Activity Recognition in Smart Phones

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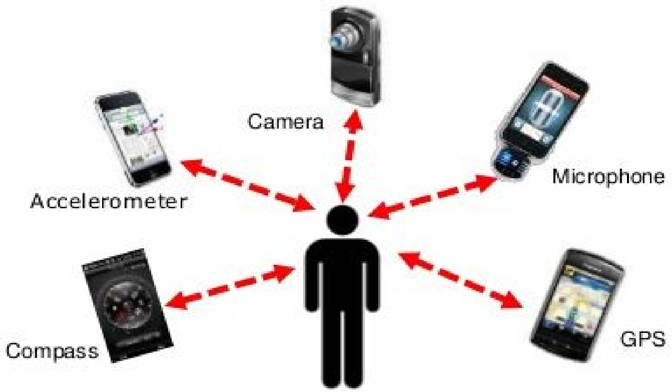
Introduction

- Motivation
- Data Collection
- Preprocessing
- Frame Analysis
- Sequential Analysis (Hidden Markov Model (HMM))
- Summary

Motivation

- Smartphones are everywhere.
- Many types of sensors are built in.
  - Accelerometer, gyroscope, gps, etc.
- We can leverage this data to determine what the user is doing.
  - Many cell phones already do this.
  - However, it is much more general. (run, walk, bike)
- Our Goal
  - Detect 5 activities:
    - Run, Sit, Stand, Downstairs, Upstairs.



Data Collection

- Used one app to collect data.
  - iPhone app: SensorLog
- 4 people * 5 activity * 10 repetition
- Collects 58 attributes per log.
- Logs 1 record every 33 ms.
- Restricted to right pocket, when recording data.
  - Chose this so we would be consistent.

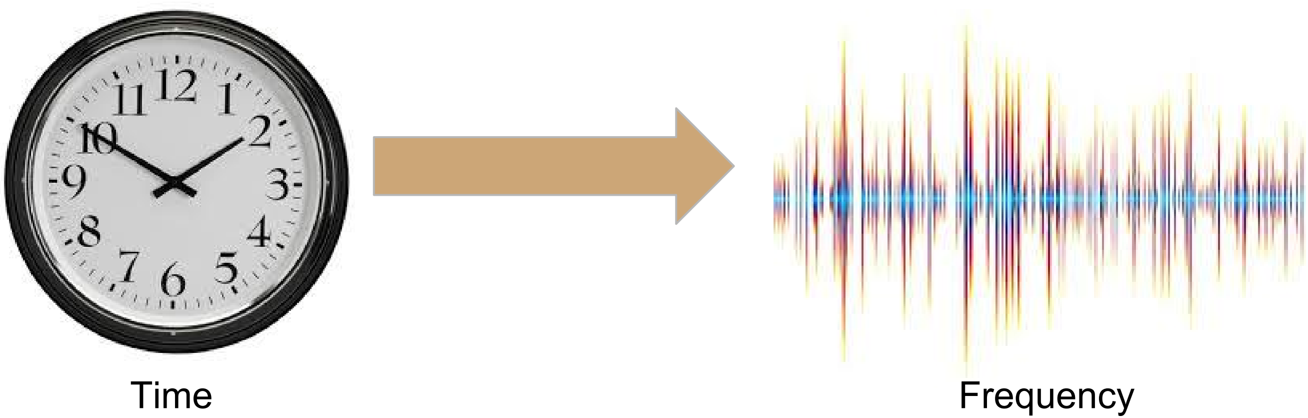
Data Preprocessing

- Don’t need all 58 attributes.
  - GPS, battery life, deviceID, etc.
- Limit data to only the accelerometer.
  - Has three attributes:
    - X, Y, and Z axis.

V	W	X
accelerometerAccelerationX	accelerometerAccelerationY	accelerometerAccelerationZ
0.117965698	-0.323181152	-0.880813599
0.198104858	-0.327148438	-0.908966064
0.192642212	-0.320648193	-0.977523804
0.185043335	-0.328796387	-0.953536987
0.145019531	-0.353729248	-0.991226196
0.141555786	-0.356002808	-0.921310425
0.143051147	-0.418060303	-0.791702271
0.118499756	-0.351501465	-0.907104492

First Step

- Need to extract features from the accelerometer data.
  - However, we need more information beyond data in the time domain.
- Conversion of data from time domain to frequency domain.
  - We achieve this by the Fourier Transformation.
  - This gets us a data frame.

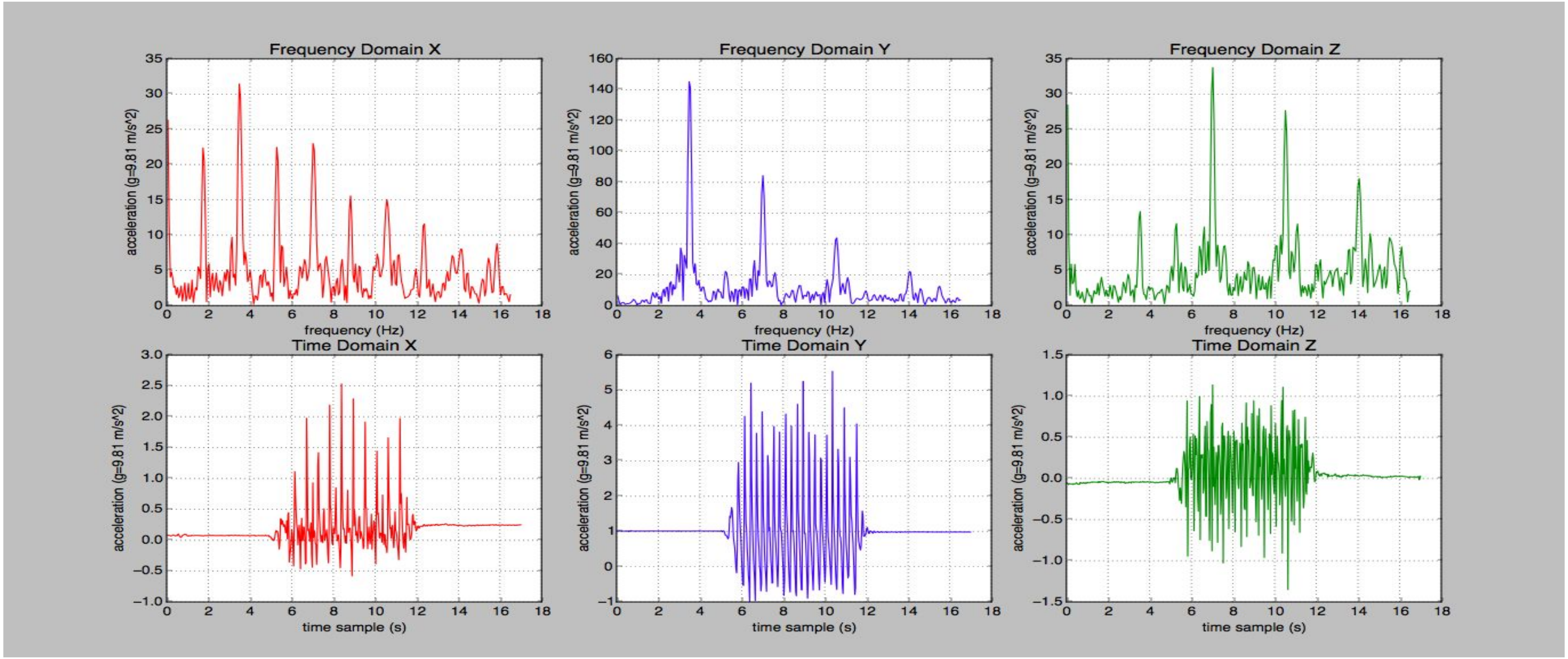


Feature Extraction

- Digital Component (DC)
- Mean in time domain
- Entropy from frequency domain
- Energy

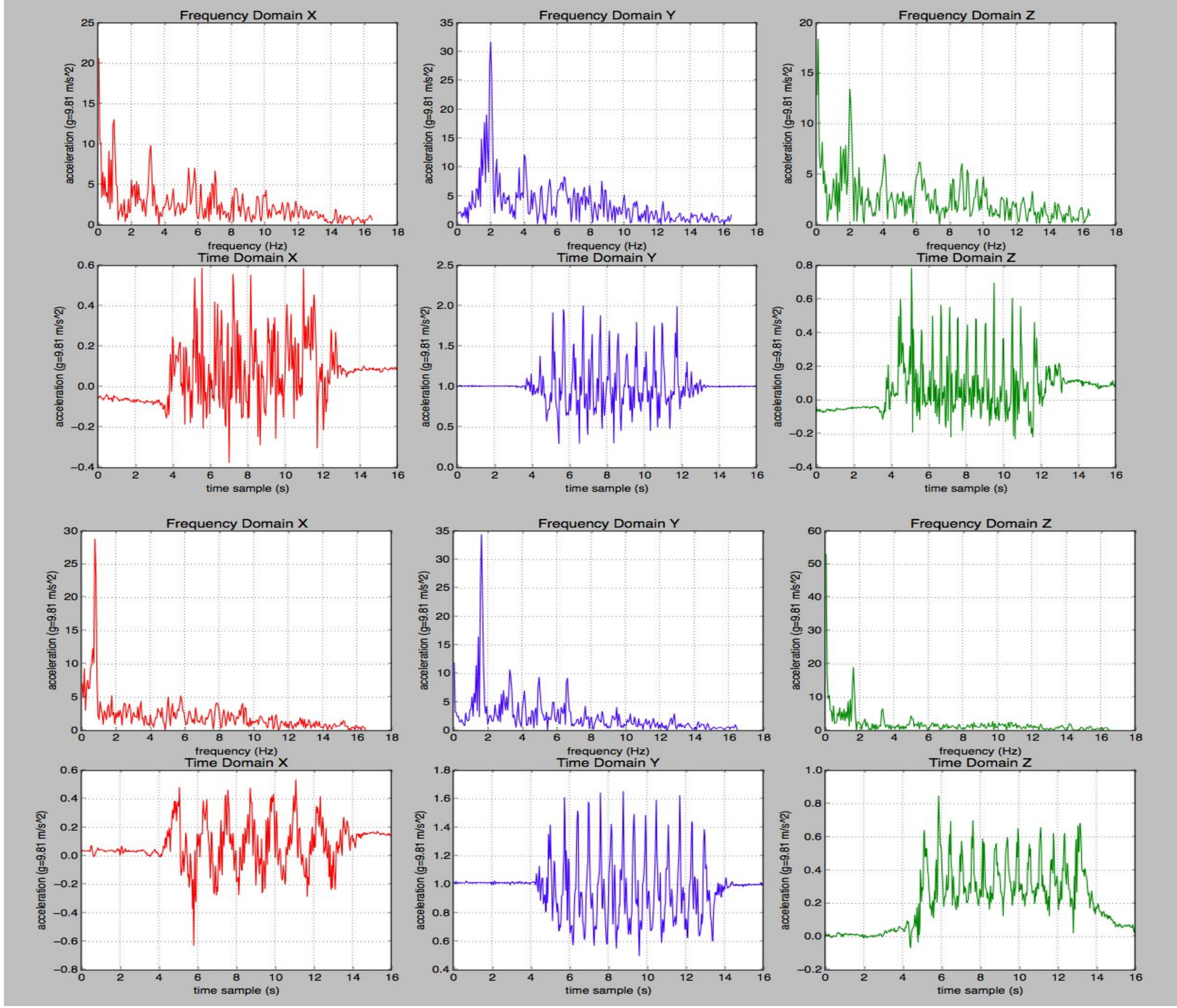
Each axis contains 4 features and we have 12 features in total (3 axises).

FFT of Run (Fourier Transform)



FFT

Downstairs
&
Upstairs

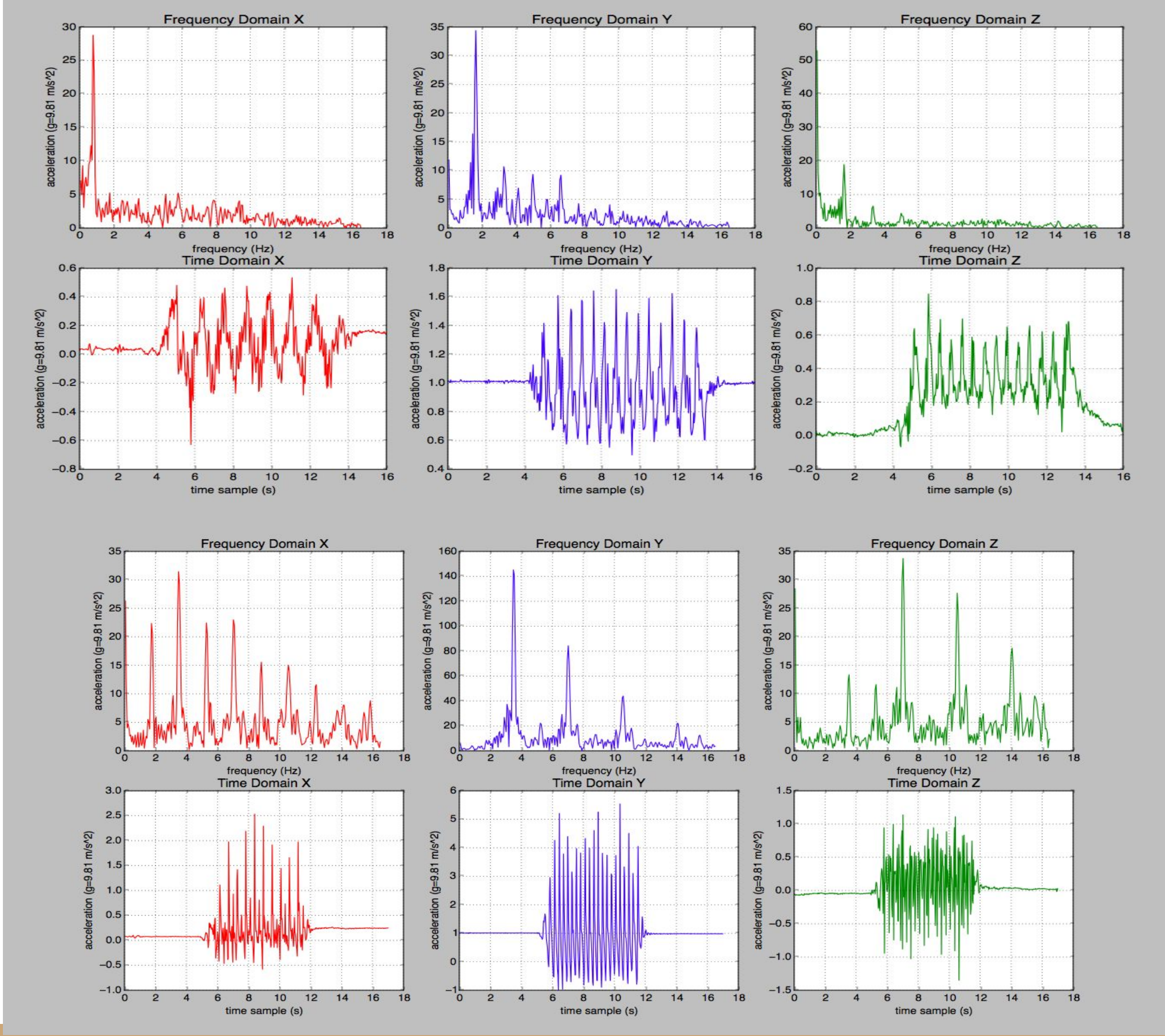


FFT

Upstairs

&

Run

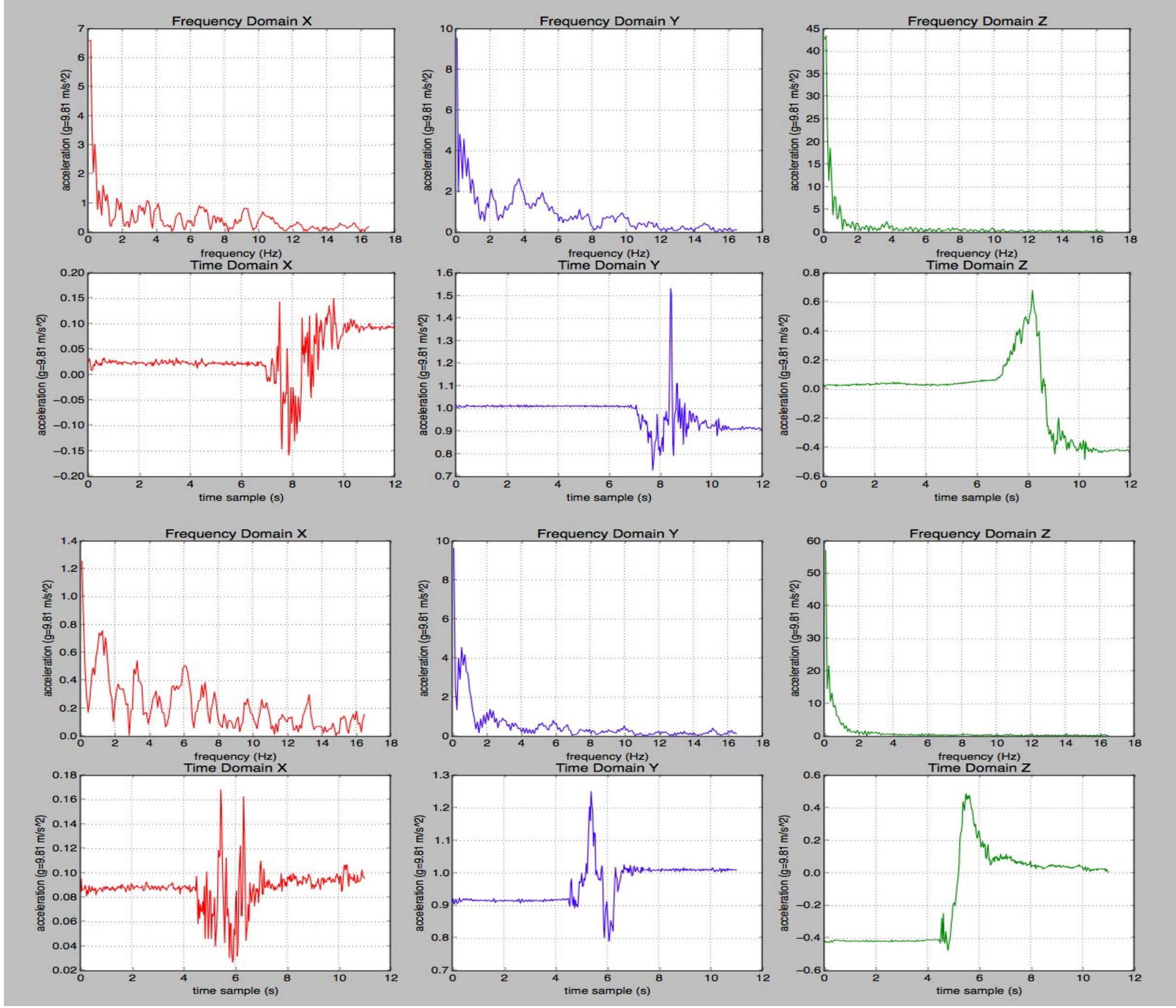


FFT of

Sit

&

Stand



Post Fourier Transformation (Second Step)

- After conversion of the data to frequency domain:
  - Extract Digital Component (DC), Entropy (without DC), Energy
- Combine those attributes with mean Value from time domain.

Weka

Results of Second Step

Model Name	Correctly Classified (%)	Incorrectly Classified (%)	Root mean squared error
Random Forest	100	0	0.0705
Naive Bayesian	48.366	51.634	0.3714
J48	94.7712	5.2288	0.1299
Bagging	93.4641	6.5359	0.1628

Can We Do Better?

- Previously we looked at 1 second frames to classify our activities.
- Looking at sequential data can give us better results.
    - Sequences are back to back frames.
        - Goal is for 6 seconds.
            - Some of these activities are less.
- Use Hidden Markov Models

Hidden Markov Model (Third Step)

1. $X = \{x_1, x_2, x_3, \ldots, x_n\}$ is observable data sequence.
2. $Y = \{y_1, y_2, y_3, \ldots, y_m\}$ is hidden state sequence.

$$P(x_1,x_2,x_3,\ldots,x_n,y_1,y_2,y_3,\ldots,y_m) = P(y_1)P(x_1 \mid y_1) \prod P(y_k \mid y_{k-1})P(x_k \mid y_k)$$

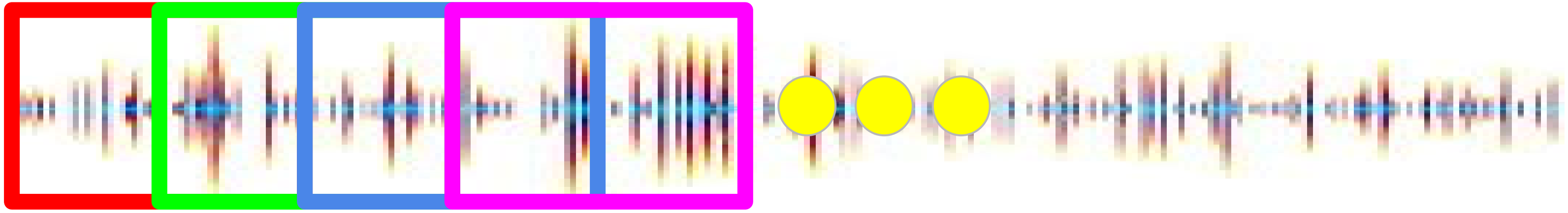
We need:

1. Initial probabilities
2. Transition probabilities
3. Emission probabilities

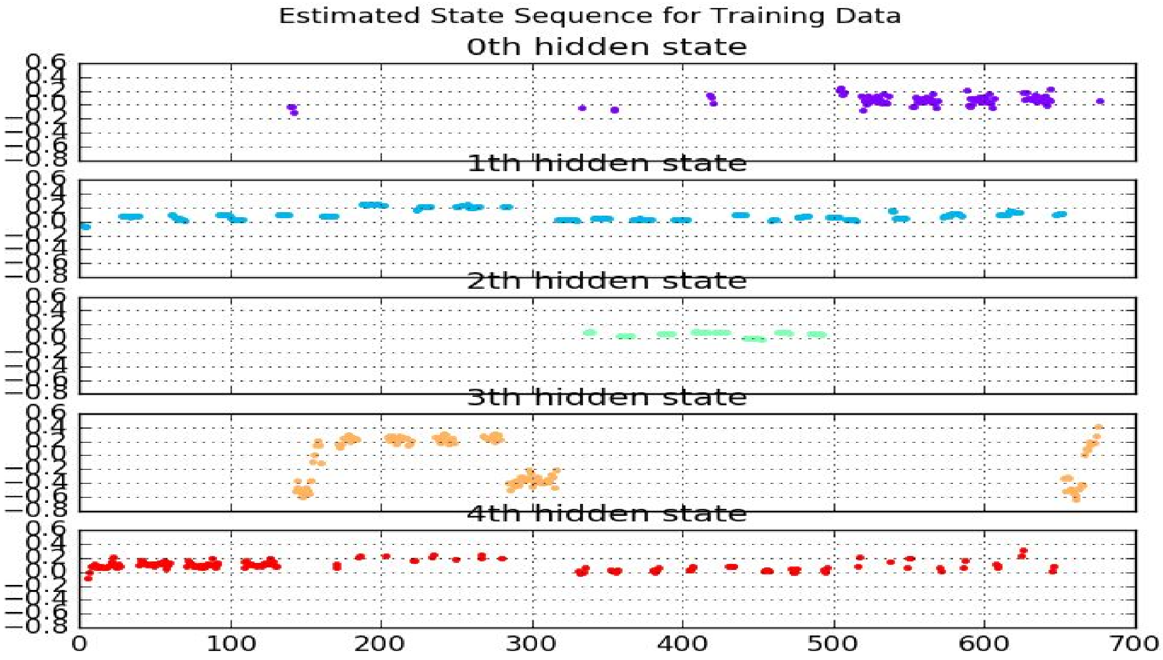
Goal: Choose $\{y_1, y_2, y_3, \ldots, y_m\}$ to maximize $P(x_1,x_2,x_3,\ldots,x_n,y_1,y_2,y_3,\ldots,y_m)$

Data Frame

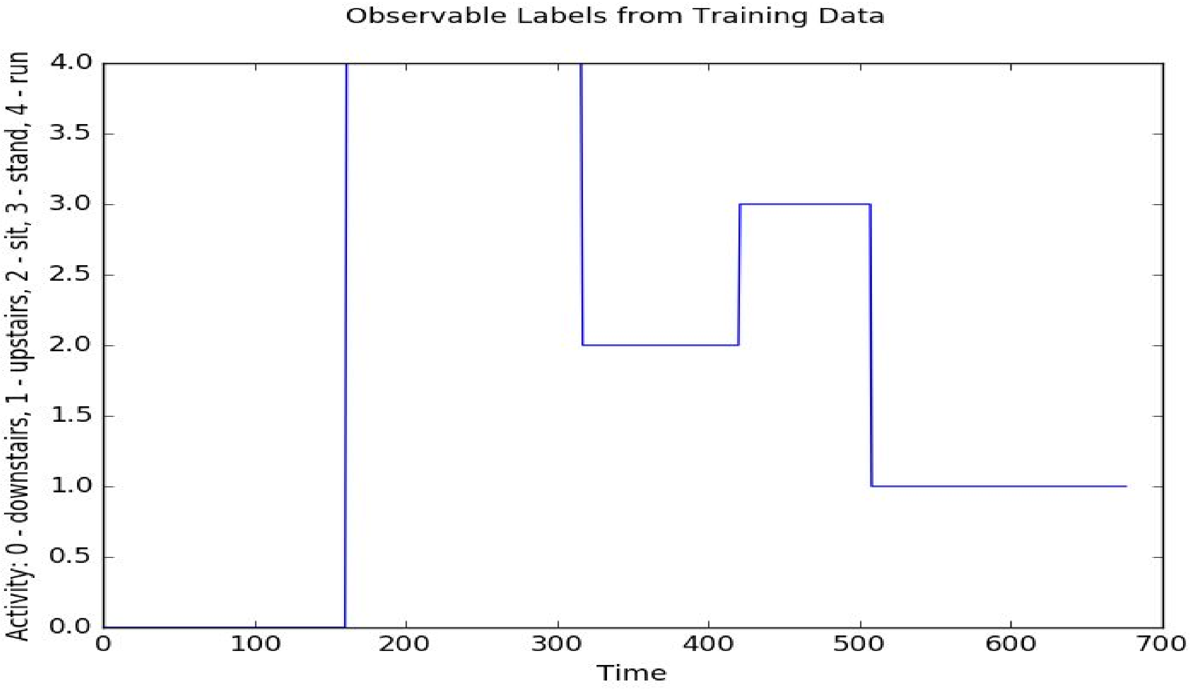
- Each data frame includes 32 samples (~1 second)
- Two data frames are overlapped with half of each other

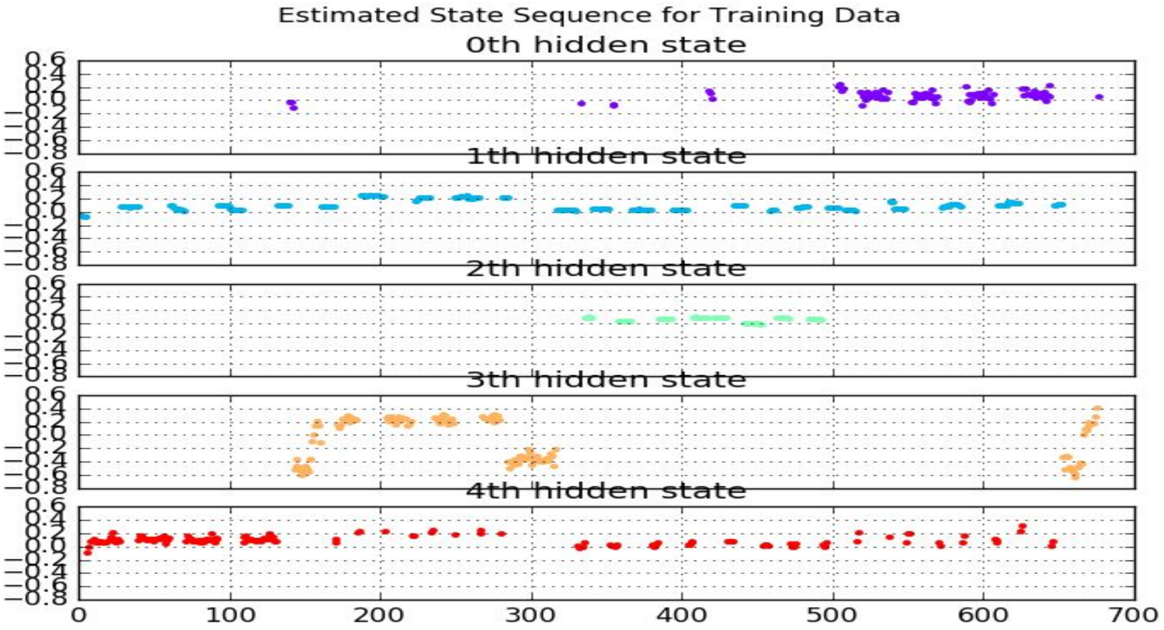


Results on training data

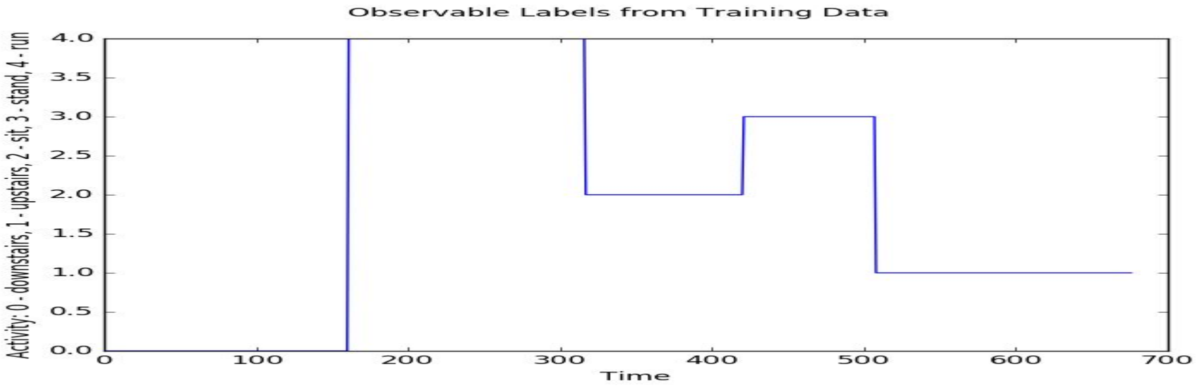


Actual activity sequence from training data



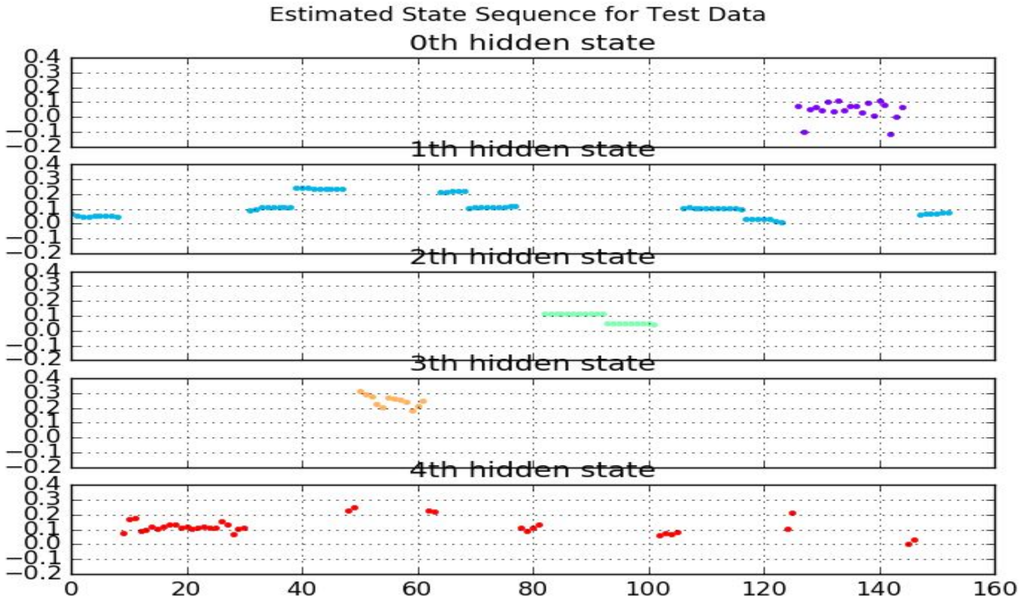


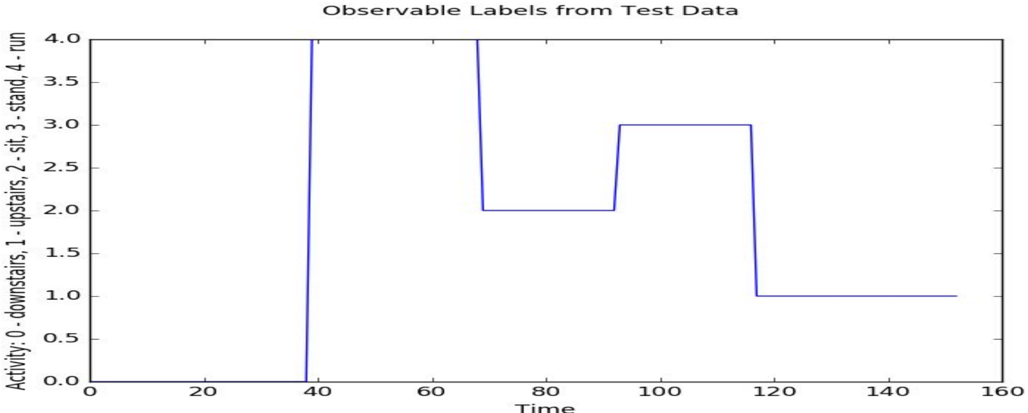
Estimated State Sequence for Training Data
0th hidden state
1th hidden state
2th hidden state
3th hidden state
4th hidden state



Observable Labels from Training Data
Activity: 0 - downstairs, 1 - upstairs, 2 - sit, 3 - stand, 4 - run
Time

Results on Testing Data





Future Work

- Detect more activities.
  - Jump, Walk.
  - Injury (hurt leg)
- HMM
  - Find relationship between cluster and real activity.
  - Add features to help classification.
    - Difference of change.

Summary

- Frame Analysis:
  - Tree based models works well.
  - Other common models do not.
- Sequential Analysis:
  - Training set works well
  - Against test data, results in some classification issues.
  - Sit and Stand are ambiguous.
  - Need to add more features.
    - Possibly gyroscope data.