Prosodic features in spoken language identification

Sam Sucik

MInf Project (Part 1) Report
Master of Informatics
School of Informatics
University of Edinburgh

2019

Abstract

TO-DO

Acknowledgements

Thanks to Paul Moore for productive collaboration while building the baseline system, to Steve Renals for his supervision and optimism, and to David Snyder for his advice.

Table of Contents

Chapter 1

Introduction

1.1 Motivation

LID is useful in ASR, in voice assistants, emergency call routing, etc. Traditionally, acoustic features are used (influence of ASR on LID and SID). Prosodic LID is much rarer, although results show that prosodic information can help identify language (Lin and Wang, 2005), and that both LID and ASR can benefit from using acoustic *and* prosodic features (González et al., 2013; Ghahremani et al., 2014). Just last year, a novel architecture for LID utilising *x-vectors* was proposed by Snyder et al. (2018a), dramatically improving the state-of-the-art results. Although the authors find that using bottleneck features from an ASR DNN yields better results than using the standard acoustic MFCC features, even the ASR DNN was trained just using MFCCs. Thus the work ignores the potential of speech information other than that captured by MFCCs.

1.2 Aims

In this work, I aim to reproduce the state-of-the-art x-vector LID system and explore the use of prosodic features in addition to acoustic ones. Because the system uses a relatively novel architecture, in which a TDNN aggregates information across a speech segment, I also compare two types of acoustic features, one which has such aggregation over time encoded (SDC) and one that only contains information about single frames (vanilla MFCC).

1.3 Contributions

1. Adapted an existing x-vector speaker verification implementation (based on Snyder et al. (2018b)) for language identification

2. Explored the choice of classifiers and chose a different one than Snyder et al. (2018a)
3. Prepared the Global Phone corpus for LID with the x-vector system, extending the original partitioning of the corpus into datasets and analysing invalid data
4. Built and evaluated a baseline, end-to-end x-vector LID system using 19 languages of the Global Phone corpus
5. Explored, set and tuned important hyperparameters of the system, mainly the number of training epochs of the x-vector TDNN
6. Researched literature concerning the use of acoustic and prosodic features in language identification, speaker verification and ASR
7. Designed, run and evaluated experiments comparing two types of acoustic features (MFCC and SDC) and two prosodic features (pitch, energy), and their combinations
8. Built a system which has the potential to be open-sourced as part of the Kaldi ASR toolkit, to be used by a wider community

Chapter 2

Background

This chapter elaborates on the key concepts relevant to my work, as shown in this condensed description of the project: Exploring **spoken language identification** in the context of the recently proposed **x-vector** system (contrasted with the more established state-of-the-art **i-vector** approach, followed by the more novel **d-vector** systems), focusing on utilising **prosodic information** in addition to the standard **acoustic information**.

2.1 The task: spoken language recognition

Spoken language recognition means recognising the language of a speech segment. The task is similar to speaker recognition and, in the past, similar systems have been used for the two tasks. Importantly, recognition is typically realised as one of two different tasks:

- Identification (multi-class classification): answering the question "For a speech segment X, which one (from a number of supported targets) is its target (language or speaker) T_x?"
- Verification (binary classification): "Is T_x the target (language or speaker) of the speech segment X?"

Identification is more suitable for use cases with a small and stable set of possible targets – such as the set of supported languages. There, computing the probability of T_x being each of the target languages is feasible. Verification, on the other hand, is more suitable for cases where the set of possible targets less constrained – such as the large and changing set of possible speakers in speaker verification systems. There, it is often infeasible to compute the probability distribution over all possible values of T_x; instead, the system typically focuses only on evaluating the probability of T_x being the hypothesised speaker. Throughout this work, I focus on *language identificaion* (LID) with a *closed set* of target languages (i.e. not including the option to identify a speech segment's language as unknown/other).

2.2 Shallow utterance-level approach to LID: i-vectors

This approach, with its numerous variations, has now been the state of the art for 8 years – since first introduced by Dehak et al. (2011) for speaker recognition and later applied by Martinez et al. (2011) in language recognition.

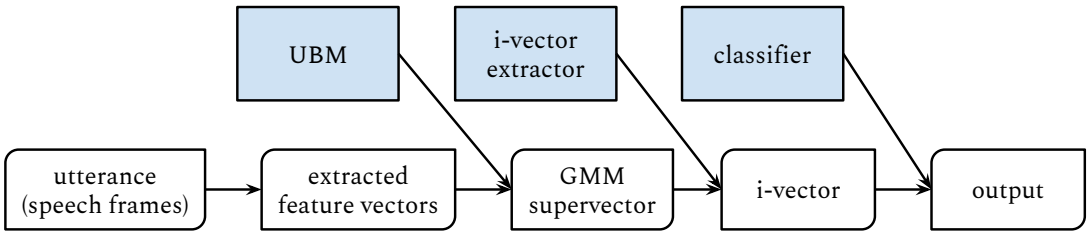


Figure 2.1: Language identification using a typical i-vector system.

The main components of a typical i-vector system, together with their use for prediction, are shown in Fig. 2.1. The universal background model (UBM) is a Gaussian mixture model (GMM) consisting of a large number (e.g. 2048) multivariate mixture components. The UBM is trained using the Expectation-Maximisation algorithm to model the observation space of frame-level feature vectors $\mathbf{x}$ computed from all training utterances (typically 39-dimensional vector using the MFCC features, see Section 2.5.1). Given the trained UBM, an utterance X can be represented by a language- and channel-specific GMM supervector M as:

$$M_X = m + Tw_X \tag{2.1}$$

Here, m is the language- and channel-independent GMM supervector of the UBM (consisting of the stacked means of all mixture components). T is the *total variability matrix* – also called the i-vector extractor, and w_x is the *identity vector* (i-vector) of sample X. The total variability matrix T is "a matrix of bases spanning the subspace covering the important [language and channel] variability in the supervector space" (Martinez et al., p.862). Effectively, T projects between the high-dimensional GMM supervector space and the low-dimensional *total variability subspace* (also called the *i-vector space*). The i-vector w_x is then a low-dimensional set of factors projecting the supervector onto the total variability subspace base vectors. The i-vector extractor T is trained again using Expectation-Maximisation (for details see Mak and Chien (2016, p. 100)). Without providing too much detail, I highlight the aspect that is most relevant to my work: training T is based on calculating and further combining the 0^{th}, 1^{st} and 2^{nd} order statistics which are computed by *summing over the frames* of an utterance.

Once the i-vector extractor has been trained, any utterance can be represented by its i-vector. This enables training a relatively simple and fast classifier operating over the low-dimensional i-vectors. Different classifiers have been successfully used with the i-vector back end; for example, Martinez et al. initially tried using these, all achieving roughly equal performance:

1. a linear generative model – modelling the i-vectors of each language by a Gaussian, with a shared full covariance matrix across all language-modelling Gaussians
2. a linear Support Vector Machine computing scores for all languages by doing binary classification in the one-versus-all fashion
3. a two-class logistic regression also doing one-versus-all classification.

At test time, a sequence of feature vectors for utterance X is projected using the UBM into the high-dimensional *supervector space*, producing M_X. Then, T is used to extract the utterance-level i-vector, which is processed by the classifier.

Despite producing utterance-level scores, I describe the i-vector pipeline as shallow because it aggregates frame-level information over time very early (when projecting X into the supervector space), effectively treating an utterance as a bag of frames and disregarding any temporal patterns spanning over multiple frames.

2.3 Less shallow approach: d-vectors

Introduced for speaker verification by Variani et al. (2014) and later adapted and applied to language identification by Tkachenko et al. (2016), this approach uses neural networks to extract frame-level information, which is then aggregated across frames to produce utterance- or language-level vectors. Importantly, nothing changes about the final classification stage itself: It is the differences in producing the vector representations what makes i-vectors, d-vectors and x-vectors differ from each other.

The biggest change introduced in d-vector systems compared to i-vectors is the notion of frame-level processing while considering each frame's temporal context, i.e. the sequence of a few preceding and following frames. While Variani et al. achieve this by simply feeding the feature vectors of the neighbouring frames together with the frame of interest into a standard deep neural network, Tkachenko et al. use a more suited architecture commonly used for processing temporal sequences in automatic speech recognition: the *time-delay neural network* (TDNN).

A TDNN works like a convolutional neural network (CNN) with 1-dimensional convolutions: only along the time axis, as opposed to the more common 2-dimensional convolutions in image CNNs. Fig. 2.2 shows a TDNN with three layers which processes information over 9-frame contexts. Note that each blue circle from any layer corresponds to the layer itself (a collection of neurons, i.e. *convolutional kernels*), and all blue circles drawn above each other as corresponding to a particular layer are in fact just one circle – the layer itself – sliding over multiple inputs. For example, the convolutional kernels from layer 1 are first applied to feature vectors $\mathbf{x_1}$-$\mathbf{x_5}$, then to vectors $\mathbf{x_3}$-$\mathbf{x_7}$ and then to $\mathbf{x_5}$-$\mathbf{x_9}$. Notice how the network is made more sparse by using *subsampling*, i.e. not using the connections drawn in light grey. A concise and commonly used description of the sketched architecture is shown in Tab. 2.1 (notice the difference between the interval and set notation); "layer context" meant relative to the preceding layer.

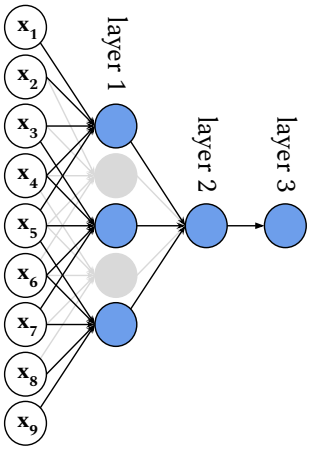


Figure 2.2: Example of a time-delay neural network.

	LAYER CONTEXT	TOTAL CONTEXT
LAYER 1	$[t-2,\ t+2]$	5
LAYER 2	$\{t-2,\ t,\ t+2\}$	9
LAYER 3	$\{t\}$	9

Table 2.1: Example of architecture description of a TDNN (corresponds to Fig. 2.2).

In a d-vector system, a TDNN is trained to do direct frame-wise language identification; for this purpose, an additional softmax layer can be added to produce classification outputs. Often, between the convolutional layers and the output layer the architecture contains a few fully connected layers. After training, the classification layer is disregarded and a frame is instead represented by the activation values from the last hidden layer. The TDNN thus serves as a feature extractor, and the representations produced are referred to as *embeddings*. A d-vector representing an entire utterance is then simply the average of the embeddings of all frames from the given utterance.

Despite the naive averaging, utterances are no longer treated merely as bags of frames because each embeddings contains features extracted over short temporal window: 21-frame windows in the case of Tkachenko et al. and 41-frame windows used by Variani et al., making d-vectors less shallow than i-vectors.

2.4 Deep utterance-level approach: x-vectors

The x-vector approach, introduced last year by the John Hopkins University team first for speaker verification (Snyder et al., 2018b) and subsequently for language identification (Snyder et al., 2018a), can be viewed as an extension to d-vectors, producing utterance-level embeddings even for variable-length speech segments. The architecture consists of (see also Fig. 2.3):

1. the context-aggregating TDNN layers operating at frame level (with the final context window of ± 7 frames),

2. a *statistics pooling layer* which computes the mean and the standard deviation over all frames, effectively changing a variable-length sequence of frame-level activations into a fix-length vector, and

3. an utterance-level part consisting of 2 fully connected bottleneck layers which extract more sophisticated features and compress the information into a lower-dimensional space, and an additional softmax output layer.

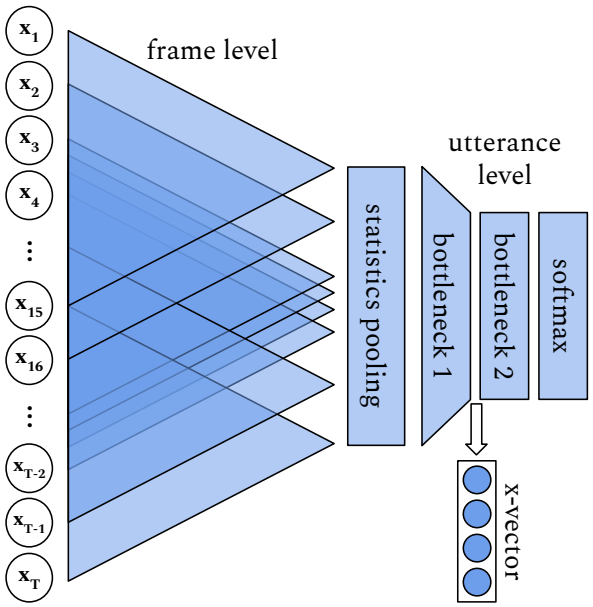


Figure 2.3: A high-level sketch of the x-vector TDNN from Snyder et al..

After the TDNN has been trained, embeddings extracted as the activations of the first bottleneck layer – named x-vectors – are then utterance-level representations and can be used directly as input for a final classifier. The biggest difference compared to the d-vector neural networks discussed in Section 2.3 is that the x-vector TDNN is trained to do not frame-level, but utterance-level classification. The utterance-level statistics (mean and standard deviation) are computed *as part of the network* and are further processed by the additional fully connected layers with non-linear activation functions. These bottleneck layers also make it possible to preserve a higher number of useful features after the statistics-pooling layer: By enabling the last frame-level layer to inflate the representations to 1500-D. The bottleneck layers then learn a transform back to the 512-dimensional space (high-dimensional vectors would be inconvenient for the final classifier) while extracting from the aggregated statistics the features most useful for utterance-level classification (not just for frame-level decisions).

Because of being an utterance-level classifier, the x-vector TDNN can be used directly as an end-to-end system, although Snyder et al. found that extracting x-vectors and training a separate classifier to classify them yielded lightly better results. Perhaps an even stronger argument in favour of the two-stage process is that, by using an external light-weight classifier, one can easily change the set of supported languages without having to expensively re-train the TDNN. Snyder et al. showed that simply re-training the classifier is enough to gain very good results for languages the TDNN has not

		Layer context	Total context	Number of units
frame level	layer 1	$[t-2, t+2]$	5	512
	layer 2	$\{t-2, t, t+2\}$	9	512
	layer 3	$\{t-3, t, t+3\}$	15	512
	layer 4	$\{t\}$	15	512
	layer 5	$\{t\}$	15	1500
statistics pooling layer		$[1, T]$	utterance	3000-dimensional output
utter. level	bottleneck 1	N/A	utterance	512
	bottleneck 2	N/A	utterance	512
	softmax	N/A	utterance	L-dimensional output

Table 2.2: Description of the x-vector TDNN from Snyder et al. and used in this work. T is the number of frames in a given utterance. Table adapted from Snyder et al. (2018a, p. 106).

observed during training (although the results are indeed worse than those for observed languages).

The x-vector system consistently beat several state-of-the-art i-vector architectures, which is a particularly interesting finding because i-vector systems have for long been dominant despite the nowadays so ”fashionable” and successful deep learning approaches. Even so, the 2-stage x-vector system using a simple classifier still dominates the end-to-end neural network alternative.

2.5 Features used in language identification

Historically, automatic speech recognition (ASR) has been the most important area of speech processing and it has driven forward other areas including language and speaker recognition. In particular, LID systems still exist mostly as part of ASR systems where the language of speech needs to be identified before attempting to transcribe the speech. Hence, data preprocessing and input feature types for LID systems often come from the ASR area. In particular, the feature extraction processes follow the ASR objectives: To extract the language- and speaker-*independent* information important for discriminating between different phonemes produced by a speaker's vocal tract. The feature types devised for this aim are termed *acoustic features*. However, these features can also be characterised by the information they disregard or at least to not capture explicitly: the language- and/or speaker-*dependent* information: intonation, stress, pitch range, tone, and others, collectively referred to as *prosodic information*.

As this work focuses on exploiting prosodic information to improve LID, it is desirable to understand both acoustic and prosodic features: how they differ, why is prosody

useful and how can prosodic information be modelled in systems that process frame sequences rather than isolated speech frames.

2.5.1 Acoustic features

The most commonly used acoustic feature type are the Mel-frequency cepstral coefficients (MFCCs). These are coefficients that aim to characterise the shape of the vocal tract, which corresponds to characterising the spectral envelope of produced sounds or, in a way, to the actual phones produced. Without providing too much technical detail, I remind the reader of the main steps in computing MFCCs in Fig. 2.4 (for details, see for example Chapter 10 of Holmes and Holmes (2002)).

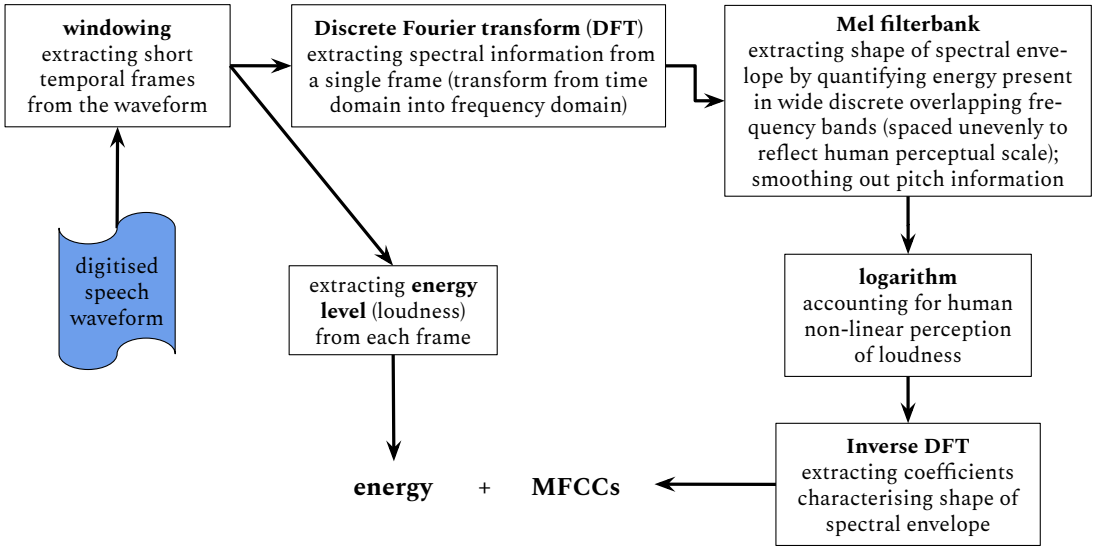


Figure 2.4: Main steps in computing the MFCC features including energy. Adapted from Shimodaira and Renals (2019, p. 10).

To capture local temporal trends going beyond the single frame level, computed features such as MFCCs are often augmented with frame-specific *dynamic* features – *delta cepstra* (also just *deltas* or Δ) and double deltas ($\Delta\Delta$). These are simple approximations of the first and second derivatives of the original acoustic feature, and are computed for frame t like this ($\mathbf{x}_t$ is the MFCC feature vector):

$$\Delta(t) = \mathbf{x}_{t+1} - \mathbf{x}_{t-1}, \quad \Delta\Delta(t) = \Delta(t+1) - \Delta(t-1) \tag{2.2}$$

using the context of ± 2 frames. Such dynamic features are justified especially in systems which apply the bag-of-frames approach, not extracting temporal trends (such as the standard i-vector architectures).

For modelling even longer-range trends specifically in the LID task, Torres-Carrasquillo et al. (2002) used an extension of simple deltas called the *shifted delta cepstra* (SDC) features – essentially, deltas computed at multiple points and stacked together. They can then be used as a new feature vector, or concatenated with the original MFCC

vector. SDCs can be configured by setting their 4 parameters: N, d, p, k corresponding to a N-d-p-k, a typical one being 7-1-3-7. N refers to the number of first cepstral coefficients taken into account (not necessarily the full MFCC vector), p denotes the distance between consecutive points at which deltas are computed, d determines the size of the window for computing deltas ($d = 1$ corresponds to Eq. 2.2) and k is the number of points at which to compute deltas. The SDC terms for frame t and to be stacked together are then:

$$\Delta_{SDC}(t+ip) = \mathbf{x}_{t+ip+d} - \mathbf{x}_{t+ip-d} \qquad \forall i \in \{0,...,k-1\} \tag{2.3}$$

As with standard deltas, capturing long-range trends with SDCs can certainly be beneficial for i-vector systems. Ferrer et al. (2016) used an i-vector system with SDC features as the state-of-the-art baseline system for their novel experiments. Additionally – following the successful application of SDCs by Torres-Carrasquillo et al. in a pre-i-vector system, Sarma et al. (2018) report slightly better results with SDCs compared to using high-resolution MFCCs when training an i-vector architecture with a deep neural network UBM. Still, the usefulness of SDCs is not so clear in architectures inherently able to extract temporal trends.

Compared to the prosodic features described next, the discussed classic acoustic features have one clear advantage where the LID system is part of a bigger ASR pipelines: The two systems can share the same feature vectors without the need to compute additional features solely for the purpose of language identification.

2.5.2 Prosodic features

Prosody is about information other than that directly describing the produced phones; the standard elements of prosody are: intonation/tone, stress and rhythm (Prieto and Roseano, 2018). As discussed below, importantly, each of these elements can be used to differentiate between languages.

- *Intonation* and *tone* are perceived qualities typically associated with the variation of the physical quality called pitch, i.e. the fundamental frequency of vibration of the vocal folds (F_0). The term 'tone' is used where pitch variation is contrastive (i.e. changes to it discriminate between different words): in the so-called *tonal languages*, such as Chinese, Vietnamese and Thai. In each of these languages, a small 'alphabet' of distinct tone levels or tone contours (also called *tonemes* (Trask, 2004)) can be observed as it conveys meaning. Intonation, on the other hand, denotes the non-contrastive pitch variation mostly associated with the speaker's emotions, language, dialect, social background, speaking style, and other factors (see, for example, the study by Grabe (2004) on the intonational differences between different British English dialects).
- *Stress* (also termed *accent*), despite being a somewhat ambiguous term, generally refers to the relative emphasis on certain syllables within a word or words within a sentence, realised as a variation in loudness (*dynamic accent*), pitch (*pitch accent*) or vowel length (*quantitative accent*). Specific *lexical* (intra-word, i.e

syllable-level) stress patterns or rules are often characteristic of a language. For instance, the within-word location of stress is fixed but different for Czech and Polish (*fixed stress*, see Goedemans and van der Hulst (2013a)), or describable by a set of rules in Arabic (*rule-based stress*, see Goedemans and van der Hulst (2013b)).

- *Rhythm* refers to regularity in sub-word unit lengths, with the most recognised theory of *isochrony* categorising languages into three types based on their rhythm: *syllable-timed* where all syllables have roughly equal durations (e.g. French or Turkish), *mora-timed* where all moras[1] have equal durations (e.g. Slovak or Japanese), and *stress-timed* languages, e.g. German and Arabic (here, the intervals between stressed syllables are of equal durations).

Before turning to bespoke alternative features for modelling prosody, it should be noted that some prosodic aspects can be captured by acoustic features like MFCCs. Because prosody surfaces as temporal variation, systems which extract information from frame sequences (such as TDNN-based systems) have the potential to capture it. MFCCs can be (and often are) used together with energy (see Fig. 2.4), which enables capturing dynamic accent. Even without using energy as part of MFCCs, the quantitative accent should be possible to capture because durations of vowels are preserved as a result of windowing extracting the frames at evenly spaced points of a speech waveform. Regarding rhythm, the duration regularity (isochrony) should be possible to capture for syllable-timed and mora-timed languages because syllable boundaries occur at phoneme boundaries, which are captured by acoustic features. For stress-timed languages, however, the units with equal durations are marked by stressed syllables, meaning that this regularity may not be fully captured – in particular if an energy measure is not included in MFCCs, or if the stress is realised as a variation in pitch rather than in loudness. Considering the prosodic aspects that acoustic features alone *could* theoretically capture, I conclude that the most important prosodic feature that can be deemed complementary to acoustic features and added to the input is pitch: to enable modelling pitch accent, tone, and language-specific intonation.

Perhaps unsurprisingly, extracting information from pitch for LID has been explored in the past – although the number of studies is very small compared to those using the conventional acoustic features. Long before i-vectors, Lin and Wang (2005) attempted to do language identification solely from the pitch contour. This was segmented into syllable-like units (around 100-200ms), each contour segment subsequently represented as the first few coefficients of its approximation by Legendre polynomials. Even though the results were far from those achieved by today's systems, it was demonstrated that LID can be done on pitch information alone. Later, Martinez et al. (2012) successfully applied a similar approach to modelling energy and pitch contours within small segments, additionally trying to capture rhythm by providing the duration of voiced speech within the segment as an additional feature. Fusing such prosodic system with an acoustic i-vector system significantly improved the performance. Later, Metze et al. (2013) showed improvements in ASR on tonal (and partly on non-tonal)

[1] Mora is a basic timing unit; a long syllable having two moras and a short syllable having one mora. See Crystal (2008, p. 312) for a broader definition and discussion.

languages when augmenting MFCCs with custom-designed F_0 variation features. Nevertheless, one disadvantage of using pitch persisted: The fact that F_0 is typically considered to be only present in voiced sounds and undefined for unvoiced ones – making a pitch contour based on F_0 discontinuous. While Martinez et al. (2012) effectively ignore this issue by discarding unvoiced frames and thus ending up modelling contours which indeed contain sudden jumps, the problem was addressed in a more elegant way recently by Ghahremani et al. (2014). They developed a pitch-tracking algorithm that approximates pitch values even for unvoiced regions and produces a continuous pitch contour. Adding this feature to MFCCs, the authors report improved ASR performance mainly on tonal languages. To the best of my knowledge, this feature type has not yet been used for language identification.

In this work, I explore two feature types that explicitly help to capture prosodic information: *energy* and *pitch*. I refer to these as the prosodic features.

- By energy I mean the logarithm[2] of the raw energy extracted in the MFCC pipeline right after windowing (as shown in Fig. 2.4). To isolate the effects of using this prosodic feature, I do not include it in any of the acoustic features used in this work. However, I do not exclude the 0^{th} cepstral coefficient from MFCCs, even though it bears some loudness-related information; more specifically, it can be considered as "a collection of average energies of each frequency bands in the signal that is being analyzed" (Zheng and Zhang, 2000).
- By pitch I mean the continuous pitch (and features derived from it) extracted using the Kaldi pitch algorithm presented by Ghahremani et al.. Because this feature type is not well known, I elaborate on it in the next section.

2.5.3 The continuous Kaldi pitch as a prosodic feature

Even though the original paper (Ghahremani et al., 2014) contains a detailed description of the Kaldi pitch algorithm (along with a working implementation as part of the Kaldi ASR toolkit), I provide an additional, more holistic view to give the reader an intuitive understanding of the algorithm and the features it produces (see Fig. 2.5). Perhaps the biggest contribution lies in abandoning the binary decision making about voiced/unvoiced speech, and only calculating pitch for the voiced frames. Instead, soft decisions are made based on the values of the normalised cross-correlation function (NCCF). For two pieces of digitised waveform separated by temporal distance l from each other and represented as vectors $\mathbf{v}_{t,0}$ and $\mathbf{v}_{t,l}$, the NCCF is computed as follows (adapted from Ghahremani et al., Eq. 2):

$$\Phi_{t,l} = \frac{\mathbf{v}_{t,0}^T \mathbf{v}_{t,l}}{\sqrt{(\mathbf{v}_{t,0}^T \mathbf{v}_{t,0})(\mathbf{v}_{t,l}^T \mathbf{v}_{t,l}) + B}} \tag{2.4}$$

[2]The use of logarithm is given solely by the Kaldi toolkit I use for feature extraction, although it is by no means an arbitrary design decision: Human perception of loudness is non-linear and logarithm is used also in the standard MFCC computation pipeline (see Fig. 2.4).

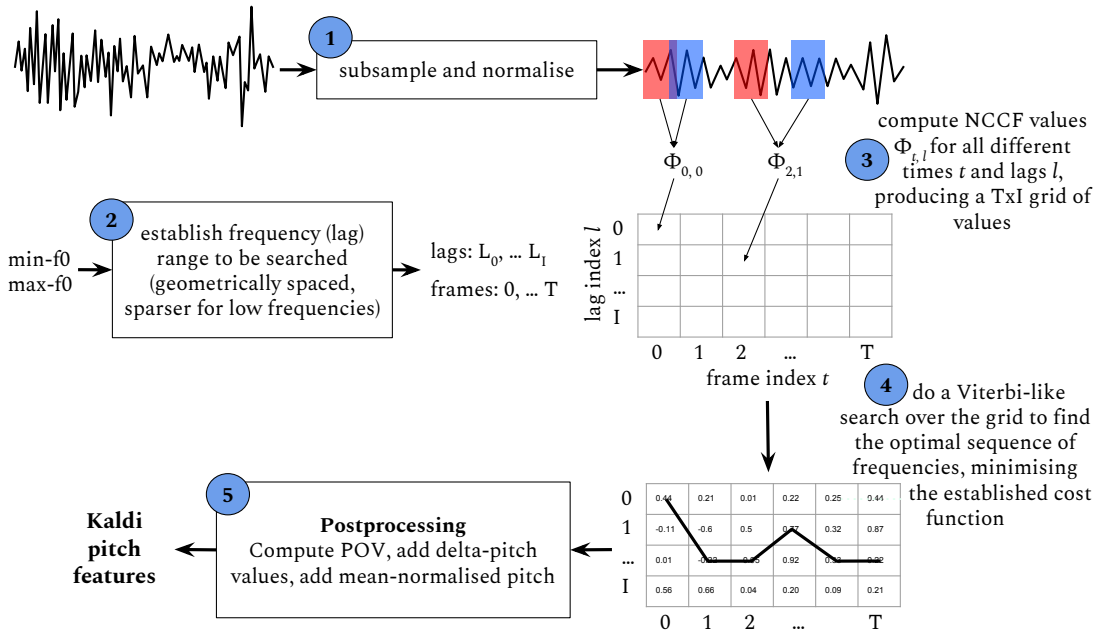


Figure 2.5: The steps of the Kaldi pitch algorithm.

where normally $B = 0$, but the authors use a non-zero value to push the NCCF values towards 0 where the cross-correlation on its own is very low. By computing NCCF for different spacings l – called *lags* by the authors, and being effectively the periods of different hypothesised frequencies – one obtains continuous confidence values about the presence of the corresponding frequencies in the signal for the time position t. After computing these for all temporal positions, the algorithm finds the optimal continuous contour by minimising the proposed cost function (see Ghahremani et al., Eq. 4), which prefers higher NCCF values and penalises too low frequencies and too big frequency jumps.

Finally, the algorithm post-processes the raw pitch contour to provide these additional features:

1. A mean-normalised pitch contour, with the mean computed over 151-frame windows and weighted by a measure roughly corresponding to the log likelihood of a particular frame being voiced (i.e. putting more weight on voiced frames).

2. *Probability of voicing* (POV): A feature which is not a probability, but acts similarly and has been empirically found by the authors to provide improvements in ASR performance.

3. Delta-pitch terms, computed in the same way as the simple deltas in Eq. 2.2.

In this work, I work with all four feature types (the raw pitch contour and the three derived feature types) and refer to them collectively as the Kaldi pitch.

2.5.4 Illustrating the prosodic features used in this work

Having familiarised the reader with the two prosodic features I will use (the energy and the Kaldi pitch), I now illustrate them on a realistic example. Because the multilingual corpus used for this project does not contain English, I used the freely accessible sample utterance from the CSR-I (WSJ0) Complete corpus[3], which has important characteristics such as the recording conditions and the speaking style the same as the corpus I later use (see Section 3.1).

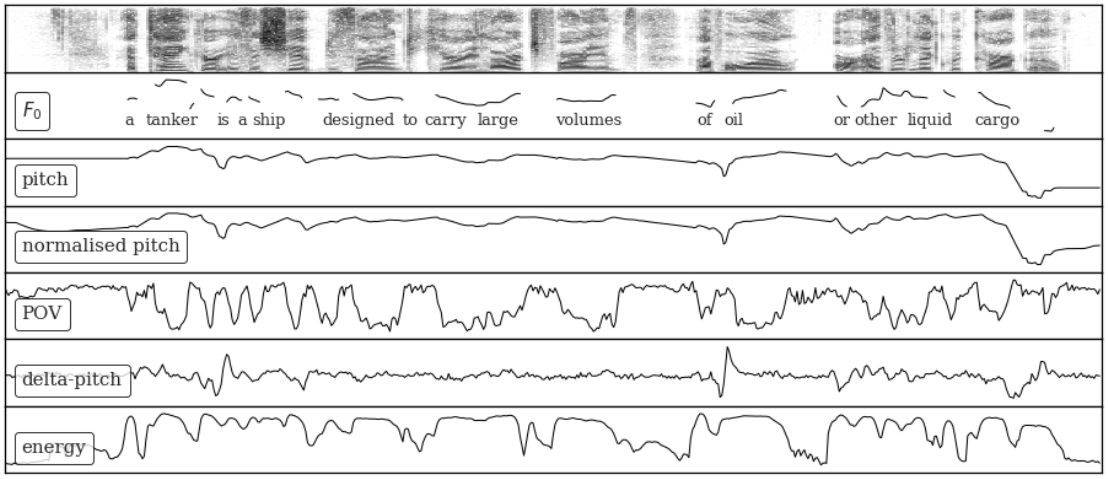


Figure 2.6: The prosodic features I use in this project (together with the spectrogram and the fundamental frequency F_0), illustrated on an English utterance. I manually created the time-aligned transcription for better understanding.

Fig. 2.6 shows the prosodic features on the English utterance. For clarity and comparison, I added the spectrogram as well as the discontinuous F_0 contour – both generated in Praat (Boersma and Weenink, 2019). As expected, the F_0 segments match the Kaldi pitch contour. Notice how the Kaldi pitch does not drop in unvoiced regions, but rather behaves like a smooth bridging between the regions. Also note that the POV values are effectively negated: High values corresponding to the regions where true F_0 is absent and low values marking the voiced regions.

[3] https://catalog.ldc.upenn.edu/LDC93S6A

Chapter 3

Data – GlobalPhone

Because LID systems are often part of ASR systems, it makes sense to use the same datasets to train both. Additionally, however, the U.S. National Institute of Standards and Technology (NIST) has been organising dedicated Language Recognition Evaluation[1] (LRE) challenges since 1996, providing multilingual datasets which are today the standard benchmark for evaluating language recognition systems (used also by Snyder et al. (2018a)). The NIST datasets, however, only focus on narrowband (8kHz) conversational telephone speech and include strong channel variability as a result of the uncontrolled recording environment, which makes it more difficult to analyse any observed effects and attribute them to particular language pair similarities or particular prosodic aspects. In this work, I use a relatively compact ($\sim$400 hours of speech) corpus which is in many aspects different from the NIST datasets.

3.1 Overview of the GlobalPhone corpus

The corpus I use is the GlobalPhone multilingual ASR corpus (Schultz et al., 2013), more precisely its newest version – updated in 2016 and covering 22 languages from around the world (see Fig. 3.1): Arabic (AR), Bulgarian (BG), Chinese-Mandarin (CH), Chinese-Shanghai (WU), Croatian (CR), Czech (CZ), French (FR), German (GE), Hausa (HA), Japanese (JA), Korean (KO), Brazilian Portuguese (PO), Polish, (PL), Russian, (RU), Spanish, (SP), Swahili (SWA), Swedish (SW), Tamil (TA), Thai (TH), Turkish (TU), Ukrainian (UA), and Vietnamese (VN). The corpus follows the style established for English by the Wall Street Journal-based corpora (Paul and Baker, 1992) such as the CSR-I (WSJ0) Complete corpus[2]. It consists of newspaper articles read by native speakers (around 100 speakers per language, each speaker producing about 20 minutes of audio by reading 3-5 articles), recorded as wideband (16kHz) audio in a controlled environment, using a close-talking microphone (in the case of GlobalPhone the Sennheiser microphone HD-440-6).

[1] https://www.nist.gov/itl/iad/mig/language-recognition

[2] https://catalog.ldc.upenn.edu/LDC93S6A

Figure 3.1: Languages of GlobalPhone as shown roughly at the location where they were recorded. Greyed out are Hausa, Swahili and Ukrainian – the three languages I did not use in this work due to corrupt data (see Section 3.4). Also notice that Russian was, in fact, recorded in Belarus, and Spanish in Costa Rica.

The controlled environment, speaking style and nature of the texts (all are major newspaper articles) make the data better suited for analysing effects of, for example, prosodic features: Any observed trends can be more reliably attributed to my controlled independent variables (such as the feature type) or to the known language differences. Another advantage of the GlobalPhone corpus is the rich vocabulary (compare with short telephone conversations in the NIST corpora). Finally, from a linguistic view, the corpus covers a wide range of language families and prosody-based categories, while also providing an interesting sample of related languages in the form of 5 Slavic languages (which the author – as a native speaker of Slovak – can relate to): Bulgarian, Czech, Croatian, Russian, and Ukrainian.

Unfortunately, the corpus does not cover spontaneous speech (which – as known in ASR – is much more challenging than read text). The extremely low channel variability is also a tight constraint and it is possible that, even if prosodic features improve LID performance on this dataset, the results will not necessarily generalise well to more realistic scenarios with greater channel variability and noise.

3.2 Data partitioning

GlobalPhone ships with a partitioning of each language's data into training, evaluation and testing (in GlobalPhone documentation referred to as training, development and evaluation, respectively) sets, with the sizes of the 3 partitions being roughly 80%, 10%, 10%, respectively. However, for the purposes of the x-vector architecture, a 4-way partitioning is required:

1. training set – for training the x-vector TDNN,
2. enrollment set – for training the x-vector classifier,
3. evaluation set – for tuning the hyperparameters of both the TDNN and the classifier,
4. testing set – for final end-to-end evaluation on unseen data.

To create the desired 4-way partitioning, I allocated part of the training data for enrollment. This way, I preserved the original evaluation and testing, enabling fairer comparisons of my results with any other future works that use the GlobalPhone corpus. Because the classifier is typically a much simpler model (with many fewer learnable parameters) than the x-vector TDNN, I allocate only $1/8$ of the training set for enrollment (splitting each language's data in equal proportion). This way, my new training set accounts for roughly 70% of the whole corpus, while the 3 other sets are roughly 10% each.

Importantly, GlobalPhone[3] still misses partitioning for certain languages:

1. no partitioning for Czech, Polish, Tamil, Swahili, Ukrainian, Vietnamese and Wu,
2. incomplete partitioning for Arabic (incomplete evaluation and test sets), and for French, Japanese, Russian (missing evaluation sets for all three languages).

Note that a partitioning in this context is represented simply in the form of partition- and language-specific lists of speakers (identified by their speaker IDs). The ASR GlobalPhone Kaldi recipe[4] extends the original GlobalPhone partitioning to also cover Czech, French, Japanese, Polish, Russian, Swahili and Vietnamese. I utilise this partitioning in order to stay consistent with previous work using the recipe. For the rest of the languages with incomplete or missing partitioning (Arabic, Tamil, Ukrainian and Wu), I partitioned the data myself, following the same approach as the GlobalPhone authors – the only imposed constraint being: "no speaker appears in more than one group [partition] and no article is read by two speakers from different groups" (Schultz, 2002, p. 348). This constraint, however, could only be satisfied for languages which contained speaker metadata information (i.e. which articles were read by the particular speaker). Because this metadata was missing for Bulgarian, French, German, Polish, Tamil, Thai and Vietnamese, the splitting of the original training set into training and enrollment portions (and, in the case of Tamil, the entire 4-way partitioning) for these languages was done solely on a random basis.

I automated the entire partitioning process such that it would never allow one speaker to appear in multiple sets. Further, the way I understand the declared 80%-10%-10% splitting is that it is the *numbers of speakers* for each languages that are split following this ratio (since there is roughly constant amount of data per speaker). Therefore, the way I realise the desired 4-way partitioning is based on distributing speakers in the desired 70%-10%-10%-10% ratio. Unfortunately, I had to somewhat relax the constraint

[3] as of newest version of its documentation I had access to: v4.1 from January 2016

[4] `https://github.com/kaldi-asr/kaldi/tree/master/egs/gp/s5`

that the same article cannot appear in multiple sets. My implementation attempts to construct such ideal partitioning, but – if it cannot be constructed – the allowed number of article overlaps is iteratively increased (from 0, incrementing by 1) until a satisfying partitioning is found. From all the languages for which the partitioning was generated non-randomly, the following languages had non-zero article overlaps: Arabic (385), Turkish (16), and Wu (49).

For the final partitioning (after excluding languages and speakers with corrupt data, see the next section) is shown in Tab. A.1.

3.3 Data preprocessing

These are the preprocessing steps that were carried out either only once (the time-consuming ones), or repeatedly (once for each of my experiments) but without any changes. Although the Kaldi GlobalPhone recipe was used as a starting point, in the end, most of the used Shell scripts were heavily adapted or re-written from scratch.

Converting data to .wav format was the most time-consuming preprocessing step (taking more than 7 hours) and was done only once. The reason for this step is that the Kaldi toolkit requires .wav files for computing features, but the GlobalPhone audio files are in the Shorten (.shn) format. The conversion itself was done using the `shorten` and `sox` command-line tools. Even though this step could have been made a part of the feature computation pipeline itself – without the need to store all the .wav files – it would be time-consuming as the conversion would have to be repeated.

Organising the data into partitions was done symbolically (without re-organising the .wav files), hence taking very short. This made it possible for the step to be a part of the pipeline repeated separately for each experiment – or each time an utterance or a speaker was found to be unusable due to corrupt data and had to be excluded from the partitioning. Because the previous step did not create any data partitioning (i.e. all .wav files were only grouped by languages), in this step, for each partition, a list referring to the .wav files for that partition's speakers across all languages was compiled (based on the files storing the partitioning described in Section 3.2). In addition to this list (named conventionally `vaw.scp`), a number of accompanying lists was generated as required by the conventions of Kaldi: `utt2spk` (mapping utterances to speakers), `utt2lang` (mapping utterances to languages), `utt2len` (mapping utterances to their lengths), and a number of further lists derived from these essential ones.

Splitting longer utterances into shorter segments was done to match the set-up used by Snyder et al. (2018a): Training set utterances were not split in this step because the x-vector TDNN splits them into chunks of at most 1000 frames (10s) at training time (TO-DO: reference the appropriate implementation section for details). Enrollment set utterances were split uniformly into segments of length 30s, and evaluation and testing set utterances were split into 10s segments (and later also into 3s segments because the trained system in each experiment was additionally tested on 3s segments). Note that I did not discard the cut-offs from the utterance ends (even though they were shorter than the desired lengths). Another downside of the uniform cutting is that

utterances were split unnaturally – not necessarily on breaks, hence creating arbitrary edge boundaries not naturally found in speech. The reason why I chose to implement this way of splitting the utterances was its simplicity; in the future, this would be one of the design decisions I would change.

Computing voice activity decision (VAD) for all segments to identify and later discard the frames containing silence. This was computed using the VAD implementation found in Kaldi, using the parameter values from the speaker recognition x-vector recipe[5], in particular the log-energy threshold of 5.5. Because in my experiments I wanted to frame-wise concatenate feature vectors of different feature types, I needed to make sure I would always discard the very same set of frames for all feature types. Hence, I computed VAD only once – on the MFCC feature vectors – and re-used it to discard silence frames throughout all experiments.

3.4 Dealing with invalid data

While carrying out the preprocessing steps, a lot of data was identified as corrupt:

- while converting .shn to .wav, converting all utterances for Hausa, Swahili and Ukrainian failed with the "No magic number" error thrown by the `shorten` tool[6]
- the following utterances were not converted due to the same error: `095_29` for Bulgarian; `003_2` for German; almost all utterances for speakers `015`, `136`, and up to 3 utterances for speakers `014`, `017`, `021`, `022`, `024`, `026`, `031`, `036`, `058`, `139` in Portuguese; utterance `087_102` in Russian; utterance `007_77` in Turkish; and utterance `084_122` for Vietnamese
- while computing VAD, the `compute-vad` binary throwing the "Empty feature matrix for utterance [utterance-ID]" error for utterances `058_16` and `058_18` in Portuguese

Naturally, the utterances which could not be converted were discarded. I also discarded the Portuguese speakers `015` and `136` altogether. Most importantly, the three problematic languages – Hausa, Swahili and Ukrainian – were not used any further, only the 19 remaining languages.

3.5 Overview of the data used

I present an overview of the data I ultimately used in my experiments – after discarding the invalid data. Tab. 3.1 shows the total data amounts for each language and partition.

[5] `https://github.com/kaldi-asr/kaldi/tree/master/egs/sre16/v2`, this is the recipe I adapted for LID in my implementation of the x-vector system.

[6] reported also here: `https://wiki.inf.ed.ac.uk/CSTR/GlobalPhone`, although only for a few utterances

A detailed list of speakers contained in each partition (so that my partitioning can be replicated by other future works) is in Tab. A.1 in the appendix.

Notice that the data amount varies across languages for a given partition (i.e. languages are represented unequally in the corpus – compare Wu and Japanese), and even the declared 80%-10%-10% split from the original GlobalPhone partitioning is not too reliable in some cases – for instance Thai, German, Mandarin and Spanish – although, in other cases, it does result in a split close to the declared one (such as for Korean, Swedish and Turkish). Further, the per-speaker amounts of data are clearly not equal, see Wu where there are 6 training-set speakers vs 4 testing-set speakers, yet the testing set has a greater total amount of data than the training set. While attempting at a perfect split is possible, instead, I appreciate the realisticity of certain languages being under-represented, and account for this in training the x-vector classifier (see [TO-DO: add reference once the section is written] for details of how this is implemented).

	TRAINING	ENROLLMENT	EVALUATION	TESTING
AR	14.5	1.4	1.7	1.4
BG	15.1	2.0	2.3	2.0
CH	23.7	3.1	2.0	2.4
CR	10.5	1.6	2.0	1.8
CZ	23.7	3.1	2.4	2.7
FR	20.1	2.7	2.1	2.0
GE	13.2	1.7	2.0	1.5
JA	29.2	3.0	0.9	0.8
KO	14.6	2.2	2.2	2.1
PL	17.0	2.3	2.8	2.3
PO	20.8	1.9	1.6	1.8
RU	17.3	2.5	2.5	2.4
SP	16.1	2.3	2.1	1.7
SW	15.4	2.0	2.1	2.2
TA	10.7	2.2	1.1	1.3
TH	22.0	2.9	2.3	0.9
TU	11.6	1.7	2.0	1.9
VN	15.8	1.7	1.4	0.8
WU	1.0	0.8	0.7	1.1

Table 3.1: Amount of data (in hours) for each language and partition after excluding invalid data

Chapter 4

Implementation

In this chapter, I describe the entire architecture and computing environment. Importantly, for the early implementation stage, I teamed up with Paul Moore and a big part of the baseline system was implemented jointly – with his contributions. Naturally, in my writing, I focus more on parts which I developed independently, without Paul's help. These are in particular: splitting utterances into shorter segments; early and intermediate fusion of different feature types; choosing and adapting the classifier; exploring the number of training epochs of the TDNN.

As a matter of fact, the codebase of this project consists primarily of adapted existing implementations. Nevertheless, I describe the architecture in detail. However, I make it explicit where the design or hyper-parameter decisions were made by myself (possibly in collaboration with Paul). In the rest of the cases, the reader should implicitly assume that the decisions were made by the authors of the original implementations and found to work well. Importantly, my work does not primarily focus on optimizing the architecture or hyperparameters – only on the different ways in which various feature types can be used and combined to improve LID performance.

4.1 The Kaldi toolkit

As hinted in earlier chapters, the system was implemented in the Kaldi toolkit[1]. First presented by its authors in (Povey et al., 2011) around the time i-vectors were first proposed, Kaldi is the most popular research toolkit for speech processing – originally developed for ASR, but nowadays also used for speaker and language recognition. As an actively maintained open-source toolkit, it reflects the state of the art research and contains working implementations of many accompanying published papers. (After all, the top-class research community significantly overlaps with the community of Kaldi developers.)

To understand what it means to implement an architecture like the one I use in Kaldi, one should understand and appreciate the three layers of code Kaldi contains:

[1] `http://kaldi-asr.org/`

1. **Kaldi binaries** (written mostly in C++) provide low-level, task-specific functions, e.g. for computing MFCC features, training a generic neural network or computing VAD. The binaries typically require input and output in the specific Kaldi formats[2] and can be heavily customised by providing values for numerous parameters. Multiple binaries are often used sequentially to create a multi-step pipelines.
2. **Kaldi scripts** (written mostly in Bash) provide convenient implementations of more high-level steps combining multiple binaries, as well as code for data manipulation. In many cases, these scripts come with useful default values (for the binaries' parameters) empirically shown to work well.
3. **Kaldi recipes** are end-to-end implementations utilising the code from layers 1 and 2 and corresponding to particular studies or experiments, or just replicating a study with a different dataset. They typically come with one top-level script called `run.sh` which calls all other recipe-specific code (or code from layers 1 and 2) and can be run to replicate the study in question provided that one has the appropriate datasets available.

4.2 Kaldi recipes used in this work

My entire implementation is simply a new Kaldi *recipe* (see previous section) and – by the nature of Kaldi – it re-uses a lot of existing code, including the following Kaldi recipes:

- The GlobalPhone (GP) recipe[3], corresponding to Lu et al. (2012), inspired my implementation of preprocessing the GlobalPhone corpus and connecting it with the rest of the architecture – however, with almost all the final code being heavily adapted or re-written altogether with respect to the recipe (see Section 3.3).
- The Speaker Recognition Evaluation 2016 (SRE16) recipe[4], corresponding to Snyder et al. (2018b) contains an end-to-end speaker verification pipeline using x-vectors. This recipe forms the basis for my implementation because there is no published recipe corresponding to the LID x-vector paper (Snyder et al., 2018a), but the two papers by Snyder et al. use the very same x-vector architecture, only substantially differing in the choice of the subsequent classifiers. Fortunately, the LID x-vector paper provides enough information on aspects that are different SRE x-vector architecture, which makes it possible to replicate the x-vector LID system very closely.
- The LRE07 recipe[5], corresponding to Sarma et al. (2018), provided me with scripts for training a logistic regression classifier for LID, which I adapted and connected with the x-vector system.

[2] for more information on Kaldi I/O see `http://kaldi-asr.org/doc/io.html`
[3] `https://github.com/kaldi-asr/kaldi/tree/master/egs/gp/s5`
[4] `https://github.com/kaldi-asr/kaldi/tree/master/egs/sre16/v2`
[5] `https://github.com/kaldi-asr/kaldi/tree/master/egs/lre07/v2`

Apart from the time spent on familiarising myself with Kaldi and understanding, adapting and integrating the enumerated recipes, I put the most effort into connecting the corpus with the x-vector architecture, implementing early and intermediate fusion, computing the various feature types, and building a robust end-to-end pipeline (within the `run.sh` script) which could be run without any changes either as a whole or step by step, only changing a simple configuration file to switch between different experiments.

4.3 Choice of classifier

As mentioned earlier, although the SRE16 Kaldi recipe provides a complete implementation of the x-vector TDNN architecture, it does not use the same classifier as the LID x-vector paper by Snyder et al.. Instead, it uses the Probabilistic Linear Discriminant Analysis (PLDA) model for *binary* classification (because the task is speaker *verification*). The LID x-vector paper, on the other hand, uses a multi-class classifier: more precisely, a GMM classifier trained using the Maximum Mutual information (MMI) criterion as presented by McCree (2014). Unfortunately, as I found out and confirmed with David Snyder, this classifier is not implemented in Kaldi (as of January 2019). While implementing the classifier by myself was an option, it would have consumed too much time and effort – whether implemented in Kaldi (including substantial changes to the Kaldi binaries), or separately (outside the toolkit). Bear in mind that my aim is to build *some* well-performing architecture that leverages the power of x-vectors and enables me to experiment with different feature types and fusion strategies. Hence, I decided to use a different classifier – ideally more established and implemented in Kaldi.

Recently, various types of classifiers have been used on top of i-vector and d-vector models, without a clear comparison – suggesting that the choice of classifier is not nearly as important as back end producing utterance-level vectors. While various varieties of Gaussian classifiers are popular (González et al., 2013; McCree, 2014; Plchot et al., 2016), other approaches such as Support vector machines (Tkachenko et al., 2016; Martinez et al., 2011) and logistic regression (Sarma et al., 2018; Martinez et al., 2011, 2012). I decided to use multi-class logistic regression as it is already implemented in Kaldi in the context of LID as part of the LRE07 recipe. Consulting my decision with David Snyder (2018) only assured me that this was a solid choice.

Of course, there are downsides to using this classifier. As McCree (2014) points out, unlike the discriminative logistic regression, a generative classifier (in this case GMM) can provide out-of-set rejection decisions. This, however, does not speak against logistic regression in my particular case as I do *closed-set* classification. Perhaps more serious inherent disadvantage is that logistic regression uses only linear decision boundaries – compare with GMMs with full covariance matrices, which can model more complex quadratic boundaries. The way this issue is addressed in Kaldi's implementation is by making logistic regression a mixture model, i.e. modelling each class by multiple decision boundaries (for more details see Section 4.4). This way, more complex boundaries can be modelled in the observation space. Because training GMMs

with full covariance matrices is also known to be data demanding and computationally expensive, logistic regression might potentially be preferred where the classifier is to be trained on limited enrollment data: I refer to the findings of Snyder et al. that solid LID performance can be achieved even for languages unseen by the x-vector TDNN. This scenario, however, is not very relevant for LID systems which are parts of ASR systems – there, just training acoustic models for ASR requires amounts of data that would likely be sufficient even for a simple GMM with a full covariance matrix.

4.4 Final architecture

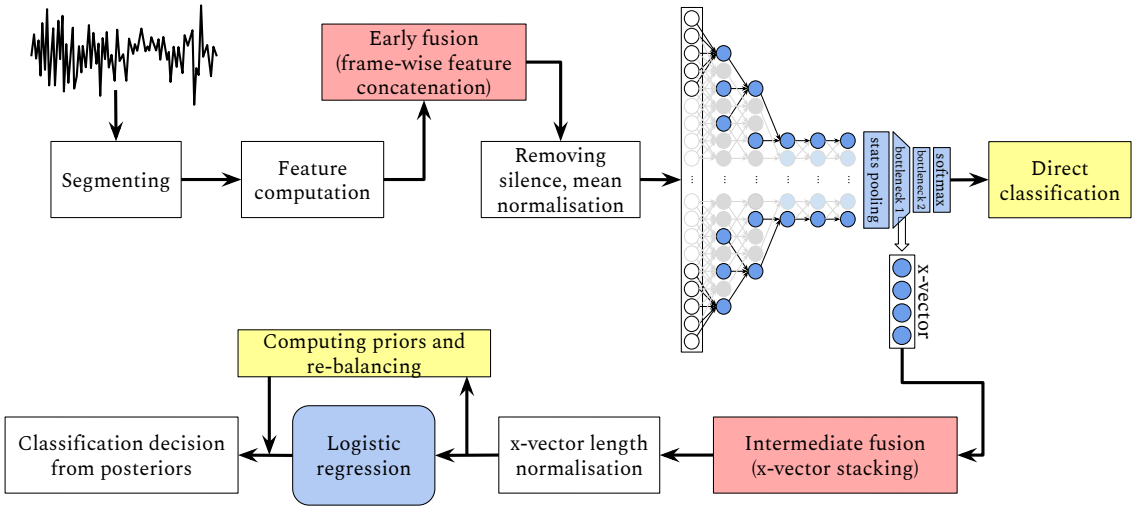


Figure 4.1: An end-to-end overview of my system. Note that the segmenting step does not apply to the x-vector TDNN training data. The fusion steps which can be omitted are highlighted in red while yellow marks the steps only performed at training time.

Fig. 4.1 shows the entire system and what the main steps in running it are. In what follows, I elaborate on each step that has not been described yet.

4.4.1 Feature computation

Throughout my experiments, the following feature types are used (as a refresher, see Section 2.5): MFCC, MFCC+Δ+ΔΔ, SDC, energy, and Kaldi pitch. For more details, see (TO-DO: link the experiments section where the dimensionalities of these are explained).

To enable frame-wise feature concatenation, all feature types were computed with the same frame width of 25ms and frame shift of 10ms. Windowing was done using the Povey window[6], a slight variation of the commonly used Hamming window (Blackman and Tukey, 1958, p. 200); see Fig. 4.2 for a comparisons.

[6]the default windowing function in Kaldi, defined and implemented here: `https://github.com/kaldi-asr/kaldi/blob/master/src/feat/feature-window.cc#L109`

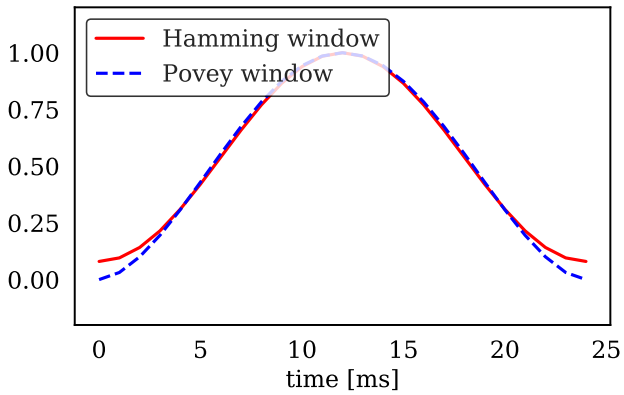


Figure 4.2: Comparison of the Hamming and Povey tapered windowing functions on a frame of length 25ms. (The frame length, however, does not make a difference, it is the different shapes of the windows that matter.)

While MFCC features were computed using the existing script `steps/make_mfcc.sh`, I adapted the script in order to conveniently compute the SDCs, MFCCs with deltas, and the Kaldi pitch. The energy feature was computed as a special case of the MFCC feature – by computing the raw log energy instead of the 0^{th} cepstral coefficient, and discarding all remaining cepstral coefficients.

4.4.2 Early fusion

By fusion I understand simply combining multiple sources of information – be it early utterance representations (feature vectors of different feature types), intermediate representations (in this case x-vectors) or even scores from multiple classifiers (perhaps each trained on x-vectors based on a different feature type). Early fusion here means combining the different feature types as early as possible in the whole pipeline: right after feature computation. For a simple example of early fusion see Martinez et al. (2012) who concatenate for each short speech segment the information about the pitch contour, the energy contour, and the voiced region duration. In this case, I created a script for frame-wise concatenation (splicing) two or more feature vectors for a given utterance. Such precise alignment was possible because I configured all feature types to be computed with the same frame length and frame shift.

4.4.3 Feature vector post-processing

This comprises two steps unchanged from the SRE16 recipe and used in the x-vector LID paper (Snyder et al., 2018a):

1. Removing frames containing silence, using the voice activity decision (VAD). The only difference with respect to the SRE16 recipe is that the VAD is computed only once – using the MFCC features – and used for these and all other feature types (see also Section 3.3).

2. Mean-normalisation is performed by subtracting from each frame the mean over the surrounding 3s window. This is a technique commonly used for processing acoustic features. It preserves relative temporal trends in feature values and discards information about the absolute values. I decided to use it for all prosodic features as well. However, it is possible that capturing tone properties for languages with register tonal systems – i.e. those that mark tone using several flat tone *levels* instead of characteristic tone *shapes* – would better be realised by preserving the absolute values (without mean normalisation).

4.4.4 The x-vector TDNN

Even though this part of the architecture was adapted from the SRE16 recipe without any major changes and is available as an open source, I still provide a description to help the reader appreciate the technical realisation of the core of an x-vector system. (Adding to what I wrote in Section 2.3 and Section 2.4.)

The TDNN's layers are described in Tab. 2.2; the network had 4.4-4.6M parameters (depending on the dimensionality of the input feature vectors). Each layer used the rectified linear unit (ReLU) activation function.

As for the handling of the training data, the first step was discarding utterances shorter than 5s. Looking back, this design decision of Snyder et al. (2018a) may have been challenged as it resulted in discarding 29% of my total number of training utterances. However, the effects of using very short training segments might potentially have a negative impact on the TDNN. After discarding short utterances, the rest of the training data was replicated 35x, randomly shuffled and distributed and saved into 70 training Kaldi archives, each archive corresponding to a training iteration and containing roughly 50,000,000 frames (feature vectors) each – around 140h of speech. This way, each training epoch consisted of processing 70 archives, which, however, translates to only 23 actual iterations as the training was using 3 parallel jobs, each processing one archive per iteration (see bellow for a description of the parallel training). The archives were processed in minibatches of 64 utterances, every minibatch shuffled in each iteration.

In the training phase, the TDNN was trained to directly classify each utterance as one of the 19 languages, the training objective function being multi-class cross-entropy. Each layer was using batch normalisation and, to prevent extreme parameter updates, the maximum parameter change per minibatch – measured as the Euclidean norm over the entire parameter vector of the network – was clipped to 2.0. The training uses several techniques developed or empirically found to be beneficial by the John Hopkins University team. (Most them are mentioned or summarised by Povey et al. (2014), even though the paper corresponds to the `nnet1` neural network implementation in Kaldi, while the SRE16 recipe uses the newer `nnet3` implementation (which contains some additional improvements).) The learning rule is the Natural gradient Stochastic gradient descent (NG-SGD) with momentum (using the coefficient of momentum value of 0.5), with the learning rate exponentially decaying across the training iterations from 0.001 to 0.0001. As a means of regularisation, weak dropout was used,

with the dropout rate varying according to the following schedule: 0 for the first 20% of training iterations, then increasing linearly to 0.1 for the following 30% and finally decreasing linearly until the value of 0 in the last iteration. Perhaps most importantly, the training was realised using 3 parallel jobs, hence speeding it up. The parallelisation translates into 3 model instances being run in parallel and their parameters synchronised (averaged) after each iteration (for mode details, see Povey et al.). Note that the SRE16 recipe varied the number of parallel jobs throughout training linearly from 3 to 8, but the constant 3 jobs better suited my computational environment, hence I made this change to the SRE16 implementation.

As a side note, even though the TDNN is presented as processing variable-length utterances, it still has an upper limit on the utterance length given by the implemented maximum temporal context over which the convolutional filters of its first layer slide: 1000 frames (roughly 10s when using the standard frame shift of 10ms). This means that utterances longer than 10 seconds were split and processed separately. When using the trained TDNN for extracting x-vectors, a long utterance could this way result in multiple x-vectors. This, however, did not apply to my evaluation and testing data as those were segmented into utterances of maximum length 10s.

In terms of runtime, training the TDNN was the most time-consuming step: It took 19 hours (for details, see Section 4.6).

4.4.5 Extracting x-vectors

In this step, 512-dimensional x-vectors were extracted for all enrollment utterances (to train the classifier), and for evaluation and testing utterances (to evaluate the system end-to-end). This step was adapted from the SRE16 recipe with only one change: I implemented discarding all utterances that were shorter than 100 frames (roughly 1s). I decided to implement this thresholding partly to not use segments that are unrealistically and unfairly short (compare with the typical length of 3s, 10s or even 30s), but also to address the issue of a small number of extremely short or corrupt audio files which were causing the Kaldi pitch-tracking binary to fail.

This step was relatively time-consuming: around 1.5h for the enrollment, evaluation and testing data combined when splitting the work into 32 jobs and running them 10 at any time (the limit of 10 given by the computing environment's limit on the number of Slurm jobs, see Section 4.5). Still, given the number of segments to be processed, the per-segment time is very low. With evaluation and testing segments being up to 10s long, I had 17212, 20349 and 18710 segments for enrollment, evaluation and testing, respectively, and the per-segment time was thus only around 100ms.

4.4.6 Intermediate fusion

Intermediate fusion, as opposed early fusion, combines utterance-level (not frame-level) representations (x-vectors) produced by multiple (up to 3) different x-vector TDNNs. The x-vectors are concatenated, creating a longer vector. In my case, the

different networks would have been trained on different feature types, and the fused vectors would be 1024- or 1536-dimensional.

The script for this step was written by me as the intermediate fusion is both an easy to implement and a seldom used strategy – typically, *late* fusion is performed, i.e. combining the final scores from different classifiers (see, for example, Snyder et al. (2018a); Martinez et al. (2012)).

4.4.7 The classifier

As mentioned earlier, the multi-class logistic regression classifier trained to optimise multi-class cross-entropy was chosen and adapted from the LRE07 recipe. I adapted the scripts such that training and scoring could be done separately. This way, both the TDNN and the classifier could be trained, then evaluated end-to-end on the evaluation set used in turn to optimise the hyperparameters of the classifier, and finally the system would be used to only score the testing set utterances.

Importantly, the whitening and dimensionality reduction steps employed by Snyder et al. (2018a) were omitted as I deemed them important for their particular classifier set up, but not necessarily mine. I decided to only keep the one preprocessing step that was included in the LRE07 recipe: length-normalising the vectors before being processed by the classifier.

Perhaps the most interesting aspect of the classifier is the possibility to use it as a mixture model. Even though this functionality is open-sourced and built right into the `logistic-regression-train` Kaldi binary, I explain it so that the reader can appreciate the capabilities of the classifier as well as my later hyperparameter tuning. In order to train the classifier, one provides the following parameters: `max-steps` (the maximum number of iterations of the L-BFGS solver in training the model), `normalizer` (the L2 regularisation coefficient), `mix-up` (the desired number of decision boundaries used to model all classes), and `power` (explained later). Then, training the model comprises the following steps:

1. Train the classifier normally with L decision boundaries ($L = 19$ being the number of classes) for `max-steps` iterations.
2. Determine which classes will be modelled by how many decision boundaries – attempting to end up with `mix-up` or fewer boundaries. In general, no class is modelled by more decision boundaries than the number of corresponding training samples, and bigger classes are modelled by more boundaries. Starting with L boundaries, iteratively, this number is incremented: In each iteration, the class currently with the biggest per-boundary occupancy is granted another boundary, where the per-boundary occupancy of class l is:

$$\frac{(\text{number of training samples for class } l)^{\texttt{power}}}{\text{number of boundaries for class } l}$$

   Notice how the `power` parameter (when set to a value closer to 0) can effectively bring the class sizes closer together, thus causing the number of boundaries to

vary less with class sizes. Values closer to 1.0 (or bigger), on the other hand, cause bigger classes to be modelled by many more boundaries than small classes.

3. Clone the trained boundary from step 1 to create as many boundaries for each class as determined in step 2; adding some random noise to each clone to ensure that the added boundaries are distinct but still roughly based on the original boundary.

4. Train the extended model (now with up to `mix-up` boundaries) for additional `max-steps` iterations.

The trained classifier is then used to compute the posterior probability for a given x-vector x and a particular class l, by accumulating the contributions across the set of boundaries B_l modelling the given class, and scaling by the class prior $p(l)$:

$$p(l|x) \approx p(l) \sum_{b \in B_l} p(x|b) \tag{4.1}$$

Subsequently, x's predicted class is taken to be the one with the maximum posterior.

As mentioned in Section 3.5, the enrollment set was imbalanced and some languages were over-represented while others were under-represented. The mechanism used in the LRE07 recipe to cope with such imbalance is computing scaling factors for the different languages and using these for re-balancing the classifier's priors after it has been trained. Given a value (typically between 0.5 and 1.0) of the parameter s, the prior for language l will be scaled by coefficient c computed as follows:

$$c_L = \left(\frac{C_{l,evaluation}}{C_{l,enrollment}} \right)^s \tag{4.2}$$

where C are the counts of utterances in language l in the respective data sets. In other words, if the distribution of languages in the enrollment set matches that in the evaluation set, all priors will be scaled by the same factor – effectively not being scaled – and the classifier's priors will reflect the distribution observed in the enrollment set. However, if the distributions do not match, the classifier's priors (driven by the enrollment set) will be corrected in the direction indicated by the distribution in the evaluation set. Of course, the evaluation set does not necessarily correctly reflect the language distribution in unseen data. Hence, by setting the s parameter to a value smaller than 1.0, correcting the priors can be made less reliant on the evaluation set's distribution. I keep the value of $s = 0.7$ as used in the LRE07 recipe – particularly because this is not a parameter that could be tuned given one's data, only set to an empirically trusted value. The scaling factors used for rebalancing the classifier (in the 10s condition) are shown in Fig. 4.3. Clearly, languages such as Arabic and Croatian were identified as under-represented and the classifier will be re-balanced to prefer them more. The opposite goes for Japanese or Vietnamese.

Compared to training the TDNN, training the classifier (with the hyperparameter values found in Section 4.6) takes only around 3.5 minutes (in the 10s condition). Producing posteriors and computing the final results for the entire test set takes only around 4 seconds (using a single CPU), corresponding to inference time of only $\sim$0.2ms/utterance.

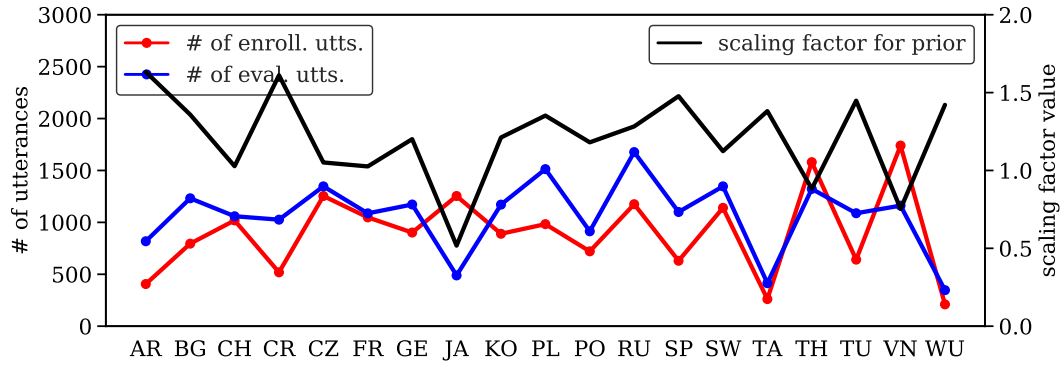


Figure 4.3: Scaling factors used for adjusting the classifier's priors based on the language distributions in the enrollment and evaluation set.

4.5 Computing environment

All experiments were carried out in the School of Informatics' Teaching cluster[7], using GPUs model GeForce GTX 1060 6GB, and CPUs model Intel Xeon E5-2620 v4 (2.10GHz). Note that the GPUs were only used in training the x-vector TDNN and in extracting x-vectors from the trained network – the two most time-consuming stages.

For running jobs requiring GPUs, the Slurm scheduler was used, configured such that a single user like me could only ever run at most 10 Slurm jobs at the same time. As a result of this restriction, in order to speed up my experiments, I set the number of parallel jobs used to train each x-vector TDNN to 3 – so that I could train as many as three TDNN networks in parallel. While the SRE16 recipe uses more jobs, decreasing this number could only help the quality of the final model[8]. Note that each Slurm job was allocated a separate GPU. Thus, each TDNN can be considered to have been trained using three GPUs of the abovementioned model.

4.6 Hyperparameters

The aim of this work is not to extensively tune the hyperparameters of the architectures; instead, I rely on values used in previous successful works of others (provided in the adapted recipes). However, there was a number of parameter which I decided to change or even fine-tune.

As discussed previously, I changed the number of parallel jobs used by the TDNN in its training, and imposed a minimum length on any utterances for which x-vectors would be extracted.

[7] `http://computing.help.inf.ed.ac.uk/teaching-cluster`

[8] as hinted by Dan Povey at `https://groups.google.com/forum/#!topic/kaldi-help/_iyJP-lHkKM`

After initially training the TDNN for 3 epochs and seeing that it took over 8 hours, I decided to first tune the classifier's hyperparameters. This way, the tuned classifier could be subsequently used for end-to-end evaluation of different TDNNs, enabling the tuning of the most important hyperparameter: E – the number of training epochs of the TDNN. As discussed previously, the classifier's hyperparameters were `max-steps`, `mix-up`, `normalizer` and `power`. The last mentioned parameter I fixed to be of the default value 0.15 (also used by the LRE07 recipe) – meaning that the number of decision boundaries was only weakly dependent on the relative class size (in terms of the number of enrollment segments). The other three parameters were tuned using enrollment and evaluation x-vectors extracted from the baseline-case TDNN (i.e. using MFCC features and 10s enrollment segments) trained for 3 epochs. I carried out a 3-dimensional grid search, exploring the following value ranges:

- `max-steps` $\in \{20, 40, 60, 80, 100, 120, 140, 160, 180, 200\}$ (the default is 20, the LRE07 recipe uses 35)
- `mix-up` $\in \{19, 50, 100, 150, 200, 250, 300\}$ (the default is 0, the LRE07 recipe uses 150 for 14 languages)
- `normalizer` $\in \{0, 0.00001, 0.0001, 0.001, 0.01\}$ (the default is 0.0025, the LRE07 recipe uses 0.001)

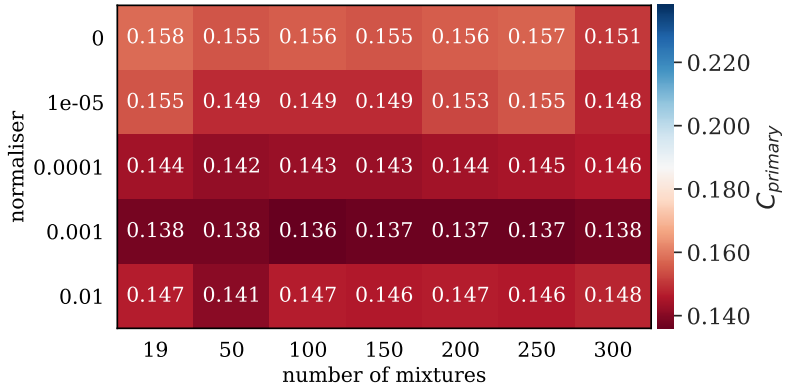


Figure 4.4: Evaluation set $C_{primary}$; the shown value is the best one across all explored values of the `max-steps` parameter.

Fig. 4.4 shows the best result across all numbers of training iterations for each combination of `mix-up` and `normalizer`, showing rather clearly that `normalizer`=0.001 (also used by the LRE07 recipe) is the optimal value within the explored range. Fixing this parameter and plotting just the performance against the number of mixture components `mix-up` (see Fig. 4.5) led me to the conclusion that `mix-up` should be chosen as 50 or 100. Further plotting the performance as varying with the number of mixture components for each number of training iterations separately (Fig. 4.6) shows how not just worse but also unstable the performance is for lower number of iterations. Thus, I decided to use `max-steps`=200 and – even though it seems to not make a big difference – I fixed `mix-up` at the best performing value of 100.

Then, I tuned E. In particular, I wanted to reach a reasonable compromise between too long training runtimes and too low evaluation set performance. E was tuned in the

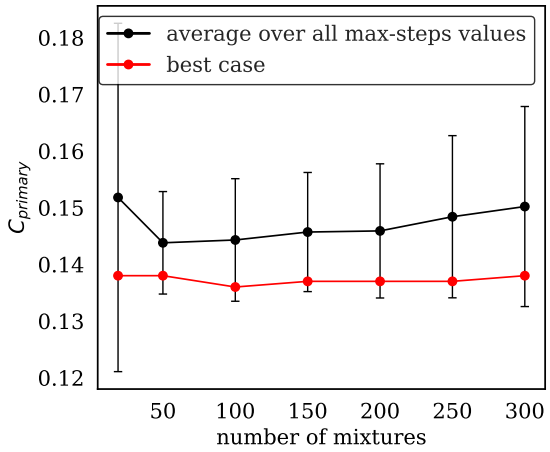


Figure 4.5: Evaluation set $C_{primary}$ varying with the number of mixture components of the classifier.

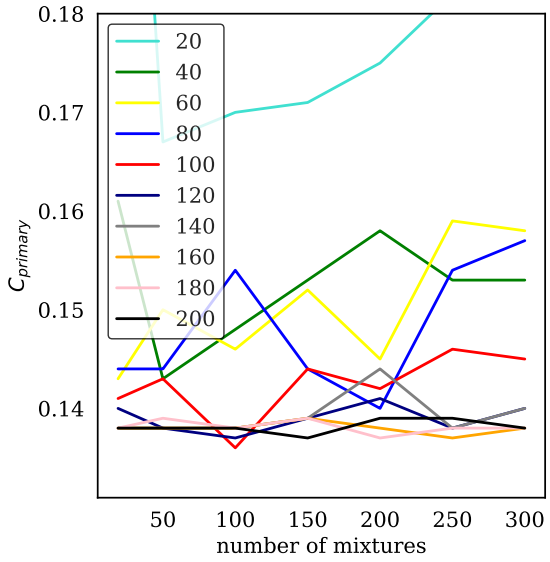


Figure 4.6: Evaluation set $C_{primary}$ varying with the number of mixture components for each explored number of training steps.

baseline condition, i.e. using MFCC features and 10s evaluation segments. The system was evaluated end-to-end, using the optimal values of the classifier established above. The results are summarised in Fig. 4.7. Clearly, the early epochs are the most important, but the performance (in terms of $C_{primary}$) also plateaus fairly quickly: beyond 10 training epochs and, when measured by accuracy, it even starts becoming worse, indicating that the TDNN probably starts to overfit the training data. AS the compromise value of E, I decided to use the ”elbow” point of the $C_{primary}$ plot in Fig. 4.7, where $E = 7$. This implies the training runtime of around 19 hours to train a single x-vector TDNN.

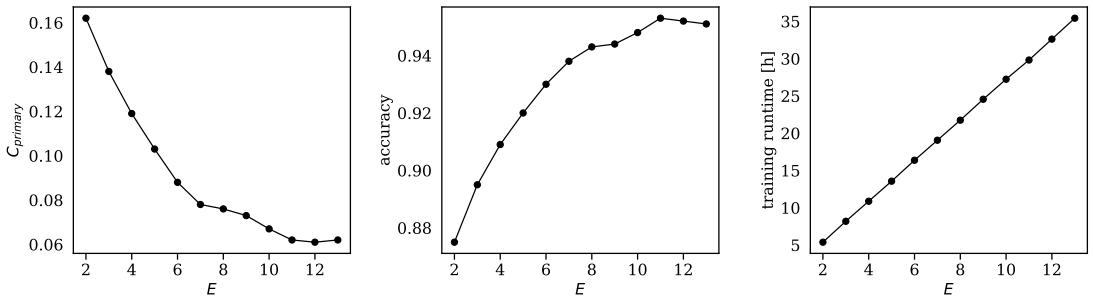


Figure 4.7: Evaluation set performance and training runtime for varying number of training epochs E of the TDNN.

Chapter 5

Experiments

In this chapter, I describe the experiments that I carried out, in the order they were designed. I provide some immediate results and discussion – especially where these directed my decisions in designing the next experiment.

My aims can be summarised into the following key points:

1. Compare the different types of acoustic features in the context of the x-vector system. Dynamic features – be it simple delta terms or the more sophisticated SDCs – were designed primarily to help frame-level models to capture temporal contexts. The x-vector TDNN, on the other hand, does capture such contexts explicitly. Therefore, a question I ask is whether the more sophisticated acoustic features can still improve performance compared to simple MFCCs.

2. Evaluate the usefulness of prosodic features alone. Even though there is no good reason to use only the prosody (i.e. to not consider acoustic features at all), I believe that building a system that uses only prosodic features can help me better understand and analyse the nature and value of the prosodic information.

3. This is my ultimate aim: to evaluate the effect of using both acoustic and prosodic information – combined in different ways.

Throughout all experiments, I use $C_{primary}$ as the main metric – staying consistent with the latest LRE 2017 challenge and the work of Snyder et al. (2018a). In the tables with results, the best result in terms of the $C_{primary}$ value is always put in bold face. Additionally, I also report accuracy and later show confusion matrices as these are easier to intuitively grasp and reason about.

5.1 The setup

definitions of features (dimensionalities) The default condition was to use 10s evaluation and testing segments. As for the feature type, the default was the MFCC features of 23 dimensions without energy (same as Snyder et al. (2018a)). The other two

acoustic features were derived from the computed MFCCs and designed such that their dimensionalities would be roughly the same (for a fairer comparison):

- the MFCC+Δ+ΔΔ features were 69-dimensional, using 23 first-order and 23 second-order delta terms,
- the SDC features were 72-dimensional, using the 9-1-3-7 configuration, i.e. computed at 7 locations using the first 9 cepstral coefficients and discarding the rest of the coefficients.

I made the decision to compute the MFCC features using the default of 23 Mel filters, and on the frequency range of 20-7800Hz inspired by the Kaldi manual[1].

As for the prosodic features, the energy was computed from the MFCCs and was simply a 1-dimensional feature vector per frame.The Kaldi pitch was 5-dimensional, computed using the default parameter values of the Kaldi `compute-kaldi-pitch-feats` binary, in particular using $B = 7000$ (see Eq. 2.4), the penalty factor for frequency jumps of 0.1, and `min-f0`= 50Hz. I changed the `max-f0` from the default of 400Hz to 500Hz, same as the upper F_0 limit used by Lin and Wang (2005).

In addition to the default 10s condition (i.e. evaluation and testing segments being of length $\leq$ 10s), I also evaluate the systems on $\leq$ 3s testing segments (the 3s condition). On these shorter segments, the systems will perform worse, but the results are important because optimising LID performance on short segments is valuable and important for: on-line settings, low-resource settings, settings with frequent code switching, and similar scenarios where the segment to process is very short.

5.2 Comparing acoustic features

In this experiment, I compare systems trained on the three types of acoustic features and evaluated on the testing segments in both the 10s and the 3s conditions.

	10s		3s	
FEATURE	$C_{primary}$	ACCURACY	$C_{primary}$	ACCURACY
MFCC	0.0660	0.943	0.148	0.875
MFCC+Δ+ΔΔ	0.0567	0.952	**0.138**	0.886
SDC	**0.0543**	0.953	0.158	0.868

Table 5.1: Comparing the systems trained on acoustic features.

The results are presented in Tab. 5.1. Clearly, both simple deltas and SDCs improve on the performance achieved by simple MFCCs in the 10s condition – in this case by 14% and 18%, respectively. The relative gain is smaller in the 3s condition. SDCs even make the performance worse, which, I hypothesise, can be attributed to the relatively big context of SDCs (in this case 33 frames), which makes a big portion of the SDC terms only partially computed: For a 3s segment with roughly 300 frames, the SDCs

[1] `http://kaldi-asr.org/doc/feat.html#feat_mfcc`

are incomplete for 32 frames – more than 10%! For the simple delta terms, only 4 terms would be incomplete (2 at either end of the segment). Thus, for shorter segments, features computed over shorter contexts may be favoured.

5.3 Comparing prosodic features

This experiment focuses on comparing systems trained on the two prosodic features, as well as systems where the Kaldi pitch and energy was combined via early and intermediate fusion.

	10s		3s	
FEATURE	$C_{primary}$	ACCURACY	$C_{primary}$	ACCURACY
PITCH	0.327	0.732	0.526	0.575
ENERGY	0.307	0.748	0.520	0.578
PITCH + ENERGY (EARLY)	**0.154**	0.872	**0.314**	0.743
PITCH + ENERGY (INTERMEDIATE)	0.180	0.851	0.347	0.712

Table 5.2: Comparing the systems trained on prosodic features and their combinations.

In line with the results of Lin and Wang (2005) and Martinez et al. (2012), prosodic information on its own is enough for a relatively well performing LID system – achieving accuracy of over 87% on 10s segments and over 74% on 3s segments (but the $C_{primary}$ score being worse by around 150% compared to the best acoustic systems). Unsurprisingly, energy and pitch seem to be capturing different and complementary information, which results in big performance improvements when the two features are combined (relative improvement of roughly 50% and 40% for the 10s and 3s conditions, respectively, when compared to the use of energy or pitch in isolation). The fact of early fusion gaining consistently better results than intermediate fusion I relate to the inherently tied relationship between energy and pitch in the realisation of stress and intonation.

5.4 Combining acoustic and prosodic features

Having shown the individual performances of acoustic and prosodic systems, this experiment finds out whether (and to what extent) the acoustic and prosodic information is complementary, i.e. leading to improved performance when combined. For each acoustic feature type, I combined it with (one or both) prosodic features using either early or intermediate fusion. Notice that – for obvious reasons – the pipeline does not allow the two prosodic features to be fused at the intermediate (x-vector) level and then combined with an acoustic system at the early level. However, three feature types can be combined all at the feature level (early fusion), or the two prosodic features (combined at any of the two levels) can be combined with an acoustic system at the intermediate level.

			10s		3s	
FEATURE COMBINATION			$C_{primary}$	ACCURACY	$C_{primary}$	ACCURACY
MFCC	+	PITCH	0.0693	0.941	0.153	0.871
		ENERGY	0.0581	0.952	0.137	0.888
		PITCH + ENERGY	0.0562	0.954	0.136	0.889
MFCC+ Δ+ΔΔ	+	PITCH	0.0577	0.950	0.134	0.886
		ENERGY	0.0523	0.957	0.129	0.895
		PITCH + ENERGY	0.0544	0.956	0.139	0.888
SDC	+	PITCH	0.0559	0.952	0.159	0.867
		ENERGY	**0.0401**	0.967	**0.128**	0.896
		PITCH + ENERGY	0.0484	0.960	0.137	0.888

Table 5.3: Combining acoustic and prosodic features (early fusion used in all instances).

		10s		3s	
	FEATURE COMBINATION	$C_{primary}$	ACCURACY	$C_{primary}$	ACCURACY
MFCC +	PITCH	0.0624	0.950	0.138	0.886
	ENERGY	0.0556	0.956	0.149	0.878
	PITCH + ENERGY (EARLY)	0.0382	0.968	0.107	0.910
	PITCH + ENERGY (INTERMEDIATE)	0.0501	0.958	0.132	0.890
MFCC+ Δ+ΔΔ +	PITCH	0.0467	0.961	0.120	0.900
	ENERGY	0.0508	0.960	0.140	0.886
	PITCH + ENERGY (EARLY)	**0.0343**	0.971	**0.0993**	0.918
	PITCH + ENERGY (INTERMEDIATE)	0.0511	0.959	0.129	0.895
SDC +	PITCH	0.0622	0.949	0.142	0.881
	ENERGY	0.0674	0.947	0.167	0.864
	PITCH + ENERGY (EARLY)	0.0376	0.968	0.114	0.906
	PITCH + ENERGY (INTERMEDIATE)	0.0545	0.954	0.139	0.883

Table 5.4: Combining acoustic and prosodic systems using intermediate fusion (the combinations of 2 prosodic features used early or intermediate fusion).

Tab. 5.3 shows the results for systems in which an acoustic system and a prosodic one were combined using early fusion, while Tab. 5.4 refers to the systems in which acoustic and prosodic information was combined at the intermediate (x-vector) level. Regardless of the fusion type, combining acoustic and prosodic information clearly improves the performance: Comparing the best acoustic system with the best combined system, the relative improvement in $C_{primary}$ is 37% and 28% for the 10s and 3s conditions, respectively. Moreover, intermediate fusion improves on early fusion by 14% and 22% in the 10s and 3s conditions, respectively, the best system using *both* prosodic features combined as a pair at the feature level (early fusion) as expected, having observed the results of prosody-only system in Section 5.3.

Chapter 6

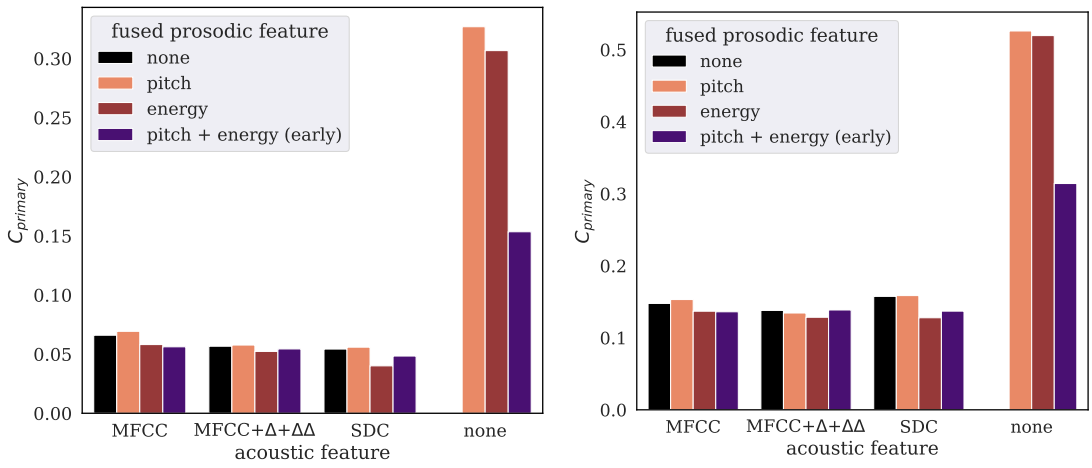
Overall results and discussion

clearly, energy helps MFCCs (compare vanilla MFCC with MFCC+energy (early))

Reporting: overall $C_{primary}$, accuracy (for illustrative purposes), confusion matrix (to see which language pairs are confusing)

Focus on Slavic languages, since there is so many of them (Czech, Croatian, Polish, Russian, Bulgarian) and intonation can be very characteristic and important here (my own intuition, based on my knowledge of Slavic languages).

I ignore BNFs (as used by Snyder and some others). In essence, they're computed from acoustic features. I just wanna know how much the prosodic information can help when combined with acoustic information.



(a) ... (b) ...

Figure 6.1: Evaluation set performance and training runtime for varying number of training epochs E of the TDNN.

Chapter 7

Future work

7.1 Possible directions

Everything that is sensible but unlikely in Year 5.

compute VAD correctly

explore segment boundary effects (but note that uniform segmentation shown to work well: Steve mentioned speaker diarization, I have González et al. (2013) that show the same...)

try late (score) fusion

try bottleneck features instead of acoustic ones and see how much prosody can help

use more noisy data or narrowband to see how well the energy and Kaldi pitch can be extracted there

7.2 Plan for Part 2 of the MInf project

Chapter 8

Conclusions

...

Bibliography

Blackman, R. B. and Tukey, J. W. (1958). The measurement of power spectra from the point of view of communications engineering – part i. *The Bell System Technical Journal*, 37(1):185–282.

Boersma, P. and Weenink, D. (2019). Praat: doing phonetics by computer [computer program]. version 6.0.49. `http://www.praat.org/`.

Crystal, D. (2008). *A Dictionary of Linguistics and Phonetics*. Blackwell, 6th edition.

Dehak, N., Kenny, P., Dehak, R., Dumouchel, P., and Ouellet, P. (2011). Front-end factor analysis for speaker verification. *IEEE Transactions on Audio, Speech, and Language Processing*, 19:788–798.

Ferrer, L., Lei, Y., McLaren, M., and Scheffer, N. (2016). Study of senone-based deep neural network approaches for spoken language recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 24:105–116.

Ghahremani, P., BabaAli, B., Povey, D., Riedhammer, K., Trmal, J., and Khudanpur, S. (2014). A pitch extraction algorithm tuned for automatic speech recognition. *IEEE ICASSP*, pages 2494–2498.

Goedemans, R. and van der Hulst, H. (2013a). Fixed stress locations. In Dryer, M. S. and Haspelmath, M., editors, *The World Atlas of Language Structures Online*. Max Planck Institute for Evolutionary Anthropology, Leipzig.

Goedemans, R. and van der Hulst, H. (2013b). Weight-sensitive stress. In Dryer, M. S. and Haspelmath, M., editors, *The World Atlas of Language Structures Online*. Max Planck Institute for Evolutionary Anthropology, Leipzig.

González, D. M., Lleida, E., Ortega, A., and Miguel, A. (2013). Prosodic features and formant modeling for an ivector-based language recognition system. *IEEE ICASSP*, pages 6847–6851.

Grabe, E. (2004). Intonational variation in urban dialects of English spoken in the British Isles. *Regional variation in intonation*, pages 9–31.

Holmes, J. and Holmes, W. (2002). *Speech Synthesis and Recognition*. Taylor & Francis, Inc., Bristol, PA, USA, 2nd edition.

Lin, C.-Y. and Wang, H.-C. (2005). Language identification using pitch contour information. *IEEE ICASSP*, 1:I/601–I/604.

Lu, L., Ghoshal, A., and Renals, S. (2012). Maximum a posteriori adaptation of subspace Gaussian mixture models for cross-lingual speech recognition. In *IEEE ICASSP*, pages 4877–4880. IEEE.

Mak, M.-W. and Chien, J.-T. (2016). Interspeech 2016 tutorial: Machine learning for speaker recognition. http://www1.icsi.berkeley.edu/Speech/presentations/AFRL_ICSI_visit2_JFA_tutorial_icsitalk.pdf.

Martinez, D., Burget, L., Ferrer, L., and Scheffer, N. (2012). ivector-based prosodic system for language identification. In *IEEE ICASSP*, pages 4861–4864. IEEE.

Martinez, D., Plchot, O., Burget, L., Glembek, O., and Matějka, P. (2011). Language recognition in iVectors space. In *Interspeech*.

McCree, A. (2014). Multiclass discriminative training of i-vector language recognition. In *Odyssey*, pages 166–172.

Metze, F., Sheikh, Z. A. W., Waibel, A., Gehring, J., Kilgour, K., Nguyen, Q. B., and Nguyen, V. H. (2013). Models of tone for tonal and non-tonal languages. In *IEEE Workshop on Automatic Speech Recognition and Understanding*, pages 261–266.

Paul, D. B. and Baker, J. M. (1992). The design for the Wall Street Journal-based CSR corpus. In *Proceedings of the workshop on Speech and Natural Language*, pages 357–362. Association for Computational Linguistics.

Plchot, O., Matejka, P., Fér, R., Glembek, O., Novotnỳ, O., Pešán, J., Veselỳ, K., Ondel, L., Karafiát, M., Grézl, F., et al. (2016). BAT system description for NIST LRE 2015. In *Odyssey*.

Povey, D., Ghoshal, A., Boulianne, G., Burget, L., Glembek, O., Goel, N., Hannemann, M., Motlicek, P., Qian, Y., Schwarz, P., Silovsky, J., Stemmer, G., and Vesely, K. (2011). The Kaldi speech recognition toolkit. In *IEEE Workshop on Automatic Speech Recognition and Understanding*. IEEE Signal Processing Society.

Povey, D., Zhang, X., and Khudanpur, S. (2014). Parallel training of DNNs with natural gradient and parameter averaging. *arXiv*, abs/1410.7455.

Prieto, P. and Roseano, P. (2018). *Prosody: Stress, rhythm, and intonation*, pages 211–236. Cambridge University Press. Retrieved from https://www.researchgate.net/publication/329541457_Prosody_Stress_rhythm_and_intonation.

Sarma, M., Sarma, K. K., and Goel, N. K. (2018). Language recognition using time delay deep neural network. *arXiv*, abs/1804.05000.

Schultz, T. (2002). Globalphone: a multilingual speech and text database developed at Karlsruhe University. In *ICSLP*, pages 345–348.

Schultz, T., Vu, N. T., and Schlippe, T. (2013). GlobalPhone: A multilingual text & speech database in 20 languages. *IEEE ICASSP*, pages 8126–8130.

Shimodaira, H. and Renals, S. (January 17, 2019). Speech signal analysis: ASR lectures 2&3. http://www.inf.ed.ac.uk/teaching/courses/asr/2018-19/asr02-signal-handout.pdf.

Snyder, D. (December 24, 2018). Language identification with x-vectors: Choice of classifier [online forum comment]. https://groups.google.com/forum/#!topic/kaldi-help/v6Uh7avv-cY.

Snyder, D., Garcia-Romero, D., McCree, A., Sell, G., Povey, D., and Khudanpur, S. (2018a). Spoken language recognition using x-vectors. In *Odyssey*, pages 105–111.

Snyder, D., Garcia-Romero, D., Sell, G., Povey, D., and Khudanpur, S. (2018b). X-vectors: Robust DNN embeddings for speaker recognition. *IEEE ICASSP*, pages 5329–5333.

Tkachenko, M., Yamshinin, A., Lyubimov, N., Kotov, M., and Nastasenko, M. (2016). Language identification using time delay neural network d-vector on short utterances. In *SPECOM*, pages 443–449. Springer.

Torres-Carrasquillo, P. A., Singer, E., Kohler, M. A., Greene, R. J., Reynolds, D. A., and Deller, J. R. (2002). Approaches to language identification using Gaussian mixture models and shifted delta cepstral features. In *Interspeech*.

Trask, R. L. (2004). *A dictionary of phonetics and phonology*. Routledge. Entry for "toneme".

Variani, E., Lei, X., McDermott, E., Moreno, I. L., and Gonzalez-Dominguez, J. (2014). Deep neural networks for small footprint text-dependent speaker verification. pages 4052–4056.

Zheng, F. and Zhang, G. (2000). Integrating the energy information into MFCC. In *ICSLP*.

Appendix A

Partitioning of the dataset

	TRAIN.	ENROLLMENT	EVALUATION	TESTING
AR	57	017, 023, 056, 104, 105, 114, 135	014, 030, 047, 067, 109, 115, 137	011, 012, 027, 050, 051, 055, 066
BG	56	042, 048, 056, 065, 088, 104, 107	051, 055, 058, 084, 090, 100, 106	040, 059, 063, 068, 095, 109, 110
CH	98	004, 005, 012, 034, 035, 036, 045, 048, 052, 053, 057, 120, 126	028, 029, 030, 031, 032, 039, 040, 041, 042, 043, 044	080, 081, 082, 083, 084, 085, 086, 087, 088, 089
CR	63	001, 010, 018, 026, 029, 032, 074, 092, 093	033, 034, 035, 036, 046, 048, 051, 053, 054, 057	037, 038, 039, 040, 041, 042, 043, 044, 045, 047
CZ	72	005, 009, 031, 033, 034, 036, 053, 061, 071, 072	083, 085, 087, 089, 091, 093, 095, 097, 099, 101	084, 086, 088, 090, 092, 094, 096, 098, 100, 102
FR	74	009, 028, 030, 031, 033, 052, 064, 065, 070, 076	082, 083, 084, 085, 086, 087, 088, 089	091, 092, 093, 094, 095, 096, 097, 098
GE	58	015, 017, 046, 056, 058, 065, 074	001, 002, 003, 004, 008, 010	018, 020, 021, 026, 029, 073
JA	119	002, 021, 037, 048, 051, 053, 057, 064, 086, 201, 202, 206, 209, 221	009, 031, 046, 081, 091	006, 025, 045, 047, 088, 101
KO	70	018, 030, 043, 044, 057, 065, 074, 078, 079, 090	006, 012, 025, 040, 045, 061, 084, 086, 091, 098	019, 029, 032, 042, 051, 064, 069, 080, 082, 088
PL	70	008, 018, 032, 076, 083, 085, 088, 096, 099	005, 011, 012, 030, 040, 041, 046, 063, 090, 097	001, 004, 009, 023, 031, 033, 043, 044, 050, 098
PO	75	070, 071, 106, 109, 117, 120, 128, 146, 148, 150	064, 072, 102, 103, 104, 132, 133, 134	135, 137, 138, 139, 142, 143, 312
RU	84	017, 023, 035, 041, 088, 101, 114, 115, 119, 121, 123	005, 033, 042, 065, 078, 097, 103, 106, 110, 122	002, 027, 036, 063, 069, 092, 102, 104, 109, 112
SP	72	037, 041, 048, 059, 060, 064, 074, 083, 098, 099	001, 002, 003, 004, 005, 006, 007, 008, 009, 010	011, 012, 013, 014, 015, 016, 017, 018

SW	70	001, 013, 023, 070, 072, 077, 078, 080, 084	045, 046, 047, 048, 049, 066, 067, 068, 069	040, 041, 042, 043, 044, 060, 061, 062, 063, 064
TA	35	022, 028, 038, 047	003, 030, 035, 039	001, 005, 033, 037
TH	73	001, 005, 027, 031, 041, 065, 067, 077, 083	023, 025, 028, 037, 045, 061, 073, 085	101, 102, 103, 104, 105, 106, 107, 108
TU	69	010, 017, 044, 048, 049, 051, 064, 091, 093, 096	001, 002, 003, 005, 006, 008, 013, 014, 015, 016, 019	025, 030, 031, 032, 037, 039, 041, 046, 056, 063
VN	103	012, 029, 031, 036, 043, 050, 053, 070, 077, 118, 119, 128	200, 201, 202, 203, 204, 205, 206, 207, 208	102, 103, 106, 110, 113
WU	6	008, 011, 013, 015	002, 004, 006, 017	001, 003, 005, 009

Table A.1: The partitioning of each language's speakers into the 4 partitions. For enrollment, evaluation and testing sets, speaker IDs are shown. For the training set, the rest of the speakers was used and only the number of speakers is shown.