# Human Activity Recognition

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# Outline

- Introduction
- Sensors
- Activities
- Activity Recognition Process
- Recent Trends and Future Directions

# Introduction

- What is Human Activity Recognition (HAR)?
  - A key research area in Human Computer Interaction (HCI)
  - A **pattern recognition** problem and more specifically as a **classification** problem
  - **Objective:** Identify the activity being performed by an individual at a given moment
- Two types of HAR
  - Vision based (video and image)
  - Sensor based

# Applications

Images: www.freepik.com/

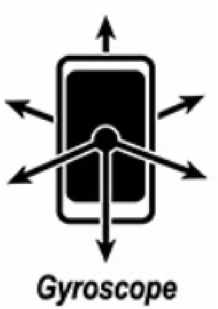
# Why Sensors?

- Nowadays, most people carry a smartphone
- Sensors are embedded in smartphones
- Computation and storage capability

# Smartphone Sensors


An accelerometer detects acceleration, vibration, and tilt to determine movement and exact orientation along the three axes


Measures the ambient magnetic field strength and direction




Gyroscope provides orientation details and direction like up/down and left/right and rotation

Form a wireless LAN by the wireless access point and the client device, transmission range of 30-50 meters


Communicates with the satellites to determine our precise location

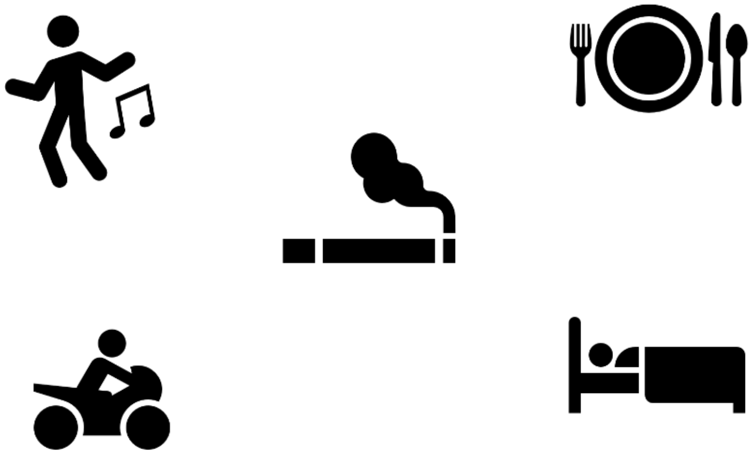
Form the data transmission link through finding, pairing and connecting between wireless devices at close range, the transmission range is 5-30 meters

# Human Activities

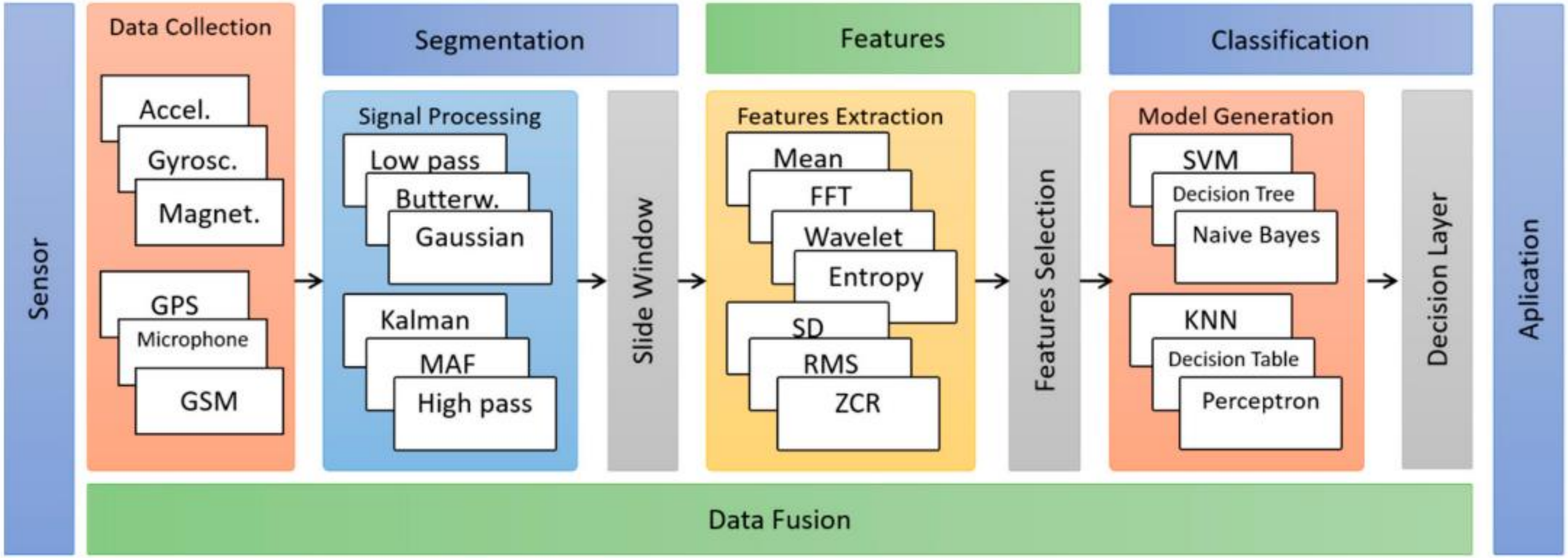
- A set of actions that can be repeated over time in a given environment (D.J. Cook, et. al, 2015)

**Simple Activities**

**Complex Activities**



# Human Activity Recognition Process




W. Sousa Lima, E. Souto, K. El-Khatib, R. Jalali, and J. Gama, "Human Activity Recognition Using Inertial Sensors in a Smartphone: An Overview," *Sensors*, vol. 19, no. 14, p. 3213, Jul. 2019.

# Data Collection

- Raw signals are collected from smartphone sensors
- Set of factors
  - **Environment** (Controlled, Semi-controlled, Uncontrolled)
  - **Frequency** (1Hz – 200 Hz)
    - Optimal value: **20HZ** (Khusainov et al., 2013)
  - **Position** (waist, hand, chest, etc.)
    - Best position: **waist** (Henpraserttae et al., 2011)

# Segmentation (1)

- Segmentation is intended to separate data into meaningful sub-groups that share the same characteristics
- Sensor data subgroups are represented by signal segments in a given time interval
- **Objective:** Each segment to contain sufficient characteristics that allow the recognition of a human activity at a given moment

# Segmentation (2)

- **Sliding Window:** The process where data is divided into consecutive segments so that each of them is analyzed separately and sequentially
- Overlapping and non-overlapping windows
- **Window size:** time interval and frequency rate of data collection
  - Optimal size: **1s**

# Feature extraction (1)

- The feature extraction reduces the signals into features that are discriminative for the activities at hand
- Features may be calculated automatically and/or derived based on expert knowledge
- Ideally, features corresponding to the same activity should be clustered in the feature space, while features corresponding to different activities should be far apart

# Feature extraction (2)

1. **Time domain**
   - Statistical functions (min, max, avg, standard deviation, mean, ….)
   - Cheaper and consume less battery power
2. **Frequency domain**
   - Calculated based on the FFT or Wavelet (Energy, power, centroid, ….)
   - More computationally demanding

# Feature Selection

- Remove irrelevant features to improve the accuracy of classification models
- **After** or **during** feature extraction
  - Info-gain + Correlation-based Feature Selection methods
  - Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Kernel Discriminant Analysis (KDA)
- The choice of features is more important than the choice of classification algorithms since the poor quality of the features can negatively impact the accuracy of any model generated by the conventional machine learning algorithms (Khusainov et al., 2013)

# Training and Classification (1)

- Classification models
  - **Impersonal or generic:** One user group (train) – Another group of different users (test)
  - **Personal or specific:** Only one user (train) – Same user (test)
  - **Mixed:** No distinction between users

# Training and Classification (2)

- **Cross-validation:** the dataset is randomly divided into 10 equal parts, where the models are generated with 9 parts and tested with the remaining part. This is repeated until all parts are individually used as training.
- **Leave-one-subject-out:** The dataset is divided by the user. The dataset of each user is used as a test.
- **Leave-30%-out:** Splitting the dataset into 70% for training and 30% for testing.

# Training and Classification (3)

- **Machine Learning algorithms**
  - Naïve Bayes
  - Support Vector Machine (SVM)
  - K-Nearest Neighbors (KNN)
- **Deep Learning algorithms**
  - Deep-connected network (DFN)
  - Convolutional Neural Network (CNN)
  - Recurrent neural network (RNN)
  - Long Short-Term Memory (LSTM)

# Recent trends and Future Directions

- **Transfer Learning** (Cook et al., 2013)
  - Allows transferring the knowledge learned from one model to another
  - Less amount of training samples -> Reduces the computational costs and annotating efforts
- **Active Learning**
  - Mitigates learning complexity and cost
  - Minimize labelling effort and increases prediction accuracy
- **Deep Learning**
  - The features are learned from the raw data hierarchically by performing some nonlinear transformation.

# References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