Activity Recognition Project Report

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1. Introduction

Hidden Markov Models (HMMs) are a powerful tool in the field of sequence classification. HMMs have the ability to capture complex patterns within a feature space and can assign labels to observations based on probabilistic estimation. Within the scope of this paper, we will focus on the application of utilizing HMMs to classify human activity, specifically standing, walking, and running.

2. Background

2.1. Data Collection

HMMs are one of the exceptions within Machine Learning where the observations you collect can have various sizes. This makes the process of data collection more streamline and can add variation to your classifier.

We can format the data as shown

$$\underline{x} = \left(\left(x_1^1, ..., x_{T_1}^1\right), \left(x_1^2, ..., x_{T_2}^2\right), \left(x_1^3, ..., x_{T_3}^3\right)\right) \tag{1}$$

Where T_1, T_2, T_3 are arbitrary sequence lengths corresponding to each class.

$$C_i : \begin{cases} \text{Standing if } i = 1 \\ \text{Walking if } i = 2 \\ \text{Running if } i = 3 \end{cases} \tag{2}$$

Each observation in the sequence is formatted as so to take in account x, y, and z acceleration values.

$$x_t^{C_i} = \begin{pmatrix} \text{X Acceleration } \left(\frac{m}{s^2}\right) \\ \text{Y Acceleration } \left(\frac{m}{s^2}\right) \\ \text{Z Acceleration } \left(\frac{m}{s^2}\right) \end{pmatrix} \tag{3}$$

To collect the accelerometer data, I used an accelerometer app available on the IOS App Store. Within two trials for each activity, I recorded myself doing the corresponding activity with my phone in my hand. Once I finished collecting the data, I exported it to my PC to continue the preprocessing.

2.2. Data Preprocessing

Before any training can begin, there is preprocessing that should be done to the data. The sensor measurements are often quite noisy, and thus can affect the quality of our data. A Moving Average Filter can be used as a Low Pass Filter to remove the noisy frequency components. With using a Moving Average Filter with a window size of 5, here is an example of the improvement in the data as shown in Figure 1.

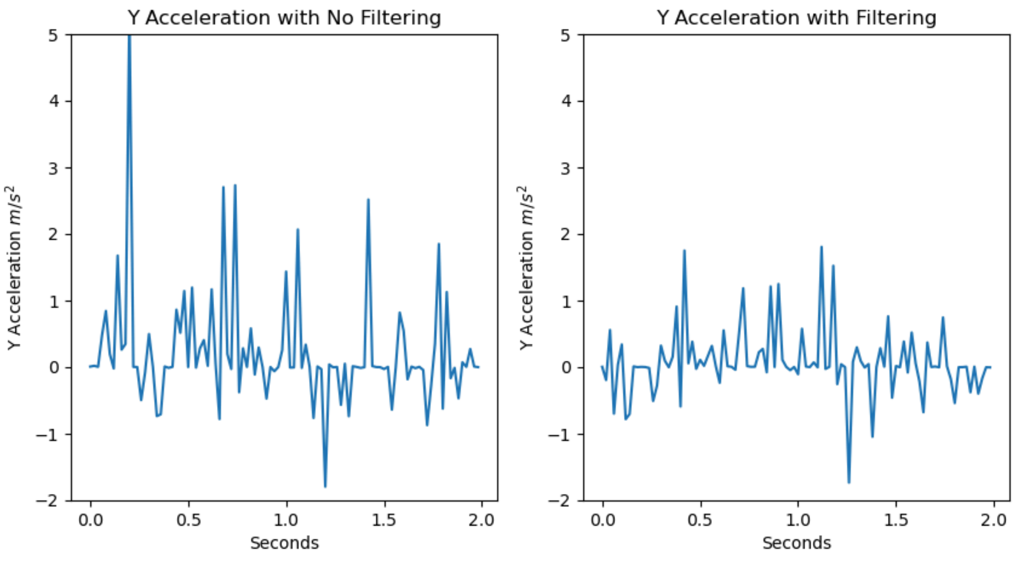

Figure 1: Comparison of Filtering

While in other Machine Learning models, you tend to do further feature extraction such as normalizing or scaling. When using HMMs, we tend to leave the data alone and let the training process capture important features.

The other preprocessing that is needed to be done is splitting our data within a training and validation set. This is important to reduce the chances of overfitting and thus increase the generalizability of our trained models. We will randomly allocate 75% of our data to the training set, and 25% to the validation set. Due to the class imbalance within our dataset, we stratify our data by the classes to ensure the training and validation set have the same class percentage as seen in Table 1.

Class	**Training Set Amount**	**Validation Set Amount**
Standing	9588	3197
Walking	8880	2960
Running	3861	1287
Total	22329	7444

Table 1: Data Statistics

3. Methodology

Now with the data preprocessing done, we can move on to the methodology of how our sequence classifier is defined. Given some input sequence of length L, $x_1, ..., x_L$, we want to classify the activity of each time step, $S_1, ..., S_L$. To do this, we must train a HMM parameters for each class defined as λ

$$\lambda_i = \{\{q_i, A_i\}, b_i\} \text{ for } i \in \{1,2,3\} \tag{4}$$

Then we can create a decision function for an observation of x_t based on the log likelihood

$$d(x_t) = \text{argmax}_i \ln(P(\lambda_i \mid x_t)P(C_i)) \tag{5}$$

3.1. HMM Overview

Before we discuss the implementation of training for our HMMs, it is important to build upon how HMMs operate in more detail. Hidden Markov Models rely on state sequences $\underline{S} = S_1, ..., S_T$ that are a Markov Chain and are driven by N sub-sources. State sequences are hidden because we can't observe the state sequences, only $\underline{x}$. We define the Markov Chain as a first order equation, thus S_t only depends on S_{t-1}. The transition matrix A is a matrix defined as $a_{ij} = P(S_t = j \mid S_{t-1} = i)$. For our case we are working with an *infinite duration* Markov Chain, thus A will be a (N, N) matrix. For our Markov Chain, we need an initial state probability distribution defined as q. This is needed for the probability mass for the first state S_1 in the sequence. Finally, we need to define the output probability distribution function $P_{X_t \mid S_t}(x \mid s)$. This is important for incorporating the conditional probability from the N sub-sources. These three parameters make up the inputs needed to calculate the log likelihood.

3.2. Training the HMM

The parameters λ_i are often difficult to calculate or know beforehand in most applications. Thus, it is necessary to use a method of estimating the parameters given our data. Using the Expectation Maximization (EM) algorithm, we can do just that. The EM algorithm operates by updating the model parameters λ_i' iteratively. This is done maximimizing the following equation and solving for λ_i'

$$\begin{gathered} \lambda_{i'} = \text{argmax}_{\lambda_i'} Q(\lambda_i', \lambda_i) \text{ where} \\ Q(\lambda_i', \lambda_i) = E[Y(\lambda_i^i) \mid \underline{x}, \lambda_i] \end{gathered} \tag{6}$$

The search is complete when the improvement in $Q(\lambda_i', \lambda_i)$ is less than some threshold ε

$$Q(\lambda_i', \lambda_i) - Q(\lambda_i; \lambda_i) < \varepsilon \tag{7}$$

3.3. Assigning class by MAP Decision Rule

As shown in Equation 5, we will calculate the Maximum A Posteriori Probability of all three models with the given observation. The model with the greatest MAP Probability will be assigned as the predicted class.

4. Results

Class	**Precision**	**Recall**	**F1 Score**	**Weighted Accuracy**
Standing	1.00	0.79	0.88	0.79
Walking	0.67	0.72	0.69	0.75
Running	0.53	0.72	0.61	0.76
			Total Accuracy:	**0.75**

Table 2: Statistics of Classifier Performance

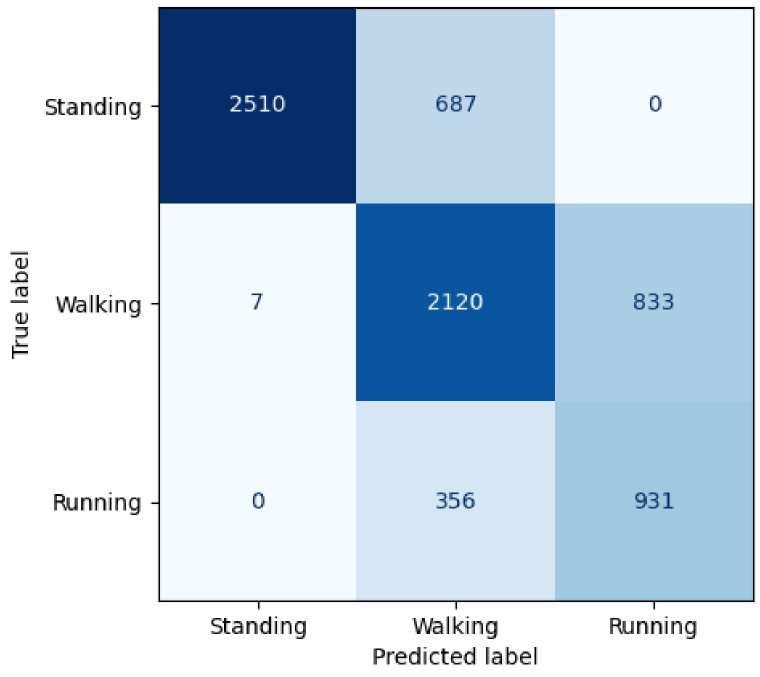

Figure 2: Confusion Matrix of Classifier

5. Discussion

Table 2 and Figure 2 show the performance of our classifier on our validation set. Our total accuracy is 0.75 which means our classifier works decently well between all classes. Our classifier has perfect percision within the standing class. This suggests our classifier has 0 false positives if the true class is standing. Comparing the walking and running statistics, it is clear that our classifier has a difficult time distinguishing the two classes. There is a possibility that between my walking and running trials that there was not a significant difference between my strides. In return, the feature space could be too similar between the two classes. Another reason could be the class imbalance that possibly creates a bias towards the standing class. I did try to address this by using MAP Probability instead of Maximum Likelihood Estimation (MLE), but in the future it may be worthwhile to use balanced classes.

While my data collection process could be the cause of lower accuracy, I think it's important to talk about the constraints of the HMM in general. It is possible that using Gaussian Emission Distributions within the HMM training is not complex enough to capture important features within our observations $\underline{x}$ to distinguish walking and running. I've done multiple iterations testing the optimal number of sub-sources, and found the best number to be $N = 4$. In the future, we could try different Emission Distributions to see if any improvement could be made.

If we were to continue this project, I think it would be worthwhile to consider the implementation of a time-varying HMM. In this project we are considering stationary HMM parameters λ_i, but it could be helpful to consider a time-varying model because the HMM may be able to capture even more features to classify the accelerometer data.

6. Conclusion

Overall in this project, we demonstrated the use of predicting human activities (standing, walking, and running). We were able to achieve 75% accuracy through data preprocessing, model training, and performance evaluation. While there was successful classification of if a human was standing, there still resides some challenges distinguishing walking and running. There was implementation of MAP decision-making to counteract class imbalance and we discussed the possible limitations of Gaussian Emission Distributions. In the future, a possible extension of the project could be using non-stationary HMMs to capture time-varying features of human activity.