Automatic Design of Prosodic Features for Sentence Segmentation

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Abstract

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Professor Nelson Morgan, Chair

This dissertation proposes a method for the automatic design and extraction of prosodic features. The system trains a heteroscedastic linear discriminant analysis (HLDA) transform using supervised learning on sentence boundary labels plus feature selection to create a set of discriminant features for sentence segmentation. To my knowledge, this is the first attempt to automatically design prosodic features. The motivation for automatic feature design is to employ machine learning techniques in aid of a task that hitherto places heavy reliance on time-intensive experimentation by a researcher with in-domain expertise. Previous prosodic feature sets have tended to be manually optimized for a particular language, so that, for instance, features developed for English are comparatively ineffective for Mandarin. While unsurprising, this suggests that an automatic approach to learning good features for a new language may be of assistance. The proposed method is tested in English and Mandarin to determine whether it can adjust to the idiosyncracies of different languages. This study finds that, by being able to draw on more contextual information, the HLDA system can perform about as well as the baseline features.

Professor Nelson Morgan
Dissertation Committee Chair

To my parents, Bing and Nancy, who supported me along my path.

To my brother, Steve, for his guidance and inspiration.

To my nieces, Evelyn and Melanie, who are the future.

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Chapter 1

Introduction

I begin with two observations:

1. Given sufficient data, statistical learning methods generally outperform systems dependent on human design.

2. Prosody is complicated, yet prosodic features in speech processing research are designed by hand.

It seems a bit of an oddity, in a field as permeated by machine learning as speech processing, that prosodic features are solely designed by a process of researchers carefully analyzing data, experimenting, and tweaking features. Furthermore, feature sets are generally designed to work for a specific task, in a particular language, or under certain conditions, and they can suffer performance degradation because the assumptions their design was based on have changed.

This dissertation proposes that statistical learning methods can take a bigger role in feature design. The goal is not to diminish the value of human expertise or linguistic theory. However, if an automatic system can learn language-specific behavior, a human researcher does not need to reproduce this work and can instead focus on other aspects of the problem.

1.1 Feature Design

Many machine learning systems achieve success with human-designed features. Researchers extract features they believe to be useful for the task, and much work goes into learning algorithms to find exploitable patterns in the features.

This dissertation studies the use of prosody in the task of sentence segmentation, which is equivalent to finding the location of sentence boundaries. Prosody will be covered in more detail in Section 2.1, but for now think of it as the pitch, energy, and duration properties of speech. Prosodic information has found uses in many speech tasks, including dialog act tagging [5, 33, 139, 165], emotion [4, 143, 171], segmentation [129, 157, 159], and speaker identity [3, 108, 114].

There are some well-known prosodic cues for breaks between syntactic units: longer pauses; a slower rate of speech before the boundary; and drop in pitch before the boundary followed by starting the next unit at a higher pitch, a phenomena called pitch reset.

Take, for example, the question of how to design feature(s) to capture pitch reset, as there are other sources of pitch variation besides syntactic unit boundaries. An upward pitch motion at the end of an utterance generally signals it is a question rather than a statement. Pitch accents may occur due to stress, which has many uses: it is what distinguishes the English verb *progress* and the noun *progress*; it occurs from the metrical pattern of the language; it provides focus within a sentence and can disambiguate between different interpretations. In tone languages, tones and pitch accents are part of the lexical identity of words. Furthermore, a speaker's pattern pitch patterns can tell the listener about the speaker's identity and emotional state.

Prosody is complicated, with all manner of information being transmitted through the manipulation of pitch, energy, and duration. As seen in a review of prosodic features in Section 2.1.3 and sentence segmentation in Section 2.2.4, many researchers borrow features from previous work. It is natural for research in the same area to not reinvent the wheel, but some features are not robust when used in new tasks or conditions. The design of original features is not trivial; the features in Shriberg [129] were developed on English data over the course of years, based upon considerable in-domain knowledge about cues and what features and normalizations would be robust to unwanted variation. This can be a barrier for researchers wishing to explore a new domain, language, or task.

Therefore this dissertation sets out to examine how much of this process can be automated. It does not seek replace human expertise or obviate the need to examine the data to understand what is going on, but perhaps not all of the feature design process needs to be done manually.

1.2 Organization

This dissertation is organized as follows: Chapter 2 provides a literature review and covers background material for the dissertation. In particular, separate sections are devoted to prosody, sentence segmentation, and feature selection. Section 2.1 covers prosody, its usage in communicating information in speech, and a survey of prosodic feature sets used in modern speech processing systems. Section 2.2 goes into detail about the speech processing task of sentence segmentation and the current state-of-the-art. Section 2.3 gives a survey of various feature selection methods, as feature selection figures prominently in this work.

Chapter 3 studies the robustness of a set of prosodic features designed by Shriberg et al. [129] when ported from English to Arabic and Mandarin. As this feature set is the foundation for the work in the rest of the dissertation, I go into detail about the features and describe the history and development of the feature set. Feature selection experiments are used to analyze the robustness of the features. The AdaBoost classifier used throughout this disseration is also described here.

The lack of robustness in the pitch features to Mandarin lexical tone motivates the study of automatic feature design. In Chapter 4, I describe the proposed heteroscedastic linear discriminant analysis (HLDA) system for the automatic design and extraction of pitch features. Background for LDA and HLDA are included. The goal of the chapter is to compare the performance of the proposed system to the baseline pitch features. The resulting linear transform on input pitch statistics is also analyzed for any hints to be gleaned for future feature design.

Chapter 5 tests the language-robustness of the proposed HLDA system by seeing if it can compensate for Mandarin lexical tone where the baseline features had trouble. A survey of tone languages and two leading models of Mandarin lexical tone are presented for background. Chapter 6 recapitulates the study and presents concluding remarks.

Chapter 2

Background

2.1 Prosody

2.1.1 Introduction

In the study of language, the term prosody has a range of definitions, depending on the field or where one looks in the literature. On one end of the spectrum are those who use an abstract definition of prosody that refers to any structure that organizes sound, including syntactic structure, metrical rhythm, lexical tone and stress, even the structure of syllables [121]. In this dissertation however, following the tradition of the speech processing literature, prosody refers to the realization of speech utterances, including quantities such as pitch intonation, loudness, tempo, and pauses. Machine learning researchers studying speech often refer to any supersegmental information not pertaining to lexical identity — words and phones — as prosody, possibly to show its relationship to the large body of text-based natural language processing research.

These two extreme definitions of prosody share the idea that there exists linguistic structure that determines, or at least influences, the realization of speech utterances. The study of prosody in speech processing deals with quantifying these supersegmental properties and using the observations to infer structure or information about the utterance. For example, this dissertation studies the use of prosodic information, especially pitch, for the automatic segmentation of speech into sentence units.

The quantities associated with prosody include pitch, energy, and duration. It is the modulation of these properties that speakers use to convey linguistic information to the listener. While all languages use prosody to communicate, the exact rules for achieving intended effects vary between languages. This ties into one of the central questions of this dissertation: How will a machine learning system designed for one language fare in another, or how much human expertise in one language will transfer to a different one?

The field of prosody is large but not all of it is relevant to the matter of this dissertation, such as the psycholinguistics of when and how prosodic information is used for spoken word recognition [54]. For a review of prosody in the comprehension of spoken language, see Cutler et al. [28]. In this chapter, Section 2.1.2 illustrates various examples of prosody. The object is to demonstrate that prosody is used to transmit a wide range of information, all of which use the same channels: pitch, energy, and duration. Thus, prosody is the product of many different demands. Section 2.1.3 gives an overview of prosodic feature sets used to quantify prosody for various speech processing tasks, which usually try to isolate particular cues from distracting information in the speech signal.

2.1.2 Uses of prosody

The following give brief summaries of several types of information that prosody is used to convey.

Syntactic boundaries. Major syntactic boundaries — for instance dialog act and sentence breaks, or breaks between phrases that might be denoted in text by a comma — are often marked by pauses, pitch reset, and pre-boundary lengthening, with stronger events correlating to stronger boundaries. Over the course of a sentence or phrase, pitch tends to drop to the lower end of the speaker's range. At the beginning of the next unit, the pitch starts higher. This kind of rapid change occurring at a boundary is called pitch reset [142]. Pre-boundary lengthening is the tendency for longer segmental duration and slower rate of speech to precede syntactic boundaries

[162]. Finally, pauses are empirically the strongest cues for breaks between prosodic units, with long pauses denoting the beginning of a new unit [51].

Resolving ambiguity. There are some word strings that have multiple interpretations. For example, Snedeker and Trueswell [135] studied sentences like, "*Tap the frog with the flower.*" For this sentence, the ambiguity lies in whether the flower is a modifier to the frog or is an instrument with which to tap the frog. In such situations, prosody is often used to denote which alternative was meant by the speaker. In the above example, the author noted that different meanings could be detected by word duration and pauses. Price et al. [110] discusses many situations where prosody aids disambiguation, including identifying parentheticals and appositions, sentence subordination, and far vs. near and left vs. right attachment.

Utterance position. Prosody can also convey where in the utterance a word occurs. For example, Grosjean [53] recorded speakers reciting sentences of various lengths. For example, the sentence "*Earlier my sister took a dip*" can be extended another three, six, or nine words with the phrases "*... in the pool / at the club / on the hill.*" When played each recording up to word "*dip*," listeners could often differentiate how many more words the utterance contained. Oller [106] studied the differences in segmental duration in the initial, medial, and final positions of utterances, including pre-boundary lengthening mentioned above.

Speaker identity. While some might not include speaker identity as part of prosody because it is a property of the speaker, not what is being said, speakers can be recognized by their distinctive usage of the components of prosody. Pitch and energy distributions and dynamics have also helped differentiate speakers [3]. Furthermore, every speaker has an idiolect, with their personal patterns of word choice and pronunciation [23].

Emotion. The speaker's emotional state can also surface in their prosody. For example, activity or arousal correlate with increased pitch height, pitch range, energy, rate of speech. In contrast, anger often exhibits a flat pitch contour with occasional spikes in pitch and energy. For a review of the use of prosody in communicating emotion, see Frick [39].

Lexical stress. While the speech processing literature generally excludes lexical information from the definition of prosody, it is important to note that the components of prosody can be used to convey lexical information as well. In English, moving word stress can change a verb into a noun, which are called initial-stress-derived nouns [61], such as *conduct* and *permit*. The realization of word stress varies from language to language and may include pitch accents, pitch excursions, or accents marked by changes in loudness or segmental duration. Stressed syllables tend to better enunciated than unstressed syllables and hence more easily recognized [88]. Kochanski et al. [77] showed that even tone languages may follow this pattern, where speakers follow the tone template more closely in syllables with greater prosodic weight than in weaker syllables.

Lexical tone and pitch accent. Tone languages use pitch to distinguish words, the common example probably being the word "*ma*" in Mandarin, which may mean *mother*, *hemp*, *horse*, or *to scold*, depending on whether tone 1 through 4 is used, respectively. I cover tone languages in more depth in Section 5.1.1.

All of the above are communicated through the modulation of the same pitch, energy, and duration characteristics of speech. Separating relevant information from distractions is thus non-trivial. Indeed, as we shall see in Chapter 3, Mandarin lexical tones are conflated with the sentence pitch contour. As a result, pitch features from Shriberg et al. [129] that work well for sentence segmentation in English and Arabic do not perform as well in Mandarin.

2.1.3 Prosodic features

The objective of the following is to give an overview of the sorts of prosodic features used in modern speech processing systems.

Sentence/Dialog act segmentation. One feature set [129] designed by Shriberg, which the work in this dissertation is based on, is detailed in Section 3.1. To summarize, it contains pause, pitch, energy, and duration features. Pause duration is a strong predictor for unit boundaries. The pitch features are based on word-level statistics of the pitch contour and aim to detect pitch reset. The duration features describe rate of speech and segmental duration, in particular the last vowel and rhyme before the candidate boundary. This feature set grew out of work on disfluency detection and speaker verification, has been employed in the segmentation of sentences, dialog acts, and topics, and has also found usage in emotion-related tasks, among others.

Warnke et al. [159] also concentrated on the word-final syllable, using duration, pause, pitch contour, and energy quantities over six syllables as the input to a multilayer perceptron (MLP). This was combined with various N-gram language models (LM). A later study by Wang et al. [157] attempted speech segmentation without using automatic speech recognizer (ASR) output included in many feature sets. They used a vowel/consonant/pause classifier based on energy. Sufficiently long pauses are candidate boundaries. Using vowels to locate syllables, they calcuated short-term rate of speech features. Pitch features are also calculated looking at the six syllables surrounding the candidate boundary, looking for pitch reset and syllable contour shape.

Dialog act tagging. Interestingly, the prosodic features used in dialog act tagging and segmentation have much in common, possibly because many researchers work in these closely related tasks. For example, the Warnke [159] paper discussed above also classified the dialog acts it identified, though this classification mainly relied on their LMs. Both Ang et al. [5] and Stolcke et al. [139] used the Shriberg feature set described in [129], though [139] focused on discourse grammar, an N-gram model of dialogue act sequencing in conversation, and lexical data.

To give an idea of dialog act tagging prosodic feature sets not borrowed from segmentation systems, Fernandez and Picard [33] took the pitch and energy contours and their first two derivatives and extracted a variety of statistics, including variance, skewness, and kurtosis. They also included a duration feature measuring the length of the voiced speech. Wright et al. [165] used similar pitch, energy, and duration features, adding pitch features from regions of interest within the utterance. For example, they identified accents [144] and extracted starting pitch, amplitude, duration, and shape of the accent. They also extracted pitch and energy features over the last 400ms of the utterance, and their analysis of feature usage found that features from the tail of the utterance and the last accent were particularly useful.

Speaker identification. As opposed to many speech processing tasks where it is desirable to normalize out variation due to speakers, speaker identification / recognition / verification seeks to do the reverse. Bimbot et al. [13] advocate the use of linear predictive coding (LPC)-based cepstral acoustic features plus delta and double delta cepstral parameters as well as delta energy parameters. Pre-emphasis is performed to enhance high frequencies, cepstral mean subtraction helps remove slowly varying convolutive noise, and frames of silence and background noise are removed to leave only speech. Because LPC cepstral coefficients reflect short-term information, care must be taken that the speaker model captures speaker characteristics instead of what is being said.

Reynolds et al. [114] combined the work of several sites. Their final system used short-term acoustic cepstral-based features like the above from Reynolds et al. [115]. From Adami et al. [3], they used frame-based log-pitch and log-energy distributions and pitch and energy gestures. These gestures are composed of sequences of pitch and energy slope states combined with segmental duration and phone or word contexts, so that is not a purely prosodic model. The system also used some duration and pitch statistics extracted over word-sized windows from Peskin et al. [108]. The combined model also made use of some phone and lexical features, among which the pronunciation modeling made the most significant contribution.

Emotion detection. To detect annoyance and frustration, say when a user finds an automated call system not helpful, Ang et al. [4] borrowed many features from the aforementioned Shriberg prosody features [129]. The duration/rate of speech and pause features are identical. The pitch and energy features used the same preprocessing, but the features were mainly interested in peaks, such as the maximum value over the utterance or inside the longest normalized vowel. Spectral tilt features, which measure the distribution of energy in the frequency spectrum, were also computed on the longest normalized vowel. Lexical information came in the form of word trigrams. The study found slower rate of speech and sharper pitch contours to be indicative of frustration.

In contrast, Tato et al. [143] and Yacoub et al. [171] attempted multi-class classification with labels 'angry,' 'bored,' 'happy', 'sad,' and 'neutral.' For prosodic features, both used statistics of the pitch contour, its derivative, and jitter; this last highlights frequency changes in the signal. The statistics were selected to describe the distribution of the variable: minimum, maximum, mean, standard deviation, etc. Corresponding energy features were calculated in the same manner on the energy contour, its derivative, and shimmer/tremor, the energy analog of jitter. Both also extracted duration features, looking for patterns in the energetic segments of the utterance, such as their length or what proportion of the utterance was energetic. Tato used voiced vs. unvoiced frames while Yacoub split loud vs. quiet frames by thresholding energy. Tato also used voice quality features related to articulatory precision and vocal tract properties. These included formant bandwidth, harmonic to noise ratio, voiced to unvoiced energy ratio, and glottal flow.

Tato found that the pitch and energy features were useful in differentiating between high, low, and neutral levels of arousal while the quality features helped decide between emotions once the arousal level was known. In distinguishing hot anger from neutral utterances, Yacoub found the most useful features were based on the derivative of the pitch contour, jitter, and maximum energy. When distinguishing between hot/cold anger and neutral/sadness, the best features instead were pitch, jitter, audible duration, and maximum energy.

To summarize these feature sets, many use pitch and energy statistics. The most commonly used statistics were mean, variance, maximum, and minimum, but first, last, skewness, and kurtosis were also mentioned. These statistics describe the distribution of the quantity in question. Where the studies differ is in the selection of statistics and the regions over which they are extracted. Another common pattern is borrowing features from previous work. I believe this reflects the fact that feature design is not trivial process, so many researcher prefer to use tried and tested features rather than spend the time to independently create their own.

2.2 Sentence Segmentation

2.2.1 Motivation

The task of sentence segmentation, as the name implies, is to segment speech input into sentences. The detection of sentence boundaries is one of the important initial steps that lead to the understanding of speech. Sentences are informational units with well-studied syntactic structure, and thus sentences are fundamental to the ability of humans and computers to understand information.

In natural language processing applications, the presence of punctuation readily segments the text into sentences. However, typical automatic speech recognition (ASR) systems only output a raw stream of words without the cues of written text such as punctuation, sentences, paragraphs, and capitalization. Therefore sentence segmentation is critical for obtaining information from speech because information retrieval systems, such as summarization [20] and question answering [66], are traditionally text-based and benefit from sentence boundaries. Annotations including sentence boundaries were also found to be useful in audio search to determine speech intervals that are semantically and prosodically coherent [27]. Sentence segmentation is also critical for topic segmentation and is useful for separating long stretches of audio data before parsing [129].

Matusov et al. [98] considers the sentence segmentation task from the perspective of a speech machine translation system. In such systems, the objective of the system is to accept a speech utterance as input and then output text in the target language. The general approach is to first perform ASR in the original language and then use text-based machine translation techniques to translate it into the target language. However, such machine translation systems have difficulties with long utterances, especially because the problems of word reordering and grammar parsing grow very quickly in computational complexity. Thus they study how their machine translation system responds to sentence segmentation and punctuation prediction at various stages of the machine translation process.

In the case of spontaneous speech, speech utterances have a tendency to contain ungrammatical constructions such as false starts, word fragments, and repetitions, which are representative of useless or distracting information. Output from ASR systems are also affected by problems such as higher than desired word recognition error rates in spontaneous speech. Sentence segmentation can lead to an improvement in the readability and usability of such data, after which automatic speech summarization can be used to extract important data [100].

2.2.2 Background

The goal of this section is to give a broad overview of how sentence segmentation is implemented before going into detail about specific developments in Section 2.2.4. Sentence segmentation is closely related to the tasks of dialog act segmentation and punctuation detection. For example, punctuation detection includes finding sentence and prosodic breaks marked by periods and commas, respectively. Though other punctuation marks and dialog act tagging often require more than segmentation, in the detection of syntactic boundaries these tasks use similar cues, so the following literature review will draw upon this larger body of work.

Features

The strongest predictor of sentence boundaries is the pause between words. Long pauses generally coincide with sentence boundaries, and so interword pause features are used in virtually every sentence segmentation system. The main source of confusion with pause features comes, of course, when the speaker pauses in the middle of a sentence, such as when taking a breath or deciding how to finish the sentence [140]. This leads to oversegmentation, and the usual way to address these classifier errors is to use additional information sources. The two most common such information sources are prosodic information and language models.

Prosodic features. Prosody was discussed in Section 2.1. In comparison to purely text-based methods, speech provides prosodic information through its durational, intonational, and energy characteristics. In addition to its relevance to discourse structure in spontaneous speech and its ability to contribute to various tasks related to the extraction of information, prosodic cues are generally unaffected by word identity. Prosodic information has been found to complement lexical data from ASR output and thus improve the robustness of information extraction methods that are based on ASR transcripts [57, 59, 129]. A sample of prosodic feature sets was given in Section 2.1.3 and the prosodic features used by this work are detailed in 3.1.

Language models. The purpose of a language model is to predict the probability of any particular word in a given situation. For example, a unigram language model considers each word independently. For any given English word, one would far more likely expect "*the*" or similar function words than "*Galapagos.*" A commonly used language model is the N-gram language model, which assumes word strings follow the Markov property and estimates the probability of a word from the contextual history of the previous $N-1$ words. That is the probability of a sequence of m words is estimated by:

$$\begin{aligned} P(w_1, \ldots, w_m) &= \prod_{i=1}^{m} P(w_i | w_1, \ldots, w_{i-1}) \\ &\approx \prod_{i=1}^{m} P(w_i | w_{i-(N-1)}, \ldots, w_{i-1}) \end{aligned}$$

To continue our example, following the word "*Galapagos,*" a language model may expect "*Islands*" more than the far more common word "*the.*" Thus language models are used to decide what words make sense together and in particular contexts.

More complicated language models can take into consideration other features of words, including their parts of speech or position in a sentence. Due to the very large vocabularies used in many tasks, common issues in language models include dealing with words not present in its training set and data fragmentation, i.e. for an N-gram, not all $N-1$ sequences of words will occur in even a very large training set, so there is very little data to train models for each context. For further discussion of language models, see [70, 97].

Classifers

Usually the simplest method of sentence segmentation from a stream of speech is through the use of word-boundaries, in which case the task becomes a classification problem: each word-final boundary is classified as the end of the sentence or not. Sentences can be further classified based on the type of sentence, for example declarative, interrogative, unfinished, etc. by dialog act tagging. I will treat sentence segmentation as binary classification of word-final boundaries into non-sentence boundaries (n) and sentence boundaries (s).

A common technique used with prosodic information is to make the simplifying assumption of a bag-of-words model, that the words (and boundaries) are unordered and conditionally independent given their observations. Then a classifier is trained to estimate the posterior probability $P(b_i = s|o_i)$, where b_i is the i^{th} boundary and o_i are its associated observations. A word-final boundary is then classified as a sentence boundary if the posterior probability exceeds a chosen threshold. Obviously the boundary decisions should not be independent — in conditions where short sentences are rare, the presence of a sentence boundary should reduce the likelihood of another boundary in the vicinity — but the idea is for the observations o_i to incorporate relevant contextual information from surrounding words in order to simplify the classifier. For these bag-of-words models, discriminative models such as classification and regression tree (CART) decision trees and support vector machine (SVM) classifiers have been used.

In contrast, lexical information in the form of N-gram LMs typically use a generative sequence model that makes use of the word sequence, such as hidden Markov models (HMM). For the purposes of sentence segmentation and punctuation prediction, sentence boundaries and punctuation may be treated as tokens in the word stream or as properties of words, such as in hidden event models. In this way, language models can utilize patterns about the placement of sentence breaks and punctuation in the data. For example, "The" commonly appears at the beginning of sentences while punctuation usually does not occur in the middle of "Queen Victoria." The following example from [51] shows one way lexical information can cue sentence boundaries (indicated in the following by a semi-colon):

> ... million pounds a year in the UK; and worldwide it's an industry worth several billion; but it's thought...

They noted that sentence structure in broadcast news speech differs from that of written language, and some words such as "and" and "but" often appeared at the beginning of new sentences. Therefore a language model trained on this data would give higher likelihoods to word strings with sentence boundaries before such words than not.

2.2.3 Evaluation measures

Before going forward, it will be useful to discuss the performance measures used in the experiments in this thesis. As a binary classification problem, each example falls into one of four categories, as seen in Table 2.1. Let $S = S_s + S_n$ be the number of true sentence boundaries, where S_n is the number of true boundaries misclassified as non-boundaries, i.e. false negative errors. Similarly, there are N_s false positive errors, true non-sentence boundaries wrongly labeled as sentence boundaries.

Precision denotes the fraction of sentence boundary labels that are correct:

$$p = \frac{S_s}{S_s + N_s}$$

To achieve high precision, a classifier could return the single sentence boundary it is more confident of. Lower precision indicates the sentence boundary labels are less likely to be correct.

		Truth	
		Non-sentence	Sentence
Classifier	Non-sentence	N_n True negative	S_n False negative
	Sentence	N_s False positive	S_s True positive

Table 2.1: The four possible outcomes for binary classification.

Recall describes what percentage of the reference sentence boundary were found:

$$r = \frac{S_s}{S} = \frac{S_s}{S_s + S_n}$$

To achieve high recall, the classifier could label all boundaries as sentence boundaries. Lower recall means the classifier failed to find all of the reference sentence boundaries.

NIST error rate is a measure commonly used in evaluations, starting with those organized by the National Institute of Standards and Technology [160]. It is defined as the average number of misclassifications per actual sentence boundary:

$$\text{NIST error rate} = \frac{S_n + N_s}{S}$$

In the case of sentence segmentation, this can exceed 100%. There are far more non-sentence boundaries than sentence boundaries, so any trigger-happy classifier may have high recall but insert sentence breaks where none exist.

As can be seen, precision and recall are designed to be in opposition, precision penalizing an overly-zealous classifier making false positive errors and recall penalizing a conservative classifier making false negative errors. The only way to score 100% in both precision and recall is to classify all boundaries correctly. F_β is a measure devised to capture both precision and recall when the user weights recall β times more than precision [153]:

$$F_\beta = (1 + \beta^2)\frac{pr}{\beta^2 p + r} \tag{2.1}$$

The most common version used is $\beta = 1$, also known as F_1 score or simply F-score or F-measure. For F_1 score, (2.1) simplifies to the harmonic mean of precision and recall:

$$\begin{aligned} F =& \frac{2pr}{p+r} \\ =& \frac{1}{1/p + 1/r} \end{aligned}$$

To give an intuition of what this means, take two numbers a and b, and let $a > b$. Then $a \geq$ their arithmetic mean $\geq$ their geometric mean $\geq$ their harmonic mean $\geq b$. That is the harmonic mean will be closer to the lower of the two values. Thus, under F_1 score, neither precision nor recall can be ignored. In the following experiments, we will find that F_1 score tends to be a more reliable measure for system performance than NIST error.

2.2.4 Previous work

Model combination

Hakkani-Tür et al. [59] used both prosodic features and language models for sentence and topic segmentation. The prosodic features used were an early version of Shriberg [129] using CART-style decision trees to predict the boundary type. Due to the greedy nature of decision trees, smaller subsets of features can produce better results than the initial larger feature set. In order to improve computational efficiency and remove redundant features, an iterative feature selection algorithm was used to locate subsets of useful task-specific features.

The training of the prosodic model was done on a training set of 700,000 words. In comparison, the HMM using an N-gram language model was trained on the same training set and also on a far larger 130 million word dataset, almost a 200-fold increase in training data. Due to data fragmentation, N-gram language models may greatly benefit from additional training data. This also reflects the relative availability of text data versus annotated speech data. The prosodic model outperformed all the language models save one, though the prosodic model had access to interword pause duration features while the language models did not. The language model exception was trained on the larger 130 million word data set and incorporated speaker turn boundaries as pseudo-words, since a speaker ceasing to speak is a good indicator of their having completed a sentence.

The classification problem is to find the optimal string of classifications T for:

$$\underset{T}{\operatorname{argmax}}\, P(T|W,F)$$

where F is the sequence of prosodic features and W is the string of words. The prosodic and lexical information were combined by using the posterior probabilities of the prosodic feature decision trees as emissions from the HMM system as likelihoods $P(F_i|T_i)$. To convert the posterior probabilities $P(T_i|F_i)$ to likelihoods, they chose to train the decision trees on a resampled version of the training set with a balanced number of sentence and non-sentence boundaries, which allowed them to avoid having to calculate prior probabilities:

$$\begin{aligned} P(T_i|F_i) =& \frac{P(F_i|T_i)P(T_i)}{P(F_i)} \\ &\propto P(F_i|T_i)P(T_i) \\ &\propto P(F_i|T_i) \end{aligned}$$

using the fact that $P(F_i)$ is constant for T_i and $P(T_i)$ is constant because of the resampling.

The prosodic feature decision achieved 4.3% classification error rate, the best language model HMM scored 4.0% error rate, and the combination of the two information sources produced a 3.2% classification error rate. Note that the chance error rate for this broadcast news domain corpus is 6.1% achievable by always guessing non-sentence labels.

Gotoh and Renals [51] approached the problem by noting that conventional ASR systems use language models that include sentence markers and are thus able to do some sentence segmentation. However, because the emphasis in large vocabulary speech recognition is on the sequence of words rather than the overall structure, the performance is unsatisfactory, with about 60% precision and recall for the broadcast news corpus they used. Thus they sought to identify sentence breaks from the ASR transcripts, which included sentence and silence markers that were very likely to be sentence breaks. They noted that the reference transcripts used for training were not exactly truth as they came from scripts prepared before the broadcast; they were quite close but might have had a slight negative impact on their results.

Their baseline system was a bigram finite state language model, with each state composed of a word and sentence boundary class pair and conditioned on the previous state. To this they added a pause duration model, estimating the probability of sentence break given the length of the pause to the nearest 0.1s. Because of the added complexity of having a bigram finite state model with states composed of sentence boundary class, word, and pause feature, they tried a couple of model decompositions, making simplifying assumptions about the independence of variables and between adjacent states, resulting in models that more closely resemble familiar HMMs with their hidden states and observed emissions. The study found their pause duration model, language model, and their combination produced 46%, 65%, and 70% F_1 score, respectively.

Shriberg et al. [129] used both prosodic and language modeling in their study. Prosodic modeling was used to extract features and language modeling to capture information about sentence boundaries and to model the joint distribution of boundary types in an HMM. The study compared several methods for combining the two models:

- Posterior probability interpolation: A linear interpolation between the posterior probabilities of the language model HMM and prosodic decision tree.
- Integrated hidden Markov modeling: An extension of Hakkani-Tür et al. [59], the prosodic observations are treated like emissions of the HMM used for lexical modeling. A model combination weight parameter was added to trade-off the contributions of the language model and prosodic information.

- HMM posteriors as decision tree features: The posterior probability of the lexical model HMM is used as a feature in the prosody decision tree. However, the authors found that the decision trees had an overreliance on the posteriors from the HMM, which was trained on correct words, while the test data was ASR outputs.

The paper argues that the main strength of HMMs, as likelihood models that describe observations given hidden variables, is that they can integrate local evidence, such as lexical and prosodic observations, with models of context, i.e. the sequence of boundary events, in a computationally efficient way. However, they make assumptions regarding the independence of observations and events which may not be entirely correct and thus limit performance.

In comparison a posterior model, such as the prosodic decision tree, tries to model the probability of the hidden variables as a function of the observations. The benefit is that model training is directed to improving discrimination between target classes and different features can generally be combined easily. The downside is that such classifiers can be sensitive to skewed class distributions, classification with more than two target classes complicates the problem because of the interaction of decision boundaries, and discrete features with large ranges — e.g. word N-grams — are not easily handled by most posterior models.

The results showed that prosodic information alone performs comparably to lexical information, and that their combination leads to further improvement. One interesting observation was that the integrated HMM performed better on reference output while interpolated posteriors were more robust to ASR output errors.

Mrozinski et al. [100] adapted the sentence segmentation model from Stolcke and Shriberg [140], which accounts for sentence boundaries truncating the word history in the training data. A hidden segment model hypothesizes the presence or absence of a segment boundary between each two words. Thus each word has two states, corresponding to whether a segment starts before the word or not, and likelihood models for each state must be derived from the traditional N-gram model to take into account truncated histories due to sentence boundary states. In this way, the model implicitly computes the likelihood of all possible segmentations. With this, [100] combined three separate language models, two using word-based language models and a class-based language model from [102]. No prosodic features were used in this system.

Adaptation

Supervised learning requires that the training corpus be labeled. Manual labeling of data is a very costly and time consuming task while automatic labeling may introduce errors, which may have repercussions for learning algorithms trained upon it. Adaptation is a method that circumvents this problem by using out-of-domain data that has already been labeled or cleaned to build or improve a classification model for in-domain data. Like supervised and unsupervised learning, there is supervised and unsupervised adaptation, depending on whether some of the in-domain data is already labeled.

Cuendet et al. state in [26] that theirs is the first published attempt to apply adaptation to sentence segmentation. The paper describes the supervised adaptation of conversation telephone speech (CTS), in this case Switchboard data, to meeting-style conversations. The benefits of using CTS include the large amounts of labeled data and the conversational speaking style that it shares with meeting data. As opposed to broadcast news, CTS and meeting conversations include speech irregularities such as disruptions and floor-grabbers/holders. The primary differences between CTS and meetings are that meetings generally have more than two speakers and the speakers also use visual contact to communicate.

The underlying assumption in adaptation is that, for each example x_i, there exists a probability distribution $p(x_i, l_j)$ for each possible label l_j. Furthermore, the probability distributions $p^{(i)}(x_i, l_j)$ for in-domain data $D^{(i)}$ and $p^{(o)}(x_i, l_j)$ for out-of-domain data $D^{(o)}$ are not independent, as otherwise there would be no sense trying to apply out-of-domain data to the in-domain classification problem. The goal of adaptation is to find a function $f(x)$ that can predict a label l for each example $x \in D^{(i)}$.

Cuendet et al. [26] tried several adaptation approaches, including data concatentation (training the classifier on the combination of out-of-domain and labeled in-domain data), logistic regression (combining the posterior probabilities of classifiers trained separately on both), using the out-of-domain posterior probability as a feature in the in-domain model, and boosting adaptation (creating an out-of-domain model and iteratively adding weak learners to adapt the model to labeled in-domain data). They also experimented with the amount of labeled in-domain data. The classifier used was AdaBoost.MH using lexical information (a combination of unigram, bigram, and trigrams) and pause duration for features.

In all the experiments, the adaptation systems were trained on the reference transcriptions and tested on both the reference and ASR transcripts. While the reference transcripts are assumed to be truth, the 34.5% word error rate on the MRDA meeting corpus ASR transcripts did raise the $\sim 42\%$ reference classification error to $\sim 56\%$ classifier error from ASR. The study found that phone conversation data can reduce the sentence segmentation error rate on meeting data, especially if there is scarcity of in-domain data, though a held-out set of in-domain data is needed to train regression parameters. For this particular task, they found the logistic interpolation method performed the best, independent of the amount of labeled in-domain data.

Semi-supervised learning

Semi-supervised learning is a class of statistical learning methods that make use of both labeled and unlabeled data. Labeled data is useful to machine learning systems as it provides positive examples it can learn from. However, labeling is often a costly or time-intensive process, and thus unlabeled data is generally more abundant.

One such semi-supervised method is co-training, where the idea is to train at least two distinct classifiers on the labeled portion of the training data and then to apply these models to the unlabeled portion. The most confidently classified examples are then added to the labeled training data, and this process can be iterated to grow the amount of labeled training data without too much loss in accuracy.

Guz et al. [57] applied co-training to sentence segmentation using classifiers trained on lexical and prosodic information, which provide separate and completary views of the sentence segmentation task. Both classifiers used a boosting algorithm (BoosTexter). The prosodic information classifier used 34 features, including pause duration and pitch and energy features. The lexical classifier used 6 N-gram features no longer than trigrams.

The exact co-training algorithms used were extensions of the one used in [158]. In general, one could view co-training as a method for improving the training set for a supervised learning classifier. However, in the case of co-training, the training set for each classifier can be adjusted independently. [57] tried two example selection mechanisms:

- Agreement: The examples that are labeled with high confidence by both classifiers are added to the training sets of both.
- Disagreement: Examples that are labeled with high confidence by one classifier while labeled with low confidence in the other are added to the training set of the less confident classifier using the more confident label. In this way, each classifier incorporates the examples it finds harder to classify.

For comparison, the study also compared the co-training systems to self-training systems which, as the name implies, have each classifier iteratively augment its labeled training set with examples it believes it correctly labeled with high confidence. Their results found that, when the original manually labeled training set is small — 1,000 examples, in this case — then co-training with 500+ thousand examples could improve the lexical and prosodic models by 25% and 12% relative, respectively. As the amount of labeled training data increases, the performance gap between the baseline and co-training systems shrinks or vanishes. The self-training systems did only slightly better than the baseline systems. The study also found that combining the prosodic and lexical systems improved performance.

Comparison across speaking styles

Somewhat related to the question of feature portability across languages central to this dissertation, Shriberg et al. [127] studied the behavior of different features for dialog act segmentation and classification across two different speaking styles, namely the more spontaneous meetings data and the read-style broadcast news data. The main contribution of this paper was not to improve classification accuracy. The learning algorithm was the BoosTexter algorithm used by [26, 43, 57] and the features consisted of pause, pitch, energy, duration, speaker turn, and lexical N-grams as used by [26, 43, 57, 59, 129].

Because of the different chance error rates of the two styles, instead of direct comparison of F_1 scores between feature sets, the author examined relative error reduction. Surprisingly, the study found the pause, pitch, and energy feature groups to have very similar relative error reduction. For example, the two speaking styles have different turn-taking behavior, yet if short pauses (< 50ms) are ignored, the distribution of pauses in the two styles is similar. This gives the possibility of performing adaptation by scaling. This comparison of features was done using the Kolmogorov-Smirnov (K-S) test [133]. The pitch and energy features are strikingly similar, both in which features are best for classification and their distributions.

Of the features that differed between styles, lexical features are much stronger in meetings than broadcast news; the difference is attributable to fillers, discourse markers, and first person pronouns often occurring at the start of dialog acts. The difference in relative error reduction by the duration features is attributable to news anchors using longer duration at non-boundaries. When normalized by speaking rate, meetings and broadcast news exhibit similar relative lengthening.

As noted in [26], having two corpora with similar speaker styles allows for the pooling of training data. Here, Shriberg et al. goes further and hypothesizes that feature distributions and decision threshold could also be shared, though possibly requiring normalization.

Other languages

Much of the recent work in sentence segmentation has been in English. Because part of the objective of this dissertation is the study of language-robust prosodic features, it behooves us to examine work in other languages.

Guz et al. [58] adapted methods to account for the agglutinative morphology of Turkish, where affixes attach to word stems and modify their meaning. More so than English, Turkish contains inflectional and derivational suffixes. Inflectional suffixes change the grammatical properties of the word within its syntactic category, for example in English "*-ed*" attaches to a verb and makes it past tense. Derivational suffixes may modify the syntactic category of the stem word, such as English "*-ment*" casts a verb into a noun meaning "the action or result of [stem verb]." [58] gives the example of the Turkish word "*yapabileceğlim*," which is parsed into the morphemes "`(yap) + (abil) + (ecek) + (im)`" roughly meaning "`(do) + (able to) + (will) + (I)`" in English. This word has three possible interpretations:

- `(yap)` verb, positive polarity + `(+yAbil)^DB` verb + `yAcAk` future tense + `(+yHm)` 1st person singular agreement = *I will be able to do it*
- `(yap)` verb, positive polarity + `(+yAbil)^DB` verb + `yAcAk^DB` adjective, future participle + `(+yHm)` 1st person singular possessive agreement = *The (thing that) I will be able to do*
- `(yap)` verb, positive polarity + `(+yAbil)^DB` verb + `yAcAk^DB` noun, future participle, 3rd person singular agreement + `(+yHm)` 1st person singular possessive agreement, nominative case = *The one I will be able to do*

where `^DB` symbolizes a derivational boundary in their representation of Turkish morphology, adapted from [105]. Concatenation results in a very large part-of-speech (POS) tag set. To handle this, the authors break up the morphosyntactic tags into inflectional groups and focus on the final inflectional group, which determines the word's overall syntactic category. For these final POS tags, the study used pseudo-morphological features consisting of the last three letters of each word, akin to looking for the "*-ed*" suffix in English.

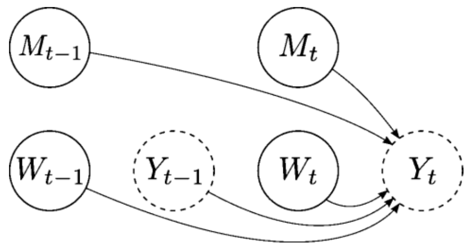


Figure 2.1: Components of a factored hidden event language model over word boundaries Y, words W, and morphological factors M. Solid circles indicate observations, and dotted circles the hidden events to be inferred. The arrows indicate variables used for estimating probabilities of boundary Y_t, that is $P(Y_t|W_t, M_t, Y_{t-1}, W_{t-1}, M_{t-1})$.

Furthermore, while it is a free-constituent-order language, Turkish tends to follow a subject-object-verb ordering. This pattern is particularly strong in broadcast news corpora; thus a verb is a good indicator of the end of a sentence. Therefore the system includes a binary feature that checks if the final category of any possible morphological parse is a verb.

To incorporate morphological information, the study implemented a factored hidden event language model (fHELM), shown in Figure 2.1. The probability of boundary Y_t is dependent on the current and previous words, W_t, W_{t-1}, and previous boundaries, Y_{t-1}, as in hidden event language models, previously used for disfluency detection in [141]. The word information is augmented with morphological factors, M_t, M_{t-1}, as in factored language models, which were used for ASR in Arabic [156], an inflectional language. Thus, boundary decisions are made according to $P(Y_t|W_t, M_t, Y_{t-1}, W_{t-1}, M_{t-1})$.

In addition to the fHELM, the authors used boosting and conditional random fields [83] discriminant classifiers using lexical, morphological, and pseudo-morpholocial features, plus prosodic features from Shriberg et al. [129] and Zimmerman et al. [175]. The discriminant classifiers were combined with the fHELM similar to work in [59, 129]. The study found that both the discriminant classifiers and fHELM benefitted from morphological information. Furthermore, the pseudo-morphological and prosodic features gave a further performance gain to the discriminant classifiers. Combination systems also led to improvement except with the discriminant classifiers with all features.

Kolar et al. [82] faced a similar problem with the highly inflectional and derivational nature of Czech. The study used a positional tag system that consisted of a string of 15 symbols to denote the morphological category of each word, resulting in 1362 distinct tags in their training data. While the language model using tag data did not perform as well as the word-based model, they found the system benefitted from replacing infrequent words and out-of-vocabulary words in testing with subtags consisting of a subset of 7 symbols. This reduced the language model vocabulary from 295k words to 62k mixed words and subtags. The work also used prosodic features borrowed from Shriberg et al. [129].

Batista et al. [7] and Batista et al. [8] have studied punctuation detection in Portuguese and, to a lesser degree, Spanish. [8] compared the detection of the two most common punctuation, full stops and commas, in English, Portuguese, and Spanish. The model used was a maximum entropy (ME) model using eight word LMs up to trigrams and the eight corresponding LMs using parts of speech, pause duration, and speaker and gender change events. In comparing the slot error rate between the three languages, they note that overall performance is weighted toward the more common comma, which is generally a harder problem because commas serve multiple purposes. The Portuguese data suffered from inconsistent annotation and a greater proportion of spontaneous speech. The spontaneous speech, being more unstructured, has a higher word error rate, which is an issue for a system heavily dependent on lexical data.

[7] extended their work on Portuguese punctuation by adding prosodic features and question mark detection. The prosodic features used are based on Shriberg et al. [127, 129], though pitch and energy features are extracted over syllable and phone regions in addition to word regions. This interest in other linguistic units is motivated by linguistic findings [41], especially in stressed and post-stressed syllables. However, they find that word pitch followed by word energy features are the most useful, in that order, and combination with syllable features does not lead to further

improvement. They partially corroborate the findings in [127] on the contribution and language-independence of various prosodic features.

The primary language specific issues discovered were in pitch and duration. Different pitch slopes are suspected of being associated with discourse functionalities beyond sentence structure. As for duration, the literature reports three segmental strategies at the end of intonational phrases: "epenthetic vowel, elongated segmental material, or elision of post-stressed segmental material" [7]. However, there are no existing features that quantify these events, and the duration features used by the system helped little. Pre-boundary lengthening was observed in Portuguese.

Kawahara et al. [72] extended their previous work on Japanese sentence and clause units by using local syntactic information. Because subjects and objects may be omitted in spontaneous Japanese, the definition of a sentence is not well-defined, and the study relied on a human annotation of three different boundary strengths. The dependency structure used is based on minimal grammatical units called *bunsetsu* consisting of one content word and adjacent functional words. Dependency is usually left-to-right with the predicate in the final position of the sentence. To extract this dependency structure, the study used a chunking algorithm to chunk words into *bunsetsu* units, determine dependency between adjacent *bunsetsu*, and determine whether a *bunsetsu* is a predicate. Separate classifiers were trained for each step, using surface forms, baseforms, and POS tags.

Both their baseline and proposed systems consisted of voting pairwise SVMs trained on the surface forms and POS tags of the three words before and three words after the candidate boundary. While in the baseline system every word-final boundary was considered a candidate boundary, the proposed system restricted candidate boundaries to edges of the generated chunks. They found that the syntactic chunking improved the detection of boundaries in ASR output, though is some confusion between different boundary strengths.

2.3 Feature Selection

Feature selection is the process of selecting a subset of features toward some objective, such as improving the performance of the learning algorithm that uses them. The benefits of a smaller feature set include:

- Reducing computation time and resources
- Avoiding overfitting model parameters by having more data per parameter
- Making data interpretation and visualization easier

Blum and Langley [14], Guyon and Elisseeff [55], and Saeys et al. [119] provide good overviews of feature selection methods.

2.3.1 Filters and ranking

Filtering and ranking are methods of scoring features according to their usefulness, either as the primary feature selection method or in aid of one. Filtering in the literature usually considers each variable independently, which makes them fast and linearly scaling with the number of features, but unable to consider feature interaction. Being classifier independent has the same trade-off as generalist approaches, aiming to be good for any given classifier selected but not guaranteed to be optimal for any. Often, filtering performs well enough to act as a baseline feature selection method.

Common ranking criteria. The correlation coefficient between input random variable X_i and outcome random variable Y is:

$$R_i = \frac{cov(X_i, Y)}{\sqrt{var(X_i)}Y}$$

However, since the distributions of these random variables are unknown, the variances and covariance are estimated from the data. In the context of linear regression, R_i^2 is the proportion of the total variance of outcome Y that can be explained by feature X_i. Correlation criteria can be extended beyond linear fitting by performing a non-linear transformation — for example, taking the log of or squaring the variable — or performing a non-linear regression and ranking the features by goodness of fit. To use correlation coefficients for binary classification, the two class labels are assigned values of y, typically ± 1, in which case it resembles Fisher's, T-test, and similar criteria [44, 50, 62, 151].

Related to the idea of selecting features based on their goodness of fit, the analogue in classification would be sorting variables by their predictive power. For binary classification, a single-variable classifier can be created by placing one decision threshold, labeling all instances of the variable above the threshold as one class and examples below as the other class. Adjusting the threshold trades off the false positive and false negative error rates; common characterizations used for error curves are the equal error rate point and area under the ROC curve.

Other filtering criteria stem from information theory [10, 30, 36, 150], many based on the mutual information between the variable x and the target y:

$$I_i = \int_{x_i} \int_y p(x_i, y) \log \frac{p(x_i, y)}{p(x_i)p(y)} dxdy$$

In the case of discrete features and targets, estimating the marginal and joint distributions is a matter of counting. However, with continuously-valued variables, their distributions need to be estimated, for example by discretization or approximating their densities [150].

Redundancy. One consequence of analyzing features separately without considering their interaction is the possibility of selecting redundant features. From an information theory point of view, redundant information cannot improve performance if there is no new information to improve decision making. However, in practice, learning algorithms might not fully utilize the information content of the input variables because of the limitations of their models and the features themselves may have observation error. Thus redundant features can improve performance through noise reduction.

Variable interaction. Another issue of ignoring feature interaction is whether two or more features, while individually not useful, may together have predictive ability. As a toy example to show this is possible, Guyon and Elisseeff [55] give an example where for one class label features (x_1, x_2) have a bimodal normal distribution about $(1,1)$ and $(-1,-1)$ with equal probability, and the other class label has a similar distribution centered around $(1,-1)$ and $(-1,1)$. From the perspective of either variable x_i, both classes have the same distribution about 1 and -1, but taken together the four modes are separable. Note that this example is commonly used in probability and statistics texts to show that independence does not imply conditional independence, in this case the variables being not conditionally independent given the class label.

2.3.2 Subset selection methods

As opposed to filtering, which examines each feature independently of the others, feature subset selection methods seek to find a set of features that optimizes an objective function, often the performance of a particular learning algorithm, sometimes with a regularization term to penalize large feature sets. For N variables, an exhaustive search over all $2^N - 1$ proper subsets is only practical for small N; thus these methods focus on algorithms that efficiently search the space of possible feature subsets.

Wrappers

Wrappers obviate the need to model the learning algorithm by treating it as a black box. Instead, different feature subsets are presented to the learning algorithm, and the fitness of a feature subset is based on the learning algorithm output. Various algorithms can be employed to efficiently search the space of variable subsets, and some common ones are detailed below. There is a trade-off between efficient search strategies and system performance, but Reunanen [113] among others notes that coarse search algorithms may reduce overfitting the feature subset to the training data.

Two commonly used search paradigms are forward selection and backward elimination. Forward search begins with an empty feature set and iteratively adds more. Backward elimination does the reverse, starting with all features and gradually removing them. See Figure 2.2 from [81]. In their simplest incarnations, these algorithms

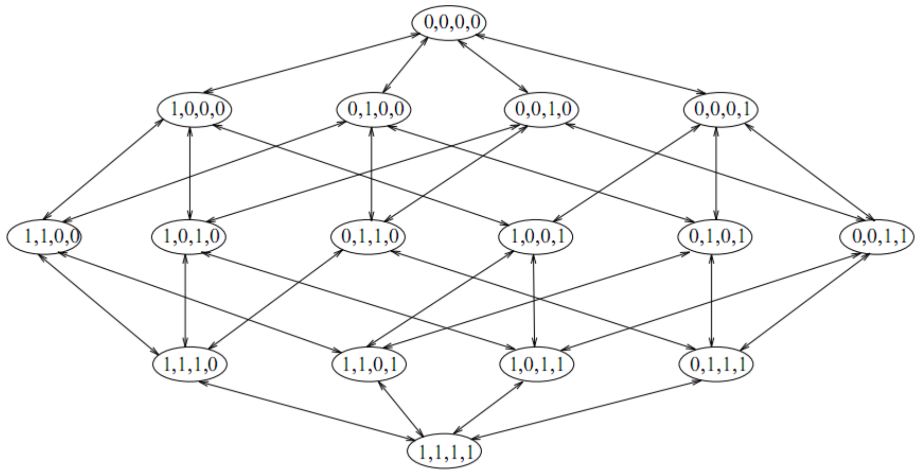


Figure 2.2: The search space of a feature selection problem with 4 features. Each node is represented by a string of 4 bits where bit $i = 1$ means the ith feature is included and 0 when it is not. Forward selection begins at the top node and backward elimination begins at the bottom node, with daughter nodes differing in one bit.

are greedy searches that explore all possible daughter nodes, e.g. in forward selection, the current feature subset plus each unselected feature individually. The highest scoring daughter then becomes the parent node explored in the next iteration.

The concern with greedy algorithms is falling into local maxima, either due to pruning a path that would lead to the global maxima or a stopping condition ending the search too early. Kohavi and John [81] show that best-first search [118] achieves more robustness than hill-climbing by making a couple alterations, namely instead of exploring only the best node, maintaining a set of nodes that are within a margin of the current best score and altering the stopping criterion by increasing the number of iterations without progress required before stopping. Empirical evidence suggests that greedy search is computationally efficient while being robust to overfitting. For further variants on forward and backward search, including beam search and bidirectional search see [111, 131].

The primary trade-off in forward versus backward search is that, while backward elimination may capture feature interaction, training models with large features sets can be computationally expensive. [80] proposes that backward search can be sped up through compound operators. For example, if past iterations have shown the

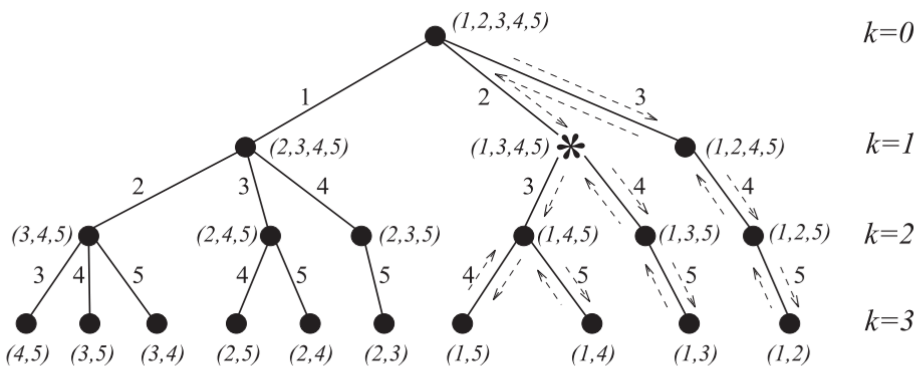


Figure 2.3: Branch and bound search for selecting a 2-feature subset from 5. By the time the algorithm reaches the starred node, it has already searched leaf node *(1,2)*. If the objective function at the starred node is below the bound set by node *(1,2)*, by the monotonicity condition the subtree below it cannot exceed the bound and can thus be pruned.

removal of features x_i and x_j to be good, their compound, removing both features, is worth exploring. Compound operators can also combine operators that add features. Thus the results of previously tested feature sets can inform further exploration of the search space, and compound operators create child nodes farther away in the search space, allowing the search algorithm to arrive at the global maximum earlier.

One alternative search strategy is the branch and bound algorithm [101]. These algorithms depend on the monotonicity of the objective function, which is not always the case with feature selection, but can be finessed [37]. The general idea behind branch and bound feature selection is that it first evaluates one leaf node at the desired depth, i.e. the algorithm is set to find the optimal size M subset, and so initializes the lower bound of the optimal objective. Because of monotonicity, if any subset scores below the current bound, its entire subtree can be pruned (see Figure 2.3 [136]). Thus the global maximum can be found without an exhaustive search. Recent work on branch and bound has been directed to speeding up search by the ordering of nodes to be searched and using predicted objective values [136].

Genetic algorithms [132, 152, 172] do not rely on monotonicity of the objective function. The algorithm maintains a population, usually 50 to 100, of feature subsets encoded as genes, using a binary state for each feature depending on whether it is included or not. The idea is for the population to improve with each iteration of evolutionary pressure by culling the weaker genes. There must be at least one way for genes to adapt, such as crossover (genes copy or swap portions of their code) or mutation (random flips in the state of a feature). Such adaptation is random but designed to keep child genes similar to their parent(s). A decision must also be made as to how to select which genes survive to the next generation, such as only keeping the top N genes or making survival probability a function of rank or fitness. The strength of genetic algorithms is that, by maintaining a sufficiently large population, they can be robust to local maxima, evaluate the fitness of large areas of the search space simultaneously, and pass on that information to the next generation, thus getting close to the global maxima fairly quickly. However, since mutation is random and not always intelligent, there is no guarantee the algorithm will find the global optimum.

Related to genetic algorithms is simulated annealing [73, 89, 132], which is named after a metallurgical process where atoms in a metal, if heated hot enough and cooled slow enough, will crystlize into a low-energy state. To translate this to the optimization problem of feature selection, the current solution is perturbed, similar to mutation in genetic algorithms. If this results in a better objective function, it replaces the current solution. Otherwise, there is a probability that it replaces the current solution anyway depending on how much the objective function drops, typically proportional to $e^{-\Delta T}$, where ΔT is the change in "temperature," i.e. objective function. In this way, the algorithm tends to follow the slope of the search space, but occasionally goes against it, which allows it to escape local maxima. A key decision is setting the probability that the algorithm accepts a lower objective function: if set too high, it regresses too often and is slow to converge; if set too low, it is more prone to local minima.

Embedded methods

As opposed to wrappers, embedded methods integrate feature selection into the learning algorithm. Some algorithms, such as CART-style decision trees [16] and the

AdaBoost classifier [38] I use in this thesis, have them built in. For example, at each node, the decision tree selects the single best feature to split the data with. The primary benefit of embedded methods over wrappers is that they need not train a new model for each potential feature set and so are faster.

For instance, [56] examined backward elimination for a support vector machine (SVM) with a linear kernel. Assuming the SVM parameters remain the same, the linear kernal allows the algorithm to quickly estimate the change in the objective function caused by removing individual features. Backward elimination removes the lowest ranking variable in each iteration. The study found the nested feature sets produced by this method to be more robust to overfitting, like those found by forward selection and backward elimination wrappers, especially when compared to combinatorial searches, i.e. exhaustively searching all subsets with a maximum size.

Other methods of predicting the change due to removing each variable include: sensitivity [107]; using the derivative of the objective function with respect to the variable or weight; and quadratic approximation [116] using a second-order Taylor expansion of the objective function $\frac{1}{2}\frac{\partial^2 J}{\partial w_i^2}(w_i)^2$, an idea borrowed from the optimal brain damage method to prune neural network weights [85]. Pruning neural networks is also a form of feature selection, reducing the number of active inputs to a node. The reasoning behind the second-order expansion is that, when objective function J is optimal, the first-order terms can be neglected.

SVMs can use objective functions with regularization terms to penalize the number of variables. These models also perform feature selection as part of their optimization. For linear SVMs with weights w, a commonly used regularization term is the l_p-norm, $\|w\|_p = (\sum_{i=1}^{n} w_i^p)^{1/p}$. Weston et al. [161] show that l_0-norm regularization, which is a penalty term proportional to the number of the non-zero weights, can be approximated by iteratively training an l_1- or l_2-norm SVM and rescaling the input variables by their weights. Bi et al. [12] show that l_1-norm SVMs can be approximated without the iterative process using an approach similar to that used by [148] for least-squares regression.

2.3.3 Feature construction

An alternative to selecting a subset of input variables is to extract features from them with the purpose of improving learning algorithm performance and/or dimensionality reduction without losing the information content of the original variables.

One common method of feature construction is forming linear combinations of the input variables. I cover linear discriminant analysis (LDA), using supervised learning to extract discriminant features, in Sections 4.1.1 and 4.1.2. Unsupervised learning transforms seek to compress the data with minimal loss. For example, principle component analysis (PCA) creates an orthogonal basis where the first component captures as much variance of the original variables as possible, and each successive component does the same under the constraint of being uncorrelated with previous components. Singular value decomposition (SVD), lifting the orthogonality condition, provides the reconstruction with minimal least squares error [31]. Depending on the data, other forms of data decomposition such as Fourier, Hadamard, or wavelet transforms may be applicable.

More recently, Globerson et al. [47] proposed an unsupervised feature construction method called sufficient dimensionality reduction that extracts the most informative features, which maximizes what they call *information in the measure.* This builds on their previous work on the information bottleneck method [149], which seeks to find the best trade-off between reconstruction and compression for a random variable. They show that the feature construction is the dual of the reverse feature design problem and equivalent to a Kullbeck-Leibler (KL) divergence minimization problem, which they solve by an iterative projection algorithm. However, it appears this work has not been extended to multiple output features.

Another method in feature construction is to cluster similar variables and replace them with a centroid feature. Duda et al. [31] covers basic approaches using K-means and hierarchical clustering. To give an example, document and text classification often uses word counts as variables under a bag-of-words model, but then the size of the variable set is equal to the size of the vocabulary. Baker and McCallum [6] and Slonim and Tishby [134] clustered word variables according to the their distribution across document classes, varying in their methods for clustering and extracting features from word clusters, Slonim and Tishby using the previously mentioned information bottleneck method. These methods maintain discriminatory information between document classes better than unsupervised learning with latent semantic analysis [29], which compresses word variables by using an SVD decomposition of word frequency across documents.

Chapter 3

Feature Robustness

This chapter provides the motivation for the experiments in Chapters 4 and 5. It examines the robustness of an existing set of prosodic features originally designed for English when ported without any changes to other languages, specifically Arabic and Mandarin. Beyond looking at the performance gains from adding prosodic features to lexical information, I use feature selection methods to compare how specific features and categories of features perform across the different languages.

What we shall see is that the feature set, which has been designed to be word-independent and have multiple similar features backing each other up, is fairly robust to different language conditions. However, beyond the ubiquitous pause feature, this redundancy makes it fairly difficult to predict *a priori* how useful any particular feature will be or which feature should be next chosen by the feature selection algorithm. One of the stronger patterns found was that the pitch features performed significantly worse in Mandarin than in Arabic or English, which is believed to be due to Mandarin lexical pitch interfering with the manner in which the pitch features are designed. This leads to the question of how a researcher should set out to design a good set of features, a question I will take up in Chapter 4.

3.1 Background

3.1.1 Feature set history and applications

The prosodic feature set studied in this chapter is the work of Shriberg. It can trace its origins to a 1997 paper on using only prosodic information for disfluency detection [126]. There, Shriberg et al. successfully found cues in segemental duration and pitch in the detection and classification of disfluencies, such as filled pauses and false starts. The design of the pitch features to measure pitch dynamics across a boundary is similar to what is described in Section 3.1.1, as are what elements the pause and segmental duration features attempt to quantify. Also, they have in common the use of both normalized and raw versions of the pitch and duration features.

This work was expanded in Sönmez et al. [137], which applied the features to the speaker verification task. Here, the pre-processing of the pitch vector is refined, using the lognormal tied mixture (LTM) model [138] to remove halving and doubling errors from the pitch tracking software. Furthermore, the LTM model provides speaker parameters that can be used for speaker normalization. This is followed by a median filter to smooth out microintonation effects and fitting piecewise linear segments to the pitch vector, called piecewise linear stylization in the literature. As a result of this smoothing, the authors were able to improve performance by adding to the existing short-term cepstrum spectra more long-term features describing the pitch contour. It should be noted that this pre-processing was also carried over to the energy features when they were introduced.

Since then, the feature set has been used in a wide variety of applications. For speaker recognition [128], the features were not used by the learning algorithm directly, but feature events were counted over syllable-based regions. This discretization could then be put in N-grams, which were the features used by the SVM learner, similar to what was done by Adami et al. [3]. The features have also been used to estimate the fluency of language learners [145], primarily checking to see that word stress was properly executed by measuring vowel duration and maximum pitch excursion.

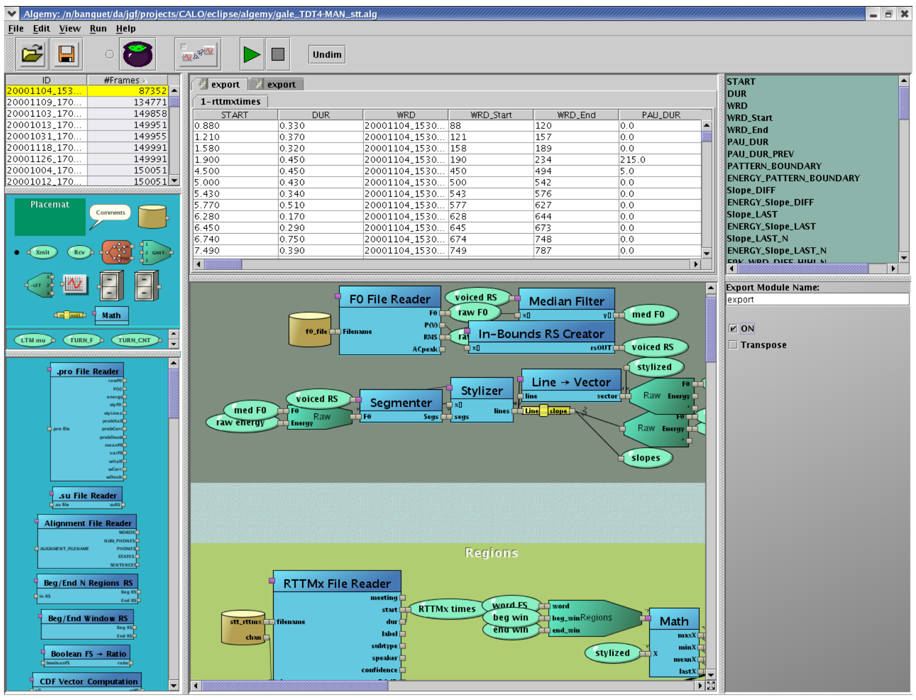
The features are able to capture emotion and have been used in several related tasks. Ang et al. [4] used the features, along with a language model and speaking style labels, to detect annoyance or frustration in users making air travel arrangements using an automatic telephone service. They found that long segmental duration, slower speaking rate, and high pitch peaks were indicative of annoyance. Hillard et al. [63] used what they called an unsupervised learning method, though more accurately it could be described as semi-supervised co-training, to cluster meeting spurts using language models into agreement, disagreement, backchannel, and other. A decision tree classifier using the prosodic features and word-based features was then trained on this automatically labeled data. The study found that the prosodic features performed almost as well as the word-based features, which included positive and negative keywords, but their combination showed little improvement. On the same meeting data, Wrede and Shriberg [164] found that some prosodic features were highly correlated with speaker involvement, which is indicative of meeting hot spots. In particular, speaker normalized pitch features involving mean or maximum were strong features, while pitch range, energy, and unnormalized features were less so. However, due to difficulties with human labeler agreement, the study did not have data to train a reliable classification system and so stopped at feature ranking.

Many of the sentence segmentation systems covered in Section 2.2.4 [26, 57, 59, 96, 129, 175] used these features, often combined with a language model. While pause duration overwhelmingly yields the most predictive set of features for detecting sentence boundaries, pitch and segmental duration features contribute significantly to overall performance. Shriberg et al. [129] also studied the use of these prosodic features in topic segmentation of broadcast news, finding similar feature usage as in their broadcast news sentence segmentation decision trees, including the importance of pause duration, though pitch range features were especially prominent. Ang et al. [5] used pause duration to segment dialog acts in meetings and then used the prosodic features to train a decision tree to classify the segments. The posterior probability of the prosodic decision tree was then used as the input to a maximum entropy classifier to incorporate lexical data. The study did not report which prosodic features were most useful, but the authors noted that ASR errors impaired the lexical-based model much more than the prosody-based model.

To summarize, this set of prosodic features has been used in a spectrum of different tasks. Rather than design new features for each new task for various cues, the features were used off the shelf, though Shriberg has modified and added to the feature set over time. Thus this feature set can be viewed as a good general-purpose set of prosodic features, quantifying a wide variety of prosodic behavior and leaving the learning algorithm to determine how to best make use the information.

The above studies have a number of points in common. Firstly, all of them used English data, and the following work was the first to study its portability to other languages. Secondly, many showed that prosodic information improved performance when added to lexical data, showing that they are complementary. Furthermore, many noted that word-independence is a positive property of the feature set. While the prosodic features do require word alignments, and for many corpora these were taken from ASR outputs, the word-independence made the prosodic features more robust to transcription errors than language models. Among the prosodic features, the most lexically dependent ones are the segmental duration features, which rely on the time alignments of vowels and rhymes. While sonority makes it easier to locate vowels than identify them, phone identities are used to calculate the mean and variance parameters used for segmental duration normalization.

The following describe the features used for this dissertation. For more precise details about the construction of individual features, see [34]. The following feature extraction was done in Algemy, a Java-based prosodic feature extraction system created by Harry Bratt at SRI International [15] (see Figure 3.1). The idea behind Algemy is that many prosodic feature extraction algorithms share common building blocks. For example, taking the mean value of frames within a window, finding which values exceed a threshold, or performing a regression or normalization over a set of frame/window values. However, prosodic feature extraction algorithms are typically written like any other computer program, leaving the author to code the operations and manage data streams themselves. This has the drawbacks usually related to computer programming, including the difficulty of reading and reusing code from other researchers. Algemy contains a graphical user interface which allows a researcher to



ID	#Frames
20001104_153...	87352
20001109_170...	134771
20001103_170...	149858
20001013_170...	149951
20001031_170...	149955
20001118_170...	149991
20001126_170...	149991
20001004_170...	150051
20001012_170...	150051

START	DUR	WRD	WRD_Start	WRD_End	PAU_DUR
0.880	0.330	20001104_1530...	88	120	0.0
1.210	0.370	20001104_1530...	121	157	0.0
1.580	0.320	20001104_1530...	158	189	0.0
1.900	0.450	20001104_1530...	190	234	215.0
4.500	0.450	20001104_1530...	450	494	5.0
5.000	0.430	20001104_1530...	500	542	0.0
5.430	0.340	20001104_1530...	543	576	0.0
5.770	0.510	20001104_1530...	577	627	0.0
6.280	0.170	20001104_1530...	628	644	0.0
6.450	0.290	20001104_1530...	645	673	0.0
6.740	0.750	20001104_1530...	674	748	0.0
7.490	0.390	20001104_1530...	749	787	0.0

START
DUR
WRD
WRD_Start
WRD_End
PAU_DUR
PAU_DUR_PREV
PATTERN_BOUNDARY
ENERGY_PATTERN_BOUNDARY
Slope_DIFF
ENERGY_Slope_DIFF
Slope_LAST
ENERGY_Slope_LAST
Slope_LAST_N
ENERGY_Slope_LAST_N

Export Module Name: export

[✓ ON]
Transpose

Figure 3.1: A screenshot of the Algemy feature extraction software. Note the modular blocks used for the graphical programming of prosodic features and handling of data streams. The center area shows the pitch and energy pre-processing steps.

create prosodic feature extraction algorithms using a graphical programming language with a wide variety of pre-made blocks.

The benefit of Algemy is that, once the learning curve has been crested, the prototyping of prosodic features using the provided blocks is very quick. It is also easy to comprehend and edit algorithms. In batch mode, feature extraction is as fast and memory efficient as traditional C++/Java implementations. The downsides to Algemy include its learning curve, especially as one needs to be familiar with what blocks are available and their function to become proficient in their usage. If a particular functionality is not available, users can code contributions to the library of blocks, as I did for this project.

Pause

Pauses often mark the boundaries between language units, such as sentences and topics. This is especially true in broadcast news, where pause cues help the audience follow the news item, relative to spontaneous speech where pauses may occur due to speakers reacting to one another or thinking of what to say next. The pause duration feature used is the inter-word times as given by the ASR output, many of which are zero during continuous speech. The feature set also includes the pause duration for the previous two and the next inter-word boundaries, making four pause features in total. These additional features inform the classifier of whether there is a break in the vicinity, which reduces the likelihood of a sentence boundary at the current boundary.

Pitch

The pitch features can be broadly classified into three categories: range, reset, and slope features, which are described individually below. All of the pitch features go through the following pre-processing steps. Fundamental frequency values are extracted using the ESPS pitch tracker `get_f0` [1] in 10ms frames over voiced speech. Pitch trackers commonly suffer from halving and doubling errors, where the tracker believes the speaker to be an octave above or below their actual pitch. A lognormal tied mixture (LTM) model [138] is employed to detect and remove these errors. Each speaker model consist of three lognormal components with equal variances and means tied log(2) apart on the lognormal scale. An expectation maximization (EM) algorithm estimates the mean, variance, and mixture weight parameters. Not only does this fix most halving and doubling errors, the speaker model provides speaker baseline and range parameters for normalization, including speaker mean, baseline and topline — located between the middle mode and halving and doubling modes, respectively.

Further pitch pre-processing includes a 5-frame median filter, which smoothes out pitch instability during voicing onset, followed by a process called piecewise linear stylization first used in [137]. A greedy algorithm fits piecewise linear segments to the pitch contour (see Figure 3.2), minimizing mean square error within the constraint

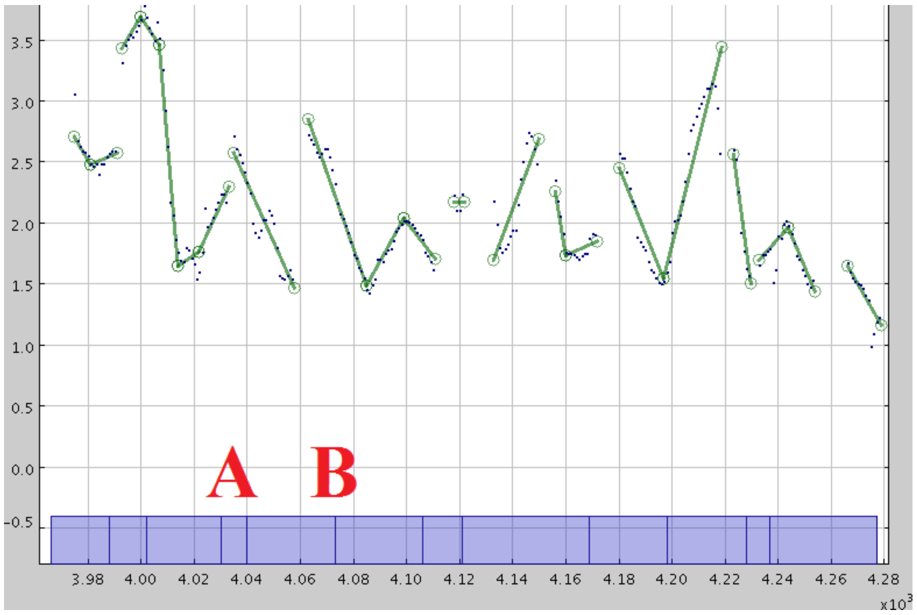


Figure 3.2: An example of the piecewise linear stylization of a pitch contour, in this case from Mandarin. The blue dots are the pre-stylization pitch values while the green lines show the piecewise linear segments. The horizontal axis is in 10ms frames with the purple blocks on the bottom showing words. Notice that while stylization tends to conform to word boundaries, the pitch contour for word A has been absorbed by the words around it and one long linear segment crosses boundary B.

of a minimum segment length. This removes microintonation and also extracts pitch slope values that are used in the pitch slope features.

From this stylized pitch, five pitch statistics are extracted over each word: the first and last stylized pitch values plus the maximum, minimum, and mean stylized pitch over the word. These statistics are similar to the prosodic features used in [33, 143, 165, 171], measuring the distribution of the pitch values. However, Shriberg derives features from these pitch statistics as explained below.

Range features. The range features quantify how far the word departs from the speaker's usual speech patterns. For instance, toward the end of sentences speakers tend to drop toward the lower end of their range. In the range features, the pitch statistics extracted above are compared to speaker baseline and topline parameters taken from the LTM models. These comparisons include both absolute differences and log-ratios, some normalized by the speaker LTM range parameter. To classify a boundary, range features are taken from both the words before and after the boundary in question, though [129] notes that the features are not symmetric, and in sentence segmentation there is preference for range features from the word before the boundary. Because these are important to the work in Chapters 4 and 5, they are detailed in Appendix A.3.

Reset features. One of the strongest pitch cues, at least in English, for the end of one syntactic unit is a drop in pitch followed by a pitch reset to start the next unit from a higher point [142]. To calculate these, the same five statistics from the stylized pitch contours over word segments were used, in this case comparing one statistic from each word on either side of the boundary in question. Like the range features, these comparisons used absolute pitch difference, log-ratios, and speaker normalization. These features are detailed in Appendix A.2.

A large number of features were extracted to quantify pitch reset. Not just comparing the last pitch of the word before the boundary to the first pitch of the word after, which may be susceptible to voicing or pre-processing steps, but all combinations of the maximum and minimum of both words as well as comparing their means are included, which capture a variety of possible word contours. Furthermore, many of these features were duplicated, except using statistics pulled from the 200ms windows before and after the boundary. The length of the 200ms window was determined empirically through experiments but is approximately the length of an English syllable.

Note that the range and reset pitch features, except the 200ms reset features, are constructed from the same five pitch statistics extracted over each word, plus some LTM speaker parameters. These will form the basis for the automatic pitch feature design in Chapters 4 and 5.

Slope features. The pitch slope features describe pitch trajectory around the candidate boundary from the slope of the piecewise linear pitch stylization. Specifically, the last pitch slope before and first slope after the boundary are extracted, as well as a continuity feature based on the difference between the two. Because stylization occurs independently of word boundaries, the piecewise linear segments may extend across words as seen at boundary B in Figure 3.2, in which case the boundary is unlikely to be a sentence break. If a linear segment encroaches into a neighboring word for a few frames by some happenstance of the stylization or word time alignments, those pitch slopes are not attributed to the word.

The pitch slope pattern features used for speaker recognition [3, 17, 114] could not be implemented in Algemy at this time, so they were excluded from these sentence segmentation experiments.

Energy

The energy features undergo pre-processing exactly like the pitch features: frame-level RMS energy values are extracted using the ESPS toolkit, median filter, followed by piecewise linear stylization. The LTM model is not used to fix halving/doubling errors, as energy tracker outputs do not have a tri-modal distribution, but is used to derive speaker energy parameters for normalization. This parallel feature extraction allowed [3] to model pitch and energy contour dynamics over approximately syllable-sized regions the same way. However, while pitch reset features are designed to quantify a well-known pitch cue, the energy range and reset counterparts are more intended to capture general energy behavior.

Segmental duration

A process called preboundary lengthening causes speech to slow down toward the end of syntactic units [162], in particular affecting syllable nucleus and/or rhyme. Thus the segmental duration features measure the lengths of the last vowel and rhyme preceding the boundary in question. For example, the vowel duration features use two normalizations, Z-normalization and ratio with respect to the mean. For normalization, both speaker-specific parameters and those extracted over the entire corpus are used. The rhyme duration features are similarly normalized with some feature accounting for the number of phones in the rhyme, since syllable structures vary between languages, with English allowing relatively complex rhymes [155].

Syllabification for these features is based on the phone string from the ASR output, using the principle of coda maximization [71] and a list of phonologically allowed codas built from training data. Note that the dependence on phones from recognizer output, including the computation of the speaker and corpus phone parameters for normalization, make these features less robust to ASR errors than the pitch and energy features.

Speaker turns

While technically not prosodic features, these are included in the feature set because they are handled by the classifier in the same way. These features measure time that has elapsed since the last speaker turn. In the absence of reference speaker labels, speaker turns are extracted by automatic speaker diarization systems [163].

3.2 System

3.2.1 Classifier

The learning algorithm used for the following experiments is AdaBoost, a member of the family of boosting algorithms [120]. The idea behind boosting is, instead of training a single strong learner, to train a set of weak learners which collectively perform well. The general approach in classification tasks is to iteratively reweight the training data to emphasize examples that are currently being misclassified, and train and add a weak classifier to address these trouble examples.

The software used, BoosTexter, is an extension of the AdaBoost algorithm [38] for text categorization, which typically are multiclass (more than two possible classifier labels) and multi-label (examples may belong to more than one class). Our research uses BoosTexter primarily for its ability to handle both discrete and continuous features, i.e. lexical and prosodic features respectively. The following experiments are neither multiclass nor multi-label, so the algorithm effectively is the original AdaBoost algorithm and will be referred to as such. The AdaBoost algorithm is trained as follows: for N labeled examples $\{(x_1, y_1), \ldots, (x_N, y_N)\}$

- Initialize weight vector w^1 comprised of weights w_i^1 for each example $i = 1, \ldots, N$. Typically, set all weights equal, $w_i = 1/N$.
- Do for iteration $t = 1, \ldots, T$:
  1. Set example distribution:
  $$p^t = \frac{w^t}{\sum_{i=1}^{N} w_i^t}$$
  2. Call weak learner $\mathcal{W}$, providing it with distribution p^t. Get back a hypothesis $h_t : X \to \{0, 1\}$.
  3. Calculate the error of $h_t : \epsilon_t = \sum_{i=1}^{N} p_i^t |h_t(x_i) - y_i|$
  4. Set $\beta_t = \epsilon_t / (1 - \epsilon_t)$.
  5. Set the new weight vector to be
  $$w_i^{t+1} = w_i^t \beta_t^{1-|h_t(x_i)-y_i|}$$
- Output hypothesis

$$h_f(x) = \begin{cases} 1, & \sum_{t=1}^{T} \left(\log \frac{1}{\beta_t}\right) h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \log \frac{1}{\beta_t} \\ 0, & \text{otherwise} \end{cases}$$

AdaBoost training algorithm

Thus the overall classifier consists of T weak learners, h_t, with associated weights, $\log \frac{1}{\beta_t}$. In the following experiments I used $T = 1000$ based on previous work [175]. It is possible to overtrain AdaBoost, and the general approach to prevent this is to use held-out data to determine a good stopping point. However, given the number of feature subsets tested during feature selection, it was not practical to continually retrain the number of iterations, so $T = 1000$ was used throughout. The weak learners used were CART trees with a single node, selecting the single feature and threshold that minimize entropy in the daughter nodes, which can be trained fairly quickly. Note that the weak learners are incapable of considering feature interaction.

The AdaBoost model produces a posterior score and, to perform classification, a threshold must be set to separate sentence-final boundaries from non-sentence-final boundaries. To tune this threshold parameter, a portion of the corpus called the `dev` set, separate from the training data and evaluation data is held-out. Separate thresholds are trained for F_1 score and NIST error. The performance of the system model is evaluated using the held-out `eval` dataset.

A support vector machine (SVM) classifier was considered as a comparison system but was ultimately dropped from these experiments. The primary reason for this was that an SVM classifier is sensitive to the setting of the cost parameters that govern the trade-off between training error and margin. For the Mandarin experiments, F_1 score could range between 30% and 60% for even small parameter changes and had no clear maxima, requiring the parameter to be readjusted for each feature set. Similar parameter settings in English created swings no bigger than 1.5%, and I believe the difference between the two languages to be due to the smaller size of the Mandarin corpus. Thus, while the following experiments could also be run with an SVM classifier, having to perform a parameter sweep for each feature set would have greatly increased the runtime of the experiments. Since the AdaBoost classifier outperforms SVM by several percent F_1 score, I chose to drop SVM for the following experiments.

3.2.2 Feature selection

Feature selection was performed to identify what prosodic features are useful in the different languages. Specifically, if a feature or set of features performs well across the three languages studied, this is a good indicator that the features are language-independent. If so, those features and perhaps even the model trained on one language can be ported to another, which may be useful if there is dearth of training data in the target language.

To explore the relevance of the different prosodic features in each language, two general feature selection methods were used: filtering and a forward selection wrapper, which were described in more detail in Sections 2.3.1 and 2.3.2, respectively. The feature selection here serves two purposes: firstly, to optimize the performance of the system; and secondly, to provide rankings and filtering measures that will allow us to compare feature performance.

Filtering

In filtering, each feature is independently scored according to its usefulness in predicting the class feature. Filtering is quick and simple, but it does not take into consideration the learning algorithm or the interaction between features. Thus, it is generally used to estimate feature relevance and filter out irrelevant features to speed up more robust feature selection methods.

I used four different measures, as implemented in the Weka toolkit [60]: Chi-Squared, Information Gain (3.1), Gain Ratio (3.2), and Symmetrical Uncertainty (3.3). The latter three are related information theoretic measures [173]:

$$IG = H(class) - H(class|feat) \tag{3.1}$$

$$GR = \frac{IG}{H(feat)} \tag{3.2}$$

$$SU = 2\frac{IG}{H(class) + H(feat)} \tag{3.3}$$

where $H(\cdot)$ and $H(\cdot|\cdot)$ are entropy and conditional entropy, respectively. The Chi-Squared statistic measures the likelihood of the joint $(class, feat)$ probability distribution assuming a null hypothesis that they are independent.

Noting that the scores from these four measures are fairly correlated and follow an exponential distribution, they were smoothed into one overall filtering score by averaging them after mean normalization.

Forward selection

Forward selection is a type of wrapper, covered in more detail in Section 2.3.2. Wrappers are feature subset selection algorithms that, unlike filtering, use the learning algorithm by providing it feature subsets and using an objective function based on the output to measure the fitness of the subset. The typical forward search wrapper initializes the feature subset to an empty set and iteratively adds the feature that improves performance the most. Hence, forward selection is a greedy algorithm and as such may fall prone to local maxima. Furthermore, by considering only one feature at a time, forward search ignores feature interaction until all but one are added to the feature subset. Despite this, forward selection is generally very effective while being computationally efficient and so is commonly used as a first pass at feature selection.

The forward search used in this study was a modified version of the N-best forward search wrapper. At the time, there was still debate as to whether F_1 score or NIST error was the more reliable performance measure. At each iteration, a variable N feature subsets were retained. The pruned subsets were those that were demonstrably inferior, that is there exists one other feature subset in that iteration with a higher F_1 score and lower NIST error. Therefore the retained feature subsets can be ordered in a progression of rising (improving) F_1 score and rising (worsening) NIST error. In addition to having the benefit of the N-best forward selection that it is more resilient to the local maxima problem associated with a greedy search, the search space of the modified algorithm includes that of forward search algorithms using each measure separately since the subsets with the highest F_1 score and lowest NIST error are always retained.

A cousin to forward selection is the backward elimination wrapper, which is initialized with all features and iteratively removes the feature that contributes the least. Because all features start included, backward search can see feature interations and generally produces higher performance. However, because of the size of the feature set and the fact that the time to train AdaBoost models increases at least linearly with the number of feature, it is not always practical.

3.2.3 Corpus

To compare the performance of the prosodic feature set between languages, experiments were run on a subset of the TDT-4 broadcast news corpus containing Arabic, English, and Mandarin. Broadcast news data is largely read speech as opposed to spontaneous, with the reporter reading from a teleprompter. This type of speech is more regular and has fewer speech disfluencies than spontaneous speech, such as telephone conversations and meetings. Generally, speaker turns are fairly long, with a reporter reading through their news item, though cutting to sound or video clips will create shorter speaker turns. Interview-style segments within broadcast news behave more like spontaneous speech.

The size of each dataset is shown in Table 3.1. For each language, the corpus was split 80/10/10% between `train`, `dev`, and `eval` sets. As mentioned in Section 3.2.1, the classifier posterior probability threshold is trained on the held-out `dev` set and system performance is evaluated using the `eval` set.

	ARB	ENG	MAN
Number of words	185608	931245	459571
Avg. sentence length	21.5	14.7	24.7

Table 3.1: Corpus size and average sentence length (in words).

3.3 Results and Analysis

To motivate the use of prosodic features, Table 3.2 compares the result of all prosodic features, a set of five lexical N-gram features, and their combination. Recall from Section 2.2.3 that higher F_1 score and lower NIST error rate indicate better performance. We see that prosodic features can make significant contributions to the sentence segmentation task. However, the Mandarin prosodic features perform significantly worse than Arabic and English, both alone and when combined with the lexical features.

3.3.1 Forward selection results

Figure 3.3 shows the performance of each iteration of the forward search experiments for Mandarin. The figure is arranged to show both the F_1 score and NIST error rate of different feature subsets, with black lines marking the performance of

		ARB	ENG	MAN
F_1 score	Lexical	46.4	47.8	43.6
	Prosody	70.2	67.9	64.2
	Lexical+Prosody	74.9	75.3	68.9
NIST error rate	Lexical	84.0	94.7	87.0
	Prosody	56.6	62.6	69.7
	Lexical+Prosody	51.8	50.0	61.8

Table 3.2: Comparison of performance of prosodic, lexical, and combination systems across all three languages. Recall higher F_1 score and lower NIST error rate are better (see Section 2.2.3).

the entire prosodic feature set before feature selection. Better performance is toward the bottom-right corner. The clear best feature selected in the first iteration was pause duration, providing the starting point in the upper-left corner. Each color represents a successive iteration, showing the best daughter nodes of the unpruned feature subsets. The thick lines show the unpruned branches after the fifth iteration. Note that it is generally the rightmost branch, the one with the higher F_1 score, that remains unpruned. This pattern was found in the other languages as well. From this, I concluded that F_1 score is a more reliable evaluation measure than NIST error rate.

Table 3.3 shows the improvement over the first seven iterations of the forward search wrapper for all languages, including the type of feature selection at each iteration. We see that with the first four to six features, the feature subset matches or exceeds the performance of using all the prosodic features in both NIST error and F_1 score, though incremental improvement is already beginning to slow and performance plateaus.

Unsurprisingly, the first feature selected in each forward search is `PAU_DUR`, the pause duration of the boundary in question. For English, the pause duration of the previous boundary was also used. While pitch reset is a cue mentioned especially frequently in the literature in relation to sentence breaks, the second feature chosen in each language came from the pitch range group. For Arabic and English, the feature is based on the last pitch in the word; for Mandarin, it is the drop in pitch over the word. However, pitch reset features are well-represented. Also, more pitch features were selected than energy features. One but not both of the speaker turn

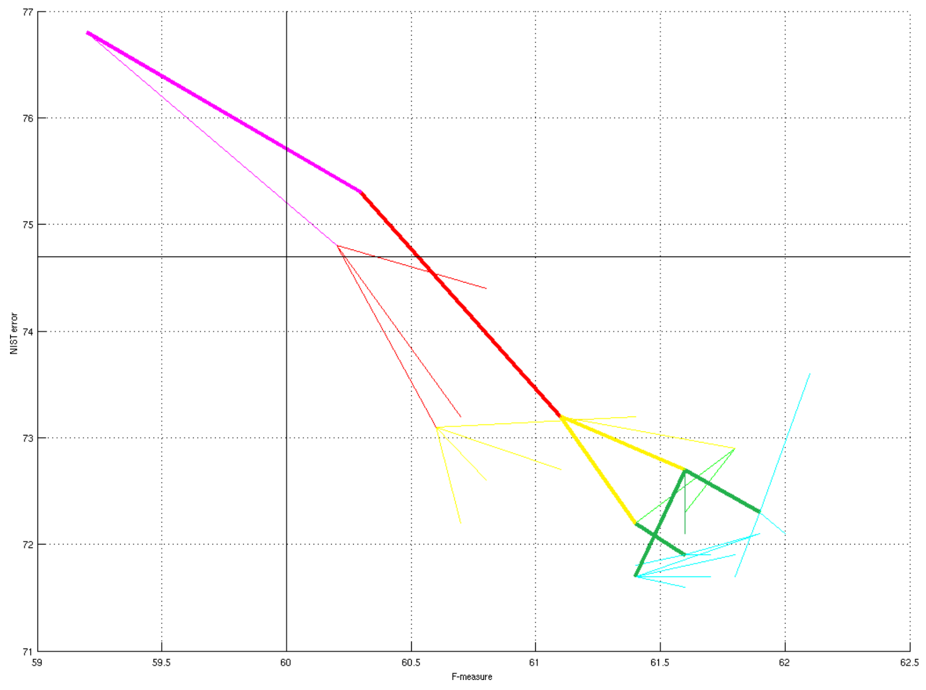


Figure 3.3: An illustration of the performance of feature subsets during forward selection for Mandarin. The horizontal axis shows F_1 score while the vertical gives NIST error rate with the two black lines showing the performance of the entire prosodic feature set before feature selection. Colors correspond to feature selection iterations: 1 provides the starting point, 2 magenta, 3 red, etc. The bold line shows which branches were not pruned by the 5th iteration. Note the preference for the rightmost branch, which corresponds to the branch with highest F_1 score.

features was also selected.

Surprisingly, no segmental duration features were selected within these top features. One explanation is that, given pause information, the vowel and rhyme duration features are not strongly relevant. Other than this, the forward selection algorithm picked features from a variety of feature groups to draw upon a wider range of information sources.

While patterns can be seen in the types of features selected, there is little pattern as to which individual features are selected by the forward search wrapper. The conjecture is that among the large number of similar pitch and energy features, one of them will be slightly stronger than the others and be selected by the forward search algorithm. In future iterations, similar pitch or energy features will now be mostly redundant and thus not be selected.

This suggests a possible heuristic for feature selection is to make a first-pass of feature selection within each feature group to reduce them to a feature subset that still covers most of the relevant information in the group. If desired, further feature selection can be performed from this reduced number.

	ARB			ENG			MAN		
Iter	Type	NIST	F_1	Type	NIST	F_1	Type	NIST	F_1
1	P	78.6	63.8	P	79.8	63.6	P	77.4	61.3
2	FN	60.3	67.2	FN	67.5	65.5	FN	74.3	62.5
3	FR	57.1	70.8	T	65.1	66.8	T	70.2	63.9
4	ER	56.6	70.2	FR	63.9	67.7	FR	68.6	64.4
5	T	56.8	70.2	FR	63.6	68.0	FR	68.6	64.3
6	FS	55.4	70.6	P	62.1	68.0	ER	68.6	64.9
7	ER	53.8	70.4	ES	61.6	68.3			
All		56.6	70.2		62.6	67.9		69.7	64.2

Table 3.3: Performance improvement in the three languages over the first seven iterations of the modified forward selection algorithm relative to the performance of the full feature set. The Type column lists the feature group to which each feature belongs using the following code: P = pause; T = speaker turn; F* = pitch (F0); E* = energy; *R = reset; *N = range; *S = slope. Note that repeated listing of FR, ER, etc. refer to different features from within the same feature group, not the same feature selected repeatedly.

From the results of the forward selection and filtering experiments, we wanted to answer two questions:

1. Which features have low relevancy and can be removed from the forward search without hurting performance?

2. How do different features perform across different languages?

3.3.2 Feature relevancy

The best single feature is `PAU_DUR`. A sizable pause is a good indication that a sentence has ended and a new one will begin. Another pause feature, `PREV_PAU_DUR`, the duration of the pause of the previous boundary, has mediocre relevancy. For TDT4-ENG, it is ranked 59th out of 84 features but was still selected in the forward search wrapper, improving NIST error by 1.5% absolute on that iteration. Although short sentences are not uncommon, it is more likely that a long `PREV_PAU_DUR` signals that the previous boundary was a sentence boundary, which lowers the posterior probability of the current boundary also being a sentence break.

It is clear that `PREV_PAU_DUR` contains nonredundant information in TDT4-ENG. Two inferences can be drawn from this. First, even weakly relevant features can contain useful information that the learning algorithm can exploit. Second, many of the features originally ranked higher by filtering now contain mostly redundant information by this early stage of the forward search wrapper. Thus, we conclude that many of our features contain redundant information, and so the feature set may benefit from feature selection. However, while some feature selection regimes use filtering to remove irrelevant features and reduce the search space before using a more sophisticated feature selection algorithm, in this feature set even low ranked features are useful and should not be pruned.

Among turn-related features, `TURN_F` and `TURN_TIME_N` are ranked very high by filtering, and one of them was selected by the forward search wrapper in each language. However, as `TURN_TIME_N` is a normalized version of `TURN_F`, at that point the other feature because almost entirely redundant. All other turn-related features performed very poorly.

Pitch and energy features make up the bulk of the features selected by the forward search wrapper, usually with more pitch features than energy. Filtering results corroborate with this, with pitch features tending to score better than energy features. This may be because pitch inherently has more useful information than energy features, or it may be because of the design of our energy features. Despite energy and pitch being two distinct entities, the extraction of the energy features involves the same pre-processing, stylization, calculation of word-level statistics, and uses the same templates for derived features.

Within the pitch features, the ones normalized by speaker pitch range generally performed badly. In comparison, the features that were normalized using speaker baseline pitch or another pitch value from the same speaker tended to do well and were the ones selected by the forward search wrapper.

Pitch slope features tended to perform poorly, though we believe this is due to the way they were calculated. Because the piecewise linear stylization operates independently of the transcript word time alignments, the piecewise linear segments often do not coincide with the word boundaries. Thus, regions of uniform slope may straddle a word boundary, as it is designed to if they appear to be part of the same pitch gesture. While the system ignores segments that only extend 30ms or less into a word, this appears to be insufficient. In this case, the feature that calculates the difference in slope across the boundary will be zero.

3.3.3 Cross-linguistic analysis

Since the filtering scores varied considerably between languages, to compare feature performance across languages we examined their relative ranking as given by filtering. The fifteen features that rose the most and dropped the lowest in comparison to other languages are summarized in Tables 3.4 and 3.3.3, respectively.

Mandarin clearly behaves differently from Arabic and English in terms of pitch features. Pitch slope features perform exceptionally badly, which we attribute to Mandarin being a tone language. Tone languages, which are explained in greater detail in Section 5.1.1, use pitch intonation to transmit lexical information. In Mandarin, every syllable has one of four tones, and these lexical tones obscure sentence-level pitch contours. The pitch slope features are calculated from the slopes of the piecewise linear stylization segments, which have a strong tendency to fit themselves to the lexical tone contour. The other pitch features perform relatively better in Mandarin. However, recall that the prosodic feature set performed worse in Mandarin than the other languages.

The energy features are more difficult to interpret. For instance, in Arabic, a number of cross-boundary energy features perform considerably better, and a number perform considerably worse. Furthermore, while it appears that energy range and energy slope do well in Arabic, more often than not this occurs because the same features scored poorly in the other languages. We partly attribute this behavior to the design of the energy features, which we plan to reexamine in future feature design cycles.

While duration features clearly perform better in English than in the other languages, they were not selected in the forward search wrapper. This leads us to believe that, while there is relevant information in the duration features, the features could be designed better or they are largely redundant in the face of other features.

	ARB	ENG	MAN
Pitch range			2
Pitch reset			8
Pitch slope	3	3	
Energy range	3		
Energy reset	4	1	5
Energy slope	3		
Duration (max)		6	
Duration (last)		5	
Pause	1		
Speaker turn	1		

Table 3.4: Feature groups of the top 15 features that ranked better in the language noted than the others.

	ARB	ENG	MAN
Pitch range	4	4	
Pitch reset	4	4	
Pitch slope			2
Energy range		4	1
Energy reset	3	3	1
Energy slope			1
Duration (max)	4		5
Duration (last)	4		4
Pause			
Speaker turn			1

Table 3.5: Feature groups of the top 15 features that ranked worse in the language noted than the others.

3.4 Conclusion

The original intention of this study was to show that the prosodic feature set could make contributions in other languages besides English, which was demonstrated, though the performance in Mandarin is considerably weaker than in Arabic or English.

The forward selection results show classification systems benefit from a variety of information sources. In particuar, pause duration is extremely useful, and certain speaker turn-related features were always selected. The remaining features are drawn from a wide-variety of pitch and energy features. There is no consensus among languages about which specific features are best. This may be explained by certain feature groups having inherent redundancy, so once a feature from within the group is selected, this makes the other features in the group less useful. Unexpectedly, no duration features were selected, possibly because of redunancy with other features.

An analysis of the relevance of the features between different languages was also performed. As a tonal language, Mandarin pitch features operate in a fundamentally different manner than the other languages. While our energy and duration features appear to work better in Arabic and English, respectively, certain behavior leads us to believe we should also reexamine their design.

Chapter 4

Feature Extraction with HLDA

One of the objectives of this dissertation is to examine whether the feature design process can benefit from statistical learning methods. Automation may speed up the feature design process, and a machine learning approach may be able to learn language- or condition-specific behavior from data rather than have a human researcher design features for them manually.

As mentioned in Section 3.1.1, up to the extraction of word-level pitch statistics, the pitch features in Shriberg et al. [129] resemble pitch distribution features used in [33, 143, 165, 171]. Shriberg et al. goes on to derive range and reset features as a function of these statistics and LTM parameters.

This chapter attempts to derive its own features by applying heteroscedastic linear discriminant analysis (HLDA) to the same pitch statistics and LTM parameters. Linear discriminant analysis (LDA) and closely related Fisher's discriminant analysis (FDA) are well-known methods in machine learning and statistics for performing a data transformation to improve the separation of different classes by finding the linear transformation that maximizes between-class variance relative to within-class variance. This provides a supervised learning method for the extraction of prosodic features with discriminant ability. However, LDA makes an assumption of homoscedascity, that all classes are distributed with the same covariance matrix. Heteroscedastic LDA, as the name implies, drops this assumption, though the underlying idea of maximizing the separation of classes remains the same.

4.1 Background

4.1.1 Linear discriminant analysis

Linear discriminant analysis (LDA) is a commonly used statistical method to find linear combinations of features to separate the classes in labeled data. In Fisher's original article [35], he posed the question of what linear combination of four features gave the maximum separation of the centroids of two classes of iris species relative to the variance of the data. Let us define between-class scatter matrix as:

$$\begin{aligned} S_B &= \sum_{i=1}^{K} p_i(\mu_i - \mu)(\mu_i - \mu)^T \\ &= \sum_{i=1}^{K-1} \sum_{j=i+1}^{K} p_i p_j (\mu_i - \mu_j)(\mu_i - \mu_j)^T \end{aligned} \tag{4.1}$$

where K is the number of classes, p_i is the a priori probability and μ_i the mean of the feature vectors of class i, and $\mu = \sum_{i=1}^{K} p_i\mu_i$ is the overall mean of the data. Also define the within-class scatter matrix as:

$$S_W = \sum_{i=1}^{K} p_i \Sigma_i$$

where Σ_i is the covariance matrix of class i. However, if we were to perform a linear transform of the data, $\tilde{x} = a^T x$, the corresponding scatter matrices would become $\tilde{S}_B = a^T S_B a$ and $\tilde{S}_W = a^T S_W a$. Thus Fisher's original problem could be rewritten as

$$\max_a \frac{a^T S_B a}{a^T S_W a}$$

This is a generalized eigenvalue problem, and the optimal a is the eigenvector corresponding to the largest eigenvalue of $S_W^{-1} S_B$.

The above transform $\tilde{x} = a^T x$ projects the data into just one dimension. LDA generalizes this to d output features by finding the $d \times n$ linear mapping A that maximizes the Fisher criterion, which makes the homoscedasticity assumption that all of the classes have the same variance Σ so that $S_W = \Sigma$:

$$J_F(A) = \operatorname{tr}\left((A S_W A^T)^{-1}(A S_B A^T)\right) \tag{4.2}$$

The rows of the optimal A are composed of the eigenvectors corresponding to the d largest eigenvalues of $S_W^{-1}S_B$ [42].

Note that LDA only concerns itself with the separation of the class centroids. As the centroids of K classes can exist in, at most, a space of rank $K-1$, the rank of S_B and the maximum number of output features d are also $K-1$. Thus in a binary classification problem, only one output feature is possible. LDA is often used for dimensionality reduction, where the researcher can project into a vector space of lower dimensionality while maintaining maximum discriminatory information.

LDA can also be used as a linear classifier. Under the assumption that class i is a multivariate Gaussian with mean μ_i and variance Σ — again, all classes are assumed to have the same variance — then the classification of point x between classes i and j using log-likelihood ratio is

$$\log\frac{P(\text{class } i|X=x)}{P(\text{class } j|X=x)} = \log\frac{p_i}{p_j} - \frac{1}{2}(\mu_i-\mu_j)^T\Sigma^{-1}(\mu_i-\mu_j) + x^T\Sigma^{-1}(\mu_i-\mu_j) \quad (4.3)$$

The first two terms are constant with respect to x, and the last term is linear in x. Thus, whatever likelihood threshold is set for classification, the boundary between any two classes will be a hyperplane [62]. It should be noted that LDA does not require that the classes be normally distributed; only to obtain a linear classifier is the Gaussian distribution assumption made.

Classifiers generally seek to maximize the separation between classes as this reduces the amount of overlap between class distributions and hence classificiation error. The vector $\mu_i - \mu_j$ is the direction with the largest distance between class centroids, and one might expect the optimal class boundary to be a hyperplane orthogonal to this vector. For example, assuming L^2 distance, the set of points equidistant from both means is the orthogonal hyperplane that bisects the vector. However, this does not take into consideration the covariance of the data. See Figure 4.1 from [62]. After sphering the data using a transform by $S_W^{-\frac{1}{2}}$, the optimal boundaries are orthogonal to the vector between the centroids as expected.

This property of maximizing discriminatory information is what I wish to utilize for feature extraction. As AdaBoost is a composite of multiple weak learners, with each weak learner intended to be quick to train, they are limited in what operations

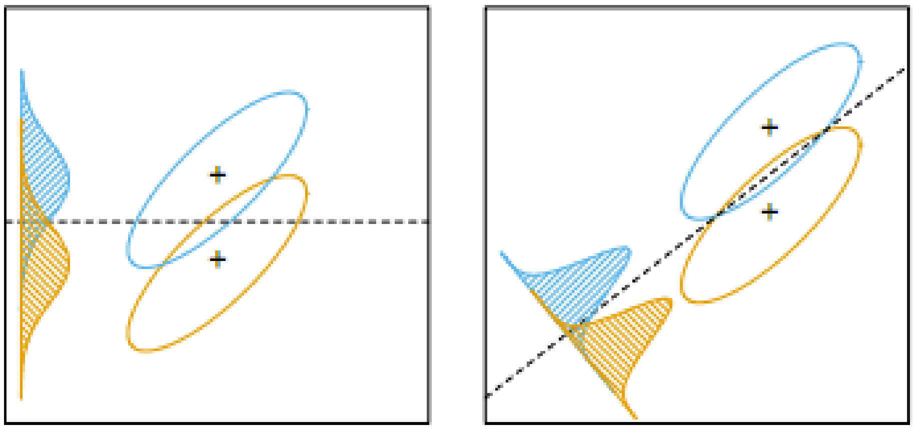


Figure 4.1: The left figure shows the distribution of the two classes if they are projected along the direction that maximizes the separation of the centroids. However, because the covariance of the distributions are not diagonal, the resulting distribution has considerable overlap. In the right figure, the data is projected along a direction taking into consideration the covariance. While the class means are closer together, there is less overlap and thus less classification error.

they can do on multiple features. In this system, AdaBoost uses single-node decision trees, so it is difficult to exploit feature interation. The LDA transform extracts feature combinations that should be useful for classification. This idea is not new, and indeed is a common linear dimensionality reduction method used in image recognition applications [11], such as face, landmark, or shape recognition. A common difficulty in applying LDA to these tasks is the "small sample size" problem, where LDA becomes unstable when the number of training samples is smaller than the dimensionality of the samples [86, 95, 176]. However, this should not apply to the sentence segmentation task.

4.1.2 Heteroscedastic LDA

As stated in Section 4.1.1, LDA makes the homoscedasticity assumption that all classes have the same covariance matrix. In practice, even when the estimated class covariance matrix from the data generally are not the same, all classes are treated as having the covariance of the whole training set. One consequence of this is that LDA cannot take advantage of the covariance matrices of different classes, and this limits the maximum number of discriminant features to the rank of the between-class scatter matrix S_B, which is at most one less than the number of classes.

Note that in the 2-class case, from (4.1) we get $S_B = p_1 p_2(\mu_1 - \mu_2)(\mu_1 - \mu_2)^T$. The matrix $S_E = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T$ encodes both the Euclidean distance and the direction between the two distributions by means of its eigenvectors. This S_E, and hence S_B as well, is rank one and has one non-zero eigenvalue, $\lambda = \mathrm{tr}(S_E)$, and the corresponding eigenvector is along $(\mu_1 - \mu_2)$. Loog [93] proposed a generalization of S_E, and by relation S_B, using directed distance matrices. Instead of Euclidean distance of the distribution means, the Chernoff distance between the two distributions is used. For multivariate Gaussians, this distance (within a constant multiplicative factor) is given in [21]:

$$\begin{aligned}
\partial_C =& (\mu_1 - \mu_2)^T(\alpha S_1 + (1-\alpha)S_2)^{-1}(\mu_1 - \mu_2) + \frac{1}{\alpha(1-\alpha)} \log \frac{|\alpha S_1 + (1-\alpha)S_2|}{|S_1|^{\alpha}|S_2|^{1-\alpha}} \\
=& \mathrm{tr}\left(S^{-\frac{1}{2}} S_E S^{-\frac{1}{2}} + \frac{1}{\alpha(1-\alpha)}(\log S - \alpha \log S_1 - (1-\alpha)\log S_2) \right) \\
\overset{def}{=}& \mathrm{tr}(S_C)
\end{aligned}$$

where $\alpha \in (0,1)$ is chosen to minimize the above expression and S is defined as $\alpha S_1 + (1-\alpha)S_2$. S_C is a positive semi-definite matrix generally of full rank. Replacing S_E in the original Fisher criterion (4.2) with S_C and accounting for the unsphered nature of data with the transform by $S_W^{\frac{1}{2}}$, this gives the 2-class Chernoff criterion [94]:

$$\begin{aligned}
J_C(A) = \mathrm{tr}\big(&(AS_W A^T)^{-1}(p_1 p_2 A S_E A^T \\
&- A S_W^{\frac{1}{2}}(p_1 \log(S_W^{-\frac{1}{2}} S_1 S_W^{-\frac{1}{2}}) + p_2 \log(S_W^{-\frac{1}{2}} S_2 S_W^{-\frac{1}{2}})) S_W^{\frac{1}{2}} A^T) \big)
\end{aligned}$$

Like the Fisher criterion problem above, the rows of the $d \times n$ matrix A that maximizes the Chernoff criterion are eigenvectors of the d largest eigenvalues of

$$S_W^{-1}\left(S_E - \frac{1}{p_1 p_2} S_W^{\frac{1}{2}}(p_1 \log(S_W^{-\frac{1}{2}} S_1 S_W^{-\frac{1}{2}}) + p_2 \log(S_W^{-\frac{1}{2}} S_2 S_W^{-\frac{1}{2}})) S_W^{\frac{1}{2}} \right)$$

This is the basis of the heteroscedastic LDA (HLDA). Like LDA, HLDA can be extended to more than two classes by distance matrices in (4.2) with their generalized

Chernoff criterion versions. However, for the purposes of the binary classification task of sentence segmentation, the 2-class HLDA is sufficient. For further reading on multiclass HLDA, see [94, 112].

An alternative to HLDA is quadratic discriminant analysis (QDA) [42], which similarly drops the homoscedasticity assumption. The log-likelihood ratio corresponding to (4.3) has quadratic boundaries. One key difference between LDA and QDA is the number of parameters needed to be estimated for the covariance matrices of each class, which is quadratic in the number of input variables. Michie et al. [99] find LDA and QDA work well on a diverse set of classification tasks. Friedman [40] proposed regularized discriminant analysis, which allows a linear scaling between class-specific covariances and a common covariance.

4.2 Method

4.2.1 Motivation

In order to study the utility of using HLDA in prosodic feature extraction, I used HLDA to create pitch features and compare them to the pitch features in the baseline feature set used in the ICSI sentence segmentation system described in Section 3.1.1. The choice of focusing on pitch features was done for the following reasons:

- **Compatibility with baseline features.** As mentioned in Section 3.1.1, many of the pitch features from Shriberg et al. [129] are linear combinations of pitch or log-pitch values. A relatively small set of pitch statistics (maximum, minimum, and mean pitch; first and last voiced pitch) and a speaker normalization parameter are calculated for each word. To generate features for each candidate sentence boundary, pitch features are extracted at every word-final boundary. The baseline pitch features are functions of these pitch statistics from the words immediately before and after the boundary in question.

  Because many of the baseline pitch features are linear combinations of these pitch or log-pitch statistics, those same features would fall within the search space of a LDA/HLDA transformation. One may question why I choose to attempt to duplicate the work of Shriberg. For example, the combination of the baseline features and resulting HLDA features probably will not give much improvement. However, the goal of this study is not purely performance driven, but to test whether statistical learning methods can be used in the design of prosodic features. Having some of the baseline pitch features within the search space of the HLDA transform provides a reference point to judge whether the HLDA system is successful or not.

- **Interpretability.** The HLDA produces a linear transformation on its input pitch/log-pitch statistics that attempts to maximize the separation between sentence and non-sentence boundary classes. This linear transformation is relatively easy to interpret as we can examine which input statistics and what relative combination of input statistics are important. This may provide insight into the further design of pitch features. For comparison, one might extract classification features from the hidden layer of a multilayer perceptron (MLP), a popular non-linear classifier. How the MLP transforms the input data is relatively opaque compared to the simple linear combination of LDA/HLDA.

- **Language-independent system.** As mentioned in Section 3.3.3, we believe that the baseline pitch features originally designed for English are less well-suited for tonal languages such as Mandarin because the lexical intonation biases the pitch statistics used in feature extraction. One intention in focusing on this known problem is to see whether the HLDA system can learn to compensate for idiosyncracies in the target language. If so, then this could save the researchers considerable effort of having to redesign prosodic features themselves when porting between different languages and domains.

4.2.2 System

The only change from the baseline system in Section 3.2 is that the HLDA system replaces the original feature extraction step (see Figure 4.2). Both systems use the

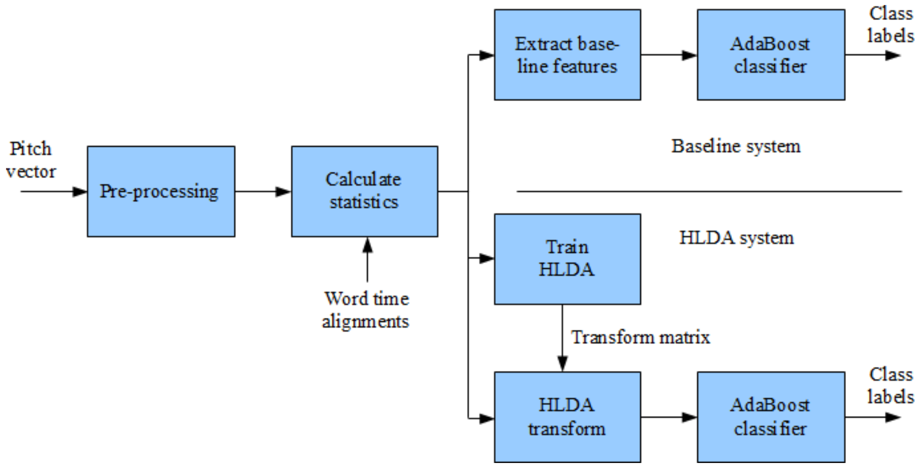


Figure 4.2: Block diagram of the HLDA feature extraction system compared to baseline system. Both share the same pitch statistics and classifier. Feature selection on HLDA features is optional.

same pitch statistics and LTM speaker parameters and classifier. In this way, we can directly compare the HLDA system to the baseline pitch feature designs.

The HLDA is trained on the training data, ideally finding a linear transformation that will maximize the separation between the class feature distributions. This transformation is applied to the `train`, `dev`, and `eval` sets. As before, the AdaBoost classifier model is trained on the `train` set, a posterior probability threshold is calculated using the `dev`, and the held-out `eval` is used for performance evaluation. What needs to be determined are the various settings in the implementation of the HLDA, which are described below.

The data sets were set up as in Section 3.2.3, with data split 80/10/10% between `train`, `dev`, and `eval` sets, respectively. In this chapter, I only used the English corpus, as the baseline feature were originally designed for English and that is the language with the most data.

4.2.3 HLDA parameters

The following describes different settings in how the HLDA system is set up.

Raw statistics vs. HLDA

To test whether the HLDA transformation leads to any improvement in performance, some experiments were performed with HLDA disabled. That is to say the input pitch statistics pass through unmodified and are used directly as the feature vectors by the AdaBoost learning algorithm. For this dissertation, I will use the following notation to differentiate between these experiments: `stat` denotes trials where HLDA is disabled, and `hlda` will denote when it is enabled.

The missing value handling setting described below is not relevant to the `stat` experiments, so they do not use that parameter. `stat` experiments are still labeled with the size of context and pitch-domain parameters according to their settings. The `hlda` is labeled with all three parameters. For example, `stat_2W_log` denotes the log-pitch statistics from the 2-word context without the HLDA transform, and `hlda_4W_pitch` corresponds to the HLDA features transformed from the non-log pitch statistics from the 4-word context.

Size of context

To calculate classification features for each candidate boundary, the baseline set of pitch features limit themselves to being functions of pitch statistics from only the words immediately before and after the boundary for simplicity and computational constraints. As mentioned in the Compatibility with Baseline Features bullet in Section 4.2.1, one objective of testing the HLDA feature extraction is to compare it to the baseline set of polished human-design features. To make this comparison as close as possible, for one set of experiments, the pitch statistics used as HLDA input are similarly limited to the words before and after the word-final boundary in question. These are referred to as the 2-word (`2W`) context experiments.

The input to HLDA is a supervector containing the pitch statistics from these words from the context. Under this construction, it is simple to expand the context used by the HLDA transformation by appending pitch statistics from more words. The experiments below tested a 4-word (`4W`) context, using pitch statistics from the two words before and the two after the candidate boundary, though larger contexts

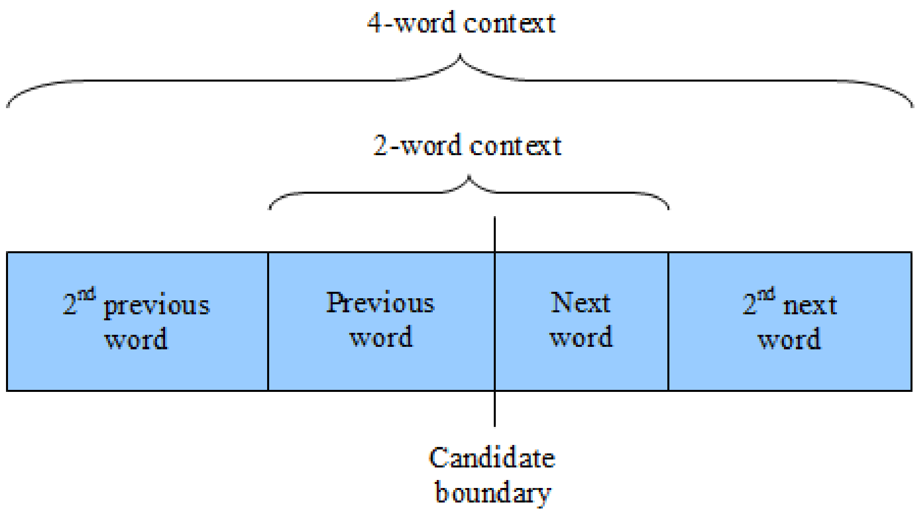


Figure 4.3: Illustration of 2-word and 4-word context. The input to the HLDA transform is comprised of the five pitch statistics extracted over each word in the context, plus the speaker LTM parameter(s).

can also be tested. See Figure 4.3.

It should be noted that, because the context is based on words, the amount of time and therefore the number of acoustic frames used to calculate each feature can vary greatly, and one may expect greater pitch variation over longer windows, which would be reflected in the pitch statistics. Alternatives to words include counting by syllables, which are of more consistent duration than words, or trying to capture suprasegmental behavior over a fixed window surrounding the word-final boundary. However, as stated, to keep the HLDA-generated features comparable to the baseline pitch features, I chose to control the amount of context as described above.

Pitch domain

As it is not clear whether it is pitch ratio or absolute pitch difference that cues sentence boundaries, three options were tested for which pitch values to use as the input to the HLDA transformation:

- Pitch: absolute pitch values.
- Log-pitch: log of the above pitch values.

- Both: both pitch and log-pitch values are concatenated, making the input supervector to the HLDA transformation twice as long. Note that this is different from concatenating the pitch and log-pitch HLDA features.

In the case of absolute pitch and log-pitch, each word contributes its five pitch statistics — maximum, minimum, mean, and first and last voiced pitch — calculated as described in Section 3.1.1. Including both absolute pitch and log-pitch values allows the HLDA transformation to compute features that examine both absolute pitch values and pitch ratios. However, it is difficult to interpret an HLDA feature that mixes absolute pitch and log-pitch values of the same statistic, let alone different statistics. There is also the issue that absolute pitch and log-pitch values will be highly correlated, which may lead to the matrices involved in the HLDA transform to appear to have less than full rank.

To create the HLDA input, in addition to the five pitch statistics from each word in the context, speaker normalization is achieved by including a speaker parameter from the word immediately before the word-final boundary. Again, to keep the HLDA features as close as possible to the baseline pitch features, the speaker parameter is the same one used by the baseline feature set, the lognormal tied mixture (LTM) model speaker baseline parameter [138]. This speaker parameter is either in absolute pitch, log-pitch, or both according to the pitch domain parameter. Although different words within the context may come from different speakers, and thus ideally have their own speaker normalization parameter, for most word-final boundaries all the words come from the same speaker, and thus all of the speaker parameters would be exactly the same. This near singularity may be problematic for the HLDA transform, so only the speaker parameter of the word immediately before the boundary in question is included in the HLDA input supervector.

The combination of size of context and pitch domain parameters determines the size of the HLDA input supervector, and therefore the number of output features as well. The smallest number of features tested is 11: 5 pitch or log-pitch values from each word in a 2-word context plus the LTM speaker baseline parameter. The largest number of features tested is 42: 5 absolute pitch values from a 4-word context plus the LTM parameter gives 21 inputs; adding the log-pitch versions of the same doubles the total to 42.

Treatment of missing data

In the cases where no voiced pitch is found within a word boundary, the algorithm has no valid pitch values to operate on and so returns a missing value in all pitch statistics for that word. This generally only happens in short words and when the pitch tracker has trouble finding the fundamental frequency of the voiced speech, thus the pitch values would be less reliable. Missing pitch values occured in 1.12% of the `words` of the TDT4-ENG corpus. Even in the absence of this information, the classification algorithm still must make a decision.

This parameter controls how the HLDA system treats missing values in the training data only; treatment of missing data during classification is described further down. Words with missing pitch values are handled in one of two ways:

- Drop: These words are considered suspect since there must be some acoustic reason that no voiced pitch was detected. All supervectors that would contain missing values (i.e. any context which includes such words) are therefore removed from the training data. The idea is to clean up the training data so a good HLDA transform can be trained.

- Mean fill: In comparison, the reasoning here is to make the training data resemble the data during classification. In the aforementioned system description, HLDA must still classify words with missing pitch values, and so those words are mean filled. Therefore missing values in the training data are similarly mean-filled in hopes that the resulting HLDA transformation learns to compensate accordingly.

A more thorough treatment of missing values would examine whether the fact that the word is missing data is useful information [91, 117]. The baseline feature set propogates missing data by labeling the features that depend on missing data to also be missing. The AdaBoost classifier can then infer which words have missing data and exploit that knowledge if it is useful.

Many approaches can be tried with HLDA feature extraction, including passing on missing values as the baseline feature set does or various methods of imputation to replace the missing data. However, Acuna and Rodriguez [2] found little difference between case deletion and various imputation approaches when missing data is rare. As I did not judge the handling of missing data to be critical to the central question of whether an HLDA transformation can aid feature design, I used the above two simple approaches. Under these conditions, the classifier will not be able infer information from missing pitch statistics as it can with the baseline feature set.

As for how HLDA treats missing values during classification, the missing values in the HLDA input supervector are mean-filled to avoid biasing the output HLDA features. Because all of the pitch statistics are missing for the word, there is no way to impute missing values using data only from that word. One may conceivably try to use regression for missing values by smoothing from surrounding words, but this is a dubious idea when we expect to detect cues by comparing pitch values between neighboring words. The `eval` data is mean-filled in both `hlda` and `stat` experiments to make them as comparable as possible.

4.2.4 Feature selection

Two feature selection procedures were used: top-N and forward search. When LDA — and by extension HLDA — is used for dimensionality reduction, the N features kept are the ones tied to the N largest eigenvalues. Under the assumptions of an LDA classifier, these are the theoretically optimal N features. Using another classifier in conjunction with pause features, they are not guaranteed to be the best size-N subset, but it is a convenient heuristic. For comparison, I also use a more general forward selection wrapper.

The forward search algorithm implemented was fairly standard. The primary consideration was how to evaluate the candidate feature sets, including thresholding the classifier posterior probabilities, while keeping the results comparable to previous experiments. Each iteration, the `dev` set is randomly split in half. One half is used to train the threshold, the other half is used for evaluation, and the greedy forward search is based on these results. By using a different random split in each iteration, the algorithm avoids biasing feature selection toward any particular portion of the `dev` set while the training set is kept the same as previously described experiments. In order to compare the candidate feature sets to earlier experiments, a threshold was trained on the full `dev` set and evaluated on the held-out `eval` set, but these results were not used by the feature selection algorithm. The modified forward selection algorithm is shown below.

```
• Initialize feature set $\mathcal{F}$ with the four pause features and $\mathcal{P}$ with pitch features
  from HLDA.

• While $\mathcal{P}$ is non-empty: let $t$ be the current iteration index

    1. Randomly split dev set $\mathcal{D}$ into $\mathcal{D}_T^t$ and $\mathcal{D}_E^t$
    2. For each feature $p_i \in \mathcal{P}$:
        (a) Create candidate feature set $\mathcal{C}_i = \{\mathcal{F}, p_i\}$
        (b) Train classifier model $\mathcal{M}_i$ using features $\mathcal{C}_i$ on training data $\mathcal{T}$.
        (c) Evaluate the classifier $\mathcal{M}_i$ on $\mathcal{D}_E^t$ using threshold trained on $\mathcal{D}_T^t$.
    3. Find the best performing feature set $\mathcal{C}_i$, remove $p_i$ from $\mathcal{P}$ and add to $\mathcal{F}$.
```

Forward selection algorithm, detailing which feature sets
are used for thresholding and evaluation

Stopping criterion. Starting with M features, the two feature selection methods produce a sequence of features sets with sizes ranging from 1 to M features. Generally feature selection experiments are allowed to terminate before reaching the full feature set if it is clear there will be no further improvement, but there was no clear indicator for that here. Indeed, for the English HLDA features, the best stopping point often included most of the feature set.

To choose among these M candidate feature sets, for both feature selection algorithms I selected the feature set that achieved the highest `dev` set F_1 score using the posterior probability threshold that maximized F_1 score for that feature set. This has the potential of overtraining on the `dev` set. As an alternative, the `dev` set could be split in half as in the forward search experiments, using one half to train a posterior probability threshold for the other and combining the resulting F_1 scores. However, as will be seen in Section 4.3, a poor posterior probability threshold can mask the performance difference between various feature sets. Therefore, I decided remove this source of varability and based the stopping criterion on the maximum F_1 score found on the `dev` set.

4.2.5 Statistical significance

Many of the F_1 scores on the `eval` set below are fairly close, which brings up the question: what is a statistically significant improvement in performance? As it is not simple to explicitly derive an expression for the distribution F_1 score, my approach is to use an empirical p-value from Monte Carlo simulations [103]. Taking as the null hypothesis that the two systems being compared are identical, each simulation resampled the `eval` set with replacement while holding the AdaBoost model and posterior probability threshold the same. The AdaBoost model used was the one trained on the pause features, as they contain much of the performance already, and we are mainly interested in gains in performance.

Running 10^5 simulations, the F_1 gains corresponding to $p = 0.1, 0.05$, or 0.01 can be found by looking at the 90, 95, and 99 percentile. Note that one should decide on a significance level beforehand then calculate the p-value to decide whether to accept or reject the null hypothesis. This is to avoid bias in interpreting the p-value. Here I give performance gains and their p-values to gauge how much different gains really matter. For the English corpus, the experiments showed that +0.49%, +0.64%, and +0.90% F_1 score correspond to $p = 0.1, 0.05$, and 0.01, respectively. Alternately, one may argue that the simulation should resample both the `dev` and `eval` sets, using the resampled `dev` set to fit a new posterior threshold to account for possible variance there. This would likely increase the performance gains necessary for the different empirical p-value levels.

4.3 Results and Analysis

It was expected that increasing the size of the context would improve performance at least slightly. As for pitch domain and treatment of missing values, there are arguments in favor of each option. As nothing in these settings appear mutually exclusive, all possible combinations of HLDA system settings were tried.

4.3.1 2-word context

Table 4.1 compares the performance of the pre-HLDA pitch statistics using only a 2-word context to various baseline feature sets. From Chapter 3, recall that we found F_1 score to be a more reliable and stable evaluation measure than NIST error for system development, even if NIST error is the measure ultimately used in system evaluations. For this reason, in this chapter and the next, my analysis will focus on the F_1 score, though NIST error results will be included for general interest.

The type of feature type most useful for establishing a baseline is the four pause features (`PAU`). Feature `PAU_DUR` is the duration of the pause at the candidate boundary in question. This is by far the best single predictor of a sentence boundary as a long pause is highly indicative of a sentence boundary. The other features are shifted versions of the same pause duration from the two word-final boundaries before and the one boundary immediately after the boundary in question. Although the AdaBoost algorithm using single node CART trees for weaker learners makes it harder to explicitly learn from feature interaction — for example, moderate pause may or may not signal a sentence boundary depending on how long the previous inter-word pause was — long pauses in the vicinity of the current word-final boundary will lower the likelihood of the current boundary being a sentence boundary.

As can be seen in Table 4.1, almost all of the system performance comes from these four features. Therefore it is pointless to discuss sentence segmentation features in the absence of pause features, and they are included in every feature set. In the case of the HLDA system, the HLDA features are derived from the pitch statistics as described in Section 4.2.3, and then `PAU` is appended to the resulting feature vector. The HLDA algorithm does not have access to `PAU` features. Indeed, the distribution of pause features, with the vast majority being duration zero and having a long one-sided tail, is not a good match to the HLDA assumptions.

The other feature set for comparison is the baseline set of 29 pitch features used in the ICSI sentence segmentation system plus the four pause features (`ICSI`), which shows a 3.3% absolute improvement in F_1 score over the pause features. Note that these do not include the 200ms window pitch features or the pitch slope features. The log-pitch statistics (`stat_2W_log`) and pitch statistics (`stat_2W_pitch`) yield most of the performance gain. Furthermore, using both pitch and log-pitch statistics exceeds the performance of the baseline pitch features. This is surprising as one would expect the pitch and log-pitch statistics to have the exact same information content. Looking at the oracle `eval` numbers, where the optimal likelihood threshold is used instead of the threshold trained on `dev` data, we see this is somewhat misleading as `ICSI` suffers slightly more than the other feature sets shown from suboptimal thresholding. Based on the relative performance of the `stat` and `ICSI` feature sets, we may conclude that a large part of feature design is the selection of the information sources — in this case, capturing pitch contour behavior in the form of these pitch statistics — though how these information sources are processed to create features can significantly contribute to classifier performance.

Table 4.2 shows how these AdaBoost F_1 scores changes when the HLDA transform is applied to the above pitch statistics, with the two columns of `hlda` representing the two methods I tested for the treatment of missing data. With the exception of dropping missing values during training (hlda-Drop) on both pitch and log-pitch statistics, the `hlda` feature sets all performed within 0.12% F_1 score of each other. It appears this outlier was due to poor thresholding, as can be seen in Table 4.3, which shows performance using oracle thresholds for the same feature sets. The oracle `hlda` results are also clustered fairly close together. This brings up the question, given the disparity between the performance of the `stat` feature sets, of why all the

Features	F_1 score (%)			NIST (%)
	dev	eval	eval (oracle)	eval
PAU	62.66	62.38	62.38	81.08
ICSI	66.53	65.70	65.86	67.37
`stat_2W_pitch`	65.67	64.63	64.85	72.84
`stat_2W_log`	66.73	65.09	65.18	72.05
`stat_2W_both`	67.54	**65.93**	66.00	69.39

Table 4.1: Performance of English pitch statistics from 2-word context without HLDA transform relative to pause and baseline pitch feature sets. The three statistics feature sets are pitch, log-pitch, and their concatenation (both). Eval columns use the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1 score on the `eval` set.

`hlda` features performed so similarly. I will address this question in Section 4.3.4.

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	64.63	65.19	65.11
Log-pitch	65.09	**65.23**	65.15
Both	**65.93**	64.95	65.20
PAU	62.38		
ICSI	65.70		

Table 4.2: F_1 scores of English HLDA feature sets from 2-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The F_1 scores for the pause and baseline pitch features are provided for comparison.

There does not appear to be much difference between dropping or mean filling missing data. Given the relative rarity of missing pitch values in this corpus, it probably should not be too surprising that it does not matter much how we deal with it. There is a slight preference for the pitch and log-pitch feature sets to prefer dropping missing values while the feature using both prefers mean filling. The difference appears to be small enough that it can be dwarfed by other issues, such as posterior thresholding and the selection of information sources, but the pattern appear to continue in other experiments, so it is worth noting.

The performance gained by the HLDA process is only about a third of the gap between `stat` and the ICSI baseline features. This implies that, while HLDA con-

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	64.85	65.22	65.13
Log-pitch	65.18	**65.29**	65.18
Both	**66.00**	65.15	65.24
PAU	62.38		
ICSI	65.86		

Table 4.3: Oracle F_1 scores of English HLDA feature sets from 2-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). Oracle uses the posterior threshold that maximizes the `eval` F_1 score for that feature set. The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The oracle F_1 scores for the pause and baseline pitch features are provided for comparison.

sistently makes a significant improvement over using the raw pitch statistics, it does not fully capture the classification ability of an expert-designed set of features. Furthermore, the HLDA transform reduced the performance compared to both the raw pitch and log-pitch statistics.

4.3.2 4-word context

Table 4.4 shows performance numbers corresponding to Table 4.1, comparing the raw statistics and baseline feature sets, except using the 4-word context where statistics from the two words before and two words after the boundary are used as inputs. We again see that the log-pitch does slightly better than pitch statistics, and together they outstrip either one individually by more than a full percentage point absolute.

Furthermore, there is a significant performance gain relative to 2-word context results, which indicates that there is information relevant to the classification task to be found from this wider context, even when presented with no processing past the pitch statistics. Shriberg et al. when designing the ICSI pitch features, constrained the features to pitch statistics drawn from the two words immediately surrounding the boundary [129]. Various combinations of pitch statistics and normalizations from this limited context produced 45 features: 29 using the same pitch statistics over words HLDA is using; 12 similar ones using statistics over 200ms windows; and 4 pitch slope features using the piecewise linear stylization. There would be exponentially many more combinations to consider when using a wider context, many of which will be useless, but this creates a practical limit to how much complexity even an expert human with considerable in-domain knowledge can handle in feature design. This again motivates the question of how computers can be used in the feature design process.

Features	F_1 score (%)			NIST (%)
	dev	eval	eval (oracle)	eval
PAU	62.66	62.38	62.38	81.08
ICSI	66.53	65.70	65.86	67.37
`stat_4W_pitch`	66.64	65.25	65.44	71.23
`stat_4W_log`	67.30	65.46	65.83	69.78
`stat_4W_both`	68.42	**66.54**	66.58	67.88

Table 4.4: Performance of English pitch statistics from 4-word context without HLDA transform relative to pause and baseline pitch feature sets. The three statistics feature sets are pitch, log-pitch, and their concatenation (both). Eval columns use the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1 score on the `eval` set.

Tables 4.5 and 4.6 likewise are counterparts to Tables 4.2 and 4.3, showing how F_1 score changes when the HLDA is applied to the raw pitch statistics, both using `dev`-trained and oracle likelihoods thresholds. As before, comparing both the oracle and non-cheating results is important as the performance gains for different pitch feature sets can be masked by suboptimal thresholding. As with the 2-word context, the best performing feature set from among these comes from using both pitch and log-pitch features, which even exceeds the oracle baseline F_1 score of 65.86%, but it is the only HLDA feature set to do so.

While the 4-word HLDA feature sets perform better than the 2-word HLDA feature sets, the performance gained by the HLDA transform here is smaller than the performance gained in the 2-word context. This could be because, since the 4-word `stat` feature sets have better performance, it is harder for the processing done by HLDA to improve upon it.

As with the 2-word context, the HLDA experiments achieved similar performance,

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	65.25	65.64	65.24
Log-pitch	65.46	65.59	65.56
Both	**66.54**	65.52	**65.93**
PAU	62.38		
ICSI	65.70		

Table 4.5: F_1 scores of English HLDA feature sets from 4-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The F_1 scores for the pause and baseline pitch features are provided for comparison.

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	65.44	65.74	65.56
Log-pitch	65.83	65.85	65.68
Both	**66.58**	65.71	**66.08**
PAU	62.38		
ICSI	65.86		

Table 4.6: Oracle F_1 scores of English HLDA feature sets from 4-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). Oracle uses the posterior threshold that maximizes the `eval` F_1 score for that feature set. The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The oracle F_1 scores for the pause and baseline pitch features are provided for comparison.

with the lowest F_1 score partly attributed to suboptimal likelihood thresholding. As mentioned above, it appears the pitch and log-pitch set prefer dropping missing values while their combination prefers mean-filling. It should be noted that the treatment of missing data is of greater importance here than in the 2-word context case since every word with missing data now appears in the supervector of four boundaries instead of two, and deleting missing values would remove all four of these boundaries from the training data.

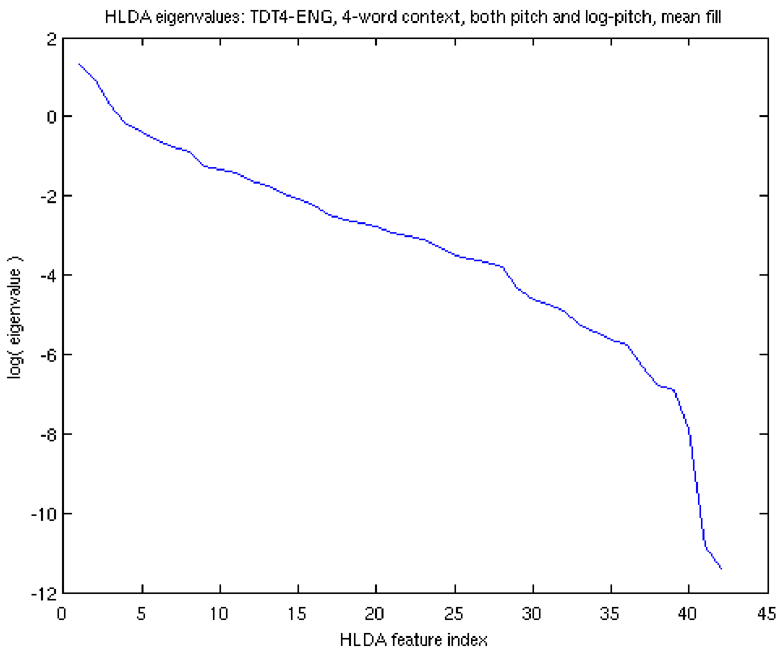


Figure 4.4: Log of the HLDA eigenvalues for English HLDA features from 4-word context and both pitch and log-pitch statistics. Note the sharp drop off at the end occurs in HLDA feature sets using both pitch and log-pitch statistics due to highly correlated inputs.

4.3.3 Feature selection experiments

Top-N

Figure 4.4 shows the log eigenvalues of the HLDA transform for the 4-word context, both pitch and log-pitch, mean fill feature set. Note that the eigenvalues decrease at a steady rate, though slightly more quickly for the first few indices. The very sharp drop at the end is common in feature sets that use both pitch and log-pitch statistics as inputs, most likely due to the pitch and log-pitch statistics being highly correlated. For comparision, Figure 4.5 shows the eigenvalues for 4-word context, log-pitch only, drop missing values feature set. The 2-word context eigenvalues follow a similar pattern. The main conclusion to be drawn from the eigenvalues is there does not appear to be a clear point at which the features become distinctly worse to help us choose a stopping point.

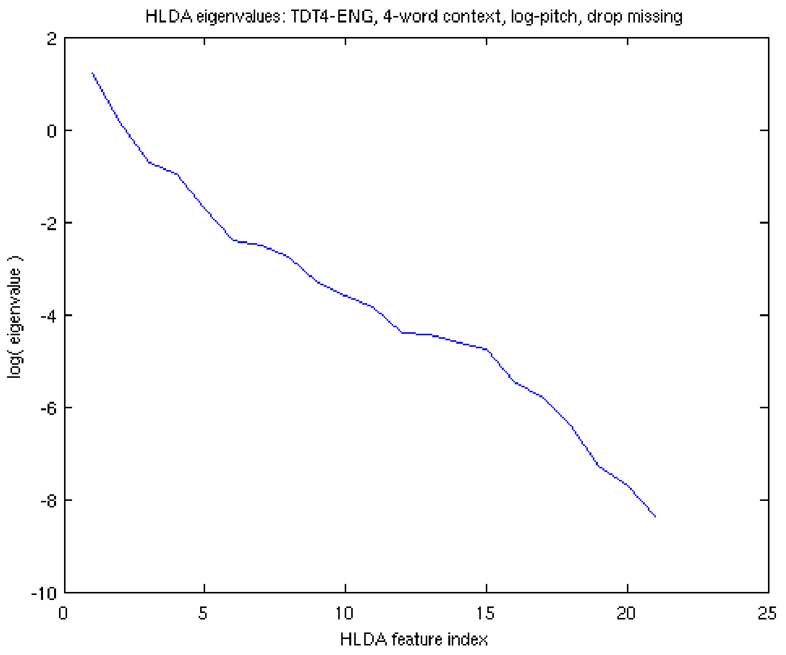


Figure 4.5: Log of the HLDA eigenvalues for English HLDA features from 4-word context and only log-pitch statistics. Compared to Figure 4.4, there is no sharp drop off at the end.

Table 4.7 shows the results of the N-best experiments for the 2-word context. Note that Oracle-N refers to using the stopping point with the highest `eval` F_1 score; none of the scores in the table use oracle posterior thresholds. Firstly, according to the oracle-N selection criterion, the best stopping point generally includes all or almost all of the HLDA features. This implies many of the HLDA features provide some additional discriminative ability.

Secondly, basing the selection criterion on the `dev` set F_1 comes pretty close to the oracle-N selection criterion, often hitting it exactly. Even when it is slightly off, the performance gap is fairly small. Given that the optimal selection criterion chooses almost all of the features, it is not surprising that the Top-N F_1 scores are very close to the results from the full feature sets, and thus still fall short of the baseline pitch features.

Feature set	All HLDA features	dev-N		oracle-N	
	eval	eval	N	eval	N
Pitch-Drop	65.19	65.30	10	65.30	10
Pitch-MeanFill	65.11	64.93	10	65.11	11
LogPitch-Drop	65.23	65.23	11	65.23	11
LogPitch-MeanFill	65.15	65.14	9	65.16	10
Both-Drop	64.95	65.06	21	65.12	19
Both-MeanFill	65.20	65.20	22	65.20	22

Table 4.7: F_1 scores of Top-N feature selection experiments for English 2-word context HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the corresponding F_1 score of the `eval` set. dev-N is based off the `dev` set scores while oracle-N chooses the N with maximum eval.

Table 4.8 shows the same Top-N numbers for the 4-word context case. In contrast to the 2-word context condition, looking at the Oracle-N results, there is room for feature selection to make a small improvement. However, using the `dev` set F_1 scores as the selection criterion appears to be less reliable than in the 2-word case. As can be seen in Figure 4.6, the `dev` set F_1 scores plateau around $N = 10$ or 11 while the `eval` scores continue to rise slightly. In both of the non-log pitch statistics feature sets, the highest peak of their `dev` F_1 scores happened to come at the start of the plateau rather than later. Compare this to Figure 4.7. In both of these experiments, the choices of N that would improve upon the performance of the feature set before feature selection would be $N \geq 16$ or 17. In light of this, the selection criterion for English feature sets may be improved by penalizing small feature sets or finding a more reliable stopping criterion.

Feature set	All features	dev-N		oracle-N	
	eval	eval	N	eval	N
Pitch-Drop	65.64	65.40	11	65.64	21
Pitch-MeanFill	65.24	65.17	11	65.51	18
LogPitch-Drop	65.59	65.72	18	65.81	20
LogPitch-MeanFill	65.56	65.57	18	65.63	17
Both-Drop	65.52	65.51	40	65.98	30
Both-MeanFill	65.93	65.84	40	65.96	38

Table 4.8: F_1 scores of Top-N feature selection experiments for English 4-word context HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the corresponding F_1 score of the `eval` set. dev-N is based off the `dev` set scores while oracle-N chooses the N with maximum eval.

Despite this difficulty in selection criterion, two of the Top-N feature sets can match the performance of the baseline pitch features, and a third could have too with a more fortunate stopping point. This shows that, by being able to process more information, a fully automated feature design system can be competitive with an expert-designed set of features.

Forward search

Table 4.9 shows the results of the forward search experiments for the 2-word context. As with the Top-N experiments, none of these F_1 scores use oracle thresholding on posterior probabilities. Looking at the oracle-N results, a forward search algorithm can usually give a slight performance gain, more so than the comparable Top-N experiments in Table 4.7. Like the Top-N experiments, we see that for the 2-word context the best feature subset will still contain most of the HLDA features.

Examining the order in which HLDA features are selected in these experiments

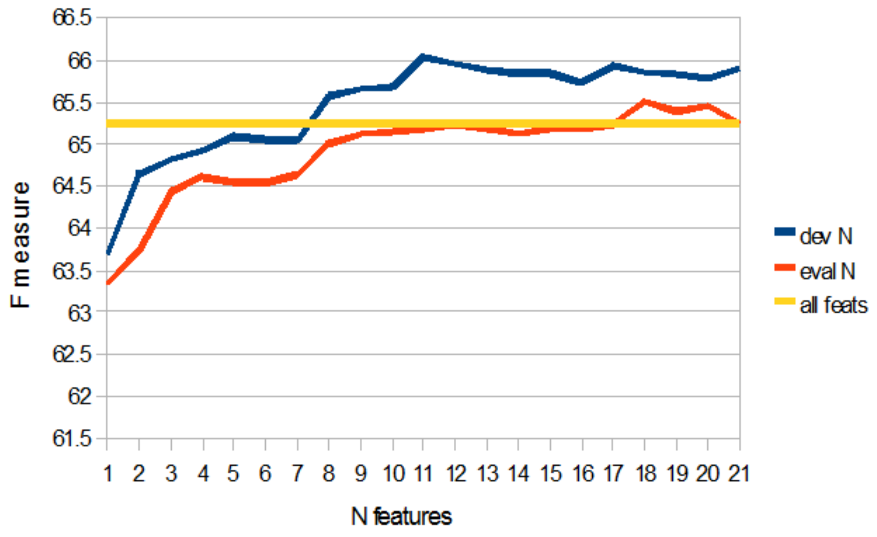


Figure 4.6: F_1 scores on `dev` and `eval` sets versus N for Top-N feature sets from English 4-word context HLDA features from pitch statistics using mean fill. `dev` scores plateau around N=11 while `eval` continues to slowly increase. An early peak in `dev` score results in a relatively poor `eval` score.

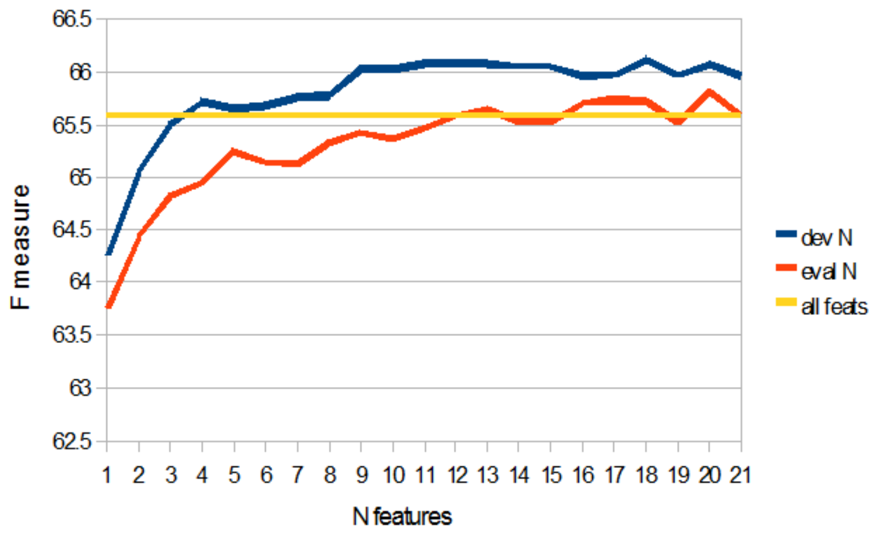


Figure 4.7: F_1 scores on `dev` and `eval` sets versus N for Top-N feature sets from English 4-word context HLDA features from log-pitch statistics dropping missing data. `dev` scores plateau around N=11 while `eval` continues to slowly increase. An late peak in `dev` score results in a relatively good `eval` score.

gives an idea of the classification ability of the different features. While there is a preference for HLDA features associated with the largest eigenvalues, it is not a strong one. This was not entirely due to temperamental posterior thresholding. Looking at oracle F_1 scores in each iteration (not shown), I found that the remaining feature with the highest eigenvalue was only slightly more likely than any other feature to have the highest F_1 score for that iteration, and similarly for the feature with the lowest eigenvalue. I conjecture this is because, in the presence of the pause features, some of the HLDA features are redundant. Furthermore, it is difficult to predict *a priori* how a feature will perform in the AdaBoost model when interacting with each other. Therefore, the forward search algorithm can be more canny than Top-N about which features to include and tends to stop at a lower N. However, because in the 2-word context the resulting feature subsets contain most of the original features, their performance is similar and falls short of the baseline features.

Feature set	All features	dev-N		Oracle-N	
	eval	eval	N	eval	N
Pitch-Drop	65.19	64.66	6	65.19	11
Pitch-MeanFill	65.11	65.26	9	65.26	9
LogPitch-Drop	65.23	65.23	6	65.34	9
LogPitch-MeanFill	65.15	64.96	11	65.16	10
Both-Drop	64.95	64.97	19	65.25	16
Both-MeanFill	65.20	65.12	20	65.20	16,22

Table 4.9: F_1 scores of forward selection experiments for English 2-word context HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the corresponding F_1 score of the `eval` set. dev-N is based off the `dev` set scores while oracle-N chooses the N with maximum eval.

In Table 4.10, which shows the corresponding results with the 4-word context, we see the above patterns, but more so. The Oracle-N now removes about a quarter of the original HLDA features and achieves about 0.2-0.3% absolute gain over the original features, all coming very close to performance of the baseline feature set.

Feature set	All features	dev-N		Oracle-N	
	eval	eval	N	eval	N
Pitch-Drop	65.64	65.66	15	65.76	17
Pitch-MeanFill	65.24	65.69	14	65.77	15
LogPitch-Drop	65.59	65.53	9	65.85	19
LogPitch-MeanFill	65.56	65.55	20	65.72	11
Both-Drop	65.52	65.46	21	65.87	38,39
Both-MeanFill	65.93	65.50	25	65.93	42

Table 4.10: F_1 scores of forward selection experiments for English 4-word context HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the corresponding F_1 score of the `eval` set. dev-N is based on the `dev` set scores while oracle-N chooses the N with maximum eval.

4.3.4 Interpretation of HLDA features

A linear transform was chosen for this initial attempt at machine designed features in hopes that it may shed light on feature design. Below are the first four HLDA features from the 2-word context, non-log pitch features, dropping missing values feature set. While the forward search AdaBoost wrapper did not strongly prefer these features, with a linear classifier and in the absence of the pause features, these are theoretically the linear combinations with the best discriminative ability. For each feature, I have normalized the largest component to norm 1 and listed all terms with coefficients with absolute value ≥ 0.25. A 2-class HLDA projects the data into feature space where, for each feature, moving in one direction represents higher likelihood of one class while moving in the other direction represents higher likelihood of the other class. In these four features, they are presented so that higher values indicate a greater likelihood of a sentence boundary, according to the AdaBoost model.

The first feature is fairly easy to interpret: it looks for a pitch reset across the boundary by comparing the last pitch of the word before to the first pitch of the word after. Here, a high p_1 would indicate a sentence boundary. The next term accounts for the mean of the previous word so that, if the mean is high, then a low last pitch indicates a sharp drop toward the end.

$$\begin{aligned}
p_1 =& -PrevLast + 0.84NextFirst + 0.46PrevMean - 0.26PrevMin \\
&+ 0.26NextMean \\
p_2 =& PrevMean - 0.42PrevMin - 0.35PrevMax - 0.30NextMean \\
p_3 =& NextMean - 0.73NextMin - 0.32NextFirst + 0.29NextLast \\
p_4 =& -PrevMin + 0.90PrevFirst + 0.63PrevLast - 0.53PrevMean
\end{aligned}$$

As for the other features, it is difficult to determine what cues or what quantities they are trying to measure. I consulted Dr. Shriberg [125], but it was not clear to her how to interpret these features. Thus, while one motivation for using a linear transform such as HLDA for this task was feature interpretability, it appears that what insights we can draw from the results are limited.

The following compares the first HLDA feature for the pitch, log-pitch, and both pitch + log-pitch feature sets for the 2-word context, dropping missing values from the training data. Again, the largest coefficient has been normalized to unity, and coefficients with magnitude smaller than 0.25 hidden. What we see explains why all of the HLDA feature sets behave so similarly, even the experiments with both pitch and log-pitch statistics that performed considerably better without the HLDA transform. Even though the pitch and log-pitch statistics are highly correlated, AdaBoost was able to exploit some non-redundant information. However, the HLDA transform effectively reduced all different input statistics sets to the same features. This implies that a different discriminant transform, preferably a non-linear one, may be better suited for this task.

$$\begin{aligned}
p_1 &= -PrevLast + 0.84NextFirst + 0.46PrevMean - 0.26PrevMin + 0.26NextMean \\
l_1 &= -PrevLast + 0.78NextFirst - 0.45PrevMean \\
b_1 &= -PrevLast_{Log} + 0.60NextFirst_{Log} - 0.44PrevMean_{Log} \\
&\quad + 0.2 * (-PrevLast_{Pitch} - 0.58NextFirst_{Pitch} - 0.45PrevMean_{Pitch})
\end{aligned}$$

While analyzing the HLDA feature coefficients, I noticed that some statistics tended to work together — that is, their coefficients usually have the same sign — while others were in opposition. To capture this behavior, the correlations between the statistic coefficients were calculated, the top five of which are shown in Table 4.11. Note that these are correlations, not correlation coefficients. Thus the *Mean* statistics, which generally are strong components of the HLDA features, are well-represented. My conjecture is that, of the five pitch statistics, the mean statistics are the most robust because they are functions of the entire word region. Thus they are useful measures of pitch height and for normalization.

Correlation	Features	
-0.314	PrevMean	PrevMin
-0.263	NextMean	NextMax
+0.178	PrevMean	NextFirst
+0.158	PrevMean	NextLast
-0.157	PrevMean	NextMin

Table 4.11: Largest correlations between HLDA feature coefficients.

4.4 Conclusion

These experiments set out to see whether machine learning methods could be applied to the design of prosodic features. The benchmark for comparison was a well-established set of features that has been used and refined in a variety of speech processing tasks for over a decade. The HLDA features and the baseline features use the same pre-processing steps up to and including the extraction of pitch statistics over word intervals. From then on, the baseline features were hand-designed by a human with expert knowledge to quantify various pitch levels and dynamics from these pitch statistics. In the HLDA features, these pitch statistics were fed into a discriminant transform to create linear combinations that would hopefully have better classification power than the input statistics.

If we split feature design into selecting a source of information and processing of that information into the features to be used by the learning algorithm, one clear message from the above experiments is that the information source is important. When the unprocessed pitch statistics were added to pause features, that already produced much of the performance gain seen in the baseline pitch feature set. Furthermore, when the contextual window was increased from the surrounding 2 words to a 4-word context, performance was given a significant boost. Recall that, during the design of the baseline pitch features, the features were intentionally limited to the statistics drawn from the two words surrounding the boundary because, even under this restriction, 45 pitch features were created. For a human to design features from a wider context would soon become impractical. In contrast, computers are designed to process large quantities of data, and with this additional contextual information HLDA achieved performance comparable to the baseline pitch features.

One may argue that the pitch statistics used already have processed the pitch information to a large degree. Indeed, the motivation for the machine-designed features is to make feature design accessible to researchers who do not already possess expert knowledge in the conditions they are working on, say if a scientist whose background is in English is tasked to design features for Mandarin or a system previously built for broadcast news is ported to meetings data. In the creation of the pitch statistics, someone chose to: remove halving/doubling pitch tracker errors with the lognormal tied mixture model; smooth it with a median filter; extract long-term information — at least longer than the typical 10ms frames — by using pitch statistics over word-sized intervals; and to focus on five specific pitch statistics. Future work could examine how well machine designed features perform if starting with less refined data, such as syllable- or frame-level pitch values.

Of the various HLDA parameter settings explored, log-pitch statistics tend to outperform absolute pitch, but they are very close. Furthermore, their combination usually performs slightly better, but as not as much as one would expect if looking at the performance of their corresponding pitch statistics sets, as will be discussed below. As for the treatment of missing data, since these examples are relatively rare, there is not much difference between dropping missing data or mean-filling. There is a tendency for the pitch and log-pitch feature sets to prefer dropping missing data and pitch + log-pitch to prefer mean-fill.

Looking at the performance of the HLDA feature sets, we find that, at least when starting with pitch or log-pitch statistics, the HLDA features perform slightly better than the pitch statistics, but still closer to the pitch statistics than the baseline pitch features. That implies the value added by the HLDA transform by itself is marginal compared to that of Shriberg in the design of the baseline pitch features. There are indications that HLDA is not a good choice for extracting features in this scenario. The most prominent evidence is that, while the combination of pitch and log-pitch statistics outperformed either separately, after each set was passed through HLDA, their performance was similar, and the pitch + log-pitch statistics set dropped in performance. This is attributed to the linear transform of the HLDA which, when supplied with the highly correlated pitch and log-pitch statistics, extracted much the same features. Future experiments should use a more general discriminant transform or learning algorithm, ideally taking into consideration the classifier to be used and the fact that the features will be used in conjunction with the pause features. Indeed, for a while I experimented with multi-layer perceptrons, but the system performed poorly and so the results are not included.

Because of the small performance differences between various feature sets, one of the issues that plagued these experiments was the thresholding for the classifier posterior probabilities. The posterior threshold trained on the `dev` set may provide an F_1 score on the held-out `eval` set close to theoretical maximum using the oracle threshold, but often suboptimal thresholding may mask performance gains made by the system, which is why I frequently referred to the oracle performance figures during data analysis.

The feature selection experiments show that most of the HLDA features do have discriminative ability as both the Top-N and forward search methods indicate that the optimal feature subset should include most of the HLDA features. However, possibly due to information redundancy in the presence of the pause features, the eigenvalues of the HLDA features are not good indicators of whether to include the feature or not. This is reminiscent of how filtering was not a strong predictor for the feature selection experiments in Chapter 3. However, even these basic feature selection methods were able to produce a small performance gain over the full HLDA feature sets. It should be noted that the posterior probability thresholding issues mentioned above interfered with the stopping criterion for the feature selection algorithms.

Chapter 5

Language Independence

One of the objectives of the proposed HLDA feature design system is to see whether it can extract prosodic features for a new language or condition without requiring considerable in-domain knowledge. A survey of sentence segmentation research in languages other than English was presented in Section 2.2.4. Guz et al. [58] addressed the agglutenative morphology of Turkish by creating morphological features, especially targeting the subject-object-verb ordering that is common to Turkish broadcast news. To make use of this information, they implemented a morphological analyzer for feature extraction and a factored version of a hidden event model to accomodate the new features. Results showed that the addition of morphological information improved performance significantly.

In contrast, Batista et al. [7] used pitch and segmental duration features based off of Shriberg et al. [129], but without tweaking the features or system much to accomodate known prosodic patterns in European Portuguese regarding stressed syllables and segmental duration. The result was that the syllable pitch and energy features and the segmental duration features contributed little to performance.

One takeaway point from this is that compensating for language-specific behavior is non-trivial. In the above examples, with human-designed features, considerable work went into making productive features. The objective for this chapter is to examine whether the proposed HLDA system can compensate for a known issue, the interference of Mandarin lexical pitch, without being explicitly programmed to. That is, while the resulting HLDA features may not be language independent, I wish to test the robustness of the algorithm.

5.1 Background

5.1.1 Tone languages

Arguably the greatest difficulty in designing pitch features for Mandarin comes from the fact that it is a tone language. As discussed in Section 2.1, the pitch component of prosody is used to communicate a variety of information, including phrasing, focus, and emotion. However, in tone languages, pitch is also used to convey lexical and/or grammatical information.

Mandarin is the most widely-spoken tone language in the world. In Mandarin, tones are differentiated by their characteristic pitch contour. Each syllable carries its own tone, and there are many minimal pairs — minimal sets may be a better description, as the examples involve more than two words, but the term *minimal pair* is the one used in linguistics literature — such as the commonly given syllable "*ma*," which can mean *mother*, *hemp*, *horse*, or *to scold* depending on whether Tone 1 through Tone 4 is used. Phonetically, these words have the same phonemes and only differ in intonation. It should be noted that such minimal pairs are composed of words with greatly different meanings and parts of speech. Thus, lexical tone is separate from inflectional morphology, such as initial-stress-derived nouns in English that can change a verb to a noun [61]. For example:

- Verb: "I wish to recórd the recital."
- Noun: "I have a récord of the recital."

where the accent mark denotes the stressed syllabe in the word. Here, a superfix — an affix that consists of a supersegmental rather than phonetic change — modifies the original morpheme's meaning from a verb to a related noun or adjective [122]. However, in the case of Mandarin, the words in the minimal pairs are quite different, and the tone is therefore is an essential component of the lexeme.

Not all tonal languages behave like Mandarin. In the Bantu family of languages of sub-Saharan Africa, as opposed to the pitch contours of Mandarin, tones are distinguished by the relative pitch level. Tones may be attributed to whole words, as opposed to individual syllables in Mandarin, and tone may convey grammatical information, such as verb tense or determining whether a pronoun is first-person or second-person [22].

In Somali, the current phonological theory is that every word consists of one or more mora, with short vowels containing one mora while long vowels contain two morae. Except for particles, one of the last two morae of each word is marked with a high tone. Therefore, in long-vowels, a High-Low mora sequence is produced as a falling tone while a Low-High sequence is transformed by a phonological process to High-High and be realized as a high tone, though sometimes it surfaces as a rising tone. All other vowels are realized with a low tone. Tones are used to mark grammatical differences rather than lexical ones, such as between singular and plural or masculine or feminine gender [69].

Tonality in Japanese is usually described as pitch accent: each word may have zero or one downsteps. Pitch gradually rises before the down step, undergoes a sudden drop between two mora, and tends to stay level or drop slowly for the remainder of the word. For example:

- At the chopsticks: háshìnì, the first mora is high while the remainder are low.
- At the bridge: hàshínì, the accent is perceived on the second mora, which is why the first mora is transcribed à.
- At the edge: hàshīní is perceived to be accentless or sound flat.

Like most languages, Japanese also features a gradual drop in pitch over a phrase. However, it appears much of this drop comes from downsteps. Thus, the rise in pitch before each downstep may be the result of the speakers needing to reset their pitch higher to keep the utterance within their pitch range [109].

From the above sample of tone languages, we can see there is a great variety in the ways tone is expressed and used to convey lexical or grammatical information.

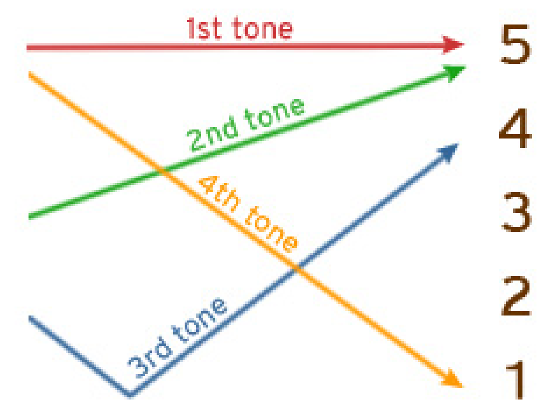


Figure 5.1: Idealized Mandarin lexical tone contours.

Thus, researchers will find it difficult to develop a one-size-fits-all approach that works across multiple tone languages. Instead, they should expect that any system or set of features that are tweaked for one language will suffer when ported over to others.

5.1.2 Mandarin lexical tone

Mandarin contains four pitch patterns, generally referred to as Tone 1 or first tone through Tone 4 or fourth tone. I will use these terms interchangably. In the 5-height pitch notation first used by Chao [18], in the Beijing dialect of Mandarin, these four tones are approximately:

1. 5-5, a high-level tone
2. 3-5, a high-rising tone
3. 2-1-4, a low or dipping tone
4. 5-1, a high-falling tone

Note these are idealized pitch contours, often taken from words spoken in isolation and so without coarticulation constraints and phonological effects. For example, during continuous speech, tone 3 often stays low, as seen in Figure 5.3. Other dialects of Mandarin have different pitch targets, though the general shape of the pitch contour remains similar [19].

There is also a fifth tone, sometimes referred to as flat, light, or neutral tone, which is pronounced as a light, short syllable. In contrast to the other tones, the fifth tone has a relatively large number of allophones, with its pitch value greatly depending on the tone of the syllable preceding it. Furthermore, while it usually appears at the end of words or phrases, there is no fixed generative rule for when neutral tone occurs. Phonologically, light tone may be viewed as a syllable with no underlying tone but is realized at the surface by the spreading of the tone of the preceding syllable. In any case, it is clear that fifth tone behaves fundamentally differently from the other four tones and should be treated differently. In the TDT4-MAN corpus I used, fifth tone was not used in the transcription, so the following experiments and analysis were performed ignoring its existance.

The realization of Mandarin tone is further complicated by tone sandhi, which may be thought of as phonological rules that alter lexical tones in certain contexts [123]. Among tonal languages, there are other processes that may affect tone; for example, in Cantonese, derivational morphology changes the low-falling tone of 'dòng' meaning *sugar*, to the derived word 'dóng,' *candy*, using a mid-rising tone [9]. However, Mandarin has relatively simple tone sandhi rules, mainly concerning the third dipping tone, which is not surprising since, as the only tone that involves two pitch changes, it is the most complex of the fundamental tones [19].

- When two consecutive third tones occur, the first one becomes a rising tone, perceptively indistinguishable from second tone. The second syllable becomes what is sometimes referred to as a half-third tone with pitch targets 2-1. For example, 'hěn hǎo,' *very good*, is pronounued 'hén hǎo.'

- When more than two third tones occur in a row, this becomes further complicated, and the exact surface realization also depends on the syllable-length of the words involved.

- When the third tone is the first syllable of a multisyllable or compound word, it is often reduced to a half-third tone during spontaneous speech. Examples of this include ‘hǎo chī,’ *good + eat = delicious*; ’hǎo kàn,’ *good + look = pretty.*

- When two consecutive fourth tones occur, the first one does not fall so much — it has been transcribed as pitch targets 5-3 — while the latter remains the same. This makes the second syllable sound more emphatic. An example of this is ‘zuòyè,’ meaning *homework.*
- Two words — ‘yī,’ *one*, and ‘bù,’ *no* — have their own special rules. For example, *no* takes on a second tone when followed by a fourth tone but becomes neutral when coming between two words in a yes-no question. *One* should be realized with Tone 1, 2, 4 or neutral, depending on the circumstances.

The presence of tone sandhi means that any pitch features that attempt to fully quantify lexical tone should not rely on the dictionary lexical tone alone but take into consideration both the surrounding tone environment and the lexical content of the utterance. However, one of the desired aspects of prosodic features, as previously mentioned, is for them to be computed and used in the absence of the lexical information.

As has been discussed, the pitch contour produced is a function of many competing influences, including lexical tone, phrase declination, stress, and semantic focus. However, as lexical tone carries information critical to the semantic content of the speech, we would expect that it has a higher priority over other considerations, and thus the pitch contour produced strongly reflects the syllable’s lexical tone. Therefore, in the case of sentence segmentation and other applications of prosodic pitch, we would expect lexical pitch to obscure the pitch contour cues and patterns we would like to employ in these tasks. In Chapter 3, we indeed saw that the baseline ICSI prosodic feature set had greater difficulty with Mandarin than English or Arabic, especially its pitch features.

Therefore, to design a set of pitch features that is better able to handle the presence of Mandarin lexical tones, one might want to study the interaction between lexical tones and the sentence pitch contour. However, I have found little literature on this topic. While there is a considerable body of work on the modeling of Mandarin lexical tone, most of the research treats the interaction between syllables and sentence as an additive or smoothing process between the two sources. Given this, it still behooves us to study the current research into lexical tone modelling, as it will at least inform us on how to compensate for the lexical tone.

Xu [170, 169, 174] argues that the fundamental representation of pitch contours are pitch targets, which come in two varieties: static and dynamic. Static targets are level and have a height — such as high, low, or mid — relative to the speaker's pitch range. Dynamic targets consist of a linear movement (in log-pitch domain).

There is a distinction between a dynamic pitch target being represented by a line compared to a beginning and ending pitch target, which is the more traditional representation from recent advancements in autosegmental and metrical phonology [48, 49]. For example, a rising pitch contour may be represented by a low-high sequence of pitch targets. Xu argues for the reality of these linear targets by observing that the later portion of pitch contours converge on a target while the early portion can vary greatly, generally due to the pitch trajectory of the previous lexical tone. From this, he concludes that the pitch contour realized is one that asymptotically and continuously approximates the pitch target. If a rising dynamic pitch target was a sequence of low-high pitch targets, then one would expect the resulting pitch to resemble the solid line in Figure 5.2 as pitch tries to converge to two pitch targets in sequence. Instead, the pitch contour observed in rising tone syllables more closely resembles the dotted line, which uses a sloping linear target.

The Stem-ML model of Kochanski, Shih, and Jing [75, 76, 77, 124] works under the assumption that each lexical tone has an exemplar, an ideal tone shape that each speaker implicitly knows. Stem-ML does not make any *a priori* assumptions as to these tone shapes — such as pitch heights, lines, or targets — but instead learns them from data. The resulting tone shapes, however, correspond well to the established contours elsewhere in the literature. Note that while they refer to these templates as tone shapes, it is not just the dynamics of the template that matters, but the absolute pitch height as well.

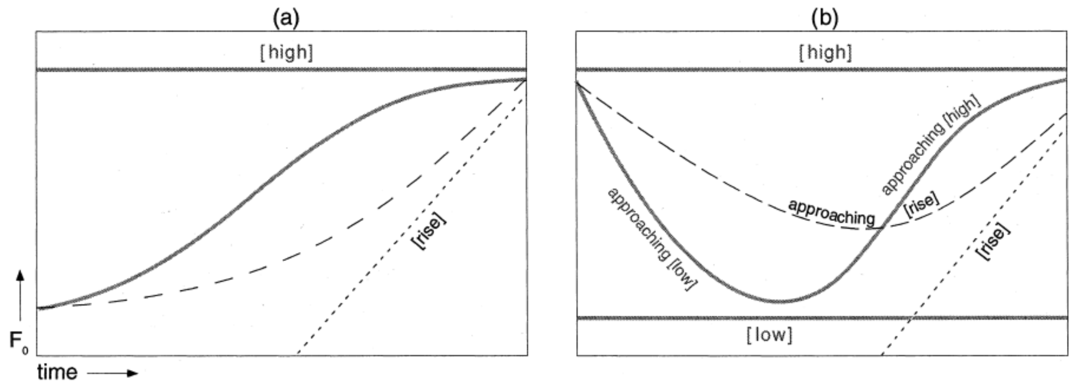


Figure 5.2: Hypothetical pitch trajectories arguing for the existance of dynamic (sloping) pitch targets rather just high and low static targets from [170]. Figure (a) compares two potential targets, a rising dynamic target (dotted) and static high target (upper solid line). Starting from a low pitch, because pitch asymptotically approaches targets, the two hypothetical targets would produce the dashed and lower solid line, respectively. Similarly Figure (b) compares a rising dynamic target (dotted) to a sequence of low-high static targets (outer solid lines). Again, these hypothetical targets would produce the dashed and middle solid line, respectively. The dashed contours are more natural, and so Xu concludes the existance of dynamic pitch targets.

The central idea behind the Stem-ML model is that the pitch contour produced is a trade-off between effort, a quantity based on muscle dynamics where effort is higher if muscles are moving faster or further from their neutral position, and error, a measure of how much pitch deviates from the ideal tone template. Unlike Xu's framework, which places more weight on reaching the pitch target toward the end of the syllable, the Stem-ML model uniformly weights pitch error over the span of the pitch template. The trade-off between effort and error changes from syllable to syllable, which they quantify using a prosodic strength parameter per syllable. If a syllable's prosodic strength is large, this represents the speaker's willingness to expend more energy to accurately produce the tone template and thus reduce communication error, such as in careful speech. See Figure 5.3 from [76].

In fitting the prosodic strength parameters, the Stem-ML corroborates many findings already present in the literature, including:

- Words follow a strong-weak metrical pattern [87].

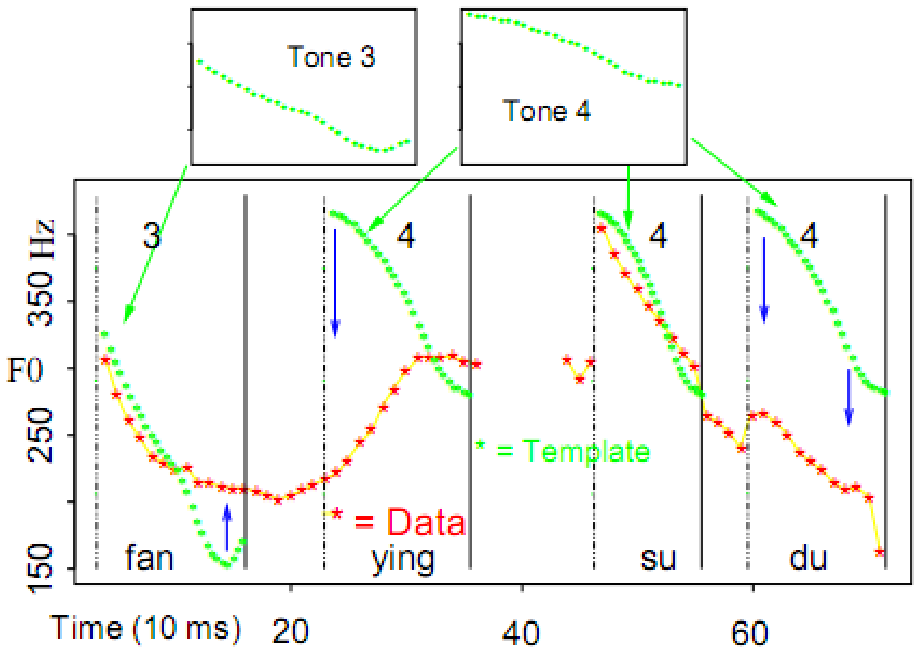


Figure 5.3: Stem-ML tone templates (green) and realized pitch (red). In the first pair of syllables, the low ending of the 3rd tone and the high start of the 4th compromise to a pitch contour between them that also does not force the speaker to exert too much effort to change quickly. The speaker also manages to hit the template target for the beginning of the first syllable and end of the last. In the second pair of syllables, the first syllable closely follows the tone template while the second syllable is shifted downward.

- Words at the beginning of a sentence, clause, or phrase have greater strength [65].
- Nouns and adverbs have greater strength than other parts of speech, and particles have the lowest. This reflects the low information content of function words [64].
- There is a correlation between stress, which prosodic strength appears to be related to, and duration [24, 74].

Their findings also suggest there is negative correlation between prosodic strength and mutual information. That is, the easier it is to guess the current syllable from previous ones — high mutual information — the lower its prosodic strength is since it is less important to carefully pronounce the syllable to avoid confusion.

There is also ongoing debate as to what is the domain of tone. Given that the pitch contour early in the syllable varies much more than the later portion, some [67] conclude that the critical period for lexical tone is the syllable rhyme, the portion of the syllable between the start of its nucleus and end of its coda, and the onset serves as a transition period between tones. Kochanski and Shih allowed Stem-ML to fit the span of the templates, which settled on approximately the last 70% of the syllable. In the pitch target framework proposed by Xu, he defines the onset of the pitch target as the time when the pitch contour begins to converge toward the target, though he does not specify when exactly that occurs. When a falling tone follows high or rising tone, i.e. tone that ends high, there is some delay before the pitch contour begins to fall, so there is a period during the second syllable where pitch continues to be high/rising. The Stem-ML model would predict such behavior as a result of minimizing effort: pitch will continue to follow the trajectory of the previous tone template and gradually transition to the following syllable's template. In comparison, when a low tone follows a high or rising tone, the pitch begins to decrease around the syllable boundary. It should be noted that if there were no delay before pitch began to lower during a falling tone, it would be hard to distinguish from a low tone, and languages evolve to avoid such ambiguous situations.

On the note of a following syllable containing a pitch target with a low point, i.e. third and fourth tone, Xu adds an additional rule to his proposed pitch target framework to allow for anticipatory raising, which is a phenonmenon where the pitch peak in such a situation is higher than it would be otherwise. Anticipatory raising is sometimes called regressive H-raising or anticipatory dissimilation, and has been observed in several tonal languages, including Enginni, Mankon, Kirimi [68], Thai [46], Yoruba [84], and Mandarin [166]. In Xu's pitch target framework, this pitch peak is not a pitch target, but its occurence and location follow as a consequence of implementing the pitch targets.

5.2 Method

The details about Mandarin lexical tone in Section 5.1.2 have numerous implications for the baseline ICSI pitch features and the proposed HLDA system. Recall that these features are based on five pitch statistics — max, min, mean, and first and last voiced pitch — over the word.

- Tone 1, which stays relatively high, will have high min and mean statistics.
- The last pitch will be heavily influenced by lexical tone of the word-final syllable.
- As the onset pitch of a syllable depends heavily on the final pitch of the preceding syllable, the first pitch statistic depends on the lexical tone of the preceding syllable. However, due to the way our system extracts pitch values, the correlation will also depend on when voicing starts in the word-initial syllable. The earlier voicing starts, the more the first pitch statistic will reflect the previous syllable.
- Anticipatory raising will affect the max pitch of the preceeding and/or subsequent syllable, depending on when the pitch peak occurs.

Table 5.1 shows the mean and standard deviation of the five pitch statistics when extracted over syllables instead of words, separating syllables by lexical tone. Some

	Tone 1		Tone 2		Tone 3		Tone 4		Overall	
Statistic	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
max	233	73	209	69	199	69	227	75	219	73
min	171	66	151	55	134	50	158	60	155	59
mean	209	66	178	57	163	55	194	64	187	63
first	186	70	184	70	189	67	191	71	188	70
last	215	72	184	62	144	57	176	65	180	68

Table 5.1: Mean and standard deviation of pitch statistics for Mandarin syllables by lexical tone.

patterns are apparent in this table. Minimum and mean pitch have the lowest standard deviation, min probably because it is tied to the speaker baseline and mean because it is a function of the entire syllable. The statistic with highest variance is maximum pitch. Interestingly, all the μ — I will refer to the distribution mean as μ to avoid confusion with the mean pitch statistic — of the first pitch are about the same, around the level of the overall mean. This may be a reflection of onset pitch depending on the preceding syllable. In contrast, the last pitch of tones 1 and 3 do not seem constrained and go quite high and low, respectively.

To examine the coarticulation of pitch contours, especially at the beginning of the syllables, Table 5.2 shows the mean and standard deviation of syllable pitch statistics when conditioned on the tone of the previous syllable. As expected, the first pitch of the syllable is the most affected, with it being particularly high after first tone and low after third tone. Indeed, third tone appears to drag down all of the pitch statistics of the following syllable. The other statistics are relatively unaffected by the identity of the previous lexical tone, especially last pitch.

Table 5.3 compares the five pitch statistics of English and Mandarin when extracted over words. Again, min and mean have the lowest standard deviation. This may explain why mean pitch was seen to be so commonly used by the HLDA system in Section 4.3.4. Another thing to note is that, while it appears Mandarin has higher standard deviation, it also has about twice the pitch range of English but not twice the standard deviation.

Statistic	Tone 1		Tone 2		Tone 3		Tone 4		Overall	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
max	233	74	225	73	207	72	219	73	219	73
min	167	63	162	59	138	53	152	58	155	59
mean	199	65	193	63	176	59	183	63	187	63
first	218	72	192	64	156	63	184	67	188	70
last	181	68	184	69	181	66	177	69	180	68

Table 5.2: Mean and standard deviation of pitch statistics for Mandarin syllables by lexical tone of previous syllable.

Statistic	English		Mandarin	
	μ	σ	μ	σ
max	180	63	232	76
min	132	46	139	53
mean	156	49	185	59
first	154	54	183	70
last	150	54	183	70

Table 5.3: Mean and standard deviation of pitch statistics for English and Mandarin words.

One method to compensate for lexical tone may be to model it and subtract it away, leaving a pitch contour that more closely resembles the sentence intonation of whatever pitch dynamics may be of interest. However, accurate lexical tone models are not simple. Firstly, the underlying pitch target(s) for each tone must be defined or calculated and, as noted in Section 5.1.2, even this fundamental issue is still under debate.

Secondly, coarticulation causes the realized pitch contour to deviate from the target, and the degree of deviation varies within the syllable. Coarticulation is typically handled by conditioning on the context surrounding the syllable in question. At a minimum, this should be whether the previous syllable ended on a high or low pitch. However, because the pitch trajectory of the preceeding syllable extends into the following one, conditioning on the lexical tone of the previous syllable is warranted.

Thirdly, as Kochanski and Shih argue, the realization of lexical tone is not uniform across all syllables, and prosodic strength depends on many factors, including the position of the syllable within the word, the position of the word within the phrase or sentence, semantic focus, and how predictable it is given its context. In the sentence segmentation task, we obviously do not know *a priori* the position of the word within the sentence, though if prosodic strength can be calculated, it may help in inferring its position within the sentence. Whether a word or syllable is predictable from its context wanders into the territory of language models, and I wish to maintain the independence of prosodic features if possible.

One of the motivations for proposing the use of machine learning techniques to extract prosodic features is that designing a good set of features for a specific application requires considerable domain knowledge, and even then feature design is not a trivial process. Even if a good lexical model can be created, there is no guarantee that it will greatly aid finding the sentence intonation that it obstructs.

To verify whether the proposed HLDA system can circumvent this requirement of detailed in-domain knowledge, I repeated the experiments in Chapter 4 without modification. Refer to Section 4.2.2 for a description of the system. The goal of this chapter is to compare how the HLDA plus feature selection design process performs here relative to English, and therefore whether the system can adapt to the complications created by Mandarin lexical tone.

As an aside, the original inspiration for the proposed HLDA feature system was the analysis of eigenpitch in Mandarin [146, 147], which performed a principal component analysis (PCA) on Mandarin syllable intonation contours. The top principal components found reflect the well-known Mandarin lexical pitch contours (see Figure 5.4). The context for this work was concatenative speech synthesis, where the desired speech utterance is created by stringing together units selected from a pre-recorded inventory. For each syllable in the target utterance, the authors used the phonetic context, which they call the prosodic template although it contains phonetic and lexical information, to select an N-best list of candidate syllables from the inventory. The syllables to be used are then chosen by a Viterbi decode that minimizes the prosody cost objective function. This prosody cost is a combination of prosodic distance, which is a function of the PCA components, and context distance.

While my thesis project differs considerably in its task and implementation, it shares some similarities. PCA and LDA are both commonly used statistical learning

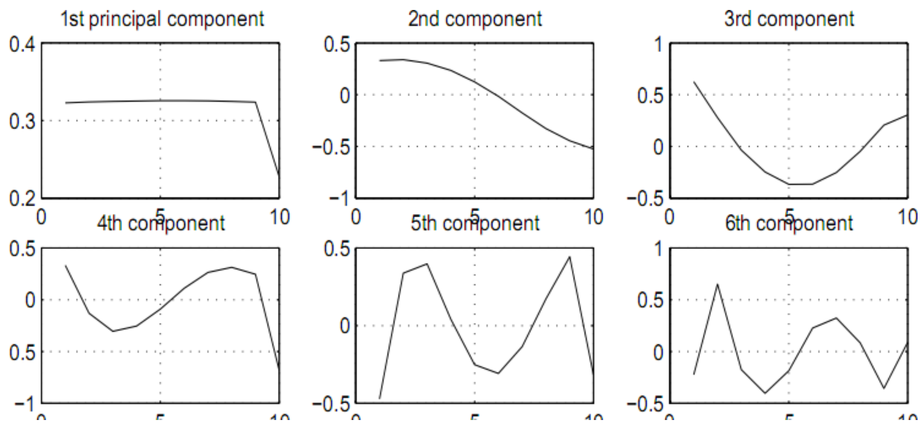


Figure 5.4: The first six principal components from [146]. The 2nd component looks like tone 4 and, if negated, resembles tone 2. The 3rd component has the falling-rising curve of tone 3.

methods for dimensionality reduction. They both share the philosophy that examples can be decomposed into component elements, that these elements tell us something about the behavior of the dataset, and that each example is best represented by its strongest components. On a personal note, the idea that data can be analyzed from the perspective of a set of basis elements has been ingrained in me, given that signal processing was my emphasis during my undergraduate education, and my teaching experience during graduate school has primarily been in the field of signals and systems.

5.3 Results and Analysis

5.3.1 Statistical significance

Empirical p-values were calculated by Monte Carlo simulations as described in Section 4.2.5. For Mandarin, F_1 score gains on the `eval` set of +1.2%, +1.5%, and +2.2% correspond to p-values of 0.1, 0.05, and 0.01. Note that these thresholds are more than double that of the English experiments. This is due to the English `eval` set being much larger, and therefore any perceived performance gain being more likely attributed to actual system improvement than chance. This also means the smaller absolute gains seen below, relative to English, are even less statistically significant.

5.3.2 2-word context

Table 5.4 compares the pre-HLDA pitch statistics feature sets to the pause duration and `ICSI` baseline pitch features discussed in Chapter 4. As noted in Chapter 3, the baseline pitch features are not well suited for the Mandarin condition. Compared to 3.3% absolute improvement over the `PAU` feature set seen in TDT4-ENG, here the rise is a much more modest 1.0% absolute.

With the English data, we saw that adding the pitch statistics to the pause features produced much of the gain made by the `ICSI` feature set. Here, the numbers are harder to interpret because of the thresholding of the posterior probabilities. As can be seen from the oracle F_1 scores on the `eval` set, the pitch statistics outperform the `ICSI`-baseline. However, I believe due to the small size of the corpus, it is difficult to train a good posterior probability threshold on the `dev` set and/or the `eval` set is sensitive to changes in the system. As mentioned in Section 3.2.1, these experiments were not run on the SVM classifier because I found that small changes in a cost parameter in the model could cause large swings in system performance for the Mandarin corpus.

The fact that the pitch statistic feature sets all have lower NIST error than the `ICSI`baseline lends credence to the hypothesis that the unprocessed pitch statistics, as they were in the English condition, can provide most of the performance gain seen of the `ICSI` pitch features, and it is likely suboptimal thresholding that produced the poor `eval` result seen in experiment `stat_2W_P`, the non-log pitch statistics.

Tables 5.5 and 5.6 show the F_1 scores of the HLDA features set on the 2-word context using `dev`-trained and oracle posterior thresholds, respectively. Unlike with the larger English corpus, the posterior probability thresholding is quite bad, ranging from 0.33-0.91% absolute F_1 score below their oracle counterparts. Considering the baseline pitch features only added 1.0% absolute F_1, this is a significant problem.

Therefore, let us examine the oracle `eval` numbers. The performance of the pitch statistics has much higher variance than with the English data. Regardless, here we see that HLDA is not performing well in this situation. Although one experiment

Features	F_1 score (%)			NIST (%)
	dev	eval	eval (oracle)	eval
PAU	63.03	60.80	60.88	84.15
ICSI	61.47	61.80	61.97	78.93
`stat_4W_pitch`	63.99	61.08	62.15	76.88
`stat_4W_log`	64.14	61.69	62.01	76.20
`stat_4W_both`	64.05	61.30	62.60	76.57

Table 5.4: Performance of Mandarin pitch statistics from 2-word context without HLDA transform relative to pause and baseline pitch feature sets. The three statistics feature sets are pitch, log-pitch, and their concatenation (both). Eval columns use the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1 score on the `eval` set.

achieved a better performance than the baseline features, almost all of the HLDA experiments deteriorated relative to their original statistics. This could be because the oracle `eval` scores for the statistics sets were quite high, at least relative to the `ICSI` baseline performance, but still it is hard to argue that the HLDA transform improves performance. Based on the feature selection results in Section 5.4, one explanation is that, unlike with the English data, many of the HLDA features are not productive.

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	61.08	61.10	61.28
Log-pitch	61.69	61.39	60.44
Both	61.30	60.65	60.62
PAU	60.80		
ICSI	61.80		

Table 5.5: F_1 scores of Mandarin HLDA feature sets from 2-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The F_1 scores for the pause and baseline pitch features are provided for comparison.

Some studies describe classifier performance using ROC curves, showing the trade-off between false positives and false negatives based on where the class boundary is set. Common measures used to compare the ROC curves of different classifiers are the area under the ROC curve or the equal error rate. Neither of these widely-

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	62.15	61.43	61.65
Log-pitch	62.01	62.18	61.00
Both	62.60	61.18	61.53
PAU	60.88		
ICSI	61.97		

Table 5.6: Oracle F_1 scores of Mandarin HLDA feature sets from 2-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). Oracle uses the posterior threshold that maximizes the `eval` F_1 score for that feature set. The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The oracle F_1 scores for the pause and baseline pitch features are provided for comparison.

accepted measures depend on a posterior probability or likelihood ratio threshold trained on held-out data, and oracle F_1 score is the same. Furthermore, oracle F_1 score is easier to interpret relative to the non-oracle F_1 scores, which are typical of sentence segmentation literature.

5.3.3 4-word context

Table 5.7 shows F_1 scores for the statistics sets using the 4-word context. The pitch and log-pitch statistics, separately, have performance comparable to the `ICSI` baseline feature set, and when combined do even better. The performance of `stat_4W_L` may be attributed to poor training of the posterior threshold. While Mandarin 4-word context statistics do not generate the same absolute performance gain of their English counterparts, the English 4-word statistics fell short of the mark set by the `ICSI` baseline. I believe this reasserts the position that the `ICSI` pitch features are not well-adapted for Mandarin and raises the question whether the HLDA feature can do better.

However, this does not appear to be the case judging by the F_1 scores of the HLDA experiments in Tables 5.8 and 5.9, using `dev`-trained and oracle posterior thresholds, respectively. Across the board, both the oracle and non-cheating F_1 scores for the HLDA feature sets are lower than their statistics counterparts. As with the 2-word

Features	F_1 score (%)			NIST (%)
	dev	eval	eval (oracle)	eval
PAU	63.03	60.80	60.88	84.15
ICSI	64.17	61.80	61.97	78.93
`stat_4W_pitch`	64.55	61.84	62.13	76.88
`stat_4W_log`	64.38	61.45	61.92	76.44
`stat_4W_both`	64.77	61.99	62.51	75.33

Table 5.7: Performance of Mandarin pitch statistics from 4-word context without HLDA transform relative to pause and baseline pitch feature sets. The three statistics feature sets are pitch, log-pitch, and their concatenation (both). Eval columns use the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1 score on the `eval` set.

context Mandarin HLDA experiments, I conjecture that many of the HLDA features have low discriminative ability. In particular, since the 4-word context HLDA feature sets are larger — 21 features in the pitch and log-pitch sets, 42 when combined — there probably are more distracting features.

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	61.84	61.38	61.08
Log-pitch	61.45	61.11	60.94
Both	61.99	61.11	61.19
PAU	60.80		
ICSI	61.80		

Table 5.8: F_1 scores of Mandarin HLDA feature sets from 4-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The F_1 scores for the pause and baseline pitch features are provided for comparison.

5.4 Feature Selection

Table 5.10 shows the results of the forward search experiments for the 2-word context. Given the difficulties with posterior probability thresholding, the results are presented differently than the English ones in Tables 4.9 and 4.10, with an emphasis on oracle threshold and selection criteria. This can be seen as, using the `dev` N selection

Statistics	stat	hlda-Drop	hlda-MeanFill
Pitch	62.13	61.42	61.17
Log-pitch	61.92	61.64	61.70
Both	62.51	61.26	61.67
PAU	60.88		
ICSI	61.97		

Table 5.9: Oracle F_1 scores of Mandarin HLDA feature sets from 4-word context relative to the pitch statistics sets they were computed from: pitch, log-pitch, or their concatenation (both). Oracle uses the posterior threshold that maximizes the `eval` F_1 score for that feature set. The stat column gives the performance of the statistics without HLDA. The two HLDA columns indicate the method of handling missing data. The oracle F_1 scores for the pause and baseline pitch features are provided for comparison.

criteria, the HLDA feature sets with threshold trained on the `dev` set perform little better that the `PAU` features alone, and with oracle thresholds they perform about the level of the full feature sets. Either more data or another method is needed to make this a viable system.

However, let us consider if we are allowed to select the optimal N stopping point that maximizes system performance both with and without the oracle posterior threshold. Note that the candidate features sets are still generated using a greedy search based on thresholding and performance on the `dev` set. The optimal N stopping points are lower than the corresponding English experiments, especially for the both-pitch and log-pitch sets, which can have up to 22 features. From this, we may conclude that the HLDA produced fewer relevant features, which explains the results of the full feature sets in Sections 5.3.2 and 5.3.3.

It is also for this reason I do not include the Top-N feature selection experiments. With fewer relevant features, and with the issue still that the features with the high eigenvalues may be largely redundant in the presence of pause information, the Top-N experiments did no better than the full HLDA feature sets.

Using oracle thresholds, HLDA performance approaches the 61.97% oracle F_1 of the `ICSI` feature set. However, we have established that the `ICSI` pitch features are less well-suited for Mandarin than English or Arabic. Unfortunately, based on that, I conclude that the HLDA is not compensating for the effect of Mandarin lexical pitch, at least in the 2-word context, which was one of ultimate objectives of the project.

Feature set	All features	dev-N			oracle-N			
	oracle	eval	oracle	N	eval	N	oracle	N
Pitch-Drop	61.43	60.84	61.45	2	61.10	11	61.45	2
Pitch-MeanFill	61.65	60.99	61.23	7	61.09	8,11	61.90	11
LogPitch-Drop	62.18	60.72	61.16	6	61.39	11	62.18	11
LogPitch-MeanFill	61.00	60.89	61.20	3	61.36	7	61.66	7
Both-Drop	61.18	61.49	61.74	12	61.69	11	61.89	5
Both-MeanFill	61.53	60.89	61.43	11	61.79	6	61.86	6

Table 5.10: F_1 scores of forward selection experiments for Mandarin 2-word HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the F_1 score of the `eval` set using the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1. dev-N selects N based off the `dev` set scores. oracle-N chooses the N that maximizes eval and oracle individually.

Feature set	All features	dev-N			oracle-N			
	oracle	eval	oracle	N	eval	N	oracle	N
Pitch-Drop	61.42	60.59	61.25	14	61.38	21	61.57	16
Pitch-MeanFill	61.17	61.02	61.38	13	61.40	7	61.70	9,10
LogPitch-Drop	61.64	61.20	61.39	11	61.46	19	61.71	19
LogPitch-MeanFill	61.70	60.89	61.16	13	61.36	20	61.98	19
Both-Drop	61.26	61.22	61.40	13	61.27	19	61.76	18
Both-MeanFill	61.67	61.48	61.93	24	61.97	29	62.22	17

Table 5.11: F_1 scores of forward selection experiments for Mandarin 4-word HLDA features. dev-N and oracle-N refer to different stopping criteria, where N gives the size of the selected feature set. eval gives the F_1 score of the `eval` set using the posterior threshold trained on the `dev` set while oracle uses the threshold that maximizes F_1. dev-N selects N based off the `dev` set scores. oracle-N chooses the N that maximizes eval and oracle individually.

5.5 Feature Analysis

Because of the above issue with thresholding posterior probability on the `dev` set and the larger F_1 score difference required to achieve the same statistical signifi-

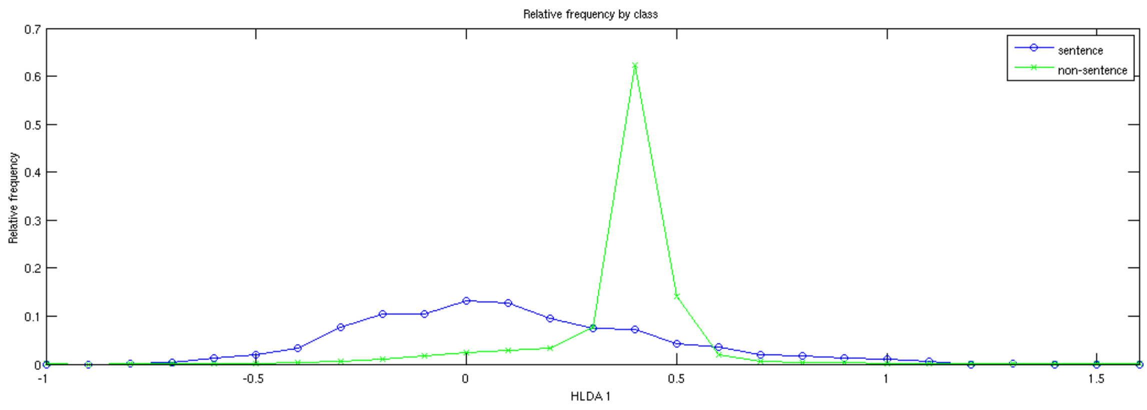
	Long pause	Short pause
Sentence boundary	1482	127
Non-sentence boundary	2726	37075

Table 5.12: Frequencies of class labels and short vs. long pauses (shorter or longer than 255ms) in Mandarin `eval` set.

cance due to smaller `eval` set size, the efficacy of the HLDA features in Mandarin is questionable. To better understand feature behavior, I analyzed the distributions of individual features relative to class and pause duration. For this purpose, pause duration is represented by a binary variable, divided into long and short pauses depending on whether they are longer or shorter than a threshold. For Mandarin, this threshold is set at 255ms based on the AdaBoost model. The frequency of these sets within the `eval` data are shown in Table 5.12. Note that this single threshold on pause duration gives 51.0% F_1 score on the `eval` set already, with 92% recall but only 35% precision.

Figure 5.5 shows the distribution of the 1st HLDA feature from the 4-word, log-pitch, drop missing values HLDA feature set. Distributions are conditioned on class label and long and short pause, where each distribution is normalized to sum to one. As can be seen in the top subplot, the 1st HLDA feature achieves fairly good separation of the classes. However, when taking into consideration short vs. long pause, class separation is dramatically diminished. After thresholding on pause duration, the classifier can receive the most benefit by reducing the non-sentence boundary labels within long pause examples, thereby improving recall. However, conditioned on long pause, the distributions of sentence and non-sentence boundaries overlap considerably, with non-sentence boundaries having slightly higher mean.

This pattern is seen in all HLDA features, where conditioning on short vs. long pauses decreases class separation for the feature, though this is not surprising since pause duration is a very strong predictor of the class label. Figure 5.6 shows relative distribution of the 12th HLDA feature from the same feature set. This was the first feature selected in the forward selection experiment. Conditioning on short pause, the class separation remains fairly robust. The same cannot be said when conditioning



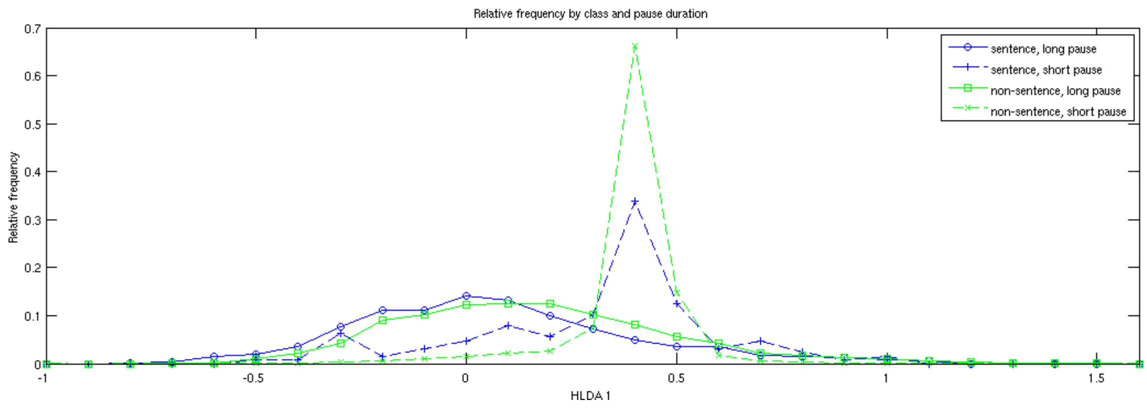


Figure 5.5: Distribution of 1st HLDA feature in Mandarin relative to class label and short vs. long pauses (shorter or longer than 255ms). Taken from the 4-word context, log-pitch, drop missing values HLDA feature set. All distributions are normalized to sum to one. Top subplot shows distribution relative to class only while bottom subplot shows distribution relative to both variables simultaneously.

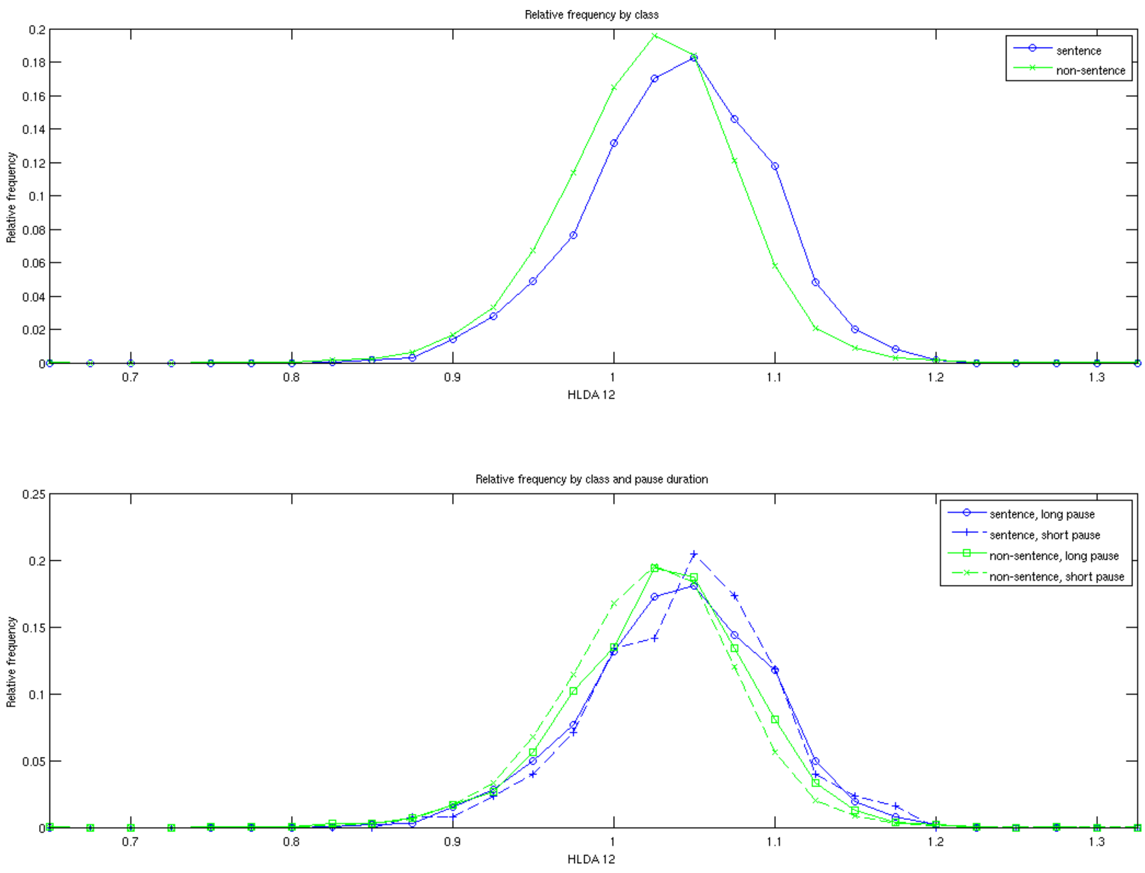


Figure 5.6: Distribution of 12th HLDA feature in Mandarin relative to class label and short vs. long pauses (shorter or longer than 255ms). Taken from the 4-word context, log-pitch, drop missing values HLDA feature set. All distributions are normalized to sum to one. Top subplot shows distribution relative to class only while bottom subplot shows distribution relative to both variables simultaneously.

on long pause, not that the 12th HLDA feature had strong class separation to begin with. The conclusion is that the training of the HLDA features should have taken into consideration the pause duration features, in particular focusing on the examples that are misclassified by pause duration.

As the HLDA features seem to reproduce pause duration information to some degree, experiments using Mandarin HLDA features without pause information were run. For comparison, a classification model using the baseline pitch feature similarly with no pause information was also trained. Without feature selection, the 4-word context HLDA feature set using both pitch and log-pitch statistics and mean-filling missing values gave 41.29% F_1 score on the `eval` set compared to 41.32% F_1 score by the baseline pitch features. Using the oracle posterior threshold, these rise to 41.63% and 41.76%, respectively. From this I conclude that, while the HLDA features do not have the performance of the pause duration features, they can achieve performance comparable to the baseline pitch features in absence of pause information if allowed access to more contextual information as before.

Results show that pitch statistics, from which the baseline pitch features and HLDA features are derived, can attain much of the performance of the derived features. Figure 5.7 shows the relative distribution of the mean pitch over the word immediately before candidate boundary. Most of the pitch statistics exhibit similar behavior: conditioned on class label alone, the feature distributions are distinct, but class separation is diminished when also conditioned on short vs. long pause.

5.6 Conclusion

In Chapter 4, we established that a feature design system combining an linear discriminant transform and a forward selection wrapper, neither particularly sophisticated methods, was able to achieve results comparable to well-established set of pitch features, though only after gaining access to additional information not used by the manually-designed features. In this chapter, making not insignificant assumptions that the problems of optimal selection criteria and posterior probability thresholding can be solved, we see the same can be said for Mandarin.

This dependence on a small `dev` set may be rectified by combining the `train` and `dev` sets and performing a K-fold cross-validation, partitioning the data into K subsamples and using each one as the held-out data for the rest. However, this would considerably slow down the feature selection algorithm, as K separate models must be trained for each feature set. Alternately, methods such as adaptation or semi-supervised learning reviewed in Section 2.2.4 could be used to augment the data set.

Returning to the comparison between this chapter and the last, the key distinction is that the `ICSI` prosodic features used as a baseline were designed for English and its

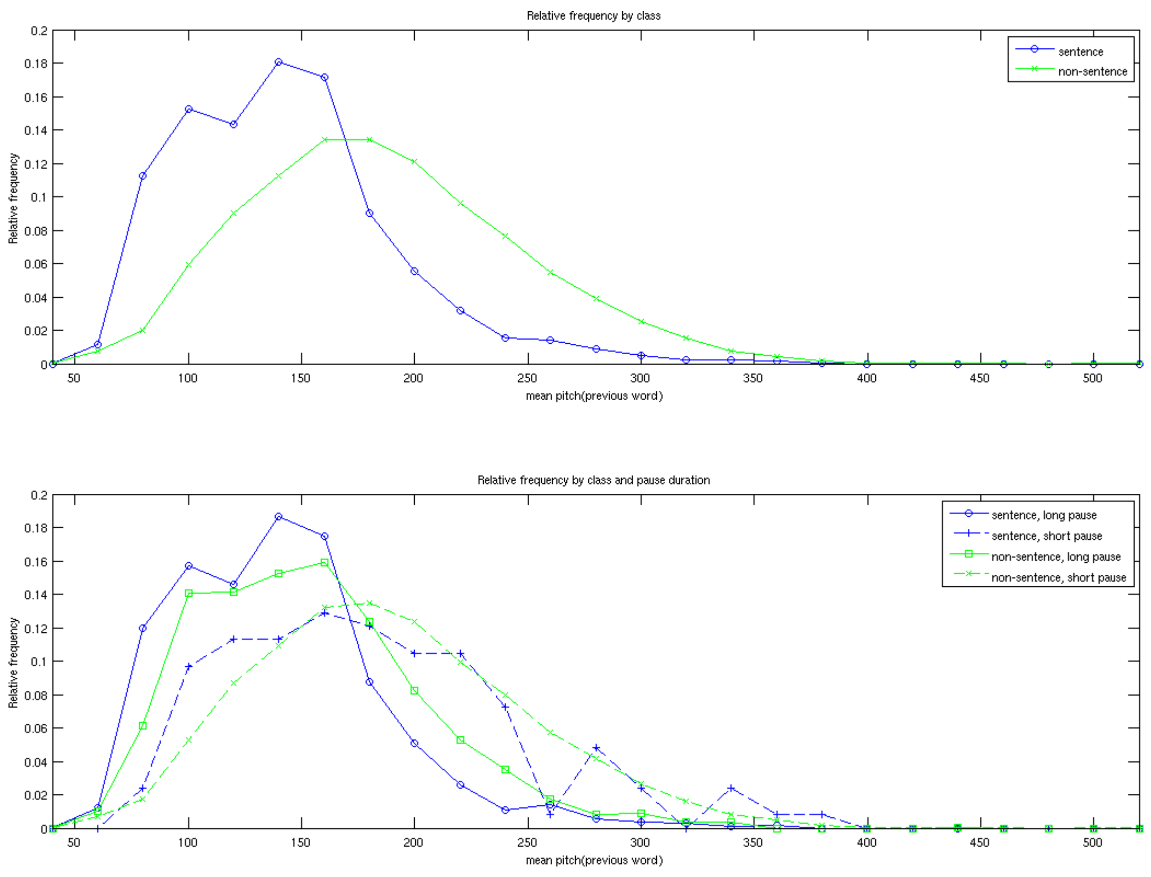


Figure 5.7: Distribution of mean pitch of the word immediately before the candidate boundary in Mandarin relative to class label and short vs. long pauses (shorter or longer than 255ms). All distributions are normalized to sum to one. Top subplot shows distribution relative to class only while bottom subplot shows distribution relative to both variables simultaneously.

pitch features are known to not perform as well in Mandarin. In English, the addition of pitch information to the pause features improves F_1 score by over 3% absolute, while in Mandarin it struggles to manage a third of that. This is attributed to complications due to lexical pitch which, as a critical component of spoken language understanding for Mandarin and other tone languages, has a higher priority than other information regarding the utterance carried by pitch intonation.

It was hoped that the HLDA transform would be able to learn how to extract discriminant features, compensating for the manner in which lexical intonation obscures the pitch contour. For example, it may compensate for the fact that the last pitch in a word strongly influences the first pitch in the next word, or it may rely on more dependable statistics. However, the experimental results show that HLDA performs no better than the `ICSI` baseline pitch features. There are a few possible explanations for this:

1. It is possible that there is no further benefit to be extracted from pitch information. However, given relative utility of pitch in other languages, I am more inclined to accept one of the other explanations.

2. As mentioned in Chapter 4, HLDA probably is not the right learner for this task. Something more general than a linear transform may achieve better results. Furthermore, the current HLDA system does not take into consideration the pause features. As the feature analysis showed, this resulted in features that lose much of their discriminative power when conditioned on pause duration information. One method to address this would be to weight the training data more strongly toward the examples that the pause features misclassify.

3. To compensate for lexical intonation, using the same pitch statistics as the baseline features might not have been the correct place to start. By the time the feature pre-processing reaches the word-level pitch statistics, either the effects of the lexical intonation have been irretrievably insinuated into the data or the HLDA learner is not powerful enough to separate it out.

It should be noted that the HLDA system does not make use of Mandarin tone identities from reference or ASR transcripts. One of the main positive points of prosodic features is their ability to be word-independent, and tying them to lexical tones undermines that, though [51] discussed in Chapter 2 does so. My reasoning for not doing so was to see whether the automatic feature design system proposed in Chapter 4 would work without changes in Mandarin, though the results show that it does not work as well as hoped.

The proposed automated feature design system was simplified by the fact that its inputs are word-level observations and its outputs are word-level features. The outputs are necessarily word-level because of the architecture of the sentence segmentation classification system. Furthermore, to directly model lexical tone, the system would have to translate syllable- or frame-level observations into word-level features, which includes accomodating a variable number of syllables/frames. A more complete treatment would include syllable coarticulation; syllable position within the word; the focus or prosodic strength of the word; etc.

However, recall that one of the motivations for automated feature design is for researchers without extensive in-domain knowledge about the language, conditions, and/or task to be able to create pitch features, which generally has been the prerequisite in modern speech research. Thus for future work, creating a language-specific model, though it will very likely produce better results, is antithetical to this objective. Instead, I believe the correct direction should be to design a language-independent system that can be flexibly applied to different scenarios and then adapted to the intricacies of the specific problem if needed.

Chapter 6

Conclusion

The work in this dissertation began with a study of the robustness of a set of prosodic features designed by Shriberg et al. [126, 129], which is well-established and has seen usage in a wide variety of speech processing tasks in English, including syntactic segmentation, speaker recognition, and emotion-related applications. The features have been honed and adapted for over a decade and are thus the product of considerable work by one of the leading researchers in the field. The ability of this feature set to work in a variety of tasks and conditions may be attributed to its diversity of information sources — pitch, energy, segmental duration, and pause duration — and the built-in feature redundancy. This redundancy can especially be seen in the design of the pitch features, which quantify various pitch levels and changes within a word and across word boundaries. While the utility of any particular feature may vary between conditions, it is generally compensated for by other features within its group or other groups of features.

However, the cross-language study in Chapter 3 showed that, while the features perform well in sentence segmentation in English and Arabic, they do not do quite as well in Mandarin. In particular, this is attributed to the pitch features, which were originally designed for and used almost entirely in English, not compensating for the Mandarin lexical tones.

This leads to the question: How does one design pitch features for Mandarin? Or, to be more precise, how does one design pitch features with little available in-domain human expertise. To take an example, the survey of tone languages in Section 5.1.1 showed that different languages, while sharing some general properties, can be quite idiosyncratic, and thus experience with one may not be that informative of others. Of course, to quote Newton, one should stand on the shoulders of giants and read the relevant literature to gain expertise, but this can be a problem with little-studied languages. While Mandarin does not fall into the category of little-studied languages, my work was prompted by shortcomings of the original pitch features in Mandarin. Furthermore, a pattern that emerges from a reading of the literature is that most prosodic features were, like the `ICSI` prosodic features designed by Shriberg, designed and tweaked by hand as a result of much experimentation, which seems odd for a field so closely related to machine learning.

Therefore this dissertation set out with two goals: (1) to see how close an automated feature design system can come to the performance of a well-designed set of features, thus saving considerable time; and (2) to determine whether the feature design system can learn to handle intricacies not explicitly programmed into its model, in this case compensating for the effect Mandarin lexical pitch has on pitch features.

The proposed method was to use an HLDA discriminant transform to train features that seek to separate the two target classes, followed by feature selection. These are combined with the strongly predictive pause features, and the sentence segmentation classification proceeds as in the baseline system. One system parameter, how the HLDA treats missing values in its training data, turned out to not make much difference as missing values are fairly rare in these corpora.

One issue that occurred was that the performance gains between different sets of pitch features could be masked by variability in scores due to thresholding the classifier posterior probability. This was especially problematic in the smaller Mandarin corpus. This led to a greater reliance during data analysis on oracle F_1 scores, which are comparable to equal error rate and other ROC curve-based measures that do not rely on held-out data to train a posterior probability threshold.

Another issue with the HLDA system was that, while pitch and log-pitch word-level statistics are highly correlated, when both were provided to the AdaBoost classifier, it was able perform better than with either one alone. However, after passing through the HLDA transform, all three sets of statistics performed much the same. An analysis of the HLDA transform matrix showed that, indeed, it was extracting similar features for all three sets of statistics. The loss of performance in the pitch + log-pitch statistics is attributed to the linear transform property of HLDA not being able to cope with the highly correlated data. For this reason, rather than refine the HLDA system, future work should employ a more general model.

From the feature selection experiments, we saw that the ordering of the HLDA features by their eigenvalues is not a strong predictor of whether to include it in the feature subset or not. Analysis of the relative distributions of the HLDA features showed that, because the HLDA did not use pause information during training, the resulting pitch features have substantial redundancy with the pause features. Given the importance of pause information in sentence segmentation, future work should make use of this information in the training of features, as well as any other known details about the system, such as the classifier.

To preempt the criticism that this work does not use particularly sophisticated machine learning methods, I note that, to my knowledge, this is the first attempt to use automatic feature design for prosodic features, though it has been applied elsewhere in speech and image processing. By first trying something simple and seeing where it falls short may be more informative than starting with an elaborate model that is more difficult to interpret. Furthermore, sometimes LDA is enough, and it has found extensive usage in automatic feature design for facial and image recognition.

Returning to above objectives, this work finds that, when limited to the same information as the expert-designed features, the HLDA system does not perform as well as the baseline pitch features. This is not surprising, as a lot of thought has gone into the baseline features and the HLDA system is rather rudimentary. However, when able to leverage more information, in this case drawing pitch statistics from a wider context around the boundaries being classified, the HLDA system can perform about as well as the baseline features. This may be the most important result of this work, that an automatic system can derive features comparable to a well-established set of features.

Each feature set plays to its strengths: the machine learning system is only as good as its model but can process large amounts of data; in contrast, the human-designed features can draw upon the knowledge and creativity of their designer, but are limited by the relevant experience of said designer and the complexity that the human brain can handle. On the latter, in the case of the baseline features, the designer voluntarily restricted the features to statistics from just the two words surrounding the boundary. Regarding the former, this was one of the motivating factors for studying automatic feature design.

As for the second objective, sadly I cannot say that the HLDA system was able to compensate for Mandarin lexical pitch. While it could, under certain conditions, perform as well as the baseline features, as mentioned above the baseline pitch features do not perform particularly well in Mandarin. One reason may be that HLDA is not the right learner for this task, again suggesting that future work use a different model rather than tweak the current one.

The other explanation segues into an issue not closely examined in the study and thus opens it up to criticism, namely the pitch pre-processing in the extraction of the pitch statistics, which are the foundation for both the baseline pitch and HLDA features. The HLDA system was originally designed under the assumption that most of the value-added in the feature design process was in the creation of various combinations and normalizations of the pitch statistics. However, results show that the pitch statistics, without further processing, contain significant discriminative ability already. Thus future work should consider other information sources and, for pitch features, examine whether a statistical learner can start from an earlier stage in the pitch feature extraction and still achieve performance comparable to the baseline.

Evidence suggests that starting with word-level statistics may be too late to address Mandarin lexical tone. Rather, future work with a model using syllable- or lower-level features and lexical tone identities may work better. The literature repeatly notes that one of the strengths of prosodic features and why they are used in a variety of speech tasks is their word-independence, making them robust to ASR errors that undermine language models while complementing their lexical information. Thus automatic feature design systems may want to be wary of being dependent on lexical tones from transcription, though energy-based syllable time alignments and lexical tone identification may be fairly reliable. For the objectives of system portability and reducing the time-investment needed for feature design, I believe the challenge should remain the creation of a lexical- and language-independent system for the analysis of prosodic components.

Finally, to quote one of my professors: "In high school, you learn to follow instructions. In undergrad, you learn to answer questions. In graduate school, you learn to ask the right question." The questions this thesis asks are, "Is the automatic feature design of prosodic features feasible? And even if so, do we care?" The results show that, yes, by being able to leverage more information, machine-designed features can perform as well as human-designed feature sets.

As for the latter, that is a more subtle question. History has shown that machine learning algorithms often outperform systems overly dependent on human design given sufficient relevant training data. That is not to say human acumen and expertise is useless or has no role in the design of better learning algorithms and systems. Granted, there are many machine learning tasks which perform quite well with human-designed features. However prosody is complicated. The modulation of pitch, rhythm, and stress intimates all manners of syntactic, semantic, and emotional information. The design of prosodic features is not straightforward, and thus I believe automating the design process is a worthwhile pursuit.

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Appendix A

Pitch Features

The following are the pitch range and pitch reset features used in this dissertation based on Ferrer [34] and Shriberg et al. [34, 129]. They are detailed here for the reader to better understand the features used in this dissertation and the process of feature design.

A.1 Basic Variables

This section contains variables extracted from the pitch contour. The pitch features used by the segmentation classifier in Sections A.2 and A.3 are functions of these variables.

A.1.1 Pitch statistics

These are word-level statistics used as the basis for the baseline pitch features and as inputs to the HLDA feature system. As mentioned in Section 3.1.1, some pre-processing is performed prior to the calculation of these features. A pitch tracking algorithm estimates the fundamental frequency of voiced speech for each 10ms frame using a 50ms window. A lognormal tied mixture (LTM) model [138] removes halving and doubling error while estimating the speaker parameters in Section A.1.2. The pitch contour is then median filtered with a 5-frame window to compensate for pitch tracker instability during voicing onset. This is followed by a piecewise linear stylization of the pitch contour [137] to remove microintonation.

From this stylized pitch contour, word-level pitch statistics are calculated over the word regions provided by ASR time alignments. The following features refer to the word before the candidate boundary; a `_NEXT` suffix denotes the word after the boundary.

- `FIRST_PWLFIT_F0` = the first pitch in the word (recall pitch is only calculated for voice speech)
- `LAST_PWLFIT_F0` = the last pitch in the word
- `MAX_PWLFIT_F0` = the maximum pitch in the word
- `MIN_PWLFIT_F0` = the minimum pitch in the word
- `MEAN_PWLFIT_F0` = the mean pitch in the word

[129] also uses pitch statistics extracted over windows: the 200ms window before the candidate boundary; and the 200ms window after the candidate boundary.

A.1.2 Speaker parameters

The following are speaker pitch characteristics parameters used for speaker normalization. Speaker segmentation and labels are provided by speaker diarization [163], and for each speaker their LTM parameters are estimated from all pitch frames with that speaker's label.

- `SPKR_FEAT_MODE` = exp(`SPKR_FEAT_MEAN_ALPHA`)
- `SPKR_FEAT_BASELN` = 0.75 exp(`SPKR_FEAT_MEAN_ALPHA`)
- `SPKR_FEAT_TOPLN` = 1.5 exp(`SPKR_FEAT_MEAN_ALPHA`)
- `SPKR_FEAT_RANGE` = `SPKR_FEAT_TOPLN - SPKR_FEAT_BASELN`

where `SPKR_FEAT_MEAN_ALPHA` is the mean LTM parameter of the speaker. Note that all of the above parameters differ only by a scaling factor. This is why the HLDA feature system used only one speaker normalization parameter.

A.2 Pitch Reset

This section contains features that measure pitch dynamics across the candidate boundary, which includes pitch reset that cues breaks between syntactic units.

The following are fairly direct measurements of pitch reset. The first is the pitch difference across the candidate boundary, and the latter compares the starting points of the two words, both features using log-ratio.

- `F0K_WRD_DIFF_ENDBEG` = log(`LAST_PWLFIT_F0` / `FIRST_PWLFIT_F0_NEXT`)
- `F0K_WRD_DIFF_BEGBEG` = log(`FIRST_PWLFIT_F0` / `FIRST_PWLFIT_F0_NEXT`)

The above two features used pitch values from a particular frame within the word, which may be less robust than the max, min, and mean statistics derived over all voiced frames in the word. As seen in Table 5.3, the first and last pitch have higher variances than the min and mean statistics while pitch peaks generally are important prosodic cues (see Section 2.1). The following log-ratio features are calculated from max, min, and mean. Note the intentional redundancy of using all the statistics instead of relying on just one statistic from each word, which makes the feature set as a whole more robust.

- `F0K_WRD_DIFF_HIHI_N` = log(`MAX_PWLFIT_F0` / `MAX_PWLFIT_F0_NEXT`)
- `F0K_WRD_DIFF_HILO_N` = log(`MAX_PWLFIT_F0` / `MIN_PWLFIT_F0_NEXT`)
- `F0K_WRD_DIFF_LOLO_N` = log(`MIN_PWLFIT_F0` / `MIN_PWLFIT_F0_NEXT`)
- `F0K_WRD_DIFF_LOHI_N` = log(`MIN_PWLFIT_F0` / `MAX_PWLFIT_F0_NEXT`)
- `F0K_WRD_DIFF_MNMN_N` = log(`MEAN_PWLFIT_F0` / `MEAN_PWLFIT_F0_NEXT`)

The following are similar features, but with speaker normalization.

- F0K_WRD_DIFF_HIHI_NG = (log(MAX_PWLFIT_F0) / log(MAX_PWLFIT_F0_NEXT)) / SPKR_FEAT_RANGE
- F0K_WRD_DIFF_HILO_NG = (log(MAX_PWLFIT_F0) / log(MIN_PWLFIT_F0_NEXT)) / SPKR_FEAT_RANGE
- F0K_WRD_DIFF_LOLO_NG = (log(MIN_PWLFIT_F0) / log(MIN_PWLFIT_F0_NEXT)) / SPKR_FEAT_RANGE
- F0K_WRD_DIFF_LOHI_NG = (log(MIN_PWLFIT_F0) / log(MAX_PWLFIT_F0_NEXT)) / SPKR_FEAT_RANGE
- F0K_WRD_DIFF_MNMN_NG = (log(MEAN_PWLFIT_F0) / log(MEAN_PWLFIT_F0_NEXT)) / SPKR_FEAT_RANGE

Shriberg et al. [129] also use versions of the above ten features using the 200ms window statistics mentioned in Section A.1.

A.3 Pitch Range

The features in this section measure pitch variation within a word with an eye toward pitch reset. There is considerable use of speaker LTM parameters as a reference point for the variation.

The following features examine how low the word before the boundary drops. Both absolute pitch difference and log-ratio are used as it is not clear which is more appropriate, though the feature are highly correlated.

- F0K_DIFF_LAST_KBASELN = LAST_PWLFIT_F0 - SPKR_FEAT_BASELN
- F0K_DIFF_MEAN_KBASELN = MEAN_PWLFIT_F0 - SPKR_FEAT_BASELN
- F0K_LR_LAST_KBASELN = log(LAST_PWLFIT_F0 / SPKR_FEAT_BASELN)
- F0K_LR_MEAN_KBASELN = log(MEAN_PWLFIT_F0 / SPKR_FEAT_BASELN)

These features are counterparts to the above features, instead looking at how high the word after the boundary rises.

- `F0K_DIFF_MEANNEXT_KTOPLN` = `MEAN_PWLFIT_F0_NEXT - SPKR_FEAT_TOPLN`
- `F0K_DIFF_MAXNEXT_KTOPLN` = `MAX_PWLFIT_F0_NEXT - SPKR_FEAT_TOPLN`
- `F0K_LR_MEANNEXT_KTOPLN` = log(`MEAN_PWLFIT_F0_NEXT / SPKR_FEAT_TOPLN`)
- `F0K_LR_MAXNEXT_KTOPLN` = log(`MAX_PWLFIT_F0_NEXT / SPKR_FEAT_TOPLN`)

As noted in Secion 4.3.4, the mean pitch of a word appears to be a reliable measure of its height. The following normalize the features based on mean above by speaker range.

- `F0K_ZRANGE_MEAN_KBASELN` = (`MEAN_PWLFIT_F0 - SPKR_FEAT_BASELN`) / `SPKR_FEAT_RANGE`
- `F0K_ZRANGE_MEAN_KTOPLN` = (`SPKR_FEAT_TOPLN - MEAN_PWLFIT_F0`) / `SPKR_FEAT_RANGE`
- `F0K_ZRANGE_MEANNEXT_KBASELN` = (`MEAN_PWLFIT_F0_NEXT - SPKR_FEAT_BASELN`) / `SPKR_FEAT_RANGE`
- `F0K_ZRANGE_MEANNEXT_KTOPLN` = (`SPKR_FEAT_TOPLN - MEAN_PWLFIT_F0_NEXT`) / `SPKR_FEAT_RANGE`

The following features look at pitch peaks in the words before and after the candidate boundary with a variety of speaker normalizations.

- `F0K_MAXK_MODE_N` = log(`MAX_PWLFIT_F0 / SPKR_FEAT_MODE`)
- `F0K_MAXK_NEXT_MODE_N` = log(`MAX_PWLFIT_F0_NEXT / SPKR_FEAT_MODE`)
- `F0K_MAXK_MODE_Z` = (`MAX_PWLFIT_F0 - SPKR_FEAT_MODE`) / `SPKR_FEAT_RANGE`
- `F0K_MAXK_NEXT_MODE_Z` = (`MAX_PWLFIT_F0_NEXT - SPKR_FEAT_MODE`) / `SPKR_FEAT_RANGE`

Lastly, this feature measures the drop in pitch over the word:

- `F0K_INWRD_DIFF` = log(`FIRST_PWLFIT_F0 / LAST_PWLFIT_F0`)