

▼ Data Cleaning & Preprocessing

```
1 # importing libraries
2 %matplotlib inline
3 import numpy as np
4 import pandas as pd
5 import matplotlib.pyplot as plt
6 import seaborn as sns
7 import warnings
8 warnings.filterwarnings('ignore')

1 # reading raw data file
2 columns = ['user', 'activity', 'timestamp', 'x-axis', 'y-axis', 'z-axis']
3 df_har = pd.read_csv('WISDM_ar_v1.1_raw.txt', header = None, names = columns)

1 # removing null values
2 df_har = df_har.dropna()
3 df_har.shape

(1098203, 6)

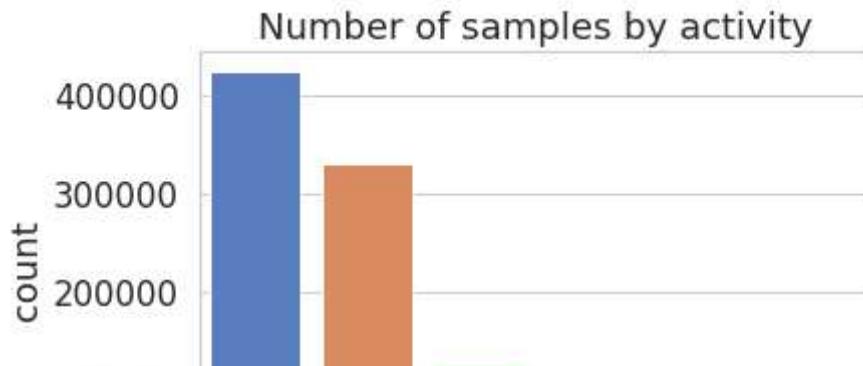
1 # transforming the z-axis to float
2 df_har['z-axis'] = df_har['z-axis'].str.replace(';', '')
3 df_har['z-axis'] = df_har['z-axis'].apply(lambda x:float(x))

1 # drop rows where timestamp is 0
2 df = df_har[df_har['timestamp'] != 0]

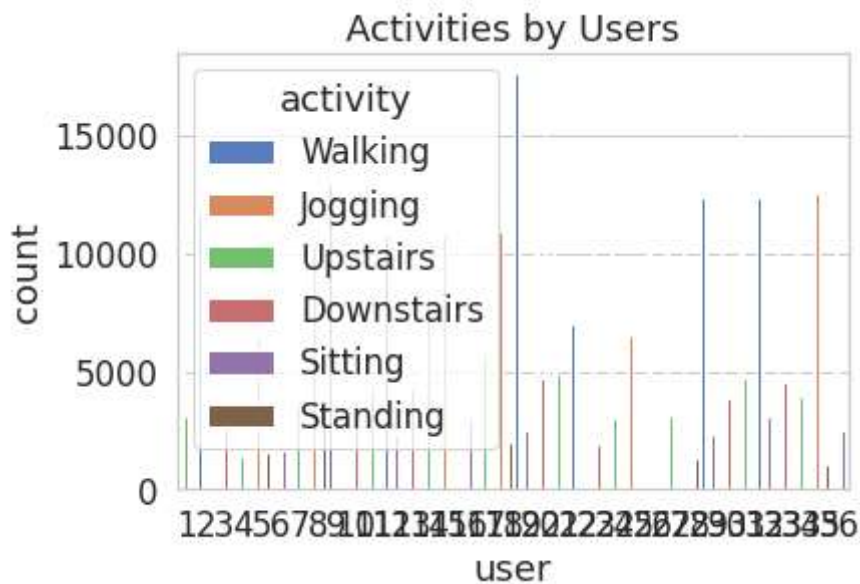
1 # arrange data in ascending order of user and timestamp
2 df = df.sort_values(by = ['user', 'timestamp'], ignore_index=True)
```

▼ Exploratory Data Analysis

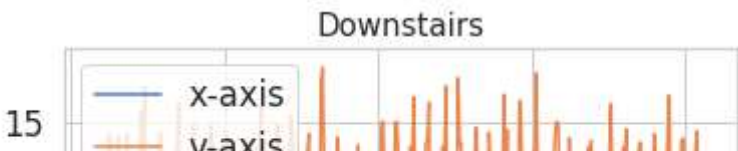
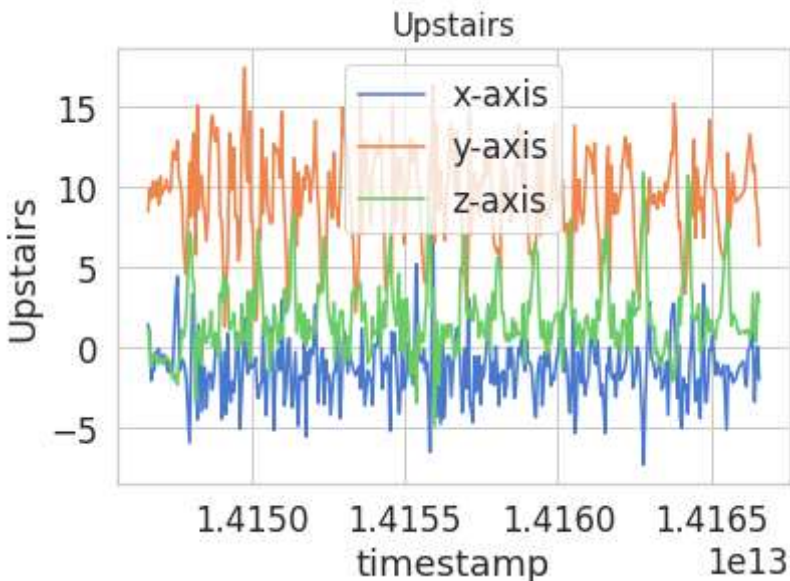
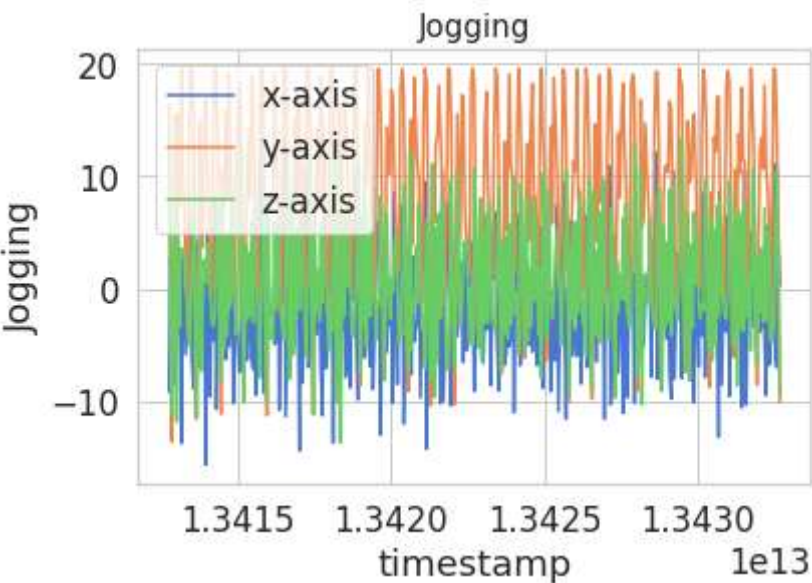
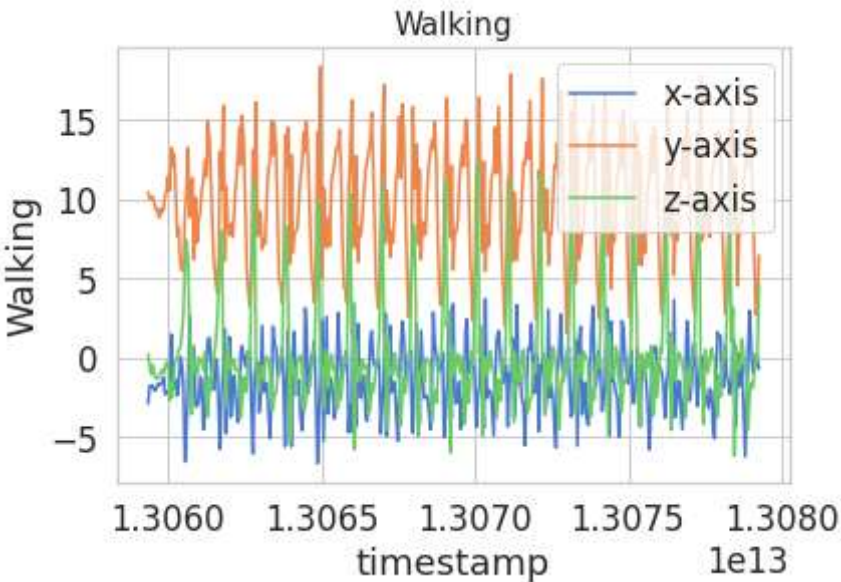
```
1 sns.set_style("whitegrid")
2 sns.countplot(x = 'activity', data = df)
3 plt.title('Number of samples by activity')
4 plt.show()
```

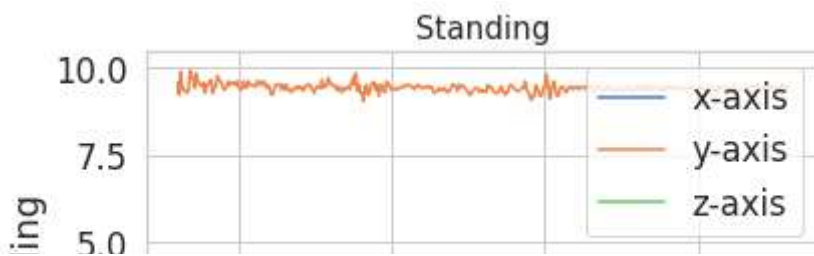
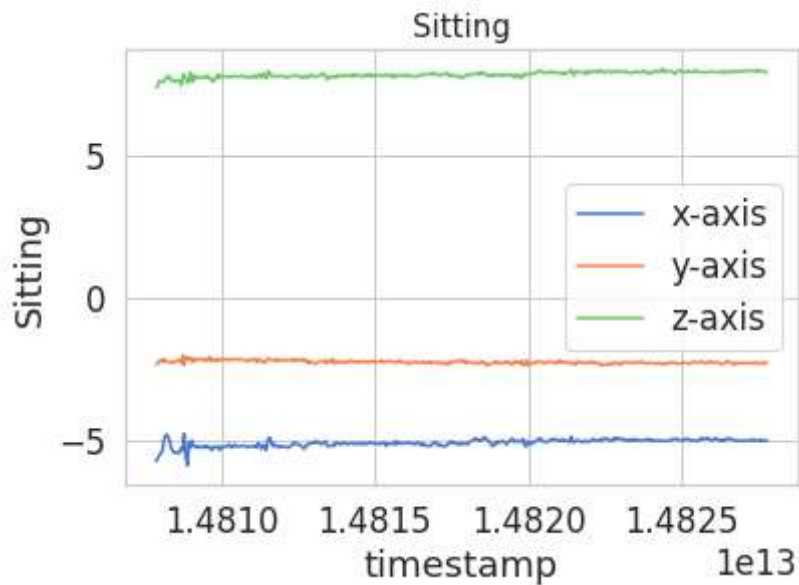
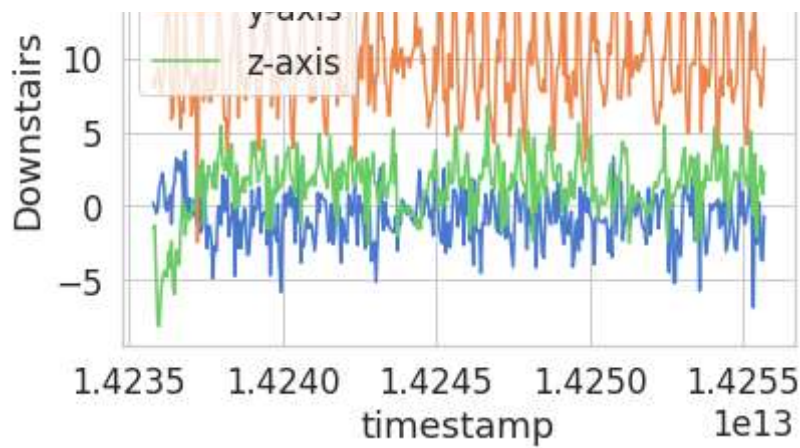


```
1 sns.countplot(x = 'user', hue = 'activity', data = df)
2 plt.title('Activities by Users')
3 plt.show()
```



```
1 activities = ['Walking', 'Jogging', 'Upstairs', 'Downstairs', 'Sitting', 'Standing']
2 for i in activities:
3     data36 = df[(df['user'] == 36) & (df['activity'] == i)][0:400]
4     sns.lineplot(y = 'x-axis', x = 'timestamp', data = data36)
5     sns.lineplot(y = 'y-axis', x = 'timestamp', data = data36)
6     sns.lineplot(y = 'z-axis', x = 'timestamp', data = data36)
7     plt.legend(['x-axis', 'y-axis', 'z-axis'])
8     plt.ylabel(i)
9     plt.title(i, fontsize = 15)
10    plt.show()
```





▼ Preparing Data

```

1 random_seed = 42
2 n_time_steps = 50
3 n_features = 3
4 step = 10
5 n_classes = 6
6 n_epochs = 50
7 batch_size = 1024
8 learning_rate = 0.0025
9 l2_loss = 0.0015

```

```

1 segments = []
2 labels = []
3

```

```

4 for i in range(0, df.shape[0]- n_time_steps, step):
5
6     xs = df['x-axis'].values[i: i + 50]
7
8     ys = df['y-axis'].values[i: i + 50]
9
10    zs = df['z-axis'].values[i: i + 50]
11
12    label = stats.mode(df['activity'][i: i + 50])[0][0]
13
14    segments.append([xs, ys, zs])
15
16    labels.append(label)
17
18 #reshape the segments which is (list of arrays) to a list
19 reshaped_segments = np.asarray(segments, dtype= np.float32).reshape(-1, n_time_steps, n_features)
20
21 labels = np.asarray(pd.get_dummies(labels), dtype = np.float32)

1 reshaped_segments.shape

(108531, 50, 3)

1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(reshaped_segments, labels, test_size = 0.2, random_st

```

▼ Building Model Architecture

```

1 from keras.models import Sequential
2 from keras.layers import LSTM, Dense, Flatten, Dropout

1 model = Sequential()
2 # RNN layer
3 model.add(LSTM(units = 128, input_shape = (X_train.shape[1], X_train.shape[2])))
4 # Dropout layer
5 model.add(Dropout(0.5))
6 # Dense layer with ReLu
7 model.add(Dense(units = 64, activation='relu'))
8 # Softmax layer
9 model.add(Dense(y_train.shape[1], activation = 'softmax'))
10 # Compile model
11 model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

1 model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
lstm (LSTM)	(None, 128)	67584

dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 64)	8256
dense_1 (Dense)	(None, 6)	390

```

=====
Total params: 76,230
Trainable params: 76,230
Non-trainable params: 0

```

▼ Model Training & Evaluation

```
1 history = model.fit(X_train, y_train, epochs = n_epochs, validation_split = 0.20, batch_size = batch_size
```

```

Epoch 23/50
68/68 [=====] - 65s 958ms/step - loss: 0.1452 - accuracy: 0
Epoch 24/50
68/68 [=====] - 66s 973ms/step - loss: 0.1369 - accuracy: 0
Epoch 25/50
68/68 [=====] - 62s 916ms/step - loss: 0.1362 - accuracy: 0
Epoch 26/50
68/68 [=====] - 62s 908ms/step - loss: 0.1316 - accuracy: 0
Epoch 27/50
68/68 [=====] - 64s 949ms/step - loss: 0.1284 - accuracy: 0
Epoch 28/50
68/68 [=====] - 63s 923ms/step - loss: 0.1240 - accuracy: 0
Epoch 29/50
68/68 [=====] - 62s 917ms/step - loss: 0.1183 - accuracy: 0
Epoch 30/50
68/68 [=====] - 64s 949ms/step - loss: 0.1119 - accuracy: 0
Epoch 31/50
68/68 [=====] - 62s 916ms/step - loss: 0.1166 - accuracy: 0
Epoch 32/50
68/68 [=====] - 63s 925ms/step - loss: 0.1143 - accuracy: 0
Epoch 33/50
68/68 [=====] - 65s 952ms/step - loss: 0.1036 - accuracy: 0
Epoch 34/50
68/68 [=====] - 67s 990ms/step - loss: 0.1084 - accuracy: 0
Epoch 35/50
68/68 [=====] - 65s 961ms/step - loss: 0.0995 - accuracy: 0
Epoch 36/50
68/68 [=====] - 74s 1s/step - loss: 0.0956 - accuracy: 0.96
Epoch 37/50
68/68 [=====] - 72s 1s/step - loss: 0.0969 - accuracy: 0.96
Epoch 38/50
68/68 [=====] - 68s 994ms/step - loss: 0.0924 - accuracy: 0
Epoch 39/50
68/68 [=====] - 64s 926ms/step - loss: 0.0881 - accuracy: 0
Epoch 40/50
68/68 [=====] - 62s 910ms/step - loss: 0.0910 - accuracy: 0
Epoch 41/50

```

```

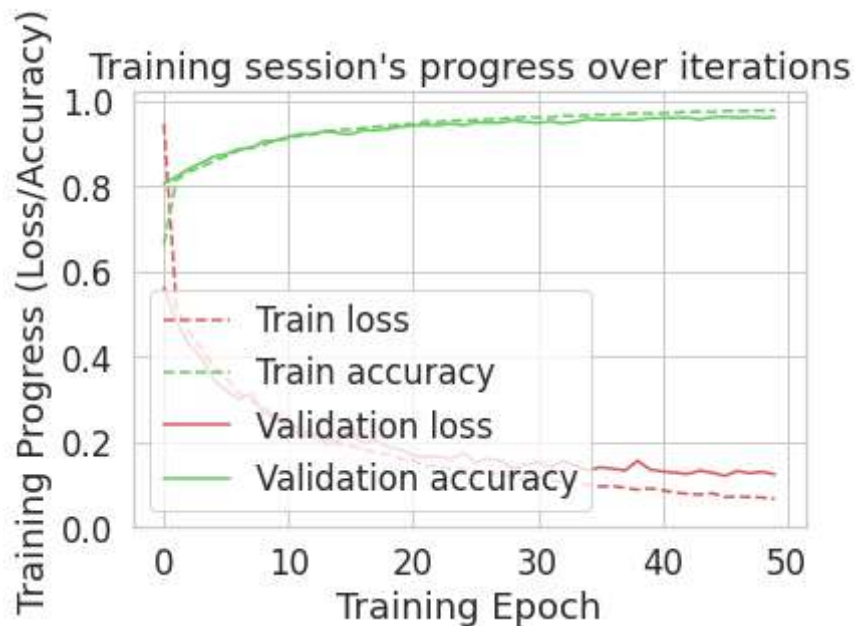
68/68 [=====] - 63s 933ms/step - loss: 0.0867 - accuracy: 0
Epoch 42/50
68/68 [=====] - 61s 903ms/step - loss: 0.0817 - accuracy: 0
Epoch 43/50
68/68 [=====] - 62s 908ms/step - loss: 0.0781 - accuracy: 0
Epoch 44/50
68/68 [=====] - 67s 981ms/step - loss: 0.0768 - accuracy: 0
Epoch 45/50
68/68 [=====] - 61s 899ms/step - loss: 0.0797 - accuracy: 0
Epoch 46/50
68/68 [=====] - 63s 925ms/step - loss: 0.0706 - accuracy: 0
Epoch 47/50
68/68 [=====] - 67s 983ms/step - loss: 0.0719 - accuracy: 0
Epoch 48/50
68/68 [=====] - 64s 940ms/step - loss: 0.0706 - accuracy: 0
Epoch 49/50
68/68 [=====] - 65s 959ms/step - loss: 0.0698 - accuracy: 0
Epoch 50/50
68/68 [=====] - 62s 917ms/step - loss: 0.0668 - accuracy: 0

```

```

1 plt.plot(np.array(history.history['loss']), "r--", label = "Train loss")
2 plt.plot(np.array(history.history['accuracy']), "g--", label = "Train accuracy")
3 plt.plot(np.array(history.history['val_loss']), "r-", label = "Validation loss")
4 plt.plot(np.array(history.history['val_accuracy']), "g-", label = "Validation accuracy")
5 plt.title("Training session's progress over iterations")
6 plt.legend(loc='lower left')
7 plt.ylabel('Training Progress (Loss/Accuracy)')
8 plt.xlabel('Training Epoch')
9 plt.ylim(0)
10 plt.show()

```



```

1 loss, accuracy = model.evaluate(X_test, y_test, batch_size = batch_size, verbose = 1)
2 print("Test Accuracy :", accuracy)

```

```
3 print("Test Loss :", loss)
```

```
22/22 [=====] - 7s 300ms/step - loss: 0.1190 - accuracy: 0.963
Test Accuracy : 0.9636062383651733
Test Loss : 0.11902851611375809
```

▼ Confusion matrix

```
1 predictions = model.predict(X_test)
2 class_labels = ['Downstairs', 'Jogging', 'Sitting', 'Standing', 'Upstairs', 'Walking']
3 max_test = np.argmax(y_test, axis=1)
4 max_predictions = np.argmax(predictions, axis=1)
5 confusion_matrix = metrics.confusion_matrix(max_test, max_predictions)
6 sns.heatmap(confusion_matrix, xticklabels = class_labels, yticklabels = class_labels, annot = True, linewidth
7 plt.title("Confusion matrix", fontsize = 15)
8 plt.ylabel('True label')
9 plt.xlabel('Predicted label')
10 plt.show()
```

