data_visualization

April 20, 2025

1 Introduction

- **Subjects**: 30
- **Sensors**: three-axis acceleration, three-axis gyroscope
- **Sampling**: 50Hz, 2.56s window (128 time points)
- **Statistical features**: 561 dimensions (such as mean, variance, FFT, etc.)
- **Original time series**: 9 signal files (body_acc_x/y/z, body_gyro_x/y/z, total_acc_x/y/z)

```
UCI_HAR_Dataset/
  README.txt
  activity_labels.txt
  features.txt
  features_info.txt
  test
    Inertial Signals
      body_acc_x_test.txt
      body_acc_y_test.txt
      body_acc_z_test.txt
      body_gyro_x_test.txt
      body_gyro_y_test.txt
      body_gyro_z_test.txt
      total_acc_x_test.txt
      total_acc_y_test.txt
      total_acc_z_test.txt
    X_test.txt
    subject_test.txt
    y_test.txt
  train
    Inertial Signals
      body_acc_x_train.txt
      body_acc_y_train.txt
      body_acc_z_train.txt
      body_gyro_x_train.txt
      body_gyro_y_train.txt
      body_gyro_z_train.txt
      total_acc_x_train.txt
      total_acc_y_train.txt
```

```
        total_acc_z_train.txt
    X_train.txt
    subject_train.txt
    y_train.txt
```

2 Data preprocessing

1. Load metadata from features.txt and activity_labels.txt;
2. Read the feature matrix and labels of the training/test sets;
3. Map the label encoding to readable activity names;

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
```

[ ]:
```
# 2.1 Path configuration
data_path = '../data/UCI_HAR_Dataset/'
# 2.2 Loading metadata
features = pd.read_csv(data_path+'features.txt', header=None, sep='\s+',␣
↪names=['idx','feature'])
activity_labels = pd.read_csv(data_path+'activity_labels.txt', header=None,␣
↪sep='\s+', names=['id','activity'])
# 2.3 Read training/test sets
X_train = pd.read_csv(data_path+'train/X_train.txt', header=None, sep='\s+')
y_train = pd.read_csv(data_path+'train/y_train.txt', header=None, sep='\s+',␣
↪names=['activity_id'])
X_test  = pd.read_csv(data_path+'test/X_test.txt',  header=None, sep='\s+')
y_test  = pd.read_csv(data_path+'test/y_test.txt',  header=None, sep='\s+',␣
↪names=['activity_id'])
# 2.4 Apply feature names and clean up
clean_feat = features['feature'].str.replace('[()]','',regex=True).str.
↪replace(',','_')
X_train.columns = clean_feat
X_test.columns  = clean_feat
# 2.5 Merge tags and names
y_train = y_train.merge(activity_labels, left_on='activity_id', right_on='id')
y_test  = y_test.merge(activity_labels,  left_on='activity_id', right_on='id')
# 2.6 Display basic information
```

```python
print(f"X_train: {X_train.shape}, y_train: {y_train['activity'].value_counts().
  ↪to_dict()}")
```

```
X_train: (7352, 561), y_train: {'LAYING': 1407, 'STANDING': 1374, 'SITTING':
1286, 'WALKING': 1226, 'WALKING_UPSTAIRS': 1073, 'WALKING_DOWNSTAIRS': 986}
```

[ ]:
```python
# Display some column names
X_train.columns[:10]
```

[ ]:
```
Index(['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'],
      dtype='object', name='feature')
```

[ ]:
```python
# Display the first few lines of labels
y_train.head(10)
```

[ ]:

	activity_id	id	activity
0	5	5	STANDING
1	5	5	STANDING
2	5	5	STANDING
3	5	5	STANDING
4	5	5	STANDING
5	5	5	STANDING
6	5	5	STANDING
7	5	5	STANDING
8	5	5	STANDING
9	5	5	STANDING

[ ]:
```python
X_train.describe()
```

[ ]:

feature	tBodyAcc-mean-X	tBodyAcc-mean-Y	tBodyAcc-mean-Z	tBodyAcc-std-X	\
count	7352.000000	7352.000000	7352.000000	7352.000000	
mean	0.274488	-0.017695	-0.109141	-0.605438	
std	0.070261	0.040811	0.056635	0.448734	
min	-1.000000	-1.000000	-1.000000	-1.000000	
25%	0.262975	-0.024863	-0.120993	-0.992754	
50%	0.277193	-0.017219	-0.108676	-0.946196	
75%	0.288461	-0.010783	-0.097794	-0.242813	
max	1.000000	1.000000	1.000000	1.000000	

feature	tBodyAcc-std-Y	tBodyAcc-std-Z	tBodyAcc-mad-X	tBodyAcc-mad-Y	\
count	7352.000000	7352.000000	7352.000000	7352.000000	
mean	-0.510938	-0.604754	-0.630512	-0.526907	
std	0.502645	0.418687	0.424073	0.485942	
min	-0.999873	-1.000000	-1.000000	-1.000000	
25%	-0.978129	-0.980233	-0.993591	-0.978162	
50%	-0.851897	-0.859365	-0.950709	-0.857328	

```
75%          -0.034231       -0.262415       -0.292680       -0.066701
max           0.916238        1.000000        1.000000        0.967664

feature  tBodyAcc-mad-Z  tBodyAcc-max-X  …  fBodyBodyGyroJerkMag-meanFreq  \
count       7352.000000     7352.000000  …                    7352.000000
mean          -0.606150       -0.468604  …                       0.125293
std            0.414122        0.544547  …                       0.250994
min           -1.000000       -1.000000  …                      -1.000000
25%           -0.980251       -0.936219  …                      -0.023692
50%           -0.857143       -0.881637  …                       0.134000
75%           -0.265671       -0.017129  …                       0.289096
max            1.000000        1.000000  …                       0.946700

feature  fBodyBodyGyroJerkMag-skewness  fBodyBodyGyroJerkMag-kurtosis  \
count                      7352.000000                    7352.000000
mean                         -0.307009                      -0.625294
std                           0.321011                       0.307584
min                          -0.995357                      -0.999765
25%                          -0.542602                      -0.845573
50%                          -0.343685                      -0.711692
75%                          -0.126979                      -0.503878
max                           0.989538                       0.956845

feature  angletBodyAccMean_gravity  angletBodyAccJerkMean_gravityMean  \
count                  7352.000000                        7352.000000
mean                      0.008684                           0.002186
std                       0.336787                           0.448306
min                      -0.976580                          -1.000000
25%                      -0.121527                          -0.289549
50%                       0.009509                           0.008943
75%                       0.150865                           0.292861
max                       1.000000                           1.000000

feature  angletBodyGyroMean_gravityMean  angletBodyGyroJerkMean_gravityMean  \
count                       7352.000000                         7352.000000
mean                           0.008726                           -0.005981
std                            0.608303                            0.477975
min                           -1.000000                           -1.000000
25%                           -0.482273                           -0.376341
50%                            0.008735                           -0.000368
75%                            0.506187                            0.359368
max                            0.998702                            0.996078

feature  angleX_gravityMean  angleY_gravityMean  angleZ_gravityMean
count           7352.000000         7352.000000         7352.000000
mean              -0.489547            0.058593           -0.056515
std                0.511807            0.297480            0.279122
```

```
min               -1.000000            -1.000000            -1.000000
25%               -0.812065            -0.017885            -0.143414
50%               -0.709417             0.182071             0.003181
75%               -0.509079             0.248353             0.107659
max                1.000000             0.478157             1.000000

[8 rows x 561 columns]
```

[ ]:
```
X_train.head()
```

[ ]:
```
feature  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

feature  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

feature  tBodyAcc-mad-Z  tBodyAcc-max-X  …  fBodyBodyGyroJerkMag-meanFreq  \
0             -0.923527       -0.934724  …                      -0.074323
1             -0.957686       -0.943068  …                       0.158075
2             -0.977469       -0.938692  …                       0.414503
3             -0.989302       -0.938692  …                       0.404573
4             -0.990441       -0.942469  …                       0.087753

feature  fBodyBodyGyroJerkMag-skewness  fBodyBodyGyroJerkMag-kurtosis  \
0                            -0.298676                      -0.710304
1                            -0.595051                      -0.861499
2                            -0.390748                      -0.760104
3                            -0.117290                      -0.482845
4                            -0.351471                      -0.699205

feature  angletBodyAccMean_gravity  angletBodyAccJerkMean_gravityMean  \
0                        -0.112754                           0.030400
1                         0.053477                          -0.007435
2                        -0.118559                           0.177899
3                        -0.036788                          -0.012892
4                         0.123320                           0.122542

feature  angletBodyGyroMean_gravityMean  angletBodyGyroJerkMean_gravityMean  \
0                             -0.464761                           -0.018446
```

```
1                            -0.732626                            0.703511
2                             0.100699                            0.808529
3                             0.640011                           -0.485366
4                             0.693578                           -0.615971

feature  angleX_gravityMean  angleY_gravityMean  angleZ_gravityMean
0                 -0.841247            0.179941           -0.058627
1                 -0.844788            0.180289           -0.054317
2                 -0.848933            0.180637           -0.049118
3                 -0.848649            0.181935           -0.047663
4                 -0.847865            0.185151           -0.043892

[5 rows x 561 columns]
```

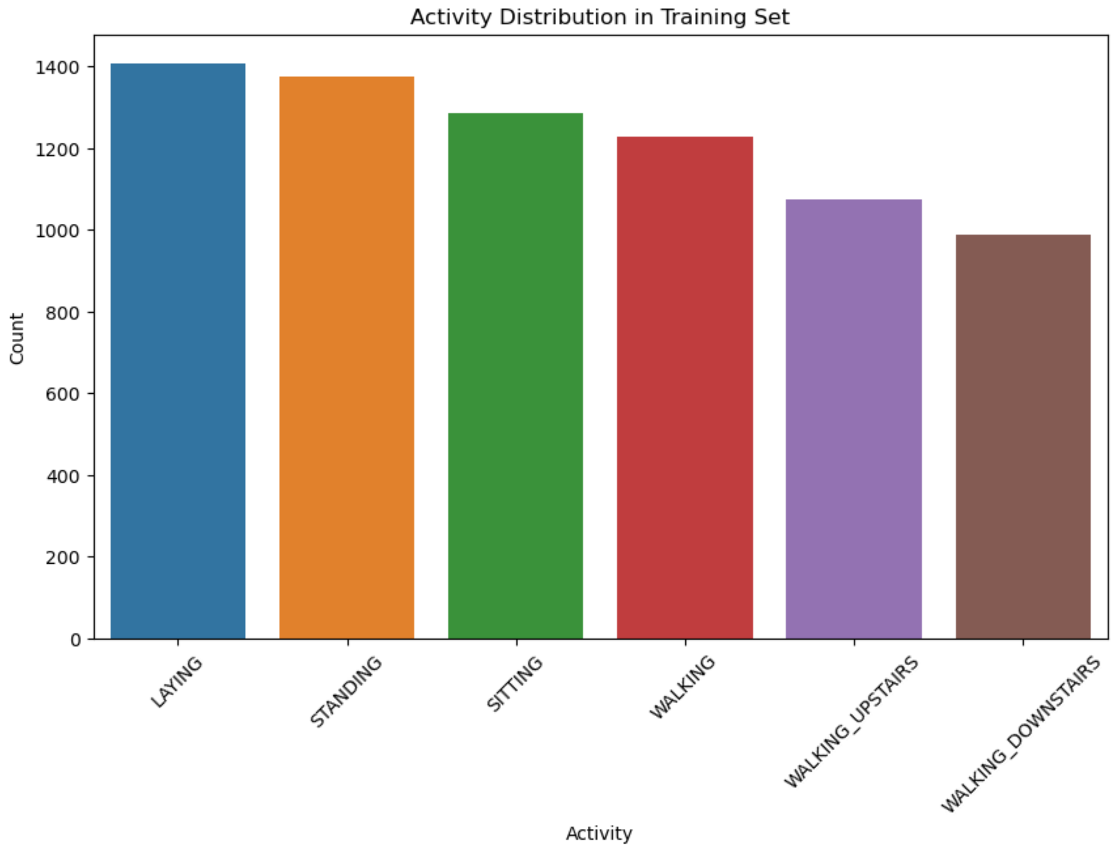
3 Exploratory Data Analysis (EDA)

3.1 Activity Label Distribution

Count the number of samples of each activity in the training set to understand whether the data is balanced:

[ ]:

```
# Plot frequency distribution of active tags
plt.figure(figsize=(10, 6))
sns.countplot(data=y_train, x='activity', order=y_train['activity'].
 ↪value_counts().index)
plt.xticks(rotation=45)
plt.title('Activity Distribution in Training Set')
plt.xlabel('Activity')
plt.ylabel('Count')
plt.show()
```



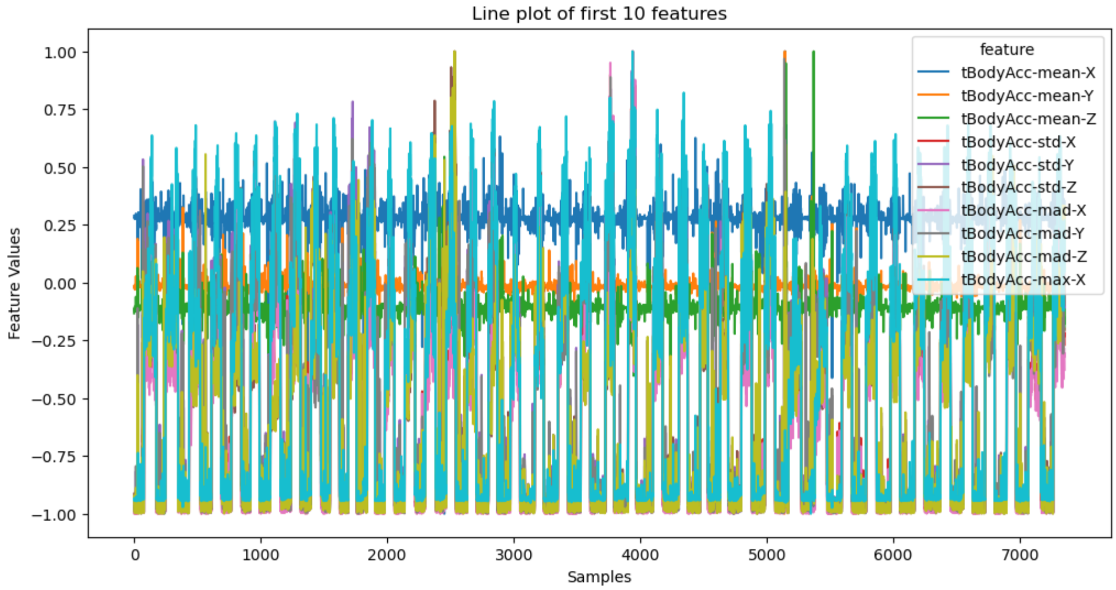
The results show that there are differences in the number of tags such as WALKING, SITTING, and LAYING, and the sampling strategy needs to be considered when modeling.

3.2 Feature statistics and distribution

3.2.1 Line plot of first 10 features

Count the number of samples of each activity in the training set to understand whether the data is balanced

[ ]:
```
# Select the first 10 features for visualization
selected_columns = X_train.columns[:10]

# Visualize the distribution of these features
X_train[selected_columns].plot(kind='line', figsize=(12, 6))
plt.title('Line plot of first 10 features')
plt.xlabel('Samples')
plt.ylabel('Feature Values')
plt.show()
```



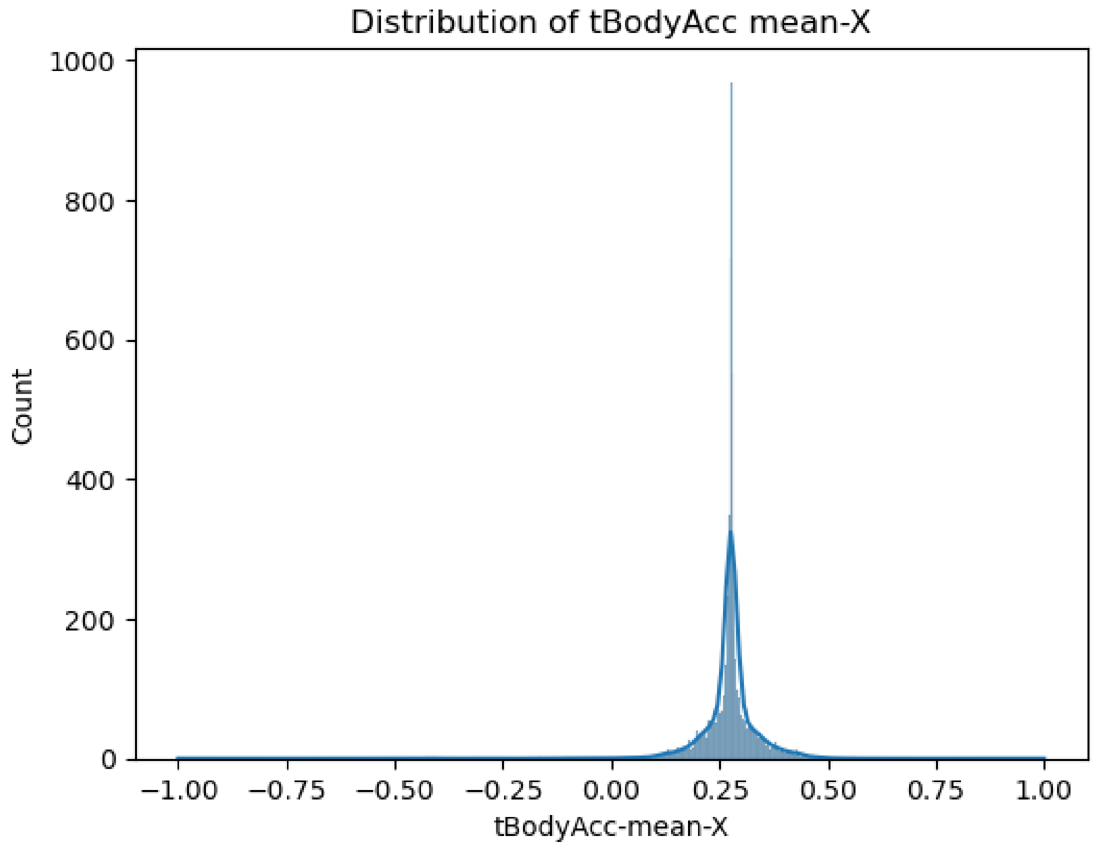
The sharp fluctuations in the curves of certain features may mean that these features contain large noise or correspond to certain specific dynamic changes.

3.2.2 Distribution of tBodyAcc mean-X

[ ]:
```
sns.histplot(X_train['tBodyAcc-mean-X'], kde=True)
plt.title('Distribution of tBodyAcc mean-X')
```

```
/opt/homebrew/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

[ ]:
```
Text(0.5, 1.0, 'Distribution of tBodyAcc mean-X')
```

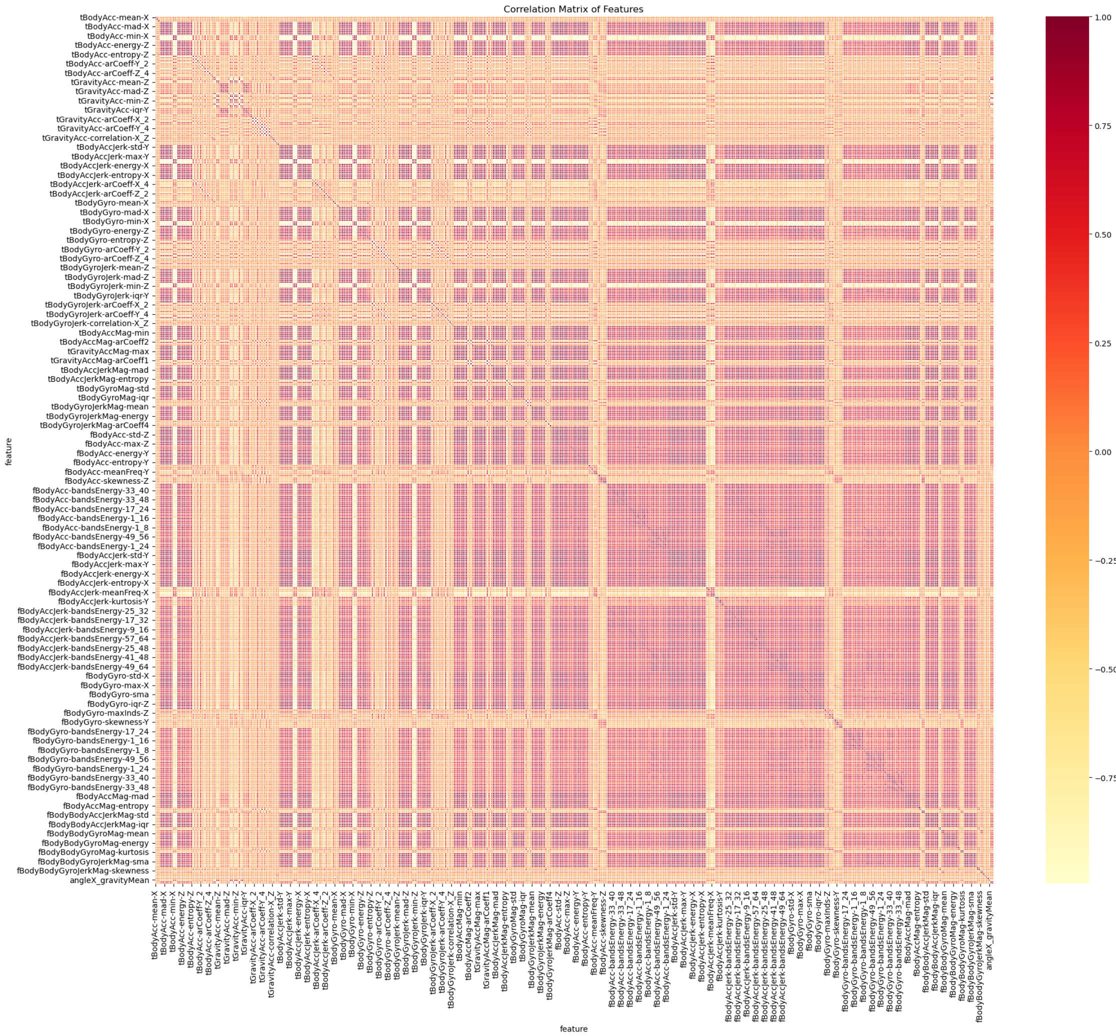


This figure shows the distribution of the tBodyAcc-mean-X feature in the training set, and further smoothes the probability density function of the feature through the kernel density estimation (KDE) curve. As can be seen from the figure, the data distribution is symmetrical and bell-shaped, which conforms to the typical form of normal distribution.

3.2.3 Correlation Matrix of Features

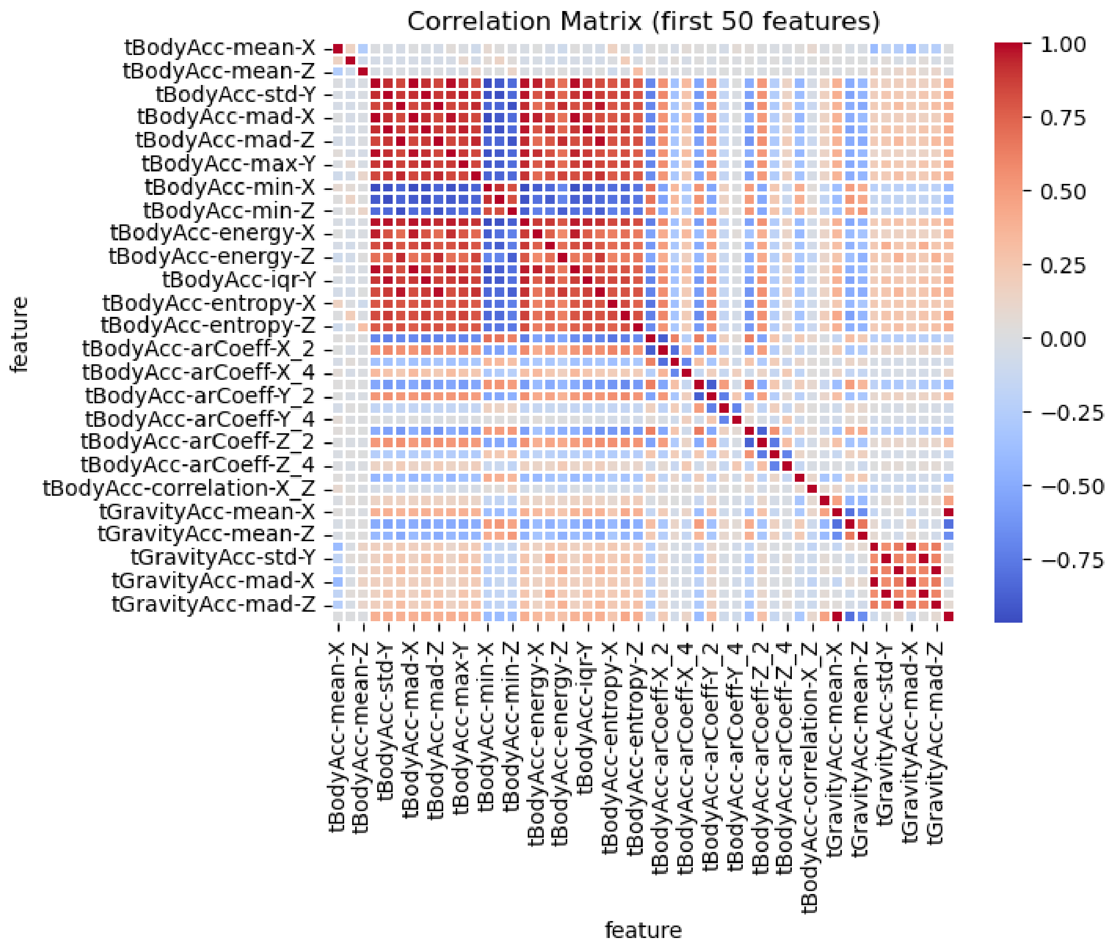
Compute the correlations between all features in the training set and visualize these correlation matrices via heatmaps.

[ ]:
```
# Calculate the correlation between features
correlation_matrix = X_train.corr()

# Draw a heat map
plt.figure(figsize=(24, 20))
sns.heatmap(correlation_matrix, annot=False, cmap='YlOrRd', fmt='.2f',␣
 ↪linewidths=0.5)
plt.title('Correlation Matrix of Features')
plt.show()
```



[ ]:
```python
# Draw a heat map for the first 50 features
corr = X_train.iloc[: , :50].corr()
sns.heatmap(corr, cmap='coolwarm', linewidths=0.3)
plt.title('Correlation Matrix (first 50 features)')
```

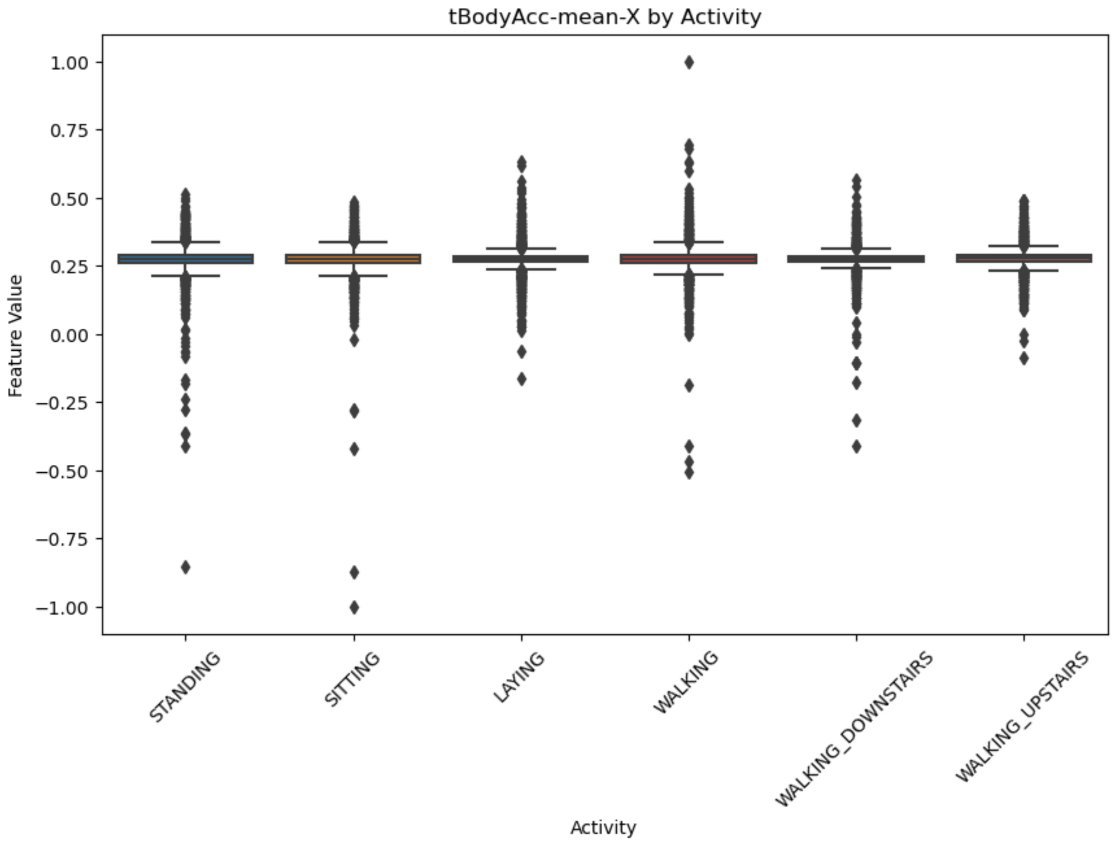
[ ]: Text(0.5, 1.0, 'Correlation Matrix (first 50 features)')



3.3 Feature by Activity

The box plot shows the distribution of tBodyAcc-mean-X features in the training set under different activities.

[ ]:
```
# Select a feature for activity comparison
feature_to_plot = 'tBodyAcc-mean-X'

plt.figure(figsize=(10, 6))
sns.boxplot(x='activity', y=feature_to_plot, data=pd.concat([X_train, y_train],␣
↪axis=1))
plt.xticks(rotation=45)
plt.title(f'{feature_to_plot} by Activity')
plt.xlabel('Activity')
plt.ylabel('Feature Value')
plt.show()
```

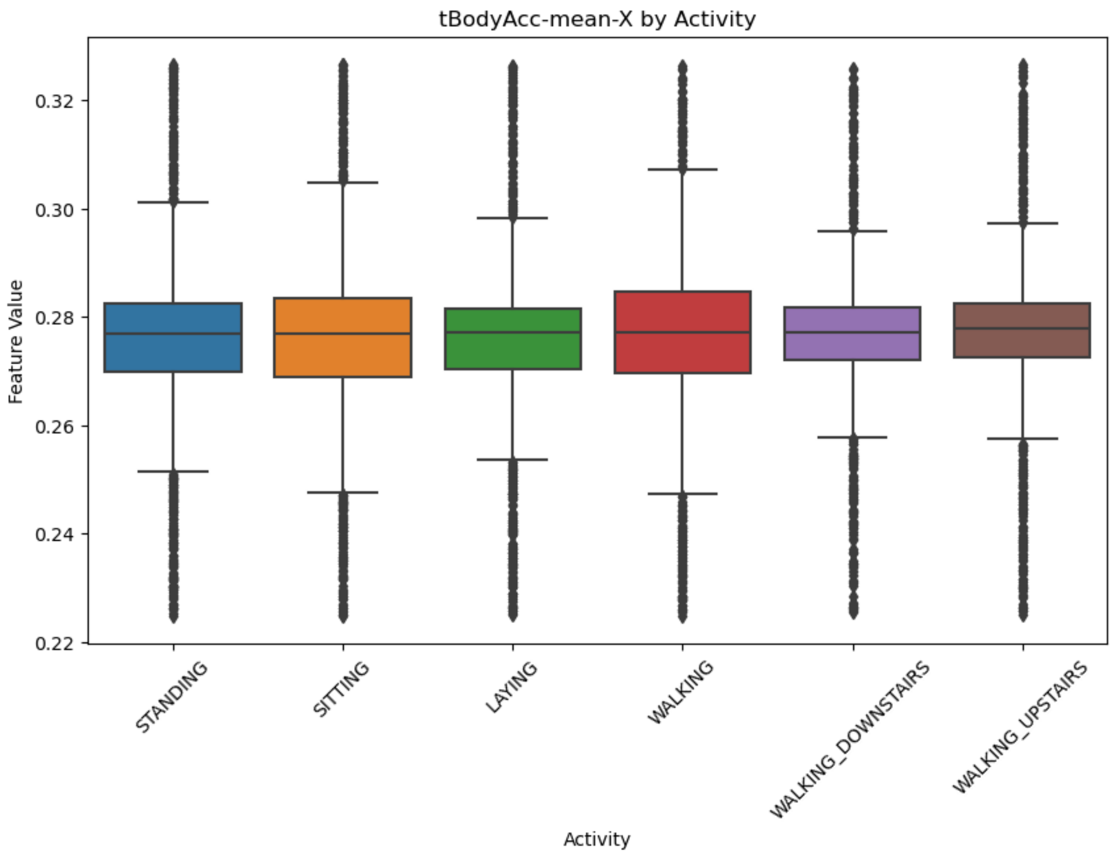


From the box plot, we can see that among all the activities, there are some significant outliers (points outside the whiskers) in the STANDING, SITTING, WALKING, and WALKING_DOWNSTAIRS activities. These outliers may represent some extreme samples, such as sensor noise, motion anomalies, or human error in labeling. **We removed these outliers from the dataset**.

[ ]:
```
# Calculate IQR (interquartile range)
Q1 = X_train['tBodyAcc-mean-X'].quantile(0.25)
Q3 = X_train['tBodyAcc-mean-X'].quantile(0.75)
IQR = Q3 - Q1

# Define upper and lower limits, data outside this range is an outlier
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
X_train_no_outliers = X_train[(X_train['tBodyAcc-mean-X'] >= lower_bound) &
 ↪(X_train['tBodyAcc-mean-X'] <= upper_bound)]

print(f"The number of rows in the original dataset {X_train.shape[0]}")
print(f"Number of rows after removing outliers {X_train_no_outliers.shape[0]}")
```

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='activity', y=feature_to_plot, data=pd.
 ↪concat([X_train_no_outliers, y_train], axis=1))
plt.xticks(rotation=45)
plt.title(f'{feature_to_plot} by Activity')
plt.xlabel('Activity')
plt.ylabel('Feature Value')
plt.show()
```

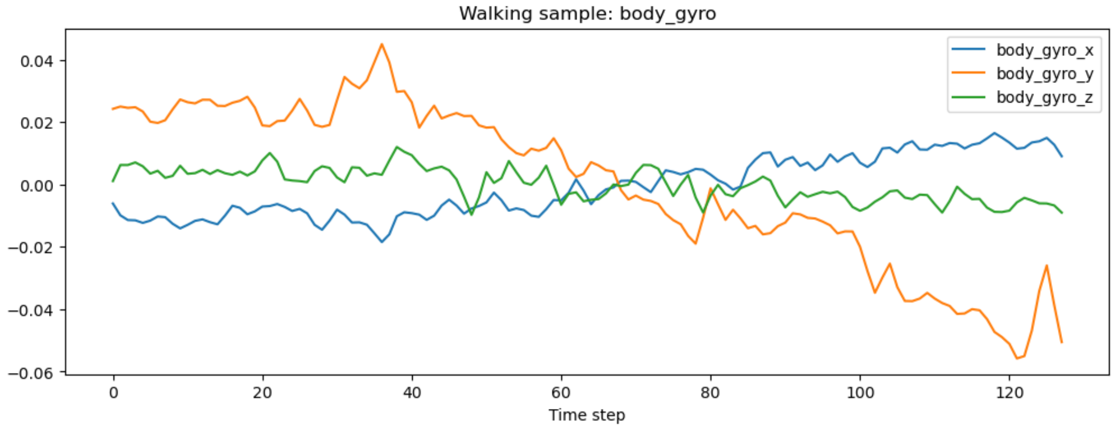
```
The number of rows in the original dataset 7352
Number of rows after removing outliers 5557
```



4 Time Series Visualization

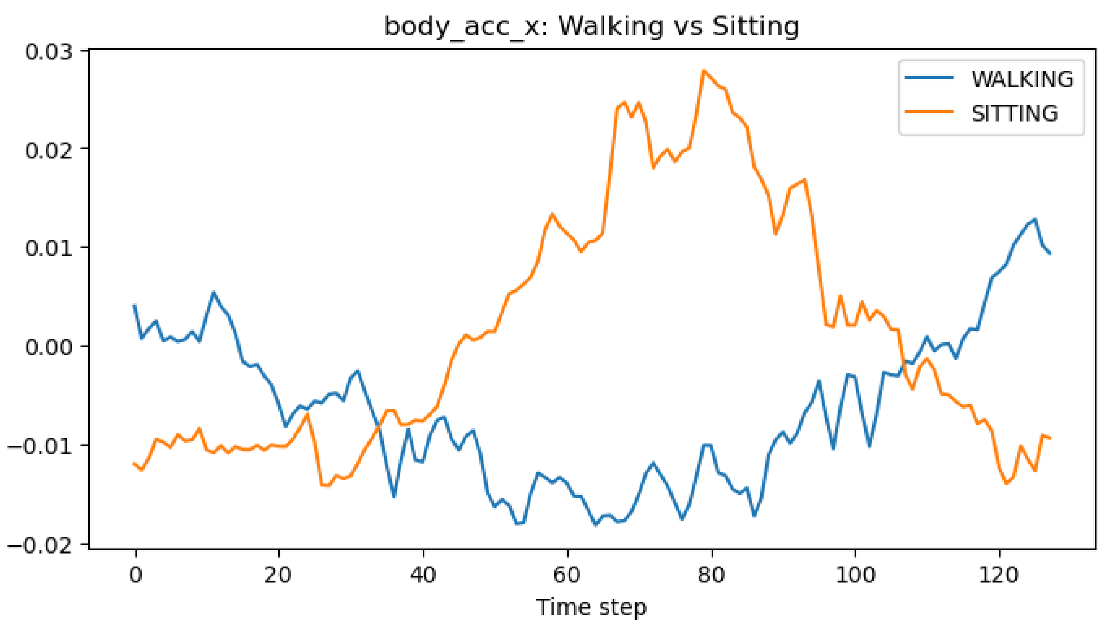
4.1 Single Activity Window

[ ]:
```
# 3.1.1 Loading original timing signal
signal_types =␣
 ↪['body_acc_x','body_acc_y','body_acc_z','body_gyro_x','body_gyro_y','body_gyro_z']
signals = {sig: pd.read_csv(f"{data_path}train/Inertial Signals/{sig}_train.
 ↪txt", header=None, sep='\s+')
           for sig in signal_types}
# 3.1.2 Select the first WALKING sample
idx = y_train[y_train['activity']=='WALKING'].index[0]
t = np.arange(signals['body_acc_x'].shape[1])  # 0-127
# 3.1.3 Drawing acceleration and gyroscope
plt.figure(figsize=(12,4))
for ax in ['body_acc_x','body_acc_y','body_acc_z']:
    plt.plot(t, signals[ax].iloc[idx], label=ax)
plt.legend(); plt.title('Walking sample: body_acc'); plt.xlabel('Time step');␣
 ↪plt.show()

plt.figure(figsize=(12,4))
for ax in ['body_gyro_x','body_gyro_y','body_gyro_z']:
    plt.plot(t, signals[ax].iloc[idx], label=ax)
plt.legend(); plt.title('Walking sample: body_gyro'); plt.xlabel('Time step');␣
 ↪plt.show()
```



4.2 Comparison of different activities

[ ]:
```
plt.figure(figsize=(8,4))
for act in ['WALKING','SITTING']:
    i = y_train[y_train['activity']==act].index[0]
    plt.plot(t, signals['body_acc_x'].iloc[i], label=act)
plt.legend(); plt.title('body_acc_x: Walking vs Sitting'); plt.xlabel('Time␣
↪step'); plt.show()
```



5 Feature Engineering

5.1 Standardization

```
[ ]: scaler = StandardScaler()
     X_scaled = scaler.fit_transform(X_train)
     X_scaled
```

```
[ ]: array([[ 0.20064157, -0.0636826 , -0.41962845, …, -0.68721921,
              0.40794614, -0.00756789],
            [ 0.05594788,  0.03148567, -0.25390836, …, -0.694138  ,
              0.40911698,  0.00787517],
            [ 0.07351535, -0.04341648, -0.07629468, …, -0.702239  ,
              0.4102883 ,  0.02650234],
            …,
            [-0.01566765,  0.0167814 ,  1.13222107, …, -0.56584847,
              0.64059683,  0.34870928],
            [ 0.21586648, -0.02812252, -0.86770988, …, -0.57766781,
              0.63147758,  0.29327564],
            [ 1.09620157,  0.12919873, -1.67268082, …, -0.57392691,
              0.63274259,  0.33396081]])
```

5.2 PCA Dimensionality Reduction

```
[ ]: pca = PCA(n_components=20)
     X_pca = pca.fit_transform(X_scaled)
     print('Explained variance ratio:', pca.explained_variance_ratio_.sum())
```

```
Explained variance ratio: 0.773708780746934
```

5.3 Discrete Wavelet Transform

5.3.1 Define DWT feature extraction function

Perform a layer of DWT on the signal sequence of each 128-step window (for example, using Daubechies 4 wavelet), and then calculate statistics (such as mean, standard deviation, energy, etc.) for each layer of coefficients.

```
[ ]: import pywt
     def extract_dwt_features(signal, wavelet='db4', level=1):
         """
         Perform DWT on a one-dimensional signal and extract the statistical␣
      ↪features of the coefficients
         signal: 1D array or pandas Series, length 128
         wavelet: wavelet name
         level: number of decomposition levels
         return: dict, keys such as 'cA_mean', 'cA_std', 'cD_mean', 'cD_std'
         """
         coeffs = pywt.wavedec(signal, wavelet=wavelet, level=level)
```

```
    features = {}
    # cA is the approximation coefficient, cD is the detail coefficient
    labels = ['A', 'D']
    for i, c in enumerate(coeffs):
        label = labels[i] if i < 2 else f"D{i}"
        features[f'c{label}_mean'] = np.mean(c)
        features[f'c{label}_std']  = np.std(c)
        features[f'c{label}_energy'] = np.sum(c**2)
    return features
```

5.3.2 Extract DWT features from selected feature columns in batches

Take `tBodyAcc-mean()-X` as an example to extract DWT features from all windows in the training set. You can also extend it to multiple axes or multiple raw signals.

[ ]:
```
# New DWT feature extraction loop:
dwt_features_list = []
for idx in range(len(signals['body_acc_x'])):
    # Select the idxth window of body_acc_x
    sig = signals['body_acc_x'].iloc[idx].values
    feats = extract_dwt_features(sig, wavelet='db4', level=1)
    feats['activity']   = y_train.loc[idx, 'activity']
    feats['window_idx'] = idx
    dwt_features_list.append(feats)

# Convert to DataFrame
df_dwt = pd.DataFrame(dwt_features_list)
print("DWT feature table shape:", df_dwt.shape)
df_dwt.head()
```

```
DWT feature table shape: (7352, 8)
```

[ ]:
```
    cA_mean    cA_std  cA_energy   cD_mean    cD_std  cD_energy  activity  \
0  0.003472  0.004193   0.001986  0.000015  0.001138   0.000087  STANDING
1  0.000392  0.002685   0.000493 -0.000006  0.000942   0.000059  STANDING
2  0.000517  0.004014   0.001097 -0.000011  0.001186   0.000094  STANDING
3  0.000422  0.003577   0.000869  0.000003  0.001004   0.000068  STANDING
4 -0.000207  0.002745   0.000508  0.000016  0.000801   0.000043  STANDING

   window_idx
0           0
1           1
2           2
3           3
4           4
```

5.3.3 Merge DWT features into the original feature table

You can merge the above df_dwt with X_train (or the feature set for subsequent modeling) horizontally to construct a final training set containing time domain + frequency domain features.

[ ]:
```
energy_cols = [c for c in df_dwt.columns if 'energy' in c]

X_train_enhanced = pd.concat([
    X_train.reset_index(drop=True),
    df_dwt[energy_cols].reset_index(drop=True)
], axis=1)

print("Shape of training set after enhancement:", X_train_enhanced.shape)
```

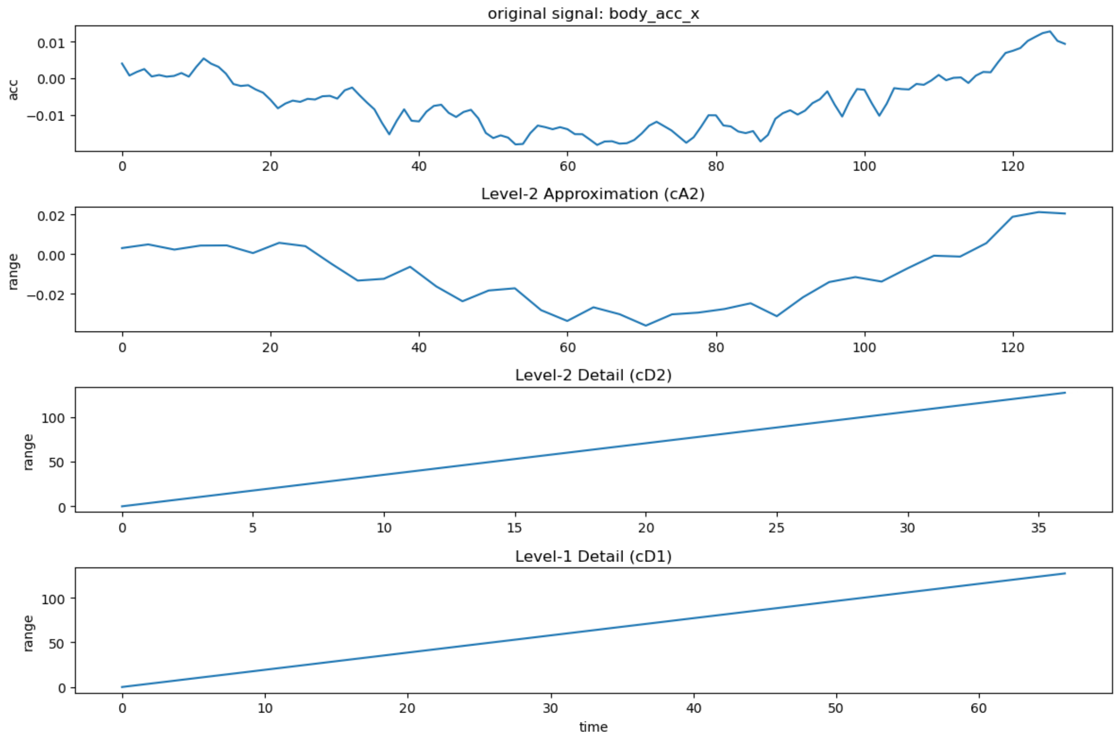
```
Shape of training set after enhancement: (7352, 563)
```

5.3.4 DWT result analysis and visualization

Discrete wavelet transform (DWT) decomposes a time domain signal of length 128 into a set of “approximation” coefficients (Approximation) and “detail” coefficients (Detail). - **Approximation coefficient (cA)**: retains the low-frequency part of the signal and reflects the overall trend; - **Detail coefficient (cD)**: retains the high-frequency component and reflects the instantaneous changes (noise, mutation, detail characteristics).

[ ]:
```
import pywt
import matplotlib.pyplot as plt

idx = y_train[y_train['activity']=='WALKING'].index[0]
sig = signals['body_acc_x'].iloc[idx].values

wavelet = 'db4'
level = 2
coeffs = pywt.wavedec(sig, wavelet=wavelet, level=level)
cA2, cD2, cD1 = coeffs

t = np.arange(len(sig))
tA2 = np.linspace(0, 127, len(cA2))
tD2 = np.linspace(0, 127, len(cD2))
tD1 = np.linspace(0, 127, len(cD1))

plt.figure(figsize=(12, 8))

plt.subplot(4,1,1)
plt.plot(t, sig); plt.title('original signal: body_acc_x'); plt.ylabel('acc')

plt.subplot(4,1,2)
plt.plot(tA2, cA2); plt.title('Level-2 Approximation (cA2)'); plt.
↪ylabel('range')
```

```
plt.subplot(4,1,3)
plt.plot(tD2); plt.title('Level-2 Detail (cD2)'); plt.ylabel('range')

plt.subplot(4,1,4)
plt.plot(tD1); plt.title('Level-1 Detail (cD1)'); plt.ylabel('range'); plt.
 ↪xlabel('time')

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



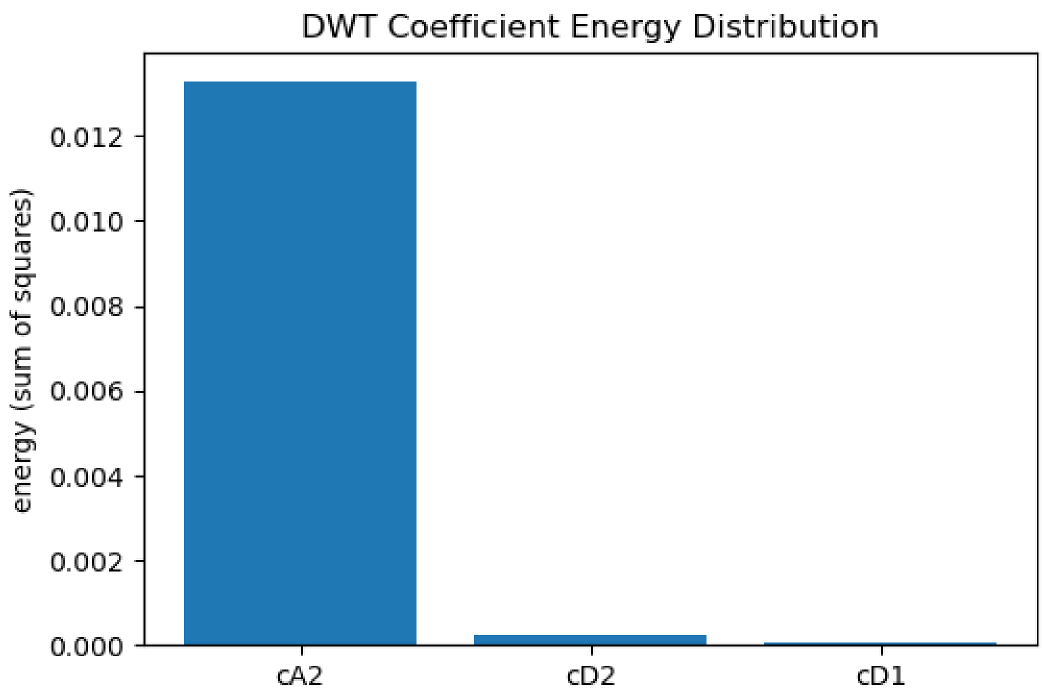
- The first image shows 128 time points of the original acceleration signal.
- The second image cA2 is shorter and only retains the low-frequency trend;
- The third and fourth images cD2 and cD1 show details at different scales, and the high-frequency oscillation is more obvious.

5.3.5 Energy distribution bar graph

You can also calculate the energy (sum of squares) of each level of coefficients and draw a bar graph to intuitively show the proportion of low frequency vs. high frequency in the signal:

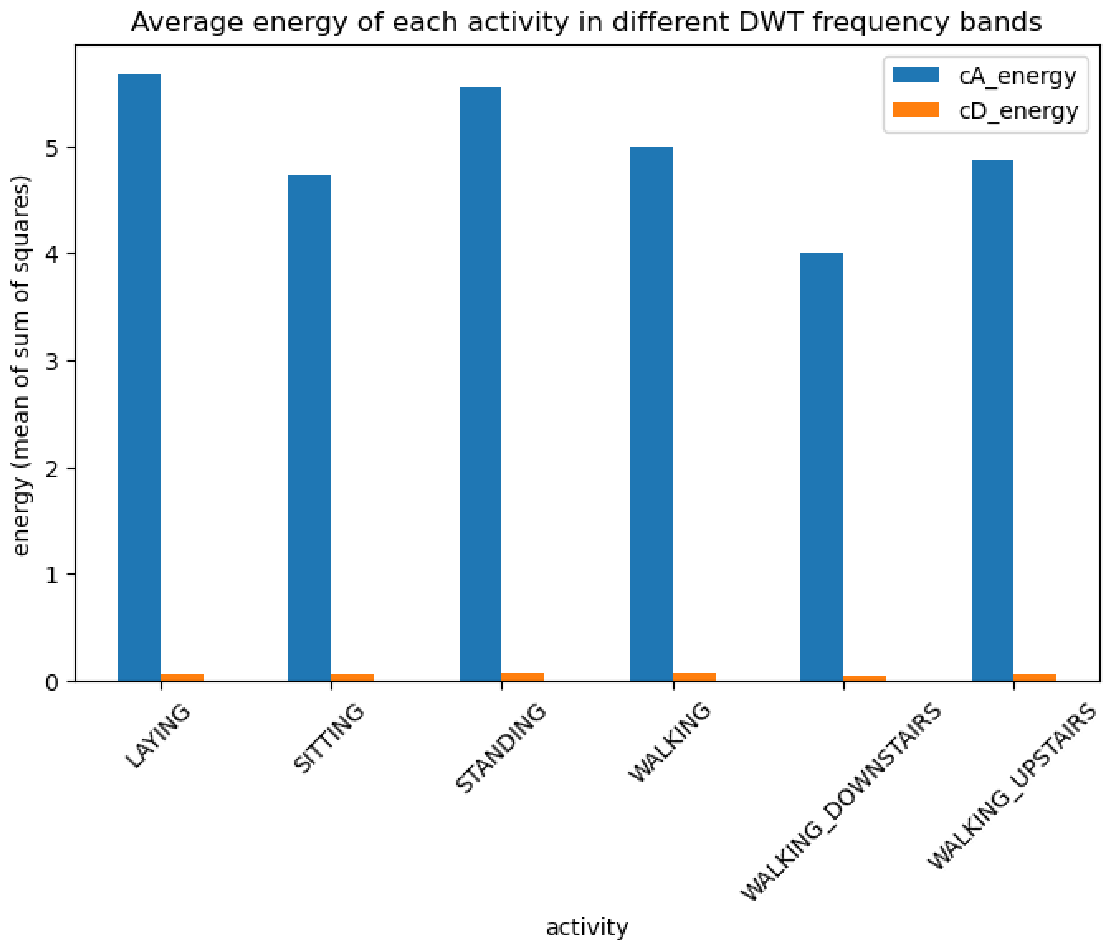
[ ]:
```
energies = {
    'cA2': np.sum(cA2**2),
    'cD2': np.sum(cD2**2),
    'cD1': np.sum(cD1**2),
```

```
}

plt.figure(figsize=(6,4))
plt.bar(energies.keys(), energies.values())
plt.title('DWT Coefficient Energy Distribution')
plt.ylabel('energy (sum of squares)')
plt.show()
```



Using DWT energy features to distinguish “WALKING” vs “SITTING”

[ ]:
```
# Count the distribution of each activity in cA2, cD2, cD1 energy
energy_cols = ['cA_energy','cD_energy']
df_plot = df_dwt.groupby('activity')[energy_cols].mean().reset_index()

df_plot.set_index('activity').plot(kind='bar', figsize=(8,5))
plt.title('Average energy of each activity in different DWT frequency bands')
plt.ylabel('energy (mean of sum of squares)')
plt.xticks(rotation=45)
plt.show()
```



From the figure, we can see that the energy of WALKING in a certain frequency band (such as cD1) is much higher than that of SITTING, which means that the frequency band feature is particularly effective in distinguishing these two types of actions and can be specially retained in subsequent modeling.

6 Baseline Classification Model

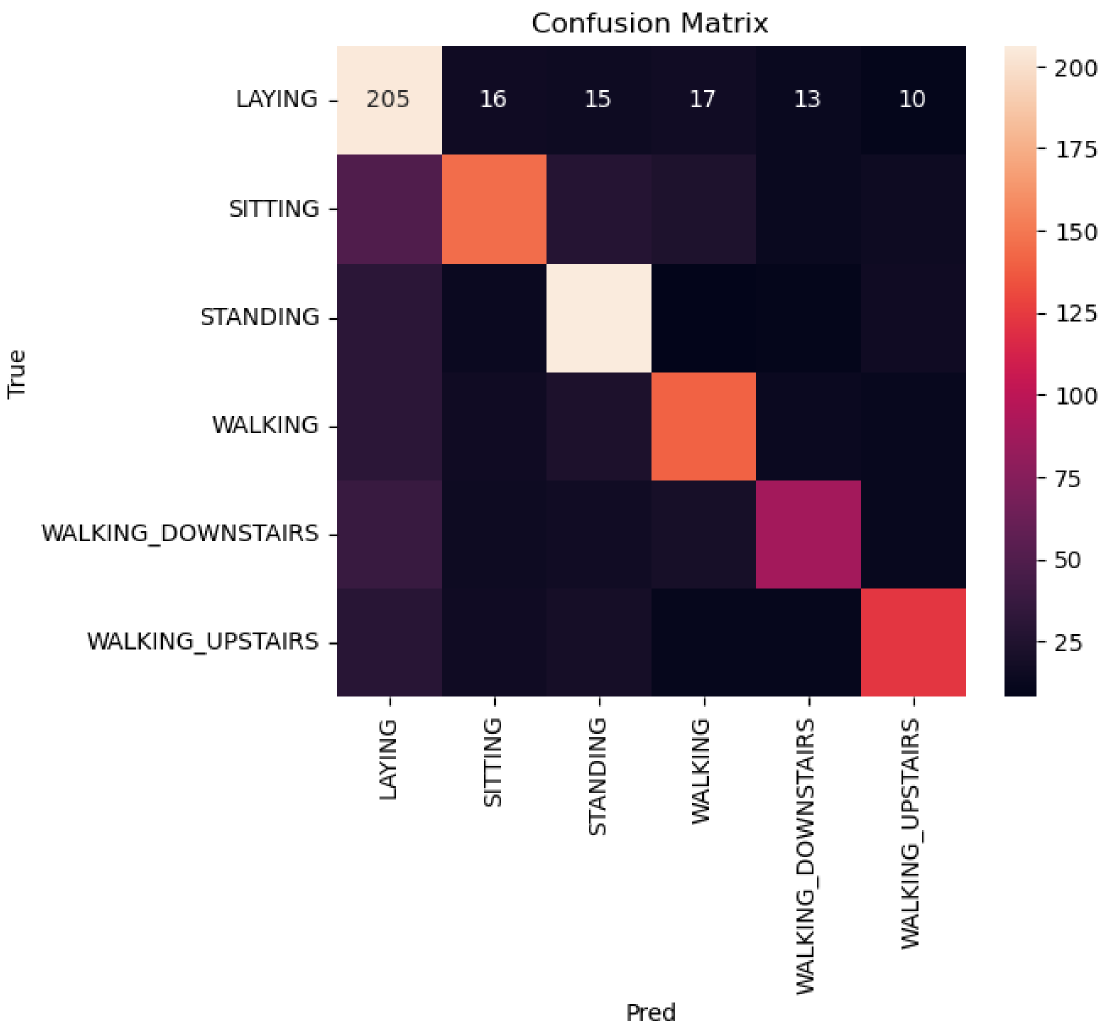
6.1 Random Forest Model

[ ]:

```
# 5.1.1 Divide the data set
X_tr, X_val, y_tr, y_val = train_test_split(X_pca, y_train['activity'],␣
↪test_size=0.2, random_state=42)
# 5.1.2 Training Random Forest
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_tr, y_tr)
# 5.1.3 Evaluation
y_pred = clf.predict(X_val)
```

```python
print('Accuracy:', accuracy_score(y_val, y_pred))
print(classification_report(y_val, y_pred))
cm = confusion_matrix(y_val, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=np.unique(y_val),␣
 ↪yticklabels=np.unique(y_val))
plt.title('Confusion Matrix'); plt.ylabel('True'); plt.xlabel('Pred'); plt.
 ↪show()
```

```
Accuracy: 0.6172671651937458
                    precision    recall  f1-score   support

            LAYING       0.54      0.74      0.62       276
           SITTING       0.65      0.53      0.58       274
          STANDING       0.67      0.72      0.69       285
           WALKING       0.64      0.59      0.62       237
WALKING_DOWNSTAIRS       0.59      0.46      0.52       190
  WALKING_UPSTAIRS       0.65      0.59      0.62       209

          accuracy                           0.62      1471
         macro avg       0.62      0.61      0.61      1471
      weighted avg       0.62      0.62      0.61      1471
```


Confusion Matrix
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
True
205
16
15
17
13
10
200
175
150
125
100
75
50
25
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
Pred