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Temporal Classification: Extending the Classification Paradigm to Multivariate Time Series

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Abstract

Machine learning research has, to a great extent, ignored an important aspect of many real world applications: time. Existing concept learners predominantly operate on a static set of attributes; for example, classifying flowers described by leaf size, petal colour and petal count. The values of these attributes is assumed to be unchanging – the flower never grows or loses leaves.

However, many real datasets are not "static"; they cannot sensibly be represented as a fixed set of attributes. Rather, the examples are expressed as features that vary temporally, and it is the temporal variation itself that is used for classification. Consider a simple gesture recognition domain, in which the temporal features are the position of the hands, finger bends, and so on. Looking at the position of the hand at one point in time is not likely to lead to a successful classification; it is only by analysing changes in position that recognition is possible.

This thesis presents a new technique for temporal classification. By extracting sub-events from the training instances and parameterising them to allow feature construction for a subsequent learning process, it is able to employ background knowledge and express learnt concepts in terms of the background knowledge.

The key novel results of the thesis are:

- A temporal learner capable of producing comprehensible and accurate classifiers for multivariate time series that can learn from a small number of instances and can integrate non-temporal features.

- A feature construction technique that parameterises sub-events of the training set and clusters them to construct features for a propositional learner.

- A technique for post-processing classification rules produced by the learner to give a comprehensible description expressed in the same form as the original background knowledge.

The thesis discusses the implementation of *TClass*, a temporal learner, and demonstrates its application on several artificial and real-world domains, and compares its performance against existing techniques (such as hidden Markov models). Results show rules that are comprehensible in many cases and accuracy results close to or better than existing techniques – over 98 per cent for sign language and 72 per cent for ECGs (equivalent to the accuracy of a human cardiologist). One further surprising result is that a small set of very primitive sub-events proves to be functional, avoiding the need for labour-intensive background knowledge if it is not available.

Declaration

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

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In the Name of The Unique God, the Beneficent, the Merciful

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I'm sure I've forgotten someone. I assure you that this is a shortcoming on my part and not on yours. I beg you to forgive me for my oversight.

Mathematical terminology

Symbol	Meaning
$\langle a, b, c \rangle$	A tuple (in this case triple) of values
$\{a, b, c\}$	A set with three elements a, b, c
$\{a_1, ..., a_n\}$	A set containing the elements a_1, a_2 etc. all the way to a_n
$a \in A$	The value a is an element of A
$[a, b, c]$	A list containing the elements a, b, c
$\{x \mid b(x)\}$	The set of all values of x for which $b(x)$ is true
$f : A \to B$	f is a function that maps from an element of A into an element of B
domain(f)	If $f : A \to B$, then domain(f) $= A$
range(f)	If $f : A \to B$, then range(f) $= B$
$\mathbb{P}(X)$	The set of all possible subsets of X
X^*	The set of all lists generated by selection of elements from X
X^+	$X^* - []$
$e_{\langle i \rangle}$	The ith value of the tuple e
$\sum_{s \in S} f(s)$	The sum of $f(s)$ over all elements in S
$\sum_{i=m}^{n} f(i)$	$f(m) + f(m+1) + ... + f(n)$
$\text{argmin}_{s \in S} f(s)$	The value of s for which $f(s)$ is the least
$\text{argmax}_{s \in S} f(s)$	The value of s for which $f(s)$ is the most

Abbreviations

Abbrev	Meaning
Abbrev	Abbreviation
AI	Artificial Intelligence
Auslan	Australian Sign Language
CBF	Cylinder-Bell-Funnel
DTW	Dynamic Time Warping
ECG	Electrocardiograph
FIR	Finite Impulse Response
HMM	Hidden Markov Model
HTK	HMM Tool Kit
ILP	Inductive Logic Programming
ML	Machine Learning
PEP	Parametrised Event Primitive
RNN	Recurrent Neural Network
SMI	Signal Match Image
TC	Temporal Classification

Chapter 1

Introduction

Machine learning has generally ignored time in supervised classification. While there are many tools for learning static information, such as classifying different flowers according to their attributes, or determining people's credit worthiness, these are not the only type of real world classification problem.

Most real domains changes over time. What is interesting and useful to learn is not just to recognise when our classification is obsolete (changes in the economic environment, for example, may affect the accuracy of a credit-worthiness classifier); but also to use the patterns of change over time itself *directly* as a means of classification.

Consider a typical real-world temporal domain: speech. Our vocal chords generate amplitude and frequency values that vary over time. These variations denote a higher level concept, such as a word. Looking at the amplitude or

frequency at one point in time is unlikely to help recognise words; it is only by looking at how the amplitude and frequency vary that classification becomes possible. Other examples include:

- Recognising action sequences or gestures. These arise in areas such as human-computer interaction, handwriting recognition and robot imitation.
- Medical applications. A patient's body rhythms are frequently recorded and used for diagnosis, for example: electrocardiographs, electroencephalographs, levels of various chemicals in the body and so on.
- Observing sequences of events and extracting higher level meaning from them. For example, looking at network logs and trying to identify causes of congestion problems.
- Economic and financial time series, where the user may be interested in event patterns indicating a particular phenomena or preceding particular phenomena. For example, the user might be interested in the events preceding a large market crash.
- Industrial/scientific data often includes temporal data; increasingly, today's production facilities have many embedded sensors which produce measurements at regular time intervals. The task of interest may, for example, be detecting when catastrophic events will occur, based on measurements of volume, pressure, temperature or thickness.

This thesis explores the design and implementation of a general classification

tool for such temporal domains that tries to balance the specific properties of each domain against the general issues that arise in temporal classification. To do so, it proceeds in the following way:

- A brief explanation of the terminology and key problems are presented together with a theoretical foundation and formalisation.
- Existing techniques for dealing with temporal classification are discussed. These include hidden Markov models, dynamic time warping and recurrent neural networks. Current research in the artificial intelligence community is also explored.
- Metafeatures, the core of the *TClass* system, are presented.
- A general system for classification of multivariate time series, based on metafeatures, is proposed.
- The performance of the new system, *TClass*, is evaluated on two artificial and two real-world datasets: sign recognition and electrocardiograph (ECG) diagnosis.
- Extensive avenues for future research are discussed. This includes both direct extensions to the current work and also some very different approaches to doing temporal classification.
- Conclusions on the work are presented.

1.1 Summary of the thesis

In this section a brief outline of the thesis is given, and its novel contributions are outlined.

One way that one might characterise multivariate time series such as sign language is by looking for sub-events that a human might detect as part of a sign. Consider one class in the Auslan domain, say `thank`. The gloss for `thank` is shown in Figure 1.1. The sign is described by its sub-events such as "placed on chin" and "moved away with stress".

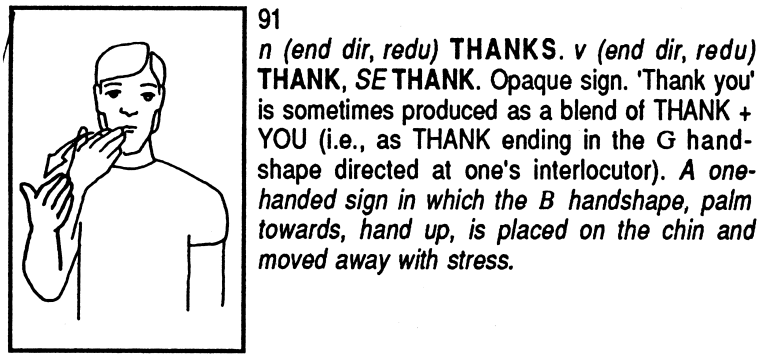


Figure 1.1: The gloss for the Auslan sign `thank` [Joh89].

The sign could be characterised as consisting of even simpler sub-events: a raising of the hand to touch the chin (in other words an increase in the vertical position of the hand), a vertical maximum as the hand touches the chin, followed by the hand moving down and away from the body (in other words a decrease in the vertical position of the hand, as well as an increase in the lateral distance from the body). Humans are quite comfortable talking about time series in these terms: increasing, decreasing, local maximum and so on. However, humans

might also talk of different sub-events – we might talk of a person making a circular movement, for example.

Metafeatures parametrise events in a way that capture their properties, including the temporal characteristics. A simple metafeature might be a local maximum. The parameters of this metafeature might be the time at which the local maximum occurs and its height. To take a more complicated example, another metafeature might be a circle motion; which is parameterised as centre, radius, angular velocity, start time and duration. Metafeatures themselves are not novel; concepts such as extracting the minima and maxima of the signal, or even increasing, decreasing, or flat periods of the signal for classification have been previously explored.

Our application of them, however, is novel. One can imagine that each local maximum we find in the training instances is a point in a 2-dimensional space (one axis being the time, the other being the height). This **parameter space** provides a rich ground for feature construction.

For example, we may find that local maxima that occur around the height of the chin result in very different classifications to signs that have local maxima only a few centimetres higher (in fact the sign `smell` is almost identical to `thank` aside from the position) – at the nose. If we discovered that the class distribution of local maxima is significantly different if it's near the nose or the chin, then two interesting local maxima are selected: one near the chin and one near the nose.

Term these "interesting examples" **synthetic events**. Features for learning are constructed by detecting if each training instance has an actual (or as it is termed in this thesis, **instantiated**) event that is similar to the synthetic one. We describe several algorithms for discovering interesting examples, including a novel and effective one: **directed segmentation**.

TClass uses these synthetic events as the basis for feature construction. For example, an unlabelled test instance would be searched for local maxima. It would be analysed to see if any of the local maxima were similar to the synthetic events. If it did have a local maximum near the nose it would be labelled as such. In fact, two new features are constructed: HasYMaxNearChin and HasYMaxNearNose. Of course, these are human labels that we've associated with each of the two centroids, and they would really be called YMax0 and YMax1. Each training and test instances is **attributed** with these newly created features.

Several metafeatures can be applied to the training instances, each constructing **synthetic features**. Each list of features is an attribute vector and hence these can be concatenated to form one long attribute vector. Furthermore, non-temporal features (like age and gender of an ECG patient) and temporal aggregate features (like standard deviations, averages, maxima and minima) can also be appended. *TClass* makes it easy to mix temporal and non-temporal features, unlike many other temporal classification systems.

These combined attribute vectors can now be used as inputs to a propositional learner to produce a classifier. Furthermore, we can replace the attributes

constructed from synthetic events with the original description, leading to a concept description expressed as the metafeatures. For example, if a rule has the form If YMax0 = True; then this could be rewritten using the original synthetic event as something like If y has local max of height 0.54 at time 20 (assuming that the chin is at a height of 0.54 units). This is a major novel contribution of this thesis: a temporal classifier that actually produces comprehensible but accurate descriptions.

However, the above gives no feel for the "scope" of acceptable variation for each metafeature. For example, if a rule contains a comparison of the form above, it is not clear what reasonable bounds are to be expected. Does "approximately 0.54" mean from to 0.4 to 0.7 or from 0 to 1? By looking at the original training data, we can extract bounds that allow the user to have a "feel" for what is reasonable. While these do not form a complete picture of the learnt concept, they give some intuition. This process of postprocessing the output of the learner to convey the bounds on variation is also novel.

We have implemented this system, and tested it on two artificial datasets and two real-world ones. We compare *TClass* with two "controls" – hidden Markov models and naive segmentation (dividing the data into a number of segments, averaging and then using a propositional learner). The first artificial dataset, proposed by other researchers, turns out to be too easy – all learners, including controls and *TClass*, attained 100 per cent accuracy. Still *TClass* generated rules that closely corresponded to the original (known) concepts. We propose our own second artificial more difficult dataset, on which *TClass* performs better

in terms of accuracy and also produces comprehensible descriptions. The two real-world domains are Auslan (Australian Sign Language) and Type I ECGs. In the Auslan domain, we obtain 98 per cent accuracy; and in the ECG domain, we obtain about 72 per cent accuracy, comparable to a human expert with accuracy of 70 per cent, and similar to a hand-extracted set of features with 71 per cent.

There is a great opening for expanded research in the field, at a time when data mining is growing at a phenomenal rate. There are many avenues of future work. Some detailed descriptions of avenues for future work are given, including some early explorations of totally different approaches to temporal classification. Finally, some important conclusions are drawn.

Chapter 2

Definition of The Problem, Terms Used and Basic Issues

This chapter begins with two simple examples of temporal classification. Terminology that is useful in discussing the problem is introduced and formal definitions are given for several important terms. This is followed by a brief discussion of the special features that make temporal classification distinct from (and more difficult than) traditional classification. This will set the foundation for subsequent chapters.

2.1 Examples of Temporal Classification

2.1.1 Tech Support

This pedagogical domain is meant as an extremely simple example of temporal classification. Consider the following scenario[1]: A computer company, called SoftCorp, makes an extremely buggy piece of software; hence they get many irate phone calls to their technical support department. These phone calls are recorded for later analysis. SoftCorp discovers that how these phone calls are handled has a huge impact on future buying patterns of its customers, so based on the recordings of tech support responses, they are hoping to find the critical difference between happy and angry customers.

An intelligent engineer suggests that the volume level of the conversation is an indication of frustration level. So SoftCorp takes its recorded conversations and analyses the phone call. They divide each phone call into 30-second segments; and work out the average volume in each segment. If it is a high-volume conversation, it is marked as "H", while if it is at a reasonable volume level, it is labelled as "L". On some subset of their data (in fact, six customers), they determine whether the tech support calls resulted in happy or angry customers by some independent means. Note that conversations are not of fixed length; some conversations can be dealt with quickly, others take a bit longer.

Six examples of recorded phone conversations (with the process discussed

[1] Any correspondence to real software companies is purely coincidental.

above applied to them) are show in Table 2.1.

Call	Volume level over time 0 1 2 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0	Outcome
1	L L L H H H L L L L L L	Happy
2	L L L H L L H L L H H H H	Angry
3	L L H L L H L L L L L L H H H	Angry
4	L L L L H H H H L L L L L	Happy
5	L L L H H H L L L L	Happy
6	L L H H L L H L L H H H	Angry

Table 2.1: The training set for the Tech Support domain.

SoftCorp would like to employ some kind of machine learning tool to aid in finding rules to predict whether, at the end of a conversation, a customer is likely to be happy or angry, based on observing these volume levels.

2.1.2 Recognition of signs from a sign language

Consider the task of recognising signs from a sign language[2] using instrumented gloves. The glove provides the information shown in Table 2.2.

Each instance is labelled with its class, and all of the values are sampled approximately 23 times a second. Each training instance consists of a sequence of measurements. Training instances differ in the number of samples; depending on the duration of the sign itself – some like `my` are short, while others like `computer` are longer.

[2]Note that recognising sign language as a whole is extremely difficult – to mention three serious difficulties: the use of spatial pronouns (a certain area of space is set to represent an entity); the use of *classifiers* – signs that are physically descriptive but are not rigidly defined; and finally improvised signs.

Channel	Description
x	Hand's position along horizontal axis (parallel with shoulders).
y	Hand's position along vertical axis (parallel with sides of body).
z	Hand's position along lateral axis (towards or away from body).
roll	Hand's orientation along arm axis (i.e. palm facing up/down).
thumb	Thumb bend (0 = straight, 1 = completely bent)
fore	Forefinger bend (0 = straight, 1 = completely bent)
middle	Middle finger bend (0 = straight, 1 = completely bent)
ring	Ring finger bend (0 = straight, 1 = completely bent)

Table 2.2: Information provided by gloves.

An example training instance is shown in Figure 2.1. This is a recording of the Auslan[3] sign `come`. The horizontal axis represents the time and the other axes represent normalised values between -1 and 1 for x, y, and z and between 0 and 1 for the remaining values.

The objective in this domain is: given labelled recordings of different signs, learn to classify an unlabelled instance.

2.2 Definition of Terms

In order to simplify the rest of the thesis, some terms are defined here. Mostly, these are related to the representation of the input data, and the format it's in. Figure 2.2 provides a visual representation of three important terms: channels, frames and streams.

[3]Auslan is the name used for AUstralian Sign LANguage, and it is the language used by the Deaf in Australia.

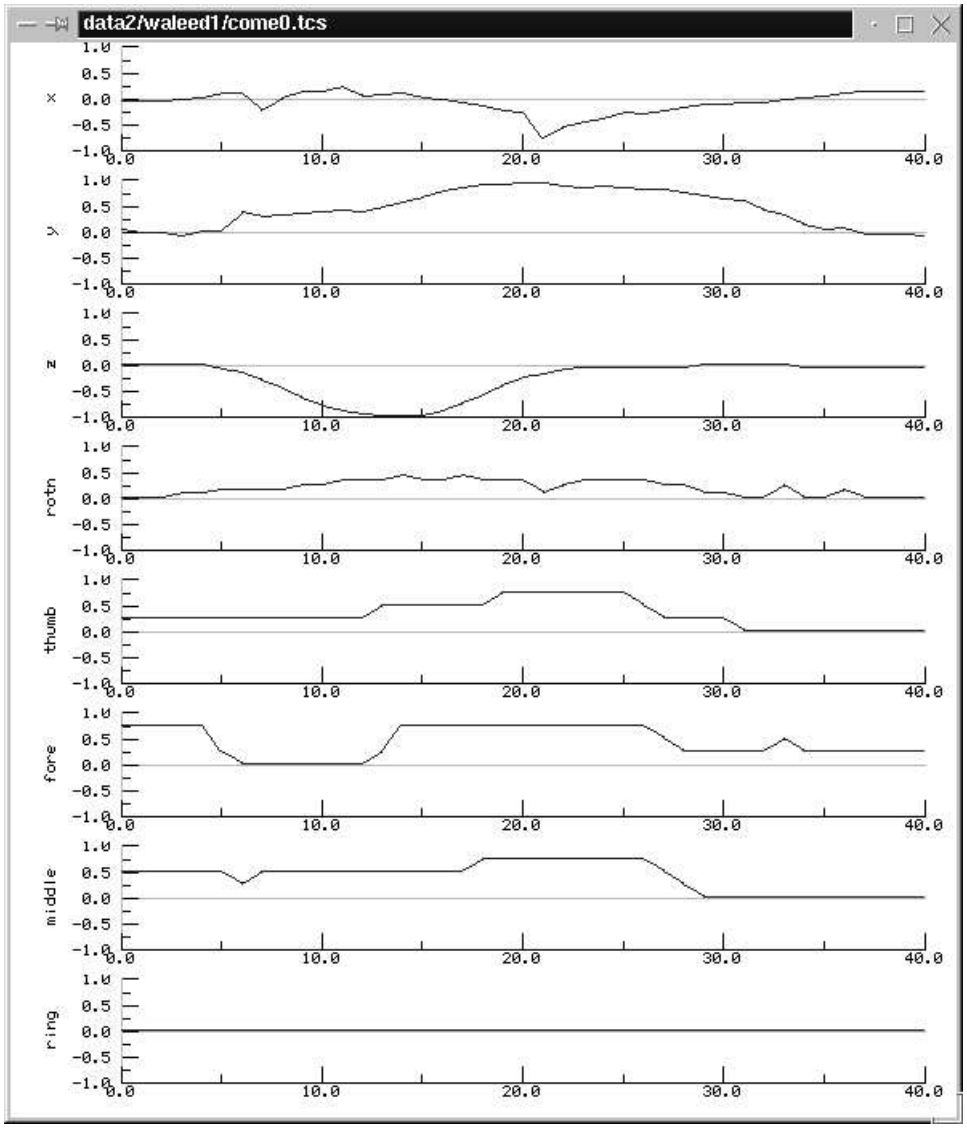


Figure 2.1: An example of a stream from the sign recognition domain with the label `come`.

2.2.1 Channel

Consider the sign language domain discussed in Section 2.1.2. There are different sources of information, each of which we sample at each time interval – things like the x position, the thumb bend and so on. Each of these "sources" of information

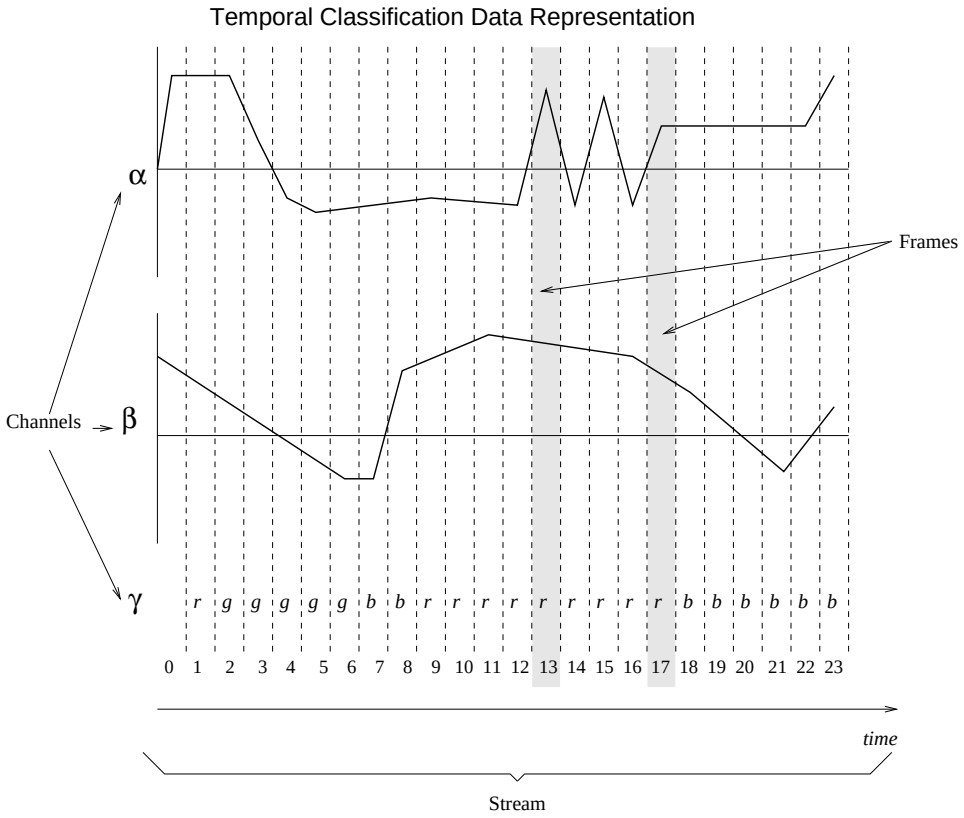


Figure 2.2: The relationship between channels, frames and streams.

we term a **channel**. In Figure 2.1, each of the sub-graphs represents a channel. The Tech Support domain contains a single channel, that of the volume of the conversation.

Formally, a channel can be defined as a function c which maps from a set of timestamps T to a set of values, V, i.e.

$$c : T \rightarrow V$$

T can be thought of as the set of times for which the value of the channel c is defined. For simplicity in this thesis, we assume that:

$$T = [0, 1, .., t_{max}]$$

In the Tech Support domains, t_{max} varies between 9 and 14. Looking at Figure 2.1 from the sign language domain, we can see that $t_{max} = 40$.

The set of values V obviously depends on the classification task. In the Tech Support domain, $V = \{L, H\}$. In the sign language domain, V for the fingers is $[0, 1]$, but for the x, y and z position may be $[-1.5, 1.5]$, since the x, y and z positions (measured in metres) can take these values.

2.2.2 Stream

Consider the sign language domain once again. Each training instance consists of the individual channels. It is convenient to talk of all of the channels collectively. For example, Figure 2.1 shows a number of channels, but we want to talk about all of the channels at once. This is the definition of a **stream**.

A stream is a sequence of channels S, such that the domain of each channel in S is the same, i.e.

$$S = [c_1, c_2, ..., c_n] \text{ s.t. } \text{domain}(c_1) = \text{domain}(c_2) = ... = \text{domain}(c_n)$$

where n is the number of channels in the stream S. Each channel has the same domain – this corresponds to the timepoints where samples of each of the channels exist.

A stream allows us to collect all these various measurements and treat them, in some ways, as part of the same object. The Tech Support domain is very

simple: each training stream has one channel. However, the Auslan domain has eight.

2.2.3 Frame

Consider once again Figure 2.1. A channel is a "horizontal" cut through the data; and a stream is the name for whole object, but at times it is useful to talk of a vertical cut through the data; in essence to talk about the data on all channels at a particular point in time. For example, one might talk about time $t = 29$ and ask what are the values of each of the channels at that time. This is exactly what a **frame** is. For a given stream $S = [c_1, c_2, ..., c_n]$, the function fr is defined as:

$$fr : \text{domain}(c_1) \rightarrow \text{range}(c_1) \times \text{range}(c_2) \times ... \times \text{range}(c_n)$$

$$fr(t) = \langle c_1(t), c_2(t), ..., c_n(t) \rangle$$

Intuitively, a frame represents a "slice" of each of the channels at a given point in time. It represents the values of each of a channel for a given time t.

Note that in the above, the domain of c_1 is used, but any other c_i would do.

The connection between channels, frames and streams is illustrated in Figure 2.2. In this diagram, we have three channels α, β and γ, with the range of the first two being the real numbers, and the range of the last being $\{r, g, b\}$. The stream consists of these three channels together. The "length" of the stream

is 24 time-slices; in other words it consists of 24 frames. Each frame has three channels, and the domain of the function fr in this case is [0..23].

2.2.4 Stream Set

At times, it might be convenient to talk about a set of streams – for example, Table 2.1 lists several streams. For the sign language domain, there may be many sign samples that have been collected. However, it's important that these sets have streams that are of the same "type".

Let SS be a set of streams of the same type. Having the same type can be defined as follows:

Let $S_a = [c_{a1}, c_{a2}, ..., c_{an}]$ and $S_b = [c_{b1}, c_{b2}, ..., c_{bn}]$. Then

$$SameType(S_a, S_b) \equiv c_{ai} = c_{bi} \text{ s.t. } \forall i : 1 \leq i \leq n$$

So the stream set SS is one with the property that:

$$\forall S_i, S_j \in SS \quad : \quad SameType(S_i, S_j)$$

In other words, the range of each channel is the same for each element of SS. Note that the domain of the streams is not necessarily the same; in other words the streams may be of different lengths or "duration" – the above imposes limits on the types of the channels, but not on the number of frames.

2.3 Statement of the problem

There are three obvious variants on the temporal classification problems: weak temporal classification, strong temporal classification and presegmented temporal classification.

2.3.1 Weak temporal classification

The simplest type of temporal classification is based on associating a single class label with each stream. In the Tech Support domain, the classification is the outcome, happy or angry, after a phone call. In the sign language problem, the classification is of the sign, based on the samples from a single stream. Each of these are weak temporal classification tasks.

Let SS be a set of streams with the same type. Let CL be a set of labels, that describes the set of possible classes.

Define a function

$$class : SS \rightarrow CL$$

which takes an element of SS and returns an element of CL.

The goal is: given a subset of the function $class$ (say $class_T$), produce a function $class_P$ which is as similar to $class$ as possible. The exact meaning of "similar" is explored in Section 2.4.

Mathematically, this can be viewed as trying to develop a function L:

$$L : class_T \rightarrow class_P$$

such that the symmetric difference between $class_P$ and *class* is as small as possible. This is the definition of traditional concept learning and is included here for completeness.

Intuitively, our goal is: given a limited example of streams and their classes, in other words, some subset of the function *class*, can we determine the rest of the function?

2.3.2 Strong classification

Consider the sign language domain. What if, when we record the original data, each stream corresponds not to a single sign, but to a sentence (i.e. a sequence) of signs? Then there would not be a simple association of one stream to a class, but from a stream to a *sequence* of classes. This would be an example of a strong classification problem.

A formal definition of strong classification is a modification of the definition of weak classification: Rather than have a function $class(S)$, we have a function $classseq(S)$ which has the following type:

$$classseq(S) : SS \rightarrow CL^+$$

In other words, $classseq(S)$ returns a *sequence* of classes for a given stream,

rather than a single class.

Our problem can be restated as: given a subset of the function *classseq* (say $classseq_T$), produce a function $classseq_P$ which is a similar to *classseq* as possible.

If there are m possible classes, and we assume that for each stream, the longest possible class sequence is n, then in general there are $\frac{m(m^n-1)}{m-1}$ possible class sequences; because there could be anywhere between 1 and n classes in the class sequence. Theoretically, therefore, the two variants are equivalent; as each sentence could be treated as a single label. This is not practical, of course, and generally, strong temporal classification is harder than weak temporal classification.

2.3.3 Pre-segmented TC

In some strong TC domains, it may be possible to obtain more information than just a sequence of classes; we may also be provided with a function *Seg* : $SS \rightarrow T^*_{SS}$, where T_{SS} is the union of the domains of all the elements of SS, in other words, all the possible timepoints in the data. This function returns the "breakpoints" between different classes in the class sequence. For example, if the strong TC domain is sign language, this function *Seg* when applied to a single stream, would return all the times when one sign ends and another begins. In general if there are n classes in the class sequence, *Seg* will return a sequence of $n-1$ time points.

In some domains, such information is provided in a slightly different form. Rather than return a single point in time, *Seg* returns a tuple, representing an interval, during which a "transition" from one class to another occurs. The first element of the tuple represents the start of the transition, and the second represents the end of the transition.

2.4 Assessing success

In order to assess success, we consider two issues: firstly accuracy and secondly comprehensibility.

2.4.1 Assessing Accuracy of Weak TC

On a single element S, one way to measure success is to say that if $class_P(S) = class(S)$ then it is accurate, and inaccurate otherwise.

This works for most cases. However, in some domains, the above is too simplistic – not all inaccuracies are equally bad. Some errors may be worse than others. For example, consider working on a medical TC application involving a diagnosis, where $CL = \{yes, no\}$, with "yes" indicating they have some condition and "no" indicating they do not. A "false positive" classification (i.e. misclassifying a negative as a positive) may not be as bad as a "false negative" (i.e. misclassifying a positive as a negative). This is an old problem in machine

learning, and a field termed *cost-sensitive learning* has studied this problem.

Typically, it is solved by introducing a function $cost(i, j) : CL \times CL \rightarrow [0..1]$ which tells us what the cost of misclassifying an i as a j. The function need not be i-j symmetric, i.e. $cost(i, j) \neq cost(j, i)$. Universally, $cost(i, i) = 0$.

We can represent the above simple case (where all errors are equally bad) as:

$$\begin{aligned} cost(i, j) &= 0, \text{if } i = j \\ &= 1, \text{otherwise} \end{aligned}$$

However, we can always have a more complex cost function.

Secondly, it is better to get higher accuracy on frequently occurring elements than on rare ones. So to give a more accurate measure of accuracy, this too must be included. We use the function $P_{SS}(S)$ to indicate the probability that a stream S has of occurring in the stream set SS.

Our goal can therefore be defined as minimising:

$$\sum_{S \in SS} cost(class(S), class_P(S))\ P_{SS}(S)$$

2.4.2 Assessing Accuracy of Strong TC

Strong TC is a little harder to assess, because the types of error that can occur are more complex.

One possible initial definition would be the following. The classification for

an unseen stream is correct if $classseq(U) = classseq_P(U)$; i.e. it is correct if and only if the predicted and actual class sequences are identical.

However, in many domains this is over-simplistic. If there are two classes a and b, then the class sequence *aaabab* is in some sense "closer" to *aabab* than *bbbbba* is, even though the above classification system would consider them both equally wrong.

To solve this problem, the notion of edit distance is introduced. In such systems, strings are not either "correct" or "incorrect", but some strings are closer to other strings. One such measure is the **Levenshtein** distance [Lev66]. The Levenshtein distance between strings x and y is the minimum number of differences between the two strings. These differences can take three forms:

- A character that is in x and is different in y. This is known as a **substitution**. For example, *aaababa* and *aabbaba* have a substitution difference on the third character.
- A character that is in x and is not in y. This is known as a **deletion**. For example *aaababa* and *aababa* have a deletion difference on the third character.
- A character that is in y and not in x. This is known as **insertion**. For example *aabbaba* and *aababababa* has an insertion difference between the third and fourth characters.

Of course, there is more than one way to get from one string to another.

For example, a substitution can be thought of as a deletion and an insertion. However, the Levenshtein distance is defined as the minimum number of changes to go from one string to the other.

The Levenshtein distance measure can be used on class sequences. Each class maps to a symbol in the alphabet, and each class sequence maps to a string. Other distance measures may be appropriate for different domains.

Again, we should give greater weight to those elements of the stream set which are likely to occur. The strong temporal classification task can now be defined as minimising:

$$\sum_{S \in SS} LevDist(classseq(S), classseq_P(S))\ P_{SS}(S)$$

2.4.3 Comprehensibility – A subjective goal

In some domains we may also be interested in gaining insight into how the classifier works. For example, if a simple rule is generated for classification that can be understood by a human, it may be more desirable than another classifier which has a greater accuracy, but whose internal representation is a list of statistical tables.

Consider once again the Tech Support domain. It is possible to build a temporal classifier that does not produce comprehensible descriptions, and that predicted whether or not the customer was happy or angry. However, this would not be very useful in helping us to understand *why* people are unhappy.

It is, however, notoriously difficult to subjectively measure "understandability", as this is a matter of taste. Some people can extract meaning from 200 numbers because of their knowledge of the domain and learning algorithm; in other cases, simple rules might provide no insight.

Although comprehensibility is subjective, researchers in machine learning often use a number of heuristics to measure comprehensibility. Unfortunately, these methods are tied to particular learners. For example, with decision trees, the number of nodes in the tree are often used as measures of comprehensibility. The number of leaf nodes is sometimes also used. This system has obvious limitations; since it ignores the complexity of the nodes – it could for example be as simple as a comparison on a single attribute, or as complex as a linear combination of all attribute values. Obviously the latter is much simpler than the former.

For decision lists, a count of the number of rules is sometimes used. However, this too has limitations, since some rules can contain more disjuncts than others, and the disjuncts themselves can vary in their complexity. Some users therefore also consider the average number of disjuncts per rule.

2.5 The major difficulties in temporal classification

What is it that makes TC such a challenge, whether it be strong or weak TC? In particular, what are the challenges that distinguish it from typical (static) temporal classification problems?

Intra-channel variation

This is similar to the variation of the values of attributes in attribute-value learning. This is where, between one instance and another instance of the same class, the value of a channel at a given time differ. In the sign language domain, consider someone trying to express great thanks, so he extends his hands further downwards than usual. Hence, the y values resulting from such an action may be much larger, although the sign is still the same.

Intra-channel temporal variation

TC has the unique problem of temporal variation. This variation is due to things happening sooner or later, or taking longer or shorter amounts of time to complete. How do we "align" events within different instances? For example, what if a signer is feeling a bit hesitant to thank someone, so he slowly raises his hands rather than quickly raising it, but the remainder of the sign remains the

same?

Cross-channel temporal variation

If there are relationships between events on various channels, so for example, event A on channel 1 usually occurs at around the same time as event B on channel 2, what do we do if event A occurs before event B instead? For example, what if a signer bends his finger slightly after his hand moves downwards, even though the beginning of the downwards movement and the bending of the finger are usually synchronous?

Noise

This is a shared problem with other learning tools. However, the forms of noise are somewhat different in TC than normal ML. Noise can take the form of temporal noise (measurements being taken slightly too soon or too late – this is unique to TC), channel noise (changes in channel values that do not represent the underlying data) and classification noise (incorrect classification of a training instance). For example, in the sign language data, the gloves themselves may use sensors that are subject to Gaussian or other noise; instead of sampling at 20 millisecond intervals, it may be that sometimes the time between this and the previous sample was 18 or 23 milliseconds; and the training data may have instances where `surprise` is mislabelled as `danger`.

Segmentation

This is unique to strong TC. Clearly, not every possible sequence of classes can be learned. Consider the speech recognition task, this would be like trying to learn how to recognise every possible sentence. Any training set is unlikely to contain even a small percentage of the possible sentences; how would it be possible to make a system that classifies all possible sentences?

The most obvious solution is to break the training sentences into individual words, learn to recognise them, and then somehow combine these individual word recognisers into something that can recognise whole sentences. However, this introduces other problems. If all that is given is a training stream and the corresponding class sequence, when does one class in the class sequence end and the next begin? How are "transition periods" from one class to the next handled? How does one cope with the problem that classes in the sequence are not independent[4]? If the stream is segmented incorrectly then any learner will then get the wrong data: one class will get a part of a stream that belongs to the next class, and the other will get less frames then it should get.

[4]For example, in the speech recognition community, this is known as "coarticulation", where the current word being pronounced depends on the prior and subsequent word. Similar problems exist in other domains.

2.6 Conclusion

We have laid the theoretical foundations for the remainder of the thesis, giving several pedagogical examples of classification tasks and showing how the theoretical model applies to them. We also briefly outlined some of the unique problems that occur in temporal classification domains.

Chapter 3

Relationship to existing work

Temporal classification is not a new problem: it has been explored extensively in different fields, although it has not emerged as a discipline in its own right. There are well-established techniques (such as hidden Markov models, recurrent neural networks and dynamic time-warping), but there has also recently been interest from the artificial intelligence and machine learning communities.

The established methods for temporal classification are first explored. Interest from the machine learning and artificial intelligence community is then discussed.

3.1 Related fields

While temporal classification may be relatively unexplored, time series have been studied extensively in different fields, including statistics, signal processing and control theory.

The study of time series in statistics has a long history [BJ76, And76]. The two main goals of time series analysis in statistics are (a) to characterise, describe and interpret time series (b) to forecast future time series behaviour [Sta02]. The focus in most of the time series analysis work is on long-duration historical data (months/years), because it was typically modelling time series from fields such as biology, economics and demographics. Approaches typically tried to model time series as an underlying "trend" – a long term pattern – together with a seasonailty – short term patterns. The most popular techniques in this type of analysis are Autoregressive Integrated Moving Averages (ARIMA) and Autocorrelation. Many of the techniques, however, make assumptions of stationarity.

The field of signal processing has also explored time series. The objective of signal processing is to characterise time series in such a manner as to allow transformations and modifications of them for particular purposes; e.g. optimal transmission over a phone line. One of the oldest techniques for time series analysis is the Fourier transform [Bra65]. The Fourier transform converts from a time-series representation to a frequency representation. Fourier's Theory states that any periodic time series can be represented as a sum of sinusoidal waves of different frequencies and phases. Converting from a time series representation to

a frequency representation allowed certain patterns to be observed more easily. However, the limitation of periodicity is quite significant, and so recently much work has focused on wavelet analysis [Mal99], where any time series can be represented not as a sum of sinusoidal waves, but "wavelets" – non-periodic signals that approach zero in the positive and negative limits. Signal processing has seen applications in the design of electrical circuits, building of audio amplifiers, the design of telecommunications equipment and more.

Control theory is another field that has explored time series. Control theory studies systems that produce output values at regular time intervals on the basis of certain inputs. However, the relationship between outputs and inputs depends on previous values of the outputs and inputs. Control theory observes patterns in the past inputs and outputs to try to set new inputs so as to achieve a desired output. Typical applications of control theory are to operating industrial equipment such as steel mills and food production processes. Recent work has seen a move towards "adaptive control" [GRC80]; approaches that modify the control theory on the basis of past observations.

All of these fields relate closely to the current work in their study of time series; however, our work differs in that its objective is not to predict future values or to modify behaviour, but rather to classify new time series based on past observations of time series, rather than analysing a single time series' patterns.

3.2 Established techniques

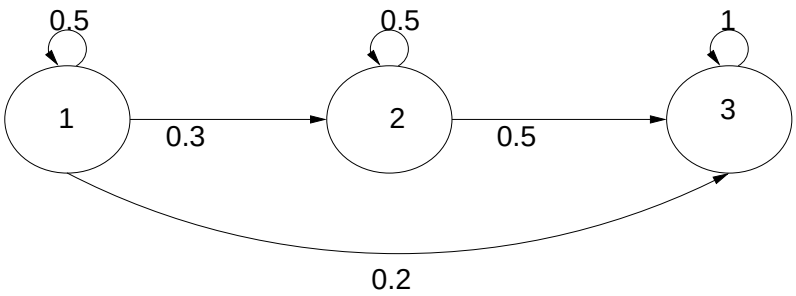
3.2.1 Hidden Markov Models

Hidden Markov models (HMMs) are the most popular means of temporal classification. They have found application in areas like speech, handwriting and gesture recognition. An excellent text on HMMs is [RJ86].

Informally speaking, a hidden Markov model is a variant of a finite state machine. However, unlike finite state machines, they are not deterministic. A normal finite state machine emits a deterministic symbol in a given state. Further, it then deterministically transitions to another state. Hidden Markov models do neither deterministically, rather they both transition and emit under a probabilistic model.

Usually, with a finite state machine, a string of symbols can be given and it can be easily determined (a) whether the string could have been generated by the finite state machine in the first place (b) if it could have been generated by the finite state machine, what the sequence of state transitions it undertook were. With a hidden Markov model, (a) is replaced with a probability that the HMM generated the string and (b) is replaced with nothing: in general the exact sequence of state transitions undertaken is "hidden", hence the name.

Formally, a HMM consists of the following parts:



State 1	
Output	Prob'y
a	0.8
b	0.1
c	0.1

State 2	
Output	Prob'y
a	0.2
b	0.6
c	0.2

State 3	
Output	Prob'y
a	0.7
b	0.3
c	0.1

What is probability of HMM producing "a,a,b,c"?

Pr(a,a,b,c) via 1,1,2,3 = 0.8 x 0.5 x 0.8 x 0.3 x 0.6 x 0.5 x 0.1 = 0.004068
Pr(a,a,b,c) via 1,2,3,3 = 0.8 x 0.3 x 0.2 x 0.5 x 0.3 x 1 x 0.1 = 0.00072
Pr(a,a,b,c) via 1,3,3,3 = 0.8 x 0.2 x 0.7 x 1.0 x 0.3 x 1.0 x 0.1 = 0.00336

Figure 3.1: A diagram illustrating an HMM and the different ways a,a,b,c can be generated by the HMM.

- A set of states $S = \{1, ..., n\}$.
- a set of output symbols Y.
- Two special subsets of S, the starting states and the ending states. Typically the HMM starts in state 1 and end in state n (although multiple start and end points are also possible).
- A set of allowed transitions T between states. T is a subset of $S \times S$, in other words, a transition goes from one state to another. Self-transitions (eg. from state 1 to state 1) are allowed.

- For each transition, from state i to state j, a probability that the transition is taken. This probability is usually represented as a_{ij}. For disallowed transitions $a_{ij} = 0$. These are known as **transition probabilities**.

- For each state j, and for each possible output, a probability that a particular output symbol o is observed in that state. This is represented by the function $b_j(o)$, which gives the probability that o is emitted in state j. These are called the **emission probabilities**.

Figure 3.1 shows an example of an HMM. Assume that the starting state is 1 and the ending state is 3. For this simple example, the output symbols (Y) are $\{a, b, c\}$. In Figure 3.1 the transition probabilities (the a_{ij}) are shown above each transition. Under each state are the emission probabilities.

The HMM can be used to calculate the probability that a particular output sequence was generated by the HMM. Consider the sequence *aabc*. Some different state sequences that generate the sequence *aabc* are also shown in Figure 3.1. For the moment, assume that we know the state sequence as well as the the observed sequence. Under these circumstances, the total probability of the observed sequence can easily be determined – it is the product of the probability of emission in each state multiplied by the probability of transition to the next state, then multiplied by the emission probability in the next state. For example, consider the sequence *aabc* and the state sequence 1, 1, 2, 3. Then we start in state 1, emit an a (probability 0.8), then a transition to state 1 (probability 0.5), then emit another a in state 1 (probability 0.8), then transition to state 2

(probability 0.3), then emit a b in state 2 (probability 0.6), then transition to state 3 (probability 0.5), then emit an c in state 3 (probability 0.1). We multiply all of these together to get the final probability for that sequence of states. The total probability that the HMM will generate the sequence *aabc* is the sum of the probabilities of all the paths that produce the sequence *aabc*.

In general, given the transition and the emission probabilities of an HMM, we can work out the probability that a sequence of observations $O = [o_1, .., o_{t_{max}}]$ (where t_{max} is the lengths of the sequence; or in our parlance, t_{max} is the number of frames) was generated by a given model λ, often expressed as $Pr(O|\lambda)$:

$$Pr(\mathbf{O}|\lambda) = \sum_{s \in valid(S)} \prod_{t=1}^{T} a_{s_{t-1}s_t} b_{s_t}(o_t)$$

where $valid(S)$ are all the valid state sequences starting in a starting state and ending in an ending state. Each state sequence therefore has the form $[s_1, ..., s_{t_{max}}]$, where s_i is the state at time i.

There are algorithms for calculating the sum of the probabilities over all possible paths. However, the algorithms are slow, so typically, only the probability of most probable path is calculated as the "merit" figure. This has been shown not to impact too adversely on accuracy, while decreasing the computational complexity substantially. The algorithm for doing so is called the **Viterbi** algorithm.

HMMs can be employed for classification in the following way: given several

models[1], it is possible to determine the model which will produce a given sequence of observations with the highest probability. Thus, if for each class there is a model with the states, transitions and probabilities set appropriately, the Viterbi algorithm can be used to calculate the model that most probably "generated" the sequence of observations. It is easy to see how this can be extended to a weak temporal classification system – a single model is constructed for each class, and given an unlabelled instance, the probability that that sequence of output symbols was generated by each HMM is calculated. The model with the highest probability is the class prediction.

There are three remaining issues to resolve. Firstly, how is the correct model chosen, i.e. what are the appropriate states and transitions? There is no definitive answer to this problem, and in general, experts use domain knowledge, experience and trial and error.

Secondly, once we have selected a model, how do we set the transition (a_{ij}) and emission probabilities ($b_j(o_t)$) so as to maximise the observed sequences that are associated with a particular class? The **Baum-Welch reestimation algorithm** provides a mechanism for doing so efficiently. It takes the sequence of observations and allocates observations to particular states based on the current values of a_{ij} and $b_j(o_t)$ using the Viterbi algorithm. It then updates a_{ij} and $b_j(o_t)$ to reflect this allocation. The process is run again until the probability converges. From the description it should be clear that it is an E-M (expectation-

[1]To avoid confusion, we use the term "model" here to represent a single hidden Markov model – that is, a single state transition diagram plus the associated probabilities – and will use the term "HMM" to represent the concept as a whole.

maximisation) style algorithm.

Thirdly, so far we have only considered simple observed symbols from a fixed alphabet. In real life, the observed symbols are actually far more complex than discrete symbols; using our notation, each observed symbol corresponds to an entire frame; usually consisting of a vector of real and discrete values. Can hidden Markov models be extended to cope with these as observations instead of single symbols?

One approach that is sometimes used is vector quantisation, which is a general approach for discretisation of multivariate data. Using this approach, a certain number of vectors is chosen, typically a power of 2; e.g. 64. These 64 vectors form the *codebook*. Each frame is represented as the element of the codebook that is most similar to it (according to some metric). Each entry in the codebook becomes an output symbol. There are well-developed techniques for generating appropriate vector codebooks from data.

The most common approach is to realise that the important aspect of the observed symbol is not the symbol itself, but the probability associated with that symbol. All that the algorithm requires to function is an estimate of the emission probability in a given state. Hence, if $b_j(o_t)$ is represented as a function over frames that returns the probability of that frame, rather than over individual symbols, the probability can be estimated as before, with no other changes to the algorithm.

This is accomplished by modelling the distribution of each state as a Gaussian

mixture (the same as a Gaussian distribution, but for vectors, rather than a scalars). Thus, for each element of the feature vector (or frame) the mean and standard deviation is calculated *for that state*. Hence, the total probability of a given frame can be calculated using the Gaussian mixture[2]. Such an HMM is termed a continuous-density hidden Markov model (CD-HMM) and it is the most commonly used HMM model.

These solutions have all been implemented in practical systems. HTK (hidden Markov model toolkit) is a freely available but very complete implementation of an HMM system that includes all of the above [YKO+].

Advantages of HMMs

HMMs are used because they have proved effective in a number of domains. The most significant of these is speech recognition, where it forms the basis of most commercial systems. They have also proved effective for a number of other tasks, such as handwriting recognition [PC97] and sign language recognition [SP95].

One of the most important advantages of HMMs is that they can easily be extended to deal with strong TC tasks. In the training stages, HMMs are dynamically assembled according to the class sequence. For example, if the class sequence was `my hat`, then two models for each word would be linked, with the

[2]Note that the Gaussian mixture is typically implemented under the assumption that the channels are independent, and hence if there are c channels, then there are $2c$ parameters – a mean and a variance for each channel. Strictly speaking, however, $c^2 + c$ parameters are required: c^2 for the covariance matrix (needed if the channels are dependent) and c for the means.

last state of the first linking to the first state of the second. The re-estimation algorithm is then applied as usual. Once training on that instance is complete, the models are unlinked again. When recognition is attempted, large HMMs are assembled from the smaller individual models. This is done by converting from a grammar into a graph representation, then replacing each node in the graph with the appropriate model. This process is called "embedded re-estimation". To find out what the class sequence was, the most probable path is calculated. The path traversed corresponds to a sequence of classes, which is our final classification.

Because each HMM uses only positive data, they scale well; since new words can be added without affecting learnt HMMs. It is also possible to set up HMMs in such a way that they can learn incrementally. As mentioned above, grammar and other constructs can be built into the system by using embedded re-estimation. This gives the opportunity for the inclusion of high-level domain knowledge, which is important for tasks like speech recognition where a great deal of domain knowledge is available.

The basic theory of HMMs is also very elegant and easy to understand. This makes it easier to analyse and develop implementations for.

Disadvantages of HMMs

However, there are several problems with HMMs:

- They make very large assumptions about the data:

  - They make the Markovian assumption: that the emission and the transition probabilities depend only on the current state. This has subtle effects; for example, the probability of staying in a given state falls off exponentially (for example the transition probability of staying in state 1 for n timesteps is a_{11}^n), which does not map well to many real-world domains; where a linear decrease in probability in duration is appropriate.
  - The Gaussian mixture assumption for continuous-density hidden Markov models a huge one. We cannot always assume that the values are distributed in a normal manner. Because of the way Gaussian mixture models work, they must either assume that the channels are independent of one another, or use full covariance matrices, which introduces many more parameters.

- The number of parameters that need to be set in an HMM is huge. For example, the very simple three-state HMM shown in Figure 3.1 there are a total of 15 parameters that need to be evaluated. For a simple four-state HMM, with five continuous channels, there would be a total of 50 parameters that would need to be evaluated[3]. Note also that 40 of the parameters are means and standard deviations, which are themselves aggregate values. Also, because of the way the Viterbi algorithm allocates frames to states, the frames associated with a state can often change, causing further susceptibility to the parameters. Those involved in HMMs often use

[3] 10 transition variables, and assuming independence of channels, a mean and standard variation for each of the 5 variables in the 4 different states; if we were using covariance matrices, there would be 130 parameters

the technique of "parameter-tying" to reduce the number of variables that need to be learnt by forcing the emission probabilities in one state to be the same as those in another. For example, if one had two words: `cat` and `mad`, then the parameters of the states associated with the "a" sound could be tied together.

- As a result of the above, the amount of data that is required to train an HMM is very large. This can be seen by considering typical speech recognition corpora that are used for training. The TIMIT database [DAR], for instance, has a total of 630 readers reading a text; the ISOLET database [CMF90] for isolated letter recognition has 300 examples per letter. Many other domains do not have such large datasets readily available.

- HMMs only use positive data to train. In other words, HMM training involves maximising the observed probabilities for examples belonging to a class. But it does not minimise the probability of observation of instances from other classes.

- While in some domains, the number of states and transitions can be found using an educated guess or trial and error, in general, there is no way to determine this. Furthermore, the states and transitions depend on the class being learnt. For example, is there any reason why the words `cat` and `watermelon` would have similar states and transitions[4]?

[4]This is not what happens in real speech recognition systems. Usually, speech recognition systems each HMM is trained on a phoneme; and these phonemes are assembled to form the starting HMMs for words. However, we do not always have this sort of information available to us.

- While the basic theory is elegant, by the time you get to an implementation, several additions have been made to the simple algorithm. We have already discussed parameter-tying and handling of continuous values, but there are also adjustments to the state duration model and adding null emissions.

- The concept learnt by a hidden Markov model is the emission and transition probabilities. If one is trying to understand the concept learnt by the hidden Markov model, then this concept representation is difficult to understand. In speech recognition, this issue is of little significance, but in other domains, it may be even more important than accuracy.

3.2.2 Recurrent Neural Networks

Another tool that has been used for temporal classification problems is recurrent neural networks. A neural network is made of individual units termed neurons. Each neuron has a weight associated with each input. A function of the weights and inputs (typically, a squashing function applied to the sum of the weight-input products) is then generated as an output.

These individual units are connected together as shown in Figure 3.2, with an input layer, an output layer and usually one or more hidden layers. Typically, the input layer consists of one unit per attribute, and the output layer of one unit per class. The number of units and topology within the hidden layer is defined by the user. Through algorithms such as backpropagation, the weights of the neural net can be adjusted so as to produce an output on the appropriate

unit when a particular pattern at the input is observed. The backpropagation algorithm works by running the training instance through the neural network, and calculating the difference between the desired and actual outputs. These differences are then "propagated back" from the output layer to the hidden and input layers in the form of modifications to the weights of each of the component neurons. This modification is done in a manner proportional to the contribution to the difference in output, so that the weights most responsible for the difference are modified the most. The interested reader may wish to find out more in [RM86].

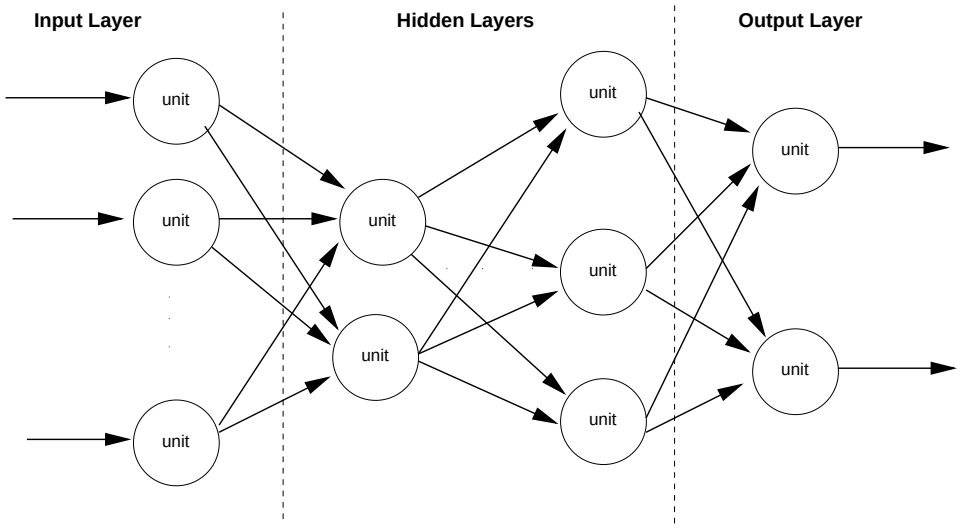


Figure 3.2: A typical feedforward neural network.

A recurrent neural network (RNN) is a modification to this architecture to allow for temporal classification, as shown in Figure 3.3. In this case, a "context" layer is added to the structure, which retains information between observations. At each timestep, new inputs are fed into the RNN. The previous contents of the hidden layer are passed into the context layer. These then feed back into the

hidden layer in the next time step.

In an algorithm similar to the backpropagation algorithm, called back propagation through time (BPTT), the weights of the hidden layers and context layers are set.

To do classification, postprocessing of the outputs from the RNN is performed; so, for example, when a threshold on the output from one of the nodes is observed, we register that a particular class has been observed.

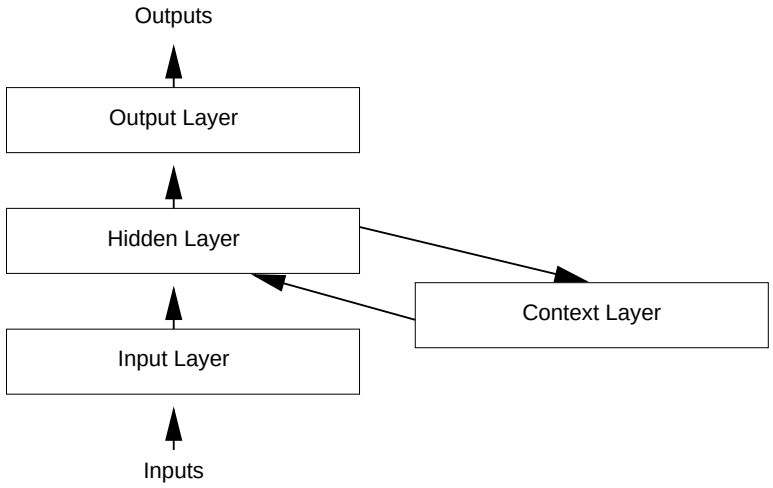


Figure 3.3: Recurrent neural network architecture.

Recurrent neural networks suffer from many of the same problems as HMMs, namely:

- There are many parameters. These include parameters such as the number of units in the hidden layer, the appropriate structure, the correct parameter adjustment algorithm (there are many alternatives to backpropagation), the learning rate, the encoding and more. Well-formed techniques

for deciding appropriate values for these parameters are in the development stage.

- Their efficacy for learning long connected sequences is doubtful. Attempts to learn long sequences of events, for example, [Ben96], lasting for hundreds of samples, have not shown good results. They do seem capable of learning short sequences (tens of frames), such as learning individual phonemes, rather than whole words.

- There is work on extracting meaning from neural networks [Thr95, TAGD98], and there is also some work on extracting meaning from recurrent neural networks for learning very simple noise-free discrete finite state automata [OG95, VO99] with mixed results. However, whether these techniques can be applied to recurrent neural networks used to classify long-term, noisy, time-series is an open question.

3.2.3 Dynamic Time Warping

An older technique that has fallen out of favour since the advent of HMMs is dynamic time warping [MR81] (DTW). It can be understood as the temporal domain equivalent of instance-based learning.

In DTW, one begins with a set of template streams, each labelled with a class. Given an unlabelled input stream, the minimum distance between the input stream and each template is computed, and the class is attributed to the

nearest template.

The cleverness of dynamic time warping lies in the computation of the distance between input streams and templates. Rather than comparing the value of the input stream at time t to the template stream at time t, an algorithm is used that searches the space of mappings from the time sequence of the input stream to that of the template stream, so that the total distance is minimised. This is not always a linear mapping; for example, we may find that time t_1 in the input stream corresponds to the time $t_1 + 5$ in the template stream, whereas t_2 in the input stream corresponds to $t_2 - 3$ in the template stream. The search space is constrained to reasonable bounds, such as the mapping function from input time to template time must be monotonically nondecreasing (in other words, the sequence of events between input and template is preserved).

This is shown in Figure 3.4, where the horizontal axis represents the time of the input stream, and the vertical axis represents the time sequence of the template stream. The path shown results in the minimum distance between the input and template streams. The shaded in area represents the search space for the input time to template time mapping function. Any monotonically nondecreasing path within the space is an alternative to be considered. Using dynamic programming techniques, the search for the minimum distance path can be done in polynomial time: $O(N^2V)$ where N is the length of the sequence, and V is the number of templates to be considered.

There are several weaknesses of DTW. Firstly, it is still $O(N^2V)$, which is

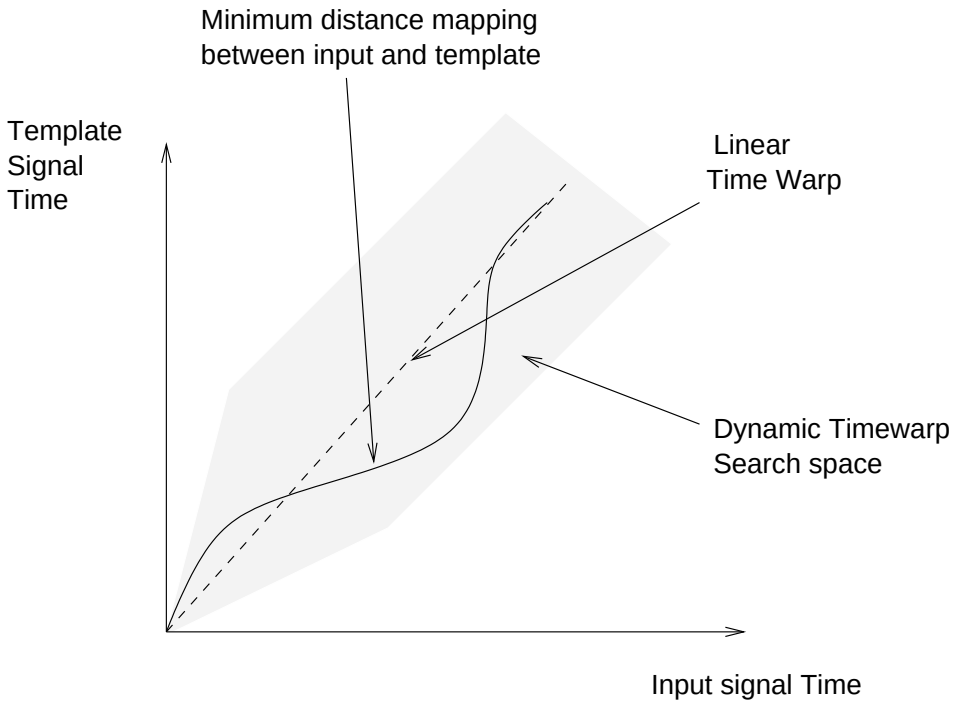


Figure 3.4: Dynamic time warping.

not particularly fast. Secondly, a distance metric between frames must be defined, which may be difficult with different channels with distinct characteristics. Thirdly, it does not create any meaningful descriptions of the data. Fourthly, creation of the template streams from data is non-trivial – and typically is accomplished by pairwise warping of training instances. Alternatively, all observed instances are stored as templates, but this is incredibly slow. Fifthly, although there have been several attempts to extend dynamic time warping to strong TC tasks, these have largely proved unsuccessful, and indeed prompted the move away from dynamic time warping towards hidden Markov models.

DTW is relatively simple and has been used commercially for several industrial weak TC tasks, like isolated spoken digit recognition.

Recently, there has been a resurgence in interest in dynamic time warping. Keogh and Pazzani [KP99, KP01] improve the performance of DTW by representing a time series hierarchically. Oates et al [OSC00] also use dynamic time warping to cluster experiences of mobile robots from real world data.

3.3 Recent interest from the AI community

Many other ML researchers have looked at issues closely related to temporal classification. These have included work on sequence prediction (e.g. Dietterich and Michalski's work with Eleusis [DM86]), temporal logics and their applications to recognising events, for example Kumar's work on temporal event conceptualisation [KM87] and the recent work in context detection and extraction for machine learning applications [Wid96, HHS98]. While some of these areas bear interesting relations to temporal classification, they differ in several regards. Sequence prediction is not about learning from labelled examples. The event conceptualisation work focuses on recognition of temporal events, but not learning the events themselves. The work on context detection is about selecting which static classifier to use on a dynamic basis; whereas temporal classification is about classifying the dynamics themselves.

There have been several other major works on issues related to temporal properties. Hau and Coiera's work on learning qualitative models of dynamic systems [HC93] is an illustrative example. Genmodel (the system developed by Coiera) might discover that the amount of blood the heart is able to pump

out depends on the the volume of blood already in the heart, and when one increases so does the other. Such work has also been explored by Bratko in various projects, most notably KARDIO [IB89] and also by his students who have extended the approach to applications in behavioural cloning of humans in dynamic systems [SB99].

Syntactic representations of signals have also been explored. Fu [Fu82] looks at hand-constructing grammars for syntactic parsing (with error correction) of signals. In the syntactic pattern recognition approach, a time series is converted to a sequence of symbols or terminals. A grammar is then defined that allows or disallows particular sequences of terminals corresponding to each class.

Lee and Kim [LK95] take this syntactic approach further by adding an inductive step and applying it to financial markets. Based on knowledge of the financial markets, they develop a grammar for events. In our parlance, they are developing a fixed set of metafeatures for the problem. Two operators are allowed between events: CONC (concurrent events) and SEQ (sequential events). In some ways their work is similar to our own. Their use of terminals with parameters correspond closely to our concept of metafeatures (see Chapter 4). However, their technique does not appear to be generalisable. They are also not interested so much in classification as prediction of financial time series.

Some research has also been conducted into exactly how to detect sub-events of time series – in other words how to build metafeature extractors. Horn [Hor93] developed RDR-C4: a system for both manually building ripple-down rules and

inducing them from data. Horn also allowed rules to be applied to time series including options such as no change, increasing, decreasing, step up, step down and peaks. Although the rule editor was developed it is unclear whether the detection algorithm was implemented or not, and if so, how it was done. He cites work by Love and Simaan [LS98] and the closely related work of Anderson et al [ACH+89] which develops techniques for extracting the following events from univariate time series data: peaks, steps and ramps. Using these three metafeatures, the authors manually develop a system for extracting these features using filters, and subsequently manually build a ruleset to classify different events that can occur based on such observations. The authors used their system for recognising "out-of-condition" detection in industrial systems rather than classification.

Shi and Shimizu [SS92] built a neuro-fuzzy controller for yeast production. They discretised both the time and concentration, and then had a temporal sliding window go through the data. Each time-concentration pair was associated with a single neuron, and this was fed into a standard backpropagation network.

Increasingly, this area has become a popular research topic. For example, a workshop held at AAAI '98 [Dan98], while focusing on temporal prediction, also contained several papers on learning from time series. For example, Keogh and Pazzani [KP98] looks at automated ways of clustering time series from ECG signals and Shuttle information, by using a piecewise model combined with segmentation and agglomerative clustering. In Oates et al. [OJC98], a system is applied to extracting patterns from network failures, by looking at all possible

sequences of events and keeping tabs on the frequency of these events.

Shahar [SM95] suggests an expert system architecture for knowledge-based temporal abstraction and also suggests that this system could be used for learning, though he does not actually do so. He then applies the techniques to clinical domains. Paliouras [Pal97] discusses refinement of temporal parameters in an existing temporal expert system; but does not have a capacity for modifying the model itself. Manganaris [Man97] developed a system for supervised classification of univariate signals using piecewise polynomial modelling combined with a scale-space analysis technique (i.e. a technique that allows the system to cope with the problem that patterns occur at different temporal scales) and applies them to space shuttle data as well as an artificial dataset.

Mannila et al [MTV95] have also been looking at temporal classification problems, in particular applying it to network traffic analysis. In their model, streams are a sequence of time-labelled events rather than regularly sampled channels. Learning is accomplished by trying to find sequences of events and the relevant time constraints that fit the data.

Das et al [DLM+98] also worked on ways of extracting rules from a single channel of data by trying to extract rules of the form "A is followed by B", where A and B are events in terms of changes in value.

Rosenstein and Cohen [RC98] used delay portraits (a representation where the state at time $t - n$ is compared to its state at time t). These delay portraits are then clustered to create new representations, but they tend to be sensitive

to variations in delay and speed.

Keogh and Pazzani, in addition to the previously mentioned work on dynamic time warping, have been working on time series classification techniques for use with large databases of time series [KCMP01], using a representation of time series as a tree structure, with the root being the mean of the time series, the two children being the mean of the first half and second half respectively and so on. This allows very fast computations to be done on time series.

Another interesting development is the application of dynamic Bayesian networks to temporal classification tasks. While they are not specifically designed for temporal classification (they are more commonly used for prediction, or for estimating current state given the previous state estimate), Zweig and Russell [ZR98] have applied them to the task of speech recognition. The main problem with using dynamic Bayesian network is that while algorithms for learning the parameters of a Bayes net are well-advanced, learning the structure of Bayes nets has proved more difficult[5]. Friedman et al. [FMR98] are developing techniques for learning the structure of dynamic Bayes networks; it remains to be seen whether these techniques can be applied in temporal classification domains.

[5]In many ways, dynamic Bayes nets suffer the same problems as HMMs. In fact, it can be proved that dynamic Bayes nets and hidden Markov models are isomorphic. Dynamic Bayes nets have the advantage that they do allow for far more complex state models and provide a much more intuitive mechanism than HMMs for inclusion of background knowledge.

Chapter 4

Metafeatures: A Novel Feature Construction Technique

This chapter focuses on metafeatures, which forms the core of our method for temporal classification. It begins with an example of the application of the techniques that will be implemented in *TClass*. *TClass* is discussed in greater depth in Chapter 5. This first taste of *TClass* is intended to give the "big picture" and to show how metafeatures are employed to accomplish temporal classification. The inspiration behind metafeatures is then outlined, followed by a formal definition of metafeatures. Practical details of metafeature implementation are discussed, and finally two cute refinements of metafeatures are given.

4.1 *TClass* Overview

A summary of how *TClass* works is as follows:

- Look for sub-events – in the form specified by the user – in the training streams.
- Analyse the extracted sub-events and select sub-events that are important, typical or distinctive.
- For each of the training instances, look for these sub-events. The presence or absence of these temporal patterns can be used as attributes for propositional learning.
- Apply a propositional learner.

To illustrate how these work in practice, we return to the Tech Support domain.

4.2 Tech Support revisited

This section continues on with the Tech Support domain described in Section 2.1.1. For convenience, Table 4.1 replicates the data of Table 2.1, but using our terminology for channels and streams. To revise, each stream represents the volume levels of phone conversations to the Tech Support line.

Stream	$v(0)...v(t_{max})$	Class
	0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0	
s_1	L L L H H H L L L L L L	Happy
s_2	L L L H L L H L L H H H H	Angry
s_3	L L H L L H L L L L L L H H H	Angry
s_4	L L L L H H H H L L L L L	Happy
s_5	L L L H H H L L L L	Happy
s_6	L L H H L L H L L H H H	Angry

Table 4.1: The training set for the Tech Support domain.

The channel v in the Tech Support dataset is discrete, and in fact, binary – i.e., the value at each time frame is either `H` (high volume) or `L` (low volume).

How could a classifier be built for the Tech Support domain? One expert advises that "runs" of high volume conversation – continuous periods where the conversation runs at a high volume level – are important for classification purposes. Runs of loud volume could be represented as a tuple (t, d) consisting of:

- The time at which the conversation becomes loud (t).
- How long it remains loud (d).

This is our first **metafeature**, called LoudRun.

Each instance can now be characterised as having a set of LoudRun events. These can be extracted simply by looking for sequences of high-volume conversation. For example, s_2, has one run of highs starting at time 3 lasting for 1 timestep, a high run starting at time 6 lasting for one timestep and a high run

starting at time 9 for 4 timesteps. Hence the set of LoudRuns produced from the training instance s_2 is $\{(3,1),(6,1),(9,4)\}$. These tuples are examples of **instantiated features**.

Stream	Instantiated features
s_1	$\{(3,3)\}$
s_2	$\{(3,1),(6,1),(9,4)\}$
s_3	$\{(2,1),(5,1),(12,3)\}$
s_4	$\{(4,4)\}$
s_5	$\{(3,3)\}$
s_6	$\{(2,2),(6,1),(9,3)\}$

Table 4.2: Instantiated LoudRun features for the Tech Support domain.

These instantiated features can be plotted in the two-dimensional space shown in Figure 4.1. This is the **parameter space**. This two-dimensional space consists of one axis for the start time and another for the duration. Each LoudRun lies within the parameter space. Figure 4.2 is the same as Figure 4.1, but each instantiated feature is marked with its original class.

Once the points are in parameter space, "typical examples" of LoudRuns can be selected. In this case, the points labelled A, B and C are selected as typical examples, as shown in Figure 4.3. These typical examples are **synthetic events**. They may or may not be the same as an observed event – so for example, point A actually corresponds to a real event (the instantiated event (3,3) actually was observed in the data), whereas B and C do not.

These synthetic events can be used to segment the parameter space into different regions in the following way: for each point in the parameter space, the nearest synthetic event is found. The set of points associated with each synthetic

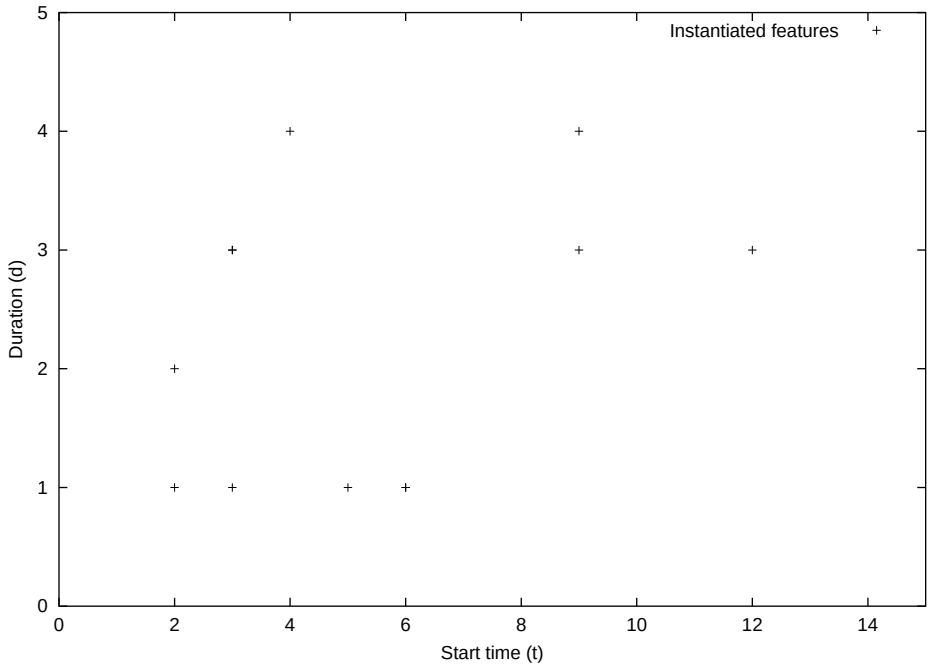


Figure 4.1: Parameter space for the LoudRun metafeature applied to the Tech Support domain.

event form a region. Without too much trouble, the boundaries of each region can be calculated. These are shown as dotted lines in Figure 4.3.

The next step is to make use of these regions. Questions like: "does a given stream have an instantiated feature that belongs in the area around A?" can be asked. If the question is repeated for B and C, the result is Table 4.3. To construct this table, Table 4.2 is examined, and for each region if there is an instantiated feature that lies within that region, a **synthetic feature** corresponding to the point is marked as a "yes".

This is now in a learner-friendly format. In fact, if it is fed it to C4.5, the simple tree in Figure 4.4 results.

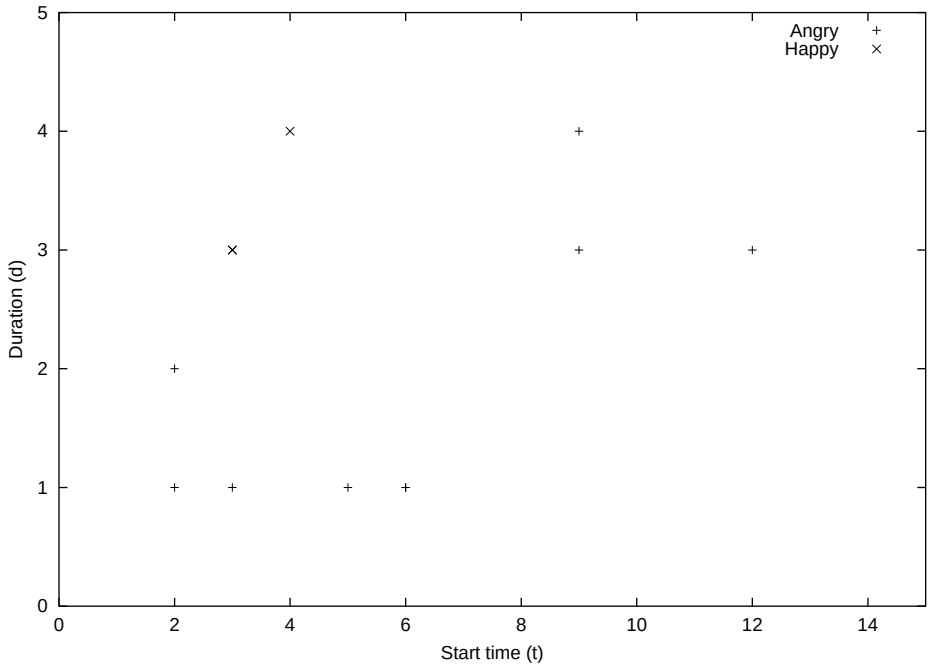


Figure 4.2: Parameter space for the LoudRun metafeature in the Tech Support domain, but this time showing class information. Note that the point (3,3) is a "double-up".

Stream	Class	Synthetic Events		
		Region A	Region B	Region C
1	Happy	Yes	Yes	No
2	Angry	No	Yes	Yes
3	Angry	No	Yes	Yes
4	Happy	Yes	Yes	No
5	Happy	Yes	Yes	No
6	Angry	Yes	Yes	Yes

Table 4.3: Attribution of synthetic features for the Tech Support domain.

This tree says that if the training instance has an instantiated feature that lies within in region C (i.e. a run of high values that starts around time t=10 and goes for approximately 3.33 timesteps), then its class is Angry. Conversely, if it doesn't have such a synthetic feature, then its classification is Happy. In

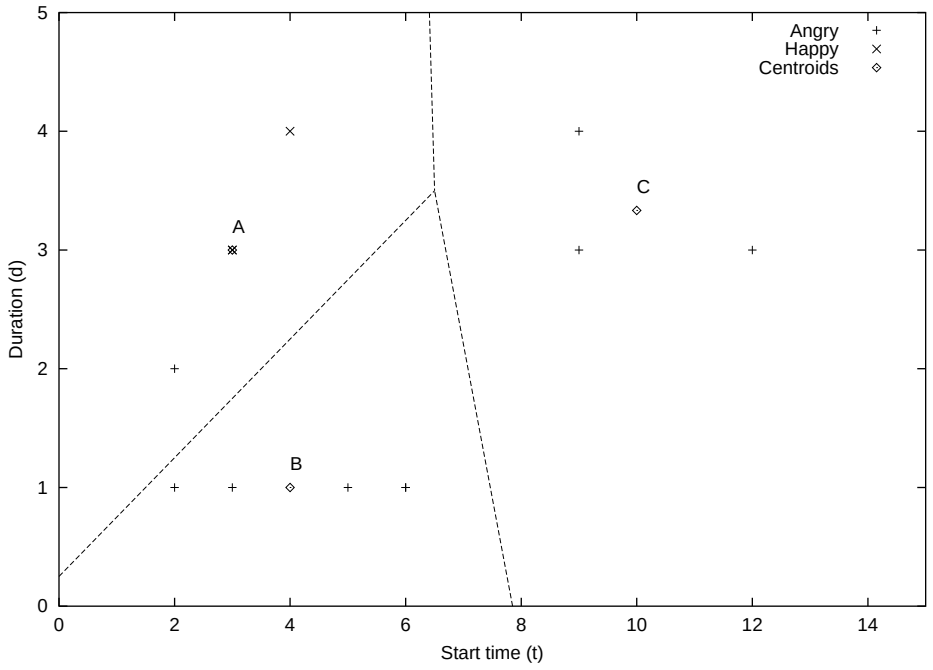


Figure 4.3: Three synthetic events and the regions around them for LoudRuns in the Tech Support domain.

```
rgnC = yes: Angry (3.0)
rgnC = no: Happy (3.0)
```

Figure 4.4: Rule for telling happy and angry customers apart.

other words, as long as there is not a long high-volume run towards the end of the conversation, the customer is likely to be happy.

This is the core of *TClass* and also shows the application of metafeatures to temporal classification tasks. Now, let's take a more in-depth look at metafeatures.

4.3 Inspiration for metafeatures

In the previous section, an overview of the application of metafeatures to a real problem was demonstrated. The motivation and inspiration behind metafeatures is now explained in greater depth.

At the core of many machine learning problems – and especially that of temporal classification – is the issue of appropriate representation: how to represent the learning problem in a manner that makes it amenable to established and well-understood machine learning techniques, and how to convert from the representation we are provided with as input into the required representation. The nature and difficulty of this change in representation depends on our target learning technique. Three possible approaches to temporal classification are:

- Develop learning algorithms to deal specifically with temporal classification. This is an approach taken, for example, with dynamic time warping and hidden Markov models.
- Represent the problem in such a way as to allow the application of relational learning techniques (e.g. ILP).
- Represent the problem in such a way as to allow the application of propositional concept learners.

Each of these approaches is valid and presents different representational challenges. Even the first approach requires a representation that makes sequential

learning possible: raw sound signals, for instance, are not usually fed directly into a hidden Markov model; rather the original audio data are converted into a sequence of short term Fourier transform coefficients and energy spectrum coefficients. It is also true that the second, theoretically, allows for a more complex representation, as relational learning systems have a richer observation language than propositional learners. In particular, unlike propositional learners, relational learning does not limit us to a fixed set of features. In practice, there are two major weaknesses of relational learners that arise in temporal domains: large data sets and noisy data. This necessitates certain cleverness in the selection of appropriate representation, and has been explored in [RAB00] to some extent[1]. Rodriguez' does this by allowing temporal statements that are more robust to noise, for instance "during this time period, the value exceeds 0.5 80 per cent of the time".

The approach taken in this thesis is the third: finding a general way to convert temporal problems into a propositional form; then using existing propositional machine learning techniques.

It also should be stated that the approaches aren't quite as discrete as the above would indicate. For example, there are relational learners such as LINUS [LD94] that accomplish relational learning by converting relational data into a propositional form. Similarly, with hidden Markov models, it is not unusual to find that emission probabilities are modelled not by the traditional Gaussian

[1]This paper makes significant use of the work presented here, although the techniques are different in many ways.

distribution, but by a neural network. Also, there is a "middle ground" between relational and propositional learning such as graph-based induction, as is explored in Section 7.2.4.

Metafeatures are the basis of the change in representation to a format for propositional learners. They allow for the inclusion of background knowledge and domain knowledge for temporal classification. They also allow concepts learnt by the propositional learner to be re-expressed in the original temporal domain.

The key steps in using metafeatures is to find some kind of sub-event, some temporal pattern that can be used in the domain for which the following can be defined:

- A set of parameters: For example, with the LoudRun metafeature, this was the start time (t) and the duration (d).
- A means of extracting such temporal patterns from training and test instances and converting them into the parameters above. In the Tech Support domain, with LoudRun, this is trivial – look for the first "high" value and count how many high values come after it before a low value. In general, however, this might be very difficult.

Once the training data has had the instantiated features extracted from it, these can be plotted in a space, termed the parameter space. Within the parameter space, we can try to find typical examples that will allow the construction

of features that make it possible to represent the original temporal data in a format that facilitates propositional learning.

The application of metafeatures is not limited to temporal domains. Any problem where we can characterise instances in the domain as having substructures that can be represented parametrically can use metafeatures. Such domains include image recognition (where lines and shapes can be represented with parameters), optical character recognition and more. The exploration of these is beyond the scope of this thesis, but it is one extremely interesting avenue of future work.

4.4 Definition

A metafeature is an abstraction of some substructure that is observed within the data. In the temporal domain, the substructures we are interested in are subevents, like the LoudRuns of the Tech Support domain. Formally, a metafeature has two parts:

- A tuple of parameters $p = (p_1, ..., p_k)$, which represents a particular **instantiated feature**. Let P_1 represent the set of possible values of the parameter p_1. Let P be the space of possible parameter values, i.e. $P = P_1 \times P_2 \times ... \times P_k$. P is termed the **parameter space**.
- An **extraction function** f which takes an instance $s \in SS$ (reminder:

SS is the set of all possible streams) for the domain and returns a set of instantiated features from P, i.e. $f : SS \rightarrow \mathbb{P}(P)$.

For every instance in the training set $class_T$ that we apply a metafeature to, a set of points in the parameter space are returned. Each point returned represents an "occurrence" or "instance" of the metafeatures, which we will term an **instantiated feature**. In other words, an instantiated feature is a tuple $(v_1 \in P_1, v_2 \in P_2, ...v_k \in P_k)$, where $v_1, ..., v_k$ are values for each of the parameters.

The parameter space represents all the possible instantiated features we could possibly generate or observe in the data. Hence all instantiated features lie in the parameter space.

A simple example is the LoudRun metafeature. As previously outlined, the LoudRun metafeature has two parameters for each instance: the starting time t and the duration d. Hence, our parameter space is two dimensional. In fact, it is easy to show that our parameter space is $\mathbb{N}^2$, although sometimes it will be convenient to treat it as $\mathbb{R}^2$.

In this case, it is easy to define the LoudRun extraction function as:

$$\begin{aligned} f(v) = \{(t, d) \quad | \quad & v(t-1) = L \\ \wedge \quad & v(t) = v(t+1) = ... = v(t+d-1) = H \\ \wedge \quad & v(t+d) = L\} \end{aligned}$$

In other words, the extraction function f, when applied to an training stream finds all the subsections of the channel when there is an extended period of high-volume conversation, flanked by low-volume conversation on either side[2]. This matches our intuition of a loud run.

4.5 Practical metafeatures

The LoudRun metafeature is a nice toy example, but there are not many domains for which LoudRun is of practical use. When we extend the concept of metafeatures to real-world problems, we encounter some difficulties. In this section, we discuss some of these issues; others will manifest themselves in the remainder of the thesis. In order to understand these issues, it is necessary to first consider such a real-world domain, and some of the data from it.

4.5.1 A more practical example

Consider the sign language domain discussed earlier. Figure 4.5 shows the gloss for `building`. It is clear that the y value (the vertical up and down movement) for this sign is important for classification.

A plot of the y value for an instance of the sign `building`, recorded from a native signer, is shown in Figure 4.6.

[2]Note the extraction function given is a little simplified and does not take into account the possibility of the sequence beginning or ending in high volume. However, in practice, we would

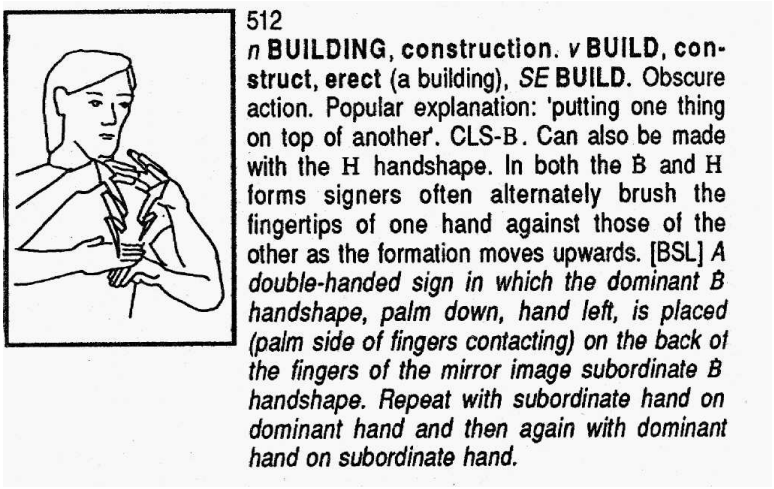


Figure 4.5: The gloss for the sign `building`, from [Joh89].

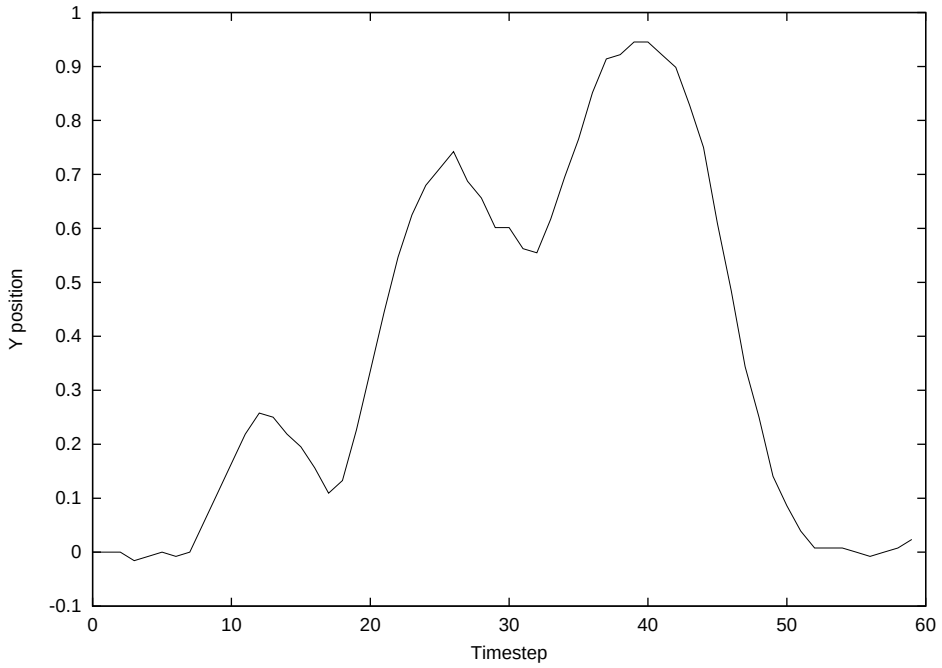


Figure 4.6: An example of the variation in the y value of the sign `building`.

One type of event of interest is intervals when the signal is increasing. Hence we might consider developing an Increasing metafeature that would allow us to

implement it to handle such cases.

extract all of the cases where the signal is increasing. We would hope that it would pick up the three periods during which the signal is clearly increasing; from around time 7 to time 11, from time 18 to time 26 and from time 32 to time 40. However, there are some practical issues that arise when doing so.

4.5.2 Representation

The first issue is that there are many possible representations for an Increasing metafeature. Most of them would have at least four parameters. For example one possible representation for an Increasing event would be: (start time, end time, start value, end value). However, another representation is possible using the following tuple: (midtime, duration, average value, gradient). Both of these representations give us information about the underlying features, and it is easy to convert from one to the other. Both of these representations are shown in Figure 4.7.

Furthermore, these are but two of a number of possibilities. Hybrids of the above exist, for example an increasing event could also be represented as: (start time, end time, gradient, average), or (middle time, duration, start value, end value). What then, is the appropriate representation? Common engineering practice would suggest that the basis for selecting a particular representation should at least include the following criteria:

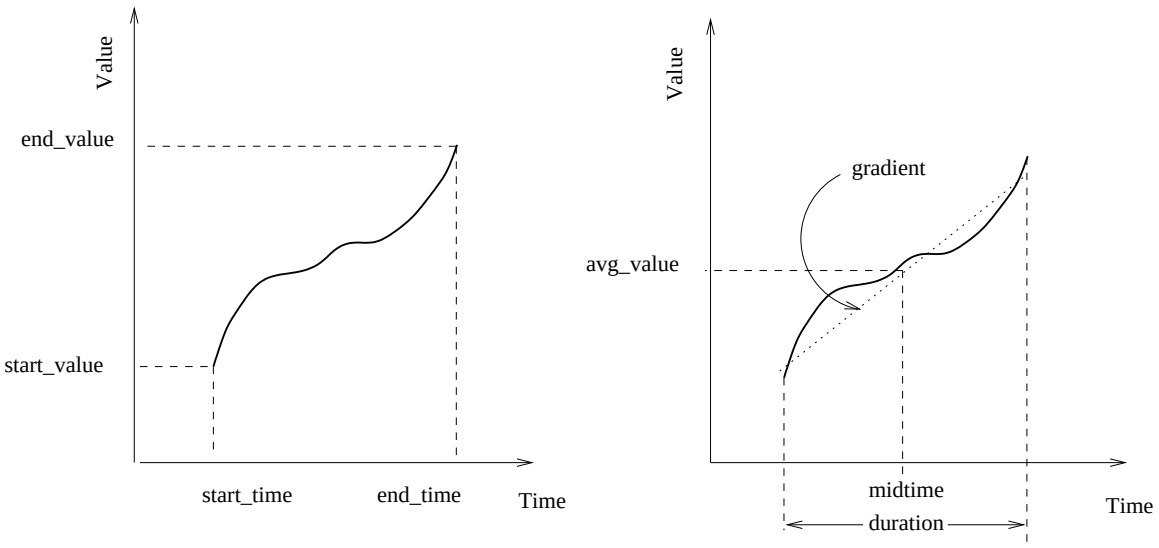


Figure 4.7: Two different possible representations of an Increasing event.

Robust to noise

We should try to choose parameters that are robust to noise. In the above example, the start value and the end value are both sensitive to noise, as compared to, say average and gradient, both of which are aggregate measures of the data points belonging to the period of increase. Hence it would be better to represent an increasing event using the latter two parameters rather than the former. In general, an aggregate of the signal will be more robust than a single measurement of the signal, so average value and gradient are robust than start value and end value.

Temporal variations are mapped to proximal parameter values

One important characteristic of any solution to temporal classification is that it should be robust to temporal variations of the kind that occur in temporal domains, which were previously discussed in Section 2.5. Careful consideration reveals that metafeatures implicitly capture the temporal variation as parameter values, and in so doing, allow temporal variation to be handled. For instance, if an Increasing event occurred slightly later than expected, then the difference is mapped into a difference of the midtime parameter; and the greater the difference in the midtime, the greater the difference in that parameter's value. Hence, the temporal variation between the two cases is mapped into proximal parameter values, where the usual distance metrics still apply in a sensible manner. In terms of the parameter space, this means that two instantiated features that occur at approximately the same time or last for approximately the same duration should be close. Hence the representation as midtime and duration would be more appropriate.

Orthogonality

The parameters in a given metafeature should be orthogonal to one another. For instance, if we were to represent an increasing event by start time, end time and duration, then this would be redundant. Any two of these would be sufficient to uniquely represent such an event. Fewer parameters reduce processing time of the instantiated features; furthermore, some learning and clustering algorithms

applied assume that the parameters of the metafeature are independent. This may be an appropriate approximation at times, but if there is a known and clearly defined dependence (eg, in this case $duration = endtime - starttime$) it might affect the performance of the algorithm.

Describes the important characteristics of the feature

The parameters should capture all the important characteristics of the feature we are trying to detect and not capture any of the ones not important to it. For example, the gradient of the increasing interval is an important characteristic for sign language: the speed of movement upwards indicates rapidity of movement – e.g. the distinction between shutting a window (a slow movement of one forearm downwards against the other forearm) and slamming a window (a much more rapid movement). On the other hand, the variance of the signal may not be important to us, as it may be, for example, the result of noise in our measurement system, rather than some important underlying property of the data.

Matches the "human" description of the event

Humans would probably, if observing a signer move his hand up and down, be interested in the general location of the movement, the speed of the movement, the duration of the movement and how it temporally relates to other events. In this particular case, both of the original representations are viable. Recall that the concepts learnt will also be explained in terms of these parameters, hence if

they are not in a form that a human comprehends, then the definitions generated by this method won't be correct either.

4.5.3 Extraction from a noisy signal

The second practical difficulty is extracting instantiated features from noisy data. For example, if one is detecting a period of increase, what if one suddenly gets a "downwards spike" caused by non-Gaussian noise (e.g. in the case of the sign language recognition using instrumented gloves, by bogus ultrasound reflections that interfere with positional triangulation used to calculate the y values shown)? One could argue that this is a preprocessing issue and not really an issue for the learner[3]. Even so, preprocessing will never get rid of all of the noise, although it may minimise it. Our extraction functions must be designed to be robust to noise. It is more important to detect a generally increasing signal, even if it means that there are short periods within the signal where the property of monotonic increase is not strictly true. For example, Figure 4.8 shows another recording of the y channel of the sign `building`, but this one with much greater noise than in Figure 4.6.

This makes the implementation of such an extraction function difficult; and in general the pursuit of the ultimate extraction function could be as consuming as the whole process of learning to classify in the first place. Certainly, it would be

[3]The line between preprocessing and learning is a blurred one. One view of *TClass* is as little more than an automated preprocessor, which doesn't do any learning itself. However, preprocessing the data into a format for learning seems to be something that machines are bad at and people are good at, so perhaps it is not so little after all.

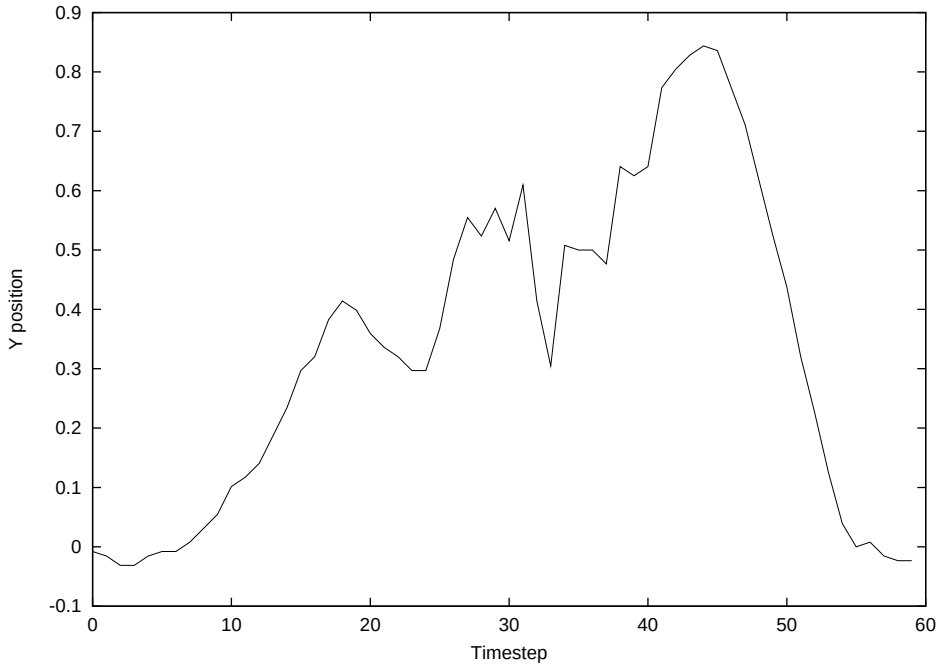


Figure 4.8: The y channel of another instance of the sign `building`, but this one with much greater noise than Figure 4.6.

possible to define a group of metafeatures IsInstanceOfClassA, IsInstanceOfClassB, etc that operated on all channels simultaneously[4] and whose parameters consist of a single boolean value that told us if the stream belonged to a particular class. If we could do so, it would be immensely useful, but if we knew how to develop the extraction functions IsInstanceOfClassX, then we would not need to learn in the first place – since all we need to know is encapsulated in our metafeatures.

Hence like most things in engineering, the development of the extraction

[4]There is nothing in the theory or the practice that prevents a metafeature from looking at multiple channels simultaneously. Recall that the extraction function takes an instance, and not a channel from an instance; hence it would be possible to look at multiple channels to extract events. This would be logical, for example, in the case of the three spatial features x,y,z, where some features e.g. circular motion in the xz plane, as occurs with the sign "all", when it is necessary to look at both planes simultaneously to determine whether in fact a circular motion was performed.

function is a tradeoff. If the extraction function is made too simple, then a useful representation will not reach the learning algorithm. If a great deal of time is spent developing the extraction function, then this undercuts the whole purpose of using a learner in the first place.

The surprising fact is, however, which we demonstrate in the remainder of the thesis, that even using a very primitive group of metafeatures, it is possible to obtain high levels of performance in temporal domains.

Consider implementing the Increasing metafeature and apply it to the y axis. Also assume that we use the representation (midtime, average, gradient, duration). Consider the period of increase from time 32 to time 45 in Figure 4.8. Then depending on how we implement the extraction function, it might be possible to ignore the small dips in the generally increasing pattern between that time; or it might be possible to break it up into three separate events: an increase from time 34 to 35, an increase from time 37 to 39 and an increase from time 40 to 43. One way to do this is to allow a certain amount of exceptions; another is to "smooth" the data to get rid of such bumps. In any case, Figures 4.9 and 4.10 show the instantiated features extracted by applying one implementation of the Increasing metafeature to Figures 4.6 and 4.8 respectively. Note that the events are in many ways similar, and that our filtering and noise handling techniques have worked to some extent.

```
midTime = 9.5 avg = 0.13671875 gradient = 0.0546873 durn = 4.0
midTime = 22.0 avg = 0.5100447 gradient = 0.08286842 durn = 7.0
midTime = 35.5 avg = 0.7942707 gradient = 0.06473206 durn = 6.0
```

Figure 4.9: Instantiated features extracted from Figure 4.6.

```
midTime = 12.5 avg = 0.1867187 gradient = 0.038778342 durn = 10.0
midTime = 26.5 avg = 0.48242223 gradient = 0.053906284 durn = 4.0
midTime = 40.5 avg = 0.7187502 gradient = 0.045982197 durn = 6.0
```

Figure 4.10: Instantiated features extracted from Figure 4.8.

4.6 Using Metafeatures

The key insight to the application of metafeatures is realising that the distribution of instantiated features in the parameter space is probably not uniform. This can be exploited to create features that may help in classification.

An initial approach might be to use normal clustering in the parameter space; i.e., clustering that groups points in such a way that distance between points within the same cluster is small, and distances between points in different clusters is large. However, this is merely one approach to answering the real question that we are interested in: "Which are the instantiated features whose presence or absence indicate that the instances belong to a particular class?" The clustering approach can certainly be used to answer this question – the theory being that the different clusters represent the different types of instantiated features. This is an example of **undirected segmentation**.

However, a more refined approach is possible: one that takes into account

the *class* of the instantiated features. One way to do this is to augment the parameter space with the class as an extra dimension. However, this would likely not work either, as the distance metric between classes is not obvious; and the weight given to the class label relative to other features in the parameter space is not easy to determine. Likely, such an algorithm would be caught between ignoring class completely, leading to traditional clustering, and paying too much attention to the class, leading to too many clusters.

Another approach is to re-pose the question as: "Are there regions in the parameter space where the class distribution is significantly different to what is statistically expected?" This question is very similar to typical problems of supervised classification; in particular, if we pose the question as "Are there attribute-value pairs for which the class distribution is significantly different to what we would expect?", then this is the same question that is the basis of many decision tree and rule induction systems. This is an example of **directed segmentation**: segmentation directed towards creating good features for learning.

This suggests that rather than looking at Figure 4.1 where class is completely ignored, a more appropriate way to look at the data is that shown in Figure 4.2.

Suddenly, one can see immediately what a learner could employ in order to make the classification. We see that all the instantiated features coming from training instances whose class label was Happy occupy the top left hand region of the space. However, there are some practical issues. How, given a parameter space, is a region defined?

The solution used in this work is as follows: We have to select a group of synthetic events to query on, and we have to divide the space into regions. Hence, one approach is to select a number of instantiated features which we will term **centroids**[5]. Let the set of all instantiated features be I. Let the set of points we select as centroids be $C = \{c_1, c_2, c_3, ..., c_k\}$, where there are k points selected. Define the set of regions $R = \{R_1, ..., R_k\}$ be defined as follows:

$$R_i = \{x \in P | closest(x, C) = c_i\}$$

and

$$\text{closest}(x, C) = \underset{c \in C}{\text{argmin}}\, dist(x, c)$$

where *dist* is the distance metric we are using for the parameter space.

In other words, each region R_i is defined as the set of points in the parameter space P for which c_i is the closest point (using the distance metric *dist*) in the set C. This is the definition of a Voronoi diagram. A good review of Voronoi diagrams and their (many) applications can be found in [AK00].

If these regions were selected randomly, it would be expected that the class distribution in each region would be similar to the global class distribution. However, if the distribution of instantiated features differed significantly from the global class distribution, then this would be interesting and useful for a machine learning algorithm. Asking whether a training stream has an instantiated feature within a region would be informative of class of the training stream that the instantiated feature came from.

[5]The use of this name will become obvious in a moment.

In general, the objective is to find the subset of the instantiated features that would give us the most "different" class distribution for each region. This would then give something for the learner in the subsequent stage to use for the basis for learning. However, one might then suggest that the solution to this problem is simple: Make $C = I$ – in other words, make each instantiated feature a centroid. Then each region will have exactly one instantiated feature in it; with a very non-random class distribution. Hence we need a measure that "trades off" number of regions for size. We will term this measure the **disparity measure**. The disparity measure measures the difference between the expected and observed class distribution. For now, let us assume that we have such a measure, say, called *DispMeas*. Then we are looking to find:

$$R = \underset{C \in \mathbb{P}(I)}{\operatorname{argmax}} \, DispMeas(C)$$

In other words, we are looking to find the subset of I (the set of all instantiated features), C, for which the disparity measure is the greatest.

The above equation looks simple, but there is a problem. The problem is the $\mathbb{P}(I)$ in the above equation: this is the set of all subsets of I. In general, if there are n elements in I (i.e. $n = \|I\|$), then there are 2^n elements in $\mathbb{P}(I)$. If we wanted to do an exhaustive search, we would therefore have to look at a number of subsets that was exponential in the number of instantiated features. For example, if there are only 100 elements in I, we would still have to check more than 10^{30} possible sets. Even if we were to constrain it to a reasonable size, say no more than 10 regions, C is still combinatorially large in I.

Still, it might be possible to search part of the feature space and come up with a reasonable set C that is effective in constructing features.

4.7 Disparity Measures

Disparity measures are a recurring theme in supervised learning. For example, in decision-tree building algorithms like C4.5 [Qui93], the algorithm proceeds by dividing the instances into two or more regions, based on attribute values. The disparity measure used by C4.5 is the gain ratio; however there are several other possible disparity measures.

In fact there is a whole area of study of different disparity measures. White and Liu [WL94] provide an extensive survey of disparity measures, and we adopt their notation. There are many similarities between decision tree induction (which is built on segmentation based on attribute values) and the creation of regions around centroids (which is built on segmentation based on a Euclidean distance measure). The only adaptation we make is that rather than talking about attributes $a_1, ..., a_m$, we use regions $R_1, ..., R_m$; and, indeed, this points to an interesting analogy.

Suppose that we are dealing with a problem with k classes and that we have m different regions. Then Table 4.4 represents the cross-classification of classes and regions.

	R_1	R_2		R_m	
L_1	n_{11}	n_{12}	$\ldots$	n_{1m}	$n_{1.}$
L_2	n_{21}	n_{22}	$\ldots$	n_{2m}	$n_{2.}$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$	$\vdots$
L_k	n_{k1}	n_{k2}	$\ldots$	n_{km}	$n_{k.}$
	$n_{.1}$	$n_{.2}$	$\ldots$	$n_{.m}$	$n_{..}$

Table 4.4: A general contingency table

In the contingency table, $L_i(i = 1, k)$ and $R_j(j = 1, m)$ represent class and region respectively; $n_{ij}(i = 1, k; j = 1, m)$ represent the frequency counts of the instantiated features in region R_j coming from an instance with class L_i. Also, define:

$$n_{i.} = \sum_{j=1}^{m} n_{ij}$$

$$n_{.j} = \sum_{i=1}^{k} n_{ij}$$

and

$$n_{..} = \sum_{i=1}^{k} \sum_{j=1}^{m} n_{ij} = N$$

We can also define the following probabilities:

$$p_{ij} = \frac{n_{ij}}{n_{..}}$$

$$p_{i.} = \frac{n_{i.}}{n_{..}}$$

$$p_{.j} = \frac{n_{.j}}{n_{..}}$$

4.7.1 Gain Ratio

Given this notation, we can define the following information measures, for each of the cell, class and regions :

$$H_{cell} = -\sum_{i=1}^{k}\sum_{j=1}^{m} p_{ij}\log_2(p_{ij})$$

$$H_C = -\sum_{i=1}^{k} p_{i.}\log_2(p_{i}.)$$

$$H_A = -\sum_{j=1}^{m} p_{.j}\log_2(p_{.}j)$$

The information gain is the difference between the information stored in the cells and the information about class, that is to say:

$$H_T = H_C + H_A - H_{cell}$$

This is the heuristic that was originally used by Quinlan in ID3 [Qui86]. However, it has one significant drawback: it does not take into account the number of regions. If information gain were to be used "raw" without regard to the number of regions, then this would lead to a bias to having a huge number of regions. Imagine a region for each point in the space, such that each region only has one instantiated feature and therefore one class. By substituting in the above formula, we get that such a selection of regions has an information gain of 1, which is the most possible. But it is of no use to us. Hence, in C4.5, Quinlan introduces the gain ratio. The gain ratio compensates for the number

of attributes by normalising by the information encoded in the split itself. It can be shown that using the above formula the gain ratio is $\frac{H_T}{H_A}$.

In these experiments with metafeatures, therefore, we used the gain ratio as one of our disparity measures. The higher the gain ratio, the more likely the subdivision into regions is useful for classification.

4.7.2 Chi-Square test

Another approach, this one from statistics, is the chi-square test. The chi-square test measures the difference between the expected values in each of the cells in the contingency table. By comparing this against a chi-square statistic, a measure of the probability that the distribution of instantiated features we see in the contingency table is random. The smaller that this probability is, the less likely it is that the distribution is due to chance. This probability is called the *power* of the test.

The χ^2 statistic can be computed as:

$$\chi^2 = \sum_i \sum_j \frac{(E_{ij} - O_{ij})^2}{E_{ij}}$$

where O_{ij} is the observed number of instantiated features belonging to region R_j in class L_i; i.e. $O_{ij} = n_{ij}$ and E_{ij} is the number of instantiated features that we would expect for n_{ij} if the region was independent of the class. Hence

$$E_{ij} = \frac{n_{.j} n_{i.}}{n_{..}}$$

In statistics, there is not one chi-square distribution but one for each *degree of freedom*. It can be shown that the degrees of freedom ν in this case are $(k-1)(m-1)$. Once we have computed the χ^2 statistic for our contingency table, we can compute the probability from the definition of the χ^2 distribution, the probability that this particular contingency table was the result of random chance. The smaller that this probability is, the more confident we can be that the distribution we have before is likely to be useful for discriminative purposes.

Unlike information gain, the χ^2 distribution does not suffer from the same issues of bias to more regions, at least theoretically. However, it is more difficult and time-consuming to calculate than the information gain or gain ratio (since to compute the probability mentioned above requires computing the integral of the probability density function of the of χ^2 function).

4.8 Doing the search

So far, we have disparity measures for judging whether a group of centroids or regions are discriminative. However, we still do not have a search algorithm to find the set of points. As pointed out in Section 4.6, the problem is that the search space is exponential in the number of instantiated features. As previously discussed, two general approaches are possible: undirected and undirected segmentation.

With undirected segmentation, any clustering or density estimation algo-

rithm can be used. There are some nice algorithms for clustering, especially if the number of clusters is known, such as K-means clustering. The algorithm for K-means is shown in Figure 4.11. Alternatively, other algorithms, such as AutoClass [CS96] and SNOB [WD94] could be used.

The algorithm works by randomly selecting centroids, finding out which elements are closest to the centroid, then working out the mean of the points belonging to each centroid, which becomes the new centroid. Region membership is checked again, and the new centroids are computed again. This operation continues until there are no points that change their region membership.

The problems with the K-means approach is that (a) we have to specify the number of clusters ahead of time (b) it can be sensitive to the initial random choice of centroids (c) it does not make any use of class information. Note also that it makes use of a special type of locality or stability in the way it works: region membership is unlikely to change too much, and the information is slowly refined to come up with the final solution.

The K-means algorithm can be made to look at a range of different number of clusters by the addition of a "quality" heuristic. The algorithm is relatively simple. Let us say we have a range of say, 2 to 10 clusters. Then we try to get the best possible clustering with 2 clusters, take a global measure of quality of clustering (e.g. total distance from centroids) and then try again with 3 centroids, etc. until we find the number of clusters that work the best.

Most importantly, it can be shown that under the assumption of there actu-

Inputs:
    $I = \{i_1, ..., i_k\}$ (Instances to be clustered)
    n (Number of clusters)
Outputs:
    $C = \{c_1, ..., c_n\}$ (cluster centroids)
    $m : I \rightarrow C$ (cluster membership)

procedure **KMeans**
    Set C to initial value (e.g. random selection of I)
    For each $i_j \in I$
        $m(i_j) = \underset{k \in \{1..n\}}{\text{argmin}}\, distance(i_j, c_k)$
    End
    While m has changed
        For each $j \in \{1..n\}$
            Recompute i_j as the centroid of $\{i | m(i) = j\}$
        End
        For each $i_j \in P$
            $m(i_j) = \underset{k \in \{1..n\}}{\text{argmin}}\, distance(i_j, c_k)$
        End
    End
return C
End

Figure 4.11: K-means algorithm.

ally being k centroids with Gaussian distribution, that the K-means algorithm will eventually converge to the correct answer. "Correct" in this case means the clustering that minimises the total distance of all points from the centroids.

However, K-Means does not make use of a disparity measure; so we would like to adapt it to take advantage of one. The problem is that we do not have this easy-to-define and "smooth" criterion. The K-means algorithm is an estimation-maximisation algorithm; it gradually moves towards a more optimal solution by using the previous iteration to "inform" the next iteration. However, in the case of directed segmentation, the solution space is not smooth – the disparity measure can vary irregularly, since it involves the choice of different centroids. There is no easy "pattern" in the solution space to exploit.

The easiest algorithm to implement would be a "random search" algorithm. This random search algorithm is shown in Figure 4.12. While it may first seem that using a random search algorithm is not productive, work by Ho [HSV92] in the field of ordinal optimisation shows that random search is an effective means of finding near-optimal solution. This was also used by Srinivarsan [Sri00] in his *Aleph* ILP system where it was shown to perform well even compared to complex search methods.

Ordinal optimisation can be applied to our problem as follows. Let us assume that our objective is to find a subset of points that is in the top k per cent of possible subsets (i.e. whose disparity measure ranks it in the top k per cent). If we test n possible subsets randomly, then the probability P of getting an

instance in the top k per cent can be shown to be:

$$\begin{aligned} P(\text{1 or more subsets in top } k\%) &= 1 - P(\text{0 subsets in top } k\ \%) \\ &= 1 - (1-k)^n \end{aligned}$$

For example, if $n = 1000$ and $k = 1\%$ then the probability of finding an instance in the top 1 per cent of possible cases is $1-(1-0.01)^{1000} = .999957$. In other words, if we try 1000 instances, then there is a better than 99.995 per cent chance that we will get one instance in the top 1 per cent. Hence by softening the goal (trying to find *one of the best* rather than *the best* subset of points) we can be highly confident of getting a solution in the top percentile.

An algorithm for random search is shown in Figure 4.12. It assumes the following auxiliary functions:

- *randBetween(min, max)* returns a random number between *min* and *max* inclusive.
- *randSubset(num, set)* returns a random subset of *set* with *num* elements in it, but with no repetitions.

Also note that *DispMeas* takes a set of centroids, a set of points and their class labels. Using this information, it then creates a contingency table as mentioned above, and then applies whatever disparity measure is required.

Inputs:
    $I = \{i_1, ..., i_k\}$ (Instances to be clustered)
    $L = \{l_1, ..., l_k\}$ (Class labels of instances)
    $N = \{n_{min}, ..., n_{max}\}$ (Possible number of centroids)
    $DispMeas(Centroids, Instances, Labels)$ (Disparity measure)
    numTrials (number of trials to attempt)
Outputs:
    $C = \{c_1, ..., c_n\}$ (cluster centroids)
procedure **RandSearch**
    bestMeasure := 0
    bestCentroids := {}
    for i := 1 to *numTrials*
        r := *randBetween*(n_{min}, n_{max})
        currentC := *randSubset*(r, I)
        currentMetric := *DispMeas*(*currentC*, I, L)
        if(*currentMetric* > *bestMetric*)
            bestMetric := *currentMetric*
            bestCentroids := *currentC*
        End
    End
C := *bestCentroids*
return C
End

Figure 4.12: Random search algorithm.

The random search is not a particularly efficient algorithm in terms of search, compared to K-Means. However, we will show that the advantage of using directed segmentation over undirected segmentation means that in practice, directed segmentation is preferred.

Also note that the random search algorithm is highly parallelisable. The main `for` loop can be run in parallel across many different processors and/or computers, provided that the final `if` statement that updates the best instance seen so far is done atomically. This is a significant advantage over the K-Means algorithm, which is not easy to parallelise at all, as it is inherently iterative.

In either case, whether using the undirected segmentation or the directed segmentation, the centroids become synthetic features; in other words, we can now ask the question: "does a particular stream have an instantiated feature lying in the region belonging to centroid X?" This binary information can be used as a synthetic feature that can be passed on to a learner. We will explore this in practice in the next two chapters.

4.9 Examples

4.9.1 With K-Means

To bring this all together, consider the following example, from the Tech Support domain. Figure 4.13 reproduces Figure 4.3 here for convenience. In fact, Figure

4.3 did in fact use K-Means clustering to determine the centroids.

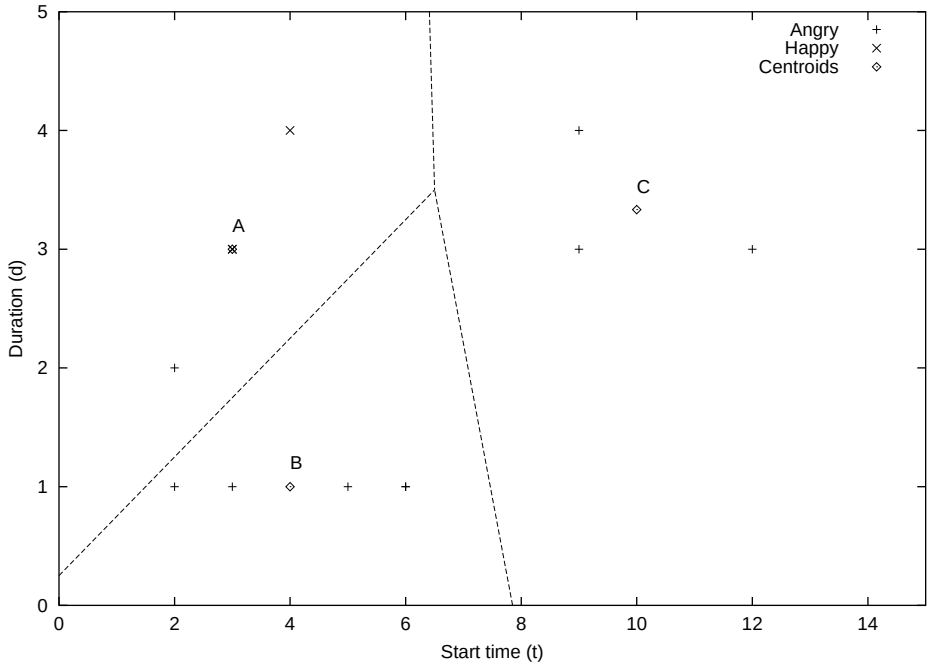


Figure 4.13: K-means clustered LoudRun parameter space for Tech Support domain.

Centroids are marked with diamonds. Also note that a simple Euclidean distance metric is used, and different standard deviations for the different axes are not taken into account (hence the results look a little unusual). Also note that *a priori* we specified three clusters. The dotted lines represent the region boundaries; these are easy to compute as they are the loci of points that are equidistant from the two nearest centroids.

4.9.2 With directed segmentation

Now, we do the same thing, using a directed segmentation approach. We will set $n_{min} = 2$, $n_{max} = 3$ and $numTrials = 3$. We will look at several disparity measures.

It should be noted that one of the advantages of directed over undirected segmentation is that it chooses an instance which is an observed instantiated feature. Quinlan [Qui93] notes that experts who look at the results of learning with continuous attributes find it easier to understand cutpoints that can be found in the data, rather than averages, since it may be that certain averages are physically impossible (e.g. in the case of the previous result, a LoudRun that has a duration of 3.33 timesteps). Although his results were with cutpoints, and ours are with regions, the result still holds. We will use the random search algorithm proposed above, but run three iterations in parallel for ease of comparison.

The first stage of the algorithm is to generate 3 random subsets with between 2 and 3 elements. The results of this step are shown in Table 4.5.

Trial	Centroids
1	$c_1 = (4, 4), c_2 = (5, 1)$
2	$c_1 = (4, 4), c_2 = (3, 1), c_3 = (9, 4)$
3	$c_1 = (3, 3), c_2 = (12, 1)$

Table 4.5: Random sets of centroids generated for the Tech Support domain.

For each of these, it is possible to generate a region boundary diagram. Figure 4.14, 4.15 and 4.16 show the parameter space using trials 1,2 and 3 respectively.

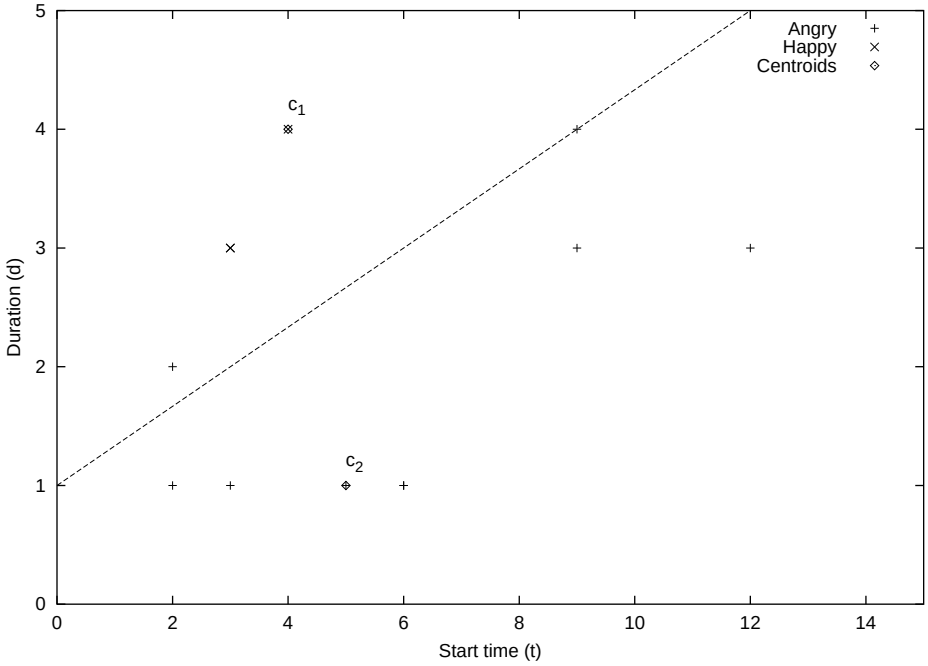


Figure 4.14: Trial 1 points and region boundaries.

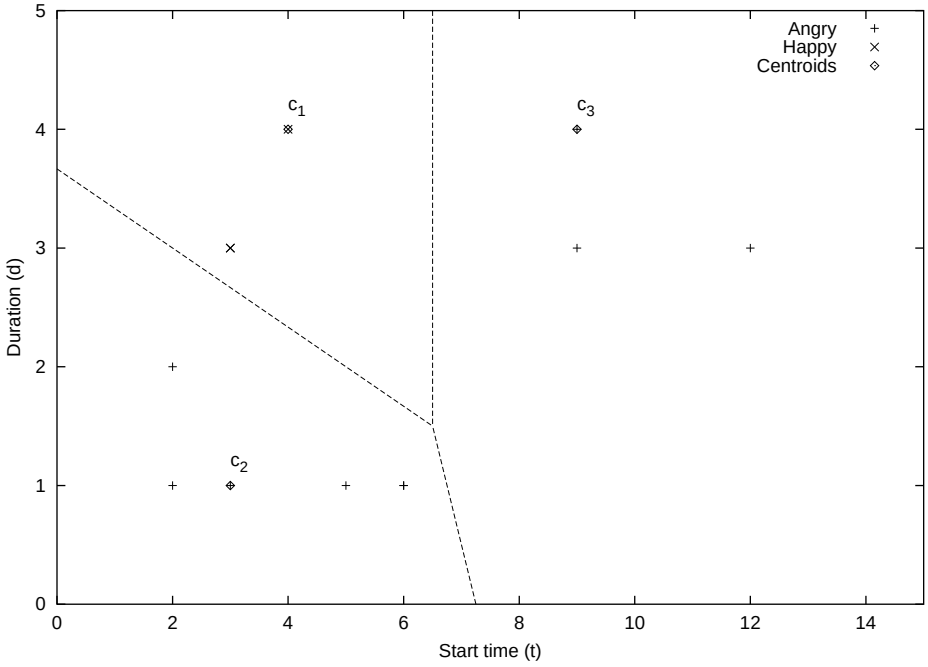


Figure 4.15: Trial 2 points and region boundaries.

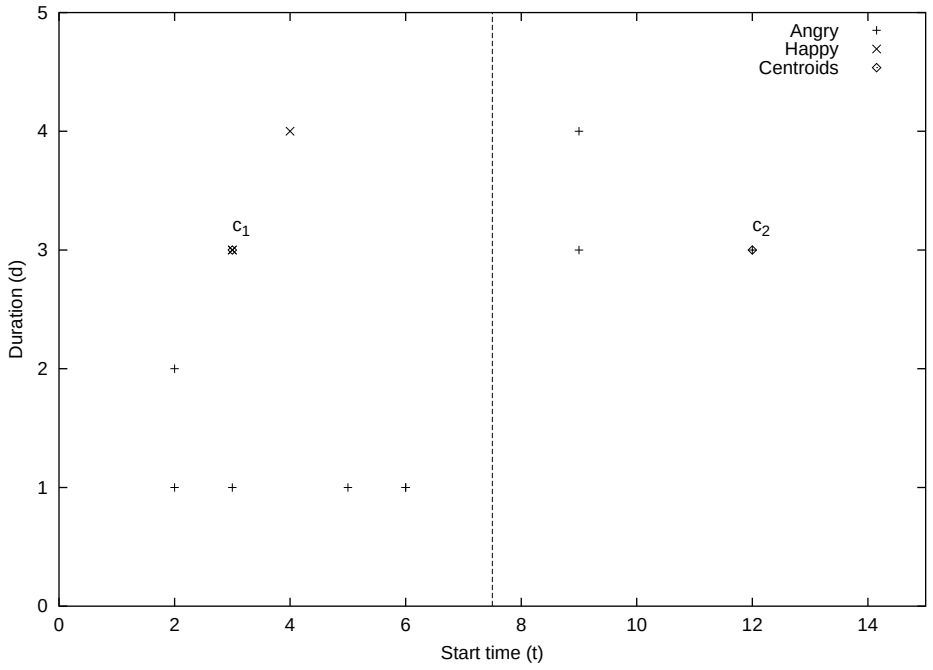


Figure 4.16: Trial 3 points and region boundaries.

Now we can calculate the contingency tables for each trial. We do this by counting the number of instances of each class in each region. For example, in Table 4.6, there is 1 instantiated feature in the region around centroid 1 (R_1) which came from a stream whose class was Angry, and 3 whose original class was Happy[6]. These go into the first column. Similarly, in region 2 (R_2), the region surrounding c_2, there are 7 "Angry" instantiated features and no "Happy" instantiated features (counting the border case as belonging to this region). This goes into the second column. The final column is just the row totals (i.e. $1+7$ and $3+0$) and the final row is just the column totals (i.e. $1+3$ and $7+0$). The value in the bottom right hand corner is the sum of either the row totals or the

[6]Note that there are two points at the location (3,3), hence it actually counts as two instances. Also note that in the case of an instance lying exactly on the border, we randomly select which region it belongs to.

column totals. These should of course be the same value and it should be equal to the total number of instantiated features.

	R_1	R_2	
Angry	1	7	8
Happy	3	0	3
	4	7	11

Table 4.6: Contingency table for Trial 1.

	R_1	R_2	R_3	
Angry	0	5	3	8
Happy	3	0	0	3
	3	5	3	11

Table 4.7: Contingency table for Trial 2.

	R_1	R_2	
Angry	5	3	8
Happy	3	0	3
	8	3	11

Table 4.8: Contingency table for Trial 3.

Finally, we can calculate a number of disparity measures from the contingency tables, based on the methods discussed in Section 4.7. The results are shown in Table 4.9.

For example, to work out the information gain in the first trial, this can be computed using:

Trial	Information Gain	Gain Ratio	Chi-squared			
			Statistic	DoF	Prob	$-\log_2$ Prob
1	0.550	0.582	9.79	1	0.0176	9.15
2	0.845	0.549	11.0	2	0.0408	7.93
3	0.151	0.179	1.55	1	0.22	2.18

Table 4.9: Evaluation of trials 1, 2 and 3 using Gain, Gain Ratio and Chi-Squared disparity measures.

$$
\begin{aligned}
Gain &= H_C + H_A - H_{cell} \\
&= \textstyle\sum_{i=1}^{k}\sum_{j=1}^{m} i(p_{ij}) - \sum_{i=1}^{k} i(p_{i.}) - \sum_{j=1}^{m} i(p_{.j}) \\
&= i(\tfrac{1}{11}) + i(\tfrac{7}{11}) + i(\tfrac{3}{11}) + i(\tfrac{0}{11}) - i(\tfrac{8}{11}) - i(\tfrac{3}{11}) - i(\tfrac{4}{11}) - i(\tfrac{7}{11}) \\
&= 0.550 \\
&\quad \text{where } i(x) = x\log_2(x)
\end{aligned}
$$

The gain ratio can be computed by dividing the information gain by H_A, which in this case is: $-(i(\frac{4}{11}) + i(\frac{7}{11})) = 0.945$. Hence the gain ratio is $\frac{0.550}{0.945} = 0.582$.

Computing the χ^2 heuristic is more involved. For first cell in trial 1, $E_{ij} = \frac{8\times4}{11} = 2.91$. We can then compute the χ^2 component for that particular cell using $\frac{(e-o)^2}{e}$ as $\frac{(1-2.91)^2}{2.91} = 1.25$. If we repeat this total for the remaining three cells in trial 1, and sum them, we get a total of 9.79. This number is known as the χ^2 statistic. Note also that there are two classes and two regions, hence the degree of freedom of the statistic is $(2-1)(2-1) = 1$.

Usually this statistic is compared against a value in a critical-values table in a *significance test*. For example, it is used to decide whether there is a less

than 5 per cent chance that such a distribution is random. However, we want to know for a particular χ^2 statistic and the degrees of freedom probability that this process was the result of random chance. This can be computed easily using the cumulative distribution function of the χ^2 distribution. The result is shown in the fourth column of Table 4.9. Finally, for comparison, we take the negative log of the probability. This is mainly for to match the direction of the other heuristics (bigger is better) and because it just as easy to compute without suffering floating-point difficulties in the implementation.

Looking at Table 4.9, it seems that the results for Trial 3 are inferior to the other two. However, Trials 1 and 2 are quite close; information gain puts Trial 2 ahead of Trial 1, unlike the other two measures. A tradeoff has occurred: even though Trial 2 produced a "purer" result (in that there is only one class in each region), it did so using 3 centroids, Trial 1 accomplishes an "almost as pure" result using only 2 centroids.

These regions, much as for the previous case with K-means, can now be used to create synthetic events. If we use Trial 2, for example, we get the features shown in Table 4.10.

Feeding it to C4.5 produces Figure 4.17. Note that we can easily post-process the result to produce something that is far more readable by using the LoudRun metafeature, which is shown in Figure 4.18.

Note that if we did the same for the K-means value, we would get the slightly nonsensical definition shown in Figure 4.19.

Stream	Class	Synthetic Events		
		Region 1	Region 2	Region 3
1	Happy	Yes	No	No
2	Angry	No	Yes	Yes
3	Angry	No	Yes	Yes
4	Happy	Yes	No	No
5	Happy	Yes	No	No
6	Angry	No	Yes	Yes

Table 4.10: Attribution of synthetic features for the Tech Support domain in Trial 2.

```
rgn1 = yes: Happy (3.0)
rgn1 = no: Angry (3.0)
```

Figure 4.17: Rule for telling happy and angry customers apart, using synthetic features from trial 2.

```
Does have a Loud run
   approximately starting from timestep 4 AND
   approximately going for 4 timesteps : Happy (3.0)
Otherwise: Angry (3.0)
```

Figure 4.18: Human readable form of rules in Figure 4.17.

```
Does have a True run
   approximately starting from timestep 10 AND
   approximately going for 3.33 timesteps : Angry (3.0)
Otherwise: Happy (3.0)
```

Figure 4.19: Human readable form of rules in Figure 4.4.

4.10 Further refinements

Metafeatures can be refined in several ways: firstly, by the addition of region membership measures and secondly by giving the user some bounds for the descriptions generated by the learner.

4.10.1 Region membership measures

In the earlier parts of this chapter, training streams either had an instantiated feature belonging to a particular region, or they didn't. For this reason, Table 4.10 contains only `yes` and `no` values – a **binary membership** test. However, it is possible to ascribe to each event a membership value that denotes the confidence that the point belongs to a particular region. It is generally the case that the closer the instance is to a particular centroid, the more confident one can be that it belongs to that region. Work in areas such as fuzzy set theory [Zad65] and rough sets [Paw82] have similarities to the idea of using non-binary region memberships.

A first guess at a region membership measure is normalised Euclidean distance from the centroid. By normalised, we mean that the distance along each axis is divided by its standard deviation. Doing so ensures that no one feature dominates the calculation of distance. This copes with differences in scale of different measurements. For example, let us assume that position is initially measured in metres; but is later changed to use millimetres. If we fail to adjust

for the fact that millimetres are three orders of magnitude as large as metres, then in our distance calculations the position would have three orders of magnitude more impact on the distance. However, if we divide by the observed standard deviation in the data, then this will adjust for the fact that different axes may have different units.

Normalised distance from the centroid is a good first approximation, however it has some notable problems. Consider a simple vertical region boundary as shown in Figure 4.20.

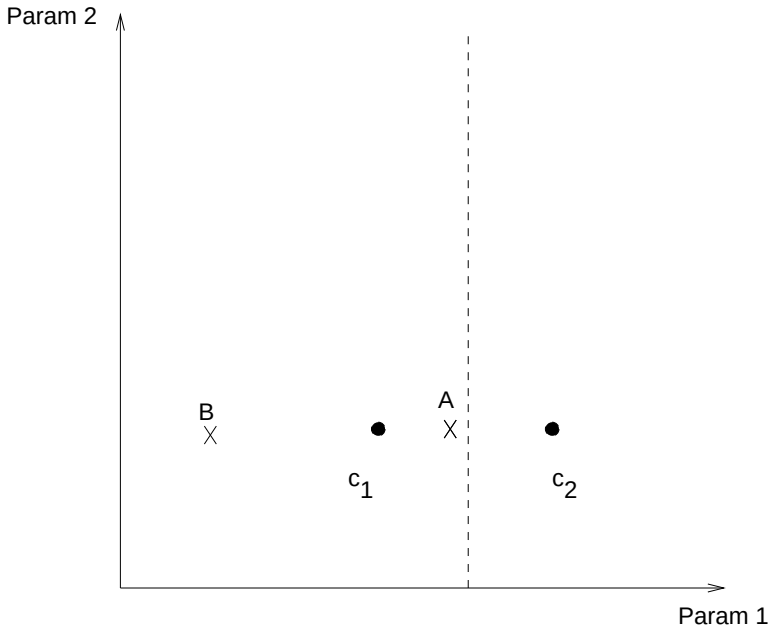


Figure 4.20: Distance measures in the parameter space. c_1 and c_2 are two centroids, A and B are instantiated features.

Point A is approximately three times as close to c_1 as B. Hence normalised distance implies that A is far more likely than B to be a member of the region around c_1. We know that though A is closer to c_1, it is also much closer to a

region boundary than B is, hence it would intuitively make sense if we were *less* confident about the membership of A then we were of B. How can we define a more appropriate region membership measure?

Recall that the region boundary tells us the points which are equidistant from two centroids, in other words, for points along the region boundary the distance between two of the centroids is equal. This suggests an alternative region membership measure: the relationship between the normalised distance to the nearest centroid and the normalised distance to the second nearest centroid.

Consider the following region membership measure. Let d_1 be the distance to the nearest centroid c_{n1} and d_2 be the distance to the second nearest centroid c_{n2}. Then consider the measure:

$$D = \log_2(\frac{d_2}{d_1})$$

We will term this measure the **relative membership**. When a point is on the the region boundary by definition the distance to c_{n1} and c_{n2} is equal. Hence the ratio $\frac{d_2}{d_1}$ will be equal to 1, hence $D = 0$. Consider a point like A in Figure 4.20. It is slightly closer to c_1 than c_2; assume that the distance to c_1 is 5 and the distance to c_2 is 6. Then the relative membership is $\log_2(6/5) = 0.263$. Now consider a point like B, which is, say 30 units from c_2 and 15 units from c_1. Its relative membership will be $\log_2(30/15) = 1$. Hence, one is *more* confident that B is in the region defined by c_1 than A, which matches our intuitions.

Note that if the point we are looking at is actually the centroid of a region,

then the relative membership is $\log_2(\frac{d2}{0}) = \infty$ This also makes sense; as we are absolutely sure that the point c_1 lies in its own region R_1.

With this minor change, relative membership can be used in place of binary membership. There are some complications, however. What happens if there is more than one instantiated feature lying in a particular region? With relative membership, two instances in the same region can have different relative memberships, unlike binary memberships. For example, consider s_3 from Tech Support domain. Its events are $\{(2,1),(5,1),(12,3)\}$. Now consider that we use the segmentation that we examined in Trial 2 of the random search (see Figure 4.15). Then both of the instances $(2,1)$ and $(5,1)$ lie within region 2. If the relative membership for each of these is calculated, we would get two different values. For the point $(2,1)$, the relative membership (using unnormalised Euclidean distance for ease) is 1.84, while for $(5,1)$ it is 0.66. Table 4.12 shows the relative membership for each point within R_2 for trial 2. There are several possible solutions to this problem; but a simple one is to take the point with the greatest relative membership[7]. So, when constructing a table for Trial 2 as before, rather than a yes/no value, we would now put in a "1.84". Table 4.11 shows the table with relative rather than binary attributes. Note that if there is no instance in the space, we simply enter a "0". This is equivalent to saying that there are no instantiated features within that region.

Feeding this into C4.5, the results in Figure 4.21 are produced.

[7]This is very similar to the approach taken in fuzzy logic. The fuzzy "or" of two fuzzy values is usually the maximum of the two.

Stream	Class	Synthetic Events		
		Region 1	Region 2	Region 3
1	Happy	0.5	0	0
2	Angry	0	∞	∞
3	Angry	0	1.84	1.35
4	Happy	∞	0	0
5	Happy	∞	0	0
6	Angry	0	0.265	2.35

Table 4.11: Numerical attribution of synthetic features for the Tech Support domain in Trial 2.

```
rgn1 <= 0: Angry (3.0)
rgn1 > 0: Happy (3.0)
```

Figure 4.21: Rule for telling happy and angry customers apart, using synthetic features from trial 2 and using relative membership.

This result seems surprising. In this case, the rule learnt is identical to the binary attribute rule learnt. `rgn1 > 0` means that there is an instance within region 1; whereas `rgn1 <=0` means that there is no instance in region 1. This also correctly indicates that by using relative membership, the hypothesis language expands greatly and is a strict superset of the binary membership system. Although there is no use made of it in this particular case, it is quite possible that a rule may take the form `rgn1 > 1`, in which case it is not simply sufficient for there to be an instance within region 1, but it would also be necessary for there to be an instance within region 1 which *also* has a relative membership greater than 1. In other words, not only must the instance lie in region 1, but it must be twice as close to the point c_1 as to any of the other centroids.

While it may at first seem that this can impede readability, it can be em-

ployed, as with the next section to *assist* in making the concept description more useful.

4.10.2 Bounds on variation

A second possible refinement is to create bounds on the variation of parameters when converting rules back to human-readable form.

In the human-readable definition generated in Figure 4.18, there is no guide given to the typical variation in attribute values. All that can be said is that it is at "approximately" time 10 and for a duration of "approximately" 4 timesteps. In real-world datasets, this may not be good enough a characterisation; in some cases "approximately" 10 means "between 9 and 11", and in other cases, it means "between 5 and 15". How can we give the user some idea of the extent of the variation?

One approach is to give the user the region boundaries as output. After all, this would provide exactly what the classifier uses. However, a moment's thought will show that this may be a less than ideal solution. Firstly, most people do not have a sufficiently good grasp of mathematics to be able to deal with the region boundary expressed in this form. Secondly, this may work for a two-dimensional metafeature like LoudRun or LocalMax, but many metafeatures are four or five-dimensional. In a five-dimensional space, the region boundaries would be expressed as convex hyper-polyhedra. This representation is not likely

to be of much use in practice.

However, there is no reason why the *explanation* of the concept learnt by our system needs to be expressed so that it exactly matches the classifier produced by our system. We can give the user a simplified explanation of what our system has learnt, but when it comes to actual classification, we need not use the simplified model at all.

This is a subtle idea[8]. For example, a traditional learner, like C4.5, outputs the scheme that it actually uses to classify – a decision tree. Imagine if, for its own internal calculations, C4.5 retained the original tree, but applied various heuristics to reduce the size of the tree so that a human reader would get an approximation of what C4.5 had learnt, with enough of a characterisation that it's still useful.

This suggests an approach: assuming that the learner uses binary membership, then one can find the bounding boxes on the instantiated features within each region. These boxes could then be included in the definition. Figure 4.22 shows the bounding boxes for each of the different centroids.

It is an approximation of the actual concept used for classification, but it does give the user some intuition about what the system was doing. Using this, the original definition would take on the form shown in Figure 4.23.

[8]This is one of those ideas that is kind of obvious once explained, but is not so obvious to one's own intuitions. The penny dropped for me during a lecture by Thierry van der Merckt at the University of Sydney.

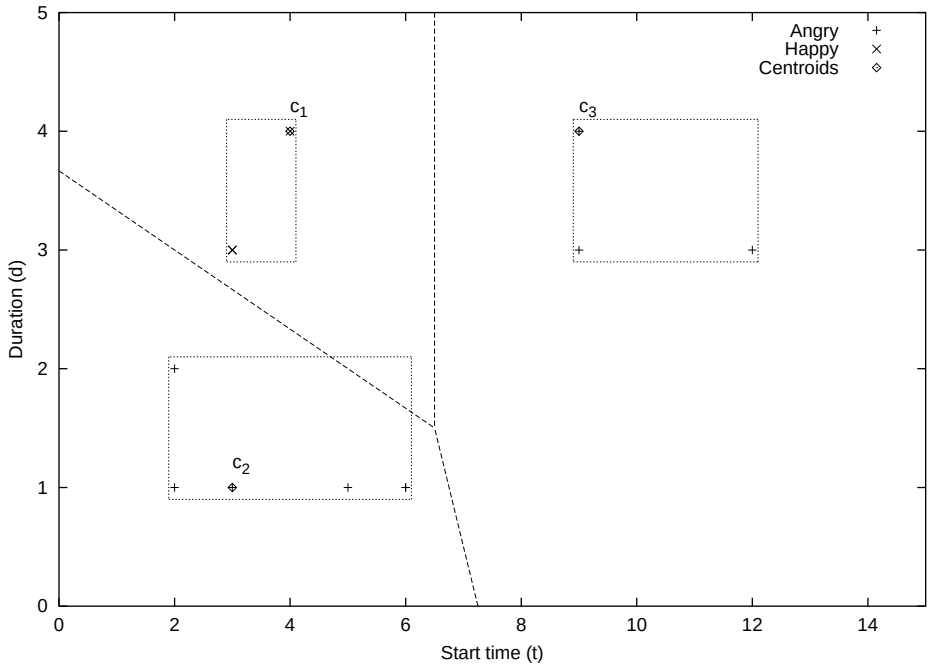


Figure 4.22: The bounding boxes in the case of Trial 2 random search.

```
Does have a True run
   starting between time 3 and 4 AND
   going for 3 or 4 timesteps : Happy (3.0)
Otherwise: Angry (3.0)
```

Figure 4.23: Human readable form of rules in Figure 4.17.

There is a complication if we want to use relative membership and variation bounds at the same time: the binary membership means we can create the "bounding box" for all the instances in a region. However, if relative memberships are used for attribute values, our propositional rule learner may produce a rule of the form `rgn2 >= 0.9` for Random Search Trial 2. This means that we can no longer use the bounding box for all of the instances in region 2 shown in Figure 4.22, as not all of the points in region fulfil the requirement.

```
Does have a LoudRun
   starting between time 2 and 3 AND
   going for 1 or 2 timesteps
```

Figure 4.24: Transforming relative membership into readable rules.

How do we solve the problem? We can still calculate the relative membership for each point in the region, and we only draw the bounding box around those points fulfilling the requirement. The relative membership for each point in region 2 is shown in Table 4.12.

Point	**RM**
(2,1)	1.85
(2,2)	1.0
(3,1)	∞
(5,1)	0.66
(6,1)	0.27

Table 4.12: Relative membership (RM) for instantiated features in region 2 of Trial 2.

Hence we can see that only the points $(2,1),(2,2),(3,1)$ lie in the region defined by the constraint `rgn2 >= 0.9`. Hence the bounding box would be $(2,1)-(3,2)$. The human-readable version of the rule `rgn2 >= 0.9` is shown in Figure 4.24.

So, rather than being a problem, the use of relative region membership allows us to build more exact definitions, especially insofar as the bounds, while also giving the learner more flexibility.

4.11 Conclusion

Metafeatures are a novel feature construction technique that can be applied whenever there is some kind of underlying substructure to the training instances and there is some way to extract these substructures. In temporal domains, these substructures take the form of sub-events, like intervals of increase or decrease.

Metafeatures first extract substructures within the training instances. Then, interesting, typical or distinctive examples are selected. These substructures become synthetic features, which are then fed to a propositional learner. We can then convert the output of the learner back to a human-readable form that is described in terms of the metafeatures we began with.

The extraction of typical or distinctive examples is done by segmenting the parameter space into regions. The division of the parameter space into regions can be approached using two methods: traditional *undirected* segmentation which simply treats each instance as a point in space; or the novel *directed* segmentation approach. The directed segmentation approach is specifically designed to facilitate subsequent learning by dividing the space into regions where the class distribution is non-uniform; hence trying to find regions which could potentially be useful for discrimination between classes.

The novelty of metafeatures lies not in the idea of parametrised substructures within training instances; these are ideas that have been used for *ad hoc* temporal classification for a very long time. However, the novelty lies in these metafeatures

as a general concept, and that they form a parameter space. The novelty lies in segmenting the parameter space in such a way as to:

- Create distinctive features so that a subsequent learning algorithm can learn effective concept descriptions.
- Define substructures within training instance that can be used to construct a description of the learnt concept in terms of those metafeatures. This makes metafeatures one of the few techniques that can produce comprehensible descriptions of multivariate time series.

Finally, two novel enhancements are suggested:

- Rather than using a simple binary measure of region membership, relative membership is used.
- Bounds on the size of the regions are produced for the definitions generated by propositional learning.

Chapter 5

Building a Temporal Learner

In Chapter 4, metafeatures were introduced as a means of feature construction, and a pedagogical example with one metafeature was demonstrated. In this chapter, we explore how to build a temporal learner (in particular, a weak temporal learner) for real-world practical domains using many metafeatures. We also consider several specific metafeatures and consider the implementation of a temporal learner called *TClass*.

5.1 Building a practical learner employing metafeatures

In Chapter 4, we discussed metafeatures generally. However, we did not consider them from a computational point of view or discuss much in the way of

implementation details. Some contemplation of the application of metafeatures leads to a natural division of their implementation into three subprocesses:

- **Instantiated feature extraction**: This involves applying the extraction function (see Section 4.4) to every training stream. The output is a set of class-labelled instantiated features.
- **Synthetic feature construction**: Given these class-labelled instantiated features, the techniques discussed in Section 4.6, namely directed and undirected segmentation, are applied to construct the synthetic features.
- **Training set attribution**: Each synthetic feature becomes an attribute for the propositional learner. For each training instance, the value of the attribute is determined by the presence of instantiated features in the region around the synthetic feature, as outlined in Section 4.10.1.

This sequence of steps is represented diagrammatically in Figure 5.1. In fact, this is exactly the steps followed in the Tech Support domain presented in Section 4.2. The training instances are shown in Table 4.1. The results of instantiated feature extraction are shown in Table 4.2. Several different possible outcomes of synthetic feature construction are shown in Table 4.5. Training set attribution leads to Table 4.10 (or, if relative membership is used, Table 4.11).

So far, only the training stage has been discussed. What are the changes that occur once we want to *apply* the system to unseen instances? The main distinguishing factor of unseen instances is that the class label is not known.

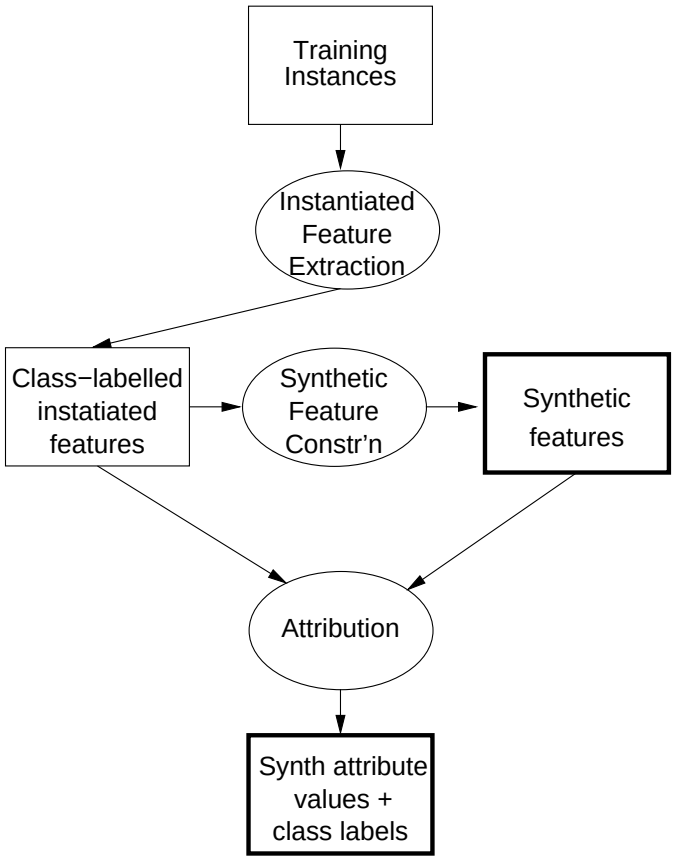


Figure 5.1: The stages in the application of a single metafeature in *TClass*.

In the field of machine learning, a strict separation of training and test sets is usually enforced. In this particular case, this separation should extend to include not only the learning algorithm, but also the synthetic feature construction stage. If synthetic features are constructed using test data, then we have access to information that should not be available to the temporal learner.

However, using the output of the synthetic feature construction in the training stage as an input to the attribution stage is no problem. Figure 5.2 shows the typical procedural pipeline for using the system for temporal classification.

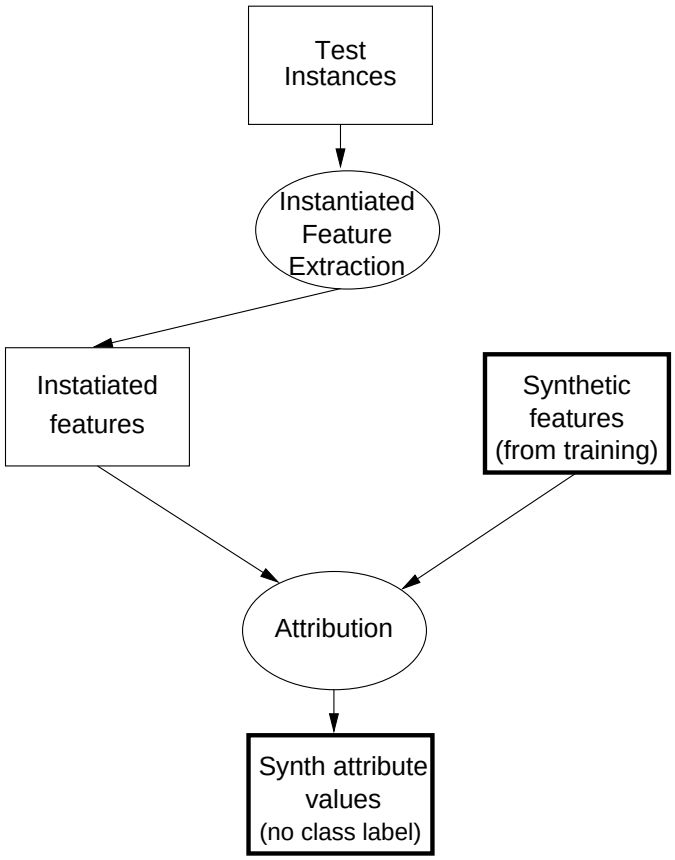


Figure 5.2: The *TClass* pipeline for processing test instances.

Note that the synthetic features created in the training stage are provided as an input in this case to the attributor. Note also that the attributor in the training and test cases need not be any different at all except in one regard: the output of the attributor in the training case includes class information that the propositional attribute-value learner system can use to build its classifier, whereas in the case of the attributor at test time, the output does not include the class information.

To further clarify the role of each of these components, Figures 5.3, 5.4 and 5.5 show pseudocode for instantiated feature extraction, synthetic feature con-

struction and attribution.

The algorithm for instantiated feature construction takes a list of training examples, a list of labels, and returns a list of tuples. Each tuple consists of a list of instantiated features, and a class. In Figure 5.3 $append(I, x)$ appends x to the list I; also assume there is a method called *extract* for each metafeature that takes a training instance and, as defined in Chapter 4, returns a list of instantiated features.

For the segmentation algorithm in Figure 5.4, the data must be converted into a format appropriate for segmentation. This means making a single list of tuples each consisting of an instantiated feature and a class label, rather than the original format, which is a list of 2-tuples, each consisting of a list of instantiated features and a class label. Also note that *SegAlg* could be any segmentation algorithm, for example either of the algorithms discussed in Chapter 4.

The attribution algorithm shown in Figure 5.5 takes a membership function, such as the ones we discussion in Section 4.10.1; such as relative membership, and finds if there is an instantiated feature from a particular training instance that is similar to each synthetic feature.

Inputs:
$T = [t_1, ..., t_n]$ (Training streams)
$L = [l_1, ..., l_n]$ (Class labels of training streams)
extract (Extraction function for this metafeature)
Outputs:
$I = [\langle [i_{11}, ..., i_{1m_1}], l_1 \rangle, ..., \langle [i_{n1}, ..., i_{nm_n}], l_n \rangle]$
(class-labelled instantiated features)

procedure **Extraction**
$I := \{\}$
For $i := 1$ to n
$append(I, \langle extract(t_1), l_1 \rangle)$
End
return I
End

Figure 5.3: Instantiated feature extraction.

Inputs:
$I = [\langle [i_{11}, ..., i_{1m_1}], l_1 \rangle, ..., \langle [i_{n1}, ..., i_{nm_n}], l_n \rangle]$
(class-labelled instantiated features)
$SegAlg(Instances)$ (Segmentation algorithm to use)
Outputs:
$C = [c1, ..., c_k]$ (synthetic features)

procedure **Construction**
/* First we must "flatten" input data. */
$D := []$
For each $\langle P, l \rangle$ in I
For each p in P
$append(D, \langle p, l \rangle)$
End
End
/* Now apply the segmentation */
$C := SegAlg(D)$
return C
End

Figure 5.4: Synthetic feature construction.

Inputs:
$I = [\langle [i_{11}, ..., i_{1m_1}], l_1 \rangle, ..., \langle [i_{n1}, ..., i_{nm_n}], l_n \rangle]$
(class-labelled instantiated features)
$C = [c1, ..., c_k]$ (synthetic features)
$mem(Centroid, Instances)$
(Membership function we are using)
Outputs:
$E = [\langle f_{11}, ..., f_{1k}, l_1 \rangle, ... \langle f_{n1}, ..., f_{nk}, l_n \rangle]$
(Training data in format for propositional learner)

procedure **Attribute**
For each $\langle P, l \rangle$ in I
$e := \langle \rangle_{k+1}$ /* e is a new tuple with $k+1$ fields */
For $i := 1$ to k
$e_i := mem(c_i, P)$
/* In other words, for each centroid, work out the
if there is an instantiated feature like c_i in P */
End
$e_{k+1} := l$ /* Append class label to attribute vector */
$append(E, e)$
End
return E
End

Figure 5.5: Training set attribution.

5.2 Expanding the scope of *TClass*

The above system is sufficient for the implementation of a single metafeature. However, in practice, there are two observations that necessitate important additions to *TClass*.

Firstly, the set of domains where a single metafeature is sufficient for learning purposes is limited. Typically, there will be many metafeatures for a given problem domain, and as we will see later, the same metafeature may be applied to a number of channels within the same problem domain. Hence we have to expand our architecture to support multiple metafeatures and multiple applications of metafeatures.

Secondly, while in general it is the temporal characteristics of a signal that are important, there are many cases when other non-temporal attributes are useful. These will be termed **global attributes**.

5.2.1 Global attributes

Aggregate global attributes

Another technique for extracting information from the training data is to evaluate some aggregate values and use them as propositional attributes. This would cover features of a stream that are not localised. For example, for continuous channels, the global maximum and minimum value of a channel, or the mean of

each channel may be useful. Such attributes are examples of **aggregate global attributes** – they measure some property of each training instance as a whole, rather than looking at the temporal structure. Such features can be surprisingly useful for classification. For example, [Kad95] shows that in the sign language domain task discussed in Section 6.3.2 almost 30 per cent accuracy can be obtained in classifying 95 signs based solely on the maxima and minima of they x, y, and z positions of the right hand.

Global features may be more complicated than simple maxima, minima and averages. For example, we could count the number of local maxima and minima, we could measure the total "distance" covered by each channel, or use some measure of energy. For discrete binary channels, it might be something like how many changes there are, the percentage of time for which the value is true and so on. Duration is another example of an aggregate temporal feature, which may be useful for some classification purposes.

Note that global features may be associated with either single or multiple channels. For example, in the Auslan domain, we could measure the distance using a Euclidean metric on the x, y and z channels, or on each channel separately. For simplicity below, we consider global feature calculation for a single channel.

Example global attributes

For a given channel, we could define the global maximum *max* for a given channel as

$$max(c) = m \text{ s.t. } \forall t \; c[t] \leq m, t \in \text{domain}(c) \wedge \exists t \text{ s.t. } c[t] = m$$

Similarly, we could define a distance measure on a single channel as:

$$dist(c) = \sqrt{\sum_{t=1}^{t_{max}} c[t]^2 - c[t-1]^2}$$

These global features can be useful for classification; in fact, in the past this has been one of the most popular means of *ad-hoc* feature extraction technique in temporal classification domains. However, they are usually not sufficient for doing high-accuracy classification. In addition, used alone, they do not usually lead to the production of useful human-readable descriptions of the learnt concept.

Other global attributes

Another type of global attribute is a conventional intrinsically non-temporal feature. For example, consider diagnosing medical patients by observing the electrical patterns and behaviour of their heart – in other words, an electrocardiograph (ECG) – as discussed in Section 6.3.3. Obviously there are important temporal characteristics of the ECG; for example, the rates of change of the elec-

trical signal, the order of various sub-components of the heart's beats and so on. Aggregate temporal attributes as outlined before are also useful. But there are also other attributes which are important to classification and diagnosis, such as the patient's age, height, weight and gender. These are not directly temporal measures, but they do have impact on the diagnosis. One of the advantages of the *TClass* approach is that it allows the integration of conventional features, aggregate global features and temporal features while other systems (such as dynamic time warping and hidden Markov models) do not. The practicalities of such integration are the topic of the next section.

5.2.2 Integration

How can we integrate all of these data sources? Since all of these processes produce attribute values, they can simply be concatenated into a single long attribute value tuple. This leads to the diagram shown in Figure 5.6.

Note that there are several new "boxes". The first of these is the learner; and the second is attribute combination. The attribute combiner takes attributes from multiple sources and concatenates the attributes from the different sources into a single attribute value tuple, ready for passing to a propositional learner.

Certain aspects of *TClass* are not included in Figure 5.6, in particular the creation of human-readable output. In Section 4.10.2, we discussed post-processing the learnt concept to generate more human-readable descriptions in situations

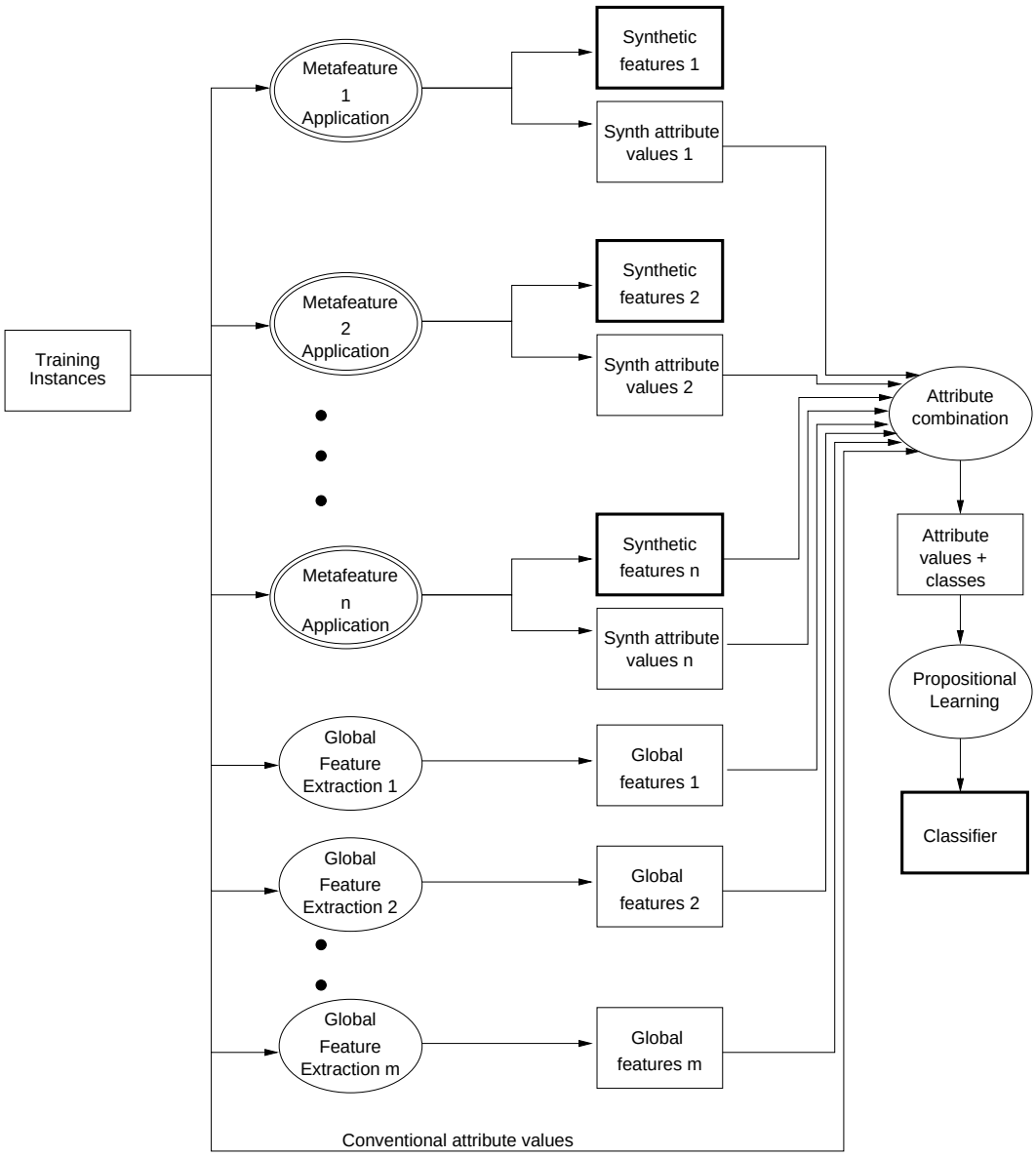


Figure 5.6: The *TClass* system: training stage.

where the generated classifier represents the concept as a set of constraints on the attribute values. This requires several sources: firstly and most obviously, the learnt concept; secondly, the synthetic features to post-process the concept description, and thirdly, the original instantiated features to generate the bounds

on values. The practical implementation of this is discussed in Section 5.5.7.

The architecture for testing is almost the same as that for training, and is shown in Figure 5.7. The most notable difference is that the synthetic features generated by parameter space segmentation in the training stage are reused.

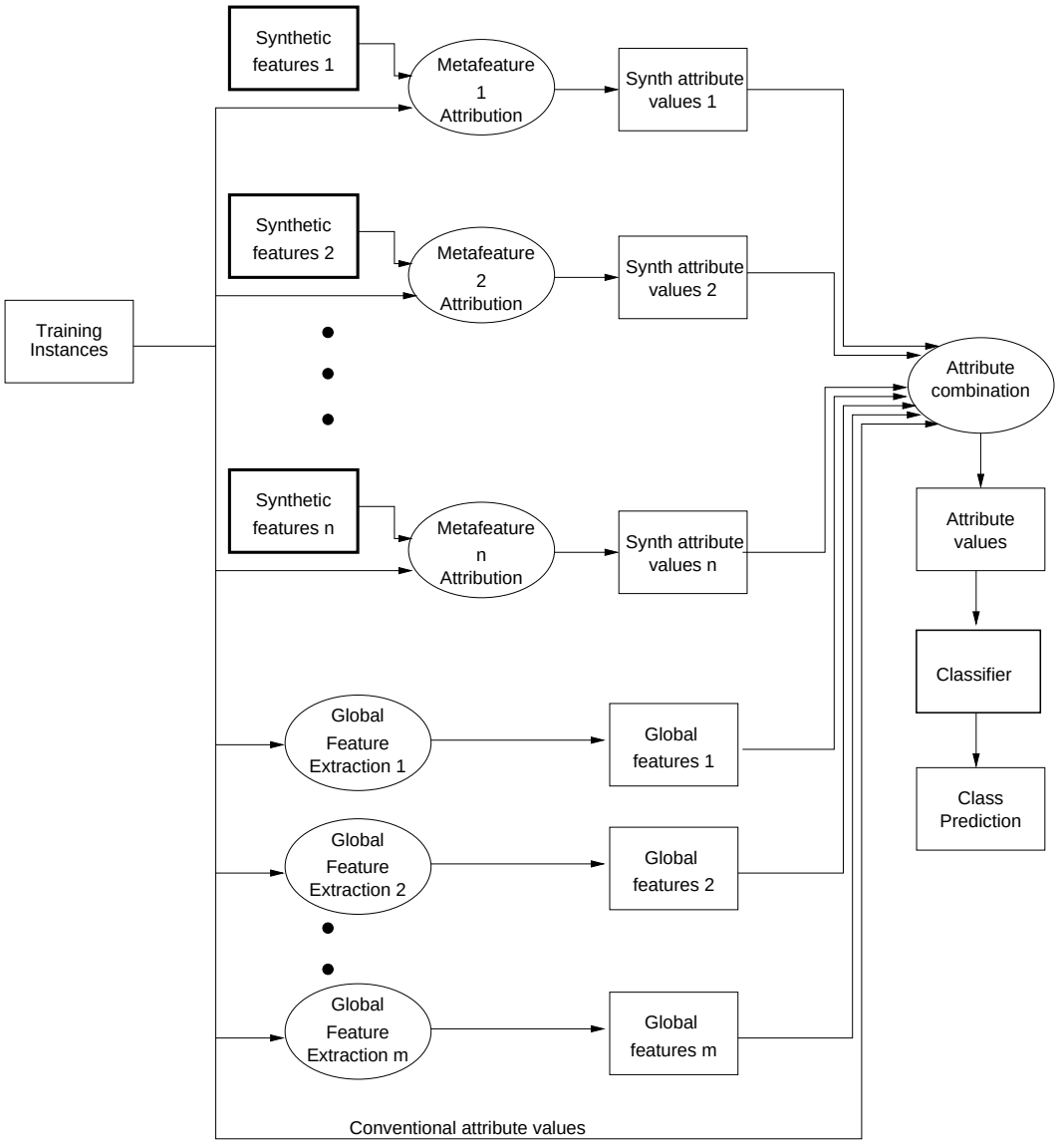


Figure 5.7: The *TClass* system: testing stage.

5.3 Signal processing

Before applying *TClass*, it is sometimes useful to use domain knowledge to manipulate the signal in some way.

5.3.1 Smoothing and filtering

Smoothing and filtering are two approaches to the same problem, but from different areas. Filtering comes from signal processing, while smoothing comes from statistics.

Filters are functions of input signal. For example, let a single channel of data be represented as $x[t]$, and the output data $y[t]$. Then any linear finite impulse response (FIR[1]) filter can be thought of as a function:

$$y[t] = \sum_{i=-j}^{k} \alpha_i x[t-i]$$

The α_i are termed the *weights* of the filter. The art and science of filter design is in the appropriate setting of these weights. For example, a simple 5th-order moving average filter might be:

$$y[t] = \frac{1}{5}x[t-2] + \frac{1}{5}x[t-1] + \frac{1}{5}x[t] + \frac{1}{5}x[t+1] + \frac{1}{5}x[t+2]$$

This averages five points to create the output. There are also non-linear filters. Non-linear FIR filters can not be expressed as a linear combination of

[1]There is another type of filter, known as the Infinite Impulse Response or IIR filter. For brevity, we will limit our discussion to FIR filters.

the input, but as some other (non-linear) function on the inputs. A simple example of a useful non-linear filter is a 5th order median filter. This is the filter represented by:

$$y[t] = \text{median}(x[t-2], x[t-1], x[t], x[t+1], x[t+2])$$

This type of filter is extremely useful for data with non-Gaussian noise, removing outliers very efficiently. A significant amount of research effort has gone into the development of appropriate filters for various purposes.

Statistics has taken a different tack to the problem: early approaches were similar to moving average filters. However, rather than using a simple moving average, the early work realised that linear regression could be used around the point we were trying to estimate; in other words, rather than simply averaging the five values around a point, a linear fit of the points, using a least squares estimate, could be used to give a better-looking result. Further, they realised that (a) if linear regression could be applied, so could other shapes, in particular splines (b) the weights for the instances used in regression could be changed. This led to further work by Cleveland [WCS92]. Friedman's super smoother [Fri84] extends Cleveland's work automatically setting parameter values based on minimising cross-validated error.

These have also been included in software. In this thesis we use the implementation provided by the statistics package *R* [Hor01] to do smoothing. In future chapters we will show the impact that using smoothing has.

Each of filtering and smoothing has their advantages. Filter design allows the use of domain knowledge to overcome domain-specific problems, while smoothing is flexible enough to be used more independently of the domain.

The main reason that smoothing is useful is that it allows the metafeature extraction functions to be simpler. Rather than a lot of effort being devoted towards making the metafeature extraction functions robust to noise, and simplify their implementation.

5.4 Learners

Learners, required to do the "backend" learning for *TClass*, are implemented through an interface to Weka, a free machine learning library [WF99]. In general *TClass* can be used with any learner. However, as previously mentioned, in order to produce comprehensible descriptions, the learner must produce a concept description that uses inequalities of single attribute values. We may also wish to consider ensemble methods of learning, discussed below.

5.4.1 Voting and Ensembles

One of the most active areas of recent research in machine learning has been the use of *ensemble classifiers*. In an ensemble classifier, rather than a single classifier, there is a collection of classifiers, each of which are built by the learner

given different parameters or data. Each classifier is run on the test instances and each classifier casts a "vote". The votes are then collated and the class with the greatest number of votes becomes the final classification.

Two approaches are popular:

1. Bagging ([Bre96]): The training set is randomly sampled with replacement so that each learner gets a different input. The results are then voted.

2. Boosting ([Sch99]): The learner is applied to the training set as usual, except that each instance has an associated weight. All instances start with equal weight. Any misclassified training instances are given greater weight. The process is repeated until (a) a maximum number of classifiers is constructed or (b) there are no incorrectly classified training instances. To make a classification, each of the individual classifiers is then applied[2], and the results are then voted.

Research indicates (in particular the excellent work in [BK99]) that bagging gives a reliable (i.e. is effective in many domains) but modest improvement in accuracy; whereas boosting produces a less reliable but greater improvement in accuracy (when it does work). The problem is that neither approach improves readability[3].

[2]Within the boosting framework, each classifier may have a different weight; not all classifiers vote with a value of 1.

[3]There has been some work on this however, also discussed in [BK99]. More recently, Freund [FM99] has introduced the concept of alternating decision trees, which incorporate boosting as part of the classifier.

With *TClass*, a third way of building an ensemble is possible if synthetic feature construction is non-deterministic (e.g. if the **RandSearch** algorithm of Figure 4.12 is used). If this is the case, each *TClass* run produces different synthetic features on the same data and hence a different classifier is produced. The outcomes of each classifier can be voted. Indeed, because *TClass* is learner-independent, the two approaches can be combined. For instance, within each run of *TClass* we could employ AdaBoost with decision trees; and then vote each of the *TClass* classifiers as well.

5.5 Practical implementation

In this section, we talk about the implementation of the *TClass* system in Java. We discuss the file formats used and the way the data is processed.

TClass consists of approximately 10,000 lines of non-comment code (approximately 23,000 lines total). It is a complex but modular and object-oriented system, the complexity attributable to the flexibility required to handle different temporal domains.

5.5.1 Architecture

TClass implements the architecture suggested in Figures 5.1 and 5.2. As a historical artifact, it also implements several other architectures (for example, the

per-class clustering approach discussed in [Kad99], and also covered in Section A.2). It also implements several baseline algorithms (for example, the naive segmentation approach, discussed in Section 6.1.1). There are classes that correspond directly to the combiners, feature extractors and learners discussed in Section 5.1. In particular, three things are implemented using inheritance; making it very easy to implement additional components:

- **Global feature extractors**: These are objects that extract aggregate global features, such as means, and global maxima and minima. Conventional attribute values (like patient age and gender) are easily implemented within this framework.
- **Metafeatures**: Metafeature objects encapsulate the extraction functions that are applied to training streams, as well as the characteristics of that metafeature's parameter space.
- **Parameter Space Segmenters**: Segementers segment the parameter space into regions marked by synthetic events. As discussed in Section 4.8, this includes undirected segmenters like K-Means and directed segmenters like the random segmenter.
- **Learners**: These are conventional attribute value learners. This is a thin wrapper around the functionality provided by Weka.

Each of these components can be mixed and matched. For example, any metafeature can be used with any segmenter.

For added flexibility, each of these components has a mechanism for setting whatever settings are useful to it. For example, if one is applying K-Means, one may wish to specify the number of clusters or ask that it be determined automatically.

5.5.2 Providing input

The input to *TClass* consists of a number of files, each describing different parts of the system. These inputs include:

- A description of the domain and the format of streams in the domain (i.e. how many channels there are, the classes in it and so on).
- A description of what metafeatures, globals and parameter space segmenters to apply.
- Training and test streams. Each stream stored in its own file.
- A list of training streams and their class labels. A test streams list may also be provided if *TClass* is being used in batch mode to estimate its accuracy.

Domain description

The first file required is a description of the domain. This consists of the classes and the types of the channels. These are usually suffixed with a ".tdd" (TClass

```
classes [ Happy Angry ] {
channel V discrete
  values "L H"
}
```

Figure 5.8: Domain description file for Tech Support Domain.

```
classes [ come thank right name read
          mine girl science maybe man ]

channel X continuous { }
channel Y continuous { }
channel Z continuous { }
channel Rotn continuous { }
channel Thumb continuous { }
channel Fore continuous { }
channel Middle continuous { }
channel Ring continuous { }
```

Figure 5.9: Domain description file for Powerglove Auslan Domain.

Domain Description). The domain description for the Tech Support domain is shown in Figure 5.8.

Figure 5.8 says there are two classes: `Happy` and `Angry`, and that there is a single discrete channel V, with a range of $\{L, H\}$.

A more complex domain description for the sign language domain is shown in Figure 5.9. In this case, there are 10 classes, and there are 8 channels. `X`, `Y` and `Z` correspond to the right hand's movement in space. `Rotn` corresponds to the roll of the hand; and `Thumb, Fore, Middle` and `Ring` correspond to measures of finger bend.

```
L
L
L
H
H
H
L
L
L
L
L
L
```

Figure 5.10: An example of a *TClass* Stream Data (tsd) file.

Stream data files

Each stream (and hence each training or test instance) is stored in an individual file; typically in a `data` subdirectory. So, for example, the first instance from the Tech Support domain s_1, might be stored in the file `data/s1.tsd`. The suffix ".tsd" stands for *TClass* Stream Data. The contents of `data/s1.tsd` are shown in Figure 5.10.

This is not a particularly interesting example. The first few lines of one stream from the sign recognition domain is shown in Figure 5.11. Rather than a single value on each line, there are 8, one corresponding to each channel. This tells us, for instance, that to start with, the x position is -0.023 (i.e. to the right of the body), and by the fifth frame, it has moved closer to the centre of the body (i.e. 0.000).

```
-0.023  0.015  0.000  0.000  0.250  0.750  0.500  0.000
-0.023 -0.015  0.000  0.000  0.250  0.750  0.500  0.000
-0.023 -0.015  0.000  0.000  0.250  0.750  0.500  0.000
-0.008 -0.039  0.000  0.083  0.250  0.750  0.500  0.000
 0.000  0.000  0.000  0.083  0.250  0.750  0.500  0.000
...
```

Figure 5.11: An example of a *TClass* Stream Data (tsd) file from the sign language domain.

```
data/s1.tsd Happy
data/s2.tsd Angry
data/s3.tsd Angry
data/s4.tsd Happy
data/s5.tsd Happy
data/s6.tsd Angry
```

Figure 5.12: An example of a *TClass* class label file from the Tech Support domain.

Class label files

In order to tell the learner what the class of each file is, a class label file (usually ending with ".tsl" for training data and ".ttl" for testing data; although this can be modified at the command line) is also provided. The format for this file is simple, and an example is shown in Figure 5.12. Each line consists of a filename (relative to the current directory, or alternatively, given as an absolute path), followed by a space and then the class label. The class label must be one of the classes listed in the domain description file.

```
globalcalc {
  global V-mean mean {
    channel V
  }
}
metafeatures {
  metafeature loudrun rle {
    channel V
    minrun "1"
    limitvalues " H "
  }
}

segmentation {
  segmenter loudrun directed {
    metafeature loudrun
    numTrials "10000"
    dispMeasure chisquare
  }
}
```

Figure 5.13: Component description file for Tech Support domain.

Domain application file

In order to decide which components are to be used for a particular problem domain, *TClass* uses an application file (usually suffixed with a ".tal" – short for *TClass* Application List). This describes what global features, metafeatures and parameter space segmenters to use for a particular domain. An example component description file for the Tech Support domain is shown in Figure 5.13[4].

The first part of the file in Figure 5.13 describes the global feature extractors.

[4]NOTE: Because the terminology has changed and to avoid confusion, we have modified the file slightly and replaced all the old terminology with the new terms. The actual file is identical structurally but uses different terms.

The first is a mean volume level (L is treated as 0 and H is treated as 1 – this is effectively the same as calculating the percentage of time the conversation volume is high). The format for the entries in the global section is:

```
global <attribute name> <feature type> {
  <parameter> <value>
  ...
  <parameter> <value>
}
```

Figure 5.13 shows a typical example of a global declaration. It creates a global attribute called `V-mean`. It is uses a `mean` global feature extractor (other types of global feature extractors would include `min` and `max`). The mean global feature extractor accepts the parameter `channel` which tells it which channel to extract the mean for. The channel must be listed the in the domain description file. More information about globals can be found in Section 5.5.3.

The next section describes which metafeatures to use. Each metafeature application is described in a section like:

```
metafeature <metafeature name> <metafeature type> {
  <parameter> <value>
  ...
  <parameter> <value>
}
```

The metafeature's name is later used in the segmentation sections. The type governs what type of metafeature will be applied. For instance, in Figure 5.13, the `rle` (short for run-length encoding) metafeature is a straightforward generalisation of the LoudRun metafeature. In this case, we are looking for "runs" on the channel V that last for a minimum of length 1. Also we are only interested in runs of high-volume, not low-volume. Hence we limit our interest to runs of "H"s.

The final section is for setting up parameter space segmentation. Typically, there will be equal number of metafeature applications and parameter space segmenters. The segmenter specifies which segmenters to apply to which metafeatures. The general format is:

```
segmenter <attribute prefix> <segmenter type>  {
   <parameter> <value>
   ...
   <parameter> <value>
}
```

The attribute prefix is the name that will be used for attribute values (although a number will be appended indicating which centroid number it is). The segmenter type governs whether we are using k-means (kmeans), expectation-maximisation (em) or directed segmentation (directed). The segmenters take one required parameter: the metafeature to apply the segmentation to. Hence we are building a segmenter for the metafeature `loudrun`, which is a directed

segmenter (i.e., the random search algorithm described in Section 4.12). We specify that it should try 10000 random subsets for centroids; and we wish to use the χ^2 disparity measure.

This describes all of the inputs into the *TClass* system. We now discuss some of the available components.

5.5.3 Implemented global extractors

The available global extractors include:

Duration

For some problem domains, the duration (i.e. the number of frames in an instance) is important attribute for a "first cut" at classification. This particular global extractor does not take any parameters.

Mean

This calculates the mean value of a channel. It assumes the channel is continuous. It takes only one parameter, the channel. If the channel is not provided, it uses the first channel defined in the domain description file.

Max and Min

These global feature extractors calculate the minimum and maximum of a channel. They take only one parameter, which is the channel to calculate the maximum or minimum for. As before, if no channel is specified, it assumes the first channel defined in the domain description file.

Mode

This calculates the mode of a channel (i.e., the most frequently observed value). It can be used for either continuous or discrete values; but is typically used for discrete values. As before, if no channel is specified, it assumes the first channel defined in the domain description file.

First

This accepts the first observed value on the channel. This is a "back-door" way to implement conventional global attributes. By simply adding the conventional attributes to the first line of each file, this can be used to add conventional attribute values within *TClass*. A better way to implement this functionality would be to have this global read values from a file. As before, if no channel is specified, it assumes the first channel defined in the domain description file.

5.5.4 Implemented segmenters

Segmenters try to create prototypical synthetic features from the instantiated features extracted from data. All segmenters in *TClass* accept a setting **meta-feature** that describes which set of instantiated features are to be segmented.

K-Means

K-Means is a simple algorithm, the pseudocode for which can be found in Figure 4.11. However, initial settings for K-means (e.g. initial cluster membership and number of clusters) are set using problem-specific information. The K-Means algorithm implementation is largely historical, and is of limited practical use in the current version of TClass, its role being largely replaced by the E-M algorithm.

In our implementation, K-Means accepts the following parameters:

- **numClusters**: The number of clusters to create. It also accepts the value "auto". Since K-Means has no mechanism for estimating the number of clusters, some alternative means must be used. Using "auto" works out the number of clusters as the average number of instantiated features of the type we are interested in per training stream. For instance, if we look at Table 4.2, we see that there are a total of 12 instantiated features from 6 training streams, and hence it would calculate that there are $\frac{12}{6} = 2$ clusters of data. Default value is "auto".

- **initialdist**: Initial distribution of points (i.e., which clusters the points end up in) can be accomplished in two ways: random, where each point is allocated to a random cluster, or ordered. In the ordered method, just as we "guessed" at the number of clusters using the average number of instances, so we can also allocate cluster membership based on the order of events. For instance, if the number of clusters is calculated automatically to be two, and there are two events, then if over all of the data we put the first instantiated feature detected into the first cluster, and the second into the second cluster, then that would be a reasonable initial distribution of instantiated features. Default value is ordered.

- **closeness**: When computing the distance of instances for the evaluation of membership measures, should the distance from the centroid to the instantiated feature being considered be used, or should the distance to the nearest point belonging to the cluster be used? Default value is distance from the centroid.

Expectation-Maximisation

Expectation-Maximisation can be thought of as the K-Means algorithm augmented with a means of evaluating the number of clusters. The approach begins by attempting to cluster the data into two clusters, and then increases to three. If, on some holdout set of unseen data (or alternatively, using cross-validation) it performs better than two clusters, then three clusters are used. This process

is repeated for four clusters, and so on until an optimal number of clusters is found.

We do not really have an implementation of the E-M algorithm. Rather, we rely on the one supplied with Weka, with some minor modifications (namely, 3-fold cross-validation is used for assessing the number of clusters, rather than 10-fold cross-validation). It accepts the following settings:

- **numClusters**: The number of clusters to create. It also accepts the valued "auto". "auto" uses the expectation-maximisation method to determine the number of clusters. If you don't use "auto" then it is equivalent to running a standard K-means algorithm.

Random Segmentation

This is an implementation of the algorithm discussed in Section 4.12. It accepts the following parameters:

- **numTrials**: The number of random trials to run. Default value is 1000.
- **minCent**: The minimum number of centroids to consider. Default value is 2.
- **maxCent**: The maximum number of centroids to consider. Default value is 8.

- **clustBias**: The algorithm currently selects a random number between *minCent* and *maxCent* based on a linear probability distribution. In other words, the probability of choosing n centroids is $(n - minCent)$ times the probability of choosing *minCent* centroids. Strictly speaking, this is incorrect, since there are far more subsets with, 8 instances than there are with 2 instances. In fact, it follows a binomial distribution – and for cases where there are far more instances than centroids, it approximates a factorial distribution. To compensate for this, one can set a cluster bias b, so that the probability of choosing a subset with n instances is proportional $(n - minCent)^b$. Default value is 1 (i.e. linear).

- **dispMeasure**: The disparity measure to use. Possible values are gainratio, gain and chisquare.

5.5.5 Implemented metafeatures

When implementing *TClass* a basic set of metafeatures were implemented that are meant to be universal. However, it is useful to have additional settings to tune the metafeatures to particular purposes. For example, all of the basic metafeatures are single-channel (that is, they only look at a single channel of information at a time). It is therefore necessary to designate which channel the metafeature should be applied to.

Increasing

The Increasing metafeature detects when a continuous signal is increasing. It operates on continuous values only. The output from Increasing is a list of tuples consisting of four parameters:

- **midTime**: The middle point temporally of the event. May be expressed in either frame number or relative representation (where the beginning of the stream is 0 and the end is 1); depending on the **useRelativeTime** setting.
- **average**: The average value of the event. This value is expressed in terms of the data type of the channel. If the **useRelativeHeight** parameter is true then this average is expressed as height above or below the mean of the channel for this training instance.
- **gradient**: This is the rate of change of the channel. To be exact, a line of best fit is fitted to the increasing interval, and the gradient of the line is calculated.
- **duration**: This is the length of the increasing interval. May be expressed in either number of frames or in a relatively (where the whole stream has a duration of 1) depending on the **useRelativeTime** setting.

It operates on a single channel. It accepts the following settings:

- **channel**: Which channel to extract increasing intervals from. Default value is the first channel defined in the domain description file.

- **exceptions**: Because of noise, it may occur that there are two intervals of increase separated by one noisy sample. Were it not for the noise, this would be considered one increasing interval. We may wish to allow a certain number of exceptional samples which do not meet the strictly increasing property. Default value is 1.

- **useRelativeTime**: Time measures (in particular duration and midtime) can be expressed either in absolute terms (i.e. if it happens at the 19th frame, it occurs at time 19), or relative terms (if it occurs at the 19th frame, and the whole stream is 38 frames long, then it happens halfway along the stream). Using relative time improves robustness to linear temporal variation, but loses absolute temporal information. Default value is false.

- **useRelativeHeight**: Just as for time measures, average values can be expressed in absolute (i.e. average value for this interval is 1.3) or relative terms (the average for the increasing interval is 0.3 higher than the mean of the channel). Default value is false.

- **minDurn**: This is the shortest duration signal (in frames) that will be accepted as an increasing interval. If there is a increasing interval shorter than this, it is not considered. Default value is 3 frames.

Decreasing

Decreasing is identical to Increasing in almost every way. It accepts the same parameters and produces the same outputs, with one obvious exception: it tries to isolate intervals of decrease rather than increase. This means that the gradient parameter is negative, not positive.

Plateau

The Plateau metafeature detects when a continuous signal is not changing, give or take noise. The output from Plateau is a list of tuples consisting of three parameters:

- **midTime**: This is as for Increasing.
- **average**: This is as for Increasing.
- **duration**: This is as for Increasing.

It operates on a single channel. It accepts the following settings:

- **channel**: This is as for Increasing.
- **exceptions**: This is as for Increasing. However, because it can be trickier to detect plateaus the default is higher. Default value is 2.
- **useRelativeTime**: This is as for Increasing.

- **useRelativeHeight**: This is as for Increasing.
- **minDurn**: This is as for Increasing; however, because it is difficult to detect if the signal is "flat", a longer interval is required. Default value is 4 frames.

LocalMax

The LocalMax metafeature detects when a signal has a local maximum; i.e. a point in time when just prior and just after that point the signal is less. It should not be confused with the global maximum and minimum functions that operate on the whole channel. It produces instantiated feature tuples consisting of the following parameters:

- **time**: This is as for the **midTime** parameter for the Increasing metafeature.
- **value**: The height of the maximum. If **useRelativeHeight** is used, then the height above the mean for the channel is given.

It operates on a single channel. It accepts the following settings:

- **channel**: This is as for Increasing.
- **useRelativeTime**: This is as for Increasing.
- **useRelativeHeight**: This is as for Increasing.

- **windowSize**: This controls the minimum "width" of the maximum. It is an odd positive integer. A value of 3, for instance, on a channel c would mean that $c[t-1] < c[t] > c[t+1]$. A value of 5 would mean that $c[t-2] < c[t-1] < c[t] > c[t+1] > c[t+2]$. In general, if the window size is w then this means that for a point to be considered a maximum $c[t - \lfloor \frac{w}{2} \rfloor] < ... < c[t-1] < c[t] > c[t+1] > ... > c[t + \lfloor \frac{w}{2} \rfloor]$. The default value is 3 (i.e., the values immediately to the left and right must be less than the current value).

LocalMin

LocalMin is identical in most respects to LocalMax, except that it detects local minima. Hence all signs must be inverted. For example, a point is considered a local minimum for a window size w if: $c[t - \lfloor \frac{w}{2} \rfloor] > ... > c[t-1] > c[t] < c[t+1] < ... < c[t + \lfloor \frac{w}{2} \rfloor]$.

RLE

Run-length encoding (RLE) is a process where a single value repeated several times is encoded as that value, its starting point and its duration. For example, the string "ABBBBBBCCCCCAAAAA" might be encoded as A1B6C5A5 (which implicitly encodes starting time, since the string is in order). RLE is the generalisation of the LoudRun metafeature. RLE instantiated features consist of the following tuple:

- **value**: The value that is repeated.
- **start**: The frame at which that sequence of repetitions begins.
- **duration**: The number of frames that the value remains the same as the starting value.

It operates on a single channel. It accepts the following settings:

- **channel**: Which channel to extract runs from. Default value is the first channel defined in the domain description file.
- **minrun**: The minimum run of identical values for a run to be of interest. Default value is 2 (i.e. runs of length 1 don't count).
- **limitvalues**: In some cases, we are not interested in runs of all possible values of a channel. For instance, in the Tech Support domain, we were only interested in runs of high-volume conversation, not low volume ones. Hence we can constrain our interest to only some possible values and not all of them.

5.5.6 Developing metafeatures

Metafeatures can be easily implemented, usually in less than 200 lines of code. To add metafeatures, they must implement the interface of the Java class `MetafeatureI`, which has a total of 8 methods. Most of these are housekeeping functions

(e.g. `String name()` to return a metafeature's name). The most important are `setParam(String param, String value)` to set the various settings above (e.g. **useRelativeTime**, etc), and `EventVec findEvents(Stream s)` that applies the metafeature extraction function to a training stream and returns a vector of events (i.e. instantiated features).

5.5.7 Producing human-readable output in *TClass*

One of the advantages of metafeatures is that they provide a mechanism for generation of human-readable descriptions of temporal processes. How then do we fit this into the *TClass* architecture?

Firstly, we can not produce human readable descriptions without making some assumptions of the learner: it must produce a classifier that expresses the learnt concept as bounds on attribute values. In other words, each part of the concept is expressed as a test on a single attribute value being less than, greater than or equal to a particular value[5]. This is a fairly wide family of learners and includes decision trees, decision lists, stumps and ensembles of any of these.

We can postprocess the generated classifier by checking for any temporal attributes[6]. We can then use an attribute relabelling approach to create a comprehensible description using the synthesised feature as a substitute for the instantiated feature as discussed in Section 4.10.2. This obviously requires the

[5]Of course, less than or equal to and greater than or equal to are also acceptable.
[6]If it is a global attribute, of either the aggregate or conventional type, we leave it alone.

synthesised features. As discussed in that section, we can also use the instantiated features to create useful bounds.

Although we do produce a classifier intended for human understanding, it is *not* the one used to classify. It is an approximation of the learnt concept, rather than the learnt concept itself. Experts exhibit similar behaviour ([Sha88] and [CJ89]) – very few can express their expertise completely enough for someone else to understand what they have learnt totally; but rather they provide an approximation for what has been learnt[7].

To describe how attribute relabelling works, let the synthetic features be denoted by the notation met_n, where met is a metafeature applied to the data and n is the attribute value based on the relative membership of the nth synthetic feature. If the classifier contains a test of the form $met_n > c$ this means that the classifier checks for an instantiated feature that has a relative membership for the nth synthesised feature exceeding c. Conversely, if it has a predicate of the form $met_n \leq c$ it is checking the absence of such an instantiated feature.

Attribute relabelling in this manner is easy to implement as a sequence of string substitutions on the output from the learner. Figure 5.14 shows the actual classifier produced by *TClass* on the Tech Support domain. Using this information, together with the information about the instantiated features, we can convert this to the form showed in Figure 5.15.

[7]The former paper is extremely interesting – it shows that in many cases, experts don't even agree with their own diagnoses after sufficient time has passed, and they disagree with their own rules. Furthermore, agreement between the expert system developed by one expert and another expert was extremely low – less than 40 per cent.

```
--- Cluster centroids ---
V-loudrun_0: Cluster centroid is: LoudRun: start = 9 durn = 3
 SDs are [ 4.78 1.59 ]
V-loudrun_1: Cluster centroid is: LoudRun: start = 3 durn = 1
SDs are [ 2.13 0.59 ]
V-loudrun_2: Cluster centroid is: LoudRun: start = 3 durn = 3
SDs are [ 1.59 1.59 ]

--- Learnt Classifier ---
PART decision list
------------------

V-loudrun_0 <= 0: Happy (3.0)

: Angry (3.0)

Number of Rules  :      2
```

Figure 5.14: Learnt classifier for Tech Support domain after running *TClass* on it.

```
PART decision list
------------------

IF V HAS NO LoudRun: start = 9 durn = 3 (*1) THEN Happy (3.0)

: Angry (3.0)

Number of Rules  :      2

Event index
-----------
*1: loudrun
   start=9.0 r=[9.0,12.0]
   durn=3.0 r=[3.0,4.0]
```

Figure 5.15: Post-processing Figure 5.14 to make it more readable.

Figure 5.15 shows the post-processed form of Figure 5.14. For simplicity, the information on the bounds has been separated to a separate event index. The event index shows the range of bounds for the start and the duration of the LoudRun.

5.6 Temporal and spatial Analysis of *TClass*

How long will *TClass* take to learn and how much memory/space will it take in order to calculate the results? A rather informal analysis of each will be presented. First, some notation: Let n be the number of streams in the training set. Let m be the number of metafeatures we are applying to the domain. Furthermore, let us assume that applying a particular metafeature will on average generate i instantiated features. Also, assume that on average, the length of the streams is t.

The instantiated feature extraction consists of an inner loop that examines each of the n streams in turn. Within that inner loop, the function *extract* is called for each instance. Assuming that the *extract* function is linear in the length of the stream (i.e. is $O(t)$)[8], then the feature extraction will take $O(tn)$ time. However, the function is called once for every metafeature, and hence the extraction stage is $O(tnm)$.

As to space, under the previous assumptions, the amount of data to be stored

[8]This is a fairly realistic assumption. All of the implemented metafeature extraction functions are linear.

is to be stored is $O(nim)$: for n streams, and for m metafeatures, i instantiated features must be stored.

Synthetic feature construction is called once for each metafeature. It is flattened into a single layer, but the amount of data for each metafeature is still $O(ni)$. Consider the random search algorithm. At each stage, it chooses a random subset of points with some upper bound (in the default case eight). It then compares each point (of which there are $O(ni)$) to each of the elements of the subset. This operation is repeated a fixed number of times, so this is still $O(ni)$. Since it is called once for each metafeature, the total amount of time is also $O(nim)$.

Since there is some upper bound on the number of regions that will be produced, then there will be $O(m)$ centroids which need to be stored.

Then there is the attribution stage. For each instance, of which there are n, i instances (on average) with m metafeatures must be compared. This involves looking against a set of centroids with an upper bound. Hence this too is an $O(nim)$ operation.

The data storage requirements are $O(nm)$, since for each instance, there are a certain maximum number of metafeatures and a maximum number of centroids per metafeature.

The final stage is the learning stage. However in general, we do not know what the amount of time for the learning algorithm is. Let us assume that the

learning algorithm depends linearly on the number of attributes and the number of instances. Then in this case, there are n instances, each with $O(m)$ features, so the learner will take $O(nm)$ time.

The global feature extraction will generate $O(ng)$ features. Since many global features depend on things like working out the mean, each one may take up to t time. Hence the total time is $O(ntg)$.

Hence finally, the total time is $O(tnm) + O(nm) + O(ntg) + O(nim)$, or after simplifying, it is $O(ntm) + O(nim) + O(ntg)$. As for the space, the most space is required to store the data is $O(ntm) + O(nim) + O(ntg)$.

This is good. It means that the total time and space used is linear in five components:

- The number of training instances.
- The number of metafeatures applied in the domain.
- The average length of each training instance.
- The average number of metafeatures extracted from each instance.
- The number of global variables.

5.7 Conclusion

TClass is a practical, working system for weak temporal classification. In this chapter we discussed the design and implementation of *TClass*. In the remaining chapters, we will look at the application of *TClass* to a number of practical problems.

Chapter 6

Experimental Evaluation

After discussing the implementation of *TClass*, it is now applied to several datasets to evaluate its behaviour.

This chapter begins with a discussion of what the issues to be investigated are and how the investigation will proceed.

TClass is tested on two artificial domains: the cylinder-bell-funnel domain, and a new artificial classification problem, the *TTest* domain. Using the lessons learnt on the artificial datasets, two real datasets are then tested: Auslan sign recognition and ECG analysis.

6.1 Methodology

There are many questions that can be asked about *TClass*' performance such as:

- How accurate is *TClass* on classification tasks?
- How comprehensible are the results and definitions generated by *TClass*?
- How much data does *TClass* need to learn concepts (i.e., data efficiency)?
- How does *TClass* compare to other learning methods in terms of performance, comprehensibility, execution time and data efficiency?
- How do the the settings of *TClass*' parameters (eg. number of random subsets to use, whether we use smoothing or not, etc.) affect its performance?
- How do different *TClass* back end learners perform?

6.1.1 Practical details

In order to answer the above questions, some decisions about practical tests need to be considered.

Metafeatures

Since *TClass* is novel, in this first series of experiments, it was decided the simple set of metafeatures discussed in the previous chapter would be used (increasing, decreasing, plateau, local maximum and local minimum). This would allow us to focus on the algorithm itself and make observations about the generalisability of these simple metafeatures. Further, these simple metafeatures provide a lower bound on performance; more complex metafeatures could only potentially improve performance (otherwise, temporal classifiers could revert to simple metafeatures).

Accuracy measurement

To measure accuracy, single runs of cross validation were used (either 5-fold or 10-fold depending on the data set). Stratified cross-validation was considered, however, the quantity of the data and the processing time are such that this would have resulted in overly long computation times.

Backend learners

TClass relies on a propositional learner at the backend. We consider four propositional learners: J48 (the Weka equivalent of `c4.5`), PART (the Weka equivalent of `c4.5rules`), IB1 (nearest neighbour algorithm) and Naive Bayes (with the Laplace adjustment to prevent zero probabilities and Fayyad-Irani [FI93] based

discretisation).

Ensemble learners

AdaBoost and Bagging can be incorporated as part of the propositional learner – that is within the *TClass* framework. We will consider both AdaBoost and Bagging, using J48 as the base learner as possible backends.

Voting

If we use a means for non-deterministic parameter space segmentation, then every time we run *TClass* we are going to get a different set of features. Hence we can vote these results. As discussed in Section 5.4.1, this be combined with boosting and/or bagging.

Smoothing

As outlined in Section 5.3.1, smoothing and filtering can be a useful tool for preprocessing data. We consider Friedman's super-smoother [Fri84] in domains where it is appropriate (i.e. high-noise).

Baseline algorithms

In order to evaluate the effectiveness of our learners, it is useful to compare the performance of *TClass* against other temporal learners. We consider:

Naive segmentation One approach that has been previously explored and employed (e.g. [Kad95]) is naive segment-based feature extraction. This can be thought of as downsampling to a fixed size. Each channel is divided into n segments temporally. For example if $n = 5$ and the stream is 35 frames long, then the first 7 frames of each channel will be "binned" in first segment, the second 7 in the next segment and so on. The mean of each segment is calculated, and this becomes an attribute.

Hence, if there are c channels, this will generate nc features. These can be used as input to a conventional attribute-value learner[1]. Four possible values of n: 3, 5, 10, 20 will be considered. In the following experiments, we also consider several different learners for the segmented attributes: J48, PART, IB1, AdaBoost with J48 and bagging with J48. Unless otherwise indicated the *best* result amongst the different learner-segment (there are 20 possible) combinations are presented. This does place a bias in the results towards the segmented learner, since it has more opportunities to randomly fit the test set. However, this was thought the fairest way to compare against *TClass*'s performance, since an average over all learners and segment counts was not fair either.

[1] We have not found references to this as a general technique. However it seemed so obvious that it was not considered worthy of publication. Other researchers such as [Geu01] have since cited us for the algorithm.

Hidden Markov Models We employed the implementation of hidden Markov models provided by HTK (the HMM Tool Kit) [YKO+]. Each class is modelled using the same topology. The following number of states are considered: 3, 5, 10, 20; and the following topologies: left-right, left-right with 1 skip allowed and ergodic. Each state in a left-right HMM allows transitions only to itself or the next state – hence each state must be visited. to A 1-skip model is a left-right model that also allows the transition from state i to state $i+2$, effectively allowing to skip certain states. Ergodic HMMs allow all possible transitions. HMMs that include the raw data as well as both the raw data and the first derivative are considered. As with the naive segmenter, unless otherwise indicated the *best* results, over all the topologies, states and both raw data and raw data with first derivative (a total of 32 possibilities) were reported. It should be noted this is biased in favour of hidden Markov models.

6.2 Artificial datasets

Now to the first tests. There are several reasons why artificial datasets are useful. These include:

- Evaluation is simplified. For example, the induced concept can be compared with the correct concept. It can also be used to explore factors of interest such as noise, etc.
- There is a chicken-and-egg problem as far as temporal learners and datasets

are concerned. Because there are few (if any) generic temporal learners, people do *ad hoc* feature extraction themselves. For example, an examination of the UCI repository ([MM98]) reveals at least seven datasets which are inherently temporal in nature, but where the researchers did the feature extraction themselves and the raw data is not available[2].

- In order to compare our results with other researchers.

6.2.1 Cylinder-Bell-Funnel - A warm-up

The first artificial domain we will be considering is a simple one, but one that has been used and explored by other researchers.

The artificial cylinder-bell-funnel task was originally proposed by Saito [Sai94], and further worked on by Manganaris [Man97]. The task is to classify a stream as one of three classes, cylinder (c), bell (b) or funnel (f). Samples are generated as follows:

[2]These datasets are: arrythmia, audiology, bach chorales, echocardiogram, isolet, mobile robots, waveform.

$$
\begin{aligned}
c(t) &= (6+\eta)\cdot\chi_{[a,b]}(t)+\epsilon(t)\\
b(t) &= (6+\eta)\cdot\chi_{[a,b]}(t)\cdot(t-a)/(b-a)+\epsilon(t)\\
f(t) &= (6+\eta)\cdot\chi_{[a,b]}(t)\cdot(b-t)/(b-a)+\epsilon(t)\\
\chi_{[a,b]} &= \begin{cases} 0 & t<a,\\ 1 & a\le t\le b\\ 0 & t>b \end{cases}
\end{aligned}
$$

where η and $\epsilon(t)$ are drawn from a standard normal distribution $N(0,1)$, a is an integer drawn uniformly from $[16,32]$ and $b-a$ is an integer drawn uniformly from $[32,96]$. Figure 6.1 shows instances of each class. The cylinder class is characterised by a plateau from time a to b, the bell class by a gradual increase from a to b followed by a sudden decline and the funnel class by a sudden increase at a and a gradual decrease until b. Although univariate (i.e., only has one channel) and of a fixed length (128 frames), the CBF task attempts to characterise some of the typical properties of temporal domains. Firstly, there is random amplitude variation as a result of the η in the equation. Secondly, there is random noise (represented by the $\epsilon(t)$). Thirdly, there is significant temporal variation in both the start of events (since a can vary from 16 to 32) and the duration of events (since $b-a$ can vary from 32 to 96).

266 instances of each class were generated. For ease of comparison with previous results, 10-fold cross validation was used.

We have previously looked at the cylinder-bell-funnel domain [Kad99]. In

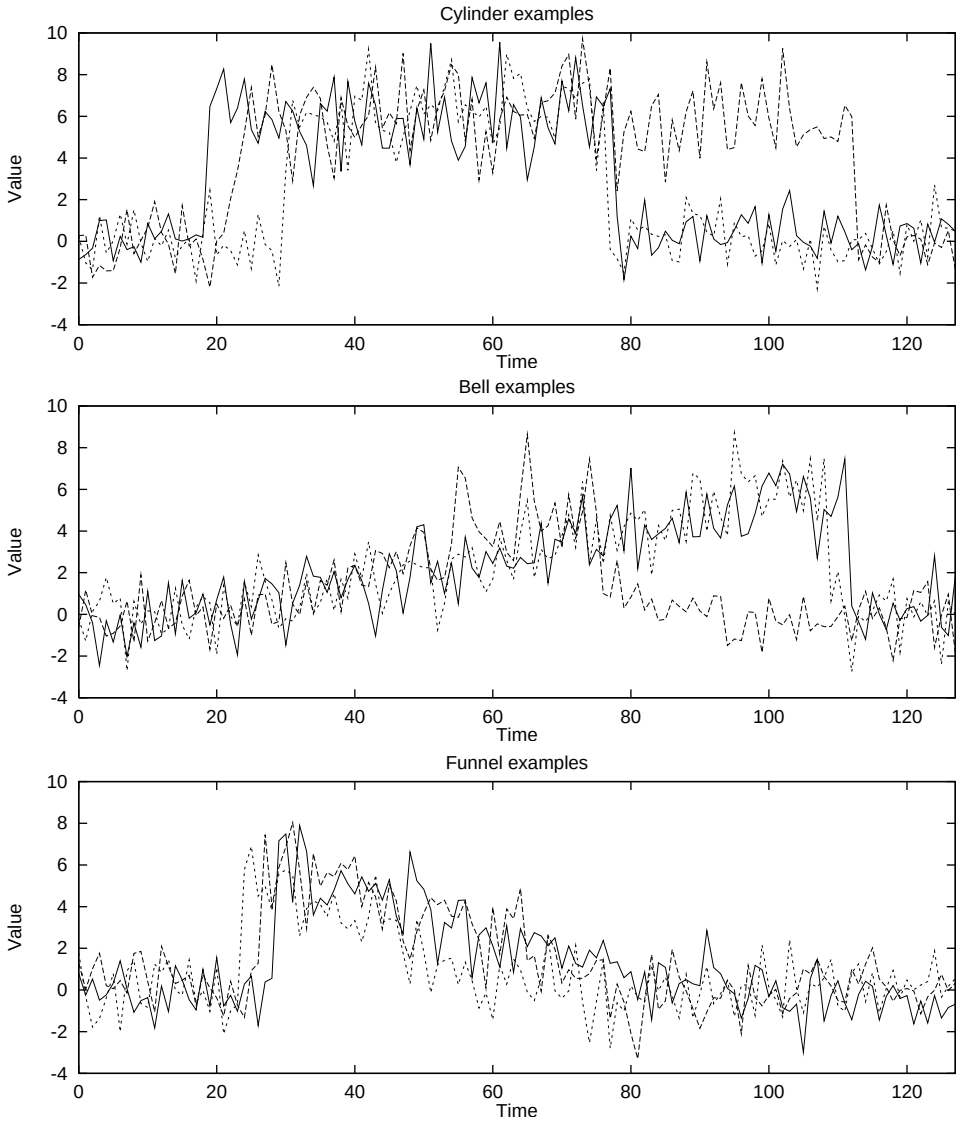


Figure 6.1: Cylinder-bell-funnel examples.

that work, we compared an earlier version of *TClass* (see Appendix A) against naive segmentation and showed that we performed significantly better. Table 6.1 shows the table of results from that work.

As an initial test, we ran all the learners, with and without smoothing. In all tables, the bounds represent the standard error of the mean (the standard

Features/Learner	CBF
TClass/Naïve Bayes	3.67 ± 0.61
Segments/Naïve Bayes	6.20 ± 0.67
TClass/C4.5	$\mathbf{1.90 \pm 0.57}$
Segment/C4.5	2.41 ± 0.48

Table 6.1: Previously published error rates on the CBF domain.

Approach	Unsmoothed	Smoothed
TClass with J48	2.28 ± 0.69	1.14 ± 0.24
TClass with PART	4.56 ± 0.82	1.77 ± 0.36
TClass with IBL	56 ± 1.24	42.78 ± 1.78
TClass with Bagging/J48	1.9 ± 0.48	1.27 ± 0.43
TClass with AdaBoost/J48	1.39 ± 0.33	1.01 ± 0.24
TClass with Naive Bayes	3.16 ± 0.70	2.78 ± 0.61
Naive Segmentation	$\mathbf{0 \pm 0}$	$\mathbf{0 \pm 0}$
Hidden Markov Model	$\mathbf{0 \pm 0}$	0.38 ± 0.18

Table 6.2: Error rates using the current version of *TClass* on the CBF domain.

deviation divided by the number of of folds).

The above table shows the best of the performers for the naive segmentation and hidden Markov models. The complete results for naive segmentation and HMMs for unsmoothed classification are shown in Tables 6.3 and 6.4.

Approach	Segments			
	3	5	10	20
J48	7.47 ± 0.90	3.16 ± 0.54	1.90 ± 0.37	1.27 ± 0.47
PART	8.10 ± 0.67	2.78 ± 0.61	2.15 ± 0.51	1.52 ± 0.69
IB1	6.58 ± 0.85	2.28 ± 0.67	$\mathbf{0.00 \pm 0.00}$	$\mathbf{0.00 \pm 0.00}$
AB	6.84 ± 0.67	2.03 ± 0.45	1.27 ± 0.47	1.01 ± 0.47
Bag	6.84 ± 0.78	2.28 ± 0.61	1.90 ± 0.45	1.27 ± 0.51

Table 6.3: Error rates for the naive segmentation algorithm on the CBF domain.

Topology	Raw	Raw + Derivative
lr-3	7.85 ± 0.87	5.06 ± 0.62
lr-5	0.25 ± 0.16	$\mathbf{0.00 \pm 0.00}$
lr-10	0.25 ± 0.16	$\mathbf{0.00 \pm 0.00}$
lr-20	0.00 ± 0.00	$\mathbf{0.00 \pm 0.00}$
lrs1-3	65.57 ± 1.22	60.38 ± 1.23
lrs1-5	0.51 ± 0.27	32.15 ± 1.32
lrs1-10	0.63 ± 0.20	$\mathbf{0.00 \pm 0.00}$
lrs1-20	0.13 ± 0.12	0.13 ± 0.12
er-3	36.20 ± 1.43	5.82 ± 0.82
er-5	36.71 ± 1.23	36.20 ± 1.53
er-10	36.71 ± 1.23	36.20 ± 1.53
er-20	36.71 ± 1.23	36.20 ± 1.53

Table 6.4: Error rates of hidden Markov models on CBF domain.

The results are very surprising. For example, one surprise is the performance of the baseline algorithms: nowhere else in the literature has their performance been compared. It's surprising therefore to see them perform amongst the best and they even do better than previously published results (including our own, which were previously the best).

It turns out that the dataset may be too simple to test the capabilities of our system. This makes it difficult to evaluate accuracy and other phenomena. Hence we need to construct a dataset that is (a) more difficult and (b) more typical of the domains that we are interested in.

Let us suggest why the two controls performed so well – they are capturing the natural aggregate nature of the data. There is only one real event in each of the three classes; and all of these events are of extended duration – at a bare minimum the one event characterises itself over 25 per cent of the data (32 frames)

and possibly as much as 75 per cent of the data (96 frames). On average, the one event therefore occupies 50 per cent of the channel. Although the underlying signal is masked by the noise; the noise has a Gaussian distribution: exactly the type of noise that aggregate approaches (such as naive segmentation and HMMs) are designed to exclude. Further investigation reveal an interesting result in the HMMs: the self-transition probability for each state was almost always approximately 0.8. This means the hidden Markov model spends approximately the same time in each state. Some simple mathematics show that if $a_{ii} = 0.8$ we stay in each state for about 7 time steps, very close to the size of a segment used by the naive segmenter (6.25 timesteps). It seems that the HMM defaulting to a naive segmentation approach: equal size regions; with a mean and an average for each region functioning as a probabilistic model.

The above results might lead one to despair of the performance of *TClass*, since it doesn't appear to compete that well in terms of accuracy. However, if one's objective becomes the relentless pursuit of accuracy, then *TClass* can be used with voting to improve accuracy. The above experiment was therefore repeated with 10 repetitions of *TClass* with an AdaBoost backend, and the outcomes voted. 100 per cent accuracy was obtained. Indeed, 100 per cent 10-fold cross-validated accuracy was obtained with as few as 3 voters – the minimum number of possible voters.

Comprehensibility

Are the results produced using *TClass* comprehensible? In this particular case, we can compare the induced to the real definitions. Output from J48 and PART, the two learners that produced comprehensible classifiers were examined. It is also compared against the definitions generated by naive segmentation.

For naive segmentation, almost identical trees were generated by different folds. An example of such a tree is shown in Figure 6.2. Examination of the trees reveals that the average value in the fifth segment (time 32 to 38) is important. this is a time guaranteed to be in the "characteristic" part of the signal, since the latest time the "middle" part (with either a plateau, increase or decrease) can begin is at time 32. Clearly, if this value is low, it can't be a cylinder or funnel, since they must be high during that period. The next point it looks at is the time period from time 51 to 57; a region that's guaranteed is soon enough in the period that either the cylinder is at its peak or the funnel has begun to reduce.

Figure 6.3 shows an example with post-processing of the decision tree generated by *TClass*. Again, there is very clear meaning here. It appears that *TClass* can not discern the underlying increase in the data, but it nonetheless produces interesting results. The accuracies of the classifiers produced above and those produced below are about the same.

Can we read anything into the meaning of the tree? Certainly we can: The

```
C_5 <= 2.86: bell (235.0)
C_5 > 2.86
|   C_8 <= 4.96
|   |   C_4 <= 5.79
|   |   |   C_9 <= 0.05
|   |   |   |   C_4 <= 2.96: bell (4.0)
|   |   |   |   C_4 > 2.96: funnel (5.0)
|   |   |   C_9 > 0.05: funnel (235.0)
|   |   C_4 > 5.79
|   |   |   C_6 <= 5.26: funnel (4.0)
|   |   |   C_6 > 5.26: cyl (7.0)
|   C_8 > 4.96: cyl (229.0)
```

Figure 6.2: An instance of the trees produced by naive segmentation for the CBF domain.

first thing it checks for is a local minimum with a high value the kind that can occur only if it's a cylinder at around time 48 (the bell and the funnel are either gradually increasing or decreasing by that time). It then checks for a local maximum very early on in the signal. This could only have come from a cylinder or a funnel. To tell these apart, it then looks for a sudden decrease (indicated by the high negative gradient of -0.5) around time 70. If it is present, this is indicative of a cylinder, whereas if it has no sudden drop, it must be a funnel. Otherwise, the classifier looks for a rapid increase at the beginning, indicated once again by the large gradient and the time early in the sequence. If it does not have this sudden increase, it's a bell; otherwise, depending once again on the sudden drop at the end, it's either a funnel or a cylinder.

As can be seen, the above definition, once translated into words, is quite comprehensible.

We did the same thing with the PART rule learner. Figure 6.5 shows a

```
IF c HAS LocalMin: time = 48.0 val = 6.04 (*1)  THEN cyl (225.0)
OTHERWISE
|   IF c HAS LocalMax: time = 23.0 val = 6.43 (*2)
|   |   IF c HAS Decreasing: midTime = 69.5 avg = 2.41  \
|   |   |  m = -0.42 d = 16.0 (*3) THEN cyl (8.0/1.0)
|   |   OTHERWISE THEN funnel (203.0/1.0)
|   OTHERWISE
|   |   IF c HAS Increasing: midTime = 22.0 avg = 3.11 \
|   |   |    m = 0.54 d = 13.0 (*4)
|   |   |   IF c HAS LocalMax: time = 90.0 val = 6.11 (*5) THEN cyl (2.0)
|   |   |   OTHERWISE THEN funnel (25.0)
|   |   OTHERWISE
|   |   |   IF c HAS Increasing: midTime = 17.5 avg = 4.13 \
|   |   |   |  m = 0.48 d = 18.0 (*6)
|   |   |   |   IF c HAS Decreasing: midTime = 69.5 avg = 2.41
|   |   |   |     m = -0.42 d = 16.0 (*3) THEN cyl (5.0)
|   |   |   |   OTHERWISE THEN funnel (8.0)
|   |   |   OTHERWISE THEN bell (243.0)


Number of Leaves  :     8

Size of the tree :      15
```

Figure 6.3: One decision tree produced by *TClass* on the CBF domain.

```
Event index
-----------
*1: lmin
   time=48.0 r=[35.0,112.0]
   value=6.04 r=[4.88,6.91]

*2: lmax
   time=23.0 r=[20.0,54.0]
   value=6.43 r=[3.18,6.58]

*3: dec
   midtime=69.5 r=[50.5,123.0]
   avg=2.41 r=[1.24,4.88]
   m=-0.42 r=[-0.94,-0.30]
   duration=16.0 r=[9.0,24.0]

*4: inc
   midtime=22.0 r=[13.5,33.5]
   avg=3.11 r=[1.42,4.18]
   m=0.54 r=[0.37,0.77]
   duration=13.0 r=[8.0,18.0]

*5: lmax
   time=90.0 r=[57.0,107.0]
   value=6.11 r=[5.00,7.42]

*6: inc
   midtime=17.5 r=[10.0,36.0]
   avg=4.13 r=[0.77,4.49]
   m=0.48 r=[0.23,0.51]
   duration=18.0 r=[12.0,32.0]
```

Figure 6.4: Events used by the decision tree in Figure 6.3.

typical ruleset created by *TClass* with PART. The first rule for instance checks for a high local minimum around time 44, which should only be possible if it is a cylinder or a funnel; and failing these, looks for a nice gentle decreasing signal that is characteristic of the funnel. If this is not present it's a cylinder. If it's not a cylinder, then it looks for a sudden increase early on in the signal (typical of cylinders or funnels) or a gradual decrease (typical of funnel). If it doesn't have either of these, then it's a bell. To finally ensure it's a funnel, it checks to see if there is either a middle time high maximum (more characteristic of a cylinder) or a middle time low maximum (only possible with a bell). If it has neither of these it must be a funnel. Between them, these three rules cover 88 per cent of instances. In the author's opinion, these rules are more comprehensible than either the naive segmentation approaches or the J48 *TClass* trees.

Conclusions

The CBF dataset turns out to be largely trivial as a learning problem. All three approaches, *TClass*, naive segmentation and hidden Markov models attain 100 per cent accuracy on it. It may be possible to prove theoretically that a naive segmentation approach with 20 segments can be guaranteed with some very high probability to produce a learner which can classify instances in the CBF domain perfectly. The effect of smoothing on the outcome appears to be minor in this case; but slightly positive overall for the *TClass* classifiers.

This makes the CBF domain a poor one for evaluation of some of the other

```
IF c HAS LocalMin: time = 44.0 val = 5.76 (*1) AND
IF c HAS NO Decreasing: midTime = 59.0 avg = 1.98 \
 m = -0.09 d = 53.0 (*2) \
 THEN cyl (239.0/1.0)

IF c HAS NO Increasing: midTime = 23.5 avg = 1.95 \
 m = 0.29 d = 18.0 (*3) AND
IF c HAS NO Decreasing: midTime = 59.0 avg = 1.98
 m = -0.09 d = 53.0 (*2) THEN bell (233.0)

IF c HAS NO LocalMax: time = 72.0 val = 6.14 (*5) AND
IF c HAS NO LocalMax: time = 65.0 val = -0.36 (*6) THEN funnel (228.0)

IF c HAS NO Increasing: midTime = 59.0 avg = 3.93 \
 m = 0.21 d = 11.0 (*7) AND
IF c HAS LocalMax: time = 27.0 val = 4.82 (*8) THEN funnel (9.0)

IF c HAS NO Increasing: midTime = 59.0 avg = 3.93 \
 m = 0.21 d = 11.0 (*8) THEN cyl (7.0)

: bell (3.0)

Number of Rules  :      6
```

Figure 6.5: A ruleset produced by *TClass* using PART as the learner.

```
Event index
-----------
*1: lmin
   time=44.0 r=[28.0,112.0]
   value=5.76 r=[4.76,6.91]

*2: dec
   midtime=59.0 r=[41.5,106.5]
   avg=1.98 r=[-0.26,6.17]
   m=-0.09 r=[-0.23,-0.01]
   duration=53.0 r=[26.0,102.0]

*3: inc
   midtime=23.5 r=[2.5,45.5]
   avg=1.95 r=[-0.74,4.81]
   m=0.29 r=[0.18,0.77]
   duration=18.0 r=[6.0,41.0]

*5: lmax
   time=72.0 r=[51.0,108.0]
   value=6.14 r=[5.01,7.90]

*6: lmax
   time=65.0 r=[42.0,76.0]
   value=-0.36 r=[-0.67,2.40]

*7: inc
   midtime=59.0 r=[35.5,88.5]
   avg=3.93 r=[1.64,6.27]
   m=0.21 r=[0.09,0.37]
   duration=11.0 r=[6.0,42.0]

*8: lmax
   time=27.0 r=[21.0,53.0]
   value=4.82 r=[2.60,5.58]
```

Figure 6.6: Event index for the ruleset in Figure 6.5.

issues we are interested in; since it is likely that in many cases we hit the "100 per cent barrier"; which does not give good guidance to the real-world performance of the classifier.

However, one thing that can be compared as a result of these experiments is comprehensibility; in particular between naive segmentation and *TClass*. While both results are readable and provide some useful description of the learnt concept; we claim subjectively that the *TClass* definitions are easier to understand, as they are expressed in terms that a human looking at the data might use: the height of maxima, gentle changes in gradient, and sudden changes in gradient; rather than averages of particular temporal segments of the data.

6.2.2 *TTest* - An artificial dataset for temporal classification

In order to better understand the behaviour of the algorithm a new artificial dataset was created to overcome the difficulties mentioned above with the CBF domain. This artificial dataset tries to capture some of the variations that occur in real-world data.

Objectives of artificial dataset

What characteristics are desirable in our artificial dataset? Firstly, it must be multivariate; that is to say, there must be more than one channel of data.

Secondly, it must show some of the forms of variation discussed in Chapter 3, namely:

- Variation in the total duration.
- Variation in the duration and timing of "sub-events" or components of the instances.
- Variation in the amplitude of the signal.
- Gaussian noise.

Thirdly, it would be worth considering the effects of noise at the feature level, as well as at the Gaussian level; that is to say, to have, say one channel of data irrelevant or insignificant. Fourthly, we want the "correct" or ideal solution to the problem to be known; hence we can compare concepts produced by *TClass* with the known concepts. Fifthly, we want it to be reproducible, so that we can produce as many data as we like.

Furthermore, we want all of these parameters to be tunable, hence allowing us to look at the effect that each has individually.

TTest

To fulfil this role, the artificial dataset *TTest* has been designed. *TTest* is a learning problems with three classes and three channels. It has a total of five parameters controlling various characteristics.

There are three classes, imaginatively called A, B and C. The three channels, likewise, are imaginatively termed alpha, beta and gamma. For each of the three classes, there is a prototype, as shown in Figures 6.7, 6.8 and 6.9. All the prototypes are all exactly a hundred units of time long.

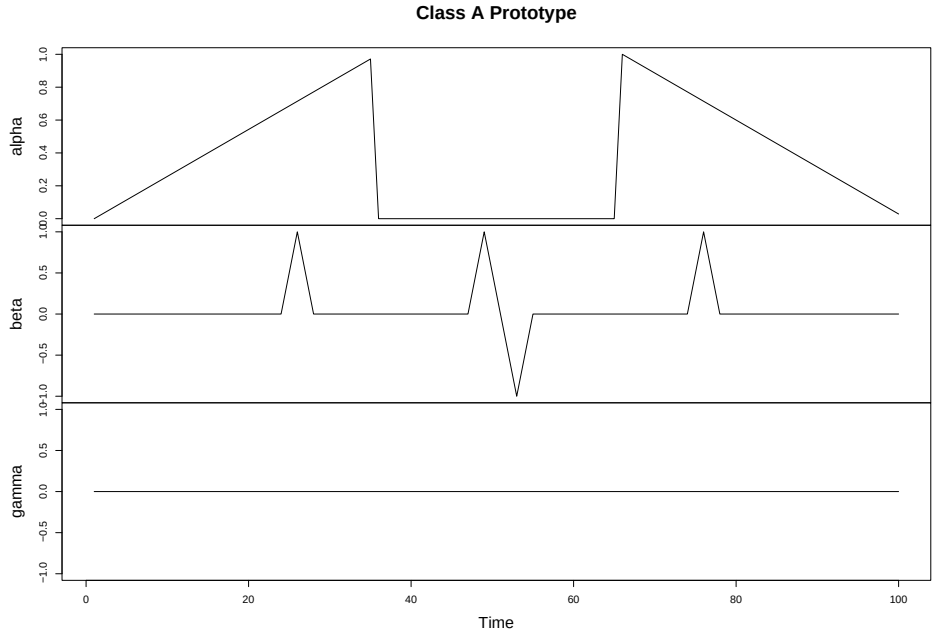


Figure 6.7: Prototype for class A

These prototypes can be mathematically defined as follows:

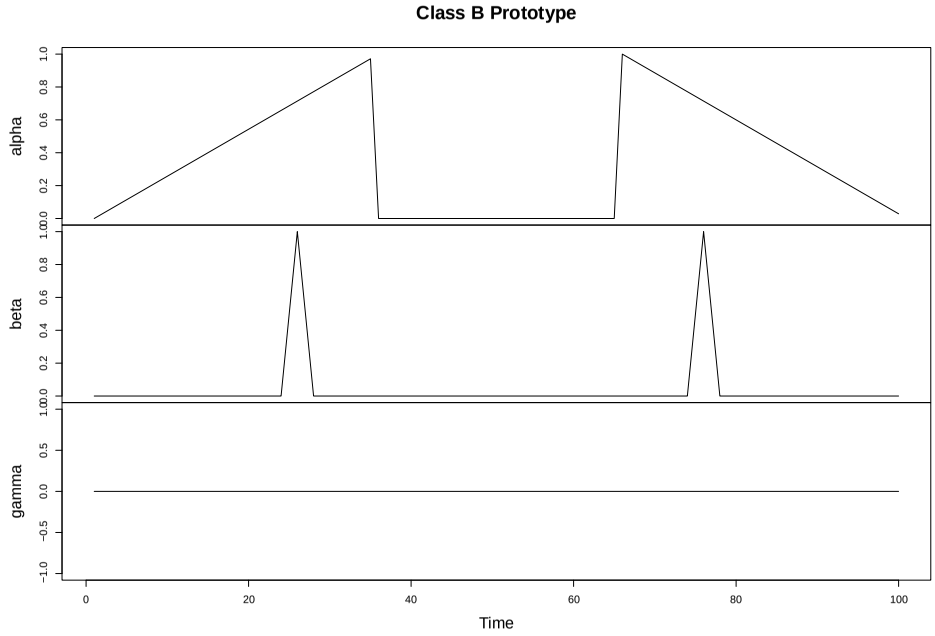


Figure 6.8: Prototype for class B

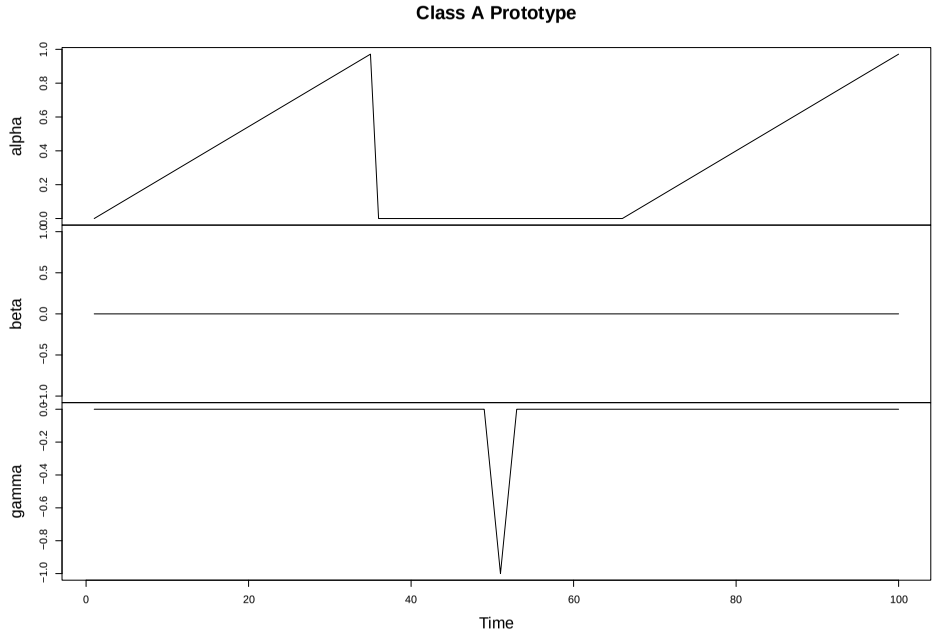


Figure 6.9: Prototype for class C

$$A\alpha(t) = \begin{cases} \frac{1}{35}t & \text{if } t \leq 35 \\ 0 & \text{if } 35 < t \leq 65 \\ \frac{1}{35}(100-t) & \text{if } 65 < t \leq 100 \end{cases}$$

$$A\beta(t) = \begin{cases} 1 & \text{if } t \in \{25, 48, 75\} \\ -1 & \text{if } t = 52 \\ 0 & \text{otherwise} \end{cases}$$

$$A\gamma(t) = 0$$

$$B\alpha(t) = \begin{cases} \frac{1}{35}t & \text{if } t \leq 35 \\ 0 & \text{if } 35 < t \leq 65 \\ \frac{1}{35}(100-t) & \text{if } 65 < t \leq 100 \end{cases}$$

$$B\beta(t) = \begin{cases} 1 & \text{if } t \in \{25, 75\} \\ 0 & \text{otherwise} \end{cases}$$

$$B\gamma(t) = 0$$

$$C\alpha(t) = \begin{cases} \frac{1}{35}t & \text{if } t \leq 35 \\ 0 & \text{if } 35 < t \leq 65 \\ \frac{1}{35}(t-65) & \text{if } 65 < t \leq 100 \end{cases}$$

$$C\beta(t) = 0$$

$$C\gamma(t) = \begin{cases} -1 & \text{if } t = 50 \\ 0 & \text{otherwise} \end{cases}$$

Now, these are not particularly interesting as a learning task. Even feeding the features into a traditional learner, such as C4.5, treating each channel/frame combination as a single feature (hence generating 300 features), would work, except that the definitions produced would be really difficult to read. So, we've got to spice it up somehow.

Obviously, the solution lies in randomisation. For the purposes of this thesis, let us define a function $unif()$, which returns a uniformly distributed real number in the range $[-1, 1]$. Also, let us define a function $\epsilon()$, which returns a real number of normal distribution, with a mean of 0 and a variance of 1.

One form of variation is temporal stretching. In general, temporal stretching is non-linear; in other words, temporal stretching need not be of the kind where the signal is uniformly slowed down or sped up; rather, some parts can be sped up while others can be slowed down. However, for simplicity, we will assume linear temporal stretching. The amount of temporal (linear) stretching for the *TTest* dataset is controlled by the parameter d (short for overall duration). The duration is computed as:

$$durn = (1 + d * unif()) * 100$$

That is to say that d specifies the percentage variation of the duration. For example, if $d = 0.1$, this would mean that duration in frames would vary from 90 to 110.

To illustrate this, consider a prototype A signal. Figure 6.10 shows a variety of different instances of A, with $d = 0.2$. Similar effects can be observed on the

other classes.

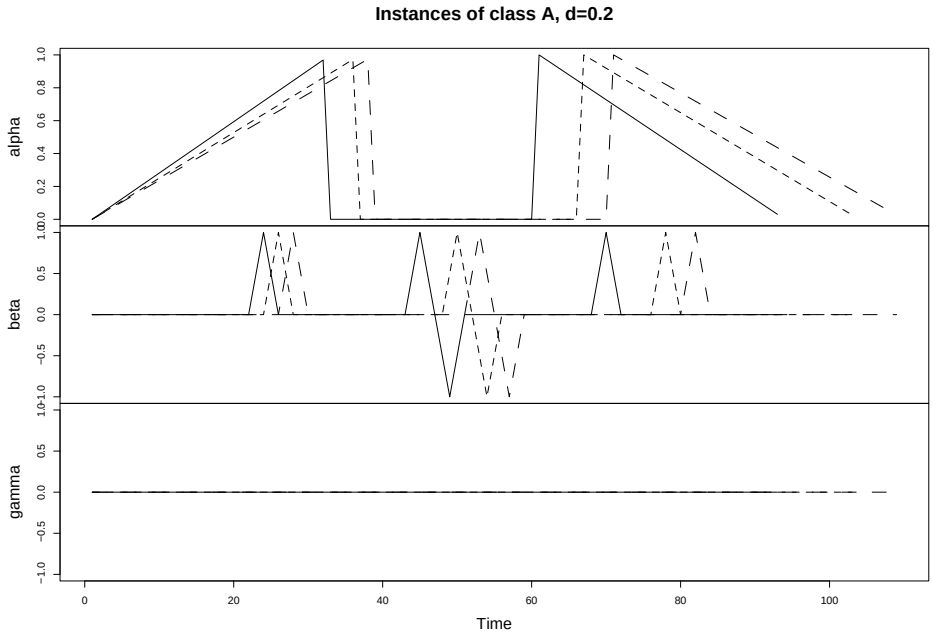


Figure 6.10: Effect of adding duration variation to prototypes of class A.

Another form of variation is random noise. For this problem, we will assume that such noise is Gaussian. This is not an unreasonable assumption, as Gaussian noise is typical of many types of sensors and measurements that are used in temporal data. For the *TTest* dataset, the amount of noise is controlled by the parameter g; the noise on all channels is taken by multiplying the parameter g by the random Gaussian noise function; i.e.,

$$noise() = g * \epsilon()$$

then this can be added to the signal. The more noise; the more the underlying signal is obscured. The effect of adding Gaussian noise with $g = 0.1$ can be seen in Figure 6.11.

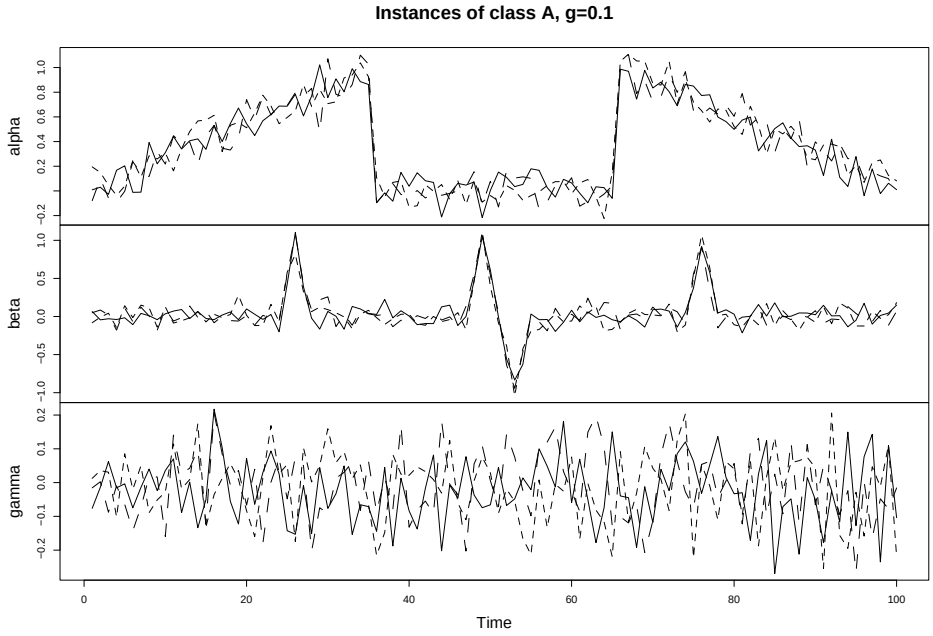


Figure 6.11: Effect of adding Gaussian noise to prototypes of class A.

As mentioned before, temporal stretching is only a linear approximation of a non-linear process. Hence, we can also modify the times of events within each instance relative to one another. In *TTest*, this is controlled by the parameter c. Within the dataset, the startpoints and endpoints of increases and decreases, as well as the timing of local maxima and minima are all randomly offset in time. The amount of variation of these temporal events is modified by a random value $c * unif() * 100$. The effect of setting $c = 0.1$ on the three instances of class A are shown in Figure 6.12.

Also, as with real datasets, sometimes the amplitudes of the various events varies. In *TTest* the parameter h determines the amount of variation in the amplitude of the local maxima of the signal. Each of these maxima is perturbed

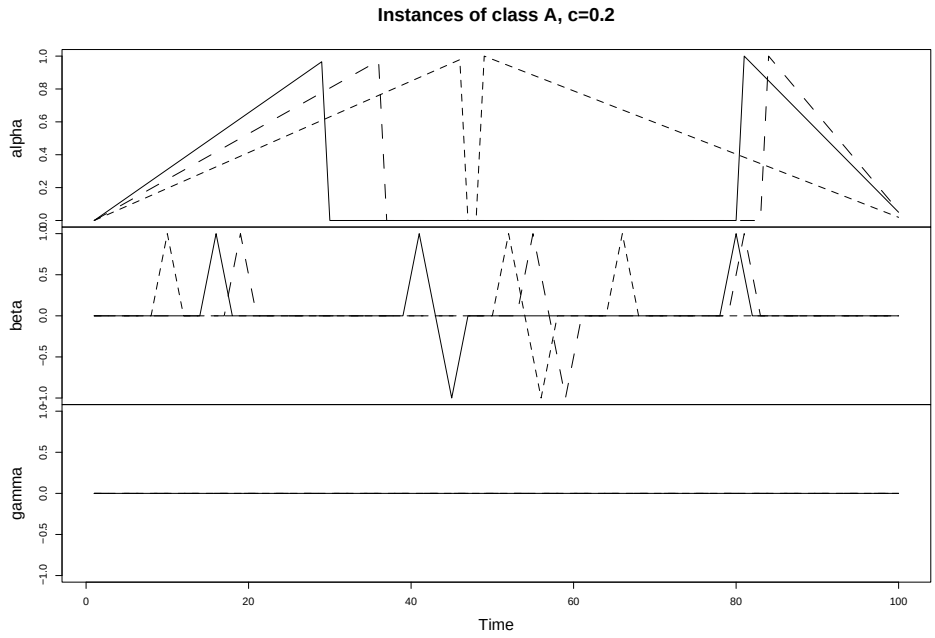


Figure 6.12: Effect of adding sub-event variation to prototypes of class A.

by an amount $h * unif()$. The effect of setting $h = 0.2$ on three instances of class A can be seen in Figure 6.13.

Finally, one thing that often occurs in real datasets is that there is some data on a channel that looks useful, but in fact is irrelevant. For this reason, for classes A and B, the gamma channel was replaced with something that looks plausible as a signal: a sequence of between 2 and 9 random line segments whose endpoints are randomly generated. For class C, the beta channel is replaced with a similarly generated sequence of random line segments. Note that this is meant to explore a different issue to that of the Gaussian noise above; this is meant to test the learner's ability to cope with data that is irrelevant.

Three instances of class A are shown in Figure 6.14, with the irrelevant

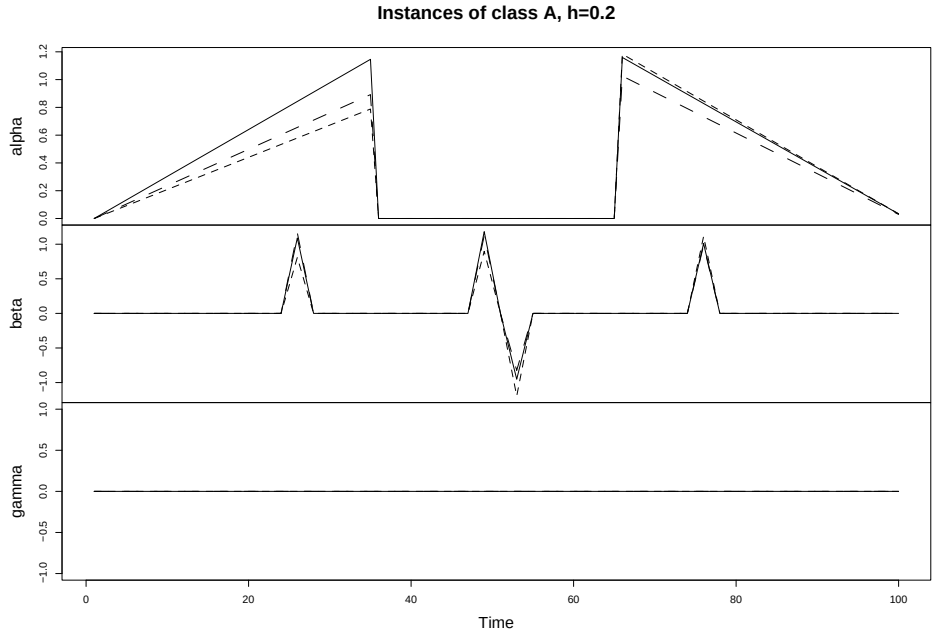


Figure 6.13: Effect of adding amplitude variation to prototypes of class A.

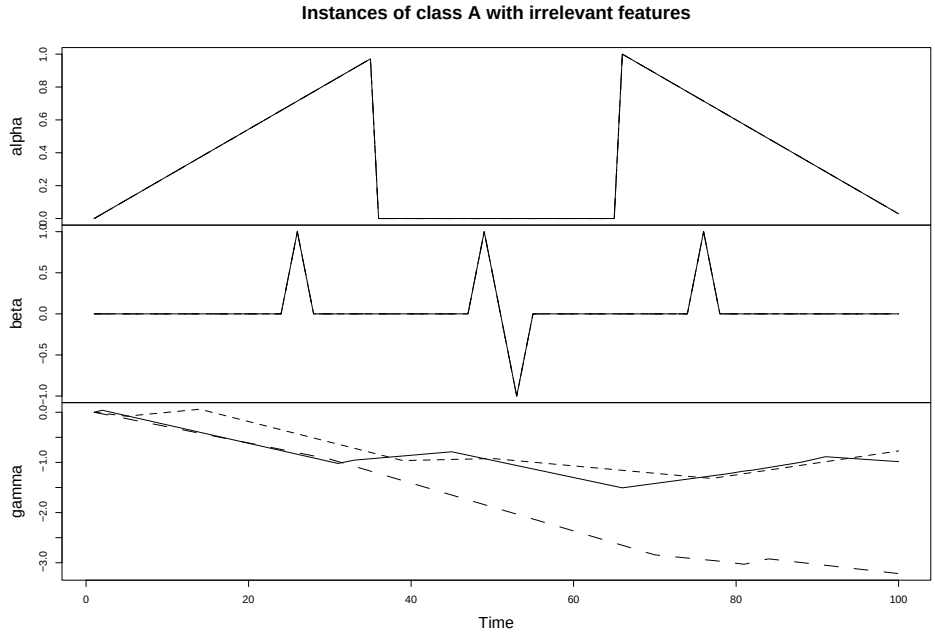


Figure 6.14: Effect of replacing gamma channel with irrelevant signal to class A.

features added.

Having included all of these factors, we can now redefine our original signals, in terms of the parameters g, c, d, h; as well as whether we choose to have irrelevant features or not. The definitions hence become:

$$
\begin{aligned}
dur &= (1 + d * unif()) * 100 \\
t_{\alpha 1} &= (0.35 + c * unif()) * dur \\
t_{\alpha 2} &= (0.65 + c * unif()) * dur \\
h_{\alpha 1} &= (1 + h * unif()) \\
h_{\alpha 2} &= (1 + h * unif()) \\
A\alpha(t) &= \begin{cases} \frac{h_{\alpha 1}}{t_{\alpha 1}} * t + g * \epsilon(t) & \text{if } t < t_{\alpha 1} \\ g * \epsilon(t) & \text{if } t_{\alpha 1} \leq t < t_{\alpha 2} \\ \frac{dur - t}{dur - t_{\alpha 2}} * t + g * \epsilon(t) & \text{if } t_{\alpha 2} \leq t \leq dur \end{cases} \\
t_{\beta 1} &= (0.25 + c * unif()) * dur \\
t_{\beta 23} &= (0.5 + c * unif()) * dur \\
t_{\beta 4} &= (0.75 + c * unif()) * dur \\
h_{\beta 1} &= (1 + h * unif()) \\
h_{\beta 2} &= (1 + h * unif()) \\
h_{\beta 3} &= (-1 + h * unif()) \\
h_{\beta 4} &= (1 + h * unif()) \\
A\beta(t) &= \begin{cases} h_{\beta 1} + g * \epsilon(t) & \text{if } t = t_{\beta 1} \\ h_{\beta 2} + g * \epsilon(t) & \text{if } t = t_{\beta 23} - 1 \\ h_{\beta 3} + g * \epsilon(t) & \text{if } t = t_{\beta 23} + 1 \\ h_{\beta 4} + g * \epsilon(t) & \text{if } t = t_{\beta 4} \\ g * \epsilon(t) & \text{otherwise} \end{cases} \\
A\gamma(t) &= \begin{cases} g * \epsilon(t) & \text{if } \textit{irrel} \text{ is off} \\ irrel(t) + g * \epsilon(t) & \text{if } \textit{irrel} \text{ is on} \end{cases}
\end{aligned}
$$

$$
\begin{aligned}
dur &= (1 + d * unif()) * 100 \\
t_{\alpha 1} &= (0.35 + c * unif()) * dur \\
t_{\alpha 2} &= (0.65 + c * unif()) * dur \\
h_{\alpha 1} &= (1 + h * unif()) \\
h_{\alpha 2} &= (1 + h * unif()) \\
B\alpha(t) &= \begin{cases} \frac{h_{\alpha 1}}{t_{\alpha 1}} * t + g * \epsilon(t) & \text{if } t < t_{\alpha 1} \\ g * \epsilon(t) & \text{if } t_{\alpha 1} \leq t < t_{\alpha 2} \\ \frac{dur - t}{dur - t_{\alpha 2}} * t + g * \epsilon(t) & \text{if } t_{\alpha 2} \leq t \leq dur \end{cases} \\
t_{\beta 1} &= (0.25 + c * unif()) * dur \\
t_{\beta 23} &= (0.5 + c * unif()) * dur \\
t_{\beta 4} &= (0.75 + c * unif()) * dur \\
h_{\beta 1} &= (1 + h * unif()) \\
h_{\beta 2} &= (1 + h * unif()) \\
B\beta(t) &= \begin{cases} h_{\beta 1} + g * \epsilon(t) & \text{if } t = t_{\beta 1} \\ h_{\beta 2} + g * \epsilon(t) & \text{if } t = t_{\beta 2} \\ g * \epsilon(t) & \text{otherwise} \end{cases} \\
B\gamma(t) &= \begin{cases} g * \epsilon(t) & \text{if } \textit{irrel} \text{ is off} \\ irrel(t) + g * \epsilon(t) & \text{if } \textit{irrel} \text{ is on} \end{cases}
\end{aligned}
$$

$$
\begin{aligned}
dur &= (1 + d * unif()) * 100 \\
t_{\alpha 1} &= (0.35 + c * unif()) * dur \\
t_{\alpha 2} &= (0.65 + c * unif()) * dur \\
h_{\alpha 1} &= (1 + h * unif()) \\
h_{\alpha 2} &= (1 + h * unif()) \\
C\alpha(t) &= \begin{cases} \frac{h_{\alpha 1}}{t_{\alpha 1}} * t + g * \epsilon(t) & \text{if } t < t_{\alpha 1} \\ g * \epsilon(t) & \text{if } t_{\alpha 1} \leq t < t_{\alpha 2} \\ \frac{t - t_{\alpha 2}}{dur - t_{\alpha 2}} * t + g * \epsilon(t) & \text{if } t_{\alpha 2} \leq t \leq dur \end{cases} \\
C\beta(t) &= \begin{cases} g * \epsilon(t) & \text{if } \textit{irrel} \text{ is off} \\ irrel(t) + g * \epsilon(t) & \text{if } \textit{irrel} \text{ is on} \end{cases} \\
t_{\gamma} &= (0.25 + c * unif()) * dur \\
h_{\gamma} &= (-1 + h * unif()) \\
C\gamma(t) &= \begin{cases} h_{\gamma} + g * \epsilon(t) & \text{if } t = t_{\gamma} \\ g * \epsilon(t) & \text{otherwise} \end{cases}
\end{aligned}
$$

This dataset has some useful properties. Firstly, it is truly multivariate. Secondly, it has variation in the length of streams and the onset and duration of sub-events. Thirdly, it has variation in the amplitudes of events as well as Gaussian noise (as does CBF). Fourthly, it has several sub-events and a complicated relation between sub-events which is typical of real-world domains. CBF only had one of these properties.

Experimental Results

As a starting dataset, we generated 1000 instances, using the following parameters: $g = 0.1, d = 0.2, c = 0.2, h = 0.2$ with irrelevant features switched on. Figures 6.15, 6.16 and 6.17 instances of classes A, B and C respectively.

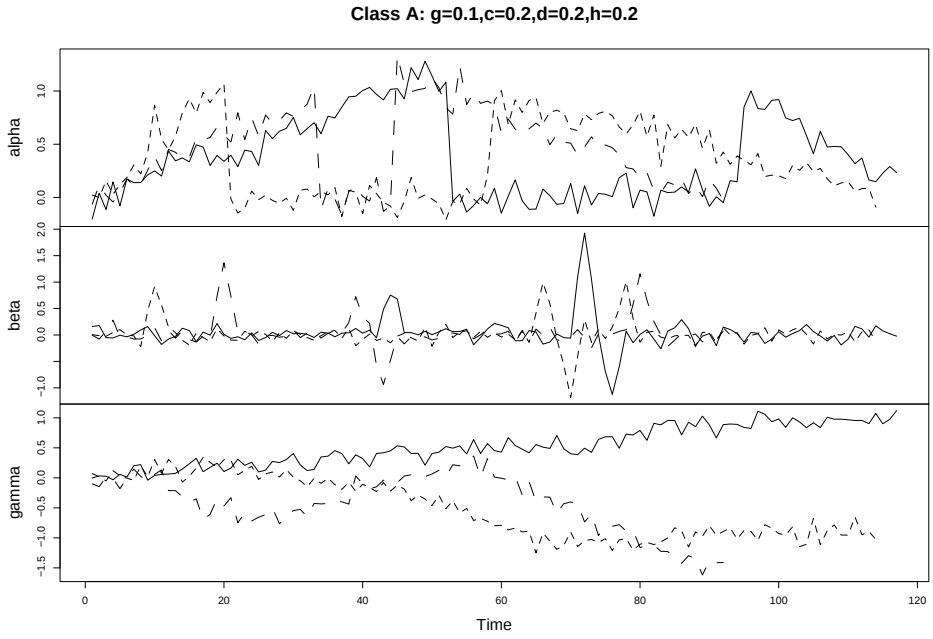


Figure 6.15: Examples of class A with default parameters.

The results are shown in Table 6.5.

As we can see, for this particular training set, *TClass* performs better in terms of accuracy.

To examine the effect of noise, we increased g to 0.2; and also looked at what happens when $g = 0$. The results for more noise are shown in Table 6.8; and the results with zero noise are shown in Table 6.9. For brevity, the in-depth results

Approach	Error
TClass with J48	3.3 ± 0.9
TClass with PART	2.3 ± 0.3
TClass with IBL	68.1 ± 1.5
TClass with Bagging/J48	2.5 ± 0.4
TClass with AdaBoost/J48	$\mathbf{1.0 \pm 0.3}$
TClass with Naive Bayes	9.8 ± 1.5
Naive Segmentation	7.2 ± 0.7
Hidden Markov Model	4.4 ± 1.5

Table 6.5: Error rates on the *TTest* domain.

Approach	Segments			
	3	5	10	20
J48	28.7 ± 0.9	34.1 ± 1.3	23.4 ± 0.9	7.4 ± 1.0
NB	28.2 ± 1.3	31.1 ± 1.3	25.9 ± 1.2	16.4 ± 1.3
IB1	34.0 ± 1.5	33.2 ± 1.3	31.6 ± 1.0	32.6 ± 1.2
AB	30.5 ± 1.5	29.7 ± 1.3	26.3 ± 1.0	7.8 ± 1.2
Bag	30.6 ± 0.9	32.3 ± 1.4	23.1 ± 1.0	$\mathbf{7.2 \pm 0.7}$

Table 6.6: Error rates of naive segmentation on the *TTest* domain.

Topology	Raw	Raw + Derivative
lr-3	17.0 ± 1.2	15.4 ± 1.7
lr-5	13.4 ± 2.1	25.3 ± 0.9
lr-10	18.3 ± 2.4	21.7 ± 1.5
lr-20	21.9 ± 1.3	19.9 ± 1.6
lrs1-3	21.8 ± 1.8	22.1 ± 1.3
lrs1-5	29.8 ± 1.9	23.5 ± 1.2
lrs1-10	26.0 ± 1.3	23.6 ± 1.9
lrs1-20	24.8 ± 1.7	24.1 ± 1.8
er-3	26.0 ± 1.7	15.9 ± 1.2
er-5	12.5 ± 1.0	4.8 ± 0.4
er-10	12.5 ± 1.0	$\mathbf{4.4 \pm 0.6}$
er-20	12.5 ± 1.0	4.8 ± 0.4

Table 6.7: Error rates when using hidden Markov models on *TTest* domain.

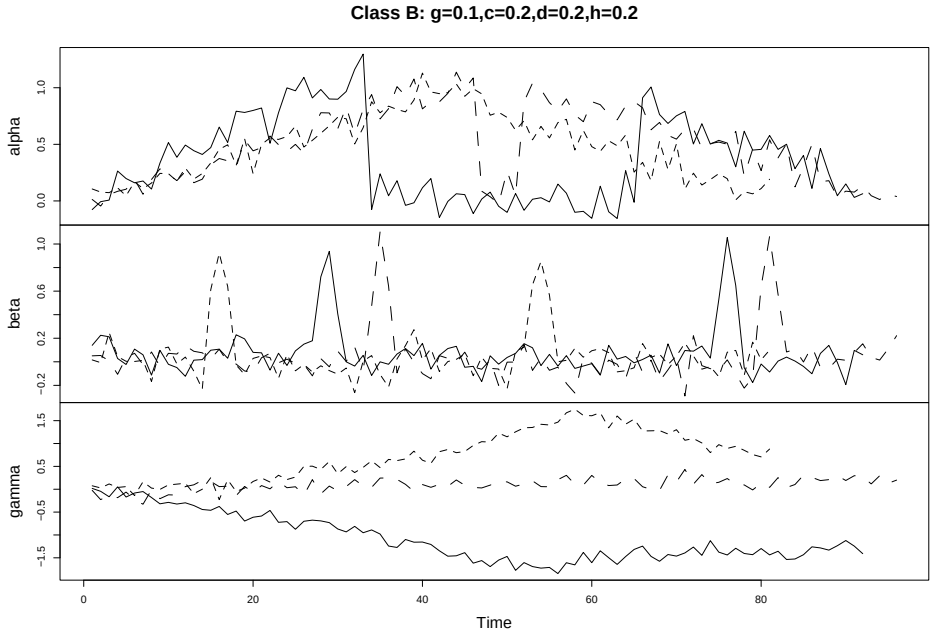


Figure 6.16: Examples of class B with default parameters.

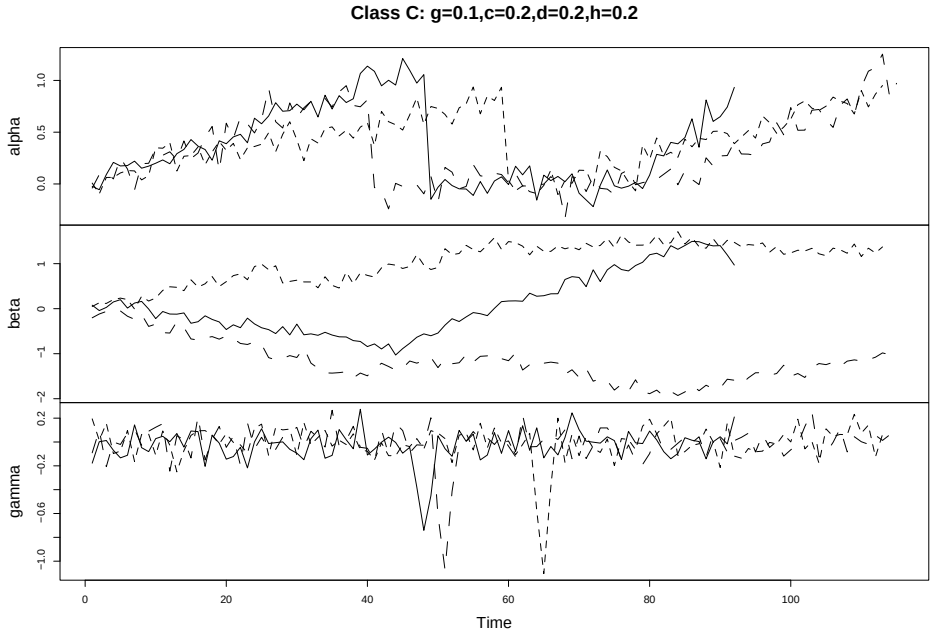


Figure 6.17: Examples of class C with default parameters.

Approach	Error
TClass with J48	17.4 ± 2.1
TClass with PART	16.1 ± 1.5
TClass with IBL	67.3 ± 1.3
TClass with Bagging/J48	11.3 ± 1.2
TClass with AdaBoost/J48	14.9 ± 2.1
TClass with Naive Bayes	13.9 ± 1.8
Naive Segmentation	13.2 ± 1.6
Hidden Markov Model	**9.9 ± 1.1**

Table 6.8: Error rates for high-noise situation (g=0.2) on *TTest* domain.

Approach	Error
TClass with J48	1.6 ± 0.4
TClass with PART	1.4 ± 0.5
TClass with IB1	66.7 ± 1.4
TClass with Naive Bayes	11.2 ± 2.3
TClass with Bag/J48	1.6 ± 0.4
TClass with AdaBoost/J48	0.9 ± 0.3
Naive Segmentation	2.1 ± 0.5
Hidden Markov Model	4.8 ± 0.9

Table 6.9: Error rates with no Gaussian noise (g=0) on *TTest* domain.

for naive segmentation and HMMs are omitted.

We plotted the results for each of these in Figure 6.18, excluding TClass/IB1, because its performance is so poor relative to the other learners.

Clearly, the noise level has a significant effect on the quality of the learning. With no noise, every *TClass* learner outperforms the baseline learners. With the noise level at 0.2, most of the learners perform poorly. The least poorly affected is the hidden Markov model; its statistical nature seems to helped it cope. Again, if we are willing to sacrifice readability, we can simply vote *TClass*. Figure 6.19 shows the effect of voting to improve accuracy, using bagging as

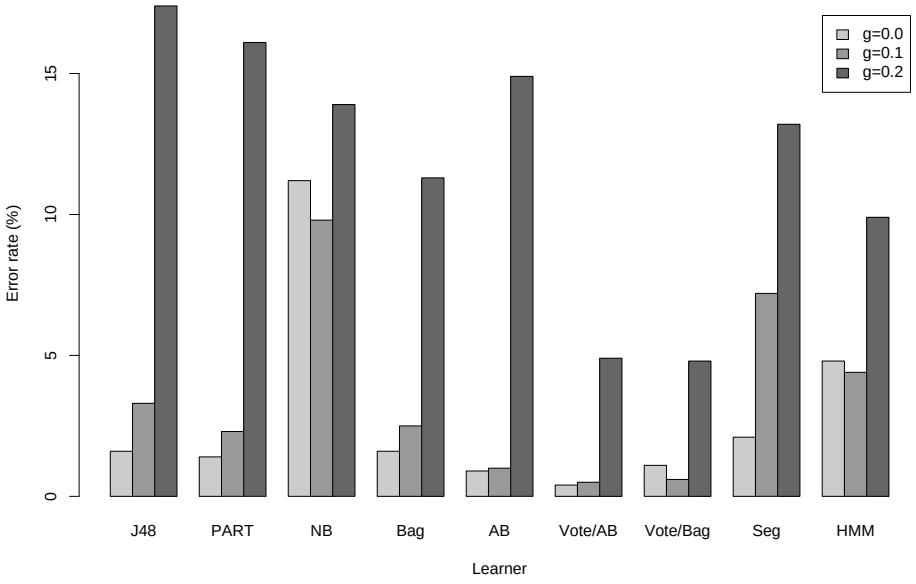


Figure 6.18: Learner accuracy and noise

the base learner. Bagging was chosen because it was the best performer in the unvoted results among the *TClass* learners, but it could be done with any of the other learners.

This shows the dramatic effect that voting can have on performance. In the limit, using voted *TClass* does approximately twice as well as the best-performing hidden Markov model: it appears to asymptotically reach an error of about 4.7 per cent, when doing voting of 11 bagged *TClass* learners[3]. Unfortunately, this comes at a price: readability. For the minimum error case, the human would have to look at the results of 110 trees and consider how each of them votes.

[3]There is no result for 2 bagged learners, since the result is arbitrary: if one learner votes one way and the other votes another then it's an arbitrary choice as to which is correct, and because of the binomial theorem, in the limit you can't do any better than a single voter.

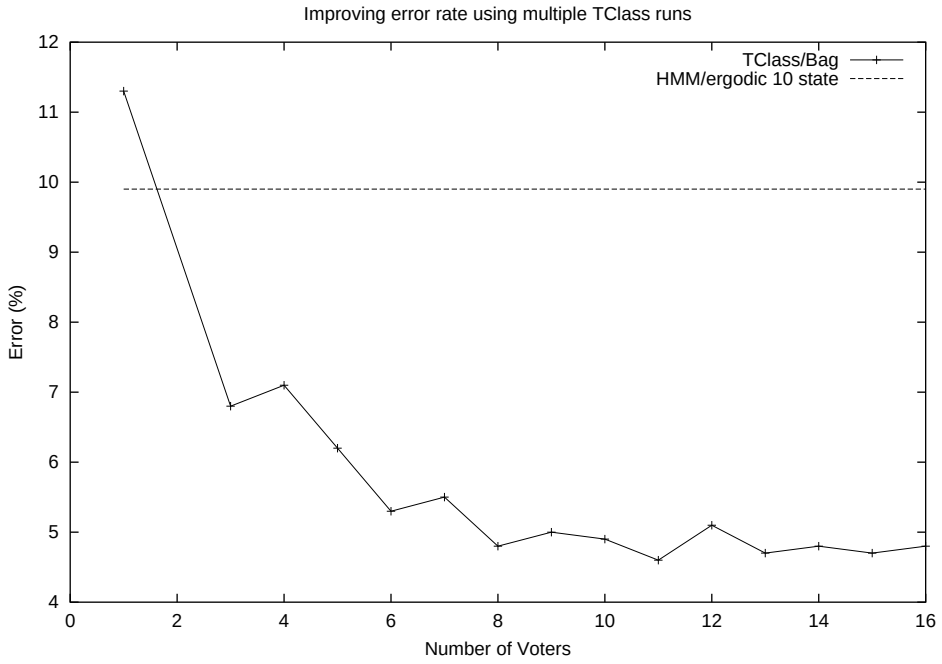


Figure 6.19: Voting different runs of TClass to reduce error with g=0.2.

We were also curious as to why hidden Markov models and naive segmentation performed so well. Since HMMs are statistical models, they perform best when there are many instances – especially with the high level of noise when $g = 0.2$. Given that in the above experiments, there are 300 training examples for each class, perhaps the *TTest* provides too many examples. We therefore generated a smaller dataset consisting of only 100 examples – hence having 30 examples per class for training.

We ran further experiments with this set of 100 examples. Abbreviated results are shown in Table 6.10. In order to get statistically significant results, the TClass runs were repeated 3 times and averaged (not voted).

The results are surprising. Firstly, note that for the *TClass* learners, the

Approach	Error
TClass with J48	16.7 ± 2.0
TClass with PART	19.7 ± 2.3
TClass with IBL	69.2 ± 2.0
TClass with Bagging/J48	12.7 ± 2.3
TClass with AdaBoost/J48	$\mathbf{11.0 \pm 1.5}$
TClass with Naive Bayes	19.0 ± 2.3
Naive Segmentation	21.0 ± 3.0
Hidden Markov Model	17.0 ± 3.5

Table 6.10: Error rates for high-noise situation (g=0.2), but with only 100 examples on *TTest* domain.

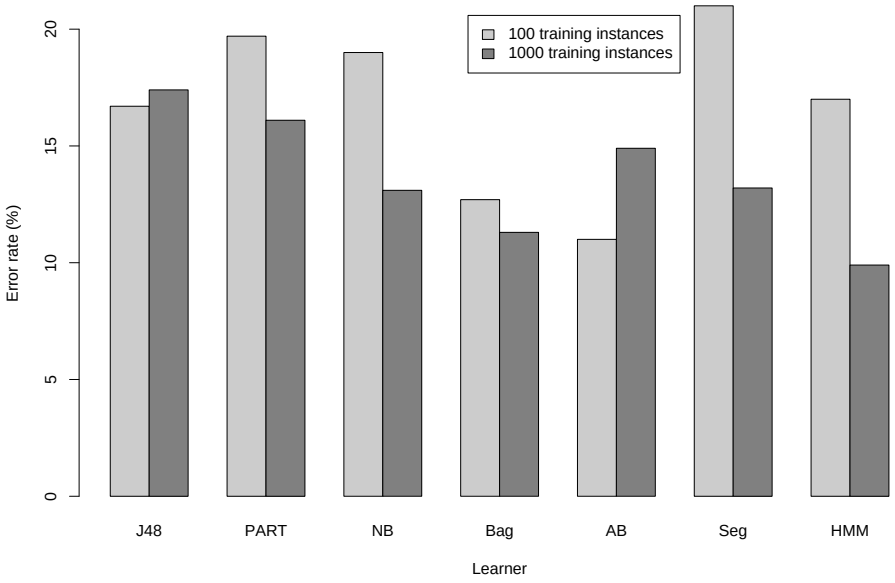


Figure 6.20: Error rates of different learners with 100 and 1000 examples.

performance of the bagging and boosting seems to have improved over when they had 300 examples. This suggests that the boosting and bagging systems are overfitting the data. To confirm this, we looked at the average number of leaves in each tree produced when bagging with 100 examples and 1000 exam-

ples. We found that with 100 examples, there were an average of 5.8 leaves per tree, whereas with 1000 examples there was an average of 37.0 leaves per tree. Theoretically, the three classes are orthogonal; in other words, we know they could, in the absence of noise, be classified with 3 leaf nodes. It does show, however, that the *TClass* learners perform better than the statistical approaches when the number of training instances in this domain is small.

This indicated that it was perhaps possible to get more accurate trees in high noise situations by setting the pruning parameters higher for the tree-based learners. We set the confidence for pruning to 5% instead of the default 25%; and set the minimum number of instances per node to 10, instead of the default 2. In the high noise case (g=0.2), this led to a massive reduction in tree size with an improvement in accuracy. For J48, the average tree size was reduced from 47.3 leaf nodes to 12.2 leaf nodes. At the same time, the error rate was reduced from 17.4 per cent to 13.2 per cent. This seems to be a strong gain; making the results both more comprehensible and at the same time more accurate.

Comprehensibility

Once the above high pruning criteria were introduced, the definitions became much clearer, even in the high noise case.

The definitions arrived at for the no-noise case shown in Figure 6.21 are exactly correct. It looks for the increasing alpha value distinctive of the C channel; as well as the fact that class A has a big decreasing timestep right in

```
IF alpha HAS Increasing: midTime = 98.5 avg = 0.47
m = 0.03 d = 30.0 (*1) THEN C (299.0)
OTHERWISE
|   IF beta HAS Decreasing: midTime = 59.5 avg = -0.28
|   m = -0.57 d = 4.0 (*2) THEN A (277.0)
|   OTHERWISE THEN B (323.0/24.0)

Number of Leaves  :     3

Size of the tree :      5
```

Figure 6.21: A decision tree produced by *TClass* on *TTest* with no noise. It is a perfect answer; ignoring gamma altogether as a noisy channel and having the absolute minimum number of nodes.

```
*1: inc
   midtime=98.5 r=[57.5,108.0]
   avg=0.47 r=[0.37,0.60]
   m=0.03 r=[0.01,0.07]
   duration=30.0 r=[12.0,62.0]


*2: dec
   midtime=59.5 r=[7.0,81.5]
   avg=-0.28 r=[-0.60,0.45]
   m=-0.57 r=[-0.90,-0.32]
   duration=4.0 r=[3.0,6.0]
```

Figure 6.22: Events used by the decision tree in Figure 6.21.

```
IF beta HAS LocalMax: time = 48.0 val = 0.07 (*1) AND
IF beta HAS NO LocalMin: time = 64.0 val = -0.72 (*2) AND
IF beta HAS NO LocalMin: time = 63.0 val = 0.31 (*3) THEN B (299.0/3.0)

IF gamma HAS LocalMin: time = 59.0 val = -0.00 (*4) AND
IF gamma HAS NO LocalMin: time = 56.0 val = 0.46 (*5) AND
IF gamma HAS LocalMax: time = 26.0 val = 0.03 (*6) THEN C (301.0/3.0)

: A (299.0/2.0)

Number of Rules  :      3
```

Figure 6.23: A decision list produced by *TClass* on *TTest* with 10 per cent noise.

the middle.

But what happens as we add noise? Do we still get such high quality definitions? If we use the high pruning levels we used above, we can sustain good definitions while $g = 0.1$. The results are shown in Figure 6.23.

The definitions here are still understandable. The first rule looks for the beta channel with no significant local minima ant at least one local maximum, indicating a B class. Similarly, it looks for the big local minimum of the C class in the gamma channel.

Finally,we look at the effect when $g = 0.2$ as shown in Figure 6.25. For brevity, we have omitted the event index. Although it is hard to understand such a complicated tree, some understanding can still be gained. For instance if the beta channel has a local maximum in the middle, and a nearby local minimum, it is likely to be of class A.

```
Event index
-----------
*1: lmax
   time=48.0 r=[1.0,52.0]
   value=0.07 r=[-0.11,0.54]

*2: lmin
   time=64.0 r=[6.0,114.0]
   value=-0.72 r=[-4.69,-0.35]

*3: lmin
   time=63.0 r=[4.0,116.0]
   value=0.31 r=[0.08,1.33]

*4: lmin
   time=59.0 r=[51.0,116.0]
   value=-0.00 r=[-0.52,0.48]

*5: lmin
   time=56.0 r=[46.0,116.0]
   value=0.46 r=[0.20,4.30]

*6: lmax
   time=26.0 r=[14.0,41.0]
   value=0.03 r=[-0.43,0.37]
```

Figure 6.24: Events used by the decision tree in Figure 6.23.

```
J48 pruned tree
------------------

IF beta HAS LocalMax: time = 57.0 val = 0.25 (*1)
|   IF beta HAS LocalMin: time = 42.0 val = -0.83 (*2)
|   |   IF beta HAS LocalMax: time = 47.0 val = -0.67 (*3)
|   |   |   IF gamma HAS LocalMin: time = 41.0 val = -0.21 (*4)
|   |   |     THEN C (44.0/4.0)
|   |   |   OTHERWISE THEN A (11.0)
|   |   OTHERWISE THEN A (261.0/13.0)
|   OTHERWISE
|   |   IF beta HAS Decreasing: midTime = 52.0 avg = 0.95
|   |      m = -0.09 d = 3.0 (*5)  THEN C (23.0)
|   |   OTHERWISE
|   |   |   IF gamma HAS Plateau: midTime = 42.0 avg = -0.03 d = 85.0 (*6)
|   |   |   |   IF gamma HAS LocalMax: time = 32.0 val = -0.54 (*7)
|   |   |   |     THEN B (28.0/5.0)
|   |   |   |   OTHERWISE THEN C (23.0/5.0)
|   |   |   OTHERWISE THEN B (281.0/31.0)
OTHERWISE
|   IF gamma HAS LocalMin: time = 41.0 val = -0.21 (*8)
|     THEN C (218.0)
|   OTHERWISE THEN A (10.0/5.0)
```

Figure 6.25: A decision tree produced by *TClass* on *TTest* with 20 per cent noise.

Conclusions

TClass is able to achieve high accuracy, comprehensible description of the *TTest* dataset; it is competitive in its generation of correct and accurate descriptions – especially in situations where there is little or no noise. Smoothing does not appear to help. If one is not interested in comprehensibility of the learnt concepts, voting methods can be employed to great effect – obtaining accuracies far in excess of those of the baseline learners; on this data, at least half the error rate. Further, it shows better results than the baseline learners with fewer instances.

There does seem to be a problem with overfitting, however. This is likely because there are so many features generated. The trees produced are much larger than optimal, and by adjusting the parameters of decision-tree based learners to be more aggressive in their pruning we can generate more comprehensible rules with equivalent or higher accuracy. We will have to take this into account with our real-world datasets.

6.3 Real-world datasets

We now examine real-world datasets to see if *TClass* functions as well on real-world problems as it did on the artificial ones.

6.3.1 Why these data sets?

Finding temporal classification data sets can be difficult. As previously mentioned (Section 6.2), although many data sets are inherently temporal, many people are eager to convert them to propositional form immediately. Although time series data is easy come by, what is hard to obtain from experts is the classification – this exclude many of the dynamic-systems or financial time series data sets.

The first data set, the Auslan data set, was selected because the author had collected the data himself and was one of the motivating problems behind this research; there did not seem to be many different algorithms for recognising time series. Secondly, unlike other data sets, rules produced by the system could be directly compared with the definitions found in the Auslan dictionary [Joh89].

The second data set, the ECG data set, was selected for a number of reasons. Firstly, work had recently concluded on a "propositionalisation" of the data set [dC98] that converted an ECG into a list of attribute values. This would allow easy comparisons between results using domain-specific information and a temporal classification system.

6.3.2 Auslan

As stated previously, Auslan is the language used by the Australian Deaf and non-vocal communities. Auslan is a dialect of British Sign Language. It is

dissimilar to American Sign Language, although some signs have been adopted.

Auslan also has about 4000 signs in it. However, there are many ways these signs can be modified to alter the meaning slightly, and even more powerfully, signs can be combined to give new signs. Fingerspelling is not the same as Auslan, it is merely a fallback used fo proper names, words for which there is no sign and people who cannot sign Auslan but still need to communicate with Deaf.

Structure of signs in Auslan

There are several components of a sign. By mixing and matching these, a wide variety of signs can be formed. These components are:

Handshape Handshapes in Auslan can be classified into 31 different shapes (although there are 63 variations, these are typically considered minor). Furthermore, there are one-handed signs (where only one hand is used), two-handed signs (where both hands are used, but each hand is executing a different handshape) and double-handed signs (where both hands have the same handshape). There is a tendency in two-handed signs for one hand to dominate (usually the right in right-handed signers) and also that double-handed signs tend to be symmetrical (that is, both hands also tend to move in the same, if mirrored, motion).

Location This is where the sign is started. If the sign is within the "neutral space" – a half-ellipsoid centred on the person's chest, the location is not important. However, if the location is outside the neutral space, it may be important.

Orientation This refers to the orientation of the hand in terms of the wrist's rotation (the **roll**), whether the hand is pointing up or down (the **pitch**) and which direction the hand is facing (the **yaw**).

Movement There are many movements used in sign language, including arcs, straight lines and "wavy" patterns. They are not necessarily two-dimensional (consider the sign for `crazy`, which in Auslan is the universal gesture of pointing to the head and making small circles directed away from the head), and can include changes in orientation and handshape as well as position. Typically, they can include multiple steps, such as the sign for `science` which is characterised by "mixing test-tubes".

Expression Facial expressions are an important part of signing. While it does not play a major role in individual signs, it becomes very important at the sentence level. For example, negation can be made by making the normal sign and shaking one's head at the same time, and questions are formed by raising the eyebrows or tilting the head (depending on the type of question).

Summary of previous research

The work that has been published in the specific area of recognition of individual signs is still limited. Murakami and Taguchi considered ten signs using a recurrent neural net and obtained accuracy of 96 per cent ([MT91]). Charayaphan and Marble considered 31 ASL symbols, but only sampled each sign once and simulated the variation and consistently got 27 out of the 31 correct, with the remaining four sometimes correct using a Hough transform. Starner considered 40 signs used in brief sentences and ([Sta95, SP95]) obtained accuracies of 91.3 per cent on raw signs and 99.2 per cent by using a very strict grammar for sentences. More detailed information can be found in [Kad95].

Two datasets of sign language data were captured. The first (original) data was captured for [Kad95], using very cheap equipment. The second, collected for this work, used much higher quality equipment. We discuss the differences between the two sources. For convenience the older dataset will be termed the Nintendo data, and the newer dataset will be termed the Flock data.

Nintendo data

The original sign language data was captured using a single Nintendo Powerglove, connected through a Powerglove Serial interface to a Silicon Graphics 4D/35G. A subset of Auslan consisting of 95 signs was selected to cover all the typical handshapes and movements. In some cases, signs that were difficult to

distinguish were deliberately chosen. A complete list of the signs chosen can be found in Appendix B of [Kad95]. For convenience, a table from [Kad95] is shown Table 6.11, giving an overview of the sign selection process.

Item	**Number of signs**
Total number of signs	95
Hand usage	
- One-handed	59
- Double-handed	27
- Two-handed	9
Reasons for selection	
- Common sign	66
- Similarity to other signs	11
- Uncommon Handshape	9
- Sign Complexity	5
- Other	4

Table 6.11: Some statistics on the signs used.

The Powerglove proved itself to be a less than stellar performer. The x, y and z position are encoded as 8-bit values. Because it used ultrasound to compute position, it was quite susceptible to bogus echoes. Finger bend was only available for the first four fingers[4], and then, only two bits. Even more disastrously, the fingers were subject to hysteresis and unpredictability. No orientation information was available other than roll, which could take one of 12 values (i.e. measurements were +/- 30 degrees). Hence, in total, there were eight channels (x, y, z, roll, thumb, fore, middle, ring).

Further, the refresh rate was very low; approximately 23 to 25 frames per

[4]The little finger is actually important in many sign languages. For example, in Auslan and British Sign Language, a fist with the little finger extended indicates *bad*. It is also used as a modifier for other signs that indicate badness - e.g. *sick* is a *bad* handshape against the body and *swear* is a *bad* handshape starting at the mouth and moving away.

second. Finally, the glove only captured one hand, as there are no left-handed Powergloves.

Data was collected from several individuals. However for these experiments we used one individual. A total of 20 samples were collected from the signer for a total of 1900 signs.

Flock data

The Flock data was based on a similar setup to the Nintendo data. In fact, the same software (with minor modifications to cope with two sets of data: one left, one right) was mostly used. However, much improved equipment was used.

The new equipment consists of:

- Two Fifth Dimension Technologies (5DT) gloves, one right and one left.
- Two Ascension Flock-of-Birds magnetic position trackers, one attached to each hand.
- A four-port serial card to cope with four data sources[5].
- A PC (128MB RAM, Intel Pentium II 266MHz) was used.

In terms of the quality of the data, the Flock system was far superior to the Nintendo system. Firstly, this was a two-hand system. Secondly, each position

[5]In practice, it proved to be easier for synchronisation purposes to link the two Flock-of-Birds units using the Flock-of-Birds Bus (FBB) and interleave their data into a single serial port.

tracker provided 6 degrees of freedom – i.e. roll, pitch and yaw as well as x, y and z. The gloves also provided a full five fingers of data. But the big improvements were in resolution – both accuracy and temporal. Position and orientation were defined to 14-bit accuracy, giving position information with a typical positional error less than one centimetre and angle error less than one half of a degree[6]. Finger bend was measured with 8 bits per finger, of which probably 6 bits were usable once the glove was calibrated. The refresh rate of the complete system was close to 100 frames per second; and all signals had significantly less noise than the Nintendo data.

Samples from a single signer (a native Auslan signer)[7] were collected over a period of nine weeks. In total, 27 samples per sign, and a total of 2565 signs were collected. The average length of each sign was approximately 57 frames.

Experimental results

We began with the Nintendo data. *TClass* was used with all five basic meta-features, as well as global feature extractors for means, maxima and minima of each channel. The results of the runs of our data with the default values are shown in Table 6.12. We have omitted the complete results for the segmentation approach and HMMs; including only the best accuracy from each family.

[6]In fact, the main source of orientation error (and to some extent position error) was the difficulty in attaching the magnetic trackers to the gloves. It is very difficult to attach these sensors to the hands in such a way that it simultaneously provides relatively free movement and also connects firmly to some reference point on the hand. Some tradeoff is involved.

[7]My deepest gratitude extends to Todd Wright for his help on this project.

Approach	Error
TClass with J48	61.0 ± 0.6
TClass with PART	67.8 ± 1.0
TClass with IB1	77.9 ± 1.7
TClass with Naive Bayes	50.5 ± 1.3
TClass with Bag	47.5 ± 0.7
TClass with AB	42.5 ± 1.2
Naive Segmentation	30.7 ± 1.0
Hidden Markov Model	$\mathbf{28.8 \pm 0.3}$

Table 6.12: Error rates for the Nintendo sign language data.

This looks very much like a disaster for our learners. However, it is actually a very hard domain: there is the noise level and the quality of the sensing. The gloves are very poor quality, and when similar samples are provided using high-quality gloves, the results are much much better – see the Flock section. Secondly, it has a number of characteristics that make it more difficult. There are many more classes than usual for machine learning tasks: 95 – an investigation of the UCI repository [MM98] reveals that only one learning task contains more classes than this. Furthermore, they occur with equal frequency. This means that a "random guess" algorithm – a generic baseline – would get an error rate of 99 per cent or so.

However, previous experiments have managed to perform well. In earlier work [Kad95], we hand-built feature extractors specifically designed for the domain that were able to achieve a 17.0 per cent error rate on this data set. Earlier work [Kad99] also achieved an accuracy of 24.0 per cent using an early version of *TClass*, that did not use the directed segmentation for generating prototypical features (the approach is discussed in greater depth in Section A.2). So the

Learner	Base	Smooth	Centroids	Relative	All Three
J48	61.0 ± 0.6	61.2 ± 0.9	58.4 ± 1.0	61.9 ± 0.9	$\mathbf{55.4 \pm 1.1}$
PART	67.8 ± 1.0	62.2 ± 0.9	60.3 ± 1.7	64.0 ± 0.9	$\mathbf{59.2 \pm 1.9}$
IB1	77.9 ± 1.7	43.2 ± 1.0	42.5 ± 1.0	80.7 ± 0.8	$\mathbf{38.7 \pm 1.0}$
Bag	47.5 ± 0.7	43.0 ± 0.4	41.4 ± 0.8	47.2 ± 0.5	$\mathbf{39.8 \pm 1.1}$
AB	42.5 ± 1.2	41.2 ± 0.6	37.4 ± 0.9	44.0 ± 1.0	$\mathbf{35.5 \pm 1.0}$

Table 6.13: Error rates with different *TClass* parameters.

results are quite disappointing.

We suspected the same overfitting phenomena exhibited in the *TTest* dataset were appearing here. However, on further examination this was not case – there is not much room for overfitting. There are only 16 samples per sign used for learning for a situation with 95 classes, so it is unlikely that overfitting is the issue. Further experiments confirmed that using pruning did not improve accuracy and had little impact on tree size.

However, we did try a number of ways of increasing the performance of the classifiers. These were (i) smoothing the data (ii) sampling more random centroids (10000 instead of 1000) and (iii) using relative values of heights and time rather than absolute values.

The results are very promising. Each of these processes improves the accuracy in this case. What is more, with the information-based learners, it actually results in a reduced tree size and/or rule size. Between the base case and the final case, tree size is reduced by 9 per cent for J48, while error rate is reduced by 11 per cent. Similarly for PART, the number of rules is reduced by 15 per cent and the error is reduced by 9 per cent. Since the remainder of the learning

algorithm remains the same in both cases, this implies that this improvement is a result of higher quality features being extracted.

Finally, in order to get higher accuracy, we voted the best performing individual *TClass* learner – AdaBoost. The results are shown in Figure 6.26.

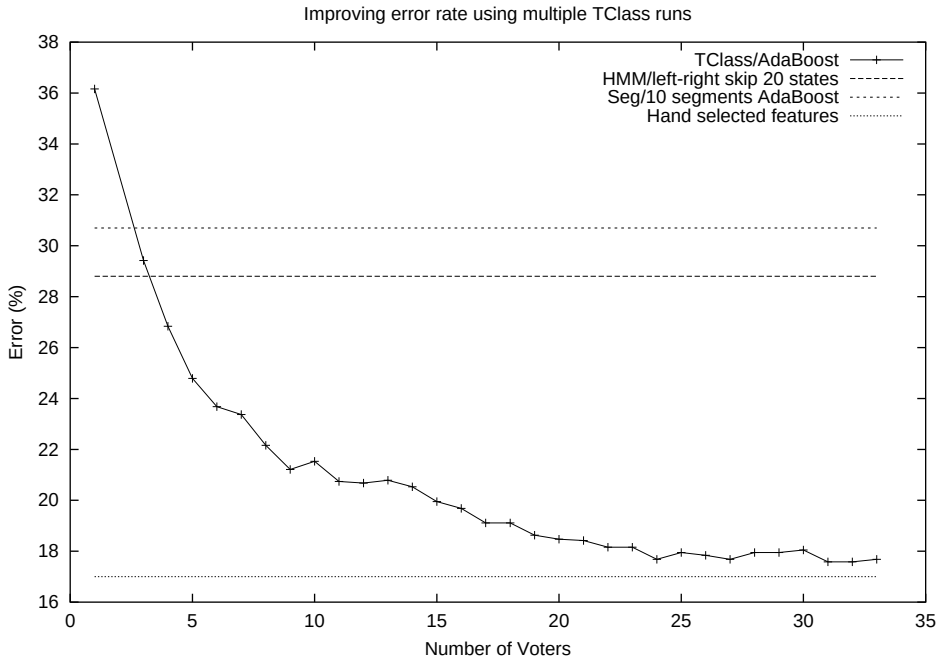


Figure 6.26: Voting *TClass* generated classifiers approaches the error of hand-selected features.

We see that this improves results. With 4 voting *TClass* classifiers, we outperform all other learners. With 25 voting *TClass* learners, it appears that we are asymptotically approaching the accuracy of the hand-extracted features. Again, this comes at the expense of comprehensibility, but the results are still good.

Comprehensibility

Determining comprehensibility for something that classifies 95 classes is somewhat difficult. For the above cases, very large trees are generated – with an average with J48 of 637 nodes. PART generates rules; and for the above case with all the bells and whistles turned on it still averages 233 rules. However, this is only 2.45 rules per class; which is reasonable.

A subjective correlation of the rules produced by PART and the Auslan dictionary proved largely unsuccessful. This was thought to be due to the large number of classes. Hence, to simplify the learning task and produce better definitions, a simple approach was taken: turn the classification problem into a binary one and see if the definitions come out clearer.

And indeed these do. Figure 6.27 shows a definition of the sign `thank`. The gloss for the sign `thank` is shown in Figure 1.1. The definition looks rather strange; however, it is the result of the way the learner works. The first two rules are "quick reject" rules to eliminate most possibilities (for example, the first rule eliminates approximately 93 per cent of all training instances). The first rule says that if there is no movement toward the body early in the sign (midtime=0.19) and then no movement away from the body late in the sign and there is no local minimum in the movement it can't be the sign `thank`. This is encouraging, since of course, the sign thank is exactly the opposite: a movement towards the body then away from the body.

Approach	Error
TClass with J48	14.5 ± 0.4
TClass with PART	16.7 ± 0.9
TClass with IB1	60.3 ± 1.1
TClass with Naive Bayes	29.2 ± 0.8
TClass with Bag	9.4 ± 0.8
TClass with AB	6.4 ± 0.4
Naive Segmentation	$\mathbf{5.5 \pm 0.5}$
Hidden Markov Model	12.9 ± 0.6

Table 6.14: Error rates for the Flock sign language data.

The second rule says that if the middle finger isn't closing towards the end of the sign, and that the z value doesn't change towards the end of the sign, then it is not thank. The y value check is probably an oddity of the data, but it doesn't matter since the first two parts of the rule will probably prevent checking of the third part. Again, since the sign is open-handed, this means that the middle finger stays stable.

The third rule says that if the the first two rules haven't eliminated the possibility and the hand moves towards the centre of the body, then it is the sign `thank`.

The fourth and fifth rules can also be explained, but it is omitted here for brevity since they cover less than 1 per cent of the training set.

Flock data

The Flock data is much "cleaner" than the Nintendo data. The results of the first test are shown in Table 6.14.

```
PART decision list
------------------

IF z HAS NO Increasing: midTime = 0.19 avg = 0.04 m = 0.41 d = 0.29 (*1) AND
IF z HAS NO Decreasing: midTime = 0.53 avg = 0.01 m = -0.77 d = 0.29 (*2) AND
IF z HAS NO LocalMin: time = 0.69 val = -0.05 (*3)
THEN not-thank (1768.0/1.0)

IF middle HAS NO Increasing: midTime = 0.63 avg = 0.01 m = 4.6 d = 0.20 (*4) AND
IF z HAS NO LocalMax: time = 0.94 val = -0.02 (*5) AND
IF y HAS NO Increasing: midTime = 0.15 avg = 0.05 m = 2.00 d = 0.33 (*6)
THEN not-thank (103.0/1.0)

IF x HAS Decreasing: midTime = 0.17 avg = 0.03 m = -1.06 d = 0.37 (*7)
THEN thank (15.0)

IF z HAS NO Plateau: midTime = 0.78 avg = -0.04 d = 0.11 (*8)
THEN not-thank (11.0)

: thank (3.0)

Number of Rules  :      5
```

Figure 6.27: A decision list produced by *TClass* on the Nintendo sign data for the sign `thank`.

```
Event index
-----------
*1: inc
   midtime=0.19 r=[0.11,0.52]
   avg=0.04 r=[-0.02,0.09]
   m=0.41 r=[0.17,0.70]
   duration=0.29 r=[0.18,0.37]

*2: dec
   midtime=0.53 r=[0.23,0.86]
   avg=0.01 r=[-0.03,0.08]
   m=-0.77 r=[-1.27,-0.52]
   duration=0.29 r=[0.12,0.42]

*3: min
   time=0.69 r=[0.59,0.75]
   value=-0.05 r=[-0.14,-0.03]

*4: inc
   midtime=0.63 r=[0.45,0.76]
   avg=0.01 r=[-0.14,0.09]
   m=4.6 r=[3.53,5.4]
   duration=0.20 r=[0.15,0.25]

*5: max
   time=0.94 r=[0.88,0.95]
   value=-0.02 r=[-0.06,-0.01]

*6: inc
   midtime=0.15 r=[0.08,0.47]
   avg=0.05 r=[-0.02,0.28]
   m=2.00 r=[0.61,3.67]
   duration=0.33 r=[0.12,0.41]

*7: dec
   midtime=0.17 r=[0.1,0.41]
   avg=0.03 r=[-0.15,0.17]
   m=-1.06 r=[-2.95,-0.57]
   duration=0.37 r=[0.12,0.53]

*8: plat
   midtime=0.78 r=[0.47,0.97]
   avg=-0.04 r=[-0.10,0.00]
   duration=0.11 r=[0.03,0.14]
```

Figure 6.28: Events referred to in Figure 6.27 with bounds.

Learner	Base	Smooth	Centroids	Relative	C + R
J48	14.5 ± 0.4	18.0 ± 0.4	15.3 ± 1.0	14.2 ± 0.4	15.1 ± 0.6
PART	16.7 ± 0.9	18.4 ± 0.6	17.6 ± 0.5	16.7 ± 0.8	16.8 ± 0.4
IB1	60.3 ± 1.1	56.5 ± 1.6	60.1 ± 1.4	52.2 ± 3.2	49.6 ± 1.5
Bag	9.4 ± 0.8	9.4 ± 0.8	8.8 ± 0.6	6.8 ± 0.3	6.7 ± 0.2
AB	6.4 ± 0.4	7.7 ± 0.6	6.2 ± 0.2	5.3 ± 0.5	$\mathbf{5.1 \pm 0.3}$

Table 6.15: Error rates with minor refinements for the Flock data.

It seems that the hidden Markov model is not performing as well as it used to. Our hypothesis for this is that the streams in this case are much longer and contain many more channels. Hence, there are likely to be confusions as to the attribution of particular states.

We ran the same tests on smoothing as before, and searching with higher number of instances to see if it had any effect.

Smoothing did not improve results – in fact it made them worse. This is because the data from our gloves is almost noise-free – the sensors are much higher quality. In fact the improvement from one to the other is huge – the error rate is typically one quarter of what it was in the Nintendo data.

This also puts paid to one of the concerns in the design – that the *TClass* system would not be able to handle copious data. Altogether, each sign in the Flock data contains approximately 11 times the data of the Nintendo data. It was feared that this additional processing load would actually have and adverse impact on the accuracy. As it turns out, this was not the case – it took full advantage of the additional channels in both accuracy and comprehensibility.

Also notable is that the difference in accuracy between the final algorithm and the base algorithm. In the case of AdaBoost, the difference is very significant; the error rate now less than any competing method, without applying voting. To see how well we could do, we ran boosting on the final method. The results are shown in Figure 6.29. The show that the accuracy obtained is significantly lower.

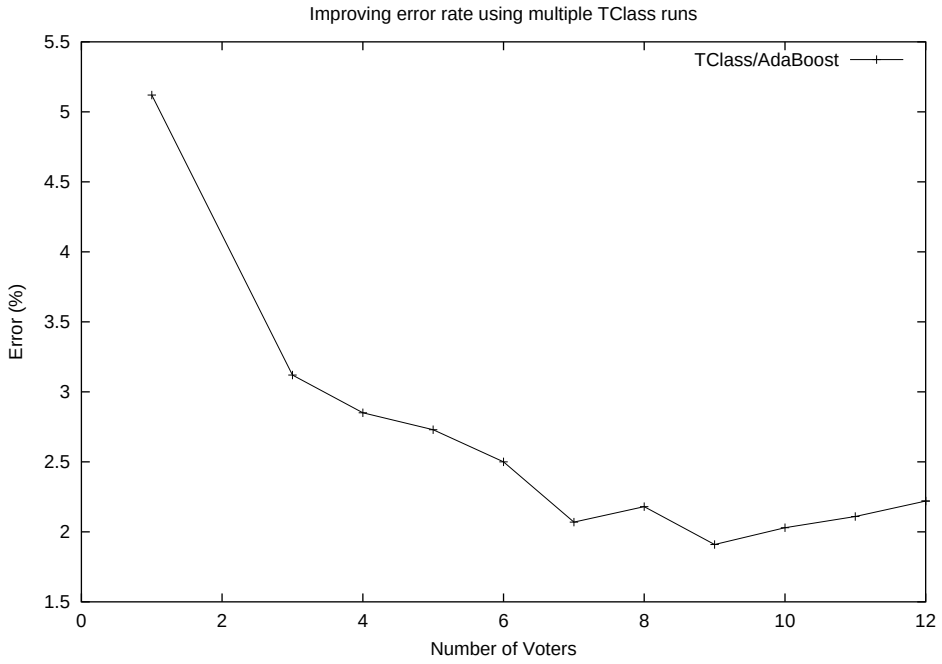


Figure 6.29: Effect of voting on the Flock sign data domain.

However, the gain from the search for more random centroids is probably not worth the additional computational effort. For example, if we look at computation times[8] for running the J48 classifier, the average with 1000 random centroids is 3542 seconds (i.e. just under an hour), while with 10000 centroids

[8]All timing results measure the user time (i.e. those directly used for calculations) on a Pentium-III 450MHz with 512MB RAM. One has to take these measurements with a grain of salt, since the code is not particularly optimised and is written in Java).

it is 27417 seconds (ie. about 7 hours 40 minutes). It does not seem to lead to an increase in accuracy in the J48 case, and the effect in the AdaBoost case of about 0.2 per cent which may not be statistically significant makes the point even further. The difference in tree size between the two is negligible.

Also notable is the effect on tree size. For almost the same learning task, the Nintendo data produces trees that contain on average 322.8 leaf nodes. With the Flock data, the tree size is massively reduced to only 132.6 leaf nodes. This is a 59 per cent reduction in tree size. 132.6 is close to the 95 classes we have; optimally the tree would have exactly 95 nodes, assuming that the concepts are disjunctive. This means that there are an average of 1.4 leaf nodes for every class. Furthermore, for the decision rule learner PART, there are 108.6 rules on average.

Comprehensibility

As with the Nintendo data, binary classification tasks were given to investigate readability. The tree produced for the sign `thank` is shown in Figure 6.30. The sign `thank` was chosen specifically to make comparisons with the results for the Nintendo sign data shown in Figure 6.27 possible.

The rules are much simpler. It makes use of the additional channels. First, it uses the roll of the hand. The first rule says: if the right hand does not roll to a palm up position early in the sign, then it can not be the sign `thank`[9]. This is

[9]There are two events tested against here; this is an artifact of the random segmentation

a logical first-cut: there are very few signs that begin in a palm-up position and it eliminates about 92 per cent of the training instances.

The second rule checks to see if the hand is moved horizontally and laterally towards the body. If it has either of these characteristics, then it can not be the sign `thank`.

The third rule checks the ring finger (a good indication of the state of the palm). If the ring finger is, on average, very close to unbent (as would be the case for an open-palm sign like `thank`) and the left hand doesn't move horizontally at all, then it is the sign for `thank`. The "at all" comes from looking at the event index. The bounds on event 6 are quite large, for example, the midtime is anywhere from 0.0 to 0.82, and the duration is anything from 0.04 to 1.0. These values are expressed in relative terms: in other words a duration of 1.0 would mean the length of the whole sign.

It's obvious that this rule is clearer than the rule shown in Figure 6.27. It uses 20 per cent fewer events and rules and uses the additional channels in a way that produces a much more intuitive description.

Conclusions on Auslan

Using *TClass* we have created a learner that can produce low error rates on classification when voted. On the Nintendo data, we are able to produce accuracy

process

```
PART decision list
------------------
IF rroll HAS NO LocalMin: time = 0.19 val = -0.28 (*1) AND
IF rroll HAS NO LocalMin: time = 0.21 val = -0.26 (*2)
THEN not-thank (2367.0)

IF rx HAS NO Increasing: midTime = 0.11 avg = 0.0 m = 0.18 d = 0.23 (*3) AND
IF rz HAS NO Decreasing: midTime = 0.14 avg = 0.04 m = -1.00 d = 0.17 (*4) AND
IF lroll HAS NO Increasing: midTime = 0.72 avg = 0.00 m = 0.01 d = 0.5 (*5)
THEN not-thank (154.0)

rring-mean <= 0.01 AND
IF lx HAS NO Increasing: midTime = 0.32 avg = -0.02 m = 0.35 d = 0.20 (*6)
THEN thank (27.0)

: not-thank (17.0)

Number of Rules  :      4
```

Figure 6.30: A decision list produced by *TClass* on the Flock sign data for the sign `thank`.

that is comparable to hand-selected set of features. On the Flock data, we attain an error of just 2 per cent.

When not voted, it can be used to create comprehensible descriptions that are easily understood in this context. The Nintendo data definitions are quite difficult to comprehend, mostly because of the limitations of the sensors. The Flock data produces definitions that can be compared (favourably) against definitions in the Auslan dictionary – perhaps not quite as comprehensible, but still, it is easy to see what the classifier is using.

```
Event index
-----------
*1: lmin
   time=0.19 r=[0.04,0.31]
   value=-0.28 r=[-0.37,-0.27]

*2: lmin
   time=0.21 r=[0.02,0.34]
   value=-0.26 r=[-0.27,-0.15]

*3: inc
   midtime=0.11 r=[0.02,0.35]
   avg=8.81E-4 r=[-0.12,0.08]
   m=0.18 r=[0.02,1.40]
   duration=0.23 r=[0.06,0.38]

*4: dec
   midtime=0.14 r=[0.03,0.46]
   avg=0.04 r=[-0.05,0.12]
   m=-1.00 r=[-2.74,-0.39]
   duration=0.17 r=[0.05,0.25]

*5: inc
   midtime=0.72 r=[0.22,0.87]
   avg=0.00 r=[-0.09,0.07]
   m=0.01 r=[0.00,0.57]
   duration=0.5 r=[0.21,0.98]

*6: inc
   midtime=0.32 r=[0.01,0.82]
   avg=-0.02 r=[-0.12,0.09]
   m=0.35 r=[0.00,2.27]
   duration=0.20 r=[0.04,0.98]
```

Figure 6.31: Events referred to in Figure 6.27 with bounds.

6.3.3 ECG

Electrocardiograms (commonly abbreviated as ECGs) are a non-invasive technique for measuring the heart's electrical activity. By "listening in" on these signals, we can diagnose problems within two main areas: firstly, the electrical system itself (these are called *Type B* diagnostic statements); and secondly tissue damage to the heart, such as valve blockages, muscle misfires and other physiological issues that manifest themselves as alterations to the heart's electrical system (these are referred to as *Type A* diagnostic statements). Type A problems are more difficult to diagnose from ECGs, since we are observing the effect of physiological phenomena on the electrical system, rather than the electrical system itself.

ECGs are captured by attaching a number of electrodes around the body, most of which are near the heart, but some of which are at the extremities. Once the electrodes are connected; voltages, and differences between the voltages at different electrodes, are recorded as time series.

The structure of an individual heartbeat is shown in Figure 6.32. As can be seen, the heartbeat is analysed in terms of several components, commonly labelled the P, Q, R, S and T waves.

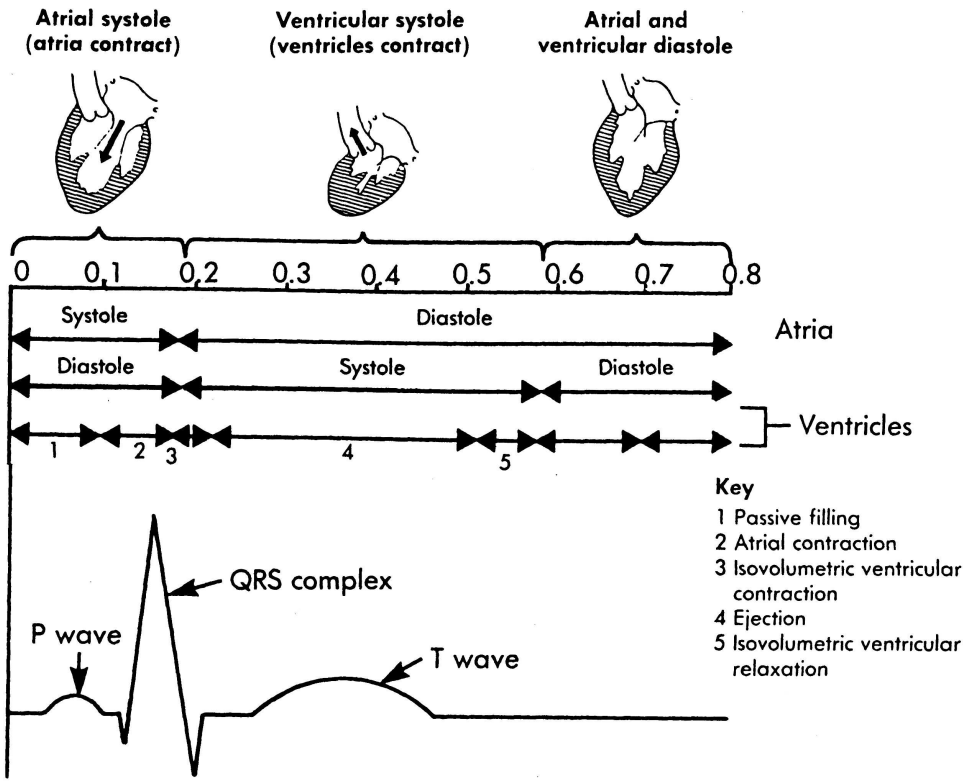


Figure 6.32: The components of a heartbeat. Taken from [dC98].

Previous work

There has been a lot of work on analysing ECGs within the artificial intelligence and machine learning communities. Perhaps the most significant of these was Bratko et al's work on the KARDIO [IB89] methodology and model for the heart. However it is interesting to note that in discussing its application in practice, he had this to say:

> In respect to clinical application of KARDIO, the cardiologists felt that a significant limitation is that KARDIO accepts as input symbolic ECG descriptions rather than the actual ECG signal. Thus

> the user is at present required to translate the patient's ECG waveform into the corresponding symbolic descriptions. ... In presently available ECG analysers, these difficulties [in extracting symbolic descriptions] lead to unreliable recognition of some of the ECG features.

TClass provides a mechanism for overcoming this problem: it takes as input the ECG with some basic filtering applied. Further, KARDIO was developed to diagnose Type B problems; whereas in this chapter we tackle the harder Type A classification problem.

Our dataset was a random selection of 500 recordings from the full CSE diagnostic database [WALA$^+$90]. This dataset was also explored by de Chazal [dC98]. The records come from men and women with an average age 52 ± 13 years. The sample rate was 500Hz. There were seven possible classes: normal (NOR), left ventricular hypertrophy (LVH), right ventricular hypertrophy (RVH), biventricular hypertrophy (BVH), acute myocardial infarction (AMI), inferior myocardial infarction and (IMI) and combined myocardial infarction (MIX). The classes are not evenly distributed, with the class distribution shown in Table 6.16. The class labels were determined independently through medical means (e.g. surgery after the ECGs were recorded), so the class labels can be assumed to be free of noise.

Each recording consists of 15 channels. These include the three Frank leads that provide a 3D representation of the heart: X, Y and Z, but also include the raw sensors V1 through to V6 as well as aVF, aVR and aVL. Figure 6.33 shows

Class	Number
NOR	155
LVH	73
RVH	21
BVH	25
AMI	75
IMI	106
MIX	31

Table 6.16: Class distribution for the ECG learning task.

the data as it reaches the *TClass* learning algorithm, after some preprocessing steps, which we discuss below.

The focus of de Chazal's thesis was the manual construction of a set of features for classification of Frank Lead electrocardiogram. As part of this project, he also created software for filtering the ECG signals to get rid of noise, and also software for automatically segmenting an ECG recording into beats.

The filter design can be found on page 48 of his thesis. It is mainly designed to exclude "baseline wander" due to the patient's respiration at about 0.5Hz, and mains electricity at 50Hz. The effects of the filter are shown in Figure 6.34 on the three orthogonal leads (X, Y and Z) over a sequence of heartbeats. For ease of comparison, we used the same filter as de Chazal.

We also used the de Chazal's segmentation of the ECG recordings into individual beats. A typical ECG recording consists of several beats. These heartbeats must be segmented into individual heartbeats so that learning can take place. For our data, the ECGs are segmented according to the Q wave onset time.

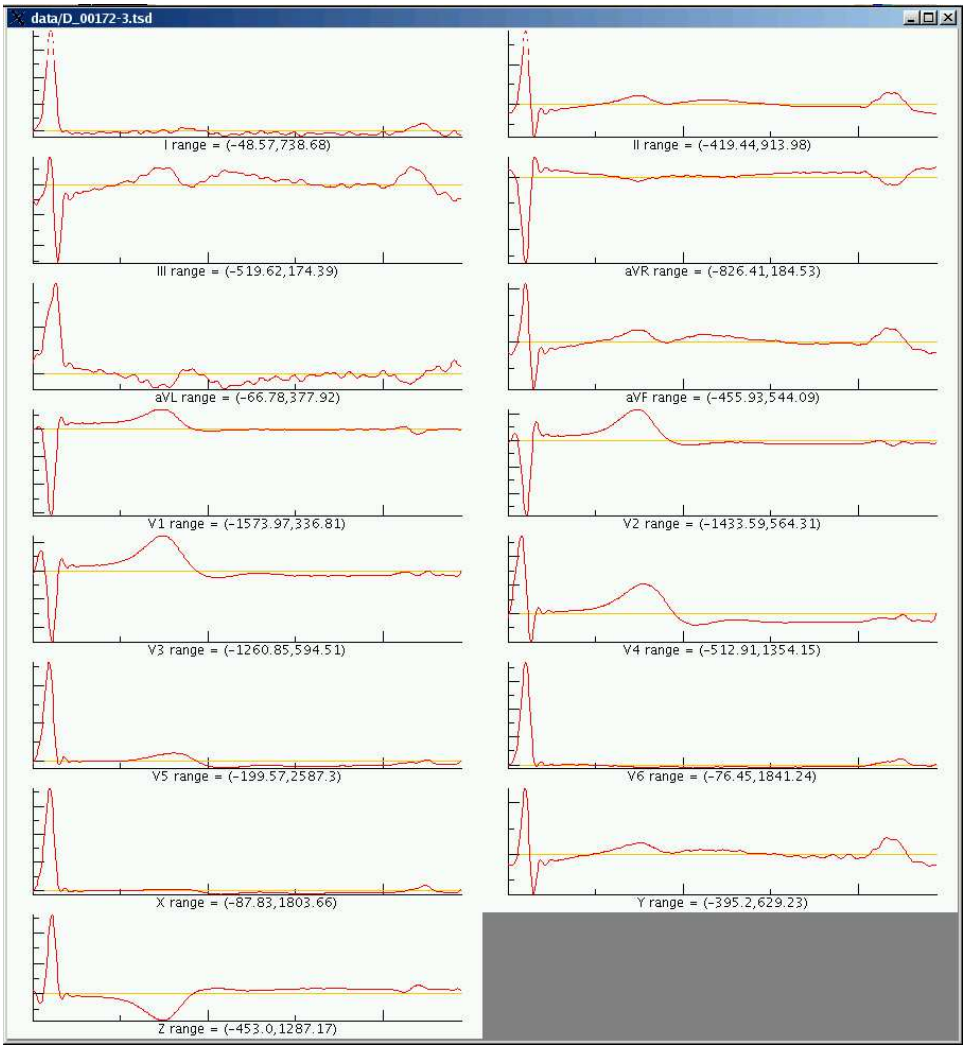


Figure 6.33: The ECG data as it arrives when seen by *TClass*.

de Chazal's feature

The features extracted by de Chazal concentrate on the X, Y, and Z axes. They fall into three main categories:

- **Scalar lead features**: These include measurements of heights, angles, time durations and areas relating to the QRS complex of the wave. For

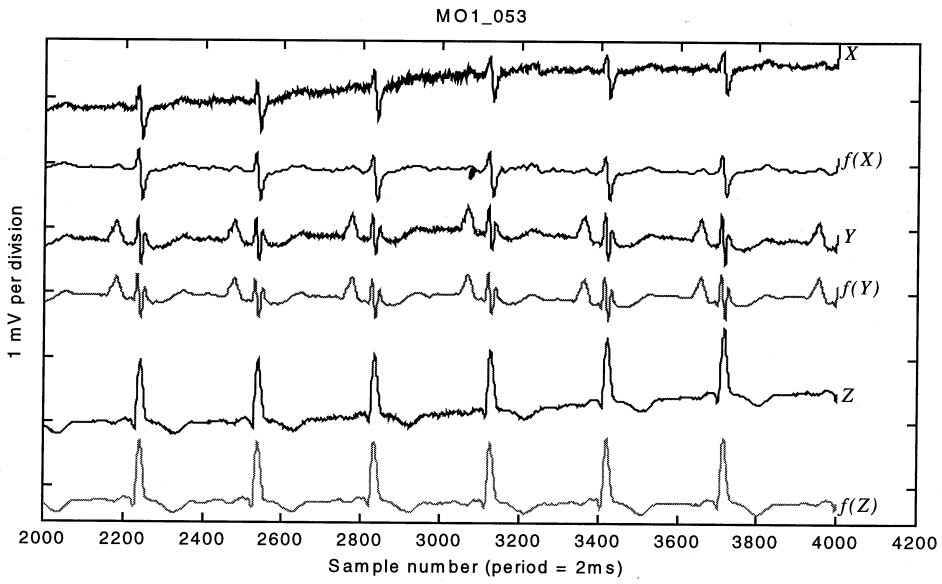


Figure 6.34: The effect of applying de Chazal's filter to the ECG data (taken from [dC98]).

example, they include scalar measurements of the heights of the QRS complex at 8 points – very similar to our naive segmentation. They also include measurements of times, and areas underneath the QRS complex.

- **Loop features**: The heart's beating can be characterised as a loop in the 3D space made by the X, Y and Z axes. Various characteristics of this loop can be captured, such as its axis, its plane, the deviation from planarity and so on.

- **Global features**: These included the age and the sex of the patient.

Other features were ratios and differences between other features. Some of these features were extracted from the ECG literature, while others were developed within the Biomedical Systems Laboratory at the University of New

South Wales. In total, 229 features were generated. In many cases, this includes both sines and cosines of angles to make presentation to the learning system simpler.

In de Chazal's work, a variety of learners were applied. The two main families examined were voted softmax neural networks and C5.0. He also employed a number of feature selection techniques.

The best accuracy value of 71.3 per cent (28.7 per cent error) was obtained by using 100 voted softmax-neural networks, each with different initial conditions applied to all features. These results compare extremely well with median values for human cardiologists of 70.3 per cent (a human panel obtained approximately 74.8 per cent accuracy).

However, there are some issues with de Chazal's work. Firstly, because neural networks were used (and in particular, 100 voted neural networks) the results are not very comprehensible. Clearly it would be desirable, especially from a medico-legal standpoint, for explanations for classifications of ECGs to be given. Secondly, de Chazal, from his work obviously a brilliant and dedicated PhD student, building on decades of research, spent at least 3 years developing software for extracting features. In other domains, such background knowledge may not be available.

Experimental results

In his thesis, de Chazal took each of the ECGs with its heartbeats, and selected what is termed the "dominant" heartbeat. The dominant heartbeat is the one that is the most free of noise. Each ECG consisted of between 4 and 16 heartbeats, with an average of approximately 8. Typically, the dominant heartbeat was the 6th heartbeat; however, domain experts analysed each example to see if they were "typical" examples of the beat. This of course, requires domain knowledge.

For comparison with de Chazal's, we used the same dominant beats as he did for our first group of experiments.

It is interesting to note that these data files are much larger than a typical instance in a propositional problem: each training instances was between 20 kilobytes and 84 kilobytes, with the average being 47 kilobytes. Even considering just dominant beats, then that is still approximately 24 megabytes of raw data.

Each dominant beat was extracted and labelled by the class. Using 10-fold cross validation (as de Chazal did), we used *TClass* to learn all 7 classes. The results of the experiments are shown in Table 6.17. For *TClass* we used both relative time and height because this makes more sense in this domain: The amplitudes depend greatly on the peculiarities of the ECG electrodes; and the beats of the heart vary greatly in duration.

The results in Table 6.17 seems to be very close between *TClass* and the

Approach	Error
TClass with J48	51.4 ± 2.0
TClass with PART	45.2 ± 3.0
TClass with IB1	52.4 ± 3.1
TClass with NB	36.6 ± 2.2
TClass with Bag	39.0 ± 2.6
TClass with AB	35.4 ± 3.8
Naive Segmentation	34.2 ± 2.7
Hidden Markov Model	34.4 ± 2.0
de Chazal	28.6 ± 2.4
Human expert	29.7
Human panel	25.2

Table 6.17: Error rates for the ECG data (dominant beats only)

baseline learners. However, it does not compare well with de Chazal's work, or even human experts. The results for human cardiologists are shown from de Chazal's thesis. The cardiologists were asked to classify the same database. The "Human expert" result is the median value for a single expert and the "Human panel" for a voted panel of experts. Note that we are learning based on a small training set of only 500 examples (or in fact, 450 examples once we take into account cross validation); and if we were given more data we may very well perform better.

As before, we can improve the results of *TClass* by using multiple runs and then voting them. Figure 6.35 shows the result of such a voting scheme on accuracy. Although this shows some improvement, it is still not competitive with de Chazal's work. Perhaps this is not unexpected; given the amount of work de Chazal put in to feature extraction.

However, there is another way to improve accuracy: As mentioned before,

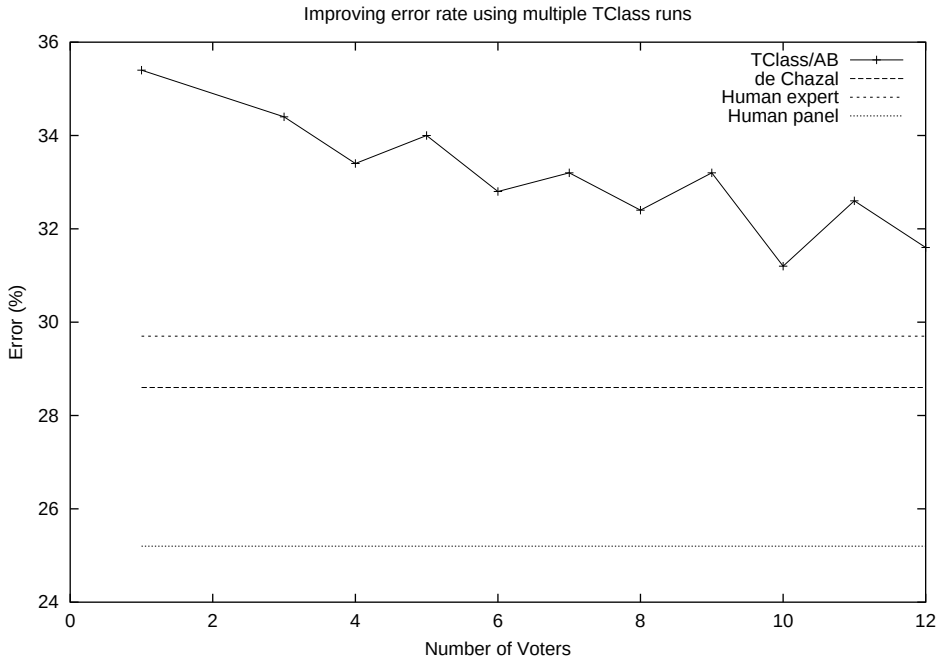


Figure 6.35: Voting *TClass* learners improves accuracy.

each ECG recording consists of multiple beats, with an average of 8 beats per recording. Unfortunately, these other beats do not represent "good" data for the following reasons:

- They are likely to very strongly correlated with other beats from the same recording – so it is not really new data in some sense. What is more, we'll be multiplying the data by a factor of 8, which will consequently have an impact on performance and time consumed.
- Some instances have more examples than others, so we may be "biasing" the learning to people with faster heartbeats (since they will have more heartbeats recorded).

Approach	Error	Reduced events
TClass with J48	51.4 ± 2.0	50.2 ± 2.5
TClass with PART	45.2 ± 3.0	46.6 ± 2.2
TClass with IB1	52.4 ± 3.1	52.6 ± 2.0
TClass with Bag	39.0 ± 2.6	35.4 ± 3.3
TClass with AB	35.4 ± 3.8	37.4 ± 2.4

Table 6.18: Effect of only allowing "wide" maxima and minima on dominant beats. There is not a significant difference in terms of accuracy.

- The data has not been "vetted" by domain experts as typical heartbeats.

Hence our algorithm will have to be robust to noise and able to cope with biases in the input data, as well as able to cope with large amounts of data. In fact, using this approach will use approximately 200 megabytes of input data.

TClass was able to cope with this amount of data, even on a computer with only 512 megabytes of RAM. It necessitated setting some of the parameters for the feature extractors to not produce superfluous events – e.g. tiny maxima and minima of no importance to classification. Tests were run to compare the effect on accuracy and *TClass*'s function was not affected by having stricter constraints that only picked up minima that were a certain width. The results are shown in Table 6.18 for the dominant beats only.

One other observation is that the results can easily be voted across all the heartbeats in the test set. Also note that this is applicable not just to the *TClass* methods but to naive segmentation and hidden Markov models as well.

Table 6.19 shows how this worked in practice.

Approach	Error
TClass with J48	45.5 ± 1.7
TClass with PART	41.9 ± 2.1
TClass with IB1	45.3 ± 1.3
TClass with Bag	35.1 ± 2.6
TClass with AB	32.9 ± 2.4
Naive Segmentation	$\mathbf{28.5 \pm 2.6}$
Hidden Markov Model	33.5 ± 1.7

Table 6.19: Error rates for the ECG data with all beats used

These results can again be improved on by applying voting across different runs of *TClass*. Figure 6.36 demonstrates the effect of repeated voted of *TClass* using AdaBoost as a base learner.

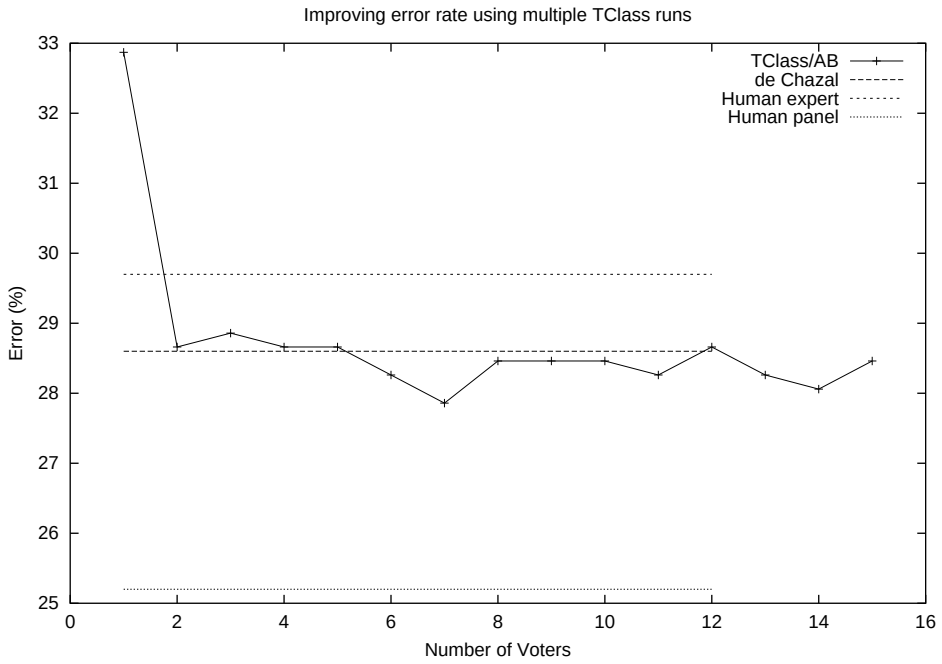


Figure 6.36: Voting *TClass* learners asymptotes to error the hand-selected feature extraction technique.

These results show that even after two runs of *TClass* with AdaBoost, our performance is indistinguishable from either a human expert or the performance

that de Chazal achieved. With minimal background knowledge about the domain, we are able to achieve equivalent accuracy results to someone who used years of domain knowledge to prepare an appropriate set of features.

Comprehensibility

We suspected that part of the cause of the lacklustre accuracy performance of *TClass* was the issue of pruning with such a large dataset. Hence we investigated by setting the minimum number of instances (m) at each leaf. For example, we tried $m = 42$. For the PART learner, the error rate actually decreased slightly to 40.5 per cent, while the average number of rules was reduced from 94 rules to 24 rules. A set of 24 rules for recognising ECGs with a 40.5 per cent error rate, when a human expert has a 30 per cent error rate is quite an accomplishment.

Still, it is hard to study the comprehensibility of such rules. Hence we used the binary classification rules approach as used on the Auslan datasets to see if there were any intelligent concepts that could be deduced. The results are shown in Figure 6.37.

To gain some insight as to whether this was a useful rule, it was compared with the rules used by a commercial ECG classifier based on an expert system [A97][10]. The definitions produced shows the same characteristics as the definitions produced in this manner for the Auslan domains: the first few rules provide

[10] Unfortunately, companies are unwilling to disclose the exact performance of their systems for direct comparison.

```
PART decision list
------------------

IF aVL HAS LocalMin: time = 0.49 val = -43.53 (*1) AND
IF x HAS NO LocalMin: time = 0.11 val = -1103.50 (*2) AND
IF V1 HAS NO Plateau: midTime = 0.55 avg = -2.38 d = 0.07 (*3)
THEN not-RVH (3727.0/32.0)

aVL-max > 554.61: not-RVH (92.0)

x-min <= -212.28 AND
IF aVL HAS LocalMax: time = 0.54 val = 45.15 (*4) AND
IF z HAS LocalMax: time = 0.42 val = 269.06 (*5)
THEN RVH (82.0/3.0)

x-min <= -221.53 AND
V1-max <= 317.57 AND
IF z HAS LocalMin: time = 0.45 val = -24.93 (*6)
THEN RVH (67.0/31.0)

V1-max <= 352.09: not-RVH (108.0/4.0)

: RVH (62.0/14.0)

Number of Rules  :      6
```

Figure 6.37: A two way classifier for the RVH class in the ECG domain.

a "first cut" exclusion. The third rule looks for a very low minimum on the X value. This is because patients with RVH have a depression in the S wave [A97], leading to a very large minimum x value. In de Chazal's work [dC98] (page 179), he found that the minimum x value is the most discriminant feature based on rank-correlation analysis. The other criteria look for local maxima in the aVL and Z channels that are unique to right ventricular hypertrophy cases: the T wave is biphasic, i.e. rather than having a single maximum, it has two maxima; while most normal heartbeats will have one maximum occurring slightly later (around time 0.7) [A97].

```
Event index
-----------
*1: lmin
   time=0.49 r=[0.01,0.60]
   value=-43.53 r=[-337.57,21.89]

*2: lmin
   time=0.11 r=[0.02,0.51]
   value=-1103.50 r=[-2877.34,-595.36]

*3: plat
   midtime=0.55 r=[0.06,0.99]
   avg=-2.38 r=[-1491.40,190.67]
   duration=0.07 r=[0.01,0.35]

*4: lmax
   time=0.54 r=[0.01,0.73]
   value=45.15 r=[12.82,286.97]

*5: lmax
   time=0.42 r=[0.02,0.65]
   value=269.06 r=[62.69,3244.42]

*6: lmin
   time=0.45 r=[0.3,0.60]
   value=-24.93 r=[-296.24,42.04]
```

Figure 6.38: Events referenced by Figure 6.37.

ECG conclusions

Our accuracy results are competitive with a median human cardiologist; and also competitive to a learner trained on the same dataset, but with the application of copious quantities of background knowledge. Given that we did not use any background knowledge, the results are good. As for comprehensibility, our system might be an appropriate "first cut" classifier that with just 24 rules obtains 60 per cent accuracy. Further investigations of individual classifiers shows some correspondence to rules found in commercial ECG classifiers and also show some correspondence to findings by de Chazal.

6.4 Conclusions

TClass has proved to be an effective learner in terms of accuracy if one is willing to use a voting mechanism. In every domain, voting different learners allowed it to exceed the performance of our baseline learners. Furthermore, on the two real-world domains, it proved competitive even with hand-selected domain-specific features. This is a somewhat surprising result.

However, clearly voting leads to a destruction of the readability of the classifier. This is a definite problem with the current implementation of *TClass*. However, the definitions it produces, while not as accurate as those created by voting, are still very informative. In the artificial domains, we saw that the induced concepts corresponded closely to the correct concepts. Similarly, in the

real-world domains, correlations between known concept descriptions and the induced concept descriptions are visible. However, as noise is increased, the readability of the induced rules is reduced.

There is a question as to which kinds of domains and problems *TClass* is suited to. Results show that *TClass* performs better, even without voting, in the following situations:

- Where there is little noise in the signal. This was particularly revealed in the *TTest* artificial domain, in Figure 6.18. This diagram showns that *TClass*' performance is much better than the baseline learners at low noise levels, but as the noise level becomes very great, the baseline learners like Naive Segmentation and Hidden Markov Models perform better.
- Where there are fewer training instances. This was particularly shown in 6.20,, where *TClass* outperformed other classifiers when there were fewer training instances.

Chapter 7

Future Work

There is much more work to do in temporal classification. In this chapter, we examine two approaches to improving temporal classification: firstly, extending *TClass*, and secondly, looking at other possible approaches encountered in the development of *TClass*.

7.1 Work on extending *TClass*

TClass presents an interesting platform for future work. The current work has explored some parameters and options, but it has barely scratched the surface. Furthermore, this work has revealed certain problems with *TClass* that need to be addressed. Some of the most important are discussed below.

7.1.1 Improving directed segmentation

Improving the directed segmentation would be the most straightforward and beneficial way to improve performance.

The indications are clear that the random search used for directed segmentation is suboptimal. The most obvious of these is the huge difference in accuracy between *TClass* when producing individual classifiers and when producing a voting ensemble. The fact that repeated executions of random segmentation improve accuracy dramatically indicate that the random segmentation algorithm could choose synthetic events better.

Here we make several suggestions for improving directed segmentation.

Issues with region description

A side effect of region segmentation is that all regions are accepted as synthetic features. Consider Figure A.3. Consider now if one centroid c_1 is placed at (5, 0.35), c_2 at (10, 0.1) and c_3 at (40,-0.1).

It is clear that the centroids c_1 and c_2 make good synthetic features. But c_3, although important for a good segmentation (indeed, it is necessary to define the concept boundaries), does not itself make a useful synthetic feature. This is because the region around c_3 contains a mix of instances from different clases, hence its usefulness as a discriminative attribute is not likely to be high. How-

ever, without c_3, all of the points formerly considered as associated with c_3 would now be associated with c_2, including the mixed class area of centred around (40, -0.1). This would make c_2 a less useful discriminative features. Hence, c_3 is useful overall for providing a highly discriminative features – in particular making c_2 more discriminative – but c_3 itself is not a discriminative feature.

If the learner we are using were smart enough, this synthetic feature should be eliminated. Quinlan points out [Qui93] that the more attributes that are given to the learner, the greater the probability that amongst them there will be one attribute that performs highly on the train data but poorly on the test data. Hence, if we can remove c_3 before it gets to the learner, it would likely improve our classification performance. Using fewer features may also aid in the production of more comprehensible rules, since it would likely lead to shallower trees.

Improving the directed segmentation search

Perhaps some kind of hill-climbing or genetic algorithm may function to improve the search.

Improving by Direct Feedback from the Learner

So far, we have used a disparity measure to evaluate the "goodness" of a particular region segmentation. This disparity measure is really a low-computation

proxy for the learner, built on the assumption that what has a high disparity measure will be useful to the learner. Realising this leads to an obvious conclusion: if the disparity measure is a proxy for the learner, then why not use the learner itself to evaluate the effectiveness of a region segmentation directly? This suggests that rather than our random search algorithm, we modify it so that it (a) the disparity measure is the cross-validated accuracy (hence, the higher the accuracy, the higher the disparity measure) (b) the most accurate subset of features is selected. This would lead to the improved algorithm shown in Figure 7.1. Here we have used the *Attribute* function defined in Figure 5.5. Also, we assume that a learner's accuracy can be evaluated using the method *crossValAcc* which takes a learner and a dataset and returns the cross-validated accuracy.

The algorithm in Figure 7.1 uses the learner to evaluate the real performance. Some difficulties arise, however: Firstly, the whole point of using the disparity measure was speed – it would be too slow to evaluate each region segmentation this way. For example, consider the new Auslan dataset. There are approximately 110 metafeatures. Let us assume we use 10-fold cross-validation with $numTrials = 1000$. Then this would require us to run a learner $110 \times 10 \times 1000 = 1.1 \times 10^6$. Even assuming that each learner takes an average of 0.1 seconds to generate a classifier, then this would still take well over a day to execute.

Secondly, we are actually testing the performance of each metafeature in isolation. As pointed out in Section 5.2.2, the results of the execution of the random search algorithms are all combined to form a single feature vector. While a particular segmentation may work well if it is the only set of synthetic features,

```
Inputs:
    I = [⟨[i_11, ..., i_1m1], l_1⟩, ..., ⟨[i_n1, ..., i_nmn], l_n⟩]
        (Feature-extracted training data)
    N = {n_min, ..., n_max} (Appropriate range of clusters)
    Learner(PropData) (What learner to use)
    numTrials (number of trials to attempt)
    mem(Centroid, Instances)
        (Membership function we are using)
Outputs:
    C = {c1, ..., c_n} (cluster centroids)
procedure RandSearch2
    /* First we must "flatten" input data. */
    D := {}
    For each ⟨P, l⟩ in I
        For each p in P
            append(D, ⟨p, l⟩)
        End
    End
    bestMeasure := 0
    bestCentroids := {}
    for i := 1 to numTrials
        r := randBetween(n_min, n_max)
        currentC := randSubset(r, D)
        /* Turn the data into propositional form */
        E := Attribute(I, currentC, mem)
        /* Find the cross-validated accuracy of the learner */
        currentMetric := crossValAcc(Learner, E)
        if(currentMetric > bestMetric)
            bestMetric := currentMetric
            bestCentroids := currentC
        End
    End
C := bestCentroids
return C
End
```

Figure 7.1: Random search algorithm, using the learner itself

it may be of no use when it is combined with the segmentation of other regions. Similarly, it may be that a set of synthetic features are only useful in combination with another set. Hence, even using the learner itself is only an approximation of how useful it would be in the end. And if it is an approximation, then what it the guarantee that cross-validated accuracy using the learner is any better a disparity measure than chi-squared or the gain ratio?

This idea has certain similarities to the "wrapper" method suggested by John, Kohavi and Pfleger [JKP94] for handling the feature selection issue, and indeed we are using a kind of wrapper, albeit in a very different way.

But what about speed? This too can be addressed. Firstly, it may not be necessary to run the same number of trials as when using the disparity measure. Secondly, it may be possible to use a hybrid approach, taking advantage of both disparity measures and cross-validation accuracy. This could be done, for instance, by using a disparity measure to "short list" the region segmentations with the highest disparity measures (say the top 20) and then the learner's cross-validated accuracy is used to choose the best among these 20 instances.

Using learners for region segmentation

One way to look at the region segmentation problem is as a learning task: to classify the areas of the parameter space that have more of one class than the other. Hence one obvious way to segment the region is to use a segmenter that subdivides the parameter space appropriately.

One obvious learner that would do this is an axis-orthogonal decision tree builder, like C4.5 or J48. However, it is unlikely that we would want to use the full depth of the tree: this would generate as many regions as there are leaf nodes. However, if we were to enforce some heavy pruning regime (for example, requiring that no leaf node contain less than 5 per cent of the instances), this would essentially segment the parameter space into hypercubes; each representing region. Hence, rather than a Voronoi tiling applying, instances would be evaluated as to their presence in different regions of the parameter space.

This would require some other minor changes to the algorithm; for instance, the region membership. Furthermore, making the definitions comprehensible would require some work – one alternative is simply to give the description of the hypercube, but this may be inappropriate or not provide enough information into what is actually happening.

7.1.2 Automatic metafeatures

Is there some way, by observing the data, to automatically make educated guesses at what the appropriate metafeatures are? This is a difficult question, and it is the temporal classification equivalent of constructive induction in inductive logic programming – something of a holy grail. It may be possible, however it looks extremely difficult.

However, there are alternatives. For instance, it may be possible to have a

good-sized library of metafeatures, and, given a new domain, somehow work out which are the appropriate metafeatures for it.

7.1.3 Extending applications of metafeatures

The scope of use of metafeatures is huge. The technique looks like it is generalisable to areas such as spatial analysis, image processing, basket analysis and more. The problem is finding the appropriate metafeatures and actually doing the experiments to see if it does work.

7.1.4 Strong Temporal Classification

Although in Chapters 1 and 2 we proposed the strong temporal classification task, the focus in this thesis has been on weak temporal classification. Since we don't know how to do weak temporal classification in a symbolic, comprehensible way, it was felt it was a more fundamental issue.

Extending the metafeatures approach to do strong temporal classification would be worthwhile, but it is probably another thesis of work. However, there are some simple and obvious things that can be done to make inroads into the problem. One potential approach to the problem is a "weak train, strong test" approach. This would be based on the "pre-segmented TC" approach discussed in Section 2.3.3. *TClass* would be trained on pre-segmented instances. However, when it came to testing, a "window" of the data observed so far could

be used to see if it matches any of the learnt classes. We then "slide" the window forward and repeat the process to get a sequence of classifications. By using some kind of voting mechanism, it might be possible to actually do strong temporal classification.

7.1.5 Speed and Space

The implementation of *TClass* was inherently experimental. There are significant optimisations possible. For example, feature extraction need only be done once and can be stored for reuse. It could be reimplemented in a faster language (eg. C++) and take advantage of certain data redundancies and repeated calculations. In particular, many data structures are non-contiguous in memory in the current implementation. By reorganising the data structures in memory to lead to greater contiguity and hence better memory locality it is likely that performance will improve significantly.

7.1.6 Downsampling

When presented with data, it is frequently presented at a high data rate. For example, sign language information about the hand might be received at 200 frames per second. Hence an average 2 second sign might be 400 frames long. Similarly, with ECG data, the electrical signals may be sample at 500 frames per second (sometimes also described as 500 Hertz); hence an individual heartbeat

consists of 400 to 700 samples (corresponding to heart rates between 70 beats per minute and 50 beats per minute). This can be a huge amount of data to consider.

Therefore, the data could be resampled at a lower frequency – commonly called **downsampling**[1]. Under certain circumstances, this may not adversely affect the learning and classification performance and simultaneously reducing feature extraction time. For example, say we were examining the sign language data at 200 frames per second. We could take every two consecutive samples from the original data for each channel, average them, and for each two frames in the input, the output would have only one frame. In this case we are applying a *downsampling factor* of two: the data is reduced in size by a factor of 2. Hence, a 400 frame sample would be reduced to a 200 frame sample – halving the amount of data that must be dealt with. Similarly, a downsampling factor of 4 would reduce the data to one quarter of its original size[2].

Of course, this works well for continuous attributes, but not so well for discrete attributes. For discrete attributes, other methods can be employed, such as voting.

[1] There is also the case of **upsampling**, but it is is of little use to us in this context.

[2] Note that the downsampling factor, strictly speaking, need not be an integer. If it is not integral, a *weighted average* must be taken of the points that are shared. For instance, with a downsampling factor of 1.5, each point in the output would average one whole value plus half of the next or prior value.

7.1.7 Feature subset selection

Another way to improve the accuracy and comprehensibility that has been explored in machine learning is the use of feature subset selection. Sometimes, using all the features available has a detrimental effect on accuracy when compared to using some subset of the features. This is because some features are dependent on other features – and hence, there is no need to include the feature – or are noisy. Furthermore, the more features there are, the more likely that some feature will randomly fit the data and hence the probability of overfitting increases. Thus removing these features would lead to both improved accuracy, and clearer descriptions of learnt concepts, since there are less features that the user has to deal with. Furthermore, since we are generating many hundreds of features, many of which are likely to be irrelevant, we would expect to benefit from finding some optimal subset of features.

However, there is a problem: feature subset selection is a difficult problem. If there are n features, then there are 2^n possible feature subsets. Searching this space for a "good" set of features can be extremely time-consuming. There are two possible approaches to feature subset selection: the wrapper approach and the filter approach [JKP94]. In the wrapper approach, the learner is applied to subsets of features and tested on an hold-out set (or, if execution time is not an issue, using cross-validation). From the results of these tests, a good subset of features is selected. For example, for *forward selection*, a classifier is built for each feature individually; and the most accurate feature is "accepted"

into the subset of good features. That feature is removed, and the process is repeated, adding each of the remaining features and evaluating its performance. The "best" set of two features is thus created. This proceeds incrementally until a feature set with maximal accuracy is achieved. Similarly, *backward selection* proceeds by eliminating one feature at a time, finding the least beneficial feature and eliminating it, and repeating the process, eliminating the least accurate features until eliminating further features decreases accuracy.

The other approach to feature subset selection is the "filter" approach, which looks at correlations between features and other performance measures to decide *a priori*, independent of any particular learner, what a good subset of features is. Although such techniques do not perform nearly as well as the wrapper approach, they are much faster. In general, if there are n features, the wrapper approach requires $O(n^2)$ runs of the learner, whereas the filter approach requires only one run of the learner and some simple statistics on the dataset to be calculated.

7.2 Alternative approaches

In developing *TClass*, some other approaches were also explored, with some preliminary experiments. We present some of the more interesting approaches here. The interested reader may also wish to read Appendix A to understand the development of *TClass* itself.

7.2.1 Signal Matching

At its core, the problem of classifying temporal signals lay in finding segments of temporal signals that recur. These segments could then be used to construct grammars or build classifiers in some way. In other words, the core of the problem is developing an intuition of what makes two temporal signals similar and what makes them different.

Hence, if temporal signals could be "matched" against one another in some way to work out parts of the signal that were similar, this could be used in some way for classification purposes.

How can one compare whole signals with one another while looking for patterns? For the moment, let us consider a single channel of data. Two such channels can be compared by creating a 2D image. Each pixel of the 2D image represents the difference between signals at that timepoint. In other words, let $x[t]$ and $y[t]$ be two signals that we are trying to compare. Let l_x and l_y be the length of each of the two. Then for each pixel a_{ij} of the image, let its intensity be determined by $|x[i] - y[j]|$. This will result in an image – which we will term the *signal match image* – or *SMI* for short.

This image is useful for a number of purposes; for instance we could use it to implement a dynamic time warping algorithm by looking at which path from the top right to the bottom left accumulates the least "black"; in other words, accumulates the least distance. But it is also useful in other ways. Anything that

has low difference along a top right to lower left diagonal indicates similarity.

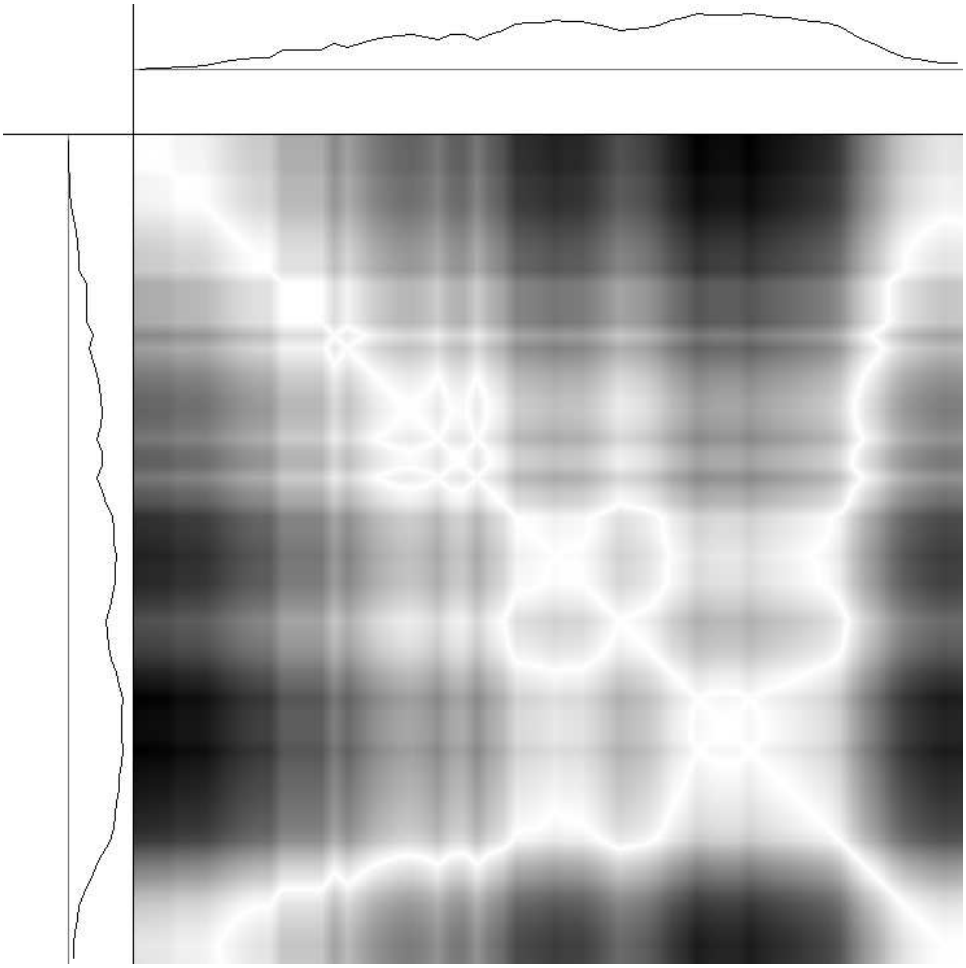


Figure 7.2: The SMI of the z channel of one instance of `building` with itself.

Figure 7.2 shows what happens when an SMI is created for a signal with itself. In this particular case, it is they z value from the Auslan sign `building`. In this case, black is used to represent the largest observed difference, and white is used for zero difference. Along the diagonal the signal is of course white, since the difference between the signal and itself is zero.

Figure 7.3 shows an instance of `building` as against an instance of `make`. As

can be seen, the instances are quite similar, and hence indicates that perhaps the z value is not a good feature to look at for telling signs like `building` and `make` apart.

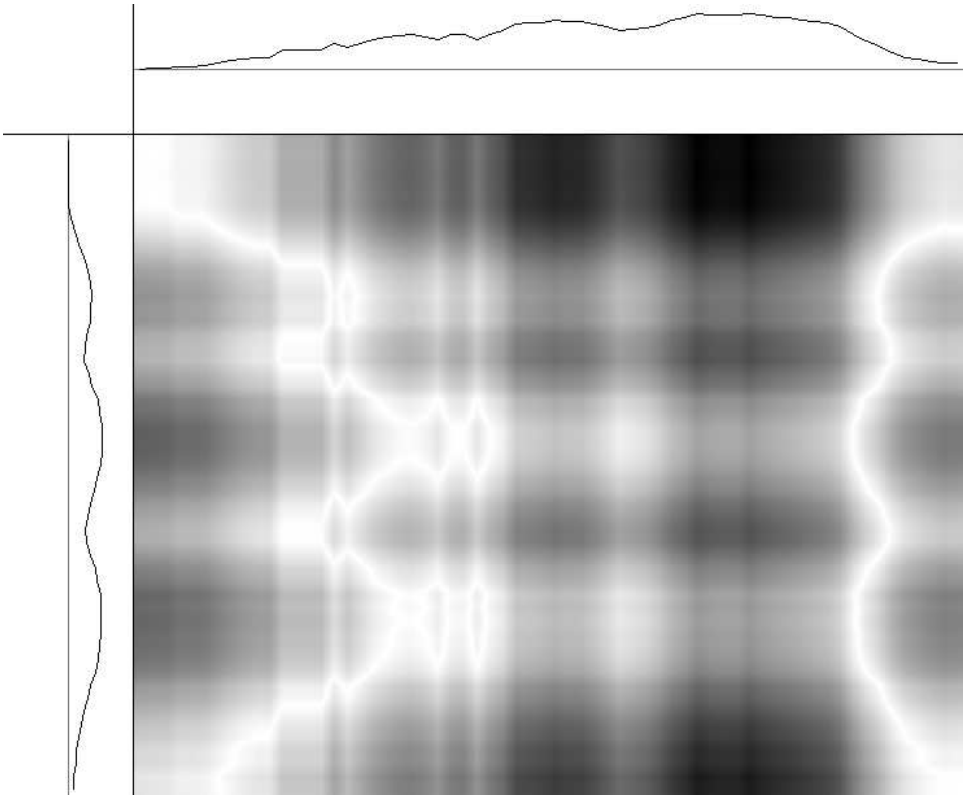


Figure 7.3: The SMI of the z channel of an instance of `building` and an instance of `make`.

At the same time as this work was being looked at, many people in the image processing world were encountering mathematical morphology, a means of image processing ideally suited to the purposes of extracting lines from such images. One way to thing of mathematical morphology is to think of each intensity point as a height, where in our case, white corresponds areas of low altitude and black to high. By modelling the flow of water in such a situation, it is easy to work out what the "valleys" are; and hence the parts of each signal that are common.

One approach to classification is to to extract typical sub-events corresponding to near-diagonal near-white lines, and then use these labelled sub-events to develop a grammar for each class.

7.2.2 Approximate string-matching approaches

Approximate string matching is an active area of research. In approximate string matching, one is given an **text** and a **target**. The objective is to find a string within the text that is similar to the target. Similarity is usually defined using the Levenshtein distance defined in Section 2.4.2.

Hence one approach to classification of temporal signals is to convert each frame into a character. Approaches such as the vector quantisation approach discussed in Section 3.2.1 could be used. Once converted, approximate string matching techniques could be used to extract discriminative string sequences.

However, the act of finding recurring approximate strings in a text and evaluating whether that is of any practical use for classification is not a well-developed area of research.

We explored techniques for finding recurring strings in a situation where the grammar is known. Techniques can be quite easily employed for doing so. For example, one can employ a minimum-message length approach to find recurring strings. Hence we implemented a simple algorithm based on the MML that looked at texts and isolate strings that recurred with sufficient frequency to sug-

gest they may have been useful as primitives on which to construct a grammar.

As an initial exploration of such techniques we looked at string constructed from the phonetic alphabet. The phonetic alphabet is used to overcome the phonetic ambiguity of spoken letters. Each letter of the English alphabet is allocated a word that begins with that letter. For instance "alpha" denotes A, "bravo" denotes B, "charlie" denotes C and so on. Let us say that we did not know the phonetic alphabet; but that we had been listening to people pronouncing phonetic alphabet sequences like "alphabravocharlie", "bravobravoalpha" (ABC and BBA respectively). Our objective was to see if we could by analysis isolate the original sequences for each letter without making use of any of the information about what the sequence of alphabet letters corresponding to each phonetic string was.

We found that we could do this. However, we then tried to extend this to another practical domain: Morse code. In Morse code, each letter of the alphabet can be represented as a binary sequence of ones and zeros. Our performance on this particular domain proved to be much worse. This may have been because Morse code was always designed to be as compressed and efficient as possible due to its historical use for telegraphic communications, whereas the phonetic alphabet is designed for redundancy.

It appears that this approach could be revisited. In view of the shift of approach to a more weak temporal classification system, a two-level approach might be possible:

1. Find the n most commonly recurring strings in the data; within a certain edit distance of each other.

2. As with its application in directed segmentation, use a chi-squared distribution to try to find recurring strings that help discriminate between one class and another.

This was the first attempt to look at recurring strings. Further research uncovered a whole area of study related to the location and search of recurring strings based on a data structure called a subword tree [AG85][3]. Given a string, the subword tree of the string can be used to quickly search the string for any substrings. A formal description is beyond the scope of this work, but perhaps an example will serve us best. Consider the string `abracadabra`. The subword tree for `abracadabra` is shown in Figure 7.4. In the diagram, nodes of the form `c=2` mean that the node has two leaf nodes among its children, and nodes of the form `p=1` mean that there is a subword beginning at position 1 (the first character is position 0). The end of the string is marked by "$".

We can use the tree in the following ways. Consider if we wish to match the substring `cad`. We begin at the root node. The first character is matched against the `c` and we hit a leaf node with `p=4`. This means that it is possible that if I look at position 4 onwards, I might find a match for `cad`. Sure enough, there is a match. Now consider searching for the string `abr`. Following the characters down the tree, I find that I get to a node that has two children. If I follow all

[3]Subword trees are known by many different names. These include B-trees, position trees, prefix trees, suffix trees, subword finders etc

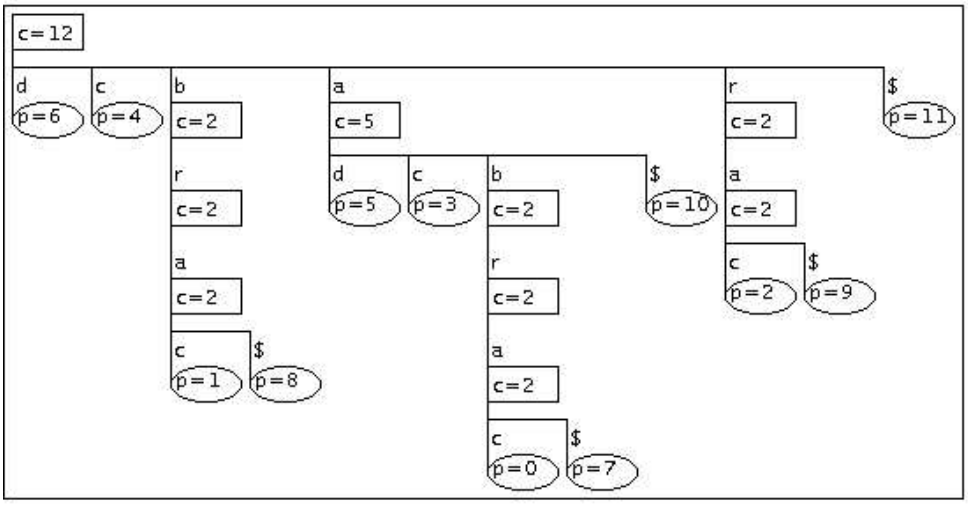


Figure 7.4: The subword tree for `abracadabra`.

subtrees to the leaf nodes, I can determine that the the string `abr` occurs twice in the string `abracadabra`: one beginning in position 0, and one at position 7.

This subword tree is ripe for the picking for discovering patterns within strings. Note the number of children gives us a very quick way to estimate the number of occurrences of any target string. If any target string occurs more than once in the text, it will appear as a node in the subword tree. For our purposes, the nodes (and hence substrings) that would be of great interest are the ones that are very deep in the tree, but with many child nodes. By using this data structure, it would be possible to quickly locate good candidate strings for recurring patterns.

As a first attempt, it was tested with finding common strings in texts. A system was developed which could read whole files, parse them, produce the subword tree and prune it[4]. This picked out interesting patterns, e.g. common

[4]Note that Figure 7.4 displays a lot of redundancy. For example, the whole subtree begin-

recurring syllables in English language (if that was what was fed to it).

It was therefore hoped that this system could be extended to learning to classify discretised time series as discussed above. Subword trees have been applied successfully to approximate string matching, and it was the hope of our research that the ability to do approximate string matching for locating substrings could be turned to advantage in finding strings that approximately recur.

However, this turned out not to be the case. Although it is possible to use subword trees to *find* approximate matches, and can also be used to discover *recurring* target strings; it can not (at least, to our knowledge) be used to find approximately recurring substrings; i.e., substrings that can be recur approximately within the text.

7.2.3 Inductive Logic Programming

After the development of metafeatures, we considered using inductive logic programming as a means of learning definitions. Inductive logic programming is a type of machine learning where the background and domain knowledge are expressed in terms of logical predicates. In particular, each instance was presented as a collection of logical predicates.

To do so, the following predicates were introduced. `instance(X)` indicated

ning with `r` is actually a subtree of the one beginning with `ab`.

that X was a training instance. `class(X)` was used to denote the possible classes of each instance. Finally a predicate called `classification(X, Y)` was also defined, linking each instance with its class.

Data was provided in the form of predicates based on metafeatures, but using only the extraction functions, rather than the parameter space. For example, there was an `Increasing` predicate that took the form `Increasing(InstanceId, Channel, Gradient, Average, Duration, EventId)`.

We also gave an extensional definition of the temporal relations between events. Our hope was that these temporal relations could be used by the ILP system. To begin with, we defined two relations, with plans of implementing full Allen's interval logic [All83]. The two relations were `during(EventId1, EventId2)` and `after(EventID1, EventID2)`.

Unfortunately, this approach did not work well for a number of reasons. FOIL [Qui90], GOLEM [MF92] and PROGOL [Mug95] were all tested on simplified datasets with unsuccessful results. Each did not succeed for different reasons. The first was the size of the dataset. Even with a small number of events and training instances, the number of generated predicates was huge – especially that extensional definitions of temporal relations had to be generated for FOIL and GOLEM. Secondly, these three ILP systems do not handle noise well at all, when the detection of sub-events of time series is inherently noisy. Thirdly, FOIL and GOLEM do not handle numerical attributes at all, and PROGOL does not do it particularly well, requiring a discretisation stage. Fourthly, the above

representation is not deterministic; for example, consider the `after` predicate. Consider a simple sequence of events that occur in the same instance in the order 1,2,3,4,5,6,7. Then `after(2,1)` is true, but so is `after(3,1)` and so on. This means, for example, that if a clause is of the form `after(X,1)` then X can take many values. This has dramatic consequences. For a specific-to-general learner like GOLEM, this means that bottom clauses are going to be gigantic. For general-to-specific learners like FOIL, this means that the search space of possible clauses is going to be very large. Fifthly, the previous effect is worsened by the need for clauses composed of many predicates. Even a relatively simple temporal concept such as "channel A goes up while channel B goes down" would require a total of 6 predicates in our representation. Most ILP systems do not handle long clauses very well.

However, some hope for future work has been given by the work of Rodriguez et al [RAB00]. Although the work is preliminary and makes use of highly simplified versions of the same datasets we employ (for example, he deals with a variant of the Auslan dataset provided by us but using only ten classes, and all instances are downsampled to a fixed length of 20 samples); one of the representations he uses that turns out to function well is a "true-percentage" predicate. A `true-percentage` predicate takes the form `true-percentage(Instance, Channel, TimeInterval, Min, Max, Percentage)`. In other words, if a channel's value is between `Min` and `Max` at least `Percentage` of the time in the `TimeInterval` on the channel `Channel`, the predicate is true.

This predicate has the advantage of being robust to noise, since the asser-

tions don't have to be absolutely true – they can be true 80 per cent of the time, for instance. Secondly, they are self-contained, removing the need for non-deterministic expressions of predicates. However, they require a very careful and customised definition of the search function. If one contemplates the above for a moment, it is clear if one naively extracted all the `true-percentage` predicates from the training instances, then very large numbers of predicates would be generated. The net result is that Rodriguez et al have to carefully constrain the search algorithm of the ILP in order to induce reasonable clauses. Their results show that the true-percentage measure is of some benefit combined with other predicates (e.g. Euclidean distance measures, etc). It is not clear whether such techniques generalise to larger, real-world domains, but it does point to the possibility of temporal classification using ILP.

7.2.4 Graph-based induction

Matsuda et al [MHMW00] propose graph-based induction as a model for learning. In graph-based induction, training instances are represented as graphs.

Temporal classification instances can also be represented as a graph: each sub-event can be represented as a node and each temporal relation (such as the `during` and `after` relations mentioned above) represented as an edge.

Graph-based induction was examined as a possibility and code provided by ISIR at Osaka University was applied to some simple test learning examples.

The *GBI* software provided works by *pairwise chunking*: looking for a pair of nodes in the training instances that recur, and turning them into a single node.

The general plan for the algorithm was as follows: use the pairwise chunking approach to find recurring subgraphs, then use tests based on the presence or absence of the subgraphs as features.

However, problems were encountered. The first has to is one of representation: In graph theory a distinction is made between uncoloured graphs (where nodes are unmarked – each node has the same "colour") and coloured graphs (where nodes are marked in some way – some nodes have the same "colour" while others may have a different colour). In general, induction on coloured graphs is more complex. If we are to represent temporal events of different types (such as increasing, decreasing, local maxima, etc), then the colours can be associated with the different types of events. If we use the type of event as the sole indication of colour, this means that all Increasing events will be treated the same. This means a slow increase or a fast increase, a high increase or a low increase will all be treated the same by the algorithm. Hence the synthetic events were generated as for *TClass* and each event was coloured by the synthetic event that most closely corresponded to it.

The second problem encountered had to do with the edges. Consider once again, the `after(ev1, ev2)` temporal relation. On average, half of events are going to occur after the other events. This means that if we want to represent the `after` relation, we are going to generate a very dense graph: one where

approximately half the maximum possible edges are present. In general, this will lead to $O(e^2)$ edges, where e is the number of events for each instance. This led to the algorithm being slow.

The third problem is that there were many frequent pairwise chunks that were found that proved not to be useful in discriminating between classes. The pairwise chunking algorithm employed does not use class information, and it is not clear how to modify it to do so. This meant that the creation of useful subgraphs for feature extraction did not work very well.

7.3 Conclusions

TClass and temporal classification have a long way to go. Ideas for extending and approaching both problems have been reviewed in this chapter.

Chapter 8

Conclusion

This thesis implements the first general, accurate, comprehensible, robust, weak temporal classifier. While other systems have implemented some of these characteristics, this is the first to capture all of them.

It is a general algorithm that has been applied to two real-world and two artificial domains, one of which was specifically designed to model the characteristics of real-world domains. It has been tested on situations with up to 22 channels, 110 metafeatures, over 200 megabytes of data, 95 classes and highly skewed class distributions (8:1 ratio between the most common and least common classes in the ECG domain).

It is accurate: in all of the domains tested it was able to equal or better the two baseline algorithms, and in the case of ECG classification, performs better than a single human expert: Our system obtains 71.5 per cent accuracy versus

a human expert with 70.3 per cent accuracy, despite the fact that *TClass* learnt with only 450 examples, including one class with only 21 examples. In the Auslan domain, it obtains an accuracy of approximately 98 per cent. Considering that there are 95 signs in the Flock Auslan domain, and the default accuracy would be approximately 1 per cent, this is no easy feat. Furthermore, it matched the performance of hand-crafted feature sets in both the ECG and Nintendo Auslan domains.

It is comprehensible: metafeatures allow the expression of learnt concepts in the background knowledge presented to the learner. Experiments show that in artificial domains, the generating concept is recovered. In the real-world domains, the produced concepts correspond to known definitions.

It is robust: in artificial domains, when the noise level was increased, classification was still possible. With the notoriously poor quality Nintendo sign language data, it was able to achieve accuracy equivalent to hand selected features.

However, it is not without its flaws. *TClass* has the following weaknesses presently:

- While it can be used to produce either accurate or comprehensible concepts, it has not proved possible to do both simultaneously.
- While it is a linear time algorithm, in cases with huge data it is not particularly fast. Run times for all of the domains were reasonable, under two

hours in most cases on a PII-450MHz PC. However, for the ECG domain, when all data were being learnt from, this extended to approximately 8 hours.

- It is still only a weak learner: it does not yet classify sequences of classes. In this regard, it particularly falls behind hidden Markov models, although it has an edge over them in terms of comprehensibility.

- While it produces readable concept descriptions in low-noise situations, it does not do so well in high-noise situations. Noise leads to an explosion in the size of decision trees and rules.

The problems above are not insoluble; merely beyond the scope of the current research – some of the problems have quite obvious solutions, which were discussed in the Chapter 7. Hopefully, *TClass* will serve as a useful platform for exploring temporal classification issues.

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Appendix A

Early versions of *TClass*

In order to understand some of the earlier papers published by the author, such as [Kad99], it may be useful to understand the development of *TClass* and some of the earlier terminology used.

A.1 Line-based segmentation

Most of our time series consist of continuous channels; and hence one obvious solution to converting a time series into a form more amenable to learning was to convert it into a sequence of lines. This idea is not novel: these ideas have been explored by both Pednault [Ped89] and Manganaris [Man97]. We contacted both authors for implementations of their algorithms for reuse, but received no replies. We therefore tried to reimplement their work using our own algorithm.

Approaches are typically based on minimum-message length (MML) [WB68] principles: Assume that you wish to transmit the time series over a communication channel, then what is the minimum number of bits required to transmit that information? The number of bits can be expressed as the number of bits required to send the model of the time series (e.g. a piecewise-linear model of the time series) plus the number of bits to transmit the deviations from the model (in other words, the error of the model). Hence all one has to do to perform line segmentation is generate all possible models, calculate the number of bits for the model, calculate the number of bits for the residuals and simply choose the model that has the lowest number of bits.

In practice, the above is slow to implement – it requires in general the consideration of $O(f^3)$ models, where f is the average number of frames. Some optimisations are therefore necessary. Furthermore, assumptions have to be made on prior distributions of values in order to get correct approximations of such models.

Our implementation used a very simple algorithm with some very basic assumptions. The assumptions were that encoding a line segment was assumed to take a fixed number of bits; and encoding the residuals depended on the normalised distance from our model for each timestep. The algorithm was also simple: to begin with, the signal starts out with each pair of points being a line segment. The algorithm then evaluates the reduction in the total number of bits for the whole signal of fusing each pair of adjacent line segments into one. The pair that maximises the reduction in message length is fused. This process is

repeated until there are no more line segment fusions that reduce the message length.

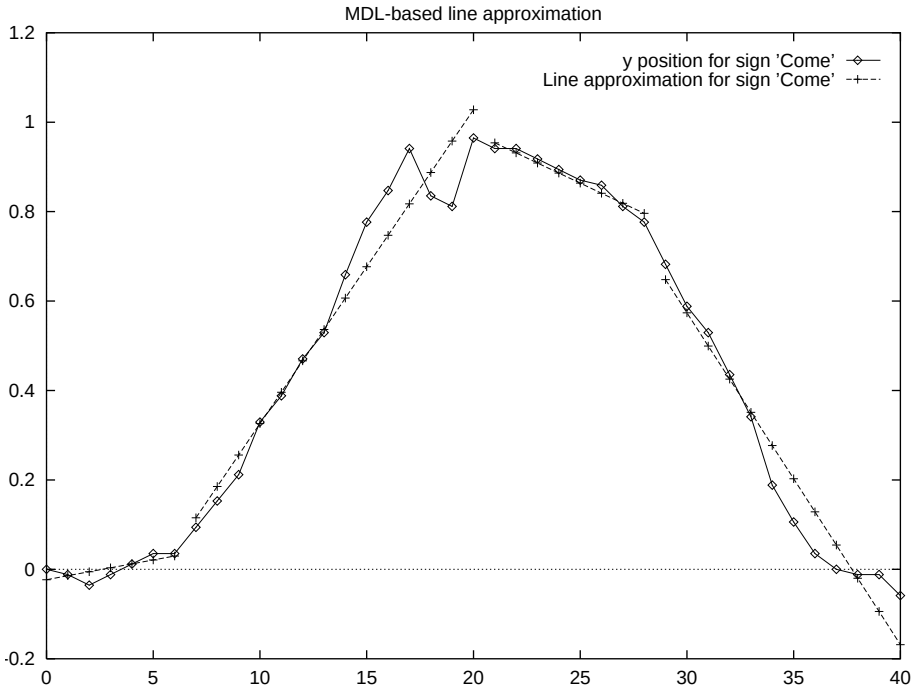

Figure A.1: Line-based segmentation example for y channel of sign `come`.

Although incredibly simple, it works well. Figure A.1 shows a typical example. However, there were a few problems with this approach:

- It's a greedy algorithm. This means, for example, that if there are two segments separated by an extremely noisy segment, the three would never be fused. It also means it can be a little bit sensitive to noise.
- Although it is faster than other approaches, it is still $O(f^2)$ and so relatively slow, compared to simply detecting when a signal is increasing.

It is also interesting to note that line segmentation could easily be included (and is in fact included) in the *TClass* system: Each line segment corresponds to a metafeature. The main problem is the speed.

The problem at the time was: what to do with these line segments? Several things were attempted:

- Label each line segment with the class of the instance it came from, throw it at C4.5 to learn to classify it; then apply voting across all line segments to produce a classification. This can be thought of as an extremely primitive one-step version of *TClass*.
- Cluster them and then use string matching – i.e. look for sequences of repeated characters, where each character represents a particular class of line segment (obviously, this is getting closer and closer to *TClass*). However, clustering did not seem to work particularly well with the tools being used at the time: AutoClass and SNOB. The reasons for this failing can be found in the next section.
- Convert these lines into a relational form and then use ILP. This also did not come to fruition; for very much the same reasons as mentioned in Section 7.2.3.

The clustering mentioned above was performed in parameter space. The parameter space for line segments was four-dimensional: midtime, gradient, duration and average.

A.2 Per-class clustering

Using line segments as the sole metafeature, the first "real" iteration of *TClass* was implemented, using the following algorithm:

- For each channel and for each instance apply line segmentation.
- In the 4-dimensional space of possible line segments, apply K-means clustering.
- For each training instance:
  - Find the nearest line segment (in parameter space) to each cluster centroid.
  - Calculate the "confidence" of the nearest line segment (based on the assumption of a Gaussian distribution).
  - Used the confidence as a feature.
  - Output as a training instance for C4.5
- Run C4.5

Early results were disappointing. Further investigation revealed that the problem lay in the clustering stage. When all line segments were thrown into the parameter space, there were no clear clusters. To illustrate this principle, Figure A.2 shows the parameter space for local maxima of the y channel from the Flock sign domain. As can be seen, clustering in this space is not going to

be easy. And in fact, K-means clustering would simply not converge even after 50 iterations.

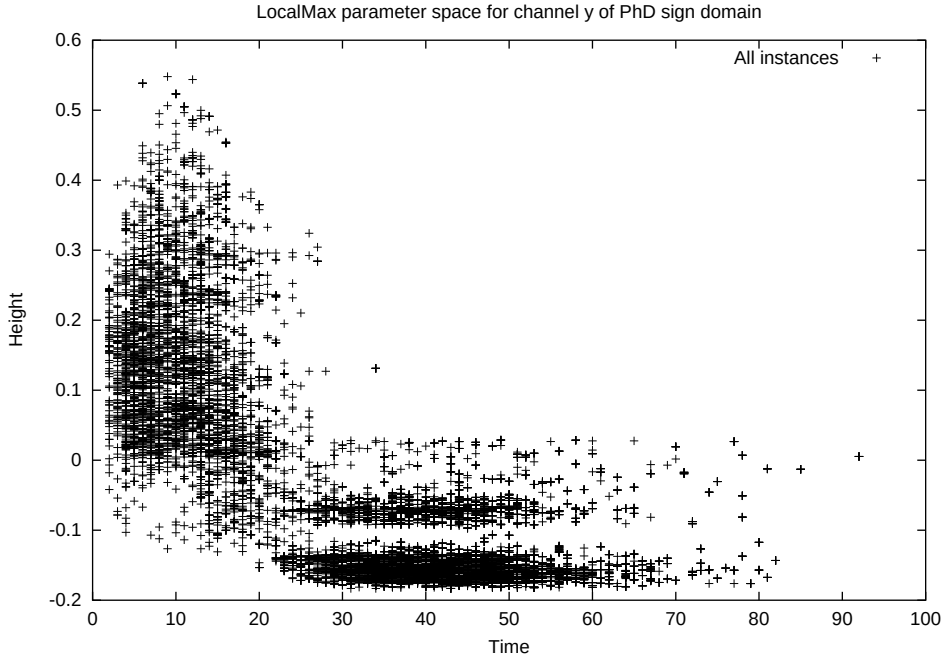

Figure A.2: The parameter space of local maxima of the y channel in the Flock sign domain. All instantiated local maxima are shown.

Hence, we sought another solution: per class clustering. Rather than clustering all instances at once, only instances belonging to a single class would be clustered. Figure A.3 shows instantiated features for two classes. As can be seen, clustering either of these two classes would be relatively easy compared to clustering the instances in Figure A.2.

Hence, early versions of *TClass*, as published in [Kad98] and [Kad99] use per-class clustering: For each class, cluster instances from only that class. Use the clusters generated to re-attribute all training instances. Create classifiers using the learner with only the synthetic features generated from that class and the

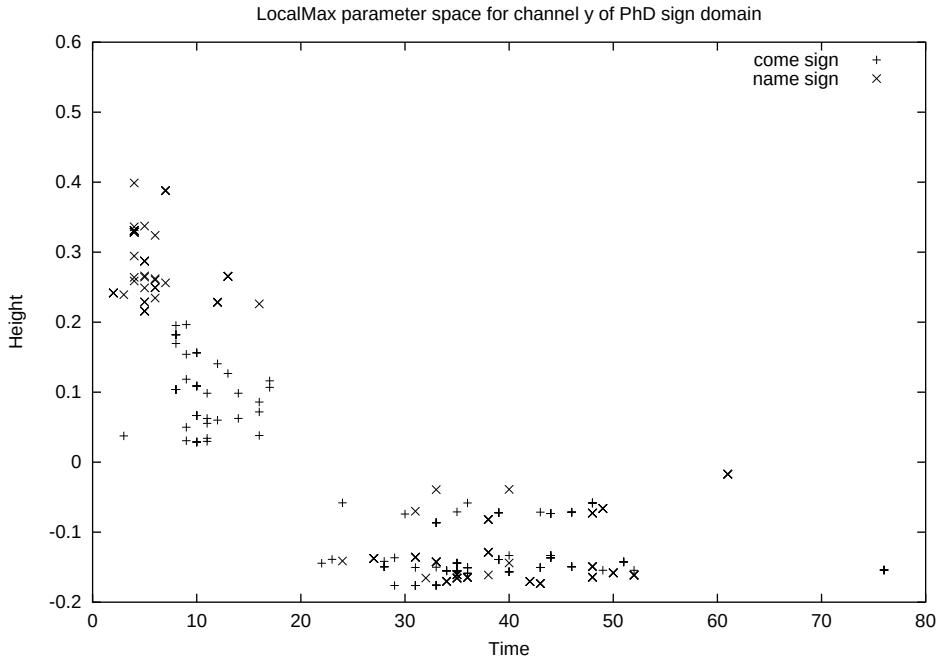

Figure A.3: The parameter space of local maxima of the y channel in the Flock sign domain, but shown for only two classes.

global features. In general, if there are c classes, c classifiers will be generated. These c classifiers vote to give a final classification. This could be considered a "brute force" manner of doing directed segmentation using and undirected clustering algorithm.

Obviously, this solution is not ideal. Firstly, there is running the learner c times, obviously not very fast. Secondly, if we look at Figure A.3, the lower two clusters would generated synthetic features in both learning tasks, creating, for all intents and purposes, two identical features. Thirdly, comprehensibility is not very good, since a total of c rulesets or decision trees must be examined.

Early papers used the term *PEPS* – short for *parametrised event primitives*, rather than metafeatures. It was not realised until after the publication of these documents that metafeatures might well have applications beyond temporal classification.