    tsne_data_up = scl.fit_transform(single_person_up)
    tsne_data_down = scl.fit_transform(single_person_down)
    # Reduce dimensions
    pca = PCA(n_components=0.9, random_state=3)
    tsne_data_up = pca.fit_transform(tsne_data_up)
    tsne_data_down = pca.fit_transform(tsne_data_down)
    # Transform data
    tsne = TSNE(random_state=3)
    tsne_transformed_up = tsne.fit_transform(tsne_data_up)
    tsne_transformed_down = tsne.fit_transform(tsne_data_down)

    # Create plot
    axarr[2*person//6][2*person%6].plot(tsne_transformed_up[:,0],␣
↪tsne_transformed_up[:,1], '.b-')
    axarr[2*person//6][2*person%6].set_title('Up: Participant #{}'.
↪format(person+1))
    axarr[2*person//6][2*person%6].axis('off')
    axarr[2*person//6][(2*person%6)+1].plot(tsne_transformed_down[:,0],␣
↪tsne_transformed_down[:,1], '.g-')
    axarr[2*person//6][(2*person%6)+1].set_title('Down: Participant #{}'.
↪format(person+1))
    axarr[2*person//6][(2*person%6)+1].axis('off')

plt.tight_layout()
plt.show()
```



[25]:

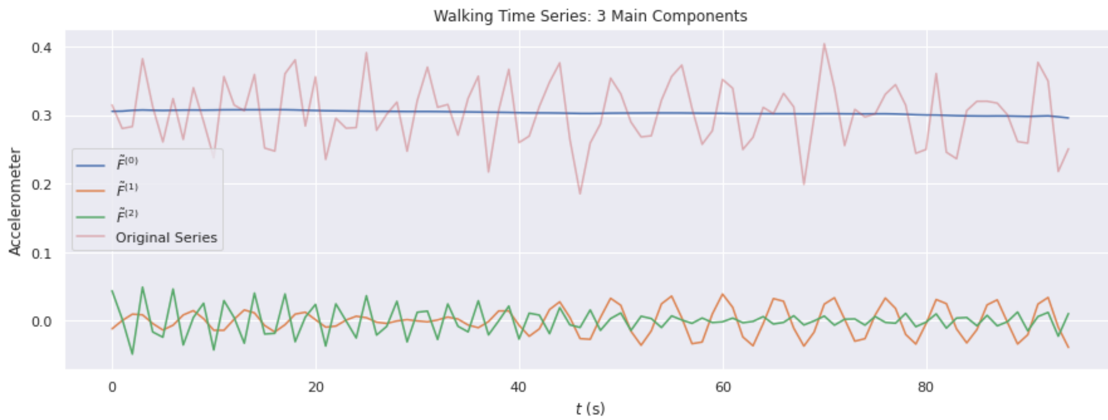
```
# Use SS class fro jdarcy
class SSA(object):
    __supported_types = (pd.Series, np.ndarray, list)

    def __init__(self, tseries, L, save_mem=True):
        '''
        Decomposes the given time series with a singular-spectrum analysis.␣
 ↪Assumes the values of the time series are
        recorded at equal intervals.

        Parameters
        ----------
```

```
        tseries : The original time series, in the form of a Pandas Series,␣
↪NumPy array or list.
        L : The window length. Must be an integer 2 <= L <= N/2, where N is the␣
↪length of the time series.
        save_mem : Conserve memory by not retaining the elementary matrices.␣
↪Recommended for long time series with
            thousands of values. Defaults to True.

        Note: Even if an NumPy array or list is used for the initial time␣
↪series, all time series returned will be
        in the form of a Pandas Series or DataFrame object.
        '''

        # Tedious type-checking for the initial time series
        if not isinstance(tseries, self.__supported_types):
            raise TypeError('Unsupported time series object. Try Pandas Series,␣
↪NumPy array or list.')

        # Checks to save us from ourselves
        self.N = len(tseries)
        if not 2 <= L <= self.N/2:
            raise ValueError('The window length must be in the interval [2, N/
↪2].')

        self.L = L
        self.orig_TS = pd.Series(tseries)
        self.K = self.N - self.L + 1

        # Embed the time series in a trajectory matrix
        self.X = np.array([self.orig_TS.values[i:L+i] for i in range(0, self.
↪K)]).T

        # Decompose the trajectory matrix
        self.U, self.Sigma, VT = np.linalg.svd(self.X)
        self.d = np.linalg.matrix_rank(self.X)

        self.TS_comps = np.zeros((self.N, self.d))

        if not save_mem:
            # Construct and save all the elementary matrices
            self.X_elem = np.array([ self.Sigma[i]*np.outer(self.U[:,i], VT[i,:
↪]) for i in range(self.d) ])

            # Diagonally average the elementary matrices, store them as columns␣
↪in array.
            for i in range(self.d):
```

```
                X_rev = self.X_elem[i, ::-1]
                self.TS_comps[:,i] = [X_rev.diagonal(j).mean() for j in␣
↪range(-X_rev.shape[0]+1, X_rev.shape[1])]

            self.V = VT.T
        else:
            # Reconstruct the elementary matrices without storing them
            for i in range(self.d):
                X_elem = self.Sigma[i]*np.outer(self.U[:,i], VT[i,:])
                X_rev = X_elem[::-1]
                self.TS_comps[:,i] = [X_rev.diagonal(j).mean() for j in␣
↪range(-X_rev.shape[0]+1, X_rev.shape[1])]

            self.X_elem = 'Re-run with save_mem=False to retain the elementary␣
↪matrices.'

            # The V array may also be very large under these circumstances, so␣
↪we won't keep it.
            self.V = 'Re-run with save_mem=False to retain the V matrix.'

        # Calculate the w-correlation matrix.
        self.calc_wcorr()

    def components_to_df(self, n=0):
        '''
        Returns all the time series components in a single Pandas DataFrame␣
↪object.
        '''
        if n > 0:
            n = min(n, self.d)
        else:
            n = self.d

        # Create list of columns - call them F0, F1, F2, ...
        cols = ['F{}'.format(i) for i in range(n)]
        return pd.DataFrame(self.TS_comps[:, :n], columns=cols, index=self.
↪orig_TS.index)


    def reconstruct(self, indices):
        '''
        Reconstructs the time series from its elementary components, using the␣
↪given indices. Returns a Pandas Series
        object with the reconstructed time series.

        Parameters
```

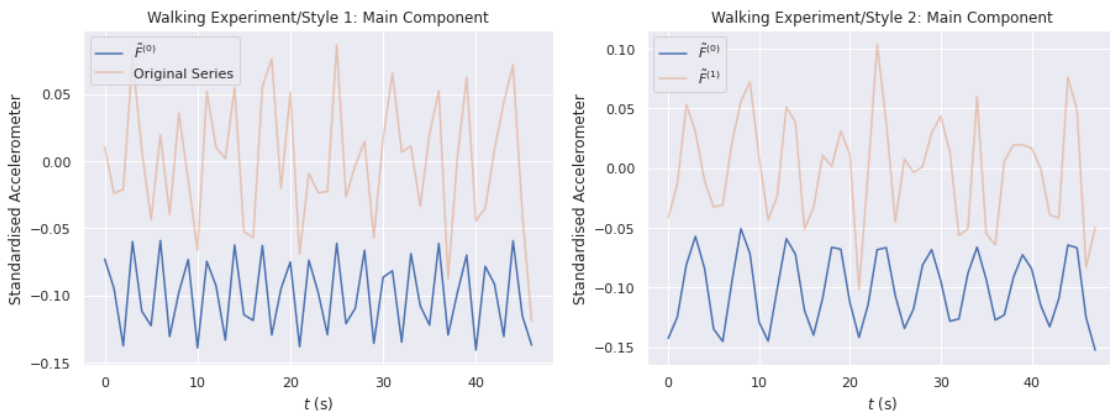
```
        ----------
        indices: An integer, list of integers or slice(n,m) object,␣
↪representing the elementary components to sum.
        '''
        if isinstance(indices, int): indices = [indices]

        ts_vals = self.TS_comps[:,indices].sum(axis=1)
        return pd.Series(ts_vals, index=self.orig_TS.index)

    def calc_wcorr(self):
        '''
        Calculates the w-correlation matrix for the time series.
        '''

        # Calculate the weights
        w = np.array(list(np.arange(self.L)+1) + [self.L]*(self.K-self.L-1) +␣
↪list(np.arange(self.L)+1)[::-1])

        def w_inner(F_i, F_j):
            return w.dot(F_i*F_j)

        # Calculated weighted norms, ||F_i||_w, then invert.
        F_wnorms = np.array([w_inner(self.TS_comps[:,i], self.TS_comps[:,i])␣
↪for i in range(self.d)])
        F_wnorms = F_wnorms**-0.5

        # Calculate Wcorr.
        self.Wcorr = np.identity(self.d)
        for i in range(self.d):
            for j in range(i+1,self.d):
                self.Wcorr[i,j] = abs(w_inner(self.TS_comps[:,i], self.
↪TS_comps[:,j]) * F_wnorms[i] * F_wnorms[j])
                self.Wcorr[j,i] = self.Wcorr[i,j]

    def plot_wcorr(self, min=None, max=None):
        '''
        Plots the w-correlation matrix for the decomposed time series.
        '''
        if min is None:
            min = 0
        if max is None:
            max = self.d

        if self.Wcorr is None:
            self.calc_wcorr()

        ax = plt.imshow(self.Wcorr)
```

```
        plt.xlabel(r'$\tilde{F}_i$')
        plt.ylabel(r'$\tilde{F}_j$')
        plt.colorbar(ax.colorbar, fraction=0.045)
        ax.colorbar.set_label('$W_{i,j}$')
        plt.clim(0,1)

        # For plotting purposes:
        if max == self.d:
            max_rnge = self.d-1
        else:
            max_rnge = max

        plt.xlim(min-0.5, max_rnge+0.5)
        plt.ylim(max_rnge+0.5, min-0.5)


# Euclidean norm of the acceleration
walking_series = both_df[(label=='WALKING') &␣
 ↪(both_df['subject']=='#1')][['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y',␣
 ↪'tBodyAcc-mean()-Z']].reset_index(drop=True)
walking_series = (walking_series**2).sum(axis=1)**0.5

# Decomposing the series
series_ssa = SSA(walking_series, 30)

# Plotting the decomposition
plt.figure(figsize=(15,5))
series_ssa.reconstruct(0).plot()
series_ssa.reconstruct([1,2]).plot()
series_ssa.reconstruct([3,4]).plot()
series_ssa.orig_TS.plot(alpha=0.4)
plt.title('Walking Time Series: 3 Main Components')
plt.xlabel(r'$t$ (s)')
plt.ylabel('Accelerometer')
legend = [r'$\tilde{{F}}^{{({0})}}$'.format(i) for i in range(3)] + ['Original␣
 ↪Series']
plt.legend(legend);
```



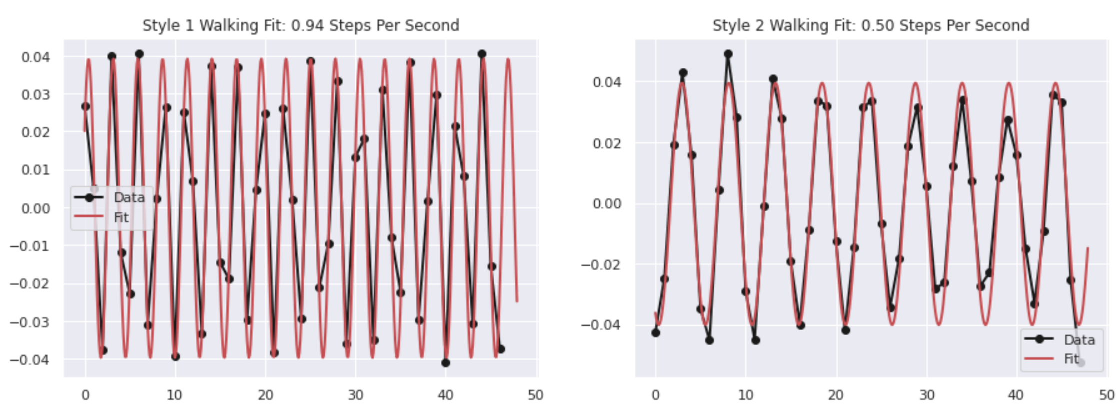
[26]:
```
# Both walking styles from a single participant
style1 = both_df.loc[78:124][['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y',␣
↪'tBodyAcc-mean()-Z']].reset_index(drop=True)
style1 = ((style1**2).sum(axis=1)**0.5)
style1 -= style1.mean()
style2 = both_df.loc[248:295][['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y',␣
↪'tBodyAcc-mean()-Z']].reset_index(drop=True)
style2 = (style2**2).sum(axis=1)**0.5
style2 -= style2.mean()

# Decompose
style1_ssa = SSA(style1, 20)
style2_ssa = SSA(style2, 20)

# Create plot
fig, axarr = plt.subplots(1, 2, figsize=(15,5))

# Plotting the decomposition style 1
(style1_ssa.reconstruct([0,1])-0.1).plot(ax=axarr[0])
style1_ssa.orig_TS.plot(alpha=0.4, ax=axarr[0])
axarr[0].set_title('Walking Experiment/Style 1: Main Component')
axarr[0].set_xlabel(r'$t$ (s)')
axarr[0].set_ylabel('Standardised Accelerometer')
legend = [r'$\tilde{{F}}^{{({0})}}$'.format(i) for i in range(1)] + ['Original␣
↪Series']
axarr[0].legend(legend);

# Plotting the decomposition style 2
(style2_ssa.reconstruct([0,1])-0.1).plot(ax=axarr[1])
style2_ssa.orig_TS.plot(alpha=0.4, ax=axarr[1])
axarr[1].set_title('Walking Experiment/Style 2: Main Component')
axarr[1].set_xlabel(r'$t$ (s)')
```

```
axarr[1].set_ylabel('Standardised Accelerometer')
legend = [r'$\tilde{{F}}^{{({0})}}$'.format(i) for i in range(3)] + ['Original Series']
axarr[1].legend(legend);
```



[27]:
```
# Function to fit a sinus
def fit_sin(tt, yy):
    '''Fit sin to the input time sequence, and return fitting parameters "amp", "omega", "phase", "offset", "freq", "period" and "fitfunc"'''
    tt = np.array(tt)
    yy = np.array(yy)
    # Assume uniform spacing
    ff = np.fft.fftfreq(len(tt), (tt[1]-tt[0]))
    Fyy = abs(np.fft.fft(yy))
    # Exclude the zero frequency "peak"
    guess_freq = abs(ff[np.argmax(Fyy[1:])+1])
    guess_amp = np.std(yy) * 2.**0.5
    guess_offset = np.mean(yy)
    guess = np.array([guess_amp, 2.*np.pi*guess_freq, 0., guess_offset])

    # Sinus
    def sinfunc(t, A, w, p, c):
        return A * np.sin(w*t + p) + c

    # Fit sinus
    popt, pcov = curve_fit(sinfunc, tt, yy, p0=guess)
    A, w, p, c = popt
    f = w/(2.*pi)
    fitfunc = lambda t: A * np.sin(w*t + p) + c
    return {"amp": A, "omega": w, "phase": p, "offset": c, "freq": f, "period": 1./f, "fitfunc": fitfunc, "maxcov": np.max(pcov), "rawres": (guess,popt,pcov)}
```

```
# Get data
main_style1 = style1_ssa.reconstruct([0, 1])
tt1 = main_style1.index
yy1 = main_style1.values
tt_res1 = np.arange(0, 48, 0.1)
# Fit data
res1 = fit_sin(tt1, yy1)

# Get data
main_style2 = style2_ssa.reconstruct([0, 1])
tt2 = main_style2.index
yy2 = main_style2.values
tt_res2 = np.arange(0, 48, 0.1)
# Fit data
res2 = fit_sin(tt2, yy2)

# Plot data
fig, axarr = plt.subplots(1, 2, figsize=(15,5))

# Plot data
axarr[0].plot(tt1, yy1, "-ok", label='Data', linewidth=2)
axarr[0].plot(tt_res1, res1['fitfunc'](tt_res1), "r-", label='Fit', linewidth=2)
axarr[0].set_title('Style 1 Walking Fit: {:.2f} Steps Per Second'.
 ↪format((res1['omega']*1.28)/(pi)))
axarr[0].legend(loc="best")

axarr[1].plot(tt2, yy2, "-ok", label='Data', linewidth=2)
axarr[1].plot(tt_res2, res2['fitfunc'](tt_res2), "r-", label='Fit', linewidth=2)
axarr[1].set_title('Style 2 Walking Fit: {:.2f} Steps Per Second'.
 ↪format((res2['omega']*1.28)/(pi)))
axarr[1].legend(loc="best")
plt.show()
```



[28]:

```
# Get data
tsne_data = both_df[label=='WALKING'].copy()
data_data = tsne_data.pop('Data')
subject_data = tsne_data.pop('subject')

# Scale data
scl = StandardScaler()
tsne_data = scl.fit_transform(tsne_data)

# Reduce dimensions
pca = PCA(n_components=0.9, random_state=3)
tsne_data = pca.fit_transform(tsne_data)

# Transform data
tsne = TSNE(random_state=3)
tsne_transformed = tsne.fit_transform(tsne_data)


# Create subplots
fig, axarr = plt.subplots(1, 1, figsize=(15,10))

### Plot Subjects
# Get colors
n = subject_data.unique().shape[0]
colormap = get_cmap('gist_ncar')
colors = [rgb2hex(colormap(col)) for col in np.arange(0, 1.01, 1/(n-1))]

for i, group in enumerate(subject_data.unique()):
    # Mask to separate sets
    mask = (subject_data==group).values
    axarr.scatter(x=tsne_transformed[mask][:,0], y=tsne_transformed[mask][:,1],␣
 ↪c=colors[i], alpha=0.5, label=group)

axarr.set_title('TSNE Walking Style By Participant')
plt.show()
```

Feature Scaling

Pre-processing and data preparation to feed data into Artificial Neural Network.

[29]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(train_df.iloc[:,0:562])
mat_train = scaler.transform(train_df.iloc[:,0:562])
print(mat_train)
```

```
[[0.64429225 0.48985291 0.43354743 … 0.79825103 0.47068654 0.        ]
 [0.63920942 0.49179472 0.4382399  … 0.79848665 0.47284164 0.        ]
 [0.63982653 0.49026642 0.44326915 … 0.79872236 0.47544109 0.        ]
 …
 [0.63669369 0.49149469 0.47748909 … 0.84506893 0.52040559 1.        ]
 [0.64482708 0.49057848 0.42085971 … 0.84323381 0.51266974 1.        ]
 [0.67575173 0.49378844 0.39806642 … 0.84348837 0.51834742 1.        ]]
```

[30]:
```
scaler = MinMaxScaler()
scaler.fit(test_df.iloc[:,0:562])
mat_test = scaler.transform(test_df.iloc[:,0:562])
print(mat_test)
```

```
[[0.6718788  0.55764282 0.52464834 … 0.62209457 0.46362736 0.        ]
 [0.69470427 0.57426358 0.42707858 … 0.62446791 0.45014396 0.        ]
```

```
[0.68636345 0.55310221 0.42794829 … 0.62380956 0.45251181 0.         ]
…
[0.74529355 0.64526771 0.43015674 … 0.62088108 0.58803909 1.         ]
[0.65638384 0.62620241 0.44817885 … 0.61581385 0.59135763 1.         ]
[0.58994885 0.56560474 0.41032069 … 0.61537208 0.59163879 1.         ]]
```

[31]:
```
temp = []
for i in train_df.Activity:
    if i == "WALKING": temp.append(0)
    if i == "WALKING_UPSTAIRS": temp.append(1)
    if i == "WALKING_DOWNSTAIRS": temp.append(2)
    if i == "SITTING": temp.append(3)
    if i == "STANDING": temp.append(4)
    if i == "LAYING": temp.append(5)
train_df["n_Activity"] = temp
```

[32]:
```
temp = []
for i in test_df.Activity:
    if i == "WALKING": temp.append(0)
    if i == "WALKING_UPSTAIRS": temp.append(1)
    if i == "WALKING_DOWNSTAIRS": temp.append(2)
    if i == "SITTING": temp.append(3)
    if i == "STANDING": temp.append(4)
    if i == "LAYING": temp.append(5)
test_df["n_Activity"] = temp
```

[33]:
```
train_df.drop(["Activity"] , axis = 1 , inplace = True)
```

[34]:
```
test_df.drop(["Activity"] , axis = 1 , inplace = True)
```

[35]:
```
from keras.utils import to_categorical
y_train = to_categorical(train_df.n_Activity , num_classes=6)
y_test = to_categorical(test_df.n_Activity , num_classes=6)
```

[36]:
```
X_train = mat_train
X_test = mat_test
```

[37]:
```
print(X_train.shape , y_train.shape)
print(X_test.shape , y_test.shape)
```

```
(7352, 562) (7352, 6)
(2947, 562) (2947, 6)
```