HAR - HUMAN ACTIVITY RECOGNITION

Project Code

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Semester : 6-C

Session : Spring 2024

Course : Artificial Intelligence

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The Human Activity Recognition database was built from the recordings of 30 study participants performing activities of daily living (ADL) while carrying a waist mounted smartphone with embedded inertial sensors. The objective is to classify activities into one of the six activities performed. The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers were selected for generating the training data and 30% the test data.

1. Import Libraries:

```
# 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
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
```

2. Load Data:

```
# Load datasets
train_df = pd.read_csv('../input/train.csv')
test_df = pd.read_csv('../input/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)

# 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()
```

OUTPUT:

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

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

5 rows × 564 columns

3. Data Exploration:

3.1 Which features are there?

The features seem to have a main name and some information on how they have been computed attached. Grouping the main names will reduce the dimensions for the first impression.

```
# 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)
```

OUTPUT:

	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

3.2 What types of data are there?

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

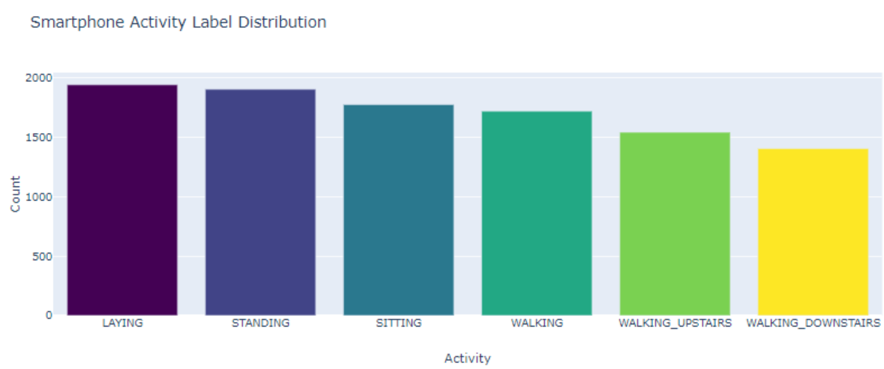
OUTPUT:

```
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
```

3.3 How are the labels distributed?

```
# 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)
```

OUTPUT:



4. Activity Exploration:

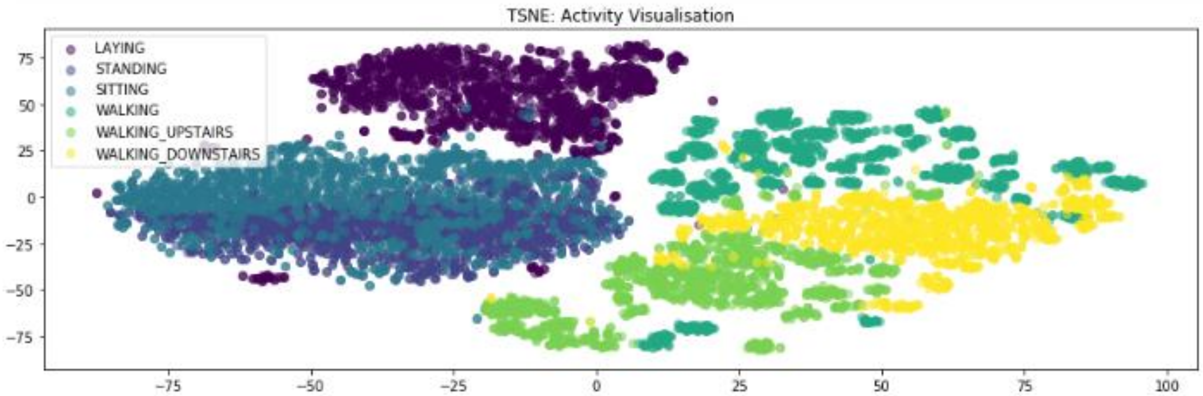
4.1 Are the activities separable?

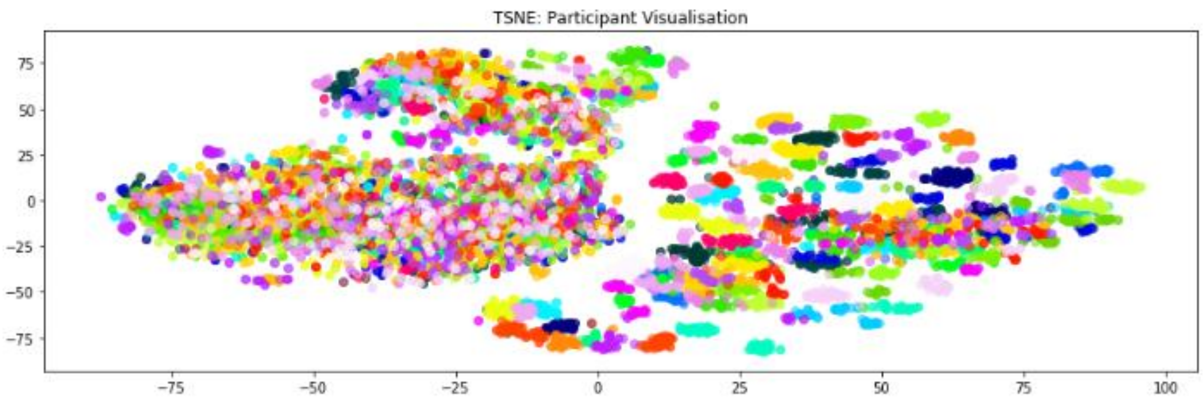
The dataset is geared towards classifying the activity of the participant. Let us investigate the separability of the classes.

```
# 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)
```

```python
# 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()
```

OUTPUT:





4.2 How good are the activities separable?

Without much preprocessing and parameter tuning a simple LGBMClassifier should work decently.

```
# 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))
```

OUTPUT:

```
Accuracy on testset:    0.9553
```

5. Participants Exploration:

5.1 How good are the participants separable?

As we have seen in the second t-SNE plot the separability of the participants seem to vary regarding their activity. Let us investigate this a little bit by fitting the same basic model to the data of each activity separately.

```
# 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])
```

OUTPUT:

```
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
```

5.2 How Long Does The Smartphone Gather Data For This Accuracy?

Single datapoint is gathered every 1.28 sec.

```
# 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)
```

OUTPUT:

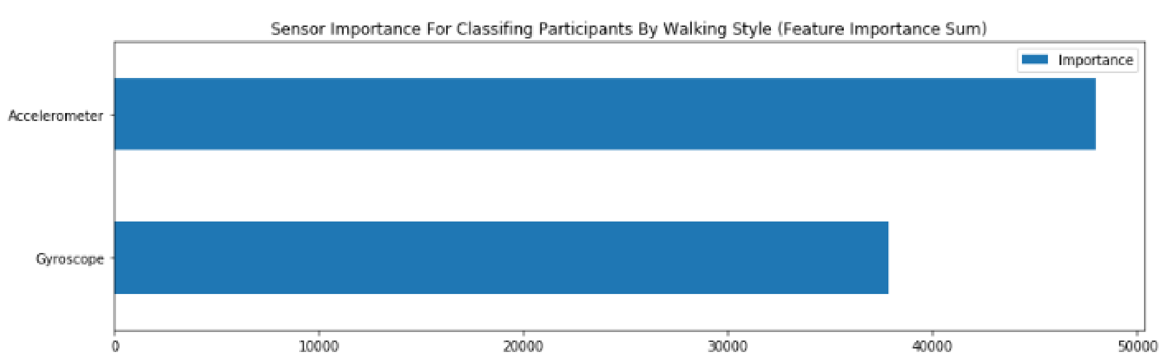
Activity	Accuracy	Seconds
LAYING	0.648148	82.944000
STANDING	0.549266	81.322667
SITTING	0.530337	75.818667
WALKING	0.951276	73.472000
WALKING_UPSTAIRS	0.924870	65.877333
WALKING_DOWNSTAIRS	0.909091	59.989333

5.3 Which Sensor Is More Important for Classifying Participants By Walking Style?

I will fit another basic model to the walking data and investigate the feature importances afterwards. Since there are so many features I am going to group them by their sensor (accelerometer = Acc, gyroscope = Gyro)

```
# 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()
```

OUTPUT:

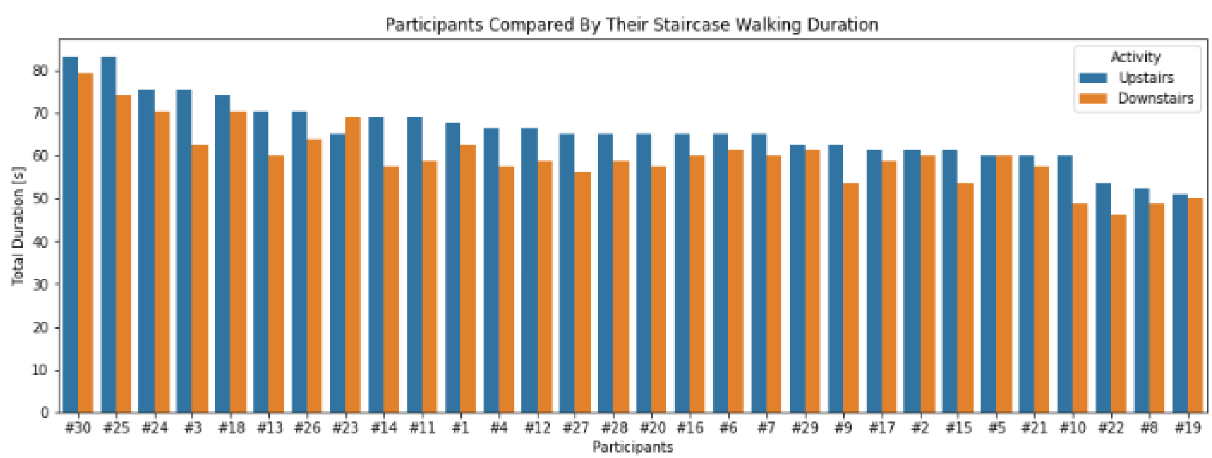


5.4 How Long Does The Participant Use The Staircase?

Since the dataset has been created in an scientific environment nearly equal preconditions for the participants can be assumed. It is highly likely for the participants to have been walking up and down the same number of staircases. Let us investigate their activity durations.

```
# 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()
```

OUTPUT:

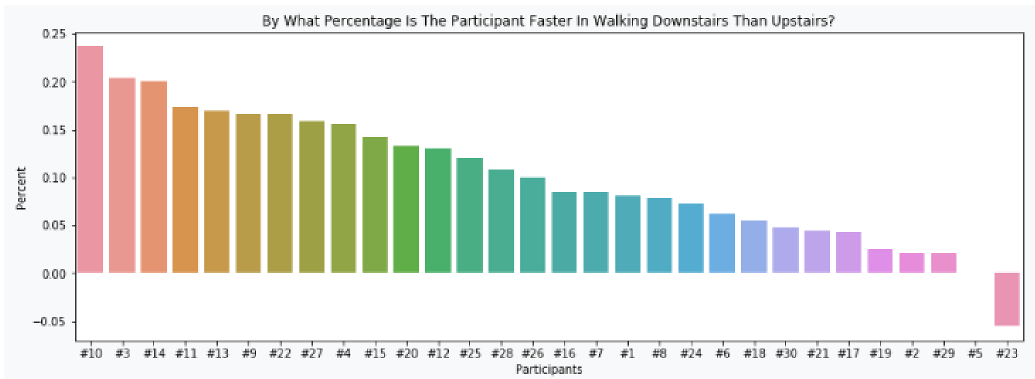


5.5 How Much Does The Up-/Downstairs Ratio Vary?

```
6.  # 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()
```

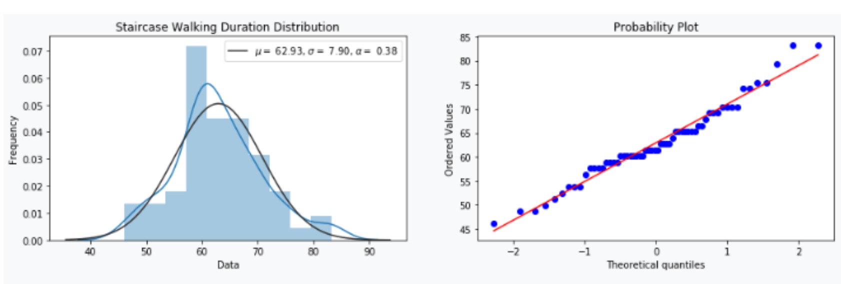
OUTPUT:



5.6 Are There Conspicuities In The Staircase Walking Duration Distribution?

```
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)
```

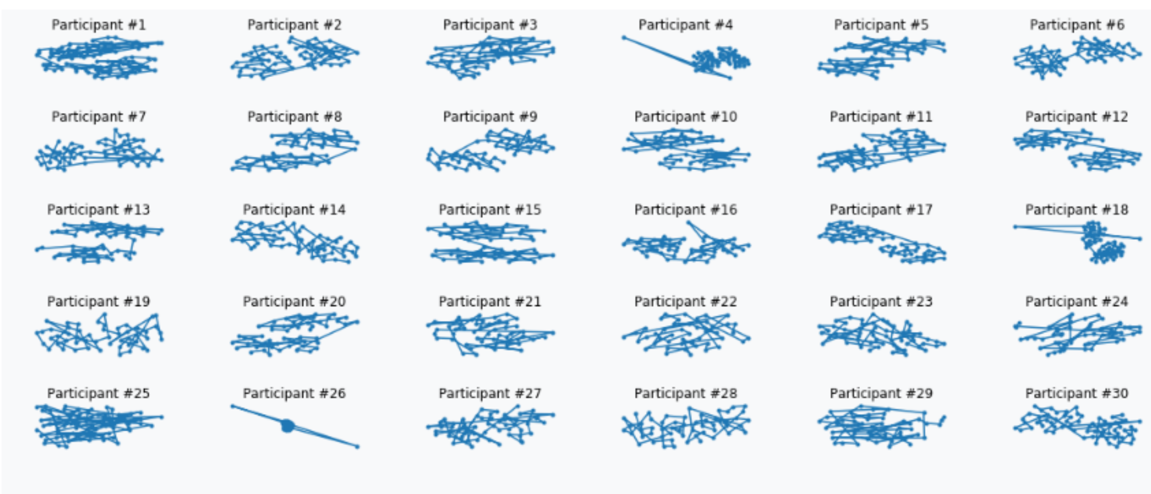
OUTPUT:



5.7 Is There A Unique Walking Style For Each Participant?

```
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()
```

OUTPUT:

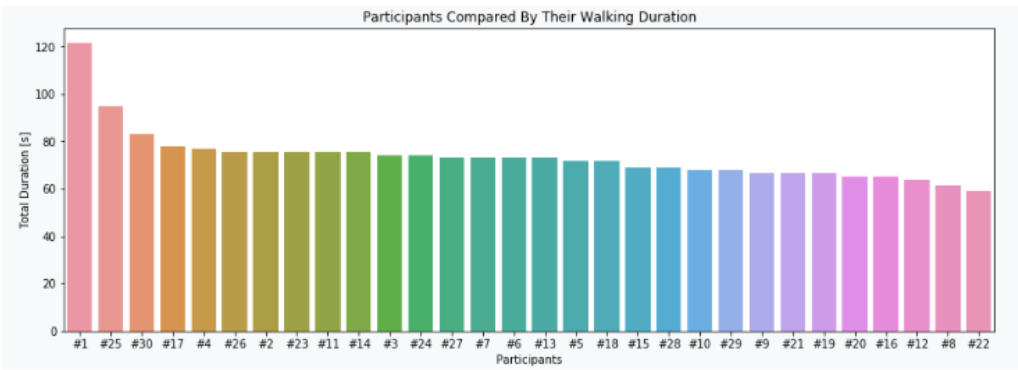


5.8 How Long Does The Participant Walk?

```
# 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()
```

OUTPUT:

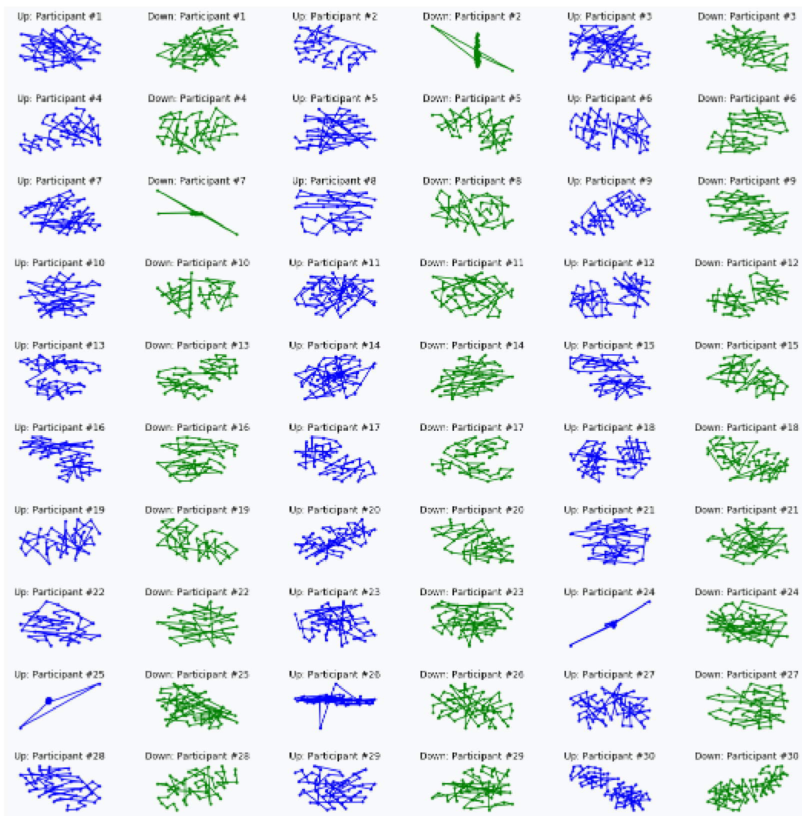


5.9 Is There A Unique Staircase Walking Style For Each Participant?

```
# 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()
```

OUTPUT:



6. Exploring Personal Information:

6.1 What Is The Walking Frequency Of A Single Participant?

We could extract the main components of the walking style of the participants using only the euclidean norm of the three accelerometer axes.

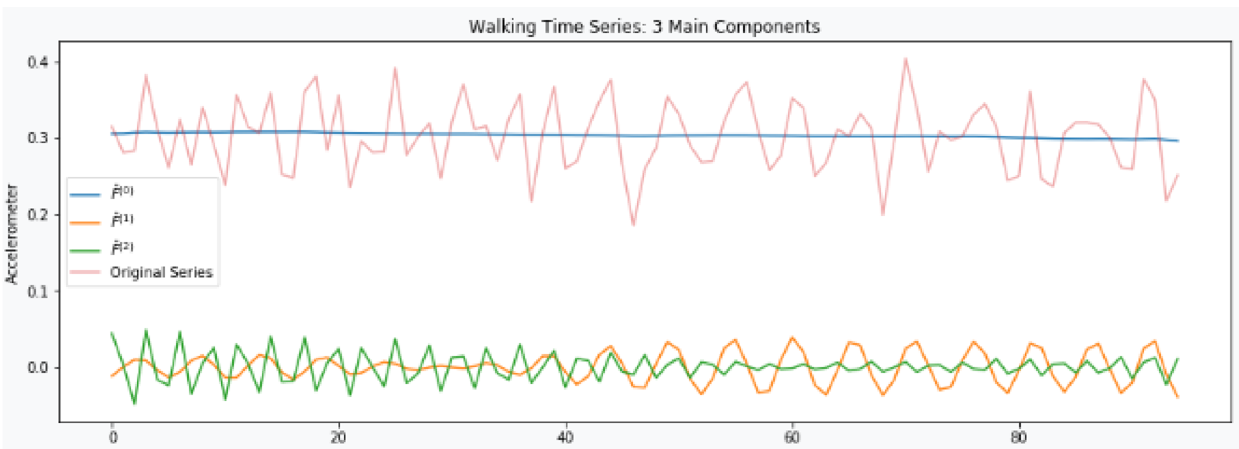
```
# Use SS class fro jdarcy
class SSA(object):
    __supported_types = (pd.Series, np.ndarray, list)

    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);
```

OUTPUT:



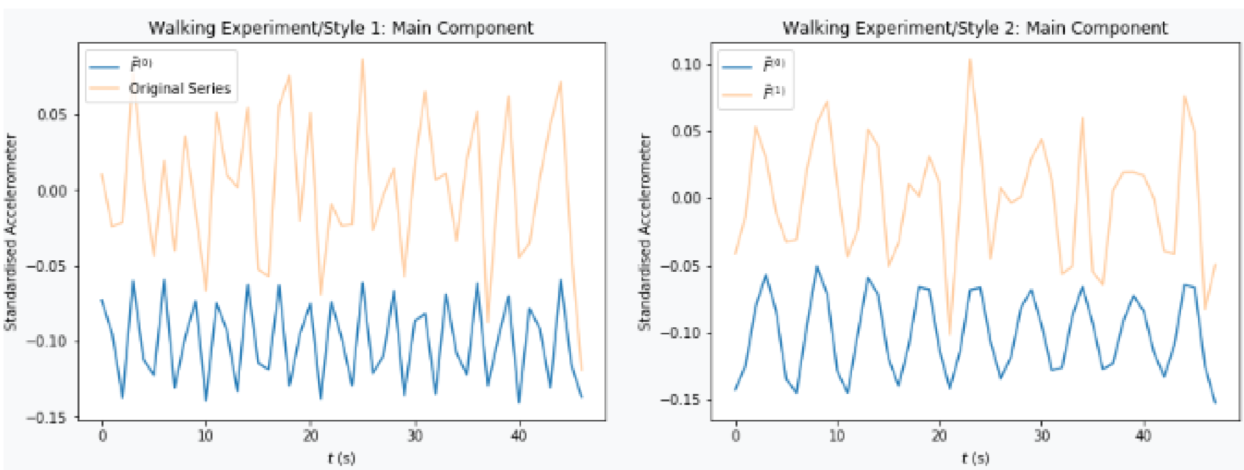
6.2 What Is The Walking Frequency Of Both Found Speeds?

Both experiments of a single person have been split and will be analysed separately.

```
# 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);
```

OUTPUT:



7. Conclusion:

Within a short time (1-1.5 min) the smartphone has enough data to determine what its user is doing (95%: 6 activities) or who the user is (Walking 94%: 30 participants) and even the basics of a person's specific walking style (Slow steps per second). By linking these insights to more personal data of the participants extensive options open up.

In addition, these insights have been extracted from only two smartphone sensors which probably could be accessed by most of our Apps.