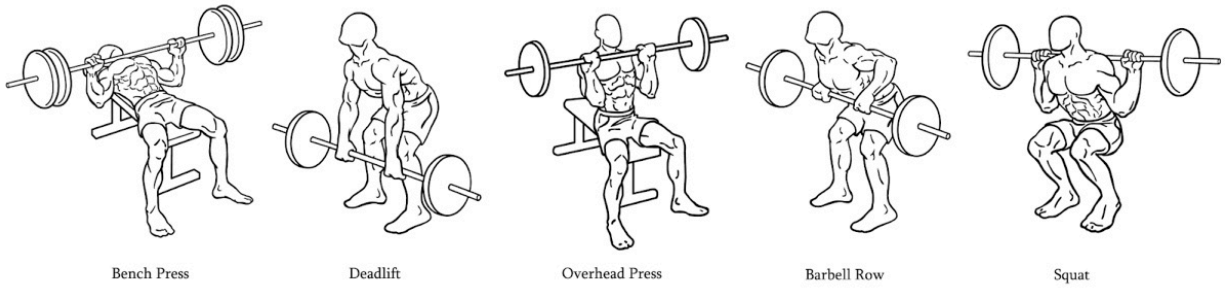
Wearable-Driven Exercise Recognition



Why This Project ?

As we move further into the era of automation, the fitness industry still has significant scop e for improvement in workout monitoring and tracking. Most individuals with regular gym e xperience rely on applications to log their workouts, such as the number of exercises, sets, and repetitions. However, this process is largely manual—users must select the exercise ty pe and enter repetitions themselves, which can be time-consuming and error-prone.

To address this limitation, this project aims to automate workout tracking by designing a m achine learning model that can detect and classify exercises using motion data captured fr om a fitness band worn on the wrist. By analyzing sensor data, the model can identify the performed exercise without requiring manual input from the user.

Currently, the model is trained to recognize barbell exercises, and future extensions may in clude additional workout types. This document focuses on the technical aspects of the proj ect, including data processing, model design, and evaluation.

Participant	Gender	Age	Weight (kg)	Height (cm)	Experience (years)
A	Male	23	95	194	5+
B	Male	24	76	183	5+
C	Male	16	65	181	< 1
D	Male	21	85	197	3
E	Female	20	58	165	1

All libraries and their use-cases:

```
import pandas as pd  # Used for all DataFrame-related operations
from glob import glob  # Used to extract all CSV files from the MetaMotion folder
import matplotlib.pyplot as plt  # Used for creating plots and visualizations
import matplotlib as mpl  # Used for configuring global Matplotlib setting
import math #Used for basic mathematical operations required in statistical formulas.
import scipy # Used for probability and statistical functions.
from sklearn.neighbors import LocalOutlierFactor # Used for distance-based, multivariate outlier detection.
from DataTransformation import LowPassFilter, PrincipalComponentAnalysis  # Noise reduction and dimensionality reduction
from TemporalAbstraction import NumericalAbstraction # Temporal (sliding-window) feature extraction
from FrequencyAbstraction import FourierTransformation # Frequency-domain feature extraction (FFT)
from sklearn.cluster import KMeans # Unsupervised clustering of motion patterns
from sklearn.model_selection import train_test_split  # split dataset into training and testing sets
from LearningAlgorithms import ClassificationAlgorithms  # custom module to manage and compare classification models
import seaborn as sns  # data visualization (EDA, heatmaps, plots)
import itertools  # efficient looping for combinations and permutations
from sklearn.metrics import accuracy_score, confusion_matrix  # evaluate model performance (accuracy and error breakdown)
```

Flow:

1. Make Dataset:

```
file = glob("MetaMotion/*.csv")
len(file)
```

- Here, we create a list containing the paths of all CSV files present in the `MetaMotion` directory.
- We can train machine learning model on one file only but as of now we have separate files for separate performer and for different sets and different weights so our first task is to merge all files into one file.

  A machine learning model can be trained on a single file; however, in this dataset the data is distributed across multiple files. Each file corresponds to a different participant, exercise

set, and weight. Therefore, the first step of this project is to merge all individual files into a single consolidated dataset that can be used for model training.

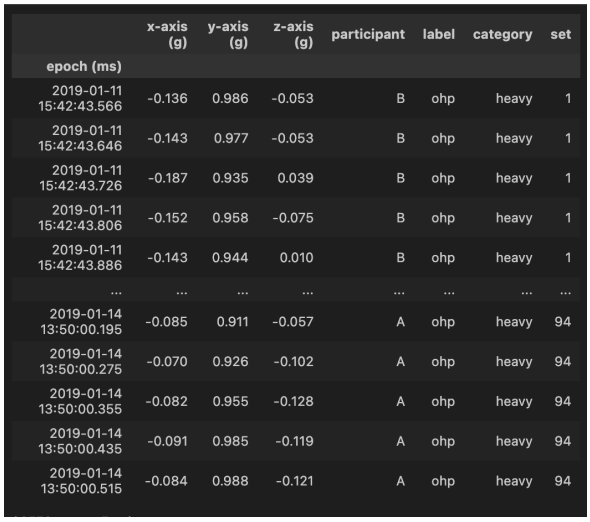
As a preliminary step, we extract metadata such as **participant**, **label**, and **category** from the filename and append this information as additional columns to the data.

```
acc_df = pd.DataFrame()
gyro_df = pd.DataFrame()

acc_set = 1
gyro_set = 1

for f in file:
  participant = f.split('-')[0].replace(datapath,'')
  label = f.split('-')[1]
  category = f.split('-')[2].rstrip("123").rstrip("_MetaWear_2019")

  df = pd.read_csv(f)
  df["participant"] = participant
  df["label"] = label
  df["category"] = category

  if "Accelerometer" in f:
    df["set"] = acc_set
    acc_set += 1
    acc_df = pd.concat([acc_df,df])

  elif "Gyroscope" in f:
    df["set"] = gyro_set
    gyro_set += 1
    gyro_df = pd.concat([gyro_df,df])
```

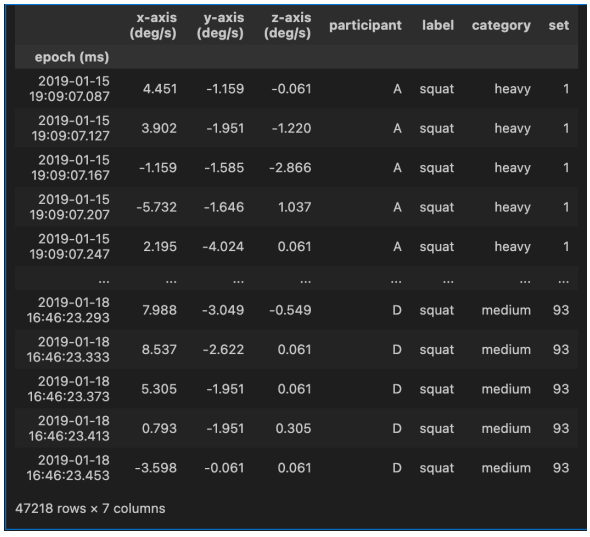
- In this step, the sensor timestamps stored as epoch time (in milliseconds) are converted into datetime format and set as the index of the accelerometer and gyroscope DataFrames. This transformation enables time-series operations such as resampling and alignment between sensors. After setting the datetime index, redundant timestamp-related columns are removed to avoid duplication and keep the dataset clean for further processing and model training.

```
acc_df.info()
pd.to_datetime(df["epoch (ms)"], unit="ms")
```

```
acc_df.index = pd.to_datetime(acc_df["epoch (ms)"], unit="ms")
gyro_df.index = pd.to_datetime(gyro_df["epoch (ms)"], unit="ms")

del acc_df["epoch (ms)"]
del acc_df["time (01:00)"]
del acc_df["elapsed (s)"]

del gyro_df["epoch (ms)"]
del gyro_df["time (01:00)"]
del gyro_df["elapsed (s)"]
```



epoch (ms)	x-axis (g)	y-axis (g)	z-axis (g)	participant	label	category	set
2019-01-11 15:42:43.566	-0.136	0.986	-0.053	B	ohp	heavy	1
2019-01-11 15:42:43.646	-0.143	0.977	-0.053	B	ohp	heavy	1
2019-01-11 15:42:43.726	-0.187	0.935	0.039	B	ohp	heavy	1
2019-01-11 15:42:43.806	-0.152	0.958	-0.075	B	ohp	heavy	1
2019-01-11 15:42:43.886	-0.143	0.944	0.010	B	ohp	heavy	1
...	...	...	...	...	...	...	...
2019-01-14 13:50:00.195	-0.085	0.911	-0.057	A	ohp	heavy	94
2019-01-14 13:50:00.275	-0.070	0.926	-0.102	A	ohp	heavy	94
2019-01-14 13:50:00.355	-0.082	0.955	-0.128	A	ohp	heavy	94
2019-01-14 13:50:00.435	-0.091	0.985	-0.119	A	ohp	heavy	94
2019-01-14 13:50:00.515	-0.084	0.988	-0.121	A	ohp	heavy	94



epoch (ms)	x-axis (deg/s)	y-axis (deg/s)	z-axis (deg/s)	participant	label	category	set
2019-01-15 19:09:07.087	4.451	-1.159	-0.061	A	squat	heavy	1
2019-01-15 19:09:07.127	3.902	-1.951	-1.220	A	squat	heavy	1
2019-01-15 19:09:07.167	-1.159	-1.585	-2.866	A	squat	heavy	1
2019-01-15 19:09:07.207	-5.732	-1.646	1.037	A	squat	heavy	1
2019-01-15 19:09:07.247	2.195	-4.024	0.061	A	squat	heavy	1
...	...	...	...	...	...	...	...
2019-01-18 16:46:23.293	7.988	-3.049	-0.549	D	squat	medium	93
2019-01-18 16:46:23.333	8.537	-2.622	0.061	D	squat	medium	93
2019-01-18 16:46:23.373	5.305	-1.951	0.061	D	squat	medium	93
2019-01-18 16:46:23.413	0.793	-1.951	0.305	D	squat	medium	93
2019-01-18 16:46:23.453	-3.598	-0.061	0.061	D	squat	medium	93

47218 rows × 7 columns

- The primary reason for converting the `epoch (ms)` column into a readable datetime format is that the other two time-related fields represent the same information in less useful forms. The epoch timestamp records time in milliseconds since 1 January 1970, providing the high precision required for sensor-based data. In contrast, the `time (01:00)` column does not reliably capture timestamps at millisecond resolution, making it unsuitable for precise time-series operations. The `elapsed (s)` column represents relative time since the start of recording, which does not add meaningful information for sensor alignment or model training. Therefore, epoch time is retained and converted to a datetime index, while the remaining time-related columns are removed.

```
data_merged = pd.concat([acc_df.iloc[:,:3],gyro_df],axis=1)
```

- In this step, accelerometer and gyroscope signals are merged using their datetime index to align measurements from both sensors. Since the sensors operate at different sampling rates, the combined dataset is resampled to a common frequency of 200 ms using mean

aggregation for sensor values and forward propagation for metadata. This process produces a synchronized and clean time-series dataset suitable for machine learning.

```
# Accelerometer:    12.500HZ
# Gyroscope:        25.000Hz
sampling = {
    "acc_x": "mean",
    "acc_y": "mean",
    "acc_z": "mean",
    "gyr_x": "mean",
    "gyr_y": "mean",
    "gyr_z": "mean",
    "participant": "last",
    "label": "last",
    "category": "last",
    "set": "last",
}
data_merged[: 1000].resample(rule="200ms").apply(sampling)
# Split by day
days = [g for n, g in data_merged.groupby(pd.Grouper(freq="D"))]
data_resampled = pd.concat([df.resample(rule="200ms").apply(sampling).dropna() for df i
n days])
data_resampled["set"] = data_resampled["set"].astype("int")
data_resampled.info()
```

- Since the accelerometer and gyroscope operate at different sampling rates, the merged dataset is resampled into fixed 200 ms time windows. Sensor values within each window are averaged to align both signals in time and reduce noise, producing a uniform time-series suitable for machine learning.

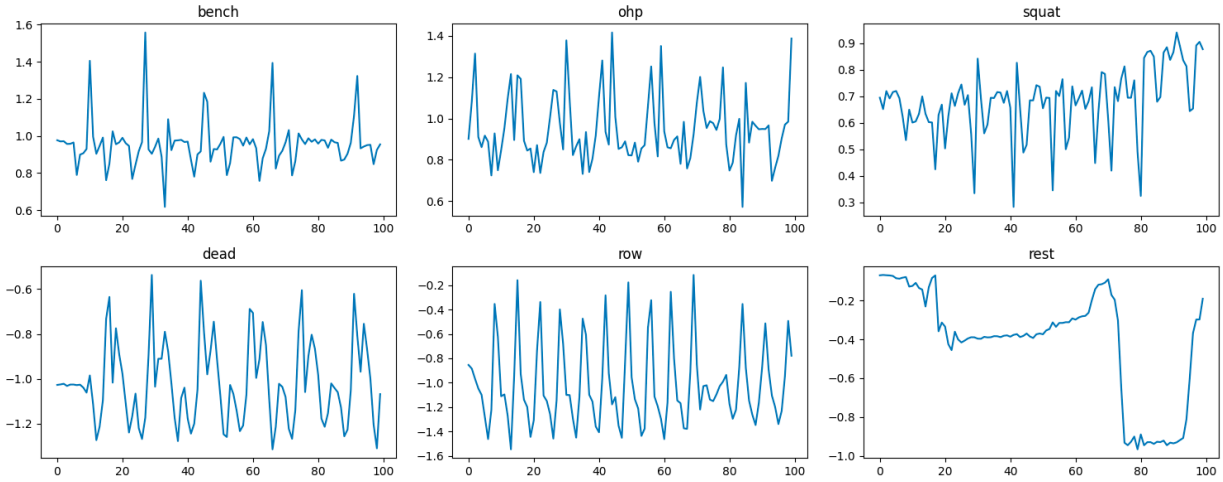
```
data_resampled.to_pickle("data_resampled.pkl")
```

- `.pkl` stands for **pickle**.
- In CSV format, data types are not preserved. For example, when a datetime column is stored in a `.csv` file, it is converted into a string and must be explicitly typecast back to a datetime object after loading. In contrast, a pickle (`.pkl`) file stores the Python object as it is, preserving data types and the DataFrame structure. This makes pickle especially useful for small to medium-sized datasets during experimentation and rapid iteration.

2. Visualisation:

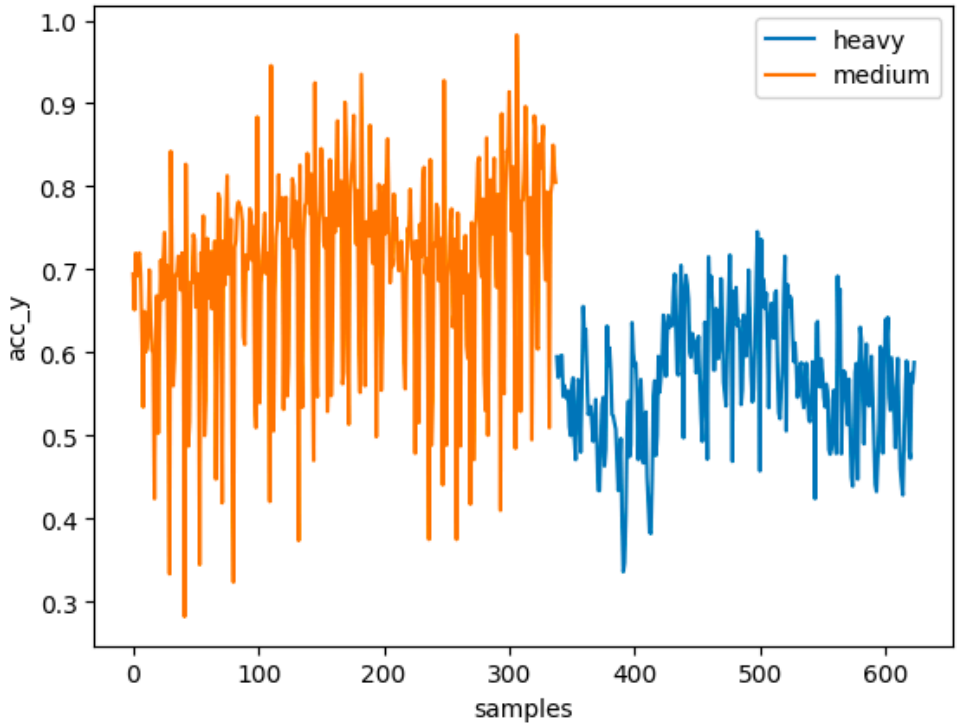
```
for label in df["label"].unique():
    subset = df[df["label"] == label]
    fig, ax = plt.subplots()
    plt.plot(subset["acc_y"].reset_index(drop=True), label=label)
    plt.legend()
    plt.show()
```

- Here we are plotting acc_y for all labels.



- Visual inspection of the accelerometer Y-axis signals reveals distinct motion patterns for each exercise. Pushing movements such as bench press and overhead press show sharp vertical spikes, while pulling movements like rows and deadlifts exhibit strong oscillatory patterns. Squats display smoother, full-body motion, and rest periods are characterised by low-variance signals. These clear differences indicate that the sensor data contains sufficient discriminative information for exercise classification.

```
category_df = df.query("label == 'squat'").query("participant == 'A'").reset_index(drop=Tru
e)

fig, ax = plt.subplots()
category_df.groupby(["category"])["acc_y"].plot()
ax.set_ylabel("acc_y")
ax.set_xlabel("samples")
plt.legend()
plt.show()
```



- For the squat exercise performed by participant A, the **medium** category shows higher variability and larger fluctuations in `acc_y`, indicating more dynamic or faster movements. In contrast, the **heavy** category exhibits lower variability with a more stable acceleration pattern, suggesting slower, more controlled motion under higher load. This difference indicates that movement intensity and control vary clearly with weight category, making `acc_y` useful for distinguishing exercise intensity.

3. Outliers Detection:

- Due to natural variations in human movement, sensor recordings may include unintended motions that appear as outliers. Identifying and removing these outliers helps improve data quality and model robustness.

```
df = pd.read_pickle("data_resampled.pkl")
outlier_columns = list(df.columns[:6])
```

- First, we load the processed dataset that was generated in the *dataset creation* (make dataset) component of the pipeline.

Method 1: IQR:

```
df[outlier_columns[:3] + ["label"]].boxplot(by="label", figsize=(20, 10), layout=(1,3))
```

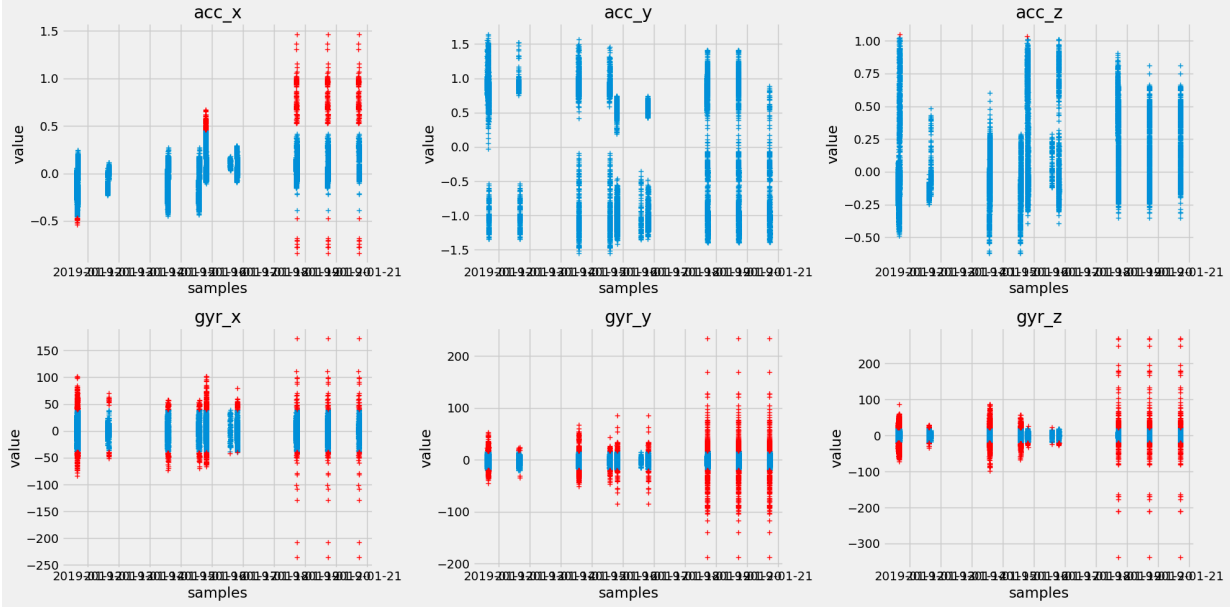
```
df[outlier_columns[3:] + ["label"]].boxplot(by="label", figsize=(20, 10), layout=(1,3))
```

- Here we are doing outliers detection using box plot.

A **box plot** is a statistical visualization technique used to summarize the distribution of a dataset and identify potential outliers. It represents the data using:

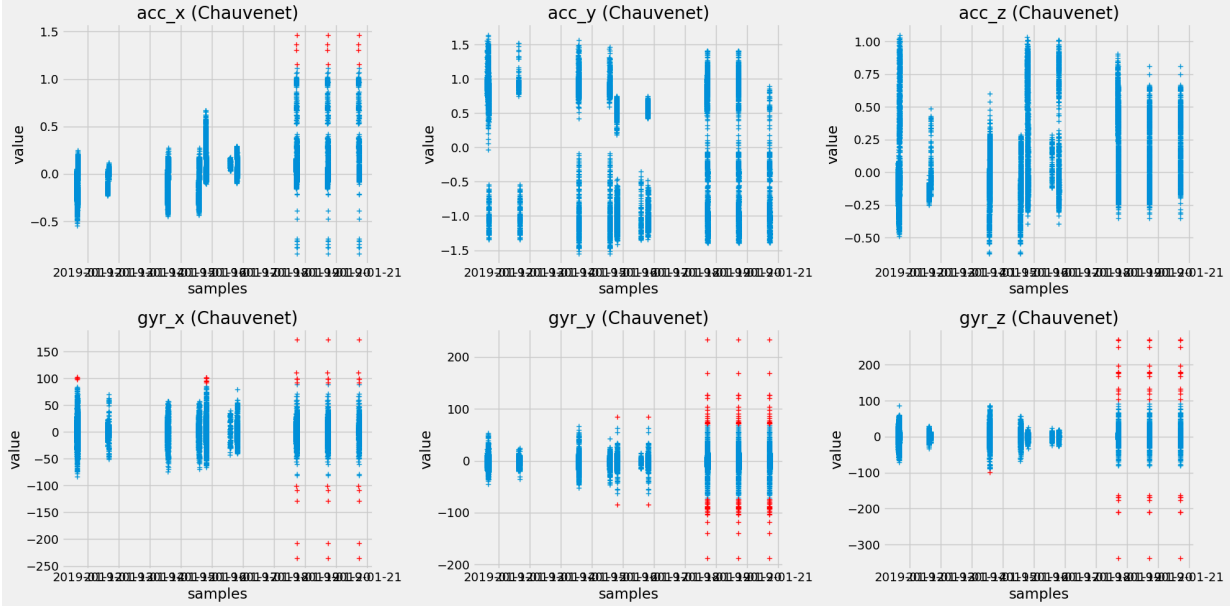
- **Median**
- **First quartile (Q1)**
- **Third quartile (Q3)**
- **Interquartile range (IQR)**

```
IQR = Q3 - Q1
Q1 - 1.5 X IQR   or   Q3 + 1.5 X IQR
```



Method 2: Chauvenet Method

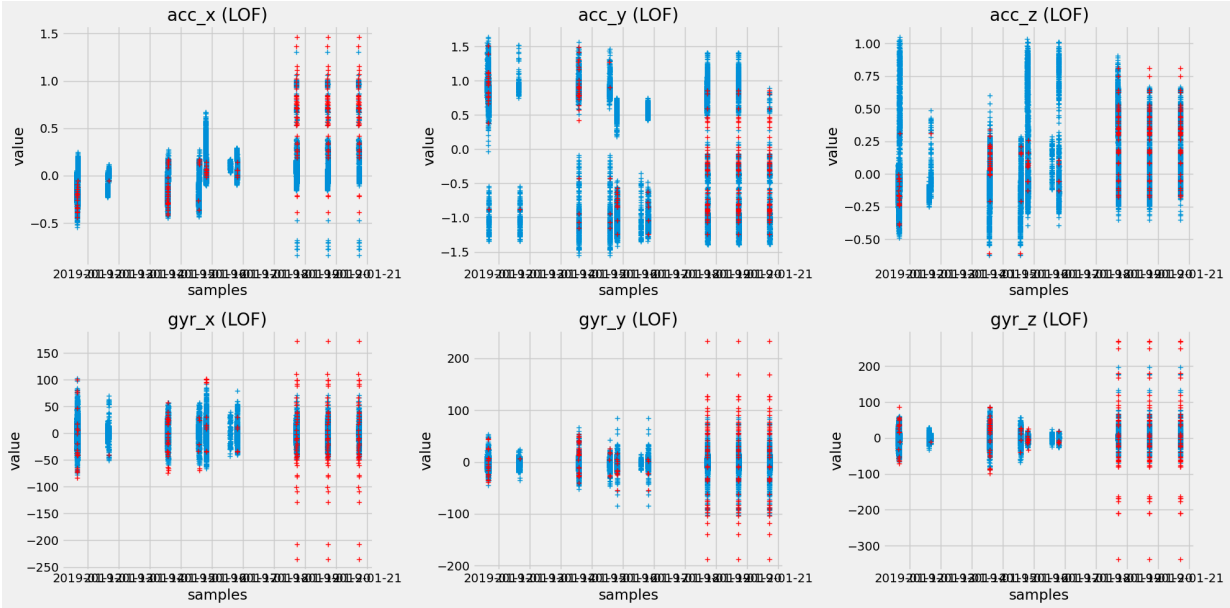
- **Chauvenet's criterion** is a **statistical, probability-based method** for detecting outliers under the assumption that the data follows a **normal (Gaussian) distribution**.
- Chauvenet removes statistically improbable sensor readings without over-filtering valid motion signals.



- Now we can notice that there are less and valid outliers.

Method 3: LOF

- **Local Outlier Factor (LOF)** is a **density-based outlier detection algorithm**.



- After analysing all we can notice that in all 3 methods Chauvenet is best method. It is manual method, we will select method which will detect outliers and reasonable amount.

```
outliers_removed_df.to_pickle("outliers_removed_chauvenet.pkl")
```

- As of now we are not removing outliers we are just marking rows as NaN(not a number). We are storing this as outliers_removed_chauvenet.pkl.

4. Feature Engineering:

```
for col in predicted_columns:
    df[col] = df[col].interpolate()
```

- Here we are handling missing values. interpolate will make a bridge in the place of missing values.

To calculate the **duration of each exercise set** and analyze how long different exercise categories take on average.

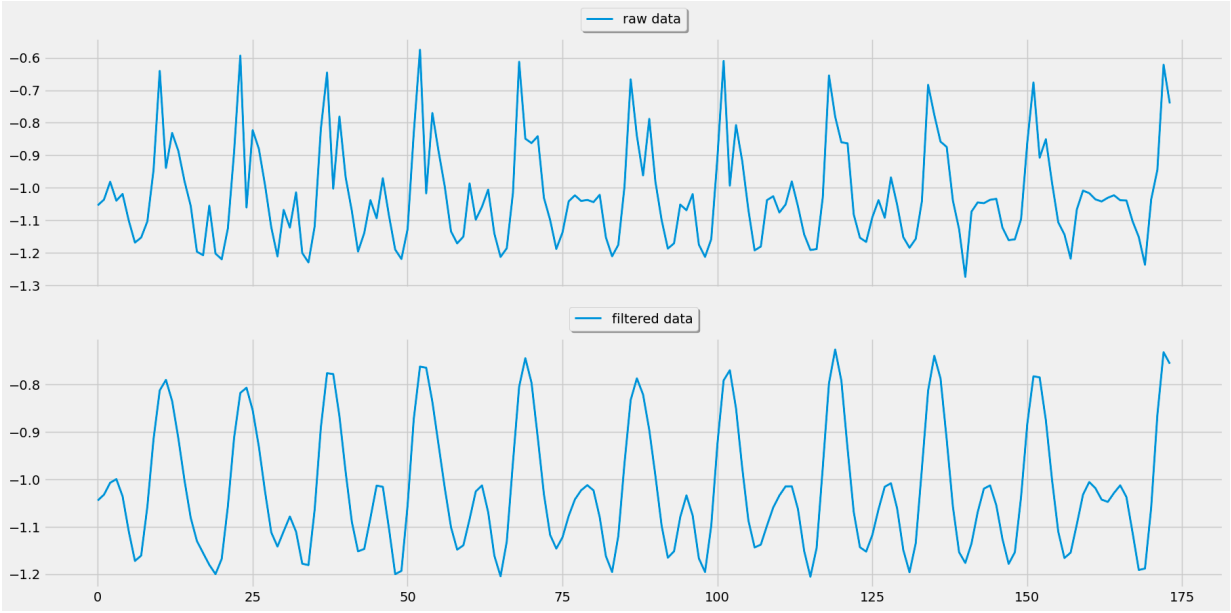
```
# Compute duration of a single set (example)
duration = df[df["set"]==1].index[-1] - df[df["set"]==1].index[0]
duration.seconds

# Compute duration for every set
for s in df["set"].unique():
    start =  df[df["set"]==s].index[0]
    stop = df[df["set"]==s].index[-1]
    duration = stop - start
    # Store duration back into the dataframe
    df.loc[(df["set"]==s), "duration"] = duration.seconds

# Analyze duration by exercise category
duration_df = df.groupby(["category"])["duration"].mean()

# Normalize duration by repetitions
duration_df.iloc[0] / 5
duration_df.iloc[1] / 10
```

- Here we compute the duration of each exercise set using timestamps and analyze how set length varies across exercise categories to understand tempo and intensity differences.

```
df_lowpass = df.copy()
LowPass = LowPassFilter()

fs = 1000 / 200
# Frequencies above 1 Hz are treated as noise
# Human exercise movements typically occur below 1 Hz
```

```
cutoff = 1

df_lowpass = LowPass.low_pass_filter(df_lowpass, "acc_y", fs , cutoff)

subset = df_lowpass[df_lowpass["set"]==45]
print(subset["label"][0])

fig, ax = plt.subplots(nrows=2, sharex=True, figsize=(20, 10))
ax[0].plot(subset["acc_y"].reset_index(drop=True), label = "raw data")
ax[1].plot(subset["acc_y_lowpass"].reset_index(drop=True), label = "filtered data")
ax[0].legend(loc="upper center", bbox_to_anchor=(0.5, 1.15), ncol=3, fancybox=True, shad
ow=True)
ax[1].legend(loc="upper center", bbox_to_anchor=(0.5, 1.15), ncol=3, fancybox=True, shad
ow=True)


for col in predicted_columns:
    df_lowpass = LowPass.low_pass_filter(df_lowpass, col, fs , cutoff, order=5)
    df_lowpass[col] = df_lowpass[col + "_lowpass"]
    del df_lowpass[col + "_lowpass"]
```

- To **remove high-frequency noise** from the sensor signals using a low-pass filter, while preserving the meaningful human motion patterns.



- High-frequency noise does not represent actual motion

- Can mislead feature extraction and ML models
- Temporal features (mean, std) become smoother
- Frequency features become more meaningful

PCA:

- To **reduce the dimensionality** of the sensor data by transforming correlated sensor axes into a smaller set of informative, uncorrelated features.

```
df_pca = df_lowpass.copy()
PCA = PrincipalComponentAnalysis()

# Applies PCA using all sensor axes
# Computes how much variance each principal component explains
pc_values = PCA.determine_pc_explained_variance(df_pca, predicted_columns)

plt.figure(figsize=(10, 10))
plt.plot(range(1, len(predicted_columns) + 1), pc_values)
plt.xlabel("principle component number")
plt.ylabel("explained variance")
plt.show()

df_pca = PCA.apply_pca(df_pca, predicted_columns, 3)

subset = df_pca[df_pca["set"]==35]
subset[["pca_1", "pca_2", "pca_3"]].plot()
```

```
df_squared = df_pca.copy()
acc_r = df_squared["acc_x"]**2 + df_squared["acc_y"]**2 + df_squared["acc_z"]**2
gyr_r = df_squared["gyr_x"]**2 + df_squared["gyr_y"]**2 + df_squared["gyr_z"]**2

df_squared["gyr_r"] = np.sqrt(gyr_r)
df_squared["acc_r"] = np.sqrt(acc_r)

subset = df_squared[df_squared["set"]==14]
subset[["acc_r", "gyr_r"]].plot(subplots=True)
```

Feature	Captures
PCA	Dominant movement directions

Feature	Captures
acc_r	Overall movement intensity

```
df_temporal = df_squared.copy()
Numbs = NumericalAbstraction()

predicted_columns = predicted_columns + ["acc_r", "gyr_r"]

ws = int(1000 / 200)

for col in predicted_columns:
    df_temporal = Numbs.abstract_numerical(df_temporal,[col], ws, "mean")
    df_temporal = Numbs.abstract_numerical(df_temporal,[col], ws, "std")

df_temporal_list = []
for s in df_temporal["set"].unique():
    subset = df_temporal[df_temporal["set"]==s].copy()
    for col in predicted_columns:
        subset = Numbs.abstract_numerical(subset,[col], ws, "mean")
        subset = Numbs.abstract_numerical(subset,[col], ws, "std")
    df_temporal_list.append(subset)

df_temporal = pd.concat(df_temporal_list)
df_temporal.info()

subset[["acc_y", "acc_y_temp_mean_ws_5", "acc_y_temp_std_ws_5"]].plot()
subset[["gyr_y", "gyr_y_temp_mean_ws_5", "gyr_y_temp_std_ws_5"]].plot()
```

- ML models struggle with millisecond-level noise
- Temporal summaries capture **behavior**, not spikes
- To extract **frequency-domain features** from sensor data in order to capture **exercise rhythm, repetition speed, and motion regularity**, which are not visible in the time domain.

These features help differentiate:

- Slow vs fast reps
- Controlled vs sloppy movement
- Different exercises with similar amplitudes

```
df_freq = df_temporal.copy().reset_index()
FreqAbs = FourierTransformation()

fs = int(1000 / 200)
ws = int(2800 / 200)

df_freq = FreqAbs.abstract_frequency(df_freq, ["acc_y"], ws, fs)

subset = df_freq[df_freq["set"] == 15]
subset[["acc_y"]].plot()

# Validate frequency features respond to motion changes
# Each feature represents:
# max_freq → dominant repetition rate
# freq_weighted → average motion speed
# pse → movement consistency
# specific Hz bins → strength at known repetition frequencies

subset[[
    "acc_y_max_freq",
    "acc_y_freq_weighted",
    "acc_y_pse",
    "acc_y_freq_1.429_Hz_ws_14",
    "acc_y_freq_2.5_Hz_ws_14",
]].plot()

df_freq_list = []
for s in df_freq["set"].unique():
    print(f"Applying Fourier transformation to set {s}")
    subset = df_freq[df_freq["set"]==s].reset_index(drop=True).copy()
    df_freq_list.append(subset)

df_freq = pd.concat(df_freq_list).set_index("epoch (ms)", drop=True)
```

```
kmeans = KMeans(n_clusters=5, n_init=20, random_state=0)
subset = df_cluster[cluster_columns]
df_cluster["cluster"] = kmeans.fit_predict(subset)

fig = plt.figure(figsize=(15, 15))
```

```
ax = fig.add_subplot(projection="3d")
for c in df_cluster["cluster"].unique():
    subset = df_cluster[df_cluster["cluster"] == c]
    ax.scatter(subset["acc_x"], subset["acc_y"], subset["acc_z"], label=c)
ax.set_xlabel("x-axis")
ax.set_ylabel("y-axis")
ax.set_zlabel("z-axis")
plt.legend()
plt.show()

fig = plt.figure(figsize=(15, 15))
ax = fig.add_subplot(projection="3d")
for l in df_cluster["label"].unique():
    subset = df_cluster[df_cluster["label"] == l]
    ax.scatter(subset["acc_x"], subset["acc_y"], subset["acc_z"], label=l)
ax.set_xlabel("x-axis")
ax.set_ylabel("y-axis")
ax.set_zlabel("z-axis")
plt.legend()
plt.show()
```

- we are doing this to check whether data points are naturally creating clusters or not?

5. Modeling:

```
learner = ClassificationAlgorithms()

max_features = 10
selected_features, ordered_features, ordered_scores = learner.forward_selection(max_feat
ures, X_train, y_train)

plt.figure(figsize=(10,5))
plt.plot(np.arange(1, max_features + 1, 1), ordered_scores)
plt.xlabel("Number of features")
plt.ylabel("Accuracy")
plt.xticks(np.arange(1, max_features + 1, 1))
plt.show()

selected_features = ['acc_y_temp_mean_ws_5',
 'gyr_z_temp_std_ws_5',
 'acc_x',
```

```
 'gyr_r_temp_mean_ws_5',
 'pca_3',
 'gyr_z',
 'acc_r',
 'gyr_x',
 'acc_y',
 'acc_z_temp_std_ws_5']
```

- Here we have more than 40 features. so we are checking which features are giving best accuracy. So we are keeping max features as 10.
- We automatically select the smallest, most informative feature subset to maximize accuracy while avoiding redundant or noisy features.

Grid Search:

Model	Feature Set	Accuracy
NN	Feature Set 4	0.992589
XG	Feature Set 4	0.991700
RF	Feature Set 3	0.989810
RF	Feature Set 4	0.988421
RF	Selected Features	0.978694
NN	Selected Features	0.977304
KNN	Feature Set 4	0.977304
DT	Feature Set 3	0.974062
DT	Feature Set 4	0.973599
DT	Selected Features	0.967114
RF	Feature Set 1	0.965262
RF	Feature Set 2	0.965262
KNN	Feature Set 3	0.962019
DT	Feature Set 2	0.951366
NB	Feature Set 3	0.949050
DT	Feature Set 1	0.948124
NN	Feature Set 2	0.938861
NN	Feature Set 1	0.930987
KNN	Selected Features	0.919407
NB	Selected Features	0.914312
NB	Feature Set 4	0.911533

Model	Feature Set	Accuracy
NB	Feature Set 2	0.882816
NB	Feature Set 1	0.873553
KNN	Feature Set 1	0.859657
KNN	Feature Set 2	0.859194

```
basic_features = ["acc_x", "acc_y", "acc_z", "gyr_x", "gyr_y", "gyr_z"]
square_features = ["acc_r", "gyr_r"]
pca_features = ["pca_1", "pca_2", "pca_3"]
time_features = [f for f in df_train.columns if "_temp_" in f]
frequency_features = [f for f in df_train.columns if ("_freq" in f) or ("_pse" in f)]
cluster_features = ["cluster"]

df_train.columns[30:]

print("Basic features", len(basic_features))
print("Square features", len(square_features))
print("PCA features", len(pca_features))
print("Time features", len(time_features))
print("Frequency features", len(frequency_features))
print("clutser features", len(cluster_features))
```

```
feature_set_1 = list(set(basic_features))
feature_set_2 = list(set(basic_features + square_features + pca_features))
feature_set_3 = list(set(feature_set_2 + time_features))
feature_set_4 = list(set(feature_set_3 + frequency_features + cluster_features))
```

Here we are dividing features into 4 stages so we can check whether our pre-processing and feature engineering is worth it or not?

- Range for grid search is already mentioned in the Algorithm initialisation itself.

Counting Repetition:

```
from scipy.signal import argrelextrema
```

argrelextrema → find peaks (repetition points)

```
df = df[df["label"] != "rest"]
```

Repetition counting only makes sense during **active exercises**, not rest periods.

```
bench_df = df[df["label"] == "bench"]
squat_df = df[df["label"] == "squat"]
```

Why
Different exercises:

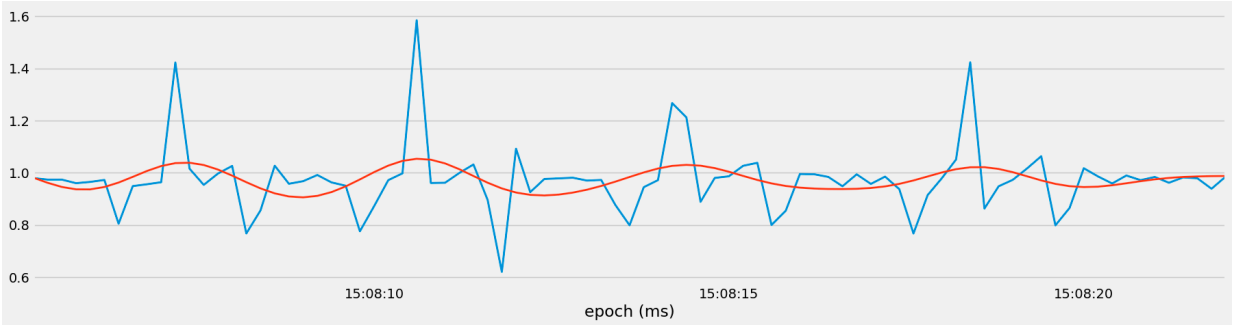
Have different motion patterns

Need different filter parameters

So we analyze each exercise separately.

```
fs = 1000 / 200
LowPass = LowPassFilter()
```

- We are using low pass filter because in normal noisy data we may have multiple spikes so we need to make signal smooth.



- Raw signal → noisy
- Filtered signal → smooth oscillations

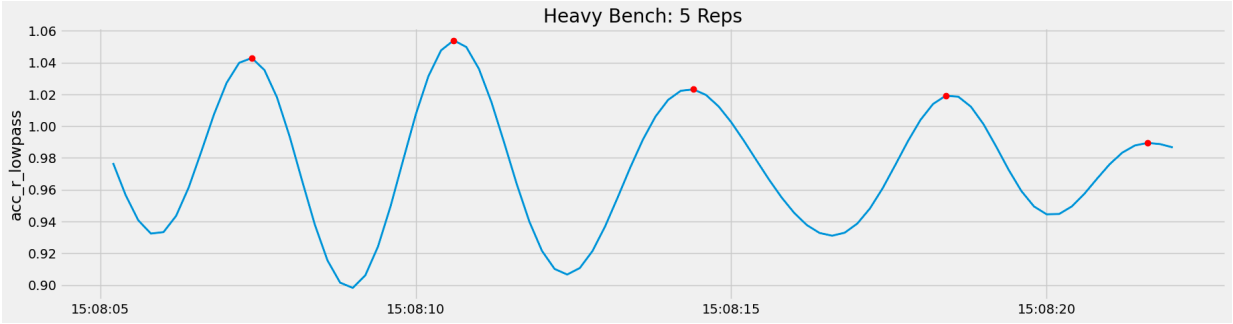
```
indexes = argrelextrema(
data[column + "_lowpass"].values, np.greater)
```

- Finds local maxima
- Each maximum corresponds to one completed movement

→ Key insight

One repetition = one dominant peak in filtered signal

```
plt.plot(peaks[f"{column}_lowpass"], "o", color="red")
```



Create a benchmark dataframe

```
df["reps"] = df["category"].apply(lambda x: 5 if x == "heavy" else 10)
rep_df = df.groupby(["label", "category", "set"])["reps"].max().reset_index()
rep_df["reps_pred"] = 0

for s in df["set"].unique():
    subset = df[df["set"] == s]

    column = "acc_r"
    cutoff = 0.4

    if subset["label"].iloc[0] == "squat":
        cutoff = 0.35

    if subset["label"].iloc[0] == "row":
        cutoff = 0.65
        col = "gyr_x"

    if subset["label"].iloc[0] == "ohp":
        cutoff = 0.35

    reps = count_reps(subset, cutoff=cutoff, column=column)

    rep_df.loc[rep_df["set"] == s, "reps_pred"] = reps

rep_df
```

Different exercises have:

- Different speeds
- Different movement smoothness

So:

- Squat → slower → lower cutoff
- Row → faster → higher cutoff
- OHP → controlled → lower cutoff

Key insight

> One filter does NOT fit all exercises
>
> Raw IMU signal
> ↓
> Vector magnitude (orientation-free)
> ↓
> Low-pass filtering (remove noise)
> ↓
> Peak detection
> ↓
> Repetition count
> ↓
> Evaluation vs ground truth