# Human Activity Recognition using Smart Phones

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## 1 Project Overview

**Human Activity Recognition (HAR)** is a field of research dedicated to identifying and classifying human activities based on data typically collected from various sensors. The activities can range from simple motions like walking and sitting to complex behaviors involving interactions with the environment and other individuals. HAR has significant applications in areas such as healthcare, sports, security, and human-computer interaction.

It also represents a fascinating and rapidly expanding field, blending insights from various disciplines such as machine learning, signal processing, and human behavior analysis. As technology and algorithms improve, the scope and accuracy of HAR systems are continuously evolving, offering new possibilities for applications that can significantly impact everyday life and various industries.

- Wearable Sensors: Devices like smartwatches and fitness bands equipped with accelerometers, gyroscopes, and heart rate monitors
- Environmental Sensors: Includes cameras and motion detectors used to monitor activities within a certain space
- Smartphone Sensors: Utilize the embedded sensors in smartphones, such as accelerometers and GPS, to detect activities passively as people carry their phones during daily routines

## 2 Dataset Description

The Human Activity Recognition (HAR) dataset used in the project consists of data collected from a group of 30 volunteers within an age bracket of 19-48 years. Each participant performed six activities: walking, walking upstairs, walking downstairs, sitting, standing, and laying. The data collection was conducted using a waist-mounted smartphone, specifically a Samsung Galaxy S II, which was equipped with embedded inertial sensors.

## 2.1 Key Features of the Dataset

- Sensor Data: The smartphone's built-in accelerometer and gyroscope provided 3-axial linear acceleration and 3-axial angular velocity measurements. The data was captured at a constant rate of 50Hz, which means readings were taken 50 times per second
- Feature Set: From the raw time-series sensor data, a 561-feature vector was derived for each window of measurements. These features are variables calculated in both time and frequency domains, including statistical measures like mean, standard deviation, and others such as energy, correlation, and entropy
- Triaxial Measurements: The '-XYZ' notation in the feature names denotes 3-axial signals in the X, Y, and Z directions, providing spatial details about the movements
- Activity Labels: Each record in the dataset is labeled with one of the six activity categories, which are encoded as part of the output variable for model training and testing.

## 2.2 Attributes

The Human Activity Recognition dataset features an extensive set of attributes derived from the accelerometer and gyroscope sensors on a smartphone. Here's a detailed look at the types of attributes included in this dataset, categorized by their extraction method and the nature of the data:

## 2.3 Time-Domain Attributes

These attributes are directly calculated from the time-based raw data collected from the sensors:

- Mean: The average value of the acceleration or angular velocity over the window
- Standard Deviation (std): Measures the amount of variation or dispersion from the mean
- Median Absolute Deviation : A robust measure of variability
- Max: The maximum value observed in the dataset window
- Min: The minimum value observed in the dataset window
- Signal Magnitude Area: The sum of the magnitudes of the three-dimensional signal.

## 2.4 Frequency-Domain Attributes

These are derived from the Fourier Transform of the time-domain signals, which helps to analyze the frequency components:

- Energy: Measures the sum of the squares of the values, normalized by the number of values
- Entropy: Used to quantify the regularity or unpredictability of the signal
- iqr (Interquartile Range): The range between the 25th and 75th percentile of the data distribution
- arCoeff (Auto-Regressive Coefficients): These coefficients describe the relation of the current value of the time series with its previous values
- Correlation: Measures the statistical correlation between two signals, like between the axes of accelerometer or gyroscope
- maxInds: The index of the frequency component with the largest magnitude
- meanFreq: The weighted average of the frequencies present in the signal, where the weights are the amplitude of the frequencies

## 2.5 Angle-Based Attributes

These attributes are derived by calculating angles between the signals:

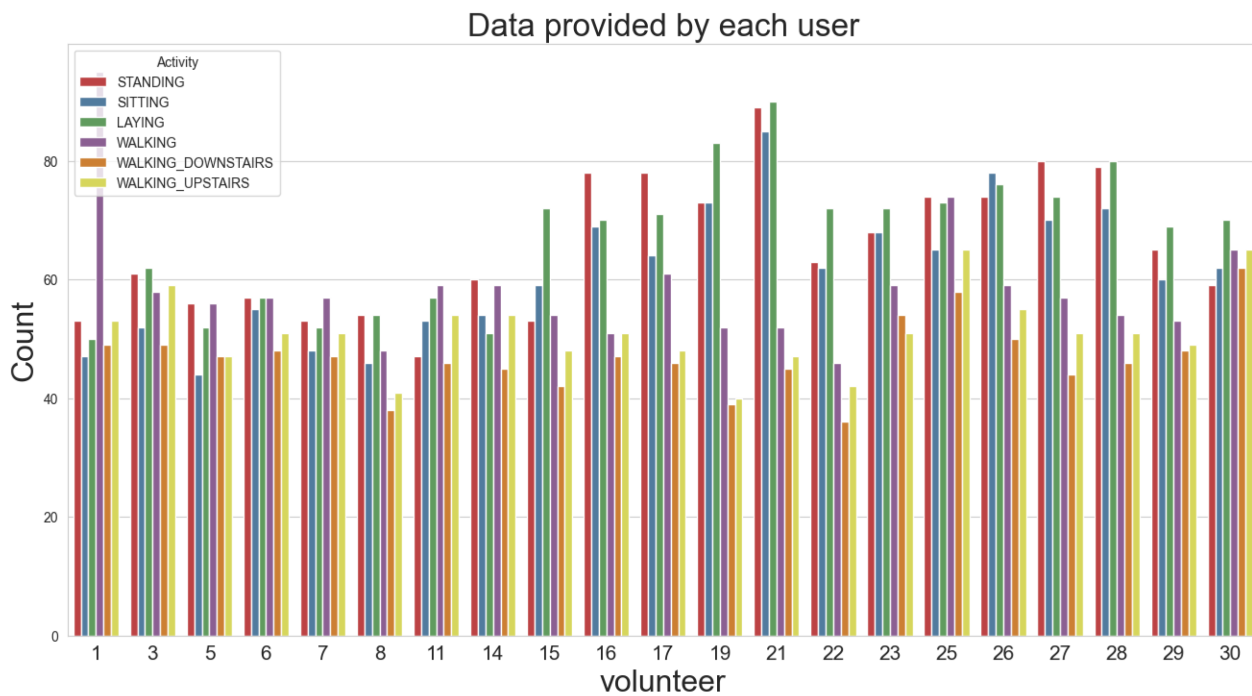
- angle(tBodyAccMean,gravity): The angle between the mean body acceleration and gravity vectors
- angle(tBodyAccJerkMean),gravityMean): Angle between the mean jerk signal and gravity
- angle(tBodyGyroMean,gravityMean): The angle between the mean gyroscope signal and gravity
- angle(tBodyGyroJerkMean,gravityMean): The angle between the mean of the gyroscope jerk signals and gravity

The dataset's attributes are rich and varied, allowing for a detailed analysis of human activity based on sensor data. By using both time and frequency domain features, along with angle-based attributes, the dataset provides a comprehensive set of variables that are useful for identifying and classifying different types of human movements and activities. The experiments were video-recorded to label the data manually, ensuring accurate activity classification. This meticulous process involved partitioning the recorded sensor data into fixed-width sliding windows of 2.56 seconds with 50% overlap between consecutive windows.

# 3 EDA

Exploratory Data Analysis (EDA) is a critical step in the data science workflow, especially where understanding the underlying patterns and distributions in the data is key to effective model building. EDA involves a series of techniques aimed at discovering patterns, spotting anomalies, framing hypotheses, and checking assumptions through summary statistics and graphical representations.

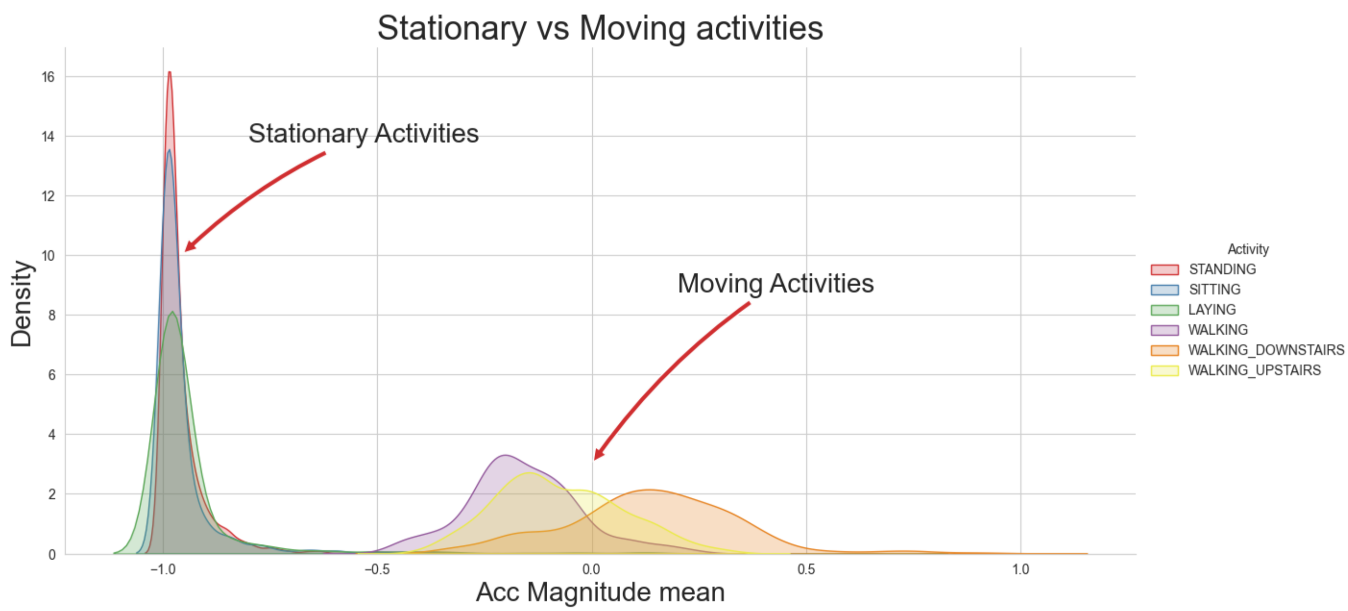
## 3.1 Data By Each User




The diagram you provided is a bar chart showing the distribution of data provided by each volunteer in a study, broken down by the type of activity recorded. Each bar represents a different volunteer, numbered from 1 to 30 along the horizontal axis. The height of each bar indicates the count of data points (or records) contributed by each volunteer for a specific activity.

- Consistency Across Volunteers: Most volunteers have contributed data across all activities, which is crucial for building a balanced and comprehensive dataset for activity recognition models

- Balancing the Dataset: This chart is particularly useful for assessing the balance of the dataset across different activities and participants. An imbalanced dataset might lead the trained models to develop a bias towards more frequently represented activities




## 3.2 Stationary vs Moving activities

- Stationary Activities (Standing, Sitting, Laying): These activities are grouped on the left side of the plot and have peaks with higher magnitude means close to zero. They are tightly clustered, indicating less variance in acceleration magnitude when a person is stationary
- Moving Activities (Walking, Walking Downstairs, Walking Upstairs): Shown on the right side, these activities demonstrate a broader spread in acceleration magnitude means, reflecting higher levels of movement and variability in movement
- Minimal Overlap Between Stationary and Moving: There is a clear separation between stationary and moving activities, which suggests that accelerometer magnitude mean is a good feature for distinguishing between these two categories of activities.

# 4 Models

The Human Activity Recognition (HAR) dataset lends itself to a variety of machine learning models that can effectively differentiate between different types of human activities based on sensor data. Here, we examine three popular models used for this task: k-Nearest Neighbors (kNN), Support Vector Machine (SVM), and Logistic Regression, focusing on their implementation specifics and performance in terms of accuracy.

## 4.1 k-Nearest Neighbors (kNN)

- Strengths: kNN is highly intuitive and easy to implement. It performs well with a sufficient number of correctly labeled data points and can handle multi-class cases naturally.

- Weaknesses: It can become significantly slow as the size of the data increases because it requires computing the distance to every training data point. Also, it is sensitive to the scale of the data and irrelevant features.
- Performance: Achieved an accuracy of 0.88, which is quite respectable but suggests there might be room for improvement, possibly by optimizing the number of neighbors (k) or choosing a more suitable distance metric.

### 4.2 Support Vector Machine (SVM)

- Strengths: Effective in high-dimensional spaces and relatively memory-efficient
- Weaknesses: SVMs can be prone to overfitting especially in cases where the number of features far exceeds the number of samples. They also require careful tuning of parameters like the kernel type and regularization term
- Performance: With an accuracy of 0.89, SVM performs slightly better than kNN, indicating its robustness in handling complex, high-dimensional data like that from accelerometers and gyroscopes

### 4.3 Logistic Regression

- Strengths: Provides probabilities for outcomes, is fast at classifying unknown records, and performs well with a linear decision boundary
- Weaknesses: Can underperform if relationships in data are non-linear and is not flexible enough to naturally capture more complex relationships without transformation or additions like polynomial regression
- Performance: This model shows the best performance with an accuracy of 0.95, making it the most effective among the three at distinguishing between different types of activities

## 5 Conclusion

In conclusion, the Human Activity Recognition (HAR) project utilizing smartphone sensor data showcases the effectiveness of various machine learning models in classifying physical activities based on accelerometer and gyroscope readings. The explored models—k-Nearest Neighbors (kNN), Support Vector Machine (SVM), and Logistic Regression—have each demonstrated notable strengths and weaknesses, contributing uniquely to the task of activity recognition.

### 5.1 Comparison of Model Performances

- Logistic Regression: proved to be the most effective model, achieving the highest accuracy of 0.95. This suggests that the relationships between the features and the activities are largely linear, which Logistic Regression can efficiently model

- SVM: followed closely with an accuracy of 0.89, underscoring its capability to handle the high-dimensional data inherent in sensor-based activity recognition
- kNN: with an accuracy of 0.88, while slightly less effective, still performed commendably, offering a simple and intuitive approach to classification

### 5.2 Overall Impact

This project not only enhances our understanding of how to effectively apply machine learning to real-world sensor data but also opens up numerous possibilities for practical applications that can improve daily living, healthcare, and user interaction technologies. The continued development and refinement of these models promise significant advancements in the field of wearable technology and activity recognition.

## References

[1] Human Activity Recognition Using Smartphones - Dataset

[2] E. Bulbul, A. Cetin and I. A. Dogru, "Human Activity Recognition Using Smartphones," 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 2018, pp. 1-6, doi: 10.1109/ISMSIT.2018.8567275.