

Fine-Grained Activity Detection in the Kitchen with UWB

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08 April 2023

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Chapter 1

Introduction

Chapter 2

Literature Review

Chapter 3

System Testing and Tuning at the Independent Living Suite

Chapter 4

Classification of Time Series Data

Based on the findings in Chapter 3, it was determined that Machine Learning (ML) would be a suitable method for classifying the data obtained from the Pozyx system. Prior to attempting any experimentation, this chapter will conduct a survey of the current ML techniques available for the classification of Time Series Data.

4.1 Classic Machine Learning Methods

4.1.1 k-Nearest Neighbours (kNN)

Overview

The k-Nearest Neighbours is a classifier that assigns a class to an unlabeled observation by looking at the class of k neighbours and choosing the class that appears the most within these k neighbours. The "nearest neighbours" are determined through a measure of Euclidean-Distance D between a neighbour p and unlabeled point q with n features is shown in Equation 4.1 [81]

$$D(p, q) = \sqrt{(p_1 - q_1)^2 + (p_1 - q_2)^2 + \dots (p_n - q_n)^2} \quad (4.1)$$

Using Equation 4.1 the top k neighbours with the lowest distance are considered and the class that occurs the most within these nearest neighbours is the class chosen for the unlabeled observation. In the event that there is a tie between the classes, resolution of the tie depends on the implementation of the library used. In R `kNN()` resolves ties by picking a random tied candidate class [81] and `scikit-learn`'s `kNeighboursClassifier` uses `scipy`'s "mode" method which returns the first class that ties in the array [82].

Dynamic Time Warping (DTW) as a Distance

Though Euclidean-Distance may be suitable for problems with a fixed feature set, or vectors with the same length, patterns that manifest in time-series data may be stretched, compressed, or shifted in the temporal domain. Using Euclidean distance, a signal compared with the same signal shifted $t + 1$ may result in large distances even though the signals compared were the same signals [83]. A method called Dynamic Time Warping (DTW), was devised to counter the shortcomings of Euclidean distance and is robust to temporal variation that occurs naturally. It achieves this by calculating all the distances from one point to every other point and chooses a path that

costs the least, finding the minimum distance between two vectors that do not have to be the same length. Mathematically, for $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_m)$ be two time series of length n and m respectively, DTW first begins with calculating the Cost Matrix which is the cost between each pair in the time series [83]

$$\forall_i \in 1, \dots, n, \forall_j \in 1, \dots, m, C_{ij} = f(i, j) \quad (4.2)$$

Where f is the squared Euclidean-Distance (equation 4.1 squared) for multivariate time-series [83].

$$f(x, y) = D(x, y)^2 \quad (4.3)$$

A warping path is defined as $p = (p_1, \dots, p_L)$ through the cost matrix C begins on $p_1 = (1, 1)$, must end on $p_L = (n, m)$ and moves with step $p_{l+1} - p_l \in \{(1, 0), (1, 1), (0, 1)\}$. The costs in the along the paths are summed And the DTW score is the path that costs the least [83].

$$DTW(X, Y) = \min_{p \in P} C_p(X, Y) \quad (4.4)$$

Though every path does not need to be calculated as dynamic programming can be leveraged, the time complexity is still high at $O(nm)$ [83] and this time complexity must be considered when designing a real-time classification system.

Tunable Parameters

The tunable parameter in kNN is k and controls the number of neighbours selected. The optimal k should be empirically chosen by varying k for the selected dataset. When using kNN, the entire training dataset is used as-is. Therefore, class imbalance should also be considered. For example, a higher number of class A than class B could lead to a higher density of class A. Even though the unlabeled observation may be closer to class B, the classifier may choose class A because class B has "run out" of neighbours. With increasing k , the inaccuracy caused by class imbalance becomes even more apparent. If k exceeds the number of samples in the class with the lower number of samples, then the class with the higher number of samples will always be chosen.

4.1.2 Support Vector Machines (SVM)

Overview

Support Vector Machines (SVM) involves finding a hyperplane that best separates 2 classes. There are two cases, the linearly separable case and the non-linearly separable case. In the linearly separable case, the hyperplane perfectly separates the two classes (see Figure 4.1). The idea is to maximize the "margin" which is the training data that is closest to the hyperplane [84]. Cervantes et al. depict this as maximizing the distance between parallel hyperplanes H1 and H2 (which pass through the "support vector" data-points of the training dataset) in Figure 4.1 to optimize the generalization capability of the model.

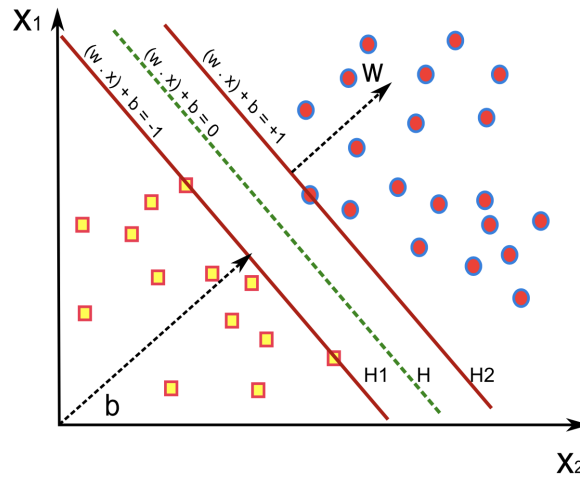


Figure 4.1: SVM Best Hyperplane in the linearly separable case [84].

The linearly separable case is rare in real life. Instead, datapoints from one class may seem to mix with the other class at the optimal boundary (Figure 4.2). To still find this optimal boundary, a positive slack factor ζ_i is introduced and controlled by a parameter C that controls the width of the margin. A lower C allows for a wider margin that may improve generalizability in real life at the cost of more misclassification of the training dataset, whereas a higher C tightens the margin and minimizes the classification errors in the training dataset but may decrease generalizability in real life [84].

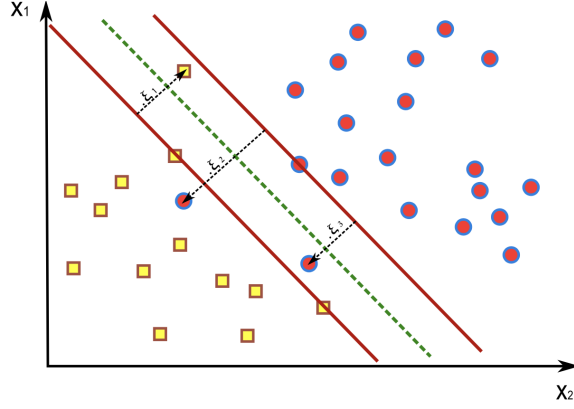


Figure 4.2: SVM Best Hyperplane in the non linearly separable case [84].

SVM can also be used separate data that is not separable by a linear hyperplane (Figure 4.3) by using a kernel. Kernels reframe the problem in a highly dimensional space called the "feature space" and in this feature space, it is simple for the algorithm to find the hyperplane. In the next subsection that will detail the convex optimization problem for SVM, it is found that the function that needs to be optimized depends on the inner product between every sample $\langle x_i \cdot x_j \rangle$. Transforming the original dataset to this feature space through a transfer function ϕ yields an optimization problem that depends on $\langle \phi(x_i) \cdot \phi(x_j) \rangle$. Kernel functions $K(x_i, x_j)$ are special functions that provide an equivalent way to calculate $\phi(x_i) \cdot \phi(x_j)$ (ie $\phi(x_i) \cdot \phi(x_j) = K(x_i, x_j)$) without having to initially transform the original dataset using ϕ since transforming the dataset to the feature space may be a costly operation if there are many features. The following are popular kernels [84]:

1. Linear Kernel: $K(x_i, x_j) = x_i \cdot x_j$
2. Polynomial Kernel: $K(x_i, x_j) = (1 + x_i \cdot x_j)^p$
3. Gaussian Kernel: $K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$
4. RBF Kernel: $K(x_i, x_j) = e^{-\gamma(x_i - x_j)^2}$
5. Sigmoid Kernel: $K(x_i, x_j) = \tanh(\eta x_i \cdot x_j + v)$

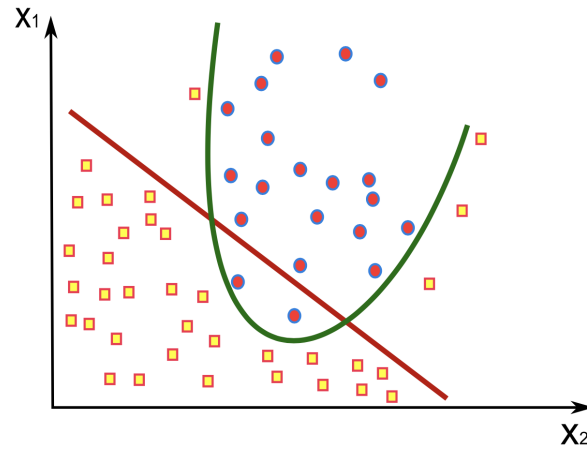


Figure 4.3: SVM non-linear classifier (green line) [84].

Since SVM can only separate between 2 classes as a binary classifier, a further step must be done to separate multiple classes. Scikit-learn uses a one vs. rest strategy by default. For each class a decision boundary between itself and the rest of the samples are created. For an unlabeled point a probability of membership to each class is calculated and an argmax function is used to determine the membership [85].

Theory of SVM: Linearly Separable

Consider a training dataset $X = \{x_i, y_i\}_{i=1}^n$ consisting of n samples of feature vectors $x_i \in \mathbb{R}$ and labels $y_i \in (-1, 1)$. In the linearly separable case of SVM, the two classes in our training dataset can be separated perfectly by a hyperplane. The data labelled with class $y = 1$ will be on one side of the hyperplane and the other class $y = -1$ will be on the other side of the hyperplane. The equation for a hyperplane is given in Equation 4.5

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \quad (4.5)$$

Where $x \in \mathbb{R}^d$, and \mathbf{w} the weights for the hyperplane and b the bias. For simplicity of visualization, consider $x \in \mathbb{R}^2$. The SVM optimization problem tries to find \mathbf{w} and b such that the margin (ie. the distance to the closest point(s) to the hyperplane) is maximized. One variation of this margin called the functional margin F uses the y_i label to ensure that the margin is positive for individual samples correctly classified by some hyperplane with parameters (\mathbf{w}, b) and is given by the Equation 4.6

$$F = \min_{i=1 \dots n} [y_i(\mathbf{w} \cdot x_i + b)] \quad (4.6)$$

In the SVM optimization problem, this functional margin is set to $F = 1$ as shown in 4.1 and results in the parallel hyperplanes H1 and H2 as the constraint of the problem (Eq. 4.7).

$$y_i(\mathbf{w} \cdot x_i + b) \geq 1 \quad \forall i \quad (4.7)$$

The goal now is to maximize the distance between the hyperplanes H1 and H2 to obtain the optimal hyperplane H which falls in the middle of H1 and H2. The minimum distance from H to H2 (or H to H1) is called the geometric margin. This minimum distance can be found by taking the vector between any point on H2: p_{H2} and any point on H1: p_{H1} and projecting it onto the unit normal vector of H1 or H2 given by \mathbf{w} . Keep in mind that p_{H2} must satisfy $\mathbf{w} \cdot \mathbf{x} + b = 1$ and p_{H1} must satisfy $\mathbf{w} \cdot \mathbf{x} + b = -1$

$$\begin{aligned}
d &= \|\text{proj}_{\mathbf{w}}(p_{H2} - p_{H1})\| \\
&= \left\| \left((p_{H2} - p_{H1}) \cdot \frac{\mathbf{w}}{\|\mathbf{w}\|} \right) \frac{\mathbf{w}}{\|\mathbf{w}\|} \right\| \\
&= \left\| (p_{H2} \cdot \mathbf{w} - p_{H1} \cdot \mathbf{w}) \frac{\mathbf{w}}{\|\mathbf{w}\|^2} \right\|
\end{aligned}$$

p_{H2} must satisfy $\mathbf{w} \cdot p_{H2} + b = 1$ (ie $\mathbf{w} \cdot p_{H2} = b - 1$) to be on hyperplane H2 and p_{H1} must satisfy $\mathbf{w} \cdot p_{H1} + b = -1$ to be on hyperplane H1 (ie $\mathbf{w} \cdot p_{H1} = -b - 1$)

$$\begin{aligned}
&= \left\| ((1 - b) - (-b - 1)) \frac{\mathbf{w}}{\|\mathbf{w}\|^2} \right\| \\
&= \left\| 2 \frac{\mathbf{w}}{\|\mathbf{w}\|^2} \right\| \tag{4.8} \\
d &= \frac{2}{\|\mathbf{w}\|}
\end{aligned}$$

To find the optimal hyperplane, the distance $d = 2/\|\mathbf{w}\|$ must be maximized or equivalently $\|\mathbf{w}\|^2$ (which is a convex function [84]) can be minimized giving rise to the following convex optimization problem that can be solved using Lagrange Duality. The primal problem is:

$$\begin{aligned}
&\min \|\mathbf{w}\|^2 \\
&\text{s.t. } y_i(\mathbf{w} \cdot x_i + b) \geq 1 \quad \forall i
\end{aligned} \tag{4.9}$$

Converting equation 4.9 to the Lagrange Formulation which causes the constraint to move to the objective function and act as a penalty if the constraint is violated:

$$L(\mathbf{w}, b, \alpha) = \frac{1}{2} \langle \mathbf{w} \cdot \mathbf{w} \rangle - \sum_{i=1}^n \alpha_i [y_i(\langle \mathbf{w} \cdot x_i \rangle + b) - 1] \tag{4.10}$$

Setting partial derivatives with respect to \mathbf{w} and b equal to zero to minimize the Lagrangian:

$$\begin{aligned}
\frac{\partial L(\mathbf{w}, b, \alpha)}{\partial \mathbf{w}} &= \mathbf{w} - \sum_{i=1}^n \alpha_i y_i x_i = 0 \rightarrow \mathbf{w} = \sum_{i=1}^n \alpha_i y_i x_i \\
\frac{\partial L(\mathbf{w}, b, \alpha)}{\partial b} &= - \sum_{i=1}^n \alpha_i y_i = 0 \rightarrow \sum_{i=1}^n \alpha_i y_i = 0
\end{aligned} \tag{4.11}$$

Substituting these into the Lagrange Formulation and simplifying yields the dual that depends only on the Lagrange Multipliers α [84].

$$L(\mathbf{w}, b, \alpha) = -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i y_i \alpha_j y_j \langle x_i \cdot x_j \rangle + \sum_{i=1}^n \alpha_i \tag{4.12}$$

Then the dual optimization problem is shown in Equation 4.13 and the solution to the dual is the same as the solution to the primal given that the Karush-Kuhn-Tucker conditions (KKT) are satisfied [84]:

$$\begin{aligned}
&\max_{\alpha_i} -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i y_i \alpha_j y_j \langle x_i \cdot x_j \rangle + \sum_{i=1}^n \alpha_i \\
&\text{s.t. } \alpha_i \geq 0, \quad 1, \dots, n \\
&\sum_{i=1}^n \alpha_i y_i = 0
\end{aligned} \tag{4.13}$$

The solution to the Lagrangian Multipliers α_i can be found using quadratic programming. It is observed that $\alpha_i > 0$ are called the support vectors and all other $\alpha_i = 0$ [84]. Once α_i is found, \mathbf{w} can be found using the training data and α_i in Equation 4.11. Since the support vectors have been found and known to fall on hyperplane H1 and H2, and the normal \mathbf{w} has been found, the optimal b can be found by isolating for b in H2: $(\mathbf{w} \cdot x_{H2}) + b = 1$ or H1: $(\mathbf{w} \cdot x_{H1}) + b = -1$ for a support vector that falls on H2 or H1 respectively.

Theory of SVM: Not Linearly Separable

The optimization problem for the not linearly separable case is very similar to the linearly separable case, only now there is the addition of a slack variables ζ_i to the constraint (see Figure 4.2). The optimization problem then becomes

(Equation 4.14) [84] with the squared sum of the slack variables modified by a weight C added to the original cost function:

$$\begin{aligned}
& \min ||\mathbf{w}||^2 + C \sum_{i=1}^n \zeta_i^2 \\
& \text{s.t. } y_i(\mathbf{w} \cdot x_i + b) \geq 1 - \zeta_i \quad \forall i \\
& \zeta_i \geq 0
\end{aligned} \tag{4.14}$$

A higher C increases the cost of permitting slack variables and therefore a higher C tends toward perfectly separating the data. The problem is solved in a similar way using Lagrangian Duality and details can be found in Cervantes et al.'s article [84]

Tunable Parameters

In SVM the tunable parameters are C , the type of kernel selected and the kernel's tunable parameter(s). In Section 4.1.2, it was discussed that the larger the C the larger the penalty on slack variables and therefore the classifier tends toward perfect separation of the data points. It doesn't seem like there is agreement on what kernel and what kernel parameter is appropriate for a specific application [84]. However, in practice it is common for datasets with many features to use the basic linear kernel [84]. If the data requires non-linear separation, the Gaussian Kernel is most widely used and its parameter σ can be appropriately chosen using a search [84].

4.1.3 Random Forests

Overview

Random Forests consist of Decision Trees that must be first discussed [86]. A decision tree can be built upon features that are categorical (eg. has astigmatism) or numerical (eg. age). Training a decision tree results in a the structure shown in Figure 4.4 with nodes representing the feature and edges representing the options or ranges of values that the feature can take. Typically, the classifier starts at a starting point called the root node. Edges extend uni-directional from the root node presents a decision that the classifier must make based on the features of the new data point. Picking an option or range of values (choosing one of the edges extending from the node) advances the classifier along that edge to the next node in the next level of the tree. The classifier repeats this decision process until there is no more next node; the classifier has reached a "leaf" node and can classify the data point.

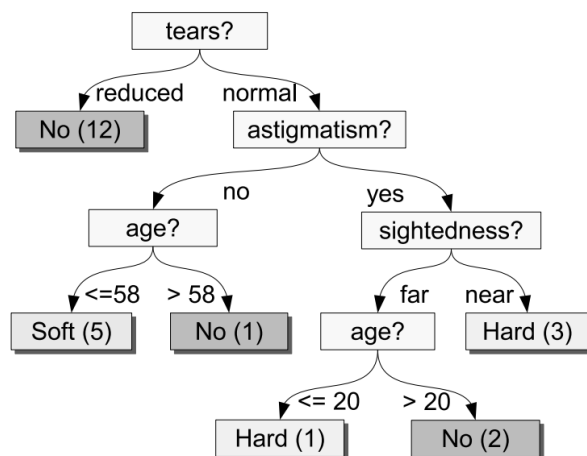


Figure 4.4: Example of a Decision Tree [87]

Random Forests extend the use of Decision Trees by training multiple trees, classifying the new data with each tree and doing a majority vote on the output of each decision tree [88]. Each Decision Tree is trained using a random subset of data drawn from the original training data with replacement. These trees are grown to maximum depth without pruning using the

Classification and Regression Tree (CART) methodology and at each node a random subset of features is used [88]. In situations where there are many features with each feature providing only a small amount of information (eg. medical diagnosis), the single decision tree will have an accuracy slightly better than random classification, whereas using a Random Forest can produce improved accuracy [88].

In time series data, features can be extracted by taking the mean, standard deviation and slope of random subsequences in sequence labelled a certain class 4.5. The number of features is then $3 * \text{the number of subsequences extracted}$. These features are used to train a random forest and new sequences of time series data can be classified by following the same methodology for feature extraction [83].

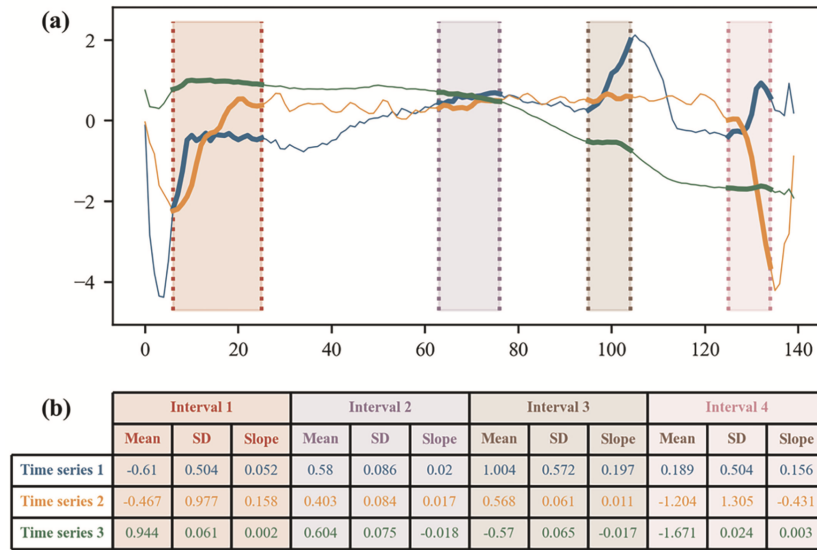


Figure 4.5: Decision Trees used for time-series classification. Mean, standard deviation and slope of random subsequences in a time-series sequence defining a class are used as features. [83]

Classification and Regression Tree (CART) Methodology

The Classification and Regression Tree (CART) method to grow trees outlined by Breiman et al. has the objective of splitting the dataset L at each node such that the descendent nodes—nodes one level down—are "purer" than

the parent node. Purity in sklearn’s implementation of decision trees can be evaluated using Gini’s Impurity and Entropy [89] and the most common, Gini’s Impurity, is shown in Equation 4.15 [89].

$$G = \sum_k p_{mk}(1 - p_{mk}) \quad (4.15)$$

Where p_{mk} is the proportion or probability of observing a class k in subset Q_m

$$p_{mk} = \frac{1}{n_m} \sum_{y \in Q_m} I(y = k) \quad (4.16)$$

At some node m , some subset of the data at node m designated as Q_m , and k classes. At each node, candidate splits $\theta = (j, t_m)$ consisting of a feature j and threshold t_m are evaluated for impurity. According to the source code for sklearn, these candidate splits are chosen by randomly selecting a feature, sorting the feature’s values, and using each of the feature’s values as a threshold t_m for a candidate split (ie. the thresholds t_m are the values of feature j for the datapoints in the subset Q_m). This process is repeated until the max number of features to be evaluated (an input argument in the Decision Tree Classifier) is reached. The candidate split θ that minimizes the (Gini) impurity is selected to split the data in a binary fashion with 2 descendant nodes [90]. The same process repeats at the descendent nodes recursively until a termination condition (eg. max depth of tree) is reached or the descendant node only contains a single class.

Tunable Parameters

The tunable parameters for Random Forests are similar to Decision Trees and the full list may be found on sklearn’s Documentation page for Random Forests [91]. Sklearn mentions that the default values for controlling the size of the tree (eg. max_depth, min_samples_leaf) leads to large, unpruned and fully grown trees which may be very memory intensive. They recommend to control these parameters to limit the memory consumption [91]. Otherwise, similar to other ML methods, a grid search should be used to find the optimal hyperparameters for the training dataset [92]. Parameters that should be considered for tuning in order of highest positive effect on the Area Under the Curve (AUC) is mtry (max_features in sklearn), sample size drawn for

training a tree, and the minimum number of observations in a terminal node (`min_samples_leaf` in sklearn) [92].

4.1.4 Shapelet Transform

Overview

A shapelet is a small but discriminating subsection of a time series waveform that represents a class [93]. To classify with shapelets, the authors in [93] propose using a decision tree with split criteria based on the inclusion shapelets from a shapelet dictionary (inclusion is determined by the distance between a subsequence from a new time-series signal and the shapelet being less than some threshold—Figure 4.6 shows that the inclusion threshold distance is 5.1). Shapelets address some of the shortcomings of using kNN-DTW presented in Section 4.1.1 that result in large time and space complexity and limit its applicability.

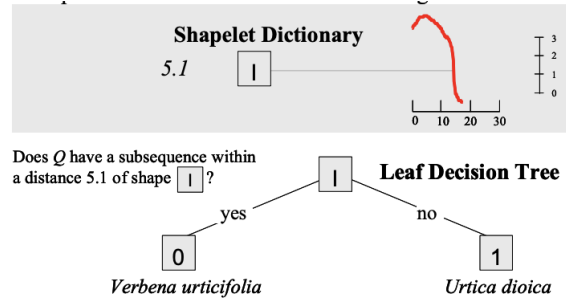


Figure 4.6: Example of a shapelet and the criteria for classifying a new time-series [93].

Determining Shapelets

The authors in [93] mention that the total number of possible shapelets can be calculated by the following equation

$$\sum_{l=MINLEN}^{MAXLEN} \sum_{T_i \in D} (m_i - l + 1) \quad (4.17)$$

for every timeseries T_i in dataset D , l is the length of a candidate shapelet and m_i is the length of the i -th timeseries in the dataset D . For the Trace

dataset with has 200 instances, each with length of 275. If $MINLEN = 3$ and $MAXLEN = 275$, the total number of candidates would be 7,480,200. A brute force approach (Algorithm 1) would be inefficient at finding the best shapelet. The time complexity is $O(\bar{m}^3 k^2)$ for average length of timeseries \bar{m} , so the authors propose a pruning strategy to find the best shapelets for classification.

Algorithm 1 Brute Force approach for finding the best shapelet [93], bsf_gain is the information gain calculated using Entropy.

```

candidates  $\leftarrow$  GenerateCandidates( $D, MAXLEN, MINLEN$ )
bsf\_gain  $\leftarrow$  0
for each  $\mathcal{S}$  in candidates do
    gain  $\leftarrow$  CheckCandidates( $D, \mathcal{S}$ )
    if gain > bsf\_gain then
        bsf\_gain  $\leftarrow$  gain
        bsf\_shapelet  $\leftarrow$   $\mathcal{S}$ 
    end if
end for
return bsf\_shapelet

```

To speed up the calculations, the authors use the *early abandon* method in the CheckCandidates(D, \mathcal{S}) function. Instead of calculating the entire Euclidean distance between the shapelet and the subsection of the time series, a minimum distance variable (initialized to infinity) is used to track the minimum distance calculated. If, at any point in the Euclidean distance calculation, the minimum distance is exceeded, the calculation is stopped and moves onto the next step. If the full distance between the shapelet and the subsection of the timeseries is less than the minimum distance in memory, then the minimum distance is updated [93].

Another optimization involves *entropy pruning* which occurs once again at the CheckCandidates(D, \mathcal{S}) function. Another variable is created to store the best so far information gain. Since the minimum distance calculation between the timeseries and the candidate shapelet is the most costly, these distances are calculated one by one. At each distance calculation, the optimal split point is determined for the distances already calculated and the information gain in the most ideal situation (the rest of Class A on one side and the rest of Class B on the other) is calculated. If the information gain in

the most ideal situation is less than the best so far gain, then the candidate shapelet can be pruned and no further minimum distance calculations will need to be done. Otherwise, continue calculating the minimum distances between the timeseries and the candidate shapelet and checking the information gain for the ideal situation at each step. If after calculating all of the distances between the candidate shapelet and the the timeseries dataset and the information gain is still greater than the best so far information gain, then the best so far gain is updated and the process continues until all of the candidate shapelets have been considered [93].

Multi-Class Classification with Shapelets

To classify multiple classes, the authors of [93] proposed growing a decision tree. At each node a shapelet is found using the optimized Algorithm 1 outlined in the previous subsection. The split point identified using the shapelet at the node splits the dataset into a left and right subset of data. On the left and right subset of data, the optimized Algorithm 1 is used to find the shapelet and the split point for that subset of data. The process continues recursively until a leaf node is reached. This process creates a decision tree and a dictionary of shapelets shown in Figure 4.7 that can be used for classifying time-series data.

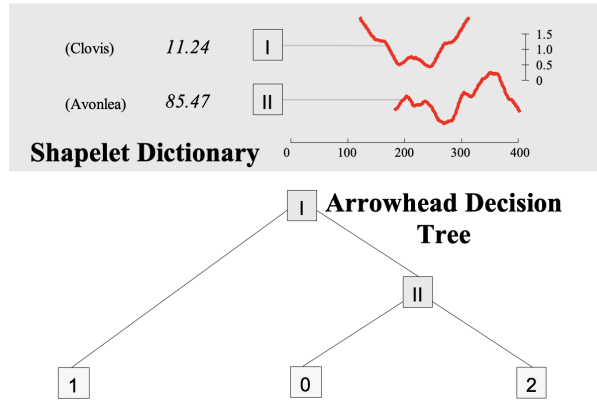


Figure 4.7: An example of a shapelet based decision tree [93].

4.2 Neural Networks

4.2.1 Deep Neural Networks

4.2.2 Convolutional Neural Networks

4.2.3 Recurrent Neural Networks

4.2.4 Long Short Term Memory

4.3 Large Language Models

4.4 Feature Extraction

Time series data is a series of data that each consists of a value at an associated timestamp. In terms of the system investigated in this thesis, this could be a series of position in the x-axis measured at time $t_1, t_2, t_3...$ respectively. The data can be said to be indexed by time [94] typically in ascending order.

Chapter 5

Pilot Testing of Detecting Activities to make a Sandwich

Chapter 6

PASS Tasks

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