In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [2]:
```
# Part 1: Introduction
# - This project demonstrates the application of Principal Component Analysis (PCA) on a dataset.
# - PCA is used to reduce the dimensionality of the data while retaining most of the variance.
# - We will visualize the results of PCA in both 2D and 3D scatter plots.

# Teil 1: Einführung
# - Dieses Projekt zeigt die Anwendung der Hauptkomponentenanalyse (PCA) auf einem Datensatz.
# - PCA wird verwendet, um die Dimensionalität der Daten zu reduzieren und dabei den größten Teil der Varianz beizubehalten.
# - Wir werden die Ergebnisse von PCA sowohl in 2D- als auch in 3D-Streudiagrammen visualisieren.
```

In [3]:
```
# Part 2: Data Loading
# - Load the dataset from a CSV file.

# Teil 2: Laden der Daten
# - Laden Sie den Datensatz aus einer CSV-Datei.

df = pd.read_csv([redacted])
```

In [4]:
```
df.head()
```

Out[4]:
```
   tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc-  tBodyAcc- ... fBodyBodyGyroJerkMag- angle(tBodyAccMea
    mean()-X   mean()-Y   mean()-Z    std()-X    std()-Y    std()-Z    mad()-X    mad()-Y    mad()-Z    max()-X                 kurtosis()
0   0.288585  -0.020294  -0.132905  -0.995279  -0.983111  -0.913526  -0.995112  -0.983185  -0.923527  -0.934724 ...             -0.710304
1   0.278419  -0.016411  -0.123520  -0.998245  -0.975300  -0.960322  -0.998807  -0.974914  -0.957686  -0.943068 ...             -0.861499
2   0.279653  -0.019467  -0.113462  -0.995380  -0.967187  -0.978944  -0.996520  -0.963668  -0.977469  -0.938692 ...             -0.760104
3   0.279174  -0.026201  -0.123283  -0.996091  -0.983403  -0.990675  -0.997099  -0.982750  -0.989302  -0.938692 ...             -0.482845
4   0.276629  -0.016570  -0.115362  -0.998139  -0.980817  -0.990482  -0.998321  -0.979672  -0.990441  -0.942469 ...             -0.699205

5 rows × 563 columns
```

In [5]:
```
# Part 3: Feature and Target Separation
# - Separate features (`X`) from the target variable (`y`).
```

```python
# Teil 3: Trennung von Merkmalen und Zielvariablen
# - Trennen Sie die Merkmale (`X`) von der Zielvariablen (`y`).


X = df.drop("subject", axis = 1).drop("Activity", axis = 1)
y = df["Activity"]
```

In [4]:

```python
X
```

Out[4]:

| | 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 | ... | fBodyBodyGyroJerkMag-meanFreq() | fBodyBodyGyro. sk |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.288585 | -0.020294 | -0.132905 | -0.995279 | -0.983111 | -0.913526 | -0.995112 | -0.983185 | -0.923527 | -0.934724 | ... | -0.074323 | |
| **1** | 0.278419 | -0.016411 | -0.123520 | -0.998245 | -0.975300 | -0.960322 | -0.998807 | -0.974914 | -0.957686 | -0.943068 | ... | 0.158075 | |
| **2** | 0.279653 | -0.019467 | -0.113462 | -0.995380 | -0.967187 | -0.978944 | -0.996520 | -0.963668 | -0.977469 | -0.938692 | ... | 0.414503 | |
| **3** | 0.279174 | -0.026201 | -0.123283 | -0.996091 | -0.983403 | -0.990675 | -0.997099 | -0.982750 | -0.989302 | -0.938692 | ... | 0.404573 | |
| **4** | 0.276629 | -0.016570 | -0.115362 | -0.998139 | -0.980817 | -0.990482 | -0.998321 | -0.979672 | -0.990441 | -0.942469 | ... | 0.087753 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **7347** | 0.299665 | -0.057193 | -0.181233 | -0.195387 | 0.039905 | 0.077078 | -0.282301 | 0.043616 | 0.060410 | 0.210795 | ... | -0.070157 | |
| **7348** | 0.273853 | -0.007749 | -0.147468 | -0.235309 | 0.004816 | 0.059280 | -0.322552 | -0.029456 | 0.080585 | 0.117440 | ... | 0.165259 | |
| **7349** | 0.273387 | -0.017011 | -0.045022 | -0.218218 | -0.103822 | 0.274533 | -0.304515 | -0.098913 | 0.332584 | 0.043999 | ... | 0.195034 | |
| **7350** | 0.289654 | -0.018843 | -0.158281 | -0.219139 | -0.111412 | 0.268893 | -0.310487 | -0.068200 | 0.319473 | 0.101702 | ... | 0.013865 | |
| **7351** | 0.351503 | -0.012423 | -0.203867 | -0.269270 | -0.087212 | 0.177404 | -0.377404 | -0.038678 | 0.229430 | 0.269013 | ... | -0.058402 | |

7352 rows × 561 columns

In [6]:

```python
X = df.drop("subject", axis = 1).drop("Activity", axis = 1)
y = df["Activity"]

# Part 4: Data Standardization
# - Standardize the features to have zero mean and unit variance.

# Teil 4: Datenstandardisierung
# - Standardisieren Sie die Merkmale, um einen Mittelwert von null und eine Varianz von eins zu erreichen.

from sklearn.preprocessing import StandardScaler
```

```
s = StandardScaler()
X = s.fit_transform(X)
```

In [7]:
```
X
```

Out[7]:
```
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]])
```

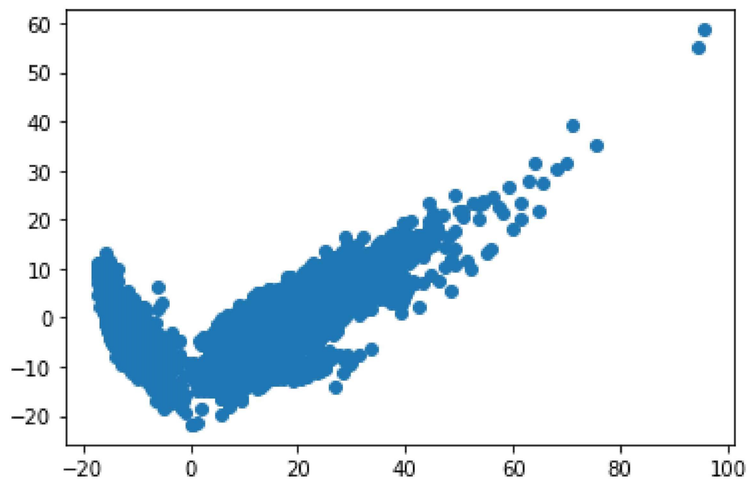
In [8]:
```
# Part 5: Applying PCA (2 Components)
# - Apply PCA to reduce the dimensionality to 2 components.

# Teil 5: Anwendung von PCA (2 Komponenten)
# - Wenden Sie PCA an, um die Dimensionalität auf 2 Komponenten zu reduzieren.

from sklearn.decomposition import PCA

p = PCA(n_components = 2)
p.fit(X)

X_transformed = p.transform(X)
```

In [9]:
```
X_transformed
```

Out[9]:
```
array([[-16.13854371,   2.15202402],
       [-15.2961943 ,   1.38714381],
       [-15.13701861,   2.47335095],
       ...,
       [ 14.33343587, -12.26071186],
       [ 12.87601895, -14.07125583],
       [ 13.01610365, -12.2442612 ]])
```

In [10]:
```
# Part 6: Visualizing 2D PCA Results
# - Visualize the transformed data in a 2D scatter plot.
```

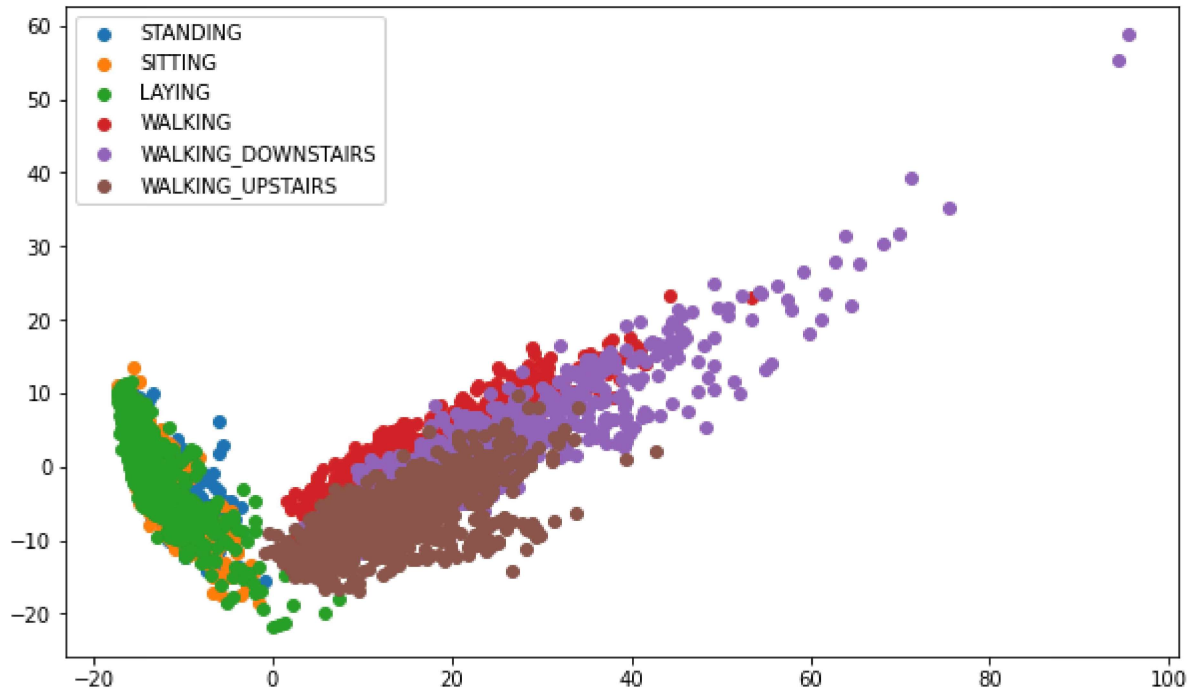
```python
# Teil 6: Visualisierung der 2D-PCA-Ergebnisse
# - Visualisieren Sie die transformierten Daten in einem 2D-Streudiagramm.

%matplotlib inline

import matplotlib.pyplot as plt

plt.scatter(X_transformed[:, 0], X_transformed[:, 1])
plt.show()
```



In [14]:
```python
y.unique()
```

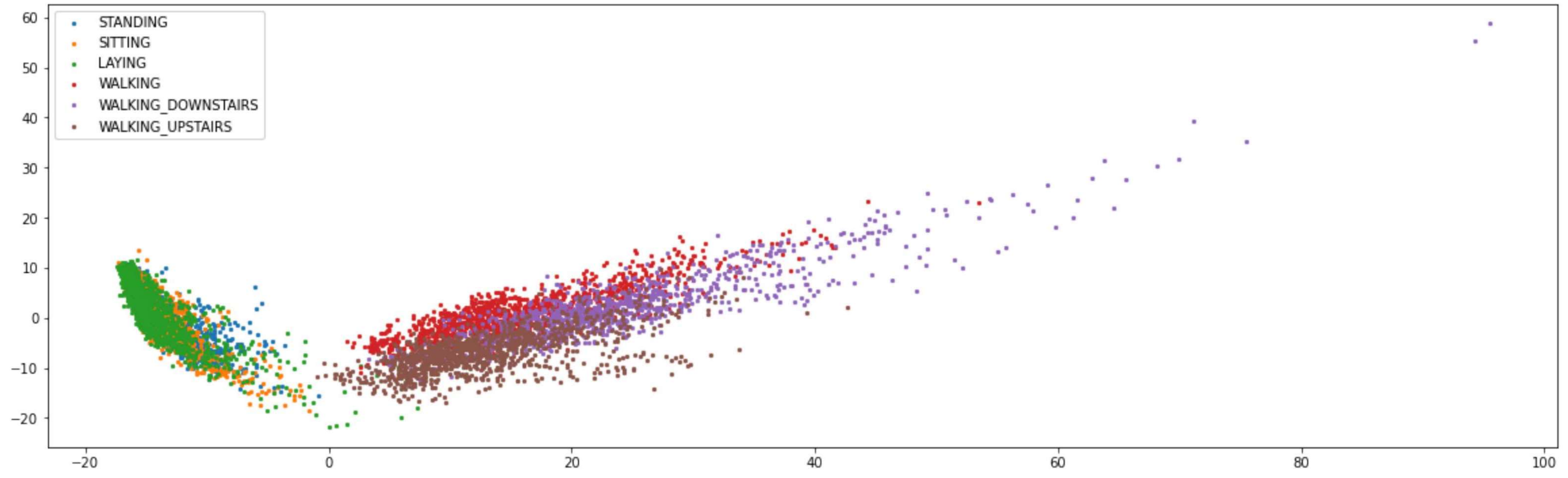
Out[14]:
```
array(['STANDING', 'SITTING', 'LAYING', 'WALKING', 'WALKING_DOWNSTAIRS',
       'WALKING_UPSTAIRS'], dtype=object)
```

In [11]:
```python
# Part 7: Enhanced 2D Visualization
# - Visualize the transformed data in a 2D scatter plot, separated by activity labels.

# Teil 7: Erweiterte 2D-Visualisierung
# - Visualisieren Sie die transformierten Daten in einem 2D-Streudiagramm, getrennt nach Aktivitätslabels.

%matplotlib inline

import matplotlib.pyplot as plt

plt.figure(figsize = (10, 6))

for activity in y.unique():
    X_transformed_filtered = X_transformed[y == activity, :]
    plt.scatter(X_transformed_filtered[:, 0], X_transformed_filtered[:, 1], label = activity)
plt.legend()
plt.show()
```



In [12]:

```
# Part 9: Applying PCA (3 Components)
# - Apply PCA to reduce the dimensionality to 3 components.

## Anwendung von PCA (3 Komponenten)
# - Wenden Sie PCA an, um die Dimensionalität auf 3 Komponenten zu reduzieren.

%matplotlib inline

import matplotlib.pyplot as plt

plt.figure(figsize = (20, 6))

for activity in y.unique():
    X_transformed_filtered = X_transformed[y == activity, :]
    plt.scatter(X_transformed_filtered[:, 0], X_transformed_filtered[:, 1], label = activity, s = 5)

plt.legend()
plt.show()
```



In [13]:

```
# Part 8: Applying PCA (3 Components)
# - Apply PCA to reduce the dimensionality to 3 components.

# Teil 8: Anwendung von PCA (3 Komponenten)
# - Wenden Sie PCA an, um die Dimensionalität auf 3 Komponenten zu reduzieren.


from sklearn.decomposition import PCA

p = PCA(n_components = 3)
p.fit(X)

X_transformed = p.transform(X)
```

In [14]:

```
X_transformed.shape
```

Out[14]:

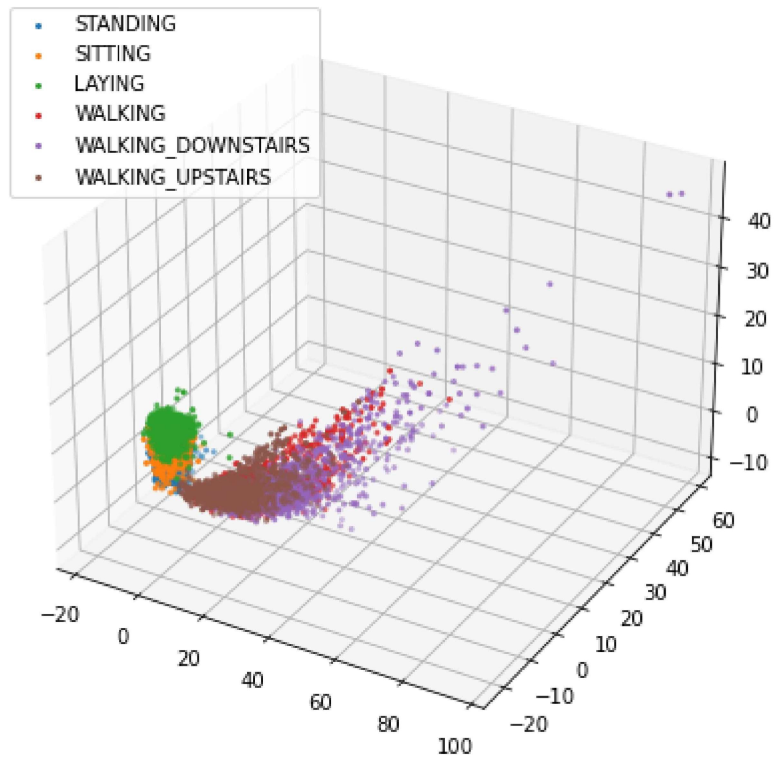
```
(7352, 3)
```

In [15]:

```
# Part 9: Visualizing 3D PCA Results
# - Visualize the transformed data in a 3D scatter plot, separated by activity labels.

# Teil 9: Visualisierung der 3D-PCA-Ergebnisse
# - Visualisieren Sie die transformierten Daten in einem 3D-Streudiagramm, getrennt nach Aktivitätslabels.

%matplotlib inline
```

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
```

In [16]:
```
s = StandardScaler()
X = s.fit_transform(X)

p = PCA(n_components=3)
p.fit(X)
X_transformed_3d = p.transform(X)

fig = plt.figure(figsize=(20, 7))
ax = fig.add_subplot(111, projection='3d')

for activity in y.unique():
    X_transformed_filtered = X_transformed_3d[y == activity, :]
    ax.scatter(
        X_transformed_filtered[:, 0],
        X_transformed_filtered[:, 1],
        X_transformed_filtered[:, 2],
        label=activity,
        s=4
    )

ax.legend()
plt.show()
```



In [17]:

```
# Part 10: Conclusion
# - PCA is an effective technique for dimensionality reduction and visualization.
# - It helps in understanding the structure of high-dimensional data.

# Teil 10: Fazit
# - PCA ist eine effektive Technik zur Dimensionsreduktion und Visualisierung.
# - Es hilft, die Struktur von hochdimensionalen Daten zu verstehen.
```

In [ ]: