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

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M.Sc. Dissertation

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Faculty of Information and Communication Technology
University of Malta
2018

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Submitted in partial fulfilment of the requirements for the Degree of
European Master of Science in Human Language Science and Technology

M.Sc (HLST)

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY

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Course Code: CSA5310 HLST Dissertation
Title of work: An investigation of accent conversion for non-native and native varieties of English

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Abstract

With the emergence of the use of technology in language learning through tools like Rosetta Stone and Duolingo, learners have slowly been given more autonomy of their language learning projection. Although these tools have allowed learners to tailor their learning to their own liking, there is a gap between the available resources to assist those that would like to improve their pronunciation. Previous research in the intersection of language learning and speech technology has made efforts to develop pronunciation training systems to address this problem, but the systems themselves tend to have gaps due to the lack of appropriate support for the users, especially in appropriately identifying errors and providing sufficient feedback to help them correct their errors.

Some researchers have purported that alongside other forms of feedback such as a visual articulatory representation, a voice conversion system could serve as a potential feedback mechanism by helping learners understand what their voice could sound like given the appropriate changes. However, like pronunciation training systems, voice conversion systems also faced many limitations due to the complex interaction of various features which made them unrenderable as useful tools. With that said, recent advances in speech technology using methods such as i-vectors and deep neural networks have become increasingly successful in achieving better accuracy and quality in a variety of tasks, allowing for the potential to return and address these said gaps in performance for voice conversion.

This dissertation investigates these advancements in applying i-vectors and deep neural networks to develop an accent conversion system (a modified voice conversion system) that could potentially serve as a feedback mechanism as a part of a larger computer-based pronunciation training system. I compare this methodology against baselines using more traditional features and conversion processes following the work of Aryal and Gutierrez (2014) among their other works, and evaluate using the responses of participants in a perceptual study. I conclude with a discussion of the current work and highlight some potential directions for future direction.

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List of Abbreviations

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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

Chapter 1

Introduction

[Cite robustness of Alexa, Siri, Google Translate and viral videos]

While 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, 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!" 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". 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. 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. 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 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. This 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.

1.1 What is an "accent"?

Before continuing on, it is best to define what accent is, especially in the context of this work. 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. [Cite this] 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 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, I consider *accent* to be variations in pronunciation in this work.

1.2 Research Questions

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

- How can we leverage accent conversion to change the accent of a *non-native speaker* into sounding more like a *native speaker*? (e.g. converting the accent of a native Spanish speaker to sound more like a US English speaker)
- How can we leverage accent conversion to change the accent of two *native speakers* of English who speak two distinct varieties? (e.g. converting the accent of a Scottish speaker to sound more like a Standard Southern English speaker)
- To what extent can we maintain the voice characteristics of the selected speakers, or *the identity* when converting their accents? (e.g. Can we convert the accent of a speaker and make sure it still sounds like the same person?)

1.3 Thesis Overview

The overview of the thesis is as follows:

In **Chapter 2**, I 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**, I present the motivation for creating an accent converison system by discussing previous findings in second language acquisition research especially in relation to speech. I 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 their relevance to this work and the fields of NLP and language learning as a whole, I detail both voice conversion and accent conversion in order to help better distinguish them. I also go over 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. Further reference is also provided for those interested in the more technical aspects and formalisms.

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 setforth 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 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. 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 spectral envelope, cepstrum, line spectral frequencies (LSF) and the aforementioned formants. 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 something known 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 recogntion systems in general. The extraction process of MFCCs and deltas/double deltas are described in further detail 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). 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.

A visual representation that summarizes the voice conversion process can be seen in Figure 2.2, courtesy of Mohammadi and Kain (2017).

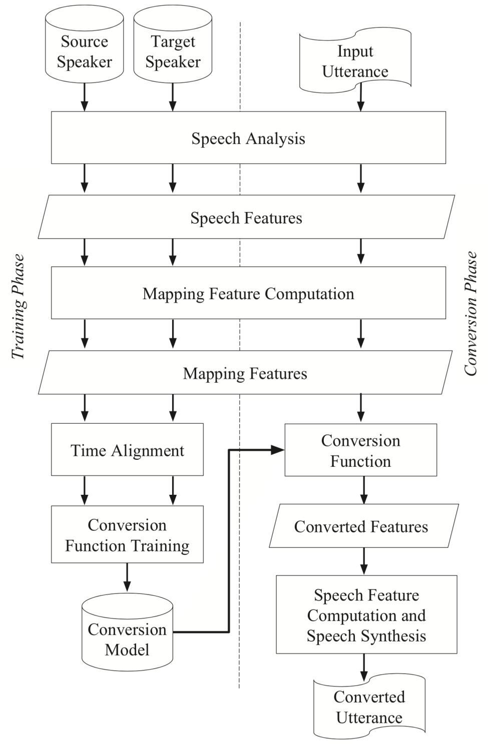


Figure 2.1: The training and conversion processes of a typical VC system.

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 (parallel) 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

Following Jurafsky (2009), mel-frequency cepstrum coefficients (MFCCs) allow us to create vectorized representation of the acoustic information.

This is done by going over the speech signal using *windows*, where each window is assumed to contain a non-changing part of the signal. In order words, each window would roughly contain one phone– or speech sound. In order to retain all of the necessary information from each part of the signal, the windows often overlap.

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. This allows us to find how much energy is in specific frequency bands.

From here the frequencies outputted by the Discrete Fourier Transform are converted onto the *mel* scale, which is where the *mel* in Mel-frequency comes from. In short, the mel scale is used to represent human hearing, which is more sensitive to lower pitch sounds (under 1000hz) as compared to higher pitch sounds. 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 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.

Although this information 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/). 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 2.2, taken from Jurafsky (2009).

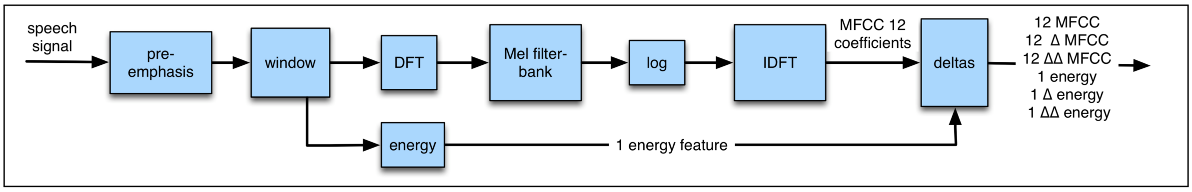


Figure 2.2: The extraction of sequence 39-dimensional MFCC vectors from a waveform.

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 2.3. [Create new graph from scratch or cite it.] 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 modelling as it has been theorized that the average of independent random variables would look like a normal distribution (McGonagle et al. 2016).

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

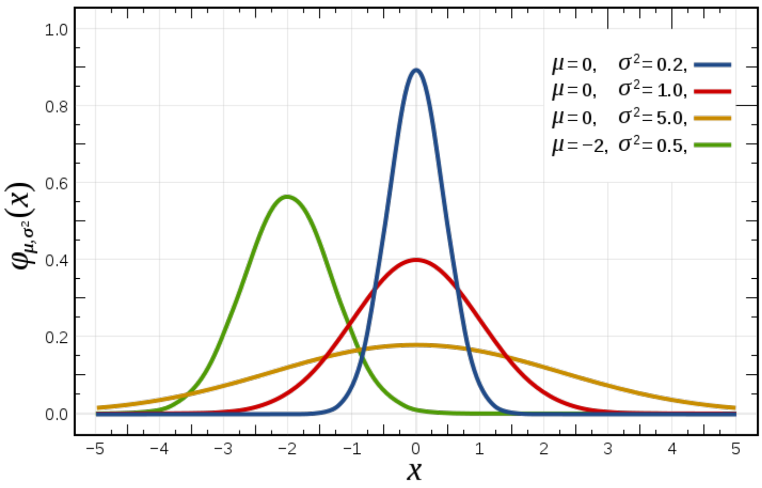


Figure 2.3: The Gaussian distribution with different means (μ) and variances (σ^2).

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 2.4. [Create new graph from scratch or cite it.]

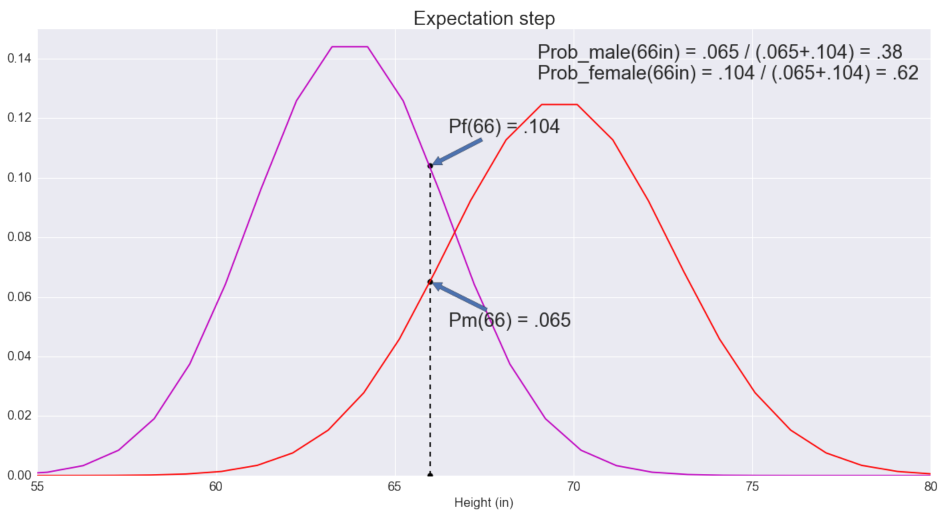
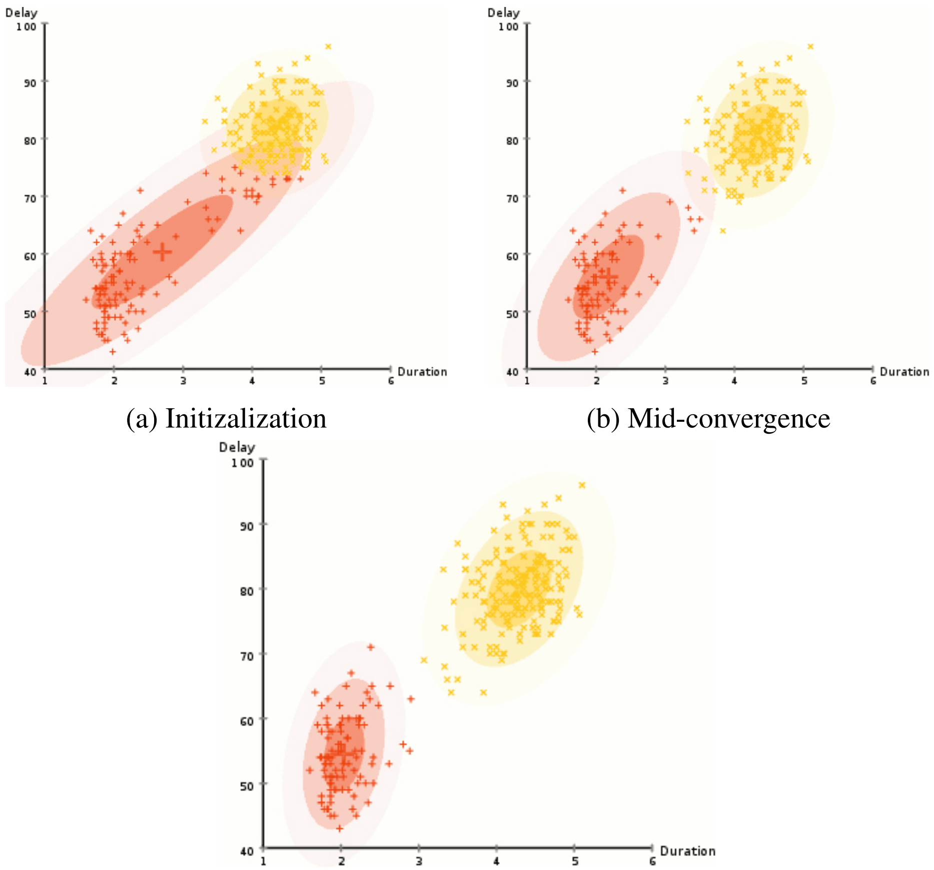


Figure 2.4: An example of a GMM using male and female height. The likelihoods for each gender for someone 168cm (66in) tall is calculated using the percentage of men and women in the dataset from the vertical axis. The probabilities are given in the top right corner.

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 datapoint.

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 maximization*. This algorithm is used for maximum likelihood estimation. In other



(a) Initizalization

(b) Mid-convergence

(c) Converged

Figure 2.5: Gaussian Mixture Model convergence using the Expectation-Maximization algorithm.

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 taken from McGonagle et al. (2016) can be seen in Figure 2.5.

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. Because MFCC feature vectors are multi-dimensional (∼39-dimensions), the 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.

Although GMMs are useful for modeling the distribution of sounds within a dataset and allow us to generate any observation, they are only capable of modeling speech as discrete MFCC vectors as opposed to a continuous sequence. Thus, GMMs are often utilized with Hidden Markov Models to remedy this issue. In short, Hidden Markov Models are models that consist of *states* and *transitions*. When utilized in speech recognition, each state represents a potential sound, while the transitions represents the probability or likelihood of the next state (e.g. sound). Gaussian mixture models can be used to represent a sound within a state [check from here; this also needs a diagram].

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.

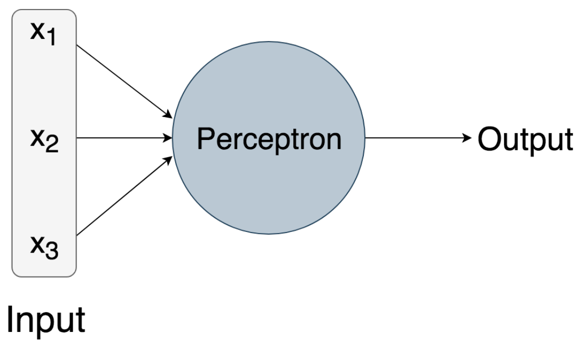


Figure 2.6: A visual representation of the perceptron.

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:

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

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.

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, 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 the following figure, we see an example of a more typical neural network.

[Replace image below]

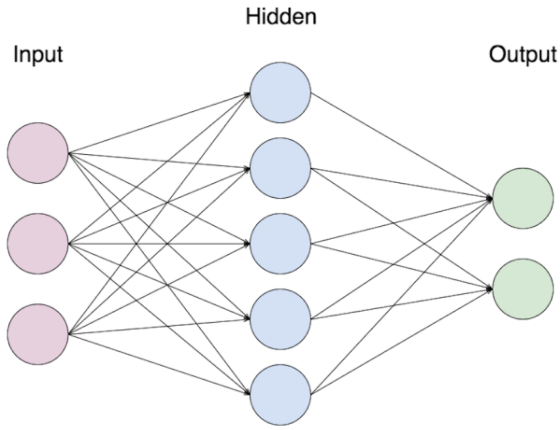


Figure 2.7: An example of a neural network.

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 and **??**.

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. I then examine 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 voice conversion and accent conversion could be applied, and then detail some important pivotal work done in the two areas.

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.

Following their review of the correlation between other potential variables and the degree of foreign accent, Piske et al. (2001) take a further look at Bongaerts et al. (1995). Although it was found that 5 out of 11 speakers were perceived as *indistinguishable* from native English speakers, Piske et al. (2001) also point to a number of other factors in play that could have potentially allowed these speakers to be perceived as such. Perhaps the most controversial factor is the fact that these speakers were native Dutch speakers. Because Dutch and English have a similar phonetic inventory, it has been argued that this allows for easier acquisition of a native-like accent. In examination of their motivation, these learners were considered highly motivated as they felt the need to speak English without a Dutch accent due to their positions as university-level English teachers. On top of this, these learners also received intensive training in the perception and production of English sounds. Examining the interaction between these variables, it may be appropriate to conclude that the reason why 5 out of the 11 speakers were evaluated as indistinguishable from native speakers is due to the fact that they are a very niche population.

Regardless, this points to the fact that there is the possibility of language learners acquiring native-like pronunciation given the right configuration, even if the said configuration may be difficult to achieve. This is contrary to what is suggested by the CP hypothesis, which suggests that *all* learners are limited by a critical period. This is not to say that learners are not still deterred by a 'sensitive period', but this does highlight the potential that learners could be taught pronunciation should they have the right tools.

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), 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 a 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'. Although this article was first published in 2002, it outlines a good fundamental structure that CAPT systems require– something that many systems still seem to be lacking.

In Eskenazi (2009), we are given a more technical review of CAPT systems with attention to the different CAPT system types and their limitations as well as some discussion on prosody detection.

The article explains that CAPT systems can be generally split into two main types: individual error detection and pronunciation assessment. As indicated, individual error detection systems are more focused on one particular aspect of the user's speech, such as the phones or pitch, while pronunciation assessment systems are more designed to represent how a human would judge a non-native utterance.

Early individual error detection systems, including one of the author's very own Eskenazi and Hansma (1998), started by using a variety of speech recognition techniques such as forced alignment or unconstrained speech recognition. They also worked with a variety of measures to detect the differences between the individual errors and gold standard. Some of these measures include hidden Markov model (HMM) based recognition scoring, a confidence score based system known as Goodness of Pronunciation (GOP), and Linear Discriminant Analysis (LDA). Each of these measures were found to somehow detect the users' errors; however they suffer from issues like low precision or the need for a very homogeneous sample (e.g. Japanese speakers).

Although some of these early systems showed some signs of promise, they tended to over-simplify the issue of pronunciation training. Eskenazi (2009) makes a point of this by emphasizing the fact that improving non-native pronunciation is not simply a binary question of native vs. non-native. Instead the L1 of the system's users must be considered as this in itself can greatly affect the evaluation. Eskenazi (2009) also points out that the level of language learning of the speakers can also impact the metrics and success of the system as well, and thus an appropriate population must be selected carefully when building a CAPT system, especially when considering individual errors.

In examining previous CAPT systems, Eskenazi (2009) briefly discusses prosody correction, an often overlooked area as previously mentioned. Eskenazi (2009) points to some pivotal works that have used a variety of methods to address the issue, including systems that use Pitch Synchronous Overlap and Add (PSOLA) to resynthesize the prosody of users to help them hear what an appropriate utterance would sound like. This has been suggested to be a potentially effective feedback mechanism to employ in future systems, as it has been said that imitating one's own voice is the most effective (Felps, Bortfeld, et al. 2009). Among prosody correction systems, Eskenazi (2009) mentions two main types– those that use appropriate L2 phonological models and break prosody down into two levels— syllable-word and utterance-phrase, and systems that detect the 'liveliness' of a speaker. However, these systems require tuning of a variety features including F0, power, duration or phonetic transcription, which makes it difficult to automatically create the necessary adjustments not just cross-linguistically, but across speakers as well. Eskenazi (2009) concludes by stating that although such limitations exist in these systems, the usage of ASR and other speech technologies has grown from such a sparse beginning, and that because the market appeal for such systems is large, they shall soon serve central roles in language education.

Aside from general discussion on CAPT systems, Chun et al. (2008) present a review of other technologies used in pronunciation training, with emphasis on feedback mechanisms used to train prosody. They discuss four main tools used in teaching prosody: 'visualization of pitch contours', 'multimodal tools', 'spectrographic displays' and 'vowel analysis programs'. Citing previous work, it appears that they suggest that the visualization of pitch contours is the most robust method of feedback for learners as it is the most intuitive and non-language specific. Aside from this however, they also discuss the potential of a multimedia approach used by Hardison (2005) that integrate both audio and video in a system called *Anvil*. Following this research, users of this system were able to generalize their training beyond a sentence level and were able to perform better at a discourse-level. This methodology encapsulates a good feedback mechanism as described by Neri et al. (2002) as it provides adequate feedback by being easily interpretable, stimulates both audio and visual channels and puts the language in context.

Chun et al. (2008) also discuss the two main methods of such prosody systems: one which utilizes isolated scripted sentences and the other utilizing imitation. While both types of systems are common, possibly due to their easier implementation, they conclude that neither method is useful for generalizing to novel speech production. Aside from the fact that the language may not be put into context, one problem with both types of systems is their limited number of sentences and limited source speakers in terms of imitation. This prevents learners from gaining an understanding of the variability of acceptable (and hence unacceptable) prosody across speakers and contexts, and may limit learners to speaking as similarly as they can to the given exemplars. Thus, while these systems might provide language learners with a basis to improve their prosody, further work needs to be put in to help them contextualize prosody as a general concept and to give learners more autonomy in developing their own speaking style.

Similar to Neri et al. (2002), Chun et al. (2008) also gives insight on potential ways to improve future CAPT systems. One particularly compelling suggestion they give is to expand systems to include gestures and movement. While most research on language education and in turn, linguistics, is focused on the spoken aspect, Chun et al. (2008) points out that spoken language is complementary with our body language. For example, when we raise our pitch, we also tend to raise our eyebrows and chin, and when we emphasize a specific, we might also stress it by opening our eyes slightly wider, bobbing our head or pointing our finger. In fact, one of the few studies that examine the effect of including body language in teaching L2 listening comprehension found that learners performed much better with these visual cues as opposed to only having audio cues. Thus they conclude that in order to create better pronunciation training systems, learners must be provided with better feedback and language must be placed into context not only in terms of real-life situations, but also in terms of communication as a whole by including gestures and movement.

With that said, 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 [insert IPA here?]. 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.

Through examining these various works, 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 CAPT systems.

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 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 (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 Wu et al. (2016) and Kinnunen et al. (2017). Following Kinnunen 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 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, 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.

As oppose to Wu et al. (2016) which utilizes the average voice model in order to create a strong voice conversion system, Kinnunen et al. (2017) takes a different approach by [hmmm...]

DeMarco and Cox (2013), present a through analysis of the usage of i-vectors in classifying native British accents. [continue here or move to accent conversion?]

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 Wu et al. (2016)[1] [Maybe change footnotes to say listen to audio on the accompanying disk?] it 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

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

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 bene other efforts to present high quality voice conversion systems in works such as and Nguyen et al. (2016) and Fang et al. (2018).

Fang et al. (2018) leverages 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. For example, GANs have been shown to be able to convert images of zebras into horses, as well as winter into summer.

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].

Also add to disc?

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 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'

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

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. [explain PSOLA] 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.

Felps and Gutierrez-Osuna (2010) ? [paper on evaluation]

Aryal, Felps, et al. (2010)

Felps, Geng, et al. (2012)

With that said, Aryal and Gutierrez-Osuna (2014b) and other works done by the group of researchers have made efforts to address the challenge. Throughout their research, they test a variety of methodologies, including accent conversion through voice morphing and articulatory synthesis. In the same work of 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.

To achieve this, 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.

Aryal and Gutierrez-Osuna (2014a)

In 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. To do this, 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 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.

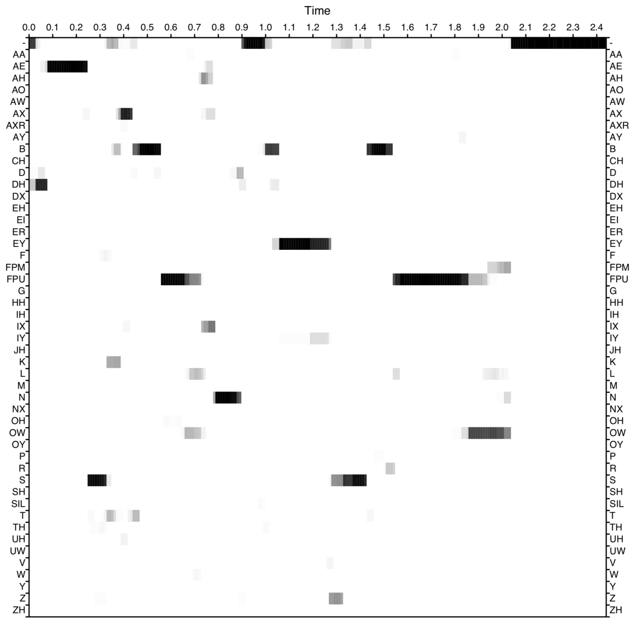


Figure 3.1: An example posteriorgram representation for the spoken phrase 'basketball and baseball'. The x-axis represents the time across the utterance and the y-axis represents the possible phonemes.

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.

[continue]

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, I hypothesize that it should be plausible to convert accents in a similar fashion and apply more recent innovations to propose state-of-the-art methods.

Chapter 4

Design and methodology

In this chapter, I introduce the dataset and tools utilized in the experiments, and detail the procedures carried out to conduct the accent conversion process.

Expand this section

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. cite this!

4.1.1 CMU ARCTIC corpus

The CMU ARCTIC corpus was originally designed to have good phonetic (specifically diphone) coverage for speech synthesis. Expand this section

4.1.2 L2-ARCTIC corpus

The L2-ARCTIC corpus currently contains 10 non-native speakers of Hindi, Korean, Mandarin, Spanish and Arabic, with a male and female speaker for each language. At the time of writing, the curators of the corpus are working to add an additional 10 speakers to the corpus by September 2018.

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.

In order to circumvent defining accent, the authors of the corpus instead chose 14 regions known for their associated accents.

The accents contained in the ABI corpus can be seen in Table 4.1:

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 4.1: 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.

4.1.4 Experimental data set-up

Using the corpora described above, I 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.

Following Zhao, Sonsaat, Levis, et al. (2018) who also works with the ARCTIC corpora, only 150 utterances or roughly [9 minutes of data] following the L2-ARCTIC average are utilized, with the utterances from the L2-ARCTIC corpus downsampled 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.

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 150 utterances that are used are chosen at random, but are ensured to be 150 utterances that all speakers have recorded. Out of these 150 utterances, 100 are randomly chosen as training utterances while the other 50 are used test utterances.

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.

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 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 have 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 (HOW MANY?) accents, the accents used in the experiments were chosen following the DeMarco study. After organizing the accents into comprehension order, these 3 accents were respectively the 100%, 50% and 25% different accents.

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, I 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, I removed the malformed recordings in order to keep the experimental corpus as parallel as possible.

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 less (INSERT TIME IN MINUTES).

Because the ABI corpus contains a large number of accents and speakers, I chose one accent as the source accent for all conversions, and three separate accents as the target accents. Specifically, I chose the Standard Southern English accent as the source accent as it

4.2.3 Tools and set-up

In order to understand more traditional mapping methods used in voice and accent conversion, I follow the methods described in [something about Toda (2007)] for voice conversion and reimplement the method described in Aryal and Gutierrez-Osuna (2014b) which utilized frame matching based on acoustic similarity.

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

In order to do GMM-based accent conversion, I utilize the `nnmnwkii`[1] Python package which provides fast and easy functions to train voice conversion systems conveniently based on [Toda(2007)]. Alongside this package, I 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, I use a custom method written to find the most acoustically similar for each frame and convert the corresponding the frames instead of frames that are matched using dynamic time warping. [Include the various versions of Python and the packages]

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

Chapter 5

Evaluation and results

In this chapter, I detail how the previously described experiments are evaluated following previous work such as Zhao, Sonsaat, Levis, et al. (2018) and present their results.

5.1 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 difficult as it requires intricate formulas that do not necessarily extrapolate across datasets or even individual audios (Felps and Gutierrez-Osuna 2010). With subjective methods,

[]In both cases, accent conversion systems are often evaluated on three features: the acoustic quality, speaker identity, and accentedness of each converted audio.]

In the case of my own experiments, I choose to evaluate using a perceptual study due its reliability and because of the complexity of using objective measures. I 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. This is done so that both experiments here can be juxtaposed against the results of their systems and because these metrics are fairly consistent throughout other perceptual evaluations of voice conversion/accent conversion systems.

Specifically, I gather a group of [???] 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 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 distributed by some participants recruited directly by the author to other acquaintances of the participants. The number of listeners were decided upon by continuing to collect results until each speaker in both corpora had at least 5 evaluators.

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. The audios embedded were in .wav format (EXPAND ON FORMAT HERE), with the original audios outputted by the programmed system converted into a separate PCM .wav format using the command line interace of `ffmpeg` in order to better support in-browser playback as the original .wav format was not compatible with current HTML5 standards. These versions of the converted audios are included on the accompanying disc alongside the originals.

They are asked to evaluate on the perceived accent similarity using an ABX format to decide whether X is more similar to A or B. They are then asked to evaluated speaker identity on a voice similarity score ranging from -7 representing 'definitely different speakers' to +7 representing 'definitely same speaker'. They are also 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.

5.2 Results

5.2.1 CMU ARCTIC Corpus

5.2.2 ABI Corpus

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