5/6/25, 2:40 AM AML_SEE_LPW.ipynb - Colab

Step 1: Mount Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

Step 2: Load and Parse the Raw Dataset

1 33 Jogging 49106062271000 5.012288 11.264028 0.953424 2 33 Jogging 49106112167000 4.903325 10.882658 -0.081722 3 33 Jogging 49106222305000 -0.612916 18.496431 3.023717 4 33 Jogging 49106332290000 -1.184970 12.108489 7.205164

```
import pandas as pd
import numpy as np
file_path = '/content/drive/My Drive/Colab Notebooks/WISDM_ar_v1.1/WISDM_ar_v1.1_raw.txt'
data = []
with open(file_path) as f:
   for line in f:
           parts = line.strip().split(',')
           if len(parts) >= 6:
              user_id, activity, timestamp, x, y, z = parts[0], parts[1], parts[2], float(parts[3]), float(parts[4]), float(parts[5].split(';')[0])
              data.append([user_id, activity, timestamp, x, y, z])
       except:
           continue
columns = ['user', 'activity', 'timestamp', 'x', 'y', 'z']
df = pd.DataFrame(data, columns=columns)
print(df.head())
\rightarrow user activity timestamp x y z
    0 33 Jogging 49105962326000 -0.694638 12.680544 0.503953
```

df						
1 to 25 of 20000 entries Filter ?						
index	user	activity	timestamp	x	у	z
0 33	Jogging	49105962326000		-0.6946377	12.680544	0.50395286
1 33	Jogging	49106062271000		5.012288	11.264028	0.95342433
2 33	Jogging	49106112167000		4.903325	10.882658	-0.08172209
3 33	Jogging	49106222305000		-0.61291564	18.496431	3.0237172
4 33	Jogging	49106332290000		-1.1849703	12.108489	7.205164
5 33	Jogging	49106442306000		1.3756552	-2.4925237	-6.510526
6 33	Jogging	49106542312000		-0.61291564	10.56939	5.706926
7 33	Jogging	49106652389000		-0.50395286	13.947236	7.0553403
8 33	Jogging	49106762313000		-8.430995	11.413852	5.134871
9 33	Jogging	49106872299000		0.95342433	1.3756552	1.6480621
10 33	Jogging	49106982315000		-8.19945	19.57244	2.7240696
11 33	Jogging	49107092330000		1.4165162	5.7886477	2.982856
12 33	Jogging	49107202316000		-1.879608	-2.982856	-0.29964766
13 33	Jogging	49107312332000		-6.1291566	6.851035	-8.158588
14 33	Jogging	49107422348000		5.829509	18.0061	8.539958
15 33	Jogging	49107522293000		6.2789803	2.982856	2.9147544
16 33	Jogging	49107632339000		-1.56634	8.308413	-1.4573772
17 33	Jogging	49107742355000		3.5276701	13.593107	9.425281
18 33	Jogging	49107852340000		-2.0294318	-5.706926	-10.18802
19 33	Jogging	49107962326000		2.7649305	10.337844	-9.724928
20 33	Jogging	49108062271000		3.568531	13.6748295	1.5390993
21 33	Jogging	49108172348000		-0.50395286	3.8681788	3.718355
22 33	Jogging	49108272262000		-2.3018389	1.6889231	0.08172209
23 33	Jogging	49108382370000		-3.568531	19.57244	6.510526
24 33	Jogging	49108492294000		-0.8036005	-3.2961242	-4.630918

Jogging **1** 2 10 100 700 790 800 Show 25 ✓ per page

Like what you see? Visit the data table notebook to learn more about interactive tables. Warning: total number of rows (1098203) exceeds max_rows (20000). Limiting to first (20000) rows. Warning: total number of rows (1098203) exceeds max_rows (20000). Limiting to first (20000) rows. Distributions **Categorical distributions** 0 1000 2000 3000 4000 5000 6000 7000 8000 2-d distributions **Values** 2-d categorical distributions

Faceted distributions <string>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect. <string>:5: FutureWarning: Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect. <string>:5: FutureWarning: Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect. ____ <string>:5: FutureWarning: — Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

Step 3: Feature Extraction via Sliding Window

```
def extract_features(df, window_size=200):
   X, y = [], []
    for i in range(0, len(df) - window_size, window_size):
       window = df.iloc[i:i+window_size]
       x_{vals} = window['x'].values
       y_vals = window['y'].values
       z_vals = window['z'].values
       features = []
       for axis in [x_vals, y_vals, z_vals]:
               np.mean(axis), np.std(axis), np.min(axis), np.max(axis),
               np.median(axis), np.percentile(axis, 25), np.percentile(axis, 75)
       label = window['activity'].mode()[0]
       X.append(features)
       y.append(label)
    return np.array(X), np.array(y)
X, y = extract_features(df)
print("Shape of X (Number of samples, Number of features per sample) = ",X.shape)
print("Shape of Y (Number of labels) = ",y.shape)
```

Step 4: Encode Labels and Train-Test Split

Y (Number of labels) = (5491,)

X (Number of samples, Number of features per sample) = (5491, 21)

```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
le = LabelEncoder()
y_encoded = le.fit_transform(y)
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.2, random_state=42)
```

Step 5: Train Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print("\nClassification Report:\n", classification_report(y_test, y_pred, target_names=le.classes_))
```

Classification Report: precision recall f1-score support Downstairs 0.87 0.81 0.94 Jogging

→ Accuracy: 0.9253867151956324

weighted avg

Sitting 0.96 Standing 0.98 0.98 0.98 0.72 0.88 0.80 138 Upstairs 0.92 Walking 0.98 0.95 accuracy 0.93 0.89 0.91 1099 macro avg

0.92

 $https://colab.research.google.com/drive/1IKMwNC_vxrHZZKH-Xvw_-o-AmbaJpsa1?usp=sharing\#scrollTo=xqjM90S3O-SP\&printMode=true$

0.93

0.92

1099

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Step 6: Visualization of Classification Results

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import seaborn as sns
import mathlotlib pyplot as plt

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred)
Plot the confusion matrix

plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

plt.figure(figsize=(8, 6))

