Human Activity Recognition using Wearable Devices Sensor Data

Shutong Zhang, Jason Wu, Chenying Zhang

Problem Formulation

Our problem includes two parts:

1. Extract useful features $F = \{F_1, F_2, ..., F_m\}$ from Raw sensor data $R = \{R_1, R_2, ..., R_m\}$ for training and test examples $X = \{x_1, x_2, ..., x_m\}$.
2. Use the features space F to predict the labels $Y_{predict} = \{y_1', y_2', ..., y_{m_{test}}'\}$ for test data X_{test}.

Feature Selection

Principal components analysis (PCA) is performed on the train and test matrix X to make feature selections. 561 features are projected to a 30-dimension space and a 50-dimension space, with total percentage of eigenvalues 88.18% and 92.47% respectively.

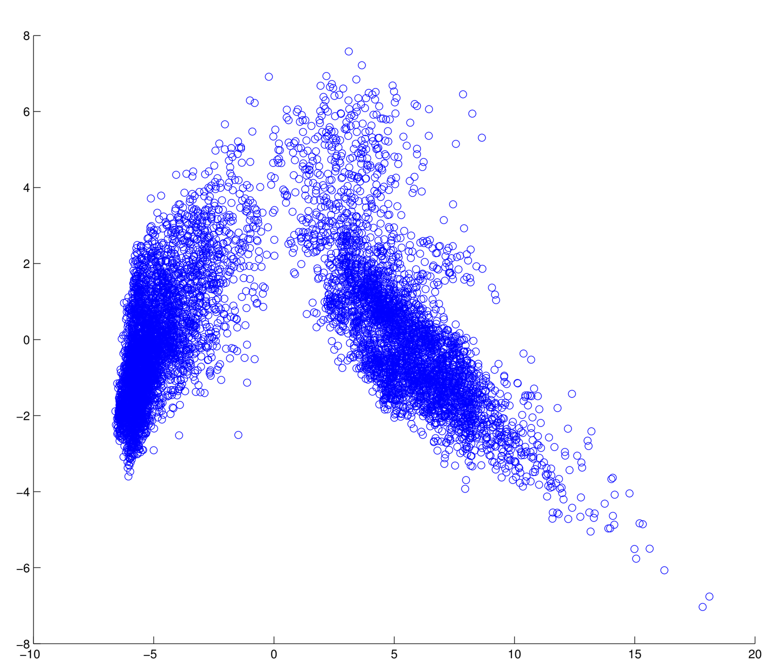

Figure 1: 2D pca component visualization

Data Preprocessing

The data set provided by [1] includes 561 features, in Section 1 we used PCA to select 30 features from those features and achieved a correctness rate of 40.8%, which is less than satisfactory. Therefore, we performed our own feature extraction process to extract a same amount of features and achieved a correctness rate of 84.93%.
The features selected for this database come from the accelerometer and gyroscope 3-axial raw signals tAcc and tGyro. These time domain signals were captured at a constant rate of 50 Hz. These signals were used to estimate variables of the feature vector for each pattern, the set of variables that were estimated from these signals are in **Table 1**.

Table 1: Selected Features

Feature	Description
max(tacc)	Largest value of acceleromete
min(tacc)	Smallest value
mean(tacc)	Mean value
std(tacc)	Standard deviation
mad(tacc)	Median absolute deviation
max(tgyro)	Largest value in gyro
min(tgyro)	Smallest value
mean(tgyro)	Mean value
std(tgyro)	Standard deviation
mad(tgyro)	Standard deviation

Classification Methods

1. **Naive Bayes**
Assigns a class label $\hat{y} = C_k$ for some k as follows:
$$\hat{y} = \text{argmax}_{k \in \{1,...,K\}} p(C_k) \prod_{i=1}^{n} p(x_i|C_k)$$

2. **KNN**
KNN estimates the conditional probability for class C_k as the fraction of points in N_0 whose response values equal j:
$$\Pr(\hat{Y} = C_k | X = x_0) = \frac{1}{K} \sum_{i \in N_0} I(\hat{y}_i = C_k)$$

3. **SVM**
The objective function for SVM is:
$$\begin{aligned} \min_{\gamma,w,b} \ & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} \xi_i \\ \text{s.t.} \ & y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i, i = 1,..,m \\ & \xi_i \geq 0, i = 1, ..., m \end{aligned}$$

4. **Softmax**
The probability that an input vector x is a member of a class i is:
$$P(Y = C_k | x, W, b) = \frac{e^{W_{C_k}x + b_{C_k}}}{\Sigma_j e^{W_j x + b_j}}$$
The prediction label $\hat{y}$ should be:
$$\hat{y} = \text{argmax}_{C_k} P(Y = C_k | x, W, b)$$

5. **Multi-Layer Perceptron**

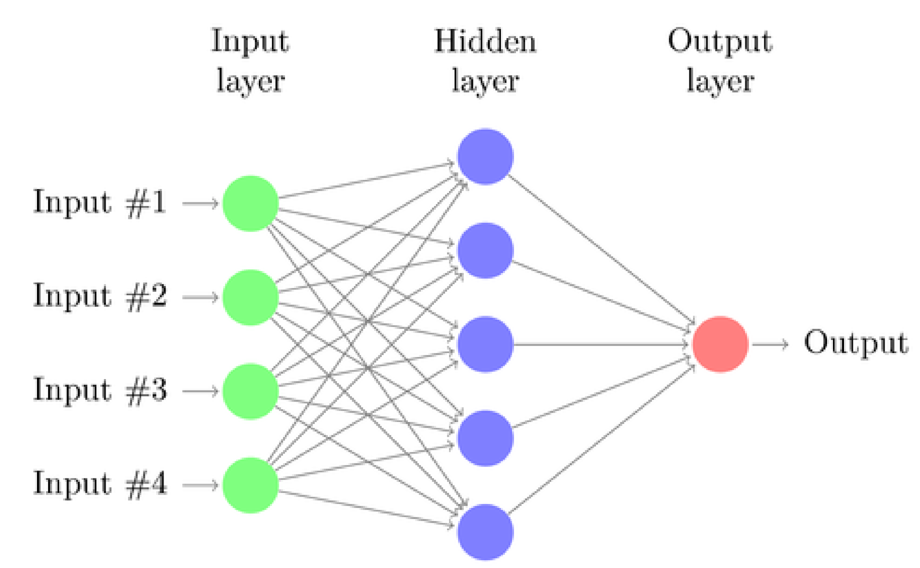

Figure 2: Structure of MLP

Results

3. Classification Results

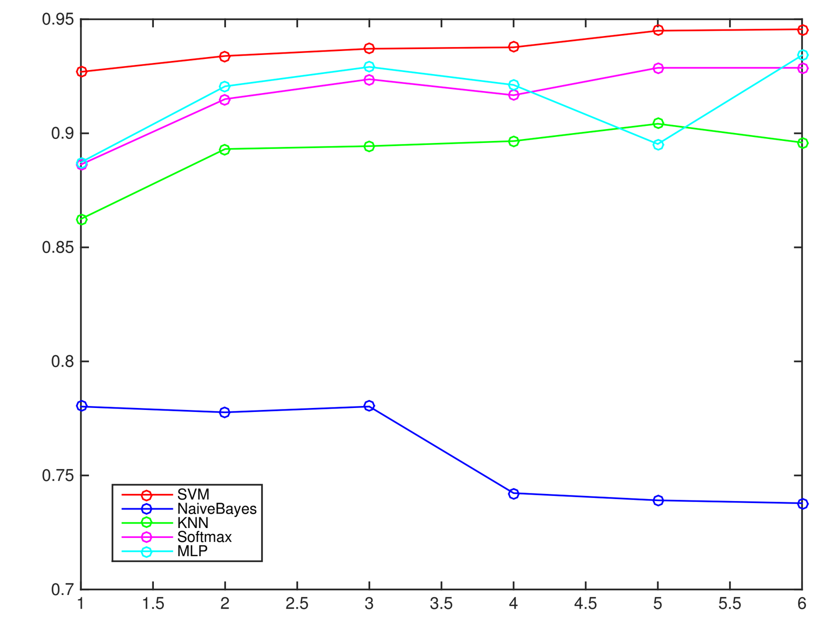

Figure 3: Classification Accuracy for Naive Bayes, KNN, SVM, Softmax and Multi-Layer Perceptron.

Table 2: Classification Accuracy Percentages for different classification models.

Model	50%	60%	70%	80%	90%	100%
Bayes	0.7802	0.7777	0.7802	0.7423	0.7391	0.7378
KNN	0.8624	0.8931	0.8933	0.8966	0.9042	0.8960
SVM	0.9269	0.9339	0.9371	0.9377	0.9450	0.9456
Softmax	0.8863	0.9150	0.9237	0.9167	0.9287	0.9287
MLP	0.8873	0.9206	0.9291	0.9212	0.8953	0.9342

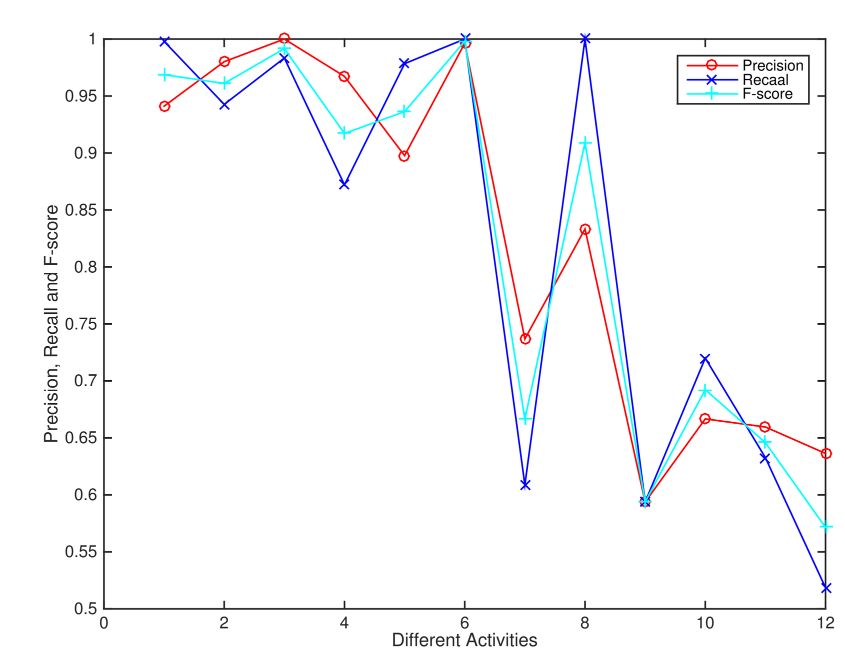

Figure 4: Precision, Recall and F-score for the existing 12 activities catagories using SVM.

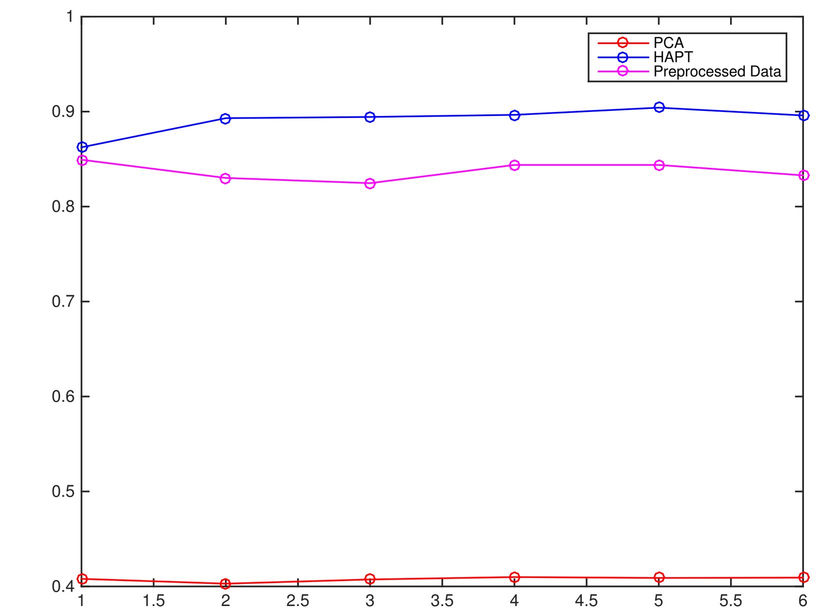

Figure 5: Classification Accuracy for HAPT features, PCA features and our preprocessed Data using KNN

Table 3: Classification Accuracy Percentages for different classification models using KNN.

Model	50%	60%	70%	80%	90%	100%
HAPT	0.8624	0.8931	0.8943	0.8965	0.9041	0.8959
PCA	0.4079	0.4029	0.4073	0.4098	0.4089	0.4092
Preprocessed	0.8493	0.8301	0.8246	0.8438	0.8438	0.8328

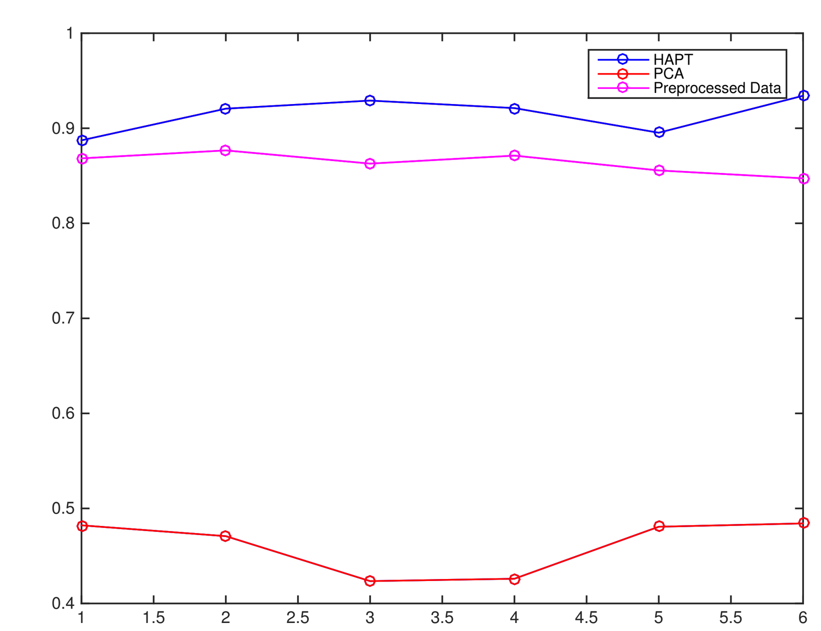

Figure 6: Classification Accuracy for HAPT features, PCA features and our preprocessed Data using MLP

References

[1] J.-L. Reyes-Ortiz, L. Oneto, A. Ghio, A. Samá, D. Anguita, and X. Parra.
Human activity recognition on smartphones with awareness of basic activities and postural transitions.
In *Artificial Neural Networks and Machine Learning–ICANN 2014*, pages 177–184. Springer, 2014.