An investigation of accent conversion for non-native and native varieties of English

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Declaration

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Abstract

Accent conversion (AC), the process of transforming the accent of one speaker as if they had the accent of another speaker, has been cited as a prospective solution for challenges faced in language learning and voice-based technologies. Works such as Aryal and Gutierrez-Osuna (2014b) and Zhao, Sonsaat, Levis, et al. (2018) have found some success in using accent conversion to minimize the accents of various non-native speakers, while work such as Mohammadi and Kain (2017) points to the multiple applications of voice conversion as a whole. Despite these works, accent conversion still remains a relatively new section of research, with plenty to be investigated.

In this master's thesis, we detail previous research as related to accents by outlining important theories from the perspective of linguistics and provide details on how accent conversion arose as a prospective solution for language learning and voice-based technologies by discussing research in computer-assisted pronunciation training and automatic speech recognition systems. We then detail our experiments with accent conversion using a traditional Gaussian Mixture Model approach following Aryal and Gutierrez-Osuna (2014b) using the ARCTIC/L2-ARCTIC corpora to test non-native to native conversion, and the Accents of the British Isles (ABI) corpus to test conversion between two native, but distinct accents. We compare the performance of accent conversion between these two separate corpora by recruiting the help of outside evaluators to do a perceptual study. Through the perceptual study, we observe that the evaluators agree that the converted audios in both corpora have the desired accent; however there are issues in maintaining the identity of the speakers. We conclude with discussion on possible sources for the results and directions for future work.

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List of Abbreviations

ABI	Accents of the British Isles Corpus
AC	Accent conversion
CAPT	Computer Assisted Pronunciation Training
CP	Critical Period
GMM	Gaussian Mixture Model
L1/L2	First and second language
LSTM	Long-short term memory
MFCC	Mel-frequency cepstrum coefficient
TTS	Text-to-speech
VC	Voice conversion

Chapter 1

Introduction

1.1 What is an "accent"?

Before continuing on, it is best to define what accent is, especially in the context of this work. The definition of 'accent', much like any other word can fluctuate based on the context it is used in, and by whom the word is used. Fundamentally, accents consist of a number of features, including the vowels and consonants, the stress, rhythm, intonation, and even pauses that a speaker uses. The variation in these features contribute to what many known as *accent*, or variations in pronunciation across speakers based on location, ethnicities, social classes, native languages, etc (Crystal 2008). Accents can be considered to be a part of dialects, where users of the same language may have variations beyond pronunciation, such as usage in vocabulary or grammar. The line between accents and dialects may often be blurred in everyday discussions and even in academic analyses as accent and dialect (as well as language) could be considered to be on a continuum, but for the sake of simplicity, we consider 'accent' to be solely variations in pronunciation in this work.

1.2 Motivation for this work

Technology has flourished and led to a number of new state-of-the-art systems such as improvements in commercial speech recognition and machine translation. However, it can be argued that these benefits have not reached all potential users and uses to the same extent. For example, many commercial systems like Google Translate, Siri, Alexa, etc. have grown in the number of languages they have available, but when considering the robustness of these systems across languages, it is often evident that the systems function much better with languages that have more speakers across the globe such as English or Spanish. In some cases such as with newer products, a user's native language might not yet even be available, which can cause them to relegate to English.

These systems are also often better equipped to work with specific language varieties, which are often considered to be the 'standard' or more common variety of that language. In the context of speech recognition systems, this means that this could cause potential challenges for speakers of other varieties– or *accents*, whether it be another native but 'non-standard' accent or a non-native accent. This issue can be observed in various viral videos, such as an Italian grandmother who is trying to activate a Google Home device by saying, "Okay Google!" (Actis 2017) or another video where a woman is trying to get her Amazon Alexa device to play a song called "Something's Cooking in My Kitchen by Dana" (Newsflare 2018). In both cases, both women have issues with their devices properly understanding them likely because they speak English with an accent that the systems are not (well-)trained on.

Yet when it comes to accents, teaching them can be as equally difficult as trying to have them recognized by speech recognition systems. This extends into language teaching and learning as well, where learners of a second language often have trouble acquiring proper pronunciation. In fact, pronunciation has been a large standing challenge in language learning due to its complex nature as observed in second language learning research (Flege et al. 1995; Lenneberg 1967; Scovel 1988). Unlike grammar and vocabulary, which many language learners acquire without issue, pronunciation can be challenging to both learn and teach due to the lack of clarity on how to teach it (Darcy et al. 2012). This is because pronunciation involves a number of nuanced characteristics, including stress, rhythm, vowels, and consonants, which can vary just small enough for one language or accent to draw a distinction, while others conflate them.

In order to address these issues in speech recognition and language learning, researchers have investigated variation solutions. Linguists focused on language learning and phonetics have examined the underlying causes of what creates obstacles in learning an accent, with some concluding that native-like accents are nearly unobtainable after a certain age threshold. Regardless of this conclusion, some researchers have turned to language technology to develop potential pronunciation training systems with the hopes of any possible accent reduction. Earlier studies using some of these pronunciation training systems have shown that while they have the potential, many of them suffer from the lack of appropriate feedback that the user can understand. Thus, some researchers have pointed to the potential use of accent conversion as a mode of feedback as it has been hypothesized that hearing one's voice pronounce something with the desired accent is better feedback as compared to a point-based system or spectrograms, which require specialized training to interpret.

Accent conversion has also been proposed as a potential solution to challenges in speech recognition. Because speech recognition is often trained on large amounts of speech data, it can be unrealistic to attempt to collect sufficient speech data for the endless possible varieties or accents that exist for a single language. Instead, researchers have pointed to accent conversion as a possible way to adapt current available systems to more speakers, with the idea that accent conversion could change the accent of a speaker into sounding more like an accent the speech recognition system can better recognize without training it on a large amount of data. Similarly, accent conversion can be applied to expand the number of available accents for text-to-speech systems for languages that may have a large number of accents such as English or Spanish. This adaptation process can be viewed similarly to other natural language processing tasks, such as text classification or part-of-speech tagging of varying genres such as formal news text vs. informal blogs or tweets, where currently available systems have been adapted to perform better on more genres instead of creating specialized systems for each genre type.

1.3 Research Questions

In this thesis, we focus on investigating the following questions:

- How effective is accent conversion in changing the accent of a *non-native speaker* into sounding more like a *native speaker* while retaining their voice characteristics, or *identity*? Concretely, how effectively can we convert the accents of learners of English to sound more like US English while retaining their identities?
- How effective is accent conversion to change the accent of two *native speakers* of English who speak two *distinct* varieties? Specifically, how effectively can we convert the accents of speakers of 'non-standard' English such as speakers from Scotland, to sound more like Standard Southern English while retaining their identities?
- Does the same methodology of accent conversion which is most often applied to the conversion of non-native to native accents work similarly for native to native accent conversion? Concretely, would we observe similar performance between non-native to native accent conversion vs. native to native accent conversion?

1.4 Thesis Overview

The overview of the thesis is as follows:

In **Chapter 2**, we give a proper definition of voice conversion and accent conversion, and a high level overview of some technical details needed to better understand the current work.

In **Chapter 3**, we present the motivation for creating an accent conversion system by discussing previous findings in second language acquisition research especially in relation to speech. We then cover previous work in voice and accent conversion to frame the advances and shortcomings of previously developed systems.

In **Chapter 4**, the design and methodology of the experiments are presented alongside the appropriate tools utilized to conduct each one.

In **Chapter 5**, the results of the experiments previously described are presented along with some short discussion and conclusions drawn from the results.

In **Chapter 6**, the thesis is concluded with a reflection on the work presented along with some appropriate suggestions for future work.

Chapter 2

Background

Before delving into previous literature and its relevance to this work and the fields of NLP and language learning as a whole, we detail both voice conversion and accent conversion in order to help better distinguish them. We also explain some common speech technology concepts typically used in these systems at a high level in order to make the current work more accessible to those unfamiliar with the area.

2.1 Voice conversion

To properly frame voice conversion, we take a look at Mohammadi and Kain (2017) who present a recent overview of the subfield. Following a definition set forth by the authors, voice conversion refers to the transformation of a speech signal of a *source speaker* to make it sound as if it were uttered by a *target speaker* in any chosen fashion with the utterance still being intact. Some of these changes can include changes in emotion, accent, or phonation (whispered/murmured speech). There have been a number of proposed uses for VC, including the transformation of speaker identity (perhaps for voice dubbing), personalized TTS systems, and protection against biometric voice authentication systems.

Voice conversion often involves a large number of processes, one of which includes deciding the appropriate type of data. To start, one must decide whether to have parallel or non-parallel speech data. Parallel speech data refers to speech data that has source and reference speakers that say the same utterance, so only the speaker-specific information is different, while non-parallel data would indicate datasets where the utterances are not the same, and thus entail further processes to create a target waveform. Even though parallel corpora are more desirable as it reduces the footprint necessary for conversion, parallel corpora are often curated for specific purposes and are not available in most cases. Because of its simplicity, in some cases, researchers have tested making a psuedo-parallel corpus using acoustic clustering when working with non-parallel data (Lorenzo-Trueba et al. 2018; Sundermann et al. 2006).

Other aspects that need to be considered as discussed by Mohammadi and Kain (2017) include whether the data is text-dependent or text-independent. Text-dependent corpora indicate that the data has word or phonetic transcription, which can ease the alignment process during training, while systems using text-independent data would need to find similar speech segments, using a method like acoustic clustering before training. Finally, one minor aspect that is not considered often is the languages of the source speaker and target speaker. Although many systems tend to focus on voice conversion between two native speakers of the same language, systems that aim to convert between two speakers speaking in different languages would have to be wary of potential mapping issues between sounds. This is especially important to consider in terms of accent conversion, which will be discussed in the following section.

Aside from considering these aspects of the corpora, the type of features extracted from the waveforms heavily impact the quality of the conversions. In investigating the most salient features of speaker individuality, previous researchers have concluded that the average spectrum, formants, and average pitch level are the most relevant. Concretely, the average spectrum, or the average of the spectral envelopes/curves in the frequency-amplitude domain is particularly useful for speaker individuality as it captures voice quality/timbre information. That is to say, while the general shape of the spectra may be somewhat similar for a single utterance due to the equivalent sounds, the spectra would also contain nuanced information on *how* an utterance was pronounced. Similarly, formants, the concentration of energy around certain frequencies, are useful for capturing speaker characteristics as although they retain mostly similar spacing between frequencies across phonemes, they can also be affected by physical features such as the length of a speaker's vocal tract. This means that although a certain sound may be most typically represented by 3 formants separated by 1000Hz each, one speaker may pronounce it with the formants at 500Hz, 1500Hz, and 2500Hz, and another may pronounce it at 1000Hz, 2000Hz, and 3000Hz.

Following these conclusions, most VC systems focus on converting these features, and often work at the frame-level (windows of $\sim$20ms), with the assumption that the frame represents a stationary sound. From these frames, there are a number of common local features that are extracted to represent the signal. These include the cepstrum, line spectral frequencies (LSF), and the aforementioned spectral envelope and formants. Like the spectral envelope, line spectral frequencies represent a speech signal in the frequency-amplitude domain, while the cepstrum can capture characteristics of individual sounds in the source-filter model of speech. We describe the cepstrum in greater detail in section 2.3 alongside the feature extraction process.

On top of these local frame-based features, contextual features can be considered as well as the local features alone are often limited in what they can model. These contextual features can be as simple as adding delta and delta delta features, although methods such as event-based encodings have been tested as well. With event-based encodings, a sequence of local features are separated into different event targets and transitions to model an utterance. However, this method faces the challenge of properly defining events within the sequence. Thus, although many algorithms and methods exist to model a signal, most systems focus on working with mel-frequency cepstrum coefficents (MFCCs) and deltas/double deltas, as they are very standard in most speech synthesis and recognition systems in general. The extraction process of MFCCs and deltas/double deltas are described in in section 2.3.

After the chosen features are extracted, the features between the source speaker and target speaker have to be matched to prepare them for conversion. In parallel conversion, this means that each sound in an utterance has to be mapped between the speakers, which can be done manually but more often is done using an algorithm such as dynamic time warping (DTW), which looks for the shortest path to match similar sounds regardless of duration.

Although this is usually an effective algorithm to find the best alignment, there can be issues in aligning the sounds as it assumes that the same phonemes of the speakers have similar features (Mohammadi and Kain 2017). This can be improved upon by adding phonetic transcription, or using methods such as forced alignment, but these methods may also have other limitations.

With non-parallel voice conversion, the alignment process becomes more complex as utterances from the source and target speakers have to be broken down into individual phonemes, and then the desired sounds must somehow be collected and synthesized to produce the converted speech. This can be done using methods like unit-selection text-to-speech (TTS), but this requires a large amount of annotated training data. Algorithms such as INCA can be used in addition to work without annotation by iteratively searching for the best frame pairs. Further information on the various alignment methods are detailed within Mohammadi and Kain (2017).

When the best frames between the source and target speakers are finally matched, a method has be to chosen to map the relationship between the frames. This has traditionally been done by using Gaussian Mixture Models, although neural networks have also become prevalent as well as they become ubiquitous throughout computational modeling. A detailed but accessible explanation of these algorithms and how they function is provided in section 2.3.

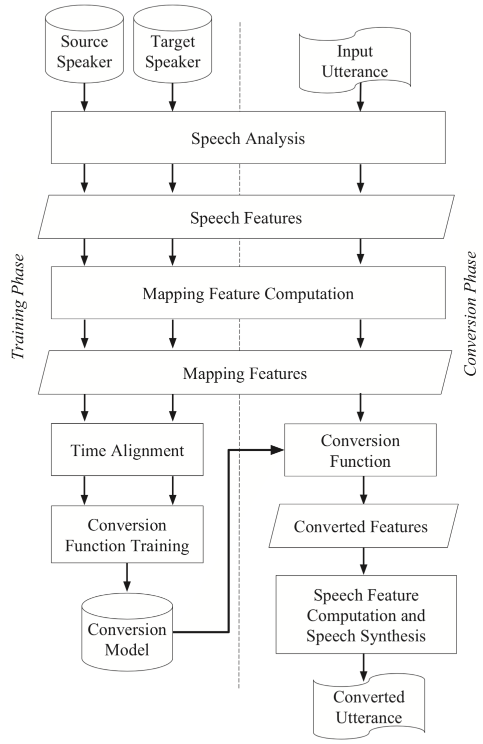


Figure 2.1: The training and conversion processes of a typical VC system. Taken from Mohammadi and Kain (2017).

A visual representation that summarizes the voice conversion process can be seen in Figure 2.1.

2.2 Accent conversion

Like voice conversion, accent conversion is dedicated to convert the speech of a *source speaker* into sounding like a *target speaker*. However, accent conversion is specifically focused on morphing the *accent* of the speech signal, as opposed to sounding directly like the target speaker. Succinctly stated, "Accent conversion seeks to transform second language L2 utterances to appear as if produced with a native (L1) accent," (Aryal and Gutierrez-Osuna 2014a). Because the confusion that can arise from using the terminology *source speaker* and *target speaker*, the *source speaker* is often referred to as the native or L1 speaker, while the *target speaker* is referred to as the non-native or L2 speaker. This seems somewhat counter-intuitive, but this allows for us to create a voice that retains the non-native speaker's identity and the native speaker's accent (Zhao, Sonsaat, Levis, et al. 2018).

Accent conversion poses a further challenge on top of voice conversion as the audio of the source speaker and target speaker cannot simply be forced-aligned due to the fact that the voice quality and accent of the target speaker would remain (Aryal and

Gutierrez-Osuna 2014b). This means that accent conversion may require more specialized alignment methods beyond standard frame-by-frame alignment that can help preserve the right speaker information while suppressing the other undesired information. This is further discussed in the examination of previous work in accent conversion in section 3.4.

2.3 Technical Background

2.3.1 Mel-frequency cepstrum coefficients

Before any actual speech processing can happen, the speech signal needs to be broken down into sizable and meaningful representations. This is most traditionally done by using mel-frequency cepstrum coefficients (MFCCs) to create vectorized representations of the acoustic information. Although MFCCs can be extracted fairly easily using a number of tools or available packages, there are a number of steps required before a speech signal can be represented as a sequence of N number of MFCC vectors. As the feature extraction process is heavily related to standard signal processing as well as acoustic and articulatory phonetics, the motivation and ideas utilized to extract features from speech signals can be extended into one large body of work itself. In order to succinctly describe the MFCC extraction process, we reference Jurafsky and Martin (2009).

The most common first step in feature extraction for speech signals is referred to as *pre-emphasis*. When we produce various sounds, the energy that each sound contains is often concentrated around the lower frequencies, which causes information in the higher frequencies to be obstructed. This is referred to as spectral tilt and is caused by the physiological nature of the speech production system. In order to balance the energy in the speech signal, the speech signal is passed through a filter which boosts the amount of energy in the higher frequencies. In terms of signal processing, this filter is referred to as a first-order high pass filter and can be represented using the formula seen in Equation 2.1 where $x[n]$ refers to the original signal and α is $0.9 \leq 1.0$.

$$y[n] = x[n] - \alpha x[n-1] \tag{2.1}$$

After the speech signal goes through pre-emphasis, the speech signal can be separated into smaller parts such as phones or subphones. Because the speech signal usually contains a whole word or utterance, it is desirable to capture consistent or 'stationary' points of the signal. This is done by going over the speech signal using a process called

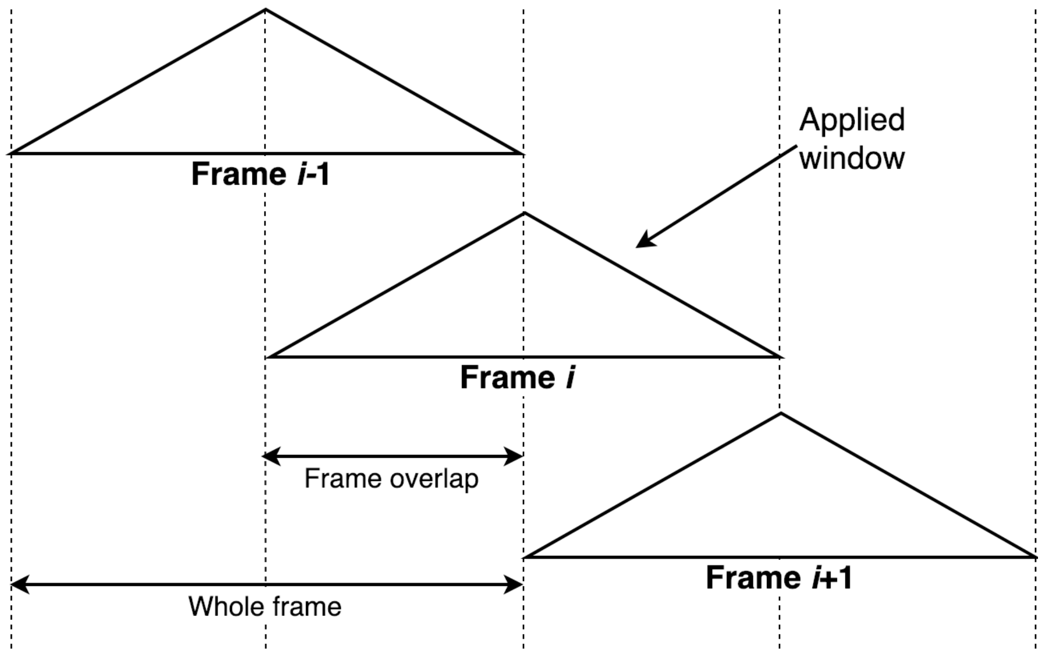


Figure 2.2: The windowing process. A reduplication of an image from DeMarco (2015).

windowing, where each window is assumed to contain a non-changing part of the signal. These windows usually contain between 10ms to 30ms of speech, and usually overlap about 30% - 50% with the previous window in order to retain all of the necessary information from each part of the signal. After the windowing process, the speech signal is said to be split up into N number of *frames*. The windowing process can be represented using the formula seen in Equation 2.2 where the signal $s[n]$ is multiplied by the window value $w[n]$ at each time n. A visual representation of the windowing process recreated from DeMarco (2015) can be seen in Figure 2.2.

$$y[n] = w[n]s[n] \tag{2.2}$$

Even though the word ‘window’ might suggest that its shape would be a rectangle, a rectangular window on its own most often leads to distorted information because of the sudden cuts that occur on the edges of the signal. In order to address this problem, special windowing functions such as the Hamming window, are used to decrease the values on the ends of a frame. An example of windowing can be seen in Figure 2.3, where the hamming window can be seen tapering off on the edges compared to the rectangular window.

After the signal is separated into different windows, the spectral information can be extracted using a special tool or formula known as the Discrete Fourier Transform (DFT). This allows us to find how much energy is in specific frequency bands. By passing

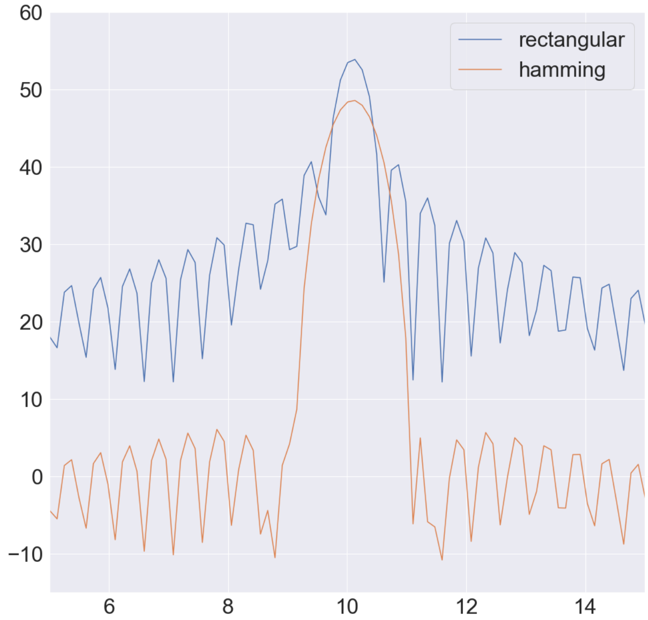


Figure 2.3: An example of the rectangular window vs. the Hamming window on a signal. Taken from Le Bourdais (2015).

the windowed discrete signal through the Discrete Fourier Transform, we can get a complex number that contains the magnitude and phase for each frequency component. After the Discrete Fourier Transform, the frequencies are converted onto the *mel* scale, using a set of filters called mel filter banks. The purpose of the mel scale is to represent human hearing, which is more sensitive to lower pitch sounds (under 1000Hz) as compared to higher pitch sounds. In the mel scale, sounds below 1000Hz are placed on a linear scale, while sounds above 1000Hz are on a logarithmic scale. The mel filter banks can be seen in Figure 2.4.

Afterwards, the *cepstrum* is calculated in order to separate source information from filter information. From a high level, the source-filter theory says that all sounds come

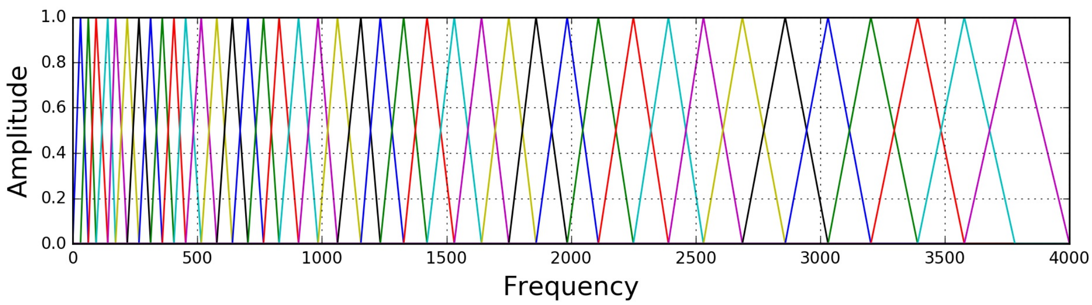


Figure 2.4: Mel-filter banks. Taken from Fayek (2016).

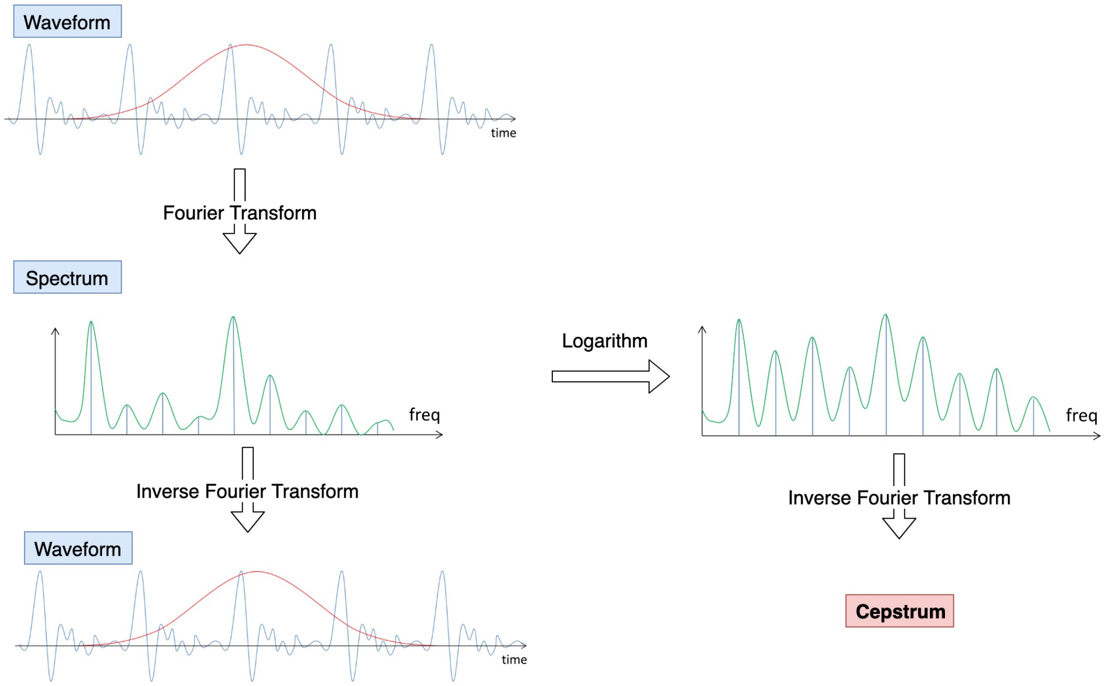


Figure 2.5: The waveform to spectrum to cepstrum process.

from the glottis (the area around our throat) and below, which contains information common to all speech sounds, such as the fundamental frequency (or pitch) of someone's voice, as well as glottal pulse information. This is compared to the filter, which says that adjusting the vocal tract (e.g. moving the tongue and other articulators) define each individual sounds. By retaining just the filter information, we can model an individual phone. In terms of the given cepstral values, the first 12 cepstral values are taken as they neatly represent the filter information. In terms of signal processing, the cepstrum is calculating by using the 'inverse discrete Fourier Transform of the log magnitude of the DFT of a signal'.The formula for calculating the cepstrum can be seen in Equation 2.3, where $x[n]$ represents our initial signal, e represents Euler's number (~ 2.718), j represents an imaginary power, N represents the number of time samples from the signal, n represents the current sample, and k represents the current frequency between 0 and $N-1$ Hertz (Azad 2017). While the Fourier Transform is challenging to follow mathematically, Figure 2.5 succinctly summarizes the process.

$$c[n] = \sum_{n=0}^{N-1} log\left(\left|\sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi}{N}kn}\right|\right)e^{j\frac{2\pi}{N}kn} \tag{2.3}$$

Even though these steps alone could be used to model a speech signal, additional information is often added to further better model each frame. Among this information is energy, which can help us further distinguish a sound, as vowels and sibilants ('breathy' sounds like /s/ or /f/) have more energy compared to stops ('hard' sounds like /k/ or /p/).

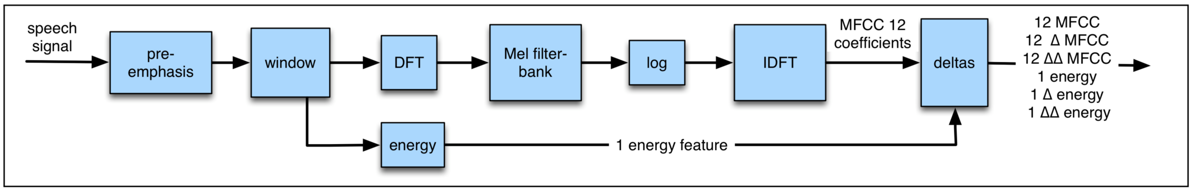


Figure 2.6: The extraction of sequence 39-dimensional MFCC vectors from a waveform. Taken from Jurafsky and Martin (2009).

Energy is calculated using the formula seen in: Equation 2.4 where x represents the signal and t represents a point in time.

$$Energy = \sum_{t=t_1}^{t_2} x^2[t] \tag{2.4}$$

On top of the 12 MFCC features and 1 energy feature, features known as deltas and double deltas are often added to represent the change in the speech signal frame to frame. Concretely, deltas can be used to model changes in formants or a change from stop closure to stop release. Double deltas are then added to represent the changes between deltas, which provide further precision in modeling an utterance. In total, this gives us 39 MFCC features from:

- **12** cepstral coefficients
- **12** delta cepstral coefficients
- **12** double delta cepstral coefficients
- **1** energy coefficient
- **1** delta energy coefficient
- **1** double delta energy coefficient

A visual representation of the whole MFCC extraction process can be seen in Figure 2.6.

2.3.2 Gaussian mixture models

A Gaussian mixture model is a type of probablistic model that aims to represent normally distributed groups within a set. This is based on the idea of the normal, or *Gaussian* distribution, which can be see in Figure 2.7. The Gaussian distribution is characterized by two main features: the mean (the arithmetic average of the data) and the variance (the spread of the data from the mean). The Gaussian distribution is the most important distribution used in probablistic modeling as it has been theorized that the average of independent random variables would look like a normal distribution (McGonagle et al. 2016).

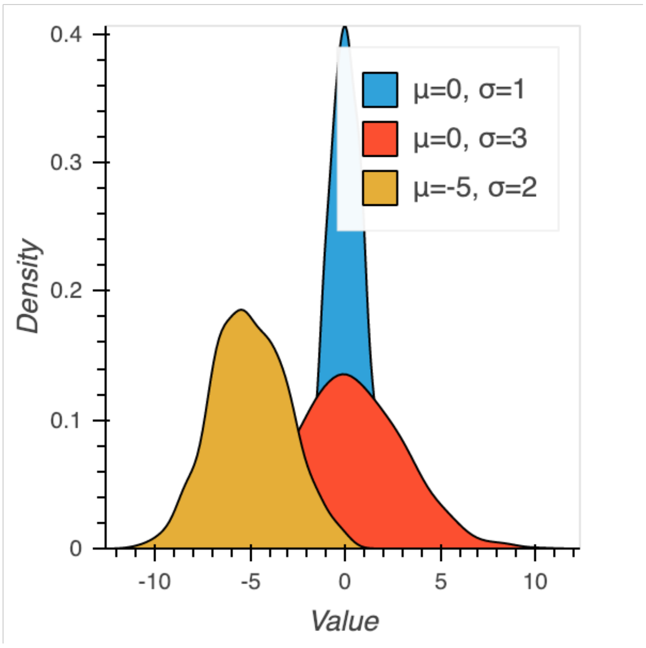


Figure 2.7: The Gaussian distribution with different means (μ) and standard deviations (σ).

Gaussian mixture models are based on the principle that if a unimodal (one 'peak') dataset can be fit with a Gaussian distribution, then a multimodal (multi 'peak') dataset is just a 'mixture' of smaller Gaussian distributions. A common example given to understand the Gaussian distribution and Gaussian mixture models often references height. It is often said that men are taller than women on average, with men being 178cm (5 foot 10 inches), and women being 165cm (5 foot 5 inches). If we used two separate Gaussians to model each gender, we could 'mix' them to model the likelihood of a certain data point (e.g. person) being a male or a female (McGonagle et al. 2016). For example, using a hypothetical example with the averages previously mentioned, we could see that the likelihood of a person that is 168cm is more likely to be a male than a female. This is demonstrated in Figure 2.8. The probabilities are calculated as the following: the Male is P(66in) = .065 / (.065 + .104) = .38 and the Female P(66in) = .104 / (.065 + .104) = .62, meaning that that for someone 66 inches, it would be much more likely that they are a woman.

However, as simple as this sounds the most advantageous point of the Gaussian mixture model is the fact that it is an *unsupervised* model that can be used when the subpopulations of the data are unknown. Thus, following the previous example of height, a Gaussian mixture model could be used to model the height of the two genders *without* knowing the gender of each data point.

Because it is an *unsupervised* model, it requires a special method to estimate the appropriate parameters. The most common method used for this is known as *expectation*

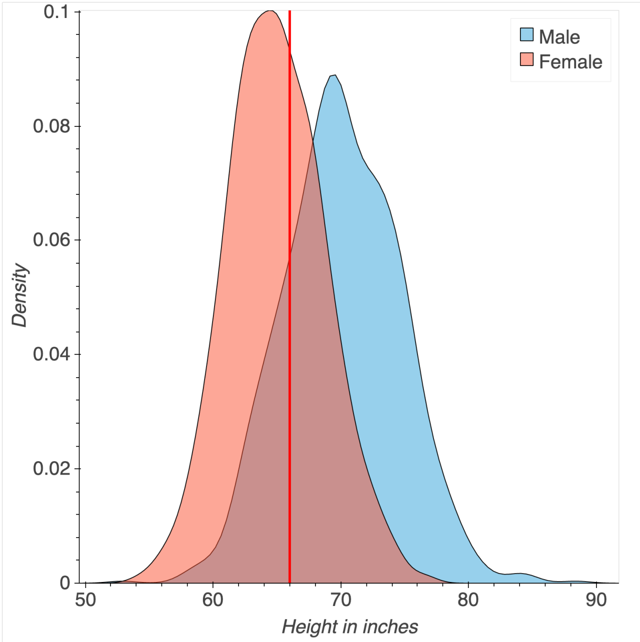


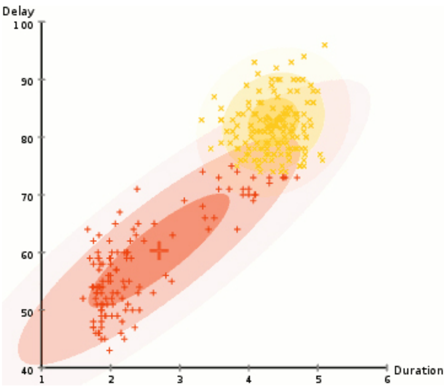
Figure 2.8: An example of a GMM using male and female height. The likelihoods for each gender for someone 168cm (66in) tall is calculated using the percentage of men and women in the dataset from the vertical axis.

maximization. This algorithm is used for maximum likelihood estimation. In mathematical terms, this can be represented by observing the average log-likelihood to know whether the GMM is modeling a set of vectors R well. A higher average log-likelihood indicates that the GMM is performing well. The formula from calculating average log-likelihood, taken from Kinnunen and Li (2009), can be seen in Equation 2.5 where M represents the number of components, K represents the number within the codebook, m describes the m^{th} Gaussian component, P_m is the prior probability of the m^{th} Gaussian component, Σ_m represents the co-variance matrix and μ_m represents the mean vector.

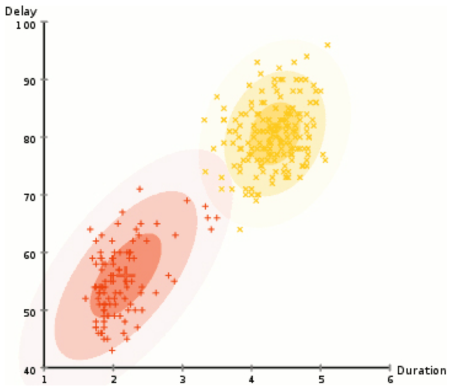
$$LL_{avg}(R,\lambda) = \frac{1}{K}\sum_{i=1}^{K} log \sum_{m=1}^{M} P_m N(r_k|\mu_m, \Sigma_m) \tag{2.5}$$

In other words, this algorithm tries to find the most appropriate group for each datapoint by calculating the probability of it being in a certain group and selecting the most likely one. This is done iteratively by initializing reasonable values, and then calculating the probability of membership in each cluster (the *expectation* step) and updating each clusters location, normalization and shape using the probabilities calculated (the *maximization* step) until the algorithms converge (VanderPlas 2016). A visual example of the convergence process can be seen in Figure 2.9.

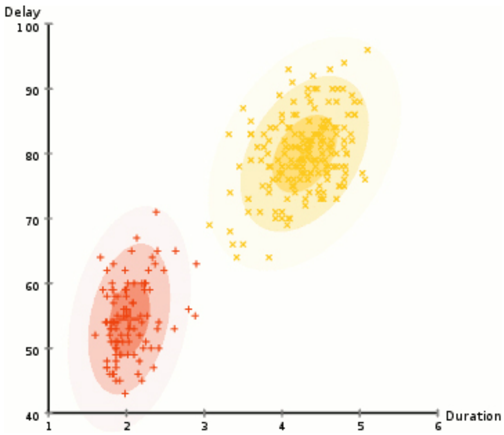
Due to the complexity of the formulas, the mathematical representations for the expectation-maximization steps are taken from the discussion of DeMarco (2015)



(a) Initialization



(b) Mid-convergence



(c) Converged

Figure 2.9: Gaussian Mixture Model convergence using the Expectation-Maximization algorithm. Taken from McGonagle et al. (2016).

which in turn cites Rose and D. Reynolds (1990). The formulas are represented as follows.

1. The E-Step: The posterior probabilities are calculating for all of the training vectors of a given class model λ using Equation 2.6.

$$P(m|r_n, \lambda) = \frac{P_m N(r_n|\mu_m, \Sigma_m)}{\sum_{i=1}^{M} P_i N(r_n|\mu_i, \Sigma_i)} \tag{2.6}$$

2. The M-Step: The M-Step utilizes the posterior probabilities from the E-Step to estimate model parameters using Equation 2.7,Equation 2.8 and Equation 2.9.

$$\hat{p}_m = \frac{1}{K}\sum_{k=1}^{K} P(m|r_k, \lambda) \tag{2.7}$$

$$\hat{\mu}_m = \frac{\sum_{K=1}^{K} P(m|r_k, \lambda) r_k}{\sum_{K=1}^{K} P(m|r_k, \lambda)} \tag{2.8}$$

$$\hat{\Sigma}_m = \frac{\sum_{k=1}^{K} P(m|r_k, \lambda)(r_k - \hat{\mu}_m)(r_k - \hat{\mu}_m)^T}{\sum_{k=1}^{K} P(m|r_k, \lambda)} \tag{2.9}$$

3. Set $P_m = \hat{P}_m$, $\mu_m = \hat{\mu}_m$, and $\Sigma_m = \hat{\Sigma}_m$ and repeat the E-step and M-step until convergence.

This model can be compared to the *k*-means clustering algorithm, as both can be used to cluster different subgroups. Like the *k*-means algorithm, GMMs also require us to specify a number of components, which usually indicate the number of subgroups we hope to cluster. However, *k*-means suffers from not using a probablistic model to assign clusters, which means that data points can only be assigned to exactly one cluster. The cluster shape of *k*-means is also limited to only circles, which makes it inadequate to model data with different distributions. GMMs manage to address these issues by using the expectation-maximization algorithm to calculate the probabilities of cluster assignment and by allowing for different covariance types which permits for different cluster shapes beyond the circle. Aside from being useful as an unsupervised classification algorithm, GMMs can also be seen as a generative algorithm as it models the overall distribution of the data (McGonagle et al. 2016). This means that a GMM can be used to generate new data points following the distribution of the given data set.

In the case of speech, Gaussian mixture models are most often used to model individual sounds using MFCC feature vectors. The usage of Gaussian mixture models to classify vocal features became popularized through the work and success of D. A. Reynolds (1995) . Because MFCC feature vectors are multi-dimensional ($\sim$39-dimensions), the

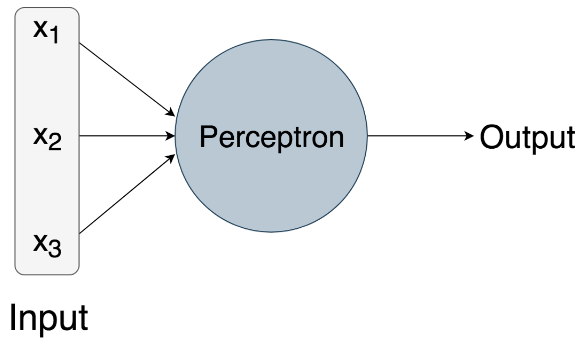


Figure 2.10: A visual representation of the perceptron.

Gaussians within the model are also multi-variate. However, the same principles described above still stand, and allow us to calculate the probability of a sound from a given frame. More formally, the most likely class for a an utterance can be described using the formula seen in Equation 2.10 taken from O'Shaughnessy (1999), where T is the test utterance and λ^n is the GMM.

$$N^* = \underset{1 \leq n \leq}{\arg\max} P(\lambda^n | T) = \underset{1 \leq n \leq}{\arg\max} \frac{P(T|\lambda^P)P(\lambda^n)}{P(T)} \tag{2.10}$$

2.3.3 Neural networks

As indicated by its name, neural networks or more formally, *artificial neural networks* are said to be based on the architecture of the brain's neurons. Like the human decision making process, neural networks take in a certain amount of information or *input*, to make a decision, or more formally, to give an *output*. This idea can be easily understood by taking a look at the *perceptron*, the most simple form of an artificial neuron.

A perceptron takes in a number of binary inputs (represented in the image by x_1, x_2, x_3) and outputs a single binary output (Nielsen 2015). The output is determined by whether the inputs are less than or greater than a defined threshold, and each input can be weighted to represent the importance of that input in determining the output. Mathematically, this can be represented as the following where w represents the weight and x represents a particular value:

$$output = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{threshold} \end{cases}$$

To provide a concrete example, we can use a yes-no question (with 0 representing 'no', and 1 representing 'yes') such as:

"Will I watch another episode of this TV show?"

As 'inputs', we can use the following questions:

1. Do I like this show?
2. Is it still before my bedtime?
3. Am I free tomorrow?

To decide the weights of these 'inputs', we can consider how important we think each question is. Perhaps the most important question is Question #1, and thus we can assign a weight of 4, while the other 2 may receive a weight of 2 and 1 respectively.

Finally, we need to define a threshold to determine whether we output a 0 (no) or a 1 (yes). Evidentally, the lower the threshold, the more likely we're going to watch another episode. For example, with the given weights and a threshold of 2, we have the following possible outputs for each question:

1. 4 * 1 = 4 OR 4 * 0 = 0
2. 2 * 1 = 2 OR 2 * 0 = 0
3. 1 * 1 = 1 OR 1 * 0 = 0

We can see that we would end up with a final output of 1 (yes) in the case that it is still before our bedtime (2 points) and/or if we like this show (6 points/4 points), and regardless of whether we are free tomorrow.

Even though the previous notation of the perceptron is more simple, the perceptron, and more generally speaking, the neuron is more often described in the following notation where w represents a vector of the weights, x represents a vector of the inputs, and b represents *bias*, to replace the threshold.

$$output = \begin{cases} 0 & \text{if } w * x + b \leq 0 \\ 1 & \text{if } w * x + b > 0 \end{cases}$$

The bias can be understood as being equivalent to -threshold. It can also be understood in terms of the neuron metaphor of how easy it is to get the neuron to 'fire'. That is to say, the bigger the bias, the more likely we output a 1, and the smaller the bias, the more likely we output a 0.

Although perceptrons are very simple to understand, they tend to not function well in more complex situations due to their structure. In particular, a small change in the weights could easily cause the output to go from a 1 to 0 and vice versa. Of course,

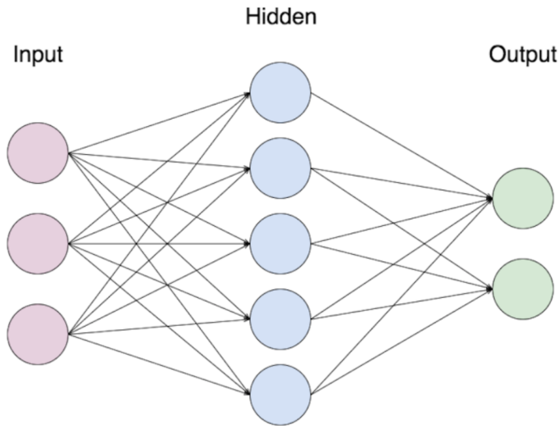


Figure 2.11: An example of a neural network.

in the case of the example above, this may not matter too heavily, but in training large systems, this property is too afflicting to be reliable (Nielsen 2015).

Instead, the most basic neuron used in machine learning is the *sigmoid* neuron, which as the name indicates, utilizes the sigmoid function to decide the threshold. This prevents the neuron from being affected by small changes like the perceptron, as the decision function is no longer linear. The sigmoid neuron is also much more flexible, as it no longer requires a binary input and can instead take on any values between 0 and 1. Aside from the sigmoid, there are other non-linear functions that can be used, such as the tanh function or another known as the rectified linear unit (ReLU) which can offer slight improvements over the sigmoid depending on the task. In general, these non-linear functions are what give neural networks their vast power to 'learn' (Nielsen 2015).

While a single neuron may be able to make very basic decisions, it is through a combination of them that we can make more complex systems that do tasks such as named entity recognition, object detection and voice conversion. From here, we get the name of neural *network*. In Figure 2.11, we see an example of a more typical neural network.

In the example above, we have three inputs and two outputs, and a new concept known as a *hidden layer*. The hidden layer is said to be able to 'uncover' more additional information about the input in order to better decide the output. While the current example only has one hidden layer, the currently popular 'deep learning' comes from adding multiple hidden layers to create a large neural network structure. Like hidden layers, the number of inputs and the number of puts can vastly vary depending on the dataset. For example, in the case of part-of-speech tagging, we would like the input and output size to be the same per sentence, as we need to have a part-of-speech tag applied to each word. The output layer can the output the probability of each possible part-of-speech tag (noun, verb, adjective, etc.) per word, and we can select the most probable as that word's part-of-speech.

While neural networks are described at a high level here in order to facilitate general understanding of this work, more complex neural network architectures and features are not addressed here. Further reference regarding neural networks can be found in Nielsen (2015), the main reference for the description here, and Goldberg (2017), which provides both an overview on neural networks and discussion of their use in natural language processing.

Neural networks in the context of voice/accent conversion will be further described in section 3.4.

Chapter 3

Literature Review

This section provides a brief overview of second language acquisition and education in order to frame the challenge of pronunciation and to motivate the potential usage of technology in language learning. We point to some previous research in spoken language technology used in the domain of language education, including discussion on computer assisted pronunciation (CAPT) systems in order to shed light on where accent conversion could be applied, and then detail some important pivotal work done in both voice and accent conversion.

3.1 Theoretical and educational motivations

Linguists have long debated over the possibility of whether second language (L2) learners (e.g. adult learners) could ever acquire a language to the extent of a native speaker. Some still cite ideas like the Critical Period (CP) Hypothesis and neuroplasticity which claims that learners cannot acquire language (at least as well as a native speaker) after a certain point in time due to the loss of plasticity in the brain (Lenneberg 1967; Scovel 1988). This theory has been particularly cited in reference to pronunciation, perhaps due to the obvious difficultly in overcoming the L1 negative transfer (e.g. effect of our native language) that many, if not all, language learners experience in speaking a new language.

Since the emergence of the CP hypothesis, many linguists have investigated the relationship between a number of variables such as age, motivation, and language use, that interact with the level of language acquisition. Piske et al. (2001) and Lengeris (2012) present an excellent review of different literature that investigates the interactions between these various variables and their effects on foreign accent. They discuss that although many L2 foreign accent studies do support the idea that the earlier a language learner learns a language, the better their accent would be, there isn't strong enough indication to support the notion of a 'critical' period. They do concede that many studies do indicate that there is a linear correlation between age and foreign accent, but this only indicates a 'sensitive' period, not a 'critical' period, a distinction that some fail to acknowledge. That is to say, following advocates of the CP, the critical period should end roughly around 12 years old (Scovel 1988), or no later than 15 years old (Patkowski 1990), and beyond this point, there would be "a sharp drop-off in a learner's abilities" (Lengeris 2012), indicating that a learner could not acquire a native-like accent beyond this period.

Other researchers such as Long (1990) suggested that an L2 learner could speak accent-free if they learned the language before 6 years old but not after 12 years old. Although this notion also has been supported through a number of studies, there has also been counter-evidence found in other studies that found that there were learners younger than 6 who had detectable traces of a foreign accent. In other studies that examined learners of English who started beyond 12 years old, they also found evidence of learners with no detectable foreign accent. For example, in Flege et al. (1995), it was found that 6% of 120 native speakers of Italian who started learning English after the age of 12 years old had native-like pronunciation, and in Bongaerts et al. (1995), it was found that 5 out of 11 speakers were rated comparable to the native English control subjects. Thus Piske et al. (2001) conclude that while there is evidence that earlier learners can learn an L2 with less chance or degree of a foreign accent, this does not necessarily support the CP hypothesis or the idea that the loss of plasticity in the brain leads to an inability to acquire language.

Aside from the issue of whether or not language learners could ever achieve native-like performance, another question that arises is whether or not there is even a *need* for learners to aim so high. In Munro and Derwing (1999), they discuss the interaction between foreign accent, comprehensibility and intelligibility and point out that the goal for many L2 learners is to communicate and not necessarily sound like a native speaker. Thus while there are unique groups of learners like those from Bongaerts et al. (1995) that do achieve native-like pronunciation, Munro and Derwing (1999) point out that most learners strive for effective communication. In order to observe the interaction between foreign accent, comprehensibility and intelligibility, a they conduct a perceptual study on the performance of native Mandarin speakers. Following this study, they found that despite the fact that some speakers may have what some consider a 'heavy accent', this does not automatically mean that they are unintelligible. However, they do cite that some accents may cause longer processing times than others. When observing the interaction of variables such as phonemic errors and intonation with intelligibility and comprehensibility, they found that intonation was the most influential factor in comprehensibility, while phonemic errors affected intelligibility. This substantiates the concepts of comprehensibility and intelligibility themselves, as intelligibility is the degree a speaker is understood without involving interpretation (e.g. "What did they say?"), while comprehensibility is the degree a speaker is understood in terms of meaning (e.g. "What do they mean?"). Thus, they suggest that successful communication requires attention to both sounds and prosody for better comprehensibility and intelligibility.

While linguists make these discoveries and observations of L2 learning, it seems that it takes a lot of effort for them to trickle down to the foreign language classroom. In Darcy et al. (2012), they find through a small survey of 14 teachers that although teachers tend to find pronunciation to be 'very important', the majority do not teach it at all. When asked why they do not teach it, they cited reasons such as 'time, a lack of training and the need for more guidance and institutional support'. Even though the number of teachers surveyed may be significantly small, this gives us a glimpse through the lens of what language teachers themselves experience in relation to pronunciation. We see that even though teachers would like to address it, this would require a restructuring in their curriculum and training– something that would undoubtedly take even more time before students get more pronunciation attention. Compounded with the issue of time and the fact that not all learners need or want equal amount of pronunciation training, it may be unlikely to see such change in second language curriculum so soon.

This points to the potential solution of employing a technology-based system to improve pronunciation as learners could individually address their needs *outside* of the classroom.

3.2 Spoken language technology for education

Over the decades, as speech technology has slowly evolved and started to show its potential, many researchers have tried to test its limits by innovating a number of systems to address the challenge of pronunciation. Included in these systems are systems such as computer-assisted pronunciation training (CAPT) systems which attempt to tutor pronunciation through explicit teaching as well as more modern gamified techniques, which attempt to coerce language learners in to practicing pronunciation by making the process more engaging.

Among the two, CAPT systems have had more history due to the extra development and testing gamified techniques require. In fact, gamified systems can be considered a subclass of CAPT systems, as both require a fundamental setup in order to assist the language learner. In general, these systems utilize some form of automatic speech recognition (ASR) to record a speaker and compares their recordings (usually) with a native speaker gold standard. They also usually include a feedback mechanism with a combination of pitch contours, spectrograms or audio recordings to help the user adjust their pronunciation, with gamified systems including at least a point mechanism to motivate the user.

In order to understand the connection between language education and spoken language technology, we take a look at Neri et al. (2002) where we are presented with a through overview between the two areas. Here, we see that aside from the classroom, there seems to be an issue in relating the findings of linguistics/language pedagogy with technology. Part of the reason, they suggest, stems from the fact that there are not 'clear guidelines' on how to adapt second language acquisition research and thus many CAPT systems 'fail to meet sound pedagogical requirements'. They emphasize the need for the learners to have appropriate input, output, and feedback and exhibit how the systems available at the time were lacking. For example, they criticize some CAPT systems that were prevalent at the time including systems like *Pro-nunciation* and the *Tell Me More* series for utilizing feedback systems that give the users feedback in waveforms and spectrograms, which cannot be easily interpreted without training. Further, they argue that although visual feedback has its merits, this kind of feedback suggests to the user that their utterance must look close to what is shown on the screen, which is not the case. An utterance can be pronounced perfectly fine, but look completely different from a spectrogram, and *especially* a waveform due to the number of features represented in each visualization, such as the intensity, which will indefinitely vary from user to user and the given examplar. They conclude their article by making it a point to discuss recommendations for CAPT systems, by stating that they should integrate what has been found in research from second language acquisition, and to train pronunciation in a communicative manner to give context to the learners. They also point to the problematic area of feedback and advise that systems provide more easily interpretable feedback with both audio and visual information, and propose that systems give exercises that are 'realistic, varied, and engaging'.

While Neri et al. (2002) makes solid recommendations in improving CAPT systems, building pronunciation systems that take all of the previous suggestions into consideration requires adept planning and expertise, and can be demanding for most research groups. Instead, some of have tried to adapt already existing technology and build a small architecture around it. For example, (Tejedor-García et al. 2017) experiment with utilizing synthetic voices for corrective feedback in a pronunciation training tool. In their study, they use Google's offline Android text-to-speech (TTS) system as feedback for B1 and B2 Spanish learners of English, and have them focus on the six most difficult pairs of vowels. In order to train the users, the researchers first had them watch videos that describe the articulatory/perceptive features of the vowels, and had them listen to a number of minimal pairs produced by the TTS system in succession. Afterwards, they were asked to discriminate minimal pairs in a listening task and then asked to pronounce them. From this study, they conclude that making use of commercial TTS systems are beneficial for users and instructors alike as indicated by both the improvement in performance by the users and the feedback given by those involved in the experiment. However, because the study was limited to individual words and only six pairs of vowels, further experimentation needs to be conducted in order to understand whether these learners can generalize their training.

While a brief overview, it is evident that there is a large potential for appropriately adapting technology to guide and help language learners and teachers alike. Yet, in order to provide long-standing worthwhile results, further consideration needs to be given to the suggestions and evidence of previous research and should be integrated in the design and implementation of future systems. This implies that the appropriate time and resources may need to be dedicated in order to push the boundaries of technology and its application in language education.

3.3 Voice conversion

There have been a number of efforts to design voice conversion systems using various methodologies. Much like the rest of the speech technology field, earlier voice conversion systems began with utilizing MFCCs and GMMs for conversion and slowly evolved towards utilizing more advanced features and adaptation techniques.

In particular, a variation of GMM voice conversion set forth by Toda, Black, et al. (2007) has become what appears to be the standard set-up. Following their reasoning, they argue that although regular GMMs perform fairly well in voice conversion, they also lead to the deterioration of speech quality. Instead, they propose that by using a maximum-likelihood estimation of the spectral parameter trajectories, issues that cause the loss of quality such as oversmoothing of the spectral features can be avoided. They provide detailed theoretical evidence to support their method which can be further observed by taking a look at their paper.

GMMs have long been used for voice conversion alongside other speech tasks, but more recently another method– or more accurately another feature in place of MFCCs, known as *i-vectors* have taken off. To put concisely, i-vectors are akin to word embeddings in text-based natural language processing tasks in the sense that i-vectors encapsulate any type of desired speech information in a vectorized fashion. This may be confusable with MFCCs, which also vectorize speech information; however MFCCs specifically vectorize individual speech sounds from frames, while i-vectors tend to vectorize more large-scale, dynamic speech information.

The usage of i-vectors have proven to be successful in a number of tasks, such as speaker verification, language identification, and native accent identification. They have become especially popular due to the fact that they work well with unlabeled acoustic data. Referring back to the overview of voice conversion in the previous section, it is mentioned that labeled acoustic data often leads to better results in the conversion, but is also often unavailable. Thus i-vectors are able to fill this gap in the lack of available labeled data and the loss of conversion quality.

In the instance of voice conversion, i-vectors are made of speaker super-vectors trained on GMMs and low dimensional features that represent an individual speaker's features (J. Wu et al. 2016). This is extracted per utterance and then averaged to form an i-vector that represents an individual speaker. In this way, a source speaker's i-vector can be approximated towards a target speaker's i-vector by a mapping function using neural networks, gaussian mixture models, or other appropriate algorithms.

The usage of i-vectors in voice conversion has been seen in works such as J. Wu et al. (2016) and Kinnunen, Juvela, et al. (2017). Following Kinnunen, Juvela, et al. (2017), the usage of i-vectors in voice conversion aligns perfectly with the task as it is highly similar to speaker verification; however instead of being a classification task (e.g. is this said speaker or not), voice conversion is a regression task. In J. Wu et al. (2016), they test and compare the performance of using plain mel-cepstral coefficients (MCCs) against i-vectors by training a variety of systems. Among their systems, they utilize a strategy known as the *average voice model*, which models what an average speaker would sound like by utilizing a large amount of parallel utterances, which also allows for conversion between two speakers *without* having parallel utterances. In order to compare MCCs vs. i-vectors, they train systems using MCCs as features with a deep bi-directional long-short term memory neural (DBLSTM) network architecture, a DBLSTM combined with an average voice model (DBLSTM + AVM), and a DBLSTM combined with an average voice model retrained on some paralleled data from the testing source-target speakers (DBLSTM + RM). They then train another system with i-vectors using the DBLSTM and average voice model (DBLSTM + AVM + i-vectors). In order to evaluate these models, they provide both an objective evaluation using a measure known as mel-cepstral distortion (MCD) and a subjective evaluation rated on quality and similarity, which was decided by the votes of 20 listeners.

Following the results of the objective evaluation, they find that the system with the lowest mel-cepstral distortion (e.g. the best system) is the DBLSTM + RM model, followed by the DBLSTM + AVM model, with the regular DBLSTM system and DBLSTM +

AVM + i-vector system performing roughly the same. They note that the DBLSTM + RM system likely performed the best because of the inclusion of parallel data from the test dataset, while the DBLSTM + AVM outperformed the regular DBLSTM likely due to the size of the training data. However, they do not give much indication as to why the DBLSTM + AVM and DBLSTM + AVM + i-vectors perform similarly. Based off of the MCD alone, it would seem that i-vectors do not provide much benefit; however they emphasize that the DBLSTM + RM system does include parallel data while the DBLSTM + AVM + i-vectors system does not.

In the subjective evaluation, they compare the four systems by using an ABX preference test to compare: DBLSTM + RM vs. DBLSTM, DBLSTM + AVM + i-vectors vs. DBLSTM + RM and DBLSTM + AVM + i-vectors vs. DBLSTM + AVM. With each pair, they have the listeners evaluate 10 sentences for a total of 200 votes for each system. Following the results, they find that the DBLSTM + AVM + i-vectors system outperforms the DBLSTM + AVM system in both the speech quality and speaker similarity categories with statistical significance, which shows that the average voice model *without* i-vectors (e.g. MCCs only cannot capture speaker specific information. They also find that the DBLSTM + RM system outperforms the plain DBLSTM system with statistical significance, indicating that the average voice model is not only useful, but also helps reduce the amount of parallel training data required to improve the performance. Finally, they find that the DBLSTM + AVM + i-vectors system was rated slightly higher in quality, but opposite in similarity. However this was without statistical significance, indicating that they perform roughly the same. From this study, J. Wu et al. (2016) concludes that the DBLSTM + AVM + i-vectors method has potential as it allows for great flexibility to generate the target speaker spectrum without using parallel data.

DeMarco and Cox (2013), present a through analysis of the usage of i-vectors in classifying native British accents using the same ABI corpus utilized in one of the experiments of this work. When comparing more traditional classifiers such as a universal background GMM, a support vector machine with GMMs, GMMs with unigrams/bigrams to various i-vector configurations, DeMarco and Cox (2013) found that utilizing i-vectors outperformed the traditional methods by as much as 25%.

Even though systematic objective and subjective evaluation against older methods do indicate that recent methods have improved upon the older ones, comparing the performance of these systems against a true human voice, or perhaps more fairly, against other recent systems in other areas of speech technology, these systems still seem to leave a lot left to be desired. For example, in listening to the audio of J. Wu et al. (2016)[1] it

[1] Visit http://www.nwpu-aslp.org/vc/apsipa-jiewu-demo.pptx to hear samples.

is apparent that regardless of the low quality of the original source and target audios, the quality of the converted audio sounds muffled. This can be attributed to the various nuanced steps and features required to have high quality voice conversion.

For example, in a shared task dedicated to voice conversion, appropriately called *The Voice Conversion Challenge* where many leading research groups involved in speech technology around the world have submitted systems in attempts to tackle the issue. In the second iteration of the challenge Lorenzo-Trueba et al. (2018), the organizers proposed both a parallel and non-parallel version of the task, both of which were evaluated on natural and similarity using crowdsourcing.

The type of systems submitted to the 2018 edition of the task displays the current state of voice conversion and perhaps machine learning research in general as this year saw a huge increase in the number of systems using neural networks. However, it does not go without saying that there were indeed systems that used more traditional statistical methods, such as Gaussian Mixture Models (GMM) and one of its variations, differential GMM (DIFFGMM).

In order to evaluate the systems, a group of roughly 300 listeners were gathered to carry out a perceptual evaluation. The systems were evaluated on two main measures: naturalness, which was evaluated on a scale of 1 (completely unnatural) to 5 (completely natural); and similarity, which was evaluated using a same/different paradigm. Following the results, only one system, referred to as N10, was able to outperform the baseline in terms of naturalness (alongside the original source and target audios). When observing the performance of other systems in terms of similarity, we see about 5 our of 23 submitted systems outperforming the baseline. From this, we can conclude that it easier to create a system with high similarity than high naturalness, which is consistent with other common systems.

In discussing the results of the N10 system, the authors credit the success of the system to the *hundreds of hours* of external speech data that was utilized to train a model to recognize content-related features, as well manual fine-tuning. The creators of this system also made use of WaveNet, a novel high-fidelity vocoder and dozens of hours of clean English speech, which could also explain the success of their results. Thus, as previously discussed, we can conclude that creating a high-fidelity voice conversion requires not only appropriate fine-tuning of the data, but also a large amount of external data to support the system.

Thus, even though many systems were neural network based, only one neural network based system was able to outperform the sprocket GMM-based baseline, which could suggest that NN-based methods require proper fine-tuning of the hyperparameters.

Although we see limitations in the systems presented in The 2018 Voice Conversion Challenge, there have been other efforts to present high quality voice conversion systems in works such as and Nguyen et al. (2016) and Fang et al. (2018). For example, in Fang et al. (2018), they leverage a cycle-consistent adversarial network (CycleGAN) architecture, a variation of the recently trending generative adversarial network (GAN) architecture, which was originally used for unpaired image-to-image translation.

While not necessarily directly related to the standard idea of voice conversion, there have also been some incredible breakthroughs in systems set forth by research teams at Google Brain. One such system involves the Tacotron end-to-end system, which has been proposed to replace the current set-up of text-to-speech systems by reducing the amount of components (decoder, vocoder, etc.) into one piece. The researchers working on this system have recently revealed a impressive system that also takes advantage of deep neural networks to encode speaker characteristics into embeddings, which are then utilized to transfer style (Wang et al. 2018). They show how their system is capable of transferring a variety of emotions and accents, making the synthesized audio sound more human-like. Samples of these audios can be found at the following link[2].

Even though the these systems created by Google Brain are highly impressive, it is evident that the reason for the success of their systems is due to very fine-grained parameter tuning and the availability of large-scale, high quality data that many research institutions likely do not have access to or have funding for. For example, if we juxtaposed the audio from the Google Brain systems to the best performing system of the Voice Conversion Challenge 2018, we can still observe some disfluencies in the audios of the best system of the VCC 2018. Thus, it may be a long while before the general public has the ability to completely replicate such systems and before this work trickles in to the domain of accent conversion.

3.4 Accent conversion

Due to the specialized nature of accent conversion as compared to voice conversion, there are fewer articles and systems available for reference. In fact, most of the recent articles that are easily accessible on accent conversion were all published by the same group of researchers at Texas A&M University.

However, before the work of these researchers, works such as Yan et al. (2004) and Huckvale and Yanagisawa (2007), explored manipulating various features in order to observe their relationship with a perceived accent. In Yan et al. (2004), they manipulate

[2] Visit https://google.github.io/tacotron/publications/global_style_tokens/ to hear samples.

spectral features, intonation patterns and duration in order to observe their correlation across British, Australian and American accents. Through an ABX perceptual test, they found that 75% of the synthesized utterances were evaluated as having the native accent, highlighting the potential for segmental accent conversion.

In Huckvale and Yanagisawa (2007), they examine the relationship between intelligibility and the of morphing various segmental and suprasegmental features such as pitch, rhythm and segments of an English TTS system designed to speak 'accented' Japanese. This TTS system was designed by creating a custom dictionary and mapping the Japanese sounds to their closest English counterpart. They found through native speaker evaluation that morphing pitch and rhythm individually had no effect, and similarly modifying segments alone only gave a small improvement. However, they discovered that combining the morphing of all of these features created a large increase in intelligibility, with intelligibility going up from 57% as seen in their lowest-performing system to 84%. The results emphasize the need to consider the interaction between segmental and suprasegmental in the conversion task.

In one of the earliest works from the Texas A&M research group, and perhaps a key influential paper to this work, Felps, Bortfeld, et al. (2009) examines the potential of using a method known as Pitch-Synchronous Overlap and Add (PSOLA) for accent with the motivation of applying it in the context of language learning. Specifically, they utilize a specialized PSOLA method known as Fourier-domain PSOLA (FD-PSOLA), as it performs best in preventing spectral distortion when modifying the pitch. In order to conduct the conversion process, they separate the converting of the segments and the converting of the prosody into two separate parts, with both parts evaluated individually and combined. In evaluating their method, they measured the accentedness, acoustic quality and identity of each converted audio using auditory tests given to a number of speakers. Similar to Huckvale and Yanagisawa (2007), they observe that the combination of prosodic and segemental transformation lead to a large improvement in reducing foreign accent. However, in terms of quality, they found that all transformations led to lower ratings, which likely indicates the loss of some spectral information. The identity ratings proved to be the most interesting as Felps, Bortfeld, et al. (2009) find that the listeners indicate a 'third' speaker. In other words, the converted audio sounds neither like the source or target speaker. Thus Felps, Bortfeld, et al. (2009) concludes that while accentedness is reduced by their system, their proposed system also loses the necessary information needed to retain the speaker's identity.

In other works done by this group of researchers such as Aryal and Gutierrez-Osuna (2014b), they continue to make efforts to address this challenge. Throughout their research, they test a variety of methodologies, including accent conversion through voice morphing and articulatory synthesis. In Aryal and Gutierrez-Osuna (2014b), they propose a variation to standard forced alignment techniques used in voice conversion to pair frames based on acoustic similarity.This particular paper serves as the main basis for the experiments and research conducted in this work due to its relative ease compared to some of their earlier and later work.

Following their methodology, they first use dynamic time warping (DTW) to align parallel utterances from the L1 and L2 speakers in order to apply vocal tract length normalization to dampen the differences in pitch. They then extract sequences of 24 MFCCs per utterance, and cluster the MFCC vectors into 512 clusters using the *k*-means algorithm to easily find the most acoustically similar sound for each frame. The most acoustically similar frames are then calculated by finding the closest L2 cluster, and then selecting the most similar frame within the cluster. After the closest vectors are paired, they map the conversion using a GMM.

In order to evaluate their system, they had a group of 13 participants rate 12 utterances from the test set for their perceived accent (Which utterance was less accented?) and perceived speaker identity (Does utterance X sound more similar to A or B?). This system was compared to a standard voice conversion system that uses standard forced alignment and trained using GMMs. They found that comparing the AC system to the original L2 audio resulted in participants rating the converted audio as sounding less accented 86% of the time, while the VC system compared to the original L2 audio was rated at 91% of the time. However, when the converted audios from both systems were compared, participants rated the AC system to be less accented compared to the VC system 59% of the time. It was also concluded that the AC system was more successful in retaining speaker identity, as the participants found the converted audio more similar to the L2 speaker 78% of the time. More interestingly, they found that the AC system was especially effective in converted utterances that are harder for the L2 speaker to pronounce. This was measured by examining the relationship between the number of phonemes that do not exist in the L2 language (in this case Spanish), and the number of listeners who judged the converted speech as sounding less accented.They found that there was a 0.86 correlation, indicating the robustness of the AC system. Thus, it appears that adjusting the alignment method to align acoustically similar sounds is a good start for accent conversion systems.

In Aryal and Gutierrez-Osuna (2014a) and Aryal and Gutierrez-Osuna (2015), we see a more novel method that looks beyond acoustic features to perform accent conversion. Citing the results of their previous work, they motivate the usage of articulatory gesture information in accent conversion reasoning that acoustic-based systems often struggle in the challenge of separating accent from speaker identity, which causes the accent converted audio to sound like a combination of the L1 speaker and L2 speaker. In order to test this idea, in Aryal and Gutierrez-Osuna (2015), they propose a system that combines both the more standard acoustic information like aperiodicity, pitch and energy from the L1 speaker with articulatory information recording using an electromagnetic articulograph (EMA). Like many recent works, they test a DNN-based mapping function between the L1 and L2 data, which they compare to the previously popular GMM-based system.

In the evaluation of their system, they again use crowdsourced efforts to rate their system based on intelligibility, accentedness, and speaker identity. According to their sample size of 15 participants, they find that the DNN-based system was rated to have a 4.3 out of 7 in terms of intelligibility as compared to 3.84 out of 7 for the GMM-based system, proving that including articulatory gesture information and DNNs are more robust in this instance. The participants also rated the DNN-based system to be more native-like in 67% of cases as compared to the GMM-based system. With that said, the test set was only 15 sentences, which indicates that 10 out of 15 sentences were better with the DNN system; thus the test set used may be too small to draw hard conclusions. The most important conclusions drawn from their experiments was that of the voice identity assessment. In asking the participants to rate whether an MFCC compression and AC audio from the DNN and GMM-based systems, they found that the participants were fairly confident that the two audios were from the same person with both systems, with the DNN-based system outperforming the GMM-based system as before at a score of 4.3 out of 7 on average, and the GMM-based system at a score of 4.0. However, this is difficult to compare to more common acoustic-only accent conversion systems, as this is not including in their evaluation. With that said, it may be possible to conclude that this would outperform acoustic-based systems, as they proposed this system to tackle flaws in their previous work.

Evidentally, although including articulatory gesture information seems to improve the performance of accent conversion systems, as discussed in the closing remarks of their paper, recording articulatory gesture information can cost a great deal of money and time (Aryal and Gutierrez-Osuna 2015). Most publically (and privatized) speech corpora also do not include this type of information, meaning that experimenting with it in accent conversion at a broader scale is unfeasibile. Thus, it is ambitious to accept adding articulatory information to accent conversion systems and further work needs to be done in order to scale standard audio-based speech corpora.

Departing from utilizing articulatory gesture information, Zhao, Sonsaat, Levis, et al. (2018) returns to a more simpler method similar to Aryal and Gutierrez-Osuna (2014b). However, instead of matching frames based on their *acoustic* similarity, they test matching frames based on their *phonetic* similarity. They do this by mapping the frames of each source and target speaker into something referred to as a *phonetic posteriorgram*. Following Hazen et al. (2009), a phonetic posteriorgram is ‘a time vs. class matrix that

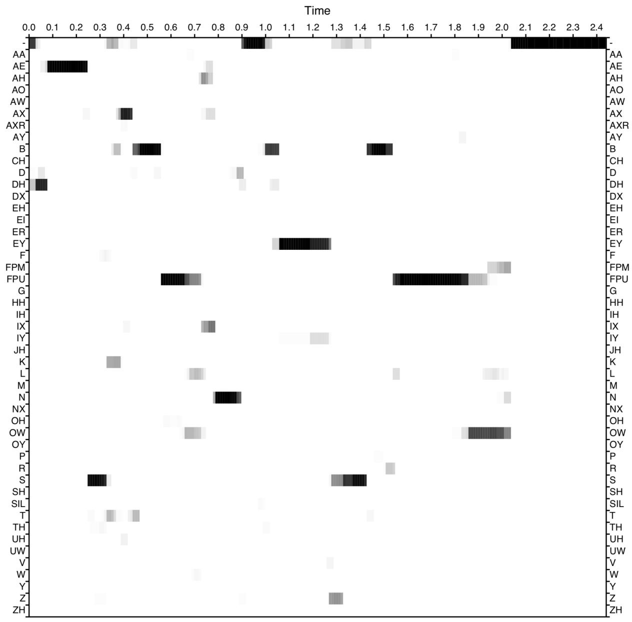


Figure 3.1: An example posteriorgram representation for the spoken phrase 'basketball and baseball'. The x-axis represents the time across the utterance and the y-axis represents the possible phonemes. Taken from Hazen et al. (2009).

represents the posterior probability of each phonetic class for each time frame'. An example of a phonetic posteriorgram taken from Hazen et al. (2009) can be seen in Figure 3.1.

The phonetic posteriorgrams are computed using a native English speaker-independent acoustic model and then the most similar source and target frames are matched by calculating something known as the Kullback-Leibler divergence (0 indicating similar or same behavior, 1 indicating completely different) between the source and target posteriorgrams. After matching the frames, they train GMMs with 128-mixture components to model the distribution of the MCEPs to convert the speech. The performance of this proposed system is then compared to a standard voice conversion system using dynamic time warping to align the frames and the system described in Aryal and Gutierrez-Osuna (2014b).

Like the previous works of Aryal and Gutierrez-Osuna (2014b) and Aryal and Gutierrez-Osuna (2015), this work also approaches evaluation using a perceptual listening test to evaluate acoustic quality, speaker identity and accentedness. However, in this work, they evaluate over 50 test utterances using 30 participants, which better substantiates their results compared to the evaluation of 10-15 utterances by 10-15 participants in some of their older studies.

In terms of acoustic quality, they found that their proposed posteriorgram method received a score of 3.0 on a Mean Opinion Score scale of 1 to 5 (with 1 being 'bad' and 5 being ‘excellent’), as compared to a score of 2.6 using the method from Aryal and Gutierrez-Osuna (2014b) and 2.5 for standard voice conversion, meaning that their system here was able to vastly improve in terms of acoustic quality. Following the average scores for speaker identity, they were also able to determine that the participants were ‘confident’ that the converted audio files were the same speaker, with a voice similarity score of 3.5 (on a scale of -7 to 7, with 7 being ‘definitely the same speaker’). Finally, in order to assess the accentedness of their posteriorgram-based converted audio, they utilized a preference test to compare standard voice converted audios with frames matched using Dynamic Time Warping, accent converted audios with frames acoustically matched as in Aryal and Gutierrez-Osuna (2014b), and their posteriorgram method. They found that the participants evaluated the posteriogram method to make the L2 audios sound more native like with a mean of 98%, and agreed that the posteriorgram method outperformed the standard voice conversion method with a mean of 69% in agreement, and a mean of 72% when compared to the previous accent conversion method. This means that currently, the posteriorgram method is the best peforming method for accent conversion as it outperforms previous methodologies in all three evaluation criteria.

Aside from the work conducted by the research group at Texas A&M University, it appears to be that there are not many, if any other researchers currently working in this subarea of accent conversion. This may be because voice conversion still leaves a lot to be desired itself, suggesting that most researchers may want to focus on perfecting standard voice conversion before attempting to tackle something more fine-grained. However, as research in voice conversion continues to expand, it also creates the potential to apply methodologies from voice conversion to accent conversion. Following the general methodologies of voice conversion, we hypothesize that it should be plausible to convert accents in a similar fashion and eventually apply more recent innovations to propose state-of-the-art methods.

Chapter 4

Design and methodology

In this chapter, we introduce the dataset and tools utilized in the experiments, and detail the procedures carried out to conduct the accent conversion process. We also go over the evaluation criteria for accent conversion systems following standards set forth by by previous work Aryal and Gutierrez-Osuna (2014b), Mohammadi and Kain (2017), and Zhao, Sonsaat, Levis, et al. (2018).

4.1 Data

The main datasets utilized in the following experiments are the Carnegie Mellon University (CMU) ARCTIC corpus (Kominek and Black 2004), the L2-ARCTIC corpus (Zhao, Sonsaat, Silpachai, et al. 2018), a non-native English counterpart to the CMU Arctic corpus and the Accents of the British Isles (ABI) corpus (D'Arcy et al. 2004).

4.1.1 CMU ARCTIC corpus

The CMU ARCTIC corpus is an older corpus that originates from sometime in 2004, following the publication date of the corpus' description. It was was originally designed to have good phonetic (specifically diphone) coverage for speech synthesis and aimed to be cleanly recorded and matched the intended domains. The corpus itself contains roughly 1200 read utterances per speaker taken from Project Gutenburg, which contains a number of modern short stories and novels. The corpus is distributed with 16KHz waveforms with full phonetic labeling and simultaneous EGG signals.

The CMU ARCTIC corpus contains 4 US English speakers, with speakers *bdl* and *slt* being experienced voice talents. It also comes with 14 other speakers with varying

Accent	Sex	Speaker ID
US	male	aew
US	male	bdl
US	female	clb
US	female	eey
US	female	ljm
US	female	lnh
US	male	rms
US	female	slt
Scottish	male	awb
Irish	male	fem
Indian	male	aub
Indian	female	axb
Indian	male	gka
Indian	male	ksp
Indian	female	slp
German	male	ahw
Dutch	male	rxr
Candian	male	jmk

Table 4.1: A complete list of the ARCTIC speakers, their accents and speaker IDs.

accents, including Canadian, Scottish, and Indian. A full list of the speakers and their speaker IDs can be seen in Table 4.1.

4.1.2 L2-ARCTIC corpus

The L2-ARCTIC corpus was recently curated by researchers as a joint collaboration between the Texas A&M University and Iowa State University with the intention of distributing the corpus for research in voice conversion, accent conversion and mispronunciation detection. At the time of writing, the L2-ARCTIC corpus contains 20 non-native speakers of Hindi, Korean, Mandarin, Spanish and Arabic, with a male and female speaker for each language, but the researchers have indicated that there may be other speakers in the future.

The original audio was sampled at 44.1 kHz, with each recording at roughly 3.7 seconds on average. In total, the duration of the corpus is 11.2 hours, with each speaker recording an average of 67 minutes of audio, or the complete ARCTIC sentence prompt list of 1,132 utterances. However, some speakers did not read all of the sentences and some recordings were removed as they did not have appropriate quality.

In addition to the audio files, the corpus also includes word and phoneme-level transcriptions and manually annotated errors for a 150-sentence subset of the corpus, designed to be used in computer-assisted pronunciation training tools. Within the subset, there are 100 sentences uttered by all speakers, and 50 sentences that contain phonemes that are considered to be difficult based on a speaker's L1. This also includes phone addition, phone substitution, and phone deletion annotations in ARPAbet format, as well as optional comments left by the annotators.

4.1.3 Accents of the British Isles (ABI) corpus

The ABI corpus was originally designed and collected to support efforts in systematic studies of the relationship between various accents in the British Isles and speech technology. At the time of its creation, there was no appropriate corpus that existed that could be used for this type of research. One of the largest obstacles in designing a succinct corpus to capture the varieties of accents across the British Isles was deciding how to define accent. As mentioned in the introduction to this work, the authors had difficulties finding suitable subjects as some people associated their accent not only with their geographic region but also their own social backgrounds.

Nonetheless, the authors of the corpus chose to define 14 regions known for their associated accents and selected towns or cities that were representative of each accent. At each location, 20 people were recorded, for a total of 10 female and 10 male. The creators of the corpus also mandated that the subjects needed to be born and have lived in that location all of their lives.

The corpus contains a variety of utterances, including word lists to contrast the different vowels across accents (e.g. 'heed', 'had', 'hide', etc.), short phrases such as 'roll of wire' or 'thin as a wafer', and long phrases that are cut up from the readings of short 'accent diagnostic' stories. The audio was recorded at a sample rate of 22.5KHz per second with 16 bit resolution.

The accents contained in the ABI corpus can be seen in Table 4.2:

4.1.4 Experimental data set-up

Using the corpora described above,we split them into two sets of experiments, with the ARCTIC corpora used in one set of experiments and the ABI corpus used in another set of experiments.

Region	Towns/Cities	Code
Standard Southern English	n/a	sse
Midlands	Birmingham	brm
Wales	Denbeigh	nwa
Scottish Highlands	Elgin	shl
Republic of Ireland	Dublin	roi
East Yorkshire	Hull	eyk
Lancashire	Burnley	lan
Ulster	Belfast	uls
NE England	Newcastle	ncl
Scotland	Glasgow	gla
Inner London	n/a	ilo
NW England	Liverpool	lvp
East Anglia	Lowestoft	ean
West Country	Truro	crn

Table 4.2: The regions of the British Isles and their corresponding cities where the ABI corpus was recorded, as well as their corresponding codes in the corpus.

4.2 Experiments

4.2.1 CMU ARCTIC Corpus

As discussed in the introduction of this work, accent conversion has been proposed as better-suited feedback mechanism for accent training systems. These two corpora are specifically used to test how effective accent conversion is on minimizing the effects of non-native speech.

Following Zhao, Sonsaat, Levis, et al. (2018) who also works with the ARCTIC corpora, only 150 parallel utterances or roughly 9 minutes of data, following the L2-ARCTIC average are utilized, with the utterances from the L2-ARCTIC corpus down-sampled to 16 kHz to match the quality of the CMU ARCTIC corpus. During the selection of the 150 utterances, any phrases not recorded by *all* of the speakers chosen for the experiments were not considered in order to maintain the parallelness of the experiments. The data used in this experiment was also text-independent as the CMU ARCTIC corpus does not contain labeled utterances. Out of the 150 utterances, 100 were randomly chosen as training utterances while the other 50 were used test utterances.

Although the sample size is very small compared to the actual size of the corpora, a small sample is chosen to acknowledge the fact that often only a little amount of data is available or acquirable in building these systems. This is done similarly in the Voice Conversion Challenge 2018 as well Lorenzo-Trueba et al. 2018.

The speakers utilized in the experiments are also limited to speakers BDL (male) and CLB (female) from the CMU ARCTIC database, who are the native reference speakers, while the non-native speakers chosen from the L2-ARCTIC corpus are the native Korean speakers (HKK, male; YDCK, female), Hindi speakers (RRBI, male; TNI, female), and Spanish speakers (EBVS, male; NJS, female). This is mostly similar to the datasets in Zhao, Sonsaat, Levis, et al. (2018), with the exception of the Korean female speaker (YDCK) in place of the male Korean speaker (YKWK), which is not included in the current release (at the time of writing) of the L2-ARCTIC corpus, and the replacement of the native male Arabic speaker (ABA) with the two native Spanish speakers.

4.2.2 ABI Corpus

Accent conversion systems have also been mentioned as a possible solution to challenges that current speech recognition systems may have. However, the few accent conversion studies (Aryal and Gutierrez-Osuna 2014a; Aryal and Gutierrez-Osuna 2014b; Aryal and Gutierrez-Osuna 2015; Zhao, Sonsaat, Levis, et al. 2018) conducted by those from the Texas A&M research group have focused on accent conversion between non-native and native speakers, and voice conversion studies such as the Voice Conversion Challenge 2016 and 2018 (Lorenzo-Trueba et al. 2018; Toda, Chen, et al. 2016) have mainly investigated conversions between US speakers. Thus, in order to see the effects of accent conversion between native speakers and to include other varieties of English, the ABI corpus was chosen.

Although the ABI Corpus contains a total of 14 accents, only 4 accents were selected, with the Southern Standard English (SSE) accent used as the source accent (the 'native' accent) and the East Anglia (EAN), Glasgow (GLA), Lancashire (LAN) used as the target accent (the 'non-native' accent) to match the structure of the CMU ARCTIC corpus experiments. These accents were chosen based on their dissimilarity from the Southern Standard English accent. Although phonological and other linguistic information could have been used to quantitatively measure the level of dissimilarity between the accents, we measured the level of dissimilarity following the word error rate of using an ASR system for each accent in the ABI corpus as seen in Najafian et al. (2014). After organizing the word error rate for each accent from high to low, the Glasgow, Lancashire, and East Anglia accents were repsectively chosen for having the worst word error rate, to being in the middle, and being fairly close to Standard Southern English.

The ABI Corpus had more coverage in terms of the number of speakers available per accent and gender, as well as variation in the recording environment and quality. Concretely, some speakers were much more quieter than others, while others spoke at a much more rapid pace than others, or enunciated much less than others. Thus, during the speaker selection process, we manually listened to a sample of each speaker, either from the ‘shortphrases’ or ‘shortsentences’ folder, and chose based on these criteria. Some of the chosen speakers had recorded some of the same words and/or phrases, mostly due to production errors such as stumbling or reading the wrong word. In the case that a chosen speaker had repeated recordings,we removed the malformed recordings in order to keep the experimental corpus as parallel as possible. The utterances were also not labeled, making this experiment also text-independent.

The experiments for the ABI corpus are set up similarly to the ARCTIC experiments in terms of the proportion of training and test set utterances. However, unlike the ARCTIC corpus, the total amount of data available for the ABI corpus was roughly 5 minutes per speaker. Because the ABI corpus also contains a mixture of word lists and phrases/sentences, this made it more difficult to randomize all of the audio into separate training and test sets. Thus, in order to maintain a similar proportion of audio like the ARCTIC experiments, we chose to use all of the word lists as the training set and the phrases and sentences as a test set. Utilizing the phrases and sentences as a test set also made more logical sense as this allowed for better comparison to the ARCTIC results and because converting the accents for a single word appeared to be more trivial in both usage and evaluation.

4.3 Tools and set-up

In order to understand more traditional mapping methods used in voice and accent conversion, we follow the Gaussian mixture model method described in Toda, Black, et al. (2007) for voice conversion by reimplementing the method described in Aryal and Gutierrez-Osuna (2014b) which utilized frame matching based on acoustic similarity. In reimplementing the methodology of Aryal and Gutierrez-Osuna (2014b), we checked for the optimal number of components for the Gaussian mixture model. We tested a variety of set-ups from 64, 128, and 256 components and found that like Aryal and Gutierrez-Osuna (2014b), a GMM of 128 mixture components sounded best. We also represented each utterance as a sequence of 24 MFCCs with deltas.

In reimplementing Aryal and Gutierrez-Osuna (2014b), certain features were removed– namely vocal length tract normalization and prosody modification. Although it is discussed that vocal tract length normalization allows for better frame matching, it was assumed that converting audio between speakers of the same gender would have less impact from differences in vocal tract length. Inspection of preliminary conversion audio without these features compared to conversion with these features as offered by

Package	Version
bokeh	1.0.3
holoviews	1.11.0
jupyterlab	0.35.4
librosa	0.6.2
nnmnkwii	0.0.17
numpy	1.15.4
pandas	0.23.4
pysptk	0.1.14
scikit-learn	0.20.2

Table 4.3: A list of the core packages and their versions used in this work.

Zhao, Sonsaat, Levis, et al. (2018) also suggested little to no impact.

In order to conduct the experiments, we utilize a 2013 Macbook Pro and Python version 3.6.6 alongside Jupyter Lab to manage all of the experiments, calculate the results and generate graphics.

For the experiments, we utilize the `nnmnwkii`[1] Python package which provides fast and easy functions to train voice conversion systems conveniently based on Toda, Black, et al. (2007). Alongside this package, we also utilize a number of other packages that `nnmnkwii` is dependent on, including `pysptk`, a Python wrapper for the Speech Processing Toolkit, `pyworld`, a Python wrapper for WORLD, a well-known tool for high-quality speech analysis and acoustic feature extraction, `librosa`, another package for audio analysis, and the common `scikit-learn` machine learning package for GMM training. In addition, we use a custom method written to find the most acoustically similar for each frame and convert the corresponding frames instead of the frames matched using dynamic time warping. This was done just as in Aryal and Gutierrez-Osuna (2014b) by clustering the source and target frames into 512 clusters using the k-means algorithm and then finding the most acoustically similar target frame for each frame in the source utterance and vice versa.

In order to calculate the results of the experiments discussed in **??**, we utilize the `pandas` package to manage the data from the survey and calculate statistical measures such as t-test and z-test using the standard `scipy` package. Graphics are generated using the `bokeh` package generated using the `holoviews` wrapper package.

The specific versions of the key packages used in the experiment and result calculating process can be seen in Table 4.3.

[1]Found at: https://github.com/r9y9/nnmnkwii

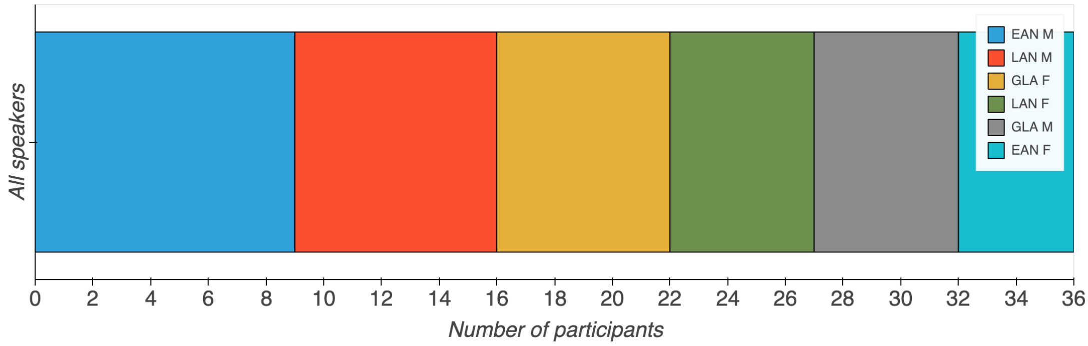
4.4 Evaluation

Voice conversion and accent conversion systems can be evaluated using either: a) objective measures or b) subjective measures. With objective measures, evaluation can be challenging as it often requires intricate formulas that do not necessarily extrapolate across datasets or even individual audios (Felps and Gutierrez-Osuna 2010). With subjective methods, it is often simpler as evaluation can be conducted by simply gathering participants and asking them to rate certain criteria.

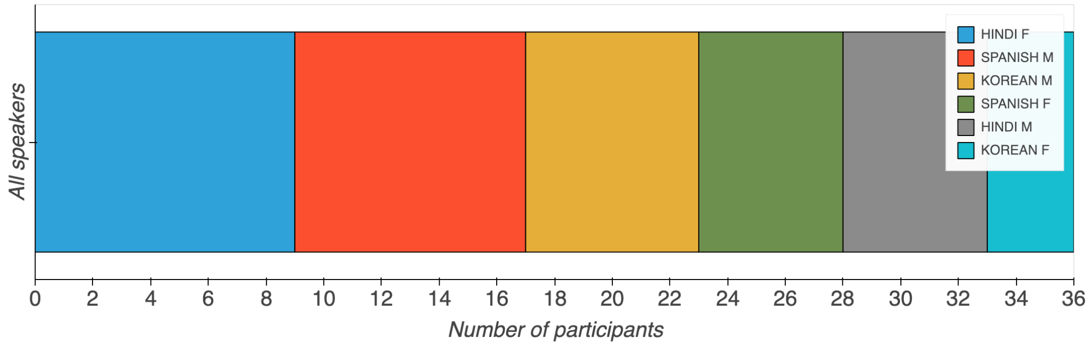
In both cases, accent conversion systems are often evaluated on three features: the acoustic quality, speaker identity, and accentedness of each converted audio. With acoustic quality, the goal is to ensure that the audio does not deteriorate from the original and source audios, while speaker identity aims to ensure that the target speaker still sounds like themselves and not the source speaker. Accentedness is the most straightforward measure of the three, as accentedness aims to measure how much the accent of a target speaker is reduced or to measure how similar the accent of the converted audio is to the source speaker.

In the case of the experiments here, we choose to evaluate using a perceptual study due its reliability and because of the complexity of using objective measures. we adapt the method utilized in Zhao, Sonsaat, Levis, et al. (2018), which in turn was adapted from Aryal and Gutierrez-Osuna (2014b), another previous work from the same research group. Specifically, we gather a group of 36 listeners to listen to 40 test samples with 20 taken from the experiment done with the ARCTIC corpus and 20 taken from the ABI corpus. 10 test samples are used for each evaluation criteria. The participants include a number of students that are a part of the Erasmus Mundus Language and Communication Technology Master's, as well as some local students from the University of the Basque Country, the University of Malta and other acquaintances of the author. The survey was also posted on Reddit under the /r/SampleSize subreddit and distributed by some participants recruited directly by the author to other acquaintances of the participants.

The number of listeners were decided by recruiting roughly 40 people with the anticipation of collecting enough results so that each speaker in both sets of corpora would be evaluated by at least 5 listeners. At the close of the survey, only the female East Anglia speaker (EAN F) from the ABI experiments and the female Korean speaker from the ARCTIC experiments had less than 5 evaluators, at a total of 4 and 3 respectively. The distribution of evaluators per speaker in the ARCTIC experiments and the ABI experiments can be seen in Figure 4.1. This graph is organized so that the colors shown in the key represent the selected speaker from either the L2-ARCTIC corpus (e.g. blue



(a) ABI experiment



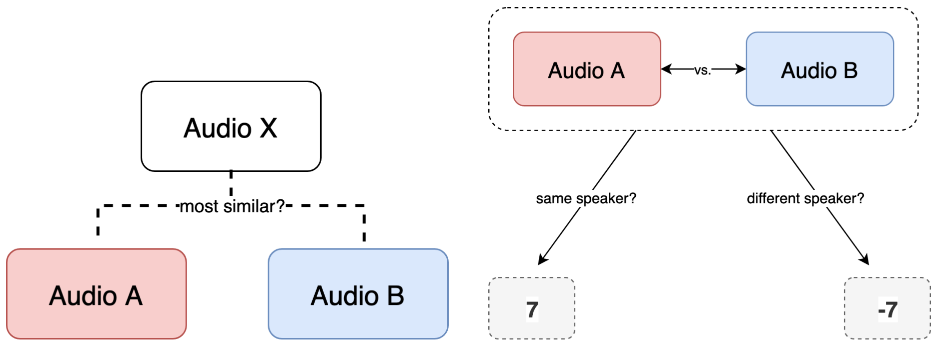
(b) ARCTIC experiment

Figure 4.1: The distribution of speakers in each experiment.

for the East Anglian male speaker) or the ABI corpus (e.g. blue for the Hindi female speaker). The 36 speakers are then divided into their appropriate groups per experiment to represent how many participants evaluated each speaker. For example, there were 6 participants who evaluated the GLA F speaker in the ABI experiment as this part of the graph ranges from 16 - 22.

The survey was uploaded on to Google Forms, with the audios embedded on a separate page found on a GitHub Page associated with the GitHub repository for this work. All listeners were asked to evaluate 1 speaker from the CMU ARCTIC experiments and 1 speaker from the ABI experiments using headphones/earphones. The speakers that each evaluator assessed were decided upon randomly using the 'shuffle option order' embedded in Google Forms. The audios embedded on the GitHub page were in PCM signed 16-bit .wav format, which were converted from the original audio files outputted by the accent conversion system. The original audios were converted using the command line interface of `ffmpeg` version 4.0.2 in order to better support in-browser playback as the original .wav format was not compatible with current HTML5 standards.

The participants in the survey were first asked to evaluate ten (10) converted audios on their perceived accent similarity using an ABX format to decide whether audio X is more similar to audio A or audio B. Audio A and audio B were randomly distributed to



(a) Perceived Accent task (b) Speaker Identity task

Figure 4.2: The structure of the evaluation questions.

be either the source speaker or the target speaker, and Audio X was the converted audio. The aim of this experiment was to observe whether the participants would evaluate the converted audio (audio X) as sounding most similar to the desired audio in terms of accent.

After this task, the participants were then asked to evaluate the speaker identity of the converted audios on a voice similarity score ranging from -7 representing 'definitely different speakers' to +7 representing 'definitely same speaker'. This was done by asking the participants to listen to ten (10) pairs of audio files and ask them to evaluate each pair on this scale. Out of the ten pairs, five pairs were chosen to be the same speaker and five pairs were chosen to be different speakers. In order to cut down on the amount of time needed to complete the survey, the participants were not asked to assess the acoustic quality, as the acoustic quality was the most likely to be stable across audios and corpora. A complete reduplication of the survey can be found in section 7.1.

In terms of demographic information, they were asked to indicate whether or not they consider themselves native speakers of English to observe whether or not there are any particular differences between the two populations in their evaluations on accent conversion. Beyond this, all other participant information was anonymized as no other information was collected.

A visual summarization of the perceived accent task and speaker identity task can be seen in Figure 4.2.

Chapter 5

Results

In this chapter, we present the results of the perceptual study which evaluated the performance of the systems in terms of perceived accent and speaker identity. We then discuss the results and point to potential reasons for the outcome.

5.1 CMU ARCTIC Corpus

5.1.1 Perceived Accent

In order to assess the performance of the participants on the perceived accent task, we compared their answers to the ABX questions to the 'correct' or desired accents. According to the distribution of their scores, the accuracy of the evaluators on the task varied from being only 30% accurate to 100% accurate, with evaluators being 92.2% accurate on average. Following the median score, the participants were 100% accurate at identifying the 'correct' accent of the converted audio. The distribution of the participants' scores on the perceived accent task can be seen in Figure 5.1. The range of the plot starts from 30% in order to better see the highly skewed data. The various data points display the outliers found in the data, which is calculated using the standard formula of 1.5 times the interquartile range below the lower quartile.

Although the evaluators had a very high mean and median, a z-test was conducted to observe whether the performance of the evaluators on this task was statistically significant. As expected, the z-test gave us a p-value of 0.007, proving that their performance was better than chance. This suggests that the evaluators were able to assess the accent of the converted audio X with a high level of confidence.

After evaluating the performance of the participants on the Perceived Accent task as a

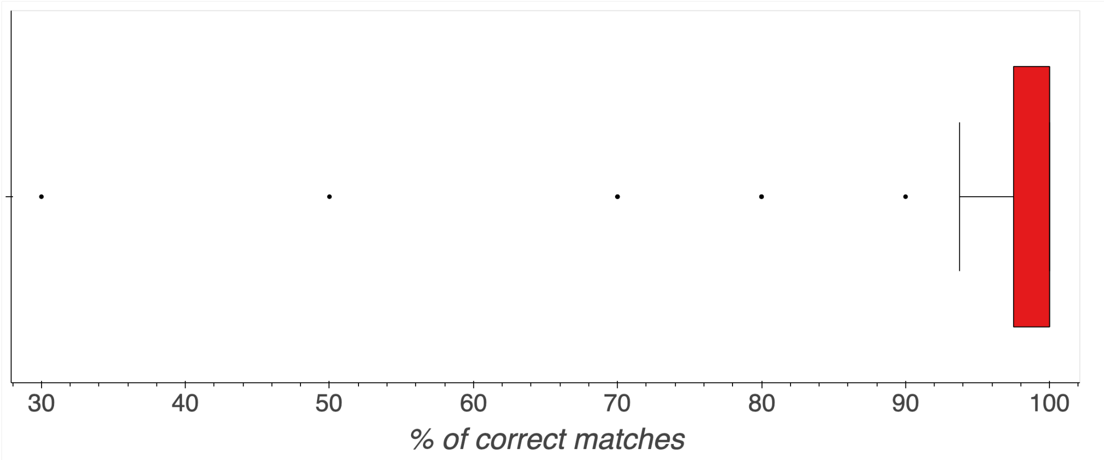


Figure 5.1: The distribution of correct answers on the Perceived Accent task for the ARCTIC Corpus per participant.

ARCTIC Speaker	Correct %
Hindi F	86.66%
Hindi M	100.00%
Korean F	100.00%
Korean M	91.66%
Spanish F	84.00%
Spanish M	96.25%

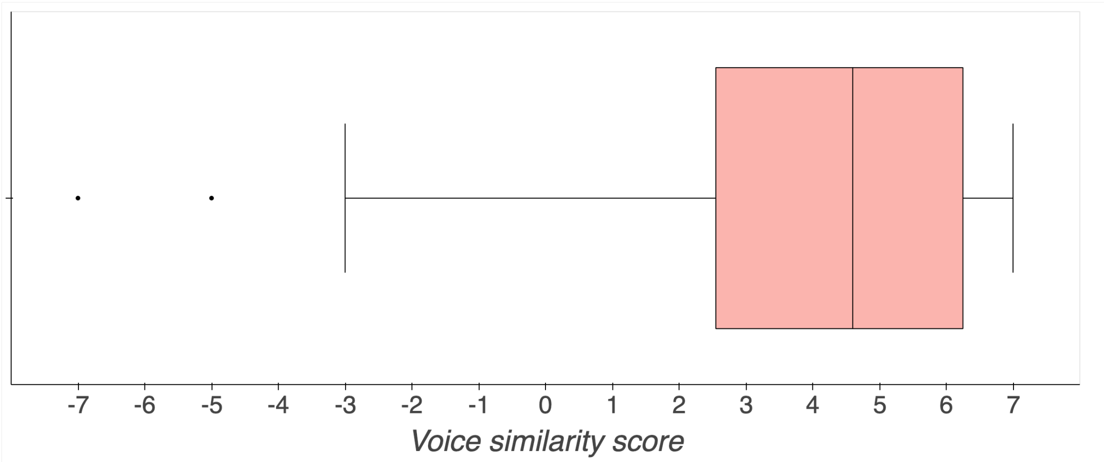
Table 5.1: The mean accuracy on the PA task for the ARCTIC experiment across accents.

whole, we also took a look at each accent individually to investigate if there were any particularities. From the mean scores of the PA task across accents, it appears that the evaluators had the most trouble with the Spanish female and Hindi female accents, with average scores of 84.00% and 86.00% respectively. However, following the p-value of 0.47 given from a one-way ANOVA test, there were no statistically relevant differences.

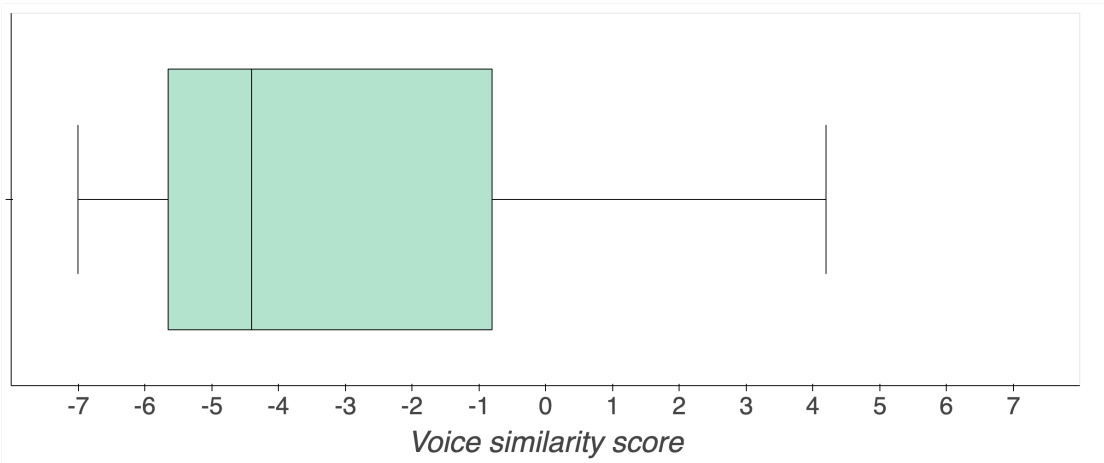
In order to confirm that there were no differences in the scores of the native speakers vs. the non-native speakers, we ran a t-test. Examining the mean scores for both groups showed that they likely performed similarly, as native speakers had a mean accuracy of 92.94%, and native speakers 91.57%. Both groups had a median score of 100%. As expected, there was no statistically significant difference between the performance of the native and non-native speakers with a high p-value of 0.80.

5.1.2 Speaker Identity

As discussed previously, the Speaker Identity task consisted of 10 pairs of audio, those of which include accent converted audios with the original native audio (AC-Native)



(a) AC-Native Questions



(b) AC-L2 Questions

Figure 5.2: The distribution of the mean voice similarity scores on the Speaker Identity task per participant.

and accent converted audios with the original L2 audio (AC-L2). During the calculations of the means, it was noted that one question was left blank by an evaluator for the Korean M speaker, so the value was imputed using the average score of the other Korean M evaluators rounded to the nearest integer.

An examination of the results showed that the evaluators found the voice similarity score to be on average, around 3.9 for the AC-Native pairs, suggesting that they were 'confident' that the AC audio and the native audio were the same speaker. Similarly, the evaluators found the speaker identity score to be on average, around -3.7 for the AC-L2 pairs, suggesting that they were 'confident' that the AC audio and the native audio were two separate speakers. The distribution of the voice similarity scores for both pair type can be seen in Figure 5.2. The range starts from -7 and goes to 7 to represent the scale used in the evaluation task. The median score does not appear in the boxplot as it coincides with the max score.

ABI Speaker	AC-Native Mean	AC-L2 Mean
Hindi F	2.8	-4.3
Hindi M	3.3	-6.2
Korean F	5.0	-3.9
Korean M	4.0	-1.7
Spanish F	4.7	-3.4
Spanish M	4.4	-3.3

Table 5.2: The average voice similarity score on the Speaker Identity task for the ARCTIC corpora across accents

In order to confirm that there were no statistically relevant differences for the speaker identity scores across accents, we utilized a one-way ANOVA test. As hypothesized, there were no statistically relevant differences between the mean voice similarity scores for both the AC-Native pairs and the AC-L2 pairs with a p-value of 0.87 and 0.16 respectively. Finally, to verify any potential differences between the assessment of the native English speaking evaluators and non-native English speaking evaluators, we ran a t-test. Similar to the ANOVA, there was no statistical difference found with a p-value of 0.77 and 0.91 for the AC-Native and AC Non-native questions. The average voice similarity score across accents can be seen in Table 5.2.

5.2 ABI Corpus

5.2.1 Perceived Accent

Like the CMU ARCTIC experiments, we compared the participants responses to the ABX questions with the 'correct' or desired accents. From taking a first glance at the results, the participants varied greatly in their responses ranging from being 100% correct about what accent the converted audio X was closest to, to being 0% correct. Following the average score, the participants were right about 81% of the time. However, when considering the median performance of the subjects, the users were able to identify the correct accent 100% of the time. A z-test using these results showed that the performance of the participants was nearly significant, with an alpha of 0.05 and a p-value of 0.051. This would suggest that the performance of the subjects were *not* better than chance. However, when re-running the z-test without the 0% correct score, we get a p-value of 0.025, thus indicating that the reviewers were able to assess the perceived accents of the converted audios with statistical significance.

The distribution of the scores on the Perceived Accent task can be seen in the boxplot of Figure 5.3. Here, the boxplot ranges from 0 to 100% as there were scores of 0% con-

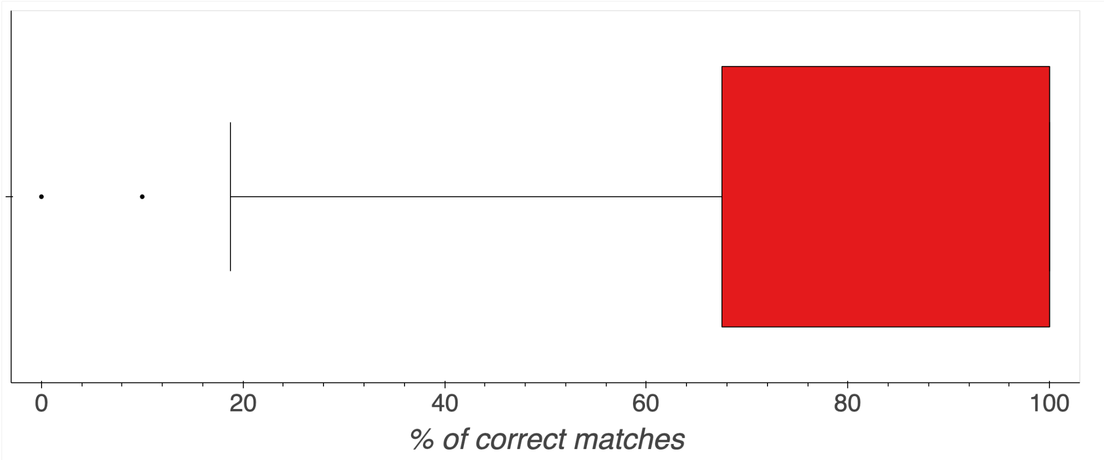


Figure 5.3: The distribution of correct answers on the Perceived Accent task for the ARCTIC Corpus per participant.

ABI Speaker	**Correct %**
EAN F	22.50%
EAN M	87.77%
GLA F	100.00%
GLA M	100.00%
LAN F	68.00%
LAN M	84.28%

Table 5.3: The mean accuracy on the PA task for the ABI corpus across accents.

tained in this dataset. The median score does not appear in the boxplot as it coincides with the maximum score.

After examining the performance of the reviewers on the perceived accent task as a whole, the performance of the reviewers was evaluated across each individual accent to observe if the lower scores were caused by a particular accent. As described in the experimental set-up, the Glasgow, Lancashire, and East Anglian accents were chosen based on their level of similarity to the Standard Southern English accent. As hypothesized, the mean percentage of correct answers were the highest for the Glasgow accent at 100%– the most dissimilar accent to the Standard Southern English accent, while the mean percentage of correct answers for the East Anglian *female* was the lowest at 22.5%. The mean accuracy on the Perceived Accent task across speaker can be seen in Table 5.3.

A one-way ANOVA test based on the mean scores per accent shows that the low results for the East Anglian female speaker was not a result of chance, with a p-value of .000002. This indicates that there were significant issues for the conversion of this accent to the Standard Southern English accent. A one-way ANOVA test was also ran for the rest of the accents, but as predicted, no statistical difference was found given a p-value of 0.07.

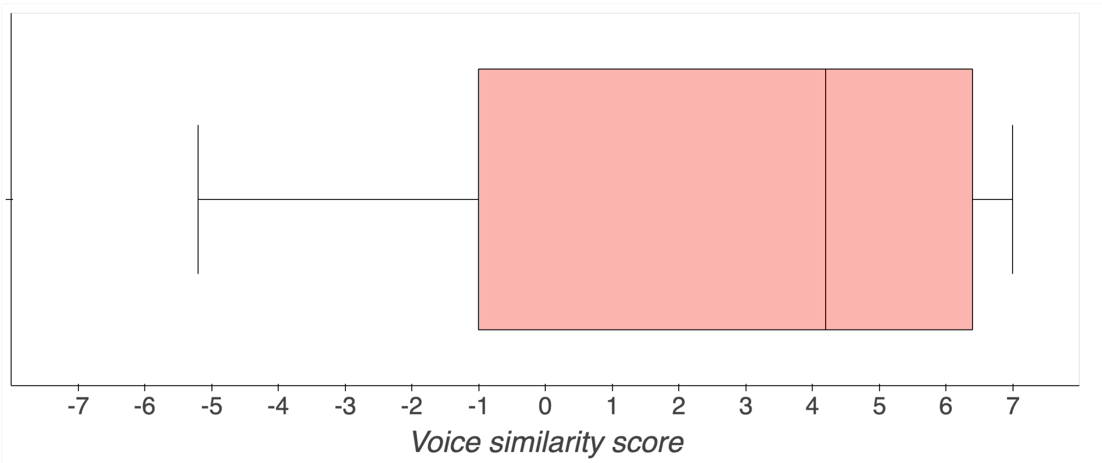
A t-test was also ran to compare the performance of the native speakers vs. the non-native speakers. A quick glance at the mean and median scores of the native speakers vs. non-native speakers showed that both groups performed about the same, with native speakers getting the accent of the converted audio correct on average 79.4% of the time, and non-native speakers getting the accent of the converted audio on average 82.1% of the time. Both groups also had a median score of 100.0%. Naturally, following the results of the t-test, both the native and non-native speakers performed equally on the task as the t-test returned a p-value of 0.79, a value much higher than an alpha of 0.05.

5.2.2 Speaker Identity

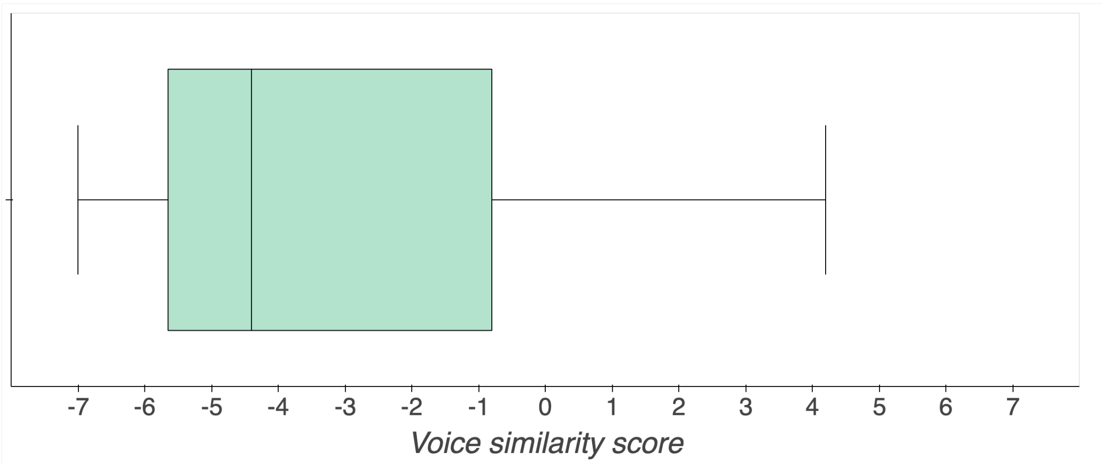
Like the CMU ARCTIC corpus, the speaker identity task for the ABI Corpus also consisted of 10 pairs of audio. However, in this case, because the speakers are all native speakers, the paired audios are better described as accented converted audios paired with the original source audio, and accent converted audios paired with the original target audio. With this said, because of the confusion nature between source vs. target audio (e.g. source speaker being the *native speaker* and target speaker being the *non-native speaker* as in the ARCTIC experiment), and to keep in tune with the ARCTIC experiment, they will still be referred to as AC-Native and AC-L2 pairs in the discussion here.

Following the results, the evaluators scored the AC-Native audios to have a voice similarity score of 2.6 on average, indicating that they were 'somewhat' certain that the AC audios were the same person as the native audios. They also scored the AC-L2 audios to have a voice similarity score of -3.2 to indicate that they were 'confident' that the AC audios were *not* the same person as L2 audios. The distribution of the overall speaker identity means per question type (AC-Native and AC-L2) can be observed in Figure 5.4. Similarly, these boxplots range from -7 to 7 to represent the possible scores in the evaluation task.

Similar to the perceived accent evaluation criteria, a one-way ANOVA test was run to compare whether there were any statistically relevant outliers for the speaker identity scores across accents. When running the ANOVA test on the AC-Native mean scores for all speakers used in the ABI experiment, there were no statistically relevant outliers, with a p-value of 0.055. However, the ANOVA test on the AC-L2 mean scores for all speakers gave a p-value of .00000694, indicating that there were indeed accents that were significantly different from the other accents. From re-running the ANOVA with various groups of accents, it was found that EAN F and LAN F were significantly



(a) AC-Native Questions



(b) AC-L2 Questions

Figure 5.4: The distribution of the mean voice similarity scores on the Speaker Identity task for the ABI corpus per participant.

ABI Speaker	AC-Native Mean	AC-L2 Mean
EAN F	-1.3	3.2
EAN M	2.7	-4.4
GLA F	4.2	-4.9
GLA M	5.4	-4.9
LAN F	-0.3	-0.7
LAN M	3.4	-4.4

Table 5.4: The average voice similarity score on the Speaker Identity task for the ABI corpus across accents.

different from the other accents, with a p-value of .0000563 for the EAN F accent compared to the other accents with LAN F removed, and a p-value of 0.024 for the LAN F accent compared to the other accents with EAN F removed. The average voice similarity score across accents can be seen in Table 5.4.

A t-test was also used in order to observe any potential differences between the assessment of the native English speaking evaluators and non-native English speaking evaluators, but there was no statistical difference found with a p-value of 0.93 and 0.77 for the AC-Native and AC Non-native questions respectively. This suggests that both native speakers and non-native speakers were able to evaluate for speaker identity with the same level of confidence.

5.3 Discussion

Following the results of the survey, there are two main points to focus on. In both the ARCTIC and ABI experiments, speakers indicated that they were very confident that the converted audios indeed had the desired accents, with both experiments having median scores of 100%. However, the results from the speaker identity task were quite contrary, with the averages for the ARCTIC corpus being 3.9 for the AC-Native pairs, and -3.7 for the AC-L2 pairs; the ABI corpus had an average of 2.6 for the AC-Native pairs, and -3.2 for the AC-L2 pairs. Referring back to the evaluation criteria, -7 on the voice similarity scale indicates that the two pairs of audio are 'definitely' 2 separate speakers, while 7 indicates that the two pairs of audio are 'definitely' the same speaker. Thus, with the AC-Native pairs, the ideal score would be closer to -7, and with the AC-L2 pairs, they should be closer to 7. This indicates that there was an issue retaining the identity of the speaker during conversion.

However, interestingly, there were a few statistically relevant outliers with speakers from the ABI corpus. Taking a look again at the mean scores in the perceived accent task, the East Anglian female had the lowest percentage correct at 22.5%. The voice similarity scores of the Lancashire and East Anglian female accents also stood out as well, with the Lancashire female having a voice similarity score of -0.7 and the East Anglian female having a mean voice similarity score of 3.2 in the AC-L2 pairs– the only positive voice similarity score. This means that the East Anglian female accent was the only accent from both experiments to have scores that were the exact mirror of the other accents.

When considering why the East Anglian female accent sticks out as compared to the other accents, there are a number of possible explanations. For one, when referring back to the selection of accents used in the experiments, the East Anglian accent was also the most similar accent to the Standard Southern English accent. This could mean that the evaluators may have had a hard time judging the distinctions between the East Anglian and Southern Standard English accents. This hypothesis also holds true when examining the other two accents, as the evaluators had a mean score of 100% for both the male and female Glasgow speakers, and a mean score of 68% and 84% on the Lancashire speakers. This means that the evaluators were able to identify the accents of the converted audios more or less in the order of the varience of accents from the Standard Southern English accent.

Upon investigating why the Lancashire and East Anglian female accents had distinct voice similarity scores, their converted audios compared with their original source and target audios gave good indication. In both cases, the speakers sounded very similar. In other words, although the source and target speakers were indeed two separate speakers, the voice quality of both speakers in each pair sounded fairly similar. This was particularly evident when listening to the original source and target audios of the East Anglian pairs. This likely explains the low mean score on the perceived accent task and the high voice similarity score on the speaker identity task.

Compared to previous work such as Zhao, Sonsaat, Silpachai, et al. (2018) which also utilizes an almost similar approach as a baseline, the performance of the current system is somewhat worse as the perceived accent and speaker identity scores from their systems are higher. However, this could possibly be attributed to the removal of the vocal tract length normalization step during conversion.

While this work does not point to any advances towards to improvement of accent conversion as a whole, it does begin the path in investigating native to native conversion. Although the results of the perceptual study do not allow us to make any concrete conclusions, the somewhat more successful results of the ABI experiments may allow us to suggest that there are more subtle nuances that may not be captured or converting using this more traditional approach to accent conversion. This would have to be further investigated in order to be confirmed.

Chapter 6

Conclusion and future work

6.1 Conclusion

In this work, we investigated how effective traditional MFCC and Gaussian Mixture Model accent conversion worked for both non-native to native and native to native accents while retaining speaker identity following the work of Aryal and Gutierrez-Osuna (2014b). Alongside this, we tried to answer whether this traditional methodology worked differently for non-native to native conversion vs. native to native conversion.

From the results of the perceptual evaluation, we found that most participants agreed that the accent converted audio did match with the desired accent in almost all cases in both experiments except for the East Anglian female speaker in the ABI experiments. This difference was found to be statistically relevant following a one-way ANOVA test.

With that said, even though the accent converted audios were assessed to have the desired accents, most participants also indicated that the converted audios were more similar to the source speaker (e.g. the 'native' speaker) in terms of speaker identity, suggesting that the accent conversion process had difficulties maintaining the speaker identity of the target speaker (e.g. the 'non-native' speaker.) This indicates that this methodology was not successful at retaining speaker identity in either experiment. This may be due to the removal of the vocal tract length normalization feature and possibly the limitations of MFCCs as they are limited in the amount of information they hold especially as compared to the methods found in more recent work such as the use of posteriorgrams in Zhao, Sonsaat, Levis, et al. (2018).

While we observed similar performance with the current method of accent conversion for both sets of experiments, neither experiment was successful in retaining the speaker identity of the target speaker, which makes it challenging to observe whether the same method of accent conversion works differently for non-native to native conversion vs. native to native conversion. However, the small difference in scores between the two experiments may hint that some difference may exist.

6.2 Future Work

In the future, it may be beneficial to have a more stringent selection process for the perceptual study. While we were able to gather a good amount of participants, their backgrounds varied greatly, which may have made it challenging for some of the participants to properly identify any variation between the audios, especially in the ABI perceived accent task. Ideally, for evaluation of the ABI experiments, it would be good to gather those more acute towards accents in the British Isles as they would likely be much more sensitive to changes in accents. Unfortunately, the experiments were restricted on time, and thus the recruiting process had to be more relaxed.

In the original brainstorming process for this project, a number of ideas were brought up for consideration, including a gamefied approach to improve pronunciation and testing more advanced methods for accent conversion. In particular, during the preparation period for the experiments, i-vectors were heavily considered as it has been shown that i-vectors are particularly successful at classifying accents (DeMarco and Cox 2013) and with voice conversion (Kinnunen, Juvela, et al. 2017; Z.-Z. Wu et al. 2010). Neural networks were also considered as research in NLP and in voice conversion has found particular success with them (Chen et al. 2014; Chorowski et al. 2017; Lorenzo-Trueba et al. 2018). However, despite the advantages that i-vectors and neural network architectures could provide, working with i-vectors proved to be much more challenging than anticipated due to the obstacle of using the Python package, `sidekit` for extracting them and the challenge of understanding the theory behind how they work. Thus, it was decided upon using more traditional methods to better understand the basis of accent conversion. Thus, in the future, it would be rewarding to work with using i-vectors as a feature and utilizing a neural network architecture in place of Gaussian mixture models as results have shown that both would likely bring further improvements.

In a larger context, it would be highly beneficial to observe how robust accent conversion systems are in aiding language learners and automatic speech recognition systems–two of the main targets mentioned for accent conversion. It would be particularly useful to run a study to observe whether accent conversion systems actually do provide language learners with the appropriate feedback and compare it to other methods of feedback, as there appears to be little to no work done so far in this cross-section. The current state-of-the-art of accent conversion would not likely compete well against other well-researched solutions to the speech recognition of non-standard accents, but it would be good to compare the performance of using accent conversion against methods such as speaker adaptation or developing accent-specific systems in a similar vain to Najafian et al. (2014). With all of this said, as a budding subfield of voice conversion (which in turn is another subfield of speech technology and etc.), accent conversion has plenty of room for growth and improvement in the forthcoming years. Should accent conversion gain more traction and more researchers, it is very likely that there will be vast gains in the area that will eventually aid language learners, automatic speech recognition systems, and other areas as intended.

Chapter 7

Annexe

This section contains mainly a reduplication of the evaluation survey that was distributed to the participants.

7.1 Annex 1: Evaluation Survey

Thank you for participating in this survey. This survey will have you evaluate various audios from speakers where their accents have been converted to sound more like the accent of another speaker. You will be evaluated two (2) speakers from two different (2) corpora on two (2) different evaluation criteria. This survey is estimated to take 10-15 minutes to complete. It is recommended that you listen to the audio with headphones.

1. Do you consider yourself a native speaker of English?
    - Yes
    - No

7.1.1 Accent of British Isles (ABI) Speaker Selection

2. The audio files used in this section are located on a separate webpage. Please click the link in the FIRST option. Your selected audios are determined randomly as they are shuffled using the 'Shuffle order option' included here in Google Surveys.
    - LAN F
    - EAN M

- GLA F
- GLA M
- LAN M
- EAN F

7.1.2 ARCTIC Corpus Speaker Selection

2. The audio files used in this section are located on a separate webpage. Please click the link in the FIRST option. Your selected audios are determined randomly as they are shuffled using the 'Shuffle order option' included here in Google Surveys.

    - KOREAN F
    - HINDI M
    - SPANISH M
    - SPANISH F
    - HINDI F
    - KOREAN M

7.1.3 Perceived Accent

For this section, you will use the audio files found under the 'Perceived Accent' section on the page you clicked in the previous section. You will listen to an audio clip (X) and compare it to 2 other clips (A and B) to decide which clips (A and X/B and X) are more similar in their ACCENTS.

For example, if you listen to 'X', and decide that 'X' sounds more similar in accent to 'A', select 'A'. If you decide that 'X' sounds more similar in accent to 'B', select 'B'.

1. Group #1: Is clip X most similar to A or B?

    - A
    - B

    -repeated until 10th question-

2. Group #10: Is clip X most similar to A or B?

- A
- B

7.1.4 Speaker Identity

For this section, you will use the audio files found under the ‘Speaker Identity’ section on the page you clicked in the first section. For each question, you will listen to 2 audio clips (A and B) and indicate how confident you are whether they are the same speaker or two different speakers on a scale of -7 (definitely different speakers) to 7 (definitely same speakers).

For example: If you are definitely sure that clip ‘A’ and clip ‘B’ are the SAME speaker, select ‘7’. If you are definitely sure that clip ‘A’ and clip ‘B’ are two DIFFERENT speakers, select ‘-7’.

These audio clips have been REVERSED so please do not be alarmed.

1. Pair #1: Rate the pair of audio clips on a scale of -7 (definitely a different speaker) to 7 (definitely the same speaker).

	Definitely a different speaker -7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	Definitely the same speaker 7
Similarity															

-repeated until 10th question-

10. Pair #10: Rate the pair of audio clips on a scale of -7 (definitely a different speaker) to 7 (definitely the same speaker).

	Definitely a different speaker -7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	Definitely the same speaker 7
Similarity															

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