# PRML Bonus Project Report

## Human Activity Recognition with Smartphones using Machine Learning


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### Problem Statement

Human activity recognition is the problem of classifying sequences of data recorded by specialized harnesses or smartphones into known well-defined human activities. The goal of this machine learning project is to build a classification model that can precisely identify human fitness activities. Working on this machine learning project will help you understand how to solve multiclass-classification problems.

### Introduction

This dataset has $562$ columns along with $1$ target column (namely $\text{Activity}$). At the first glance, I thought that I would apply some kind of Dimensionality Reduction technique to reduce the number of features while still retaining some properties of the original data.

I didn't have an idea about which model would work best but I knew it had to be some sort of Tree based algorithm. Nevertheless, I decided I would test different types of algorithms to decide the best one.

My idea of a $\text{Pipeline}$ was of an object that stored all the progress I made while exploring this task. It should be able to classify the data along with the usual evaluation metrics in one go. So I decided I will first finalize my model then build a pipeline around it.

### Experiments

#### Exploratory Data Analysis

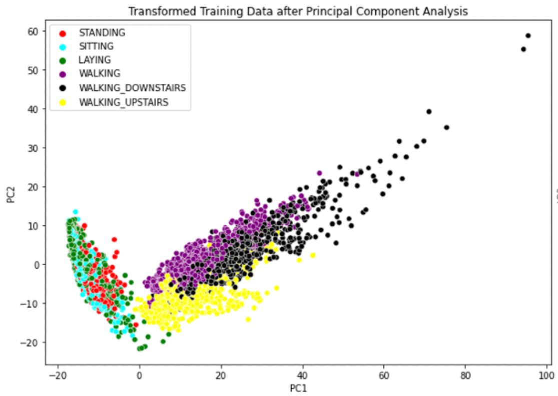
After importing the $\text{Train}$ dataset, I first checked it for any $\text{NULL}$ values which were none for all columns. I dropped the $\text{subject}$ column since it was useless for classification and applied a $\text{StandardScaler}$ to all features. Next up was $\text{Label Encoding}$ which I applied on the target column with its 6 classes:

- WALKING
- WALKING_UPSTAIRS
- WALKING_DOWNSTAIRS
- SITTING
- STANDING

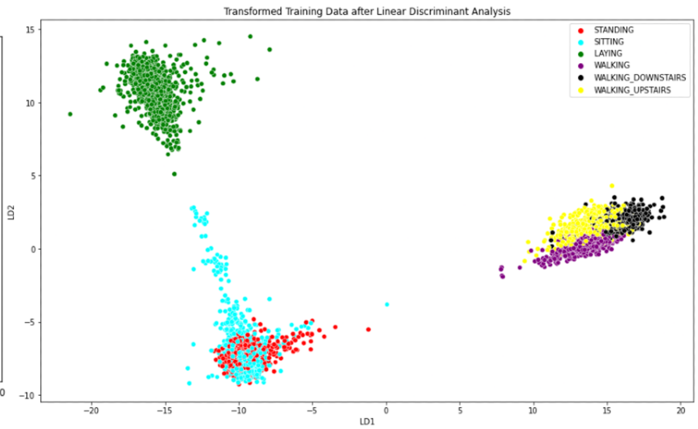
- LAYING

I applied $\mathrm{PCA}$ and $\mathrm{LDA}$ as a part of Dimensionality Reduction techniques. With the best $2$ components in each technique, this was the 2D dataset visualisation:

PCA




LDA




It is visible that even with $2$ components $\mathrm{LDA}$ is able to distinguish between different clusters.

The target column was well-balanced so when I split the train dataset into train and validation datasets, I used the $\mathrm{stratify} = \mathrm{TRAINY}$ option to preserve this distribution of the $\mathrm{Activity}$ column.

Next, I started training different models and tuning them using the validation dataset. I considered $7$ models for training:

- $\mathrm{LDA}$
- $\mathrm{QDA}$
- $\mathrm{RandomForestClassifier}$
- $\mathrm{XGBoostClassifier}$
- $\mathrm{LightGBMClassifier}$
- $\mathrm{KNN}$
- $\mathrm{MLPClassifier}$

I imported the $\mathrm{classification\_report}$ library from $\mathrm{sklearn}$ which allows me to print various metrics for each class in a single table.

I tuned a few hyperparameters independently for some models like $\mathrm{RandomForestClassifier}, \mathrm{XGBoostClassifier}, \mathrm{LightGBMClassifier}, \mathrm{KNN}\text{ and }\mathrm{MLPClassifier}.$ I do not guarantee that these are the best hyperparameters for this dataset (and the corresponding model). I have settled with a suboptimal solution since it would take a long time to go through all possible combinations of even a few hyperparameters.

After training and tuning the models I decided to test all these models with their final hyperparameters on the $\mathrm{Test}$ dataset. First, I applied the same preprocessing on this dataset as I had applied on the $\mathrm{Train}$ dataset. Then I trained these models on the entire training dataset and evaluated them on the $\mathrm{Test}$ dataset.

## Results

I concluded that $\mathrm{LDA}$ and $\mathrm{XGBoostClassifier}$ are the best models for this dataset.

Next, I implemented an end-to-end pipeline which consisted of:

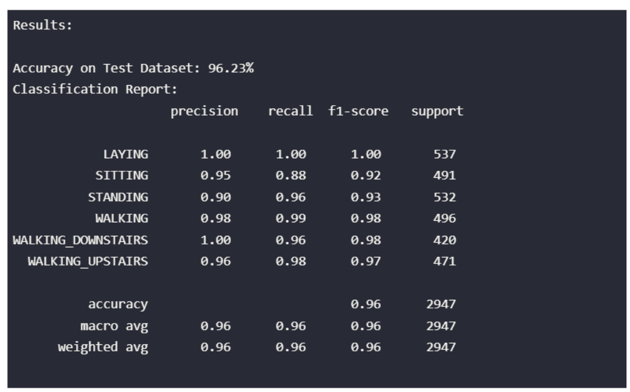
- Data Import
- Preprocessing
- Model Training
- Evaluation

The pipeline is a class with many private methods and one public method $\mathrm{evaluate}$. Once, you initialize the $\mathrm{Pipeline}$ object with your choice of model (either $\mathrm{XGBC}$ or $\mathrm{LDA}$) and scaler $(\mathrm{StandardScaler}/\mathrm{MinMaxScaler}/\mathrm{MaxAbsScaler})$ along with the $\mathrm{Train}$ and $\mathrm{Test}$ dataset, it stores all these inputs. Then when the $\mathrm{evaluate}$ function is called through the object, then all the private methods are called sequentially and finally the predictions along with a few classification metrics are outputted. If any error is encountered while executing the pipeline, an error message is printed at the step where the error occurred.

```
PL = Pipeline("LDA", "train.csv", "test.csv", "Activity", "MaxAbsScaler")
PL.evaluate()
```

```
Initializing Pipeline... ✓
Setting up the Pipeline... ✓
Importing Data... ✓
Preprocessing Data... ✓
Training Model... ✓
Evaluating Model...✓
```

Running the pipeline



Results:

Accuracy on Test Dataset: 96.23%
Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| LAYING | 1.00 | 1.00 | 1.00 | 537 |
| SITTING | 0.95 | 0.88 | 0.92 | 491 |
| STANDING | 0.90 | 0.96 | 0.93 | 532 |
| WALKING | 0.98 | 0.99 | 0.98 | 496 |
| WALKING_DOWNSTAIRS | 1.00 | 0.96 | 0.98 | 420 |
| WALKING_UPSTAIRS | 0.96 | 0.98 | 0.97 | 471 |
| accuracy | | | 0.96 | 2947 |
| macro avg | 0.96 | 0.96 | 0.96 | 2947 |
| weighted avg | 0.96 | 0.96 | 0.96 | 2947 |

Obtaining results from the pipeline

## Instructions for running the notebook

- Use `git clone https://github.com/sawmill811/Human-Activity-Recognition.git` in your terminal to clone the repository. If you wish to run the file on **Google Colaboratory**, then here is the link to the notebook.
- To run the pipeline, simply run the first cell in the `HAR.ipynb` notebook - this will import the necessary libraries.

- Next, skip all cells under the heading "*Exploring the Task*" and run the cells under the heading "*Creating a Pipeline*".
- The predictions for the test data will be stored in the working directory under the filename `predictions.csv`.

## Pipeline Performance

- **LDA**: Predictions are obtained in less than $10$ seconds on my PC as well as Google Colaboratory.
- **XGBoostClassifier**: Predictions are obtained in about $30$ seconds on my PC (using $\text{GPU}$) and $1.5$ minutes (using $\text{CPU}$). It takes about $4$ minutes to run the pipeline on Google Colaboratory.

## Troubleshooting

If you are getting an error message then try removing the `tree_method = "gpu_hist"` parameter from the `XGBClassifier` model. This is used to speed up the training process using $\text{GPU}$ resources. Other than that, the code should run fine on most systems.

## Abbreviations

$\text{HAR}$ — Human Activity Recognition
$\text{PCA}$ — Principal Component Analysis
$\text{LDA}$ — Linear Discriminant Analysis
$\text{QDA}$ — Quadratic Discriminant Analysis
$\text{XGBC}$ — XGBoostClassifier
$\text{KNN}$ — K-Nearest Neighbours
$\text{MLPClassifier}$ — MultiLayerPerceptronClassifier