Towards improved children automatic speech recognition

Thesis

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Abstract

Speech is a fundamental communication skill used for social interaction, express feelings and needs, among others. Unfortunately, there is an increasing number of people who suffer from debilitating speech pathologies, including children. A childhood speech disorder that is not properly diagnosed and treated can have long-term negative effects in social, communication and educational situations. Hence the importance of speech therapy.

In recent years, machine learning has proven to have many applications in the health field, both for diagnosis and monitoring. Particularly, there is a growing interest in the development of automatic tools to assist speech-language pathologists. Furthermore, some automatic tools allow patients to do exercises outside the session with the therapist, for example at home. In the case of children, the exercises can be provided in a gamification context, which contributes to motivate them to practice more often. Most of these tools require reliable automatic speech recognition systems, as these are commonly used to provide pronunciation quality scores. However, despite recent significant improvements in the performance of automatic speech recognition systems for healthy adults, these systems' performance dramatically drops when considering speech from children and speakers with speech pathologies. This is mainly due to the high acoustic variability and the reduced amount of training data available.

In this proposal, we propose to investigate how machine learning algorithms in speech recognition tools for children can enable more complex exercises and better feedback. We first present a summary of existing automatic speech recognition techniques for children. In view of the need for a robust oracle model for children, this proposal will mainly focus on improving the automatic speech recognition system for children. Therefore, we identified several methods for improvement. i) Knowledge transfer on Hybrid and end-to-end models by using transfer and multi-task learning and ii) Adapter transfer in end-to-end speech recognition for a parameter efficient transfer.

Keywords

Automatic Speech Recognition Children, Children speech, Atypical speech, Atypical speech recognition

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Introduction

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1.1 Context

The faculty of expressing or describing thoughts, feelings and needs by using language is a fundamental ability in our daily lives. As per by the Oxford dictionary, *language is defined as the system of communication in speech and writing that is used by people of a particular country or area.* Consequently, language can be conceptualised as a intricate and rule-governed system that empowers individuals to convey abstract concepts, share experiences, and take part in nuanced forms of communication. Effective communication through language begins with the conceptualization of the message to be transmitted (*conceptualisation*), followed by the selection of appropriate lexical items and subsequent grammatical encoding, culminating by their meaningful organisation (*formulation*). Subsequently, the linguistic representation is transformed into sound through the transmission of this representation from the brain to the muscles of the complex speech system including lips, larynx, glottis, lungs, jaw and tongue (*articulation*) [9]. Unlike language, which encompasses both spoken and written forms, speech specifically refers to the spoken manifestation of language.

This capability to speak and comprehend language is not inherently present but rather develops gradually over time with experience. Babies instinctively engage in pre-linguistic communication, using gestures, facial expressions, and vocalisations to articulate their basic needs. As language acquisition progresses, children transition to the babbling stage, experimenting with sound patterns. Eventually, speech emerges, marking a crucial milestone in communication development, and typically, children reach specific language milestones at particular ages. For example, around 12 to 18 months, a child usually utters their first words and starts imitating sounds. By the age of 4 to 5, children tend to formulate sentences and grasp more intricate concepts. Regarding speech sounds, younger children, approximately 1 year old, can produce basic speech sounds like */p/*, */b/*, */m/* while older children, around 5 years old, can articulate more complex sounds such as */r/* and */th/*. This developmental stage is referred as language acquisition, and it plays a crucial role in a child's overall development. Indeed, our daily dependence on social and communication skills endures throughout our entire lives. Consequently, it is imperative for children to develop the capacity to interact effectively with others to achieve seamless integration into society across all aspects of their lives.

Regrettably, a subset of children experience speech disorders stemming from congenital conditions such as cleft palate, cerebral palsy, and prelingual deafness. Alternatively, certain individuals may acquire speech-related issues during childhood, encompassing cognitive developmental delays, breathing-feeding-swallowing disorders and traumatic brain injuries. Notably, in 2012, empirical data [10] highlighted that 7.7% of children aged 3 to 17 in the United States exhibited communication disorders, with 5.0% of this cohort specifically presenting speech-related problems.

Furthermore, findings [11] suggests that individuals afflicted with childhood speech disorders may confront an increased prevalence of mental health challenges, diminished social well-being, and reduced

academic accomplishments in comparison to their peers. This highlights the complex nature of speech disorders in children, the consequences of which extend into adolescence and adulthood. Hence, early identification and intervention play a pivotal role in mitigating the enduring effects on these children's social interactions, society integration, communication skills, educational progress, and overall well-being.

Pediatric Speech and Language Pathologists (SLPs) play a crucial role in providing therapy to help children overcome the effects of speech disorders and offer early diagnosis. The therapy typically includes exercises and assessments, which can be based on perceptual speech evaluations or standardised tests. To effectively engage children, these activities are often presented as games, taking into consideration the inherently limited attention span of children. Notably, SLPs frequently maintain long-term follow-ups with their patients, allowing them to monitor the evolution of speech quality over time and tailor exercises to the specific needs of each child. The adoption of this individualised therapeutic approach is essential for helping children achieve improved speech and communication skills.

However, a prominent challenge arises concerning the accessibility and availability of speech therapy services. Numerous children, particularly those residing in underserved or remote areas, encounter obstacles in accessing speech therapy resources. Additionally, the hospital environment introduces an additional layer of stress for children. While clinically necessary, the setting may inadvertently contribute to heightened anxiety and discomfort, as children may perceive it as intimidating. Furthermore, the logistical challenges associated with frequent hospital visits impose a substantial financial and time burden on families.

Another obstacle pertains to the continuity and consistency of therapy. Children may experience interruptions in their therapeutic journey due to factors such as financial constraints, scheduling conflicts, or alterations in healthcare coverage. These disruptions have the potential to impede progress and undermine the effectiveness of the therapy. Lastly, it is imperative to acknowledge that, despite professional training, inter-expert variability in perceptual assessments may persist, resulting in disparate diagnostic conclusions. To address these challenges, adopting a hybrid approach that combines in-person therapy with technology holds potential benefits [12, 13]. Teletherapy, for instance, has emerged as a promising avenue to bridge geographical gaps and deliver therapy services remotely [14].

In this context, Speech and Language Technologies (SLT) have emerged as highly pertinent within the domain of speech therapy [15]. These technologies encompass a spectrum of computational tools designed to analyse, understand and provide objective and precise automated assessments. Another benefit lies in their potential integration into gamification frameworks, thereby augmenting children's involvement during therapy [16]. Moreover, the ability to record speech utter by the patient during a session using SLT enables post-session thorough analysis and long-term monitoring by the therapist. Due to the aforementioned reasons, the development of such tools has gained considerable attention, empowering patients to engage in exercises beyond therapy sessions, notably in a home setting. Several SLT examples

Figure 1.1: Illustrated herein are some examples of children's Speech and Language Technology applications that were developed during the course of this thesis. On the left is a running platformer game, where the user's voice controls the character. Pitch dictates running and jumping actions, while energy modulates the velocity of these actions. On the right, a reading task game is depicted, wherein a robot instructs the user to read designated words.

developed within the scope of this thesis are illustrated in Figure 1.1.

1.2 Problem statement

Recent years have seen an increased integration of SLT into various aspects of our daily lives, impacting a wide range of environments, including homes, transportation, education, and even the military. Noteworthy examples encompass voice assistants, hands-free computing, healthcare systems, automatic helplines, and speech-to-speech translation services. The performances progress in these applications was made possible through the use of machine learning techniques, espacially deep learning approaches, the increasing computational capacities of our devices, and the ever-growing volume of data available to train and improve these systems.

Children represent a promising target audience for SLT due to the inherent complexities of conventional computer interfaces, which pose challenges for them, limiting their capacity to fully benefit from digital platforms. Children commonly face difficulties to manipulate mouse and keyboard inputs. Additionally, the abstract nature of traditional man-machine interfaces can impede the understanding necessary for effective interaction. In this context, speech-based systems emerge as a promising alternative, offering a more natural and accessible means for children to interact with technology. Through the use of speech recognition technologies, these speech systems mitigate the barriers associated with conventional interfaces, providing a fluid and intuitive interaction paradigm that aligns more closely with the developmental stages and cognitive abilities of young users.

As previously mentioned, SLTs are gradually making their way into the field of atypical speech, particularly for children. While these automatic tools are currently in their early stages and have limitations, there is indeed a rising interest in implementing atypical speech and language therapy cutting-edge systems with a focus on assisting SLPs. In this context, systems capable of automatically recognising speech

content, assessing pronunciation quality and detecting speech pathologies could be highly valuable in supporting pediatric SLPs and patients.

All of these objectives require the implementation of a robust automatic speech recognition (ASR) system specifically tailored for healthy children, serving as a foundational model. Nevertheless, while speech recognition technologies have made substantial advancements, leading to increased accuracy, the performance of ASR systems for children remains underperforming in comparison to their adult-oriented counterparts. This discrepancy results leads into unreliable systems for children's speech. The diminished performance can be atributed to a combination of factors, including intra- and inter-speaker variability, limited linguistic and phonetic knowledge, and the scarcity of available data.

In this thesis, we will undertake a comprehensive investigation into the intricacies of children's speech, closely examining the inherent differences between children and adults in the domain of ASR. Through this examination, the objective is to analyse the constraints associated with the application of adult-based systems to children's speech and, subsequently, to outline methodologies for enhancing ASR systems specifically designed to accommodate the variability present in children's speech. The overarching aim is to establish a robust foundational system that effectively addresses the recognition of children's speech characteristics.

Our work specificialy aims to answer the following research questions:

1. Which knowledge transfer approach is best for efficiently modelling and improving automatic recognition of children's speech? Can these approaches be used to efficiently exploit low-resource children's speech data from multiple languages?

2. How do end-to-end automatic speech recognition models achieve state-of-the-art results for children's ASR when finetuned from an adult model? Particularly, what are the components that are most important to fine-tune?

3. Is it possible to develop an speaker-based, parameter-efficient automatic speech recognition model?

4. Is it possible to use children's synthetic speech to extend the amount of children's data? How can we control the quality and speakers' variability?

1.3 Contributions

This thesis began with a thorough exploration of the current state-of-the-art of children's ASR. The primary objective was to identify the various avenues by which improvements could be envisaged throughout this thesis. The state-of-the-art review constituted a thorough examination of existing literature, research papers, and technological advancements related to children's speech processing in general. The aim was

to understand the fundamental determinants that contribute to the decline in ASR performance for children's speech. By meticulously assessing current research on children speech, we identified challenges and potential areas for possible impact.

Subsequent to the exhaustive literature review, our research transitioned into the implementation of Hidden Markov Model-Deep Neural Network (HMM-DNN) models for children ASR. We explored different strategies to reduce the gap observed between childrren and adult in the context of both English and European Portuguese speech. We identified the effectiveness of knowledge transfer methods, specifically transfer learning and multi-task learning. Transfer learning adapt speech recognition adult models, fine-tuning them for children's speech. In the other hand, multi-task learning exposed models to both adult and children's speech datasets simultanously during training. In an innovative synthesis, we combined transfer learning and multi-task learning into a unified approach, the multi-task transfer learning framework. We applied this approach to multiple low-resource children's datasets from diverse language sources:

- **Rolland, Thomas**, Alberto Abad, Catia Cucchiarini, and Helmer Strik. "Multilingual Transfer Learning for Children Automatic Speech Recognition." *Language Resources and Evaluation Conference* (2022).

Thereafter, our research turned to the end-to-end paradigm, motivated by the encouraging improvements observed in the end-to-end children's ASR performance. By adopting a detailed transfer learning approach, we aimed to gain a comprehensive understanding of the specific components of the end-to-end architecture that proved most relevant and played a central role in these notable score enhancements. The identification of the most relevant components allowed the development of specific algorithms aimed at further improving the model. Particularly, we explored the integration of an additional set of parameters directly into the original ASR model. This integration facilitated a parameter-efficient approach to fine-tuning the model:

- **Rolland Thomas** and Alberto Abad. "Exploring adapters with conformers for children's automatic speech recognition." *International Conference on Acoustics, Speech and Signal Processing* (2024).

In response to the scarcity of large children's speech datasets, we delved into the exploration of leveraging synthetic speech to augment the existing dataset. However, our investigation revealed that a mismatch between real and synthetic data hindered the results. To address this challenge, we introduced additional processing steps to efficiently incorporate synthetic data. We proposed a double-way approach, wherein the synthetic data underwent an additional set of parameters. This innovative methodology contributed to an enhanced ASR system tailored for children:

- **Rolland Thomas** and Alberto Abad. "Improved children's automatic speech recognition combining adapters and synthetic data augmentation." *International Conference on Acoustics, Speech and Signal Processing* (2024).

In tandem with the primary focus of enhancing children's ASR, this thesis extends its scope to the detection of pathologies from speech. This secondary investigation retains relevance within the broader context of the thesis, particularly as we aim to address the specific needs of children with pathological speech. We explored the use of embedding extracted from pre-trained model for the detection of differents pathologies such as Alzheimer, Parkinson's disease, obstructive sleep apnea and Covid-19:

- Anna Pompili, **Thomas Rolland**, and Alberto Abad. "The INESC-ID multi-modal system for the ADReSS 2020 challenge." *Interspeech* (2020).
- Catarina Botelho, Francisco Teixeira, **Thomas Rolland**, Alberto Abad, and Isabel Trancoso. "Pathological speech detection using x-vector embeddings." *arXiv preprint* arXiv:2003.00864 (2020).
- Rubén Solera-Ureña, Catarina Botelho, Francisco Teixeira, **Thomas Rolland**, Alberto Abad, and Isabel Trancoso. "Transfer Learning-Based Cough Representations for Automatic Detection of COVID-19." *Interspeech* (2021).

1.4 Structure for the thesis

The structure of this thesis comprises five chapters. In Chapter 2, a comprehensive review of related work is conducted to establish the context and understanding of the challenges associated with automatic children's speech recognition. Furthermore, we provides an overview of the history of automatic speech recognition systems, along with an examination of the latest approaches specifically tailored to address the unique challenges posed by children's ASR. Finally, a compilation of children's speech corpora, available online and referenced in prior literature, is presented.

Following this, Chapter 3 we present our work done on the hybrid speech recognition framework.

2

Background - Children automatic speech recognition

Contents

Automatic Speech Recognition (ASR), or Speech-to-text (STT) refers to the process of mapping a raw spoken audio utterance into its corresponding text. The potential use of ASR applications across diverse fields has motivated the need for robust and reliable ASR systems. These applications extend across various sectors, encompassing academia, medicine, industry, and the military. Notably, ASR has made significant progress in recent years, thanks to the attention and investment from both industry and public authorities. This support has resulted in the deployment of applications such as voice assistants, hands-free interfaces, medical assistance, live translation, and more, all of which are widely used and accepted today. Nowadays, the majority of ASR applications are mainly developed and optimised for adult speech. Demonstrating high performance in conditions close to those encountered during the training phase. This focus on adult speech is explained by the potential immediate applications of ASR systems for this target audience. In addition, training ASR models on adult speech has both advantages of data availability and relatively stable aspects of adult speech characteristics. Indeed, adult speech is often more standardised, with established linguistic conventions and stable features. However, the challenge arises when such systems are applied to recognise speech in mismatched scenarios, like children's speech. For example, in the context of children speech, ASR algorithms often exhibit a decline performances, frequently two to five times worse [17]. In this context of children's speech, this difference of performance can be mostly attributed to the intra- and inter-speaker variability. In fact, speech serves as a channel not only for linguistic content, but also for paralinguistic cues that reveal aspects of the speaker's identity, including age, gender, state of health, emotional state and regional origin. While this additional layer of information is incredibly valuable for human-to-human communication, it introduce more complexity and challenges for the development of a reliable ASR systems [18]. Moreover, several external factors further negatively impact the performance, including noise, speaker variability, mispronunciation, and the quality of the recording [19, 20].

The potential applications of automatic speech recognition in education and entertainment have led to a growing interest in automatic speech recognition for children. Indeed, children represent a demographic group that could well benefit from such applications for a number of reasons. Firstly, the complexity of traditional computer interfaces, such as keyboards and mice, can pose problems for young children, making speech interfaces a more accessible and user-friendly option. Secondly, speech and language applications, including reading tutors and speech and language acquisition assistants, promise to address educational inequalities among children and facilitate their integration into society by giving them personal and tailored attention.

In this chapter, we first present the various challenges associated with children's speech recognition. These challenges encompass the unique characteristics of children's speech, including high acoustic and linguistic variability, as well as the limited amount of labelled data available for training. We then provide a brief introduction to ASR, tracing its historical development from early pattern recognition approaches

to the advent of statistical models and the contemporary move towards end-to-end models. This historical background provides an understanding of the underlying principles behind ASR technologies. Then, the chapter then moves on to a review of state-of-the-art methods specifically designed to address the challenges posed by children's ASR. The aim of this in-depth exploration is to provide a clear overview of the different techniques that are being used to improve children's speech recognition. Finally, the chapter concludes with a discussion that synthesises the different perspectives presented earlier and the ones selected for this thesis.

2.1 Children speech recognition challenges

In this section, we explore the distinct challenges posed by children's speech to ASR systems. In particular, we will explore the main differences with adult speech. Indeed, the main divergence between child and adult speech is mainly due to the continuous growth and intellectual development of children and has direct repercusions on automatic speech recognition scores. In order to present the different challenges associated with ASR for children, we have identified at least three of the main factors that degrade performance. First, we examine the acoustic variability of children's speech. The acoustic characteristics of children's speech differ considerably from those of adults due to factors such as vocal tract size, pitch modulation and articulatory differences. These variations represent a significant challenge for speech recognition systems, which are often trained on adult speech datasets. Taking this acoustic variability into account becomes imperative for the development of accurate and robust ASR models adapted to the unique characteristics of children's speech. Next, we will present the linguistic and phonetic knowledge inherent for children. Indeed, children's language evolves dynamically over time, with vocabulary expansion, phonetic development and language mastery. This linguistic evolution also poses challenges for ASR systems, as they need to be robust to age-specific linguistic variation and imprecise pronunciation. As with acoustic variability, effective modelling of these linguistic subtleties is important for child speech recognition systems. Finally, we present the challenge posed by the limited availability of corpora of children's speech. Unlike adult speech, data corpora containing labelled examples of children's speech are relatively rare and small in size. This scarcity constrains the training of robust ASR models, as it limits their exposure to the various linguistic and acoustic variations in children's speech.

2.1.1 Speech variability

Speech production is a complex process involving the synchronised actions and collaboration of several elements of the speech production apparatus. These include the vocal cords, tongue, lips and mouth. The coordination of these elements leads to fluctuations in air pressure, producing a wave called speech. Speech is therefore essentially a measure of air pressure over time. The waveforms of human speech encompass

a range of frequency components from 20 Hertz (Hz) to 20 kHz. These are detected and processed by the auditory system and the human brain. Because speech is based on frequency components, an accurate understanding of frequency components, such as fundamental frequency and formant frequencies, is essential for the development of reliable speech processing tools.

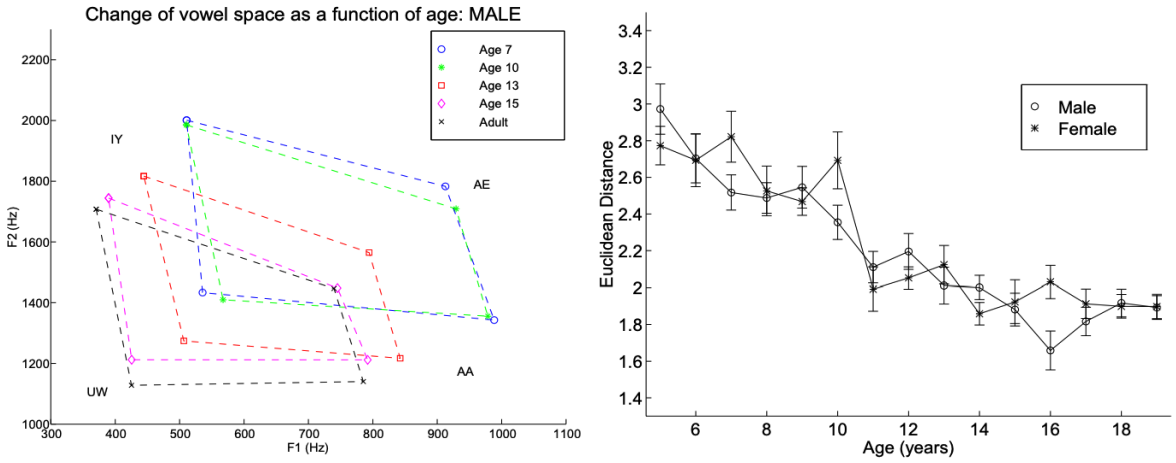
The fundamental frequency, often called F0, plays a crucial role in the analysis of speech signals. It characterises the (quasi-) periodic average oscillations produced by the vibrations of the vocal folds. Measured in Hz, F0 is often considered to be the acoustic correlate of pitch. F0 shows an inverse relationship with the vibrating mass of the vocal cords, leading to distinct F0 values for different demographic groups. As a general rule, adult males have lower F0 values, ranging from around 100 to 150 Hz. Women, on the other hand, tend to have higher F0 values, generally between 200 and 300 Hz. Children, whose vocal cords are smaller, often have even higher F0 values, generally ranging from 300 to 450 Hz. These variations in F0 contribute to the perceptual differences in pitch between individuals of different ages and genders. According to [2], significant differences in F0 between male and female speakers generally appear from the age of 12. For male speakers, decreases in F0 were observed on average between the ages of 11 and 15, at the time of puberty, and did not change significantly after the age of 15. Furthermore, it was observed that the relatively large variation between male subjects at the ages of 13 and 14 also implies that the time of the beginning of puberty varies among speakers in these age groups. For female speakers, pitch drops between the ages of 7 and 12, and there is no significant change in pitch after this age. In addition, the change in F0 in female subjects is more gradual as compared to male speakers.

It is essential to emphasise that F0 is not a static parameter; on the contrary, it exhibits continuous variation within a sentence. This dynamic nature allows F0 to be used expressively in speech, conveying nuances such as accent, emotion and intonation patterns. Variations in F0 help to distinguish between different types of speech acts, such as statements, questions and exclamations.

A formant refers to a concentration of acoustic energy centred around a specific frequency in a speech waveform. As defined by the Acoustical Society of America, it is *"a range of frequencies in which there is an absolute or relative maximum in the sound spectrum. The frequency at the maximum is the formant frequency"*. Formants play a crucial role in characterising vowel sounds and distinguishing between them. In speech analysis, the first three formants, known as F1, F2 and F3, are commonly used for their importance in capturing the acoustic characteristics of vowels and their contribution to the timbre of speech sounds.

The pioneering study by Peterson and Barney in 1952 [21] marked a turning point in the exploration of the formant components of vowels, particularly in the context of children's speech. Researchers undertook a comparative analysis, examining vowel frequencies in children's speech and comparing them with those of adult men and women. This research was the first to show significant variations in vowel frequencies based on the speaker's age and gender. Building upon this foundational work, subsequent studies [1,2,22]

have provided further insights into the acoustic characteristics of children's speech. These investigations have consistently demonstrated a correlation between acoustics and children's age, attributing these variations primarily to the growth of the children's vocal apparatus. The scaling behavior of formant frequencies with respect to age is showed in Figure 2.1(a). Here, the evolving vowel space, defined by four reference vowels (*/IY/,/AE/,/AA/* and */UW/*) linearly decreases with age and aligns with the adult level around the age of 15. Additionally, as highlighted in [1], the vowel space becomes more compact as age increases, indicative of a downward trend in the dynamic range of formant values. These variations and age-related differences emphasise the critical challenge of inter-speaker variability, especially for young children.



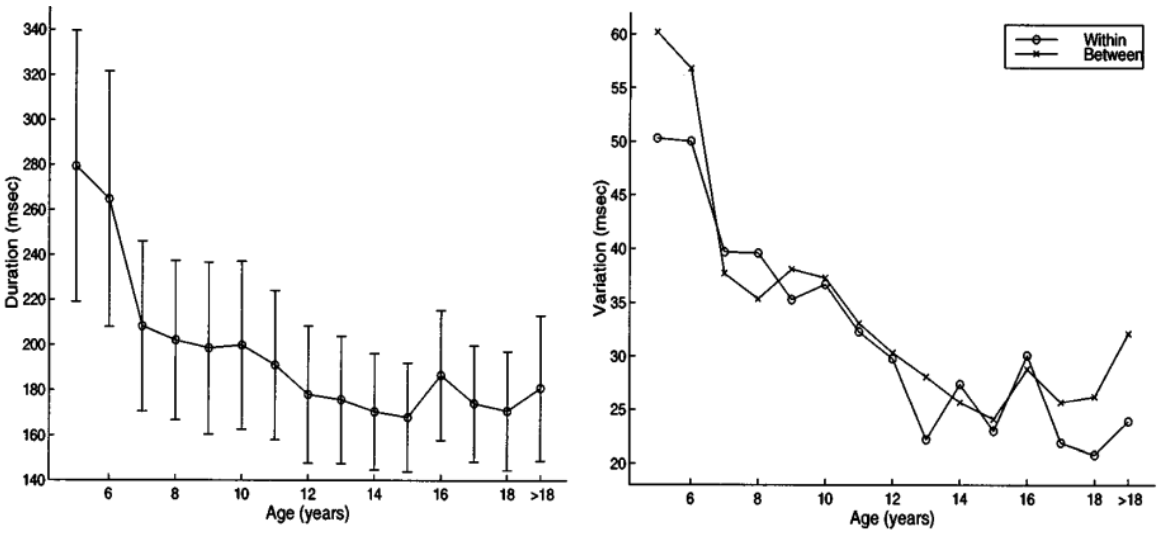
(a) Changes in F1-F2 vowel space as a function of age

(b) Mean cepstral distance between the two repetitions of the same vowels

Figure 2.1: Formant and cepstral variability. Figures taken from [1]

In addition to inter-speaker variability, [2] also highlight the fact that children's speech exhibits intra-speaker variability, signifying that the speech within the same individual can exhibit variations. This variability arises from two primary sources. Firstly, as previously discussed, the acoustic characteristics of children can significantly differ at different ages due to the ongoing growth of their vocal apparatus. Secondly, even at the same age, the same child may produce variable speech, even when articulating the same vowel. As depicted in Figure 2.1(b), the average cepstral distance between two repetitions of the same vowels by the same child tends to decrease with age, particularly after the age of 10. This reduction in intra-speaker variability is attributed to the progressive mastery of speech articulation components as children grow and mature their motor skills abilities. The decrease in cepstral distance suggests a more coherent and standardised articulation of vowels over time.

Segmental duration is another important aspect of human speech. A segment, as defined by Crystal [23], is: *"Any discrete unit that can be identified, either physically or auditorily, in the stream of speech"*.



(a) Averaged-vowel duration across all vowels and subjects in each age group

(b) Within- and between-subject variations. The between-subject variation is reduced by a factor of 2.0

Figure 2.2: Segmental duration variability. Figures taken from [2]

These segmental durations could be of vowel or sentence duration. Vowel duration, in particular, is of significant importance in vowel discrimination. Research, as presented in [2], investigates how these characteristics change in children's speech. As demonstrated in Figure 2.2(a), the average vowels duration in children exhibits variations with age. On average, younger children tend to have longer vowel durations, resulting in a slower speaking rate. However, as children become more comfortable with the processes of speech production with age, vowel duration gradually decreases. Similarly to children frequency variations, segmental duration exhibits intra-speaker variability, as illustrated in Figure 2.2(b).

In conclusion, dealing with both intra- and inter-speaker variability in children's speech, particularly in those under the age of 15, poses a substantial challenge for developing high-performance speech processing models. Especially, this challenge is exacerbated in the context of children's ASR where the age of the child is often unknown. In addition, the dynamic processes of the vocal tract growth, changes in linguistic knowledge and the maturation of control of speech apparatus occur simultaneously and overlap, making it considerably more challenging to accurately disentangle and model their effects. The intricate nature of children's speech, marked by intra and inter-speaker variations, underscores the necessity for sophisticated and adaptive models that can accommodate the unique characteristics of these speakers.

2.1.2 Language and phonetic knowledge

Language is a complex and multifaceted system of communication that involves the use of symbols, such as words to convey meaning. It is a uniquely human ability and serves as a fundamental aspect of

human cognition and social interaction. Linguists have identified five basic components of language [24], including phonology (sounds), morphology (struce and construction of words) , semantics (meaning), syntax (grammar and sentence structure), and pragmatics (how language is used in context). It allows individuals to express thoughts, share information, and engage in social interactions. It is important to note that, languages vary across cultures and regions, exhibiting a rich diversity of sounds, structures, and expressions. Additionally, language can be spoken, written, or signed, and evolves over time. For children, the mastery of language is crucial milestone in their cognitive development. Futhermore, language plays a central role in shaping culture, identity, and the transmission of knowledge to them. The children's ability to use language develops with age, achieving adult capabilities around the age of 13 , as indicated by research [2]. This progression enables the children to transition from producing simple sounds and words to generating more complex sounds and fully articulated sentences.

During the process of language acquisition, children, constrained by their limited linguistic knowledge, often make pronunciation errors and encounter disfluencies [25]. According to [26], these errors may include a variety of phenomena, such as:

- **Substitution**: Involves the inadvertent replacement of the correct pronunciation of an entire word with an alternative rendition.
- **Omission**: Refers to the act of leaving out or neglecting a part of speech, a word, or a phrase that would typically be included in a grammatically correct or complete sentence.
- **Mispronunciation**: Involves the act of pronouncing a word or a part of a word incorrectly, deviating from the standard or expected pronunciation in a particular language or dialect.
- **Pause and Hesitation**: Entails temporary breaks or delays in speech during which a speaker might refrain from producing sound or articulate speech in a hesitant manner.
- **Filler and mumbling**: Filler encompasses linguistic elements used during pauses or hesitations when a speaker needs time to think, including unintelligible sounds, words, or phrases without significant meaning. Mumbling is characterised by unclear or indistinct speech, often marked by low volume, unclear articulation, and imprecise pronunciation.
- **False-start**: Refers to an instance where a speaker begins a sentence or an utterance and then stops abruptly before completing it. This interruption is often followed by a restart or a correction to articulate the intended message more accurately.
- **Sound-out**: Involves a pronunciation strategy in which a speaker articulates a word by pronouncing each sound or phoneme separately, rather than blending them together seamlessly.

Potamianos and Narayanan's study [27] revealed significant insights into the variability and characteristics of children's linguistics. They found that inter-speaker variability is approximately twice as much

as intra-speaker variability. Additionally, their research found that the rate of mispronunciations is twice as high for children aged 8 to 10 compared to those aged 11 to 14. Conversely, the trend is reversed for filler and pauses, where the older group exhibits a higher rate. Furthermore, younger children, of 8 to 10 years, tend to produce more false-starts and breathing.

In adult speech, pronunciation errors and disfluencies are also present, but their occurrence is typically lower than what is observed in the speech of children, as supported by studies such as [28,29]. In addition, these studies used language models specifically trained on children's speech, demonstrating their advantages over the use of adult language models. The findings underscored the differences between children's and adults's linguistics, encompassing variations in grammatical structures as well as the presence of mispronunciations and disfluencies. Such insights are crucial for the development of effective language models tailored to the unique characteristics of children.

2.1.3 Data scarcity

In recent years, the emergence of deep learning has brought about significant advancements in the ASR field. The combination of increased computational power and the availability of large datasets has played a pivotal role in these improvements. The success of deep learning is largely attributed to deep neural networks (DNNs), which can approximate complex non-linear functions. With the help of this capability, DNNs excel in capturing complex patterns and accurate representation in speech data. However, the efficacy of a DNN in capturing speech patterns depends a lot on the availability of training data. Indeed, using large-size datasets is pivotal for enhancing the capabilities and generalization of DNN-based ASR systems. Notably, top-performing ASR systems like Whisper have been trained on exceptionally large dataset, surpassing 680,000 hours of data collected from the web [30]. There is a noticeable trend in the speech research community towards the collection of larger datasets, exemplified by initiatives such as the LibriSpeech dataset, which comprises around 1,000 hours of speech [31], and the GigaSpeech dataset, featuring 10,000 hours of speech [32].

Unfortunatly, despite rare recent efforts to collect larger children datasets [33–35], the majority of publicly available children corpora include fewer than fifty hours of speech. This is significantly less than a typical adult speech corpora, which usually contains hundreds or even thousands of hours of data. Furthermore, the majority of the accessible children's data are English corpus [33, 35–38]. However, English is a resource-rich pluricentric language which should be seen more as an exceptional case, rather than an average representative. A compilation of existing datasets containing children's speech will be presented in 2.4.

The scarcity of children's speech datasets availability can be partially attributed to a combination of ethical, legal, and technical challenges. Collecting speech data from children raises ethical concerns related to obtaining consent, ensuring privacy, and protecting minors. The heightened awareness of online safety

and security concerns further complicates the creation and sharing of datasets that include children's speech, as there is a need to safeguard against potential misuse and ensure the anonymity of participants. Beyond ethical and legal considerations, technical challenges also play a role. Children's speech patterns, language development, and pronunciation can vary significantly across different age groups, as explained in previous sections, making it challenging to create datasets that accurately represent the diversity of children's speech. Moreover, the resource-intensiveness of collecting high-quality speech data from children, which involves careful planning, recruitment efforts, and coordination with schools or parents, can further contribute to the limited availability of such datasets. Finally, collecting speech data from children is a challenging and time-consuming task. Various factors can significantly impact the quality of the gathered speech. These include children's short attention spans, recording environments that might be noisy (such as a classroom), and the quality of the speech, which is highly dependent on the task at hand (reading tasks are generally more complex for children).

The importance of having a large database of children's speech to cover different variabilities has been emphasised in a study conducted by Liao in 2015 [39]. In this work, the researchers trained an ASR model using a large in-house corpus of children's speech. Notably, this corpus was comparable in size to typical adult speech corpora. The result was the attainment of state-of-the-art performance by the ASR model, even demonstrating competitiveness with adult speech recognition systems. This study underscores the crucial role of large-size and diverse children's speech datasets in developing robust and high-performance ASR models tailored to the unique characteristics of children's speech.

2.2 Introduction to automatic speech recognition

In this section, a brief historical overview of ASR is presented, laying the foundation for a subsequent exploration of predominant trends and modules within ASR systems. This comprehension is necessary for the following sections of this thesis. While not exhaustive, this overview provides essential insights, with certain topics falling beyond the scope of this thesis are intentionally omitted. For a more exhaustive understanding of ASR, readers are encouraged to consult references such as [40–42]. The section is structured as follows: Firstly, we present the historical evolution of ASR, followed by an description of traditional ASR systems, succeeded by an explanation of the end-to-end paradigm. Concluding this section, a discussion on automatic speech recognition metrics is presented.

2.2.1 A brief history of Automatic Speech Recognition

2.2.1.A Early Days

The origins of speech recognition technology can be traced back to the 1950s and 1960s, with initial projects focusing on isolated word recognition in a speaker-dependent context. One of the earliest project in this domain was the creation of a digit recognizer at Bell Telephone Laboratories in 1952. This recogniser demonstrated the automatic recognition of telephone-quality digits spoken at normal speech rates by a single adult male, achieving an impressive accuracy of up to 99%. The system relied on formant frequency approximations to recognise entire words. It is impotant to underscore that within this recogniser, there was an absence of explicit modeling of syllables, consonants, vowels, or any other sub-word units. In this recogniser, a word was treated as a single unit, which was then compared with ten standard digit patterns to find the best match. The recognition process first involved extracting two frequency ranges, below and above 900 Hz. Motivated by the observation that these two frequency ranges approximately align with the frequencies of the first two formants in speech. Then, these formant approximations were plotted on a 2D-plot with a trace interruption period of 10ms. Finally, when presented with new audio, the system generated a plot, compared it to the reference plots of the ten digits, and returned the closest match by computing the highest relative correlation coefficient. Figure 2.3 illustrates an example of the 2D representation of the ten digits.

In 1962, IBM developed Shoebox, a device capable of recognising 16 spoken words, including the ten digits and command words such as "plus," "minus," and "total." This system employed a pattern-matching algorithm similar to the pattern-matching approach used in the Bell Telephone Laboratories's recogniser.

Nevertheless, extending such a system for a larger vocabulary would be impractical. Indeed, the template-matching approach necessitated saving each word representation on disk and comparing the unknown spoken word with all these representations. Therefore, when attempting to scale this approach

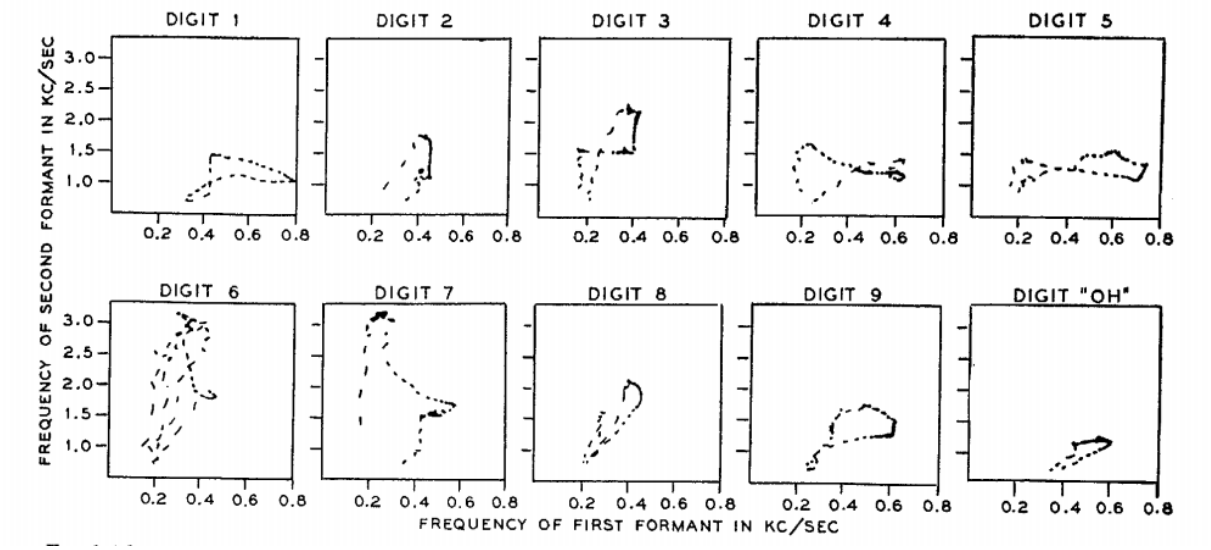


Figure 2.3: Example of a standard digit pattern from Davis et al. 1952

to automatic large vocabulary recognition, issues of time and disk usage complexity emerged as significant challenges. Furthermore, in order for the circuit to deliver an accuracy of the same range for a new speaker, a preliminary analysis of the speech of that individual and subsequent circuit adjustments were necessary. These limitations underscored the need for more scalable and adaptive approaches and led the field of automatic speech recognition to continued to evolve.

2.2.1.B The Speech Understanding Research program

In the early 1970s, subsequent to the initial success of pattern matching algorithms in single-word recognition, the Advanced Research Program Agency of the U.S. Department of Defense, ARPA, initiated funding for a five-year program called Speech Understanding Research (SUR). The overarching goal of SUR was to "obtain a breakthrough in speech understanding capability that could then be used toward the development of practical man-machine communication system ". Within the context of this program, four distinct research groups were funded: two from Carnegie-Mellon University (CMU), one from Bolt Beranek and Newman Inc. (BBN Hwim), and the last one from System Development Corporation (SDC). Each group was assigned a specific task, such as dealing with facts about ships, travel budget management, and document retrieval. The ultimate objective for each group was to create a system capable of recognising simple sentences within the context of their assigned task, from a vocabulary of 1,000 words, achieving a Word Error Rate (WER) of 10% in a reasonable amount of time.

The realisation that the pattern-matching word identification strategy could not be directly applied to the challenge of sentence understanding prompted a redesign of the single-word identification system. In the first hand, one key recognition was that the acoustic characteristics of words can vary considerably based on the context of the sentence. The impracticality of storing each word and all its possible different

variations on disk became apparent. Moreover, determining the boundaries of each word was an almost impossible task, and even if these boundaries were identified, the pattern-matching computation, involving comparisons with each of the 1,000 stored words and all their possible variations, would be time-consuming and exceed the reasonable time requirement. Secondly, another crucial consideration in the redesign of the system was that the length of the spoken sentence is variable and unknown, in contrast to the relatively fixed length in single-word identification tasks. In sentence understanding, the system needed to handle variable sentence lengths, making it necessary to adopt a more flexible approach in modeling and recognizing speech.

To address these challenges, a shift was made to a smaller unit than the word for modeling speech -namely, phonemes. Phonemes are the smallest distinctive and meaningful units that compose speech. Each language is associated with a finite set of phonemes, typically fewer than 50, which can be combined to form words. This shift enabled a more efficient and flexible representation of speech, accommodating the variability in the pronunciation of words.

Among all the systems proposed in the project, the Harpy system implemented by Lowerre in 1976 by the Carnegie Mellon team exhibited the best performances [3]. Harpy is a speaker-specific system that use a pattern-matching algorithm at the phoneme level instead of the word level. The system employs a set of 98 phonemes and diphones -a pair of consecutive phonemes- , encompassing pronunciations of all words, along with a graph compiling all accepted sentences using 15,000 states. When a new spoken utterance is provided to the system, it undergoes an initial processing phase, involving low-pass filtering at 5 kHz, digitization at 10,000 samples per second, and computation of 14 linear prediction coefficients with a 10ms shift. To speed-up the decoding process, analogous adjacent acoustic segments are grouped together. Subsequently, these audio segments are compared against the 98 phoneme templates, and the system deduces the optimal path over the decoding graph. Figure 2.4 provides an exemplar illustration of a decoding graph in the Harpy system.

Notwithstanding the achievements and success of the Harpy system, it has limitations that hinder its broader applicability. As a speaker-specific system, it requires tuning for each new speaker over the 98 phoneme templates. Additionally, the system is constrained to recognising a vocabulary of no more than 1,000 words and relies on a simple handcrafted grammar, making it less reliable for handling spontaneous speech. Moreover, the decoding time of the system falls short of real-time requirements. These constraints highlight the need for more generalisable and efficient speech recognition systems, especially for handling diverse speakers and spontaneous speech scenarios. Therefore, as research progressed, the limitations of template-based approaches became apparent. This realisation prompted the exploration of probabilistic modeling techniques, marking a shift towards more sophisticated and adaptable approaches in automatic speech recognition.

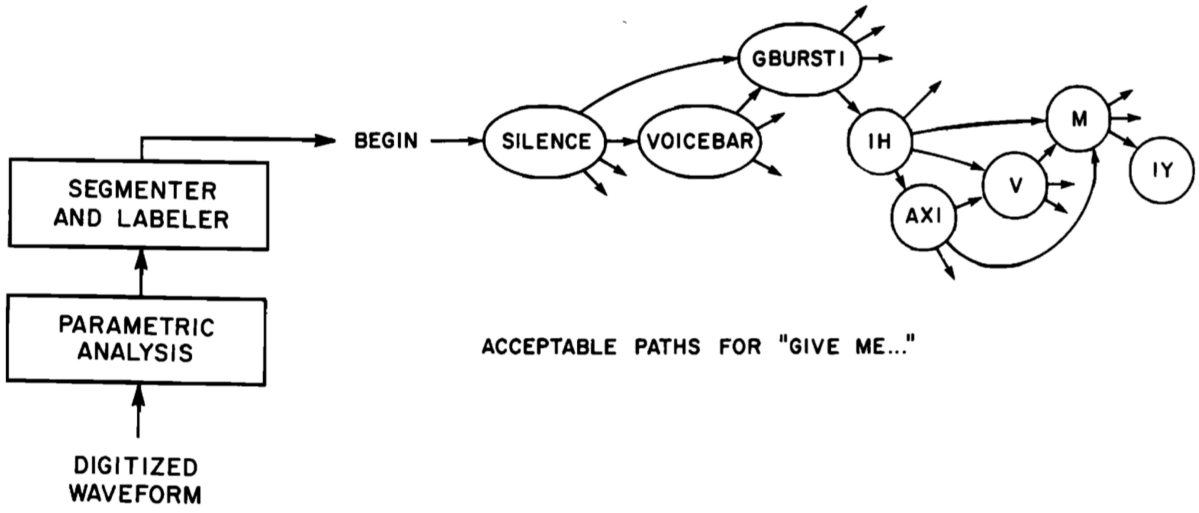


Figure 2.4: Example of a decoding graph from the Harpy system for the sentence "GIVE ME" from [3]

2.2.2 Traditional automatic speech recognition systems

In the 1970s, the introduction of Hidden Markov Models (HMMs) led to a paradigm shift in ASR research, moving away from traditional pattern-matching methods towards statistical modelling [43]. Indeed, HMMs are particularly effective at capturing the sequential and temporal nature of speech. They assume that speech can be represented as a sequence of hidden states, each state corresponding to a distinct phonetic unit. HMMs model the transitions between these states and, at each state, generate observable acoustic features. The hidden aspect refers to the fact that the underlying states are not directly observed but inferred from the observable features. HMMs are particularly well suited to modelling speech dynamics, as they can represent the variability of speech sounds over time. In the context of ASR, HMMs have been widely used to model phonemes, words or sub-word units.

Building on this foundation, the 1980s saw the emergence of Gaussian Mixture Models (GMMs), which further enhanced the statistical modeling capabilities of ASR [44]. GMMs allowed for a more flexible representation of the probability distributions underlying speech features. GMMs are used to model the statistical distribution of acoustic features associated with each hidden state in an HMM. They assume that the distribution of features can be approximated by a mixture of several Gaussian distributions. GMMs are versatile in capturing the variability of speech sounds, allowing a more flexible representation of the acoustic units. In ASR, GMMs are commonly used to model the emission probabilities associated with each state in an HMM. This means that given a particular state, the GMM provides the likelihood of observing a specific set of acoustic features. By combining the temporal modeling capabilities of HMMs with the statistical representation power of GMMs, this framework effectively captures the complex relationship between acoustic features and phonetic units.

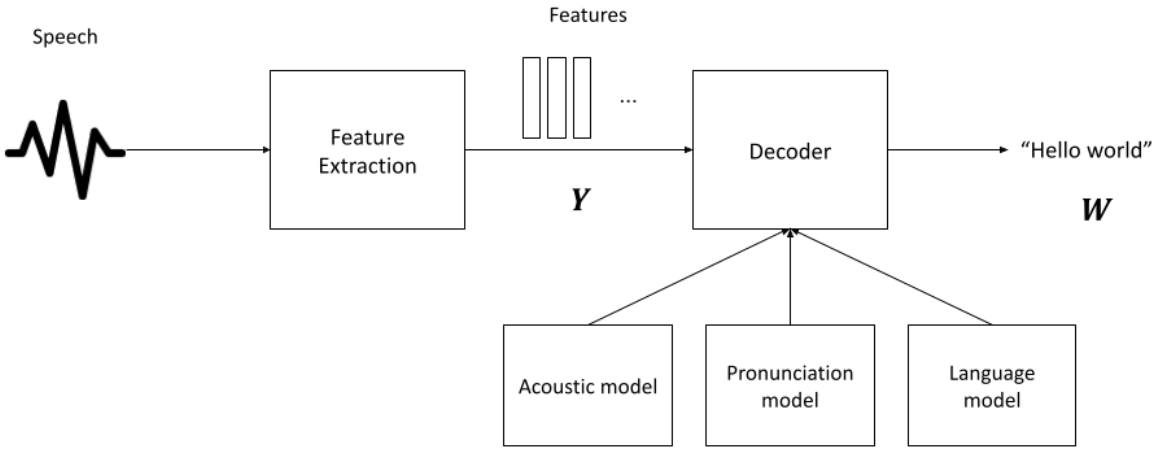


Figure 2.5: Architecture of a HMM-based speech recognition system

Finally, in the 1990s, statistical grammars also played a crucial role, providing a structured framework for incorporating linguistic into ASR systems [45]. Statistical grammars represent a category of grammars that integrate statistical information to characterise the probability of diverse linguistic structures. In contrast to traditional rule-based grammars, which articulate a language's syntax through explicit rules, statistical grammars adopt a data-driven methodology. They assign probabilities to various linguistic constructions based on observed frequencies within a designated corpus.

The components illustrated in Figure 2.5 represent the traditional ASR pipeline. These components continue to form the core of modern HMM-based ASR systems. However, in more recent times, the field of ASR has witnessed a transformative shift with the adoption of deep neural networks (DNNs) instead of GMM. Called hybrid models, they combining the strengths of HMMs and DNNs and have further improved the ASR system performance [46]. A DNN is a subtype of artificial neural networks consisting of multiple layers of interconnected neurons. These neurons, organised in layers, receive an input signals, and each connection between neurons is characterised by a weight that signifies its strength. In addition, each neuron is associated with a bias, provide an additional learnable parameter. During training, the network adjusts these weights and biases to minimise the difference between predicted and actual outputs, a process known as backpropagation. Moreover, there is a non-linear activation functions within neurons, as it enables the network to model intricate, non-linear patterns of the data. The weights, biases and non-linearity allow DNNs to capture complex relationships and representations from the data,learning hierarchical features and abstracting information across multiple layers of the network.

In this statistical framework, the continuous speech audio waveform is transformed into a sequence of fixed-size acoustic vectors, denoted as $\boldsymbol{X} = x_1, ..., x_T$. The goal of the Automatic Speech Recognition (ASR) system is to determine the sequence of words, $\boldsymbol{w} = w_1, ..., w_L$, that is most likely to have produced the observed acoustic vector sequence $\boldsymbol{X}$. This is formulated as finding the word sequence $\hat{w}$

that maximises the conditional probability $P(\boldsymbol{w}|X)$. More formally:

$$\hat{\boldsymbol{w}} = \underset{\boldsymbol{w}}{\text{argmax}}\{P(\boldsymbol{w}|X)\} \tag{2.1}$$

However, directly modeling the conditional probability $P(\boldsymbol{w}|X)$ can be challenging. Bayes' Rule offers a way to express this probability in terms of more manageable components, specifically by decomposing it into the product of the likelihood of the observed acoustic vector sequence given the word sequence $P(X|\boldsymbol{w})$ and the prior probability of the word sequence $P(\boldsymbol{w})$. Therefore, equation 2.1 became:

$$\hat{\boldsymbol{w}} = \underset{\boldsymbol{w}}{\text{argmax}}\{\frac{P(X|\boldsymbol{w})P(\boldsymbol{w})}{P(X)}\} = \underset{\boldsymbol{w}}{\text{argmax}}\{P(X|\boldsymbol{w})P(\boldsymbol{w})\} \tag{2.2}$$

Here, the likelihood $P(\boldsymbol{X}|\boldsymbol{w})$ is determined by the acoustic model component, capturing the probability of observing the acoustic vector sequence $\boldsymbol{X}$ given the word sequence $\boldsymbol{w}$. In parallel, the prior probability $P(\boldsymbol{w})$ is determined by the language model component. The term $P(X)$ is not essential for determining the maximum probability and can be omitted in the context of finding the most likely word sequence. Subsequent sections will provide a more in-depth exploration of these distinct components and their processes.

2.2.2.A Feature extraction

The feature extraction component plays a crucial role in capturing pertinent information about the linguistic content of speech. The efficacy of speech recognition systems is intricately tied to the quality of the extracted features. To this end, for each time step, the continuous waveform is transformed into a small fixed-size vector. A acceptable assumption is that speech is considered as stationary within the time span covered by a single vector. Consequently, feature vectors are typically computed at intervals of 10 milliseconds, often with a 25-millisecond overlapping window.

Within the domain of ASR, a broad range of different acoustic features can be employed. However, in the context of HMM-based models, the predominant features encompass perceptual linear prediction (PLP), mel spectrograms (melspec), filterbanks (fbanks), and Mel-frequency cepstral coefficients (MFCC). However, MFCCs as introduced by Davis and Mermelstein [47], stand as the predominant features in HMM-GMM and HMM-DNN architectures. The process of extracting MFCCs typically involves several steps to capture essential information from the speech signal. First, a preemphasis filter is applied to the signal. Subsequently, the signal is segmented into frames, and a Hamming window with a duration of 25 milliseconds is applied to each frame. The frames are then transformed into the frequency domain using the discrete Fast Fourier Transform (FFT), resulting in the magnitude spectrum. The next stage involves passing the magnitude spectrum through a bank of triangular-shaped filters. Extracting features at this point yields melspec features. The energy output from each filter is log-compressed, and

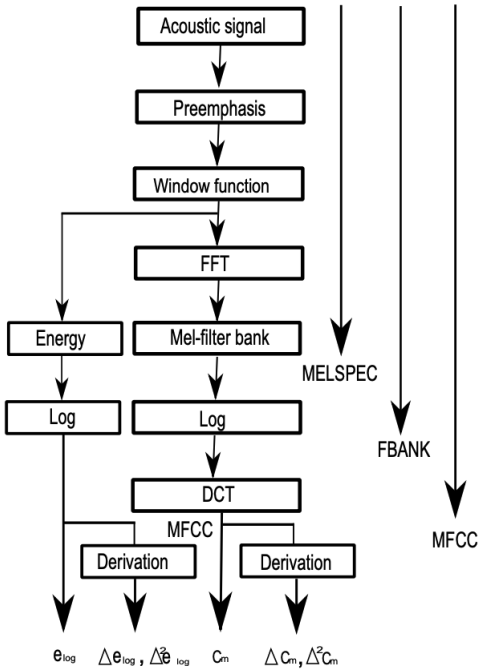


Figure 2.6: Principal block scheme of main speech features for ASR: Melspec, fbanks and MFCC coefficients from [4]

concluding the extraction process at this stage results in fbanks features. Finally, MFCCs are obtained by transforming the filterbank features into the cepstral domain using the Discrete Cosine Transform (DCT) to decorrelate the energies obtained from the filterbanks. The representation of this extraction process is illustrated in Figure 2.6.

To incorporate information about the dynamics of the speech signal, the feature vector for each time step is augmented with the first and second-order derivatives, commonly denoted as Δ (Delta) and $\Delta\Delta$ (Delta-Delta), respectively. The first-order derivative coefficients, often referred to as Δ coefficients, are calculated by taking the difference between consecutive feature vectors. Mathematically, the Δ coefficients for a feature vector at time t are computed as follows:

$$\Delta_i = \frac{\sum_{n=1}^{N} n(f_{i+n} - f_{i-n})}{2\sum_{n=1}^{N} n^2} \tag{2.3}$$

Here, f_i represent the feature at the instant i.Typically, n is set to 2, indicating that the first-order derivatives are calculated by considering the differences between the feature at the current time t and its neighboring features at $t \pm 2$.The $\Delta\Delta$ coefficients, also written Δ^2, represents the second-order derivatives and are computed in a similar manner as Δin equation 2.3 by taking the difference between consecutive Δ coefficients instead of the spectral feature f. The concatenation of the first-order derivative (Δ) and second-order derivative (Δ^2) features with the spectral features is denoted as x_i. Mathematically, this

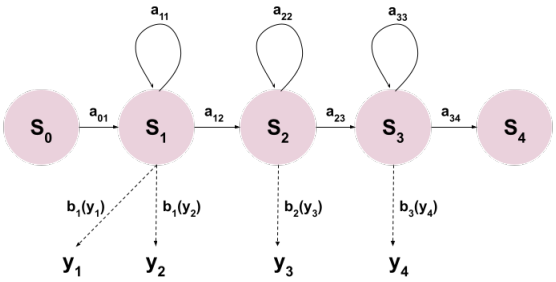


Figure 2.7: Three-state Hidden Markov Model for modelling phones

concatenation can be expressed as follows:

$$\boldsymbol{x_i} = [f_i \qquad \Delta_i \qquad \Delta_i^2] \tag{2.4}$$

Here, f_i represents the spectral feature at the instant i, Δ_i represents the first-order derivative feature at the same instant, and Δ_i^2 represents the second-order derivative feature at the same instant. The resulting feature vector x_i encapsulates information about the spectral content of the speech signal as well as its temporal dynamics, providing a more comprehensive representation for subsequent processing by the ASR system, espacially the acoustic model.

2.2.2.B Acoustic model

The role of the acoustic model (AM) is to determine $P(\boldsymbol{X}|\boldsymbol{w})$. While employing a classifier such as GMM models with one GMM per phone is a straightforward approach, it tends to disregard the temporal dependencies inherent in speech, such as co-articulation. Indeed, accurately categorizing each frame necessitates the consideration of not only the current frame but also its context, encompassing both previous and following frames. Additionally, there are acoustic differences at the beginning, middle, and end of each phone, further complicating the classification task. To address these concerns, the HMM framework has been proposed as a solution [48]. HMMs offer temporal flexibility, incorporating concepts such as self-looping, and provide a well-understood framework with effective learning (Expectation Maximization) and decoding (Viterbi) algorithms.

In the HMM terminology, the observed variables, denoted as y_i, correspond to the acoustic features (e.g., speech signal), while the hidden variables are represented as states, denoted as s_i. The states are generated using a first-order Markov process, where the i^{th} state s_i depends solely on the previous state s_{i-1}. The transition from one state to another is determined by the transition probability a_{ij}. Upon entering a state s_i, an observation in the form of an acoustic vector is emitted, and this emission is modeled by the distribution $b_i(\cdot)$ associated with that state. Typically, this emission distribution is modeled by a GMM. It is assumed that all observations are independent given the states that generated them. A

fundamental configuration in HMMs for speech recognition involves a three-state model representing the beginning, middle, and end of a phoneme, along with an initial and final state. This model, known as a monophone HMM-GMM, constitutes a basic unit for phonetic modeling. For example, since English has 44 phonemes [49], a monophone system on English will have 44 separate HMM-GMM. However, due to the influence of co-articulation effects and the desire to capture phonetic variations based on context, more complex models, such as triphone systems, are employed [50]. A triphone system aims to model each phoneme in its specific phonetic context, leading to a significantly larger number of required models. Indeed, or a language with N phonemes, there should be N^3 models to train. For example, in English, which has 44 phonemes, the total number of models would be $44 * 44 * 44$ resulting in 85,184 models. To manage the computational complexity, these models are often clustered using decision trees [51]. This hierarchical clustering helps capture phonetic variations efficiently while working with limited available data.

The concept of hybrid models gained prominence in the 1990s with the integration of multi-layer perceptrons (MLP) as replacements for GMMs in the HMM-GMM system [52, 53]. Subsequently, the introduction of DNNs, which are MLPs with a large number of hidden layers, in 2012 marked a significant advancement in various ASR tasks [46]. The efficacy of DNNs lies in their capability to capture complex and highly non-linear relationships between inputs (e.g., audio features) and outputs (e.g., phoneme labels) due to the substantial number of parameters induced by the deep architecture.

However, the training of HMM-DNN and HMM-GMM models differs. Neural networks necessitate labeled data for training, which includes both input features and corresponding output labels (e.g., phoneme labels). Standard speech training data often lacks this detailed labeling, providing only audio waveforms and utterance transcriptions. Consequently, the training of HMM-DNN models relies on alignments generated by an HMM-GMM. Therefore, the training process involves initial flat-start monophone training with HMM-GMM, followed by iterative steps into triphone training with more precise alignments. In consequence, the precision of the HMM-GMM alignment directly impacts the efficacy of DNN model training. As ASR continues to advance, the integration of various DNN architectures, including Convolutional Neural Networks (CNNs) [54], Long Short-Term Memory networks (LSTMs) [55], and Time-Delay Neural Networks (TDNNs) [56], further refines the modeling of spatial and temporal relationships, laying the foundation for more sophisticated and context-aware speech recognition systems.

2.2.2.C Pronunciation model

The pronunciation model in Automatic Speech Recognition (ASR), often referred to as a dictionary or lexicon, plays a crucial role in establishing the correspondence between phonetic units, such as phonemes, and the respective words in the language. In ASR systems, words are essentially comprised of phonetic segments, and the pronunciation model specifies how these segments combine to articulate the pronun-

Phoneme	Example	Translation
AA	odd	AA D
AE	at	AE T
AH	hut	HH AH T
AO	ought	AO T
AW	cow	K AW
AY	hide	HH AY D
B	be	B IY
CH	cheese	CH IY Z
D	dee	D IY
DH	thee	DH IY
EH	Ed	EH D
ER	hurt	HH ER T
EY	ate	EY T
F	fee	F IY
G	green	G R IY N
HH	he	HH IY
IH	it	IH T
IY	eat	IY T
JH	gee	JH IY
K	key	K IY

Phoneme	Example	Translation
L	lee	L IY
M	me	M IY
N	knee	N IY
NG	ping	P IH NG
OW	oat	OW T
OY	toy	T OY
P	pee	P IY
R	read	R IY D
S	sea	S IY
SH	she	SH IY
T	tea	T IY
TH	theta	TH EY T AH
UH	hood	HH UH D
UW	two	T UW
V	vee	V IY
W	we	W IY
Y	yield	Y IY L D
Z	zee	Z IY
ZH	seizure	S IY ZH ER

Figure 2.8: Phoneme set and examples of CMU dictionary using 39 phonemes from [5]

ciation of each word. This mapping takes the form of an entry where all possible words are associated with their corresponding sequence of phones. Examples of words along with their corresponding phonetic sequences are illustrated in Figure 2.8. Traditionally, this mapping is obtained manually, relying on phonetic and linguistic knowledge. It's noteworthy that a single word may have multiple pronunciations.

Furthermore, the integration of statistical grapheme-to-phoneme (G2P) tools [57] augments the lexicon by facilitating the generation of pronunciations for words that may not be explicitly included in the dictionary.

2.2.2.D Language model

The language model (LM), often referred as grammar, holds a pivotal role in ASR, responsible for determining the probability $P(\boldsymbol{w})$ of equation 2.2. Beyond its use in ASR, the applications of language models extends into diverse fields including Natural Language Processing (NLP) [58], computational biology [59], and data compression [60]. The two most successful approaches to language modeling widely adopted in ASR are, respectively, statistical methods and models based on deep learning.

Statistical language models rely on traditional techniques like HMM and n-grams. N-grams, which are the simplest approach for language modelling, estimate the likelihood of the next word based on the

context of the preceding n words as follows:

$$P(\boldsymbol{w}) = P(w_1, w_2, \ldots, w_L) = \prod_{i=1}^{L} P(w_i | w_{i-n}, \ldots, w_{i-1}) \tag{2.5}$$

The granularity of context varies from the case when $n = 1$, the 1-gram -or unigram (considering each word independently) to higher-order n-grams that incorporate more extensive context for enhanced accuracy. The unigram model would be defined as follows:

$$P(\boldsymbol{w}) = P(w_1, w_2, \ldots, w_L) = \prod_{i=1}^{L} P(w_i) \tag{2.6}$$

Despite the evident advantages of employing a larger n for enhanced contextual information in language modeling, practical considerations and computational limitations often impose constraints on the choice of n in real-world ASR applications. The escalating combinational complexity associated with higher n values becomes computationally demanding, presenting challenges for efficient processing, storage, and training. As a result, the majority of ASR applications typically use trigrams or 4-grams, striking a balance between contextual accuracy and computational feasibility.

Furthermore, determining the start of sequence probability precisely introduces intricacies, especially with larger n-grams. Additionally, the reliance on training data poses a notable limitation for n-grams, particularly in estimating the likelihood of unseen words. This deficiency becomes apparent when facing vocabulary expansion or encountering out-of-vocabulary terms, necessitating specific techniques such as smoothing to address these challenges. [61].

In contrast, deep learning-based language models have opened up a new era, employing neural networks with complex architectures to achieve remarkable modeling capabilities. Unlike traditional n-grams, these models demonstrate a high degree of flexibility, ease training and do not require as many resources as n-grams to be efficient. Recent advances in language modeling, exemplified by state-of-the-art models such as Bidirectional Encoder Representations from Transformers (BERT) [62] or Generative Pre-trained Transformer (GPT) [63], are built on deep learning networks.

A key factor contributing to the success of deep learning language models is the incorporation of attention mechanisms. Unlike the limited contextual awareness of n-grams, attention mechanisms allocate varying degrees of importance to different words within a sentence. This approach enables the model to focus more on crucial elements, capturing intricate dependencies and semantic information that contribute to a more accurate language representation. The attention mechanism's ability to discern and prioritise important words enhances the overall performance and effectiveness of deep learning language models.

2.2.2.E Decoder

In the context of ASR, the decoder role is to use the language, acoustic, and pronunciation models to determine the most likely word sequence, denoted as $\hat{\boldsymbol{w}}$, given a corresponding sequence of acoustic features, denoted as $\boldsymbol{Y}$ (as refered in equation 2.1). This is achieved by employing dynamic programming to search through all potential sequences. Notably, the Viterbi algorithm [64], are instrumental in efficiently solving this decoding problem. However, in practical applications, a direct implementation of the Viterbi algorithm becomes challenging, especially for continuous speech, where considerations such as model topology, language model constraints, and computational constraints must be taken into account. N-gram language models and cross-word triphone contexts further complicate the search space. To address these challenges, various approaches have emerged.

One approach involves constraining the search space by maintaining multiple hypotheses in parallel [65] or dynamically expanding it as the search progresses [66]. Another alternative is to use beam search where the idea is to prune search path which are unlikely to successed. More recently, recent advancements in weighted finite-state transducer (WFST) technology offer a comprehensive solution by integrating all necessary information, including acoustic models, pronunciation, and language model probabilities, into a single, highly optimised network [67,68]. This approach provides both flexibility and efficiency, making it valuable for both ASR research and practical applications. As demonstrated by the Kaldi speech recognition toolkit [69], which stands out as a widely adopted toolkit that leverages WFSTs for decoding.

Although decoders are primarily designed to find the best solution to the aforementioned probability computation in equatio 2.1, they can also generate the N-best set of hypotheses. This capability enables multiple passes over the data without incurring the computational expense of repeatedly solving the probability computation from scratch. The word lattice [70] serves as a convenient structure for storing these hypotheses, consisting of nodes representing points in time and spanning arcs representing word hypotheses. Word lattices offer remarkable flexibility, allowing for rescoring by using them as input recognition networks. Furthermore, they can be expanded to facilitate rescoring by a higher-order language model.

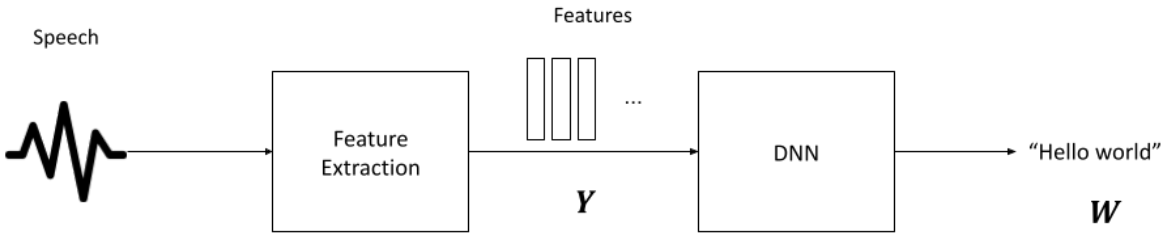


Figure 2.9: Architecture of an end-to-end speech recognition system

2.2.3 End-to-end automatic speech recognition

End-to-end speech recognition signifies a transformative paradigm in the field, presenting a streamlined and holistic approach compared to traditional HMMs-based systems. In contrast to conventional modular systems that incorporate distinct acoustic, pronunciation, and language models, end-to-end architectures propose to simplify the ASR process by directly map input audio signals to transcriptions within a single neural network model as illustrated in 2.9. Indeed, One of the key disadvantages of hybrid models is the factorized training of all modules independently, which can lead to error accumulation and mismatches between the different components. Therefore end-to-end strategy simplifies the overall system design, eliminating the requirement for pre-aligned training data and post-processing of outputs, thereby fostering a more data-driven and automatic learning process. In this paradigm, word-level transcriptions are transformed into character-level transcriptions. Considering the sequence of fixed-size acoustic vectors $\boldsymbol{X} = x_1, ..., x_T$ and the corresponding character sequence $\boldsymbol{Y} = y_1, ..., y_N$, where T and N represent the numbers of frames and the length of the character sequence respectively, the objective of end-to-end models is to learn the conditional probability of the character y_i given the input $\boldsymbol{X}$ and the preceding output $y_{<i}$:

$$P(Y|X) = \prod_{i=1}^{N} P(y_i|X, y_{<i}) \tag{2.7}$$

In recent years, with the growing interest in the end-to-end ASR paradigm, these systems have demonstrated increasing performances. Particularly, in scenarios where a large amount of labelled training data is available, end-to-end systems have demonstrated comparable or even superior performance compared to traditional HMM-based systems across various ASR datasets [71, 72]. However, despite its promising results, end-to-end speech recognition faces a several challenges. Most importantly, these systems require a large corpus of training data to operate effectively. In the absence of such a corpus, the model may struggle to perform correctly [73]. In addition, handling rare or out-of-vocabulary words remains a significant challenge. Finally, the generalisation across new acoustic conditions of the model can be issue. Therefore, there is a need of research on end-to-end speech recognition, particularly to simplify the end-to-end design, training, and robustness of these speech recognition systems.

The overall struture of end-to-end systems depicted in figure 2.9 highlight the integration of acoustic model, pronunciation model, and language model into a single neural network in end-to-end architectures. Nevertheless, feature extraction stage remains identical to traditional ASR systems. In end-to-end systems, the most commonly employed fixed-size acoustic features are filterbanks. Motivated by the higher flexibility they provide when capturing relevant information from the speech signal compared to MFCCs.

Transitioning to the end-to-end paradigm has necessitated the development of new training approaches. Indeed, training an end-to-end model differs significantly from training traditional HMM-based systems. Notably, two training procedures have emerged in the literature of end-to-end ASR: Connectionist Temporal Classification and sequence-to-sequence architectures. Each approach comes with its own distinct features and advantages, and the subsequent sections offer a more in-depth exploration of these two methodologies. It is worth mentioning that while these are distinct methods that can function independently, they can also be employed in conjunction.

2.2.3.A Connectionist Temporal Classification

The first step towards end-to-end automatic speech recognition was made with the introduction of the Connectionist Temporal Classification (CTC) objective function, introduced by Grave et al. [74]. The main innovation of CTC is that it eliminates the need for pre-segmented training data, enabling the model to automatically learn the alignments between the N input speech frame $\boldsymbol{X}$ and the output sequence of T phones $\boldsymbol{Y}$ if $N \leq T$, representing a departure from the traditional HMM-based models

To this end, the CTC objective function consists of two essential sub-processes: path probability calculation and path aggregation. Consider $\mathcal{V}$ as the set of possible paths of phone-label sequences of length T, and let p_k^t denote the probability of observing the label k at time t. It is noteworthy that CTC necessitates the length of the label sequence Y to be equal to T. To address any length difference between N and T, a blank label "-" is introduced, representing the probability of observing no label.

First, the path probability calculation involves computing the conditional probability of any path $\pi \in \mathcal{V}$ given the observed acoustic features $\boldsymbol{X}$.Mathematically, this is expressed as:

$$p(\pi|X) = \prod_{t=1}^{T} p_{\pi_t}^t, \forall \pi \in \mathcal{V} \tag{2.8}$$

Where π_t denotes the label at time t in sequence path π. Considering all possible paths and their respective probabilities is crucial, but direct computation becomes infeasible due to the exponential number of potential paths.

To address the computational challenges, the path aggregation step comes into play. Its purpose is to sum the probabilities of paths that correspond to the same label sequence $\boldsymbol{Y}$ by marginalizing over all possible paths. The path aggregation also merge the same contiguous labels and deletes the blank

label. For example two different paths “b-ii-r-d” and “b-i-r-dd” becomes “bird”. This is mathematically represented as:

$$p(Y|X) = \sum_{\pi \in \theta_Y} p(\pi|X) \tag{2.9}$$

Where θ_Y is a subset of $\mathcal{V}$ of all possible path π corresponding, after aggregation, to the label sequence Y.

2.2.3.B Sequence to sequence

The sequence-to-sequence (Seq2seq) architecture, initially proposed by Sutskever for machine translation [75] and stands as a important paradigm of end-to-end ASR systems. The original context of its application was for machine translation tasks where a word sequences were translated from one language to another. The inherent challenge lies in the differing lengths of input and output sequences. However, this architectural framework, especially with the integration of attention mechanisms [76], has showcased remarkable versatility, extending its efficacy across diverse applications such as image captioning [77], conversational modeling [78], text summarisation [79], and ASR [80].

The core components of a standard Seq2seq model consist of an encoder and a decoder. The encoder processes input sequences of variable length, transforming them into a sequence of vectors often denoted as the ”internal state” or ”hidden representation.” This sequence of vectors encapsulates the crucial information extracted from the input features. Subsequently, the decoder uses this sequence of vector representation to generate an output sequence of tokens iteratively. Mathematically expressed as:

$$p(y_1, ..., y_T) = \prod_{i=1}^{T} p(y_i|y_0, ...y_{i-1}, f(H)) \tag{2.10}$$

where $f(H)$ represents a function of the encoder's output $H = (h_1, ..., h_N)$. Notably, in Seq2seq models incorporating attention mechanisms, $f(H)$ includes attention to selectively focus on relevant segments within H for predicting the current target token. The seq2seq objective function is formulated to train the model by maximizing the conditional probability of generating the target sequence given the input sequence using negative log-likelihood loss (NLL) or cross-entropy loss (CE).

A significant difference from CTC-based models lies in the fact that Seq2seq models do not make independent assumptions about output labels. Instead, they directly model the conditional probability of each target token given the preceding tokens in the output sequence and the encoder's output. This end-to-end approach empowers Seq2seq models to handle sequences of varying lengths, making them particularly advantageous for tasks, like speech recognition, where precise alignment between input and output is challenging.

2.2.4 Automatic Speech Recognition metrics

In the domain of ASR, metrics serve as indispensable tools for assessing the accuracy and effectiveness of systems. These metrics provide quantitative evaluations that act as a crucial benchmark, enabling researchers, developers, and engineers to objectively measure the performance of their ASR models. The evaluation process of ASR systems involves a meticulous comparison between system-generated transcriptions and reference transcriptions. Among these metrics, Word Error Rate (WER) is the most commonly used for assessing speech-to-text systems. The ASR system's output word sequence is matched with a reference transcription, and the number of substitutions (S), deletions (D), and insertions (I) are summed. As a result, WER is calculated as follows:

$$WER = \frac{S + D + I}{N} \times 100 \tag{2.11}$$

Where N is the total number of words in the reference transcription. As a result, a lower WER score is indicative of better system performance. The computation of WER is based on the Levenshtein distance, operating at the word level rather than the phoneme level. The primary goal is to quantify the dissimilarity between the ASR system's output and the reference transcription. Notably, a WER score greater than 100% can be attained when the number of mistakes surpasses N, while a score of 0% is the minimum achievable when there are no errors in the ASR hypothesis compared to the reference.

State-of-the-art ASR systems developed by leading research institutions and companies have achieved WER scores ranging from around 4.3% to 8.13% on well resourced benchmark datasets such as the Switchboard corpus for conversational speech recognition [81] and the French subset of the read speech Common voice dataset [82] respectively. However,it is important to note that WER scores can be task-specific, and achieving high WER scores, especially in challenging conditions or for certain languages and accents, such as 38.9% for the CHiMIE-6, a low resource noise speech dataset [83].

Beyond WER, there exist other metrics derived from the same fundamental equation but operating at different levels of transcription. Examples include Phone Error Rate (PER) for languages based on phonemes and Character Error Rate (CER) which operates on character instead of word. These metrics provide a nuanced evaluation by concentrating on specific linguistic units, contributing to a comprehensive assessment of ASR system performance in diverse contexts.

2.3 Children automatic speech recognition

Addressing the challenges highlighted in Section 2.1 has prompted diverse initiatives across various segments of the ASR pipeline. This involves exploring improvements at the feature level, with the development of novel extraction techniques and adaptations. Data augmentation strategies have been employed to enrich training datasets, offering the model exposure to a more diverse range of children speech patterns. Modifications in annotation detail have been explored, refining the labeling process to better capture the nuances of children's speech.

Beyond feature-level interventions, advancements in acoustic model structures have been pursued. This involves exploring new architectures and refining existing ones to better accommodate the characteristics of children's speech. In addition, innovative training procedures have been introduced to optimise model learning from the available data.

This section reviews state-of-the-art for each of these aspects in more detail. Following this comprehensive review, we will identify and delineate the specific approaches that emerge as promising or particularly impactful for addressing the challenges associated with children's ASR. These identified approaches will serve as the focal points for the subsequent phases of the thesis.

2.3.1 Feature extraction stage

Feature extraction stage is critical for identifying relevant speech signal components for both traditional and end-to-end ASR. This phase is characterised by the intentional elimination of speaker-dependent attributes, such as fundamental frequency, while simultaneously preserving the integrity of phoneme-dependent characteristics, notably exemplified by formant frequencies as described in section 2.2.2.A. In the context of children's speech recognition, the acoustic characteristics pose unique challenges, including close fundamental frequency and formant values, as well as phonetic class overlap due to formant variability. In addition, studies by [84,85] demonstrated that in mel-filterbank-based cepstral features commonly used in the ASR field, the acoustic mismatch is exacerbated by insufficient smoothing of pitch-dependent distortion present for child speakers To tackle these challenges, various strategies have been proposed to enhance acoustic features for children's speech, encompassing new feature extraction, feature adaptation, and the concatenation of new features.

An early step in the direction of better feature extraction for children was the introduction of perceptual linear predictive (PLP) features in 1990 by Hermansky [86]. Indeed, PLP features demonstrated a more accurate representation of formants in children's speech. An additional strategy employed was the use of binary-weighting of MFCCs. This approach involves truncating some of the higher coefficients to remove those with non-sufficient smoothing, as proposed by [84]. The objective is to refine the representation of MFCCs by selectively retaining non-distorted coefficients. Furthermore, Gamma-tone filterbanks were employed to wrap the spectrum on a different scale, aiming to decrease variance compared to mel-

filterbank features [87]. More recently, there has been a shift in the feature extraction stage from a hand-crafted approach to a data-driven strategy, focusing on learning relevant features directly from the raw speech signal. This approach, initially proposed by [88], is motivated by the understanding that hand-crafted features are often based on the analysis of adult speech, and they may not be optimally suited for the acoustic variability present in children's speech. In the study conducted by [88], data-driven feature extraction was performed using CNN-based models. The results indicated that the features learned in a data-driven manner outperformed standard hand-crafted features, emphasising the potential benefits of adapting feature extraction to the specific characteristics of children's speech. Another similar approach was proposed by [89], where the convolutional layers of the feature extractor were replaced by SincNet layers [90]. SincNet use rectangular band-pass filters instead of the standard CNN filters, enabling a reduction in the number of parameters required for raw waveform modeling. Additionally, this approach involves restricting the filter functions rather than having to learn every tap of each filter.

An alternative approach to mitigate the acoustic variability in children's speech involves working directly with adult features and adapting them to reduce children's acoustic variability. One common technique for this purpose is Vocal Tract Length Normalization (VTLN), which has been widely employed to normalize spectral features into a canonical space [91, 92]. Research conducted using VTLN indicates a higher recognition rate when the ASR system is trained with adult speech and subsequently tested with children's speech [93, 94]. Indeed, [95] showed a strong relationship between the optimal warping factor and the age of speakers. VTLN is typically applied as a front-end processing step at the end of the feature extraction. The VTLN process involves stretching or compressing the frequency axis of the spectrum accoding on a warping function. This process leads to a normalisation of the spectral representation, reducing the impact of speaker variance. Nevertheless, it is important to acknowledge that recognition results achieved with VTLN compensation alone may still be sub-optimal. This is attributable to the presence of various factors, extending beyond variations in vocal tract length, that contribute to the distinct characteristics between adult and children's speech. In addition to directly adaptating speech feature, researchers have explored the normalisation of specific aspects of children's speech to better align with adult speech characteristics. Several studies investigated the use of pitch normalisation to reduce the spectral mismatch between children's and adult's speech [87, 96–98], while other direclty normalised formant values [99, 100]. Furthermore, adapting speaking rate through time-scale modification approaches has been investigated [101]. Children's speech is typically slower than that of adults, and adjusting the speaking rate can aid in creating a more consistent representation for ASR models.

Moreover, in line with the trend of transitioning from knowledge-based to data-driven, some recent studies have explored data-driven feature adaptation methods using deep learning approaches. For instance, studies like [102, 103] employed adversarial multi-task learning to generate age-invariant features. The goal is to minimise the acoustic mismatch between adult and children's speech by leveraging adversar-

ial training techniques. Adversarial training introduces a form of competition between neural networks, with one network generating features used by the ASR and another network attempting to distinguish between the adapted children's features and the real adult's features. This adversarial approach aims to extract features that are less influenced by age-related variations, contributing to improved model generalisation across different age groups.

In addition to feature extraction and feature-level adaptation, certain studies have emphasised the efficacy of appending supplementary information to the acoustic features. For instance, it is a common practice to concatenate speaker embeddings, such as i-vectors [104], with acoustic features to achieve a more speaker-independent model [105]. Speaker embeddings are compact, fixed-size representations of the features of a speaker's voice derived from their speech signals. Concatenating speaker embeddings with the acoustic features enables the model to be more robust to speaker variability, as it incorporates an explicit representation of it. Similarly, both [106, 107] proposed to concatenate various prosodic features, including loudness, voice intensity, and voice probability, with standard acoustic features. This approach has demonstrated success in reducing inter-speaker variances and enhancing discrimination between phoneme classes.

2.3.2 Pronunciation and language model

The conventional information provided in speech corpora typically includes audio signals, corresponding text transcriptions, and anonymized speaker identifiers. However, augmenting this data with additional information holds promise for improving children's speech recognition systems. One pertinent aspect is incorporating the speaker's age, a critical factor, as described in section 2.1, that could facilitate the development of age-dependent ASR systems [108, 109]. Moreover, annotating at the sub-word level, rather than the word level, has demonstrated increased performances, particularly in addressing challenges such as mispronunciations or hesitations [110]. This approach enhances robustness by focusing on smaller linguistic units allowing more flexibility. Another strategy involves the implementation of children specific pronunciation model, as illustrated in [111, 112]. These lexicons are specifically created to handle pronunciation divergences from canonical adult patterns with knowledge based children patterns. Finally, the creation of language models explicitly tailored for children's speech can further improve the recognition accuracy [28, 29]. These models capture the linguistic nuances and variations intrinsic to children's language. The integration of these strategies collectively contributes to the development of more effective and adaptive ASR systems for children.

2.3.3 Design of acoustic models

The acoustic model is a pivotal component in ASR for children's speech, as acoustic variability significantly affects the degradation of recognition accuracy compared to linguistic variability. Consequently,

the design of the acoustic model is crucial for ensuring robustness to the specific characteristics of children's speech.

Initially, the transition from monophone to triphone Hidden Markov Model-Gaussian Mixture Model (HMM-GMM) models helped improve performance by capturing coarticulation effects [27, 94]. A literature review [113] indicates that much of the research on children's ASR is based on HMM-GMM models [113]. However, acoustic models for children naturally align with the latest advancements in acoustic modeling for adults. Therefore, the design transitions from HMM-GMM to Hidden Markov Model-Deep Neural Network (HMM-DNN), as proposed by [6].

The limitations of traditional fully connected neural networks in providing sufficient contextual informations prompted their replacement by TDNN layers, as proposed in [114]. TDNNs function similarly to one-dimensional convolutional neural networks. At each time step, both the current time-step frame and its corresponding left and right context are considered, in contrast to traditional DNNs that focus solely on the current time step.To further improve the model's capacity to capture extensive contextual information, multiple layers of TDNN. In addition, motivated by the large overlaps between neighboring input context sub-sampling was introduce. Sub-sampling involves allowing gaps between frames in the context window. While TDNN were demonstrated as successful desing for children ASR [115], they were quickly replaced by factorised time-delay neural network (TDNN-F). Indeed, TDNN-F were introduced as an improvement of regular TDNN [116] by decomposing the weight matrix using singular value decomposition (SVD). A more detailed explanation of TDNN-F will be provided in section 3.2.2 (FAKE REF). This enhancements was especially proven effective for children's ASR [117], outperforming both GMM and TDNN approaches in multiple children datasets. This efficacy can be attributed the SVD factorisation which divided the weight matrix into two smaller rank matrices, functioning as bottleneck layers. To this day, TDNN-F are the state-of-the-art design for efficient HMM-based children ASR system.

These advancements in neural network architectures, such as TDNN and TDNN-F, showcase the ongoing efforts to refine acoustic models for children's speech recognition, addressing specific challenges and optimising model capabilities to adapt to the unique characteristics of children's speech.

2.3.4 End-to-end models

The success of end-to-end paradigm in outperforming traditional HMM-based models across various ASR adult datasets has prompted exploration in the domain of children's ASR. However, when attempting to train end-to-end models from scratch using limited children's datasets, these models were found to underperform compared to their HMM-based counterparts [118]. To address this challenge, a different training approach was adopted, leveraging pre-trained adult models as a starting point for training, transfer learning, this strategy will be explained in more detail in section 2.3.6.A. Using this transfer learning strategy in conjunction of end-to-end models, they have been able to outperform HMM-based

models. In their experiments, [118–121] explored various end-to-end architectures for children's ASR. The architectures investigated included Listen, Attend, and Spell [122], recurrent neural networks (RNN), ResNet [123], and Transformer [124]. Among these architectures, [118] demonstrated that the Transformer model using a mix of Sequence-to-sequence and CTC losses emerged was the most effective in many cases, demonstrating promising results in the context of children's ASR.

2.3.5 Data augmentation

Deep learning's success can be largely attributed to its ability to effectively use massive amounts of data to recognise patterns and be robust to variabilities. However, the scarcity of data of children's speech significantly contributes to performance deterioration as compared to adults. This challenge is even more pronounced for languages other than English, where fewer resources are generally available. To address this problem of data scarcity, researchers have explored various data augmentation approaches with the aim of artificially increasing the amount of training data. In the literature, there are two main approaches to data augmentation: using solely the data that is currently available or incorporating external data from diverse sources.

2.3.5.A Using external data

The most natural source of speech data to augment children speech training data, is the one which is available in extensive quantity, adult speech data. Studies [125, 126] validate the idea that leveraging out-of-domain adult speech data effectively in enhanced the automatic recognition of children's speech. Notably, improvements were observed when incorporating adult female speech, given the inherent narrower frequency ranges mismatch between females and children compared to adult men speech. Similarly, the study presented in [127] suggested augmenting speech training data by directly incorporating additional children's data. The observed improvements underscore the significance of leveraging a diverse range of children's speech samples in the augmentation process.

Beyond traditional sources of speech data, researchers have delved into the use of synthetic data as a supplementary resource for training children's ASR. The idea behind employing synthetic speech data revolves around generating speech signals that perceptually resemble children's speech. In this regard, voice conversion has emerged as a notable method. Voice conversion involves leveraging extensive adult datasets and transforming them into children's speech while preserving the content.

Various voice conversion approaches have been applied to the generation of synthetic children's speech, encompassing classical signal processing manipulations such as vowel stretching [128], fundamental frequency shift [129], and spectral envelope wrapping [130]. Additionally, studies like Shuyang's work [131] have investigated the combined use of these signal processing manipulations to further improve the ASR system. Moreover, deep learning methods, particularly Generative Adversarial Networks (GANs), have

also played a role in voice conversion. In [132], a GAN was used to transform children's speech into adult-like speech by reducing variability. Therefore, this approach can use non-transformed adult speech as data augmentation rather than converting adult speech into children's speech. This strategy aims to reduce variability by training the generator to produce adult-like speech from children's speech. The GAN model comprises a generator responsible for creating synthetic data and a discriminator distinguishing between generated and real data samples in a adversarial way. During inference, the discriminator is removed, leaving only the generator to convert children's speech into adult-like speech.

Beside voice conversion, Text-to-Speech (TTS) systems have been use to generate speech examples directly from text. Recent advancements in TTS systems, such as Tacotron2 [133] and VITS [134], have enhanced the realism of generated speech utterances. Consequently, some researchers have explored the use of TTS outputs as data augmentation for adult ASR tasks [135]. However, children's speech exhibits more complex traits than adults, including substandard or unclear pronunciation and acoustic variability. As a result, the quality of children's TTS is often inconsistent. To address this, [136] proposed data selection strategies based on speaker embedding similarity between the reference speaker and the speaker embedding extracted from generated speech utterances. Hence, eliminating synthetic utterances that significantly deviate from their reference examples. This approach significantly improved the recognition score for various children's speech recognition tasks.

2.3.5.B Using available data

In scenarios where the inclusion of external data is not possible, there is a necessity to enhance model robustness by directly modifying the existing dataset. An established approach to enhance the model robustness involves generating augmented versions of the original data, by adding diverse acoustic perturbations to them. Typically, these perturbations are additive noise, babel noise, white noise, music and reverberation [137–141]. This augmentation strategy whihc introduces noise and reverberation into the existing dataset, aims to simulate real-world conditions where environmental factors can impact the recognition of speech signals.

An alternative strategy for augmenting the original speech dataset involves creating copies where the dimensions of the speech signal are perturbed. These perturbations include modifications along the time axis, as demonstrated by speed perturbation to better match children's speaking rate variability [142], and modifications along the frequency axis [143] through vocal tract length perturbation [144], simulating variations in vocal tract dimensions. More recently, techniques like SpecAugment [145] were found particularly effective, especially in the end-to-end paradigm. SpecAugment involves random masking of frequencies and time bands within the spectrogram in conjunction with time and frequency warping.

Finally, as mentioned in Section 2.1.2, it is crucial to recognise the presence of disfluencies and errors in children's speech, presenting inherent challenges to the learning process of ASR models, espacially

in reading tasks. Therefore, to enhance the model's robustness in handling such errors, a noteworthy proposition by [146] involves the manual creation of synthetic reading errors. This involves manual interventions, specifically achieved by cutting the signal, resulting in a deletion error, or incorporating speech elements produced by other children to simulate substitution or insertion errors.

2.3.6 Training procedure for children speech recognition

In the domain of HMM-based ASR systems for children, several strategies have been employed to adapt acoustic models for enhanced performance. Notably, adaptation techniques such as Maximum Likelihood Linear Regression (MLLR) and Maximum A-Posteriori (MAP) have been applied with success. Additionally, the use of Speaker Adaptive Training (SAT), specifically based on Feature MLLR (fMLLR) or Constrained MLLR (CMLLR), has proven effective in improving the performances of ASR systems designed for children [1, 29, 111, 147].

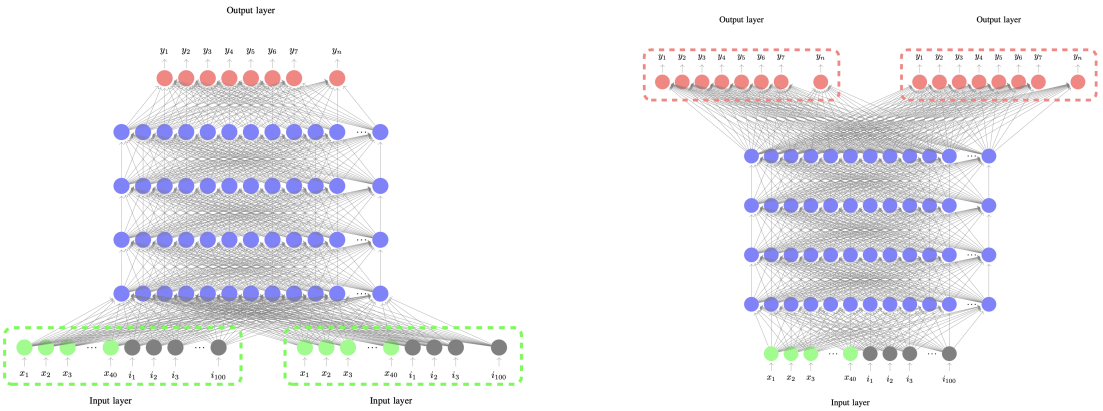
As mentioned in Section 2.1.3, the integration of DNNs into children's ASR systems necessitates a substantial amount of labeled data to provide optimised performances. The efficacy of DNNs rely on their two-pass iterative training procedure, involving a forward and a backward pass. In the forward pass, the input corpus is fed to the network, generating prediction outputs. Subsequently, the loss is computed by comparing these predictions with the groundtruth target values. To mitigate prediction errors, adjustments to network weights are made through the use of gradient descent technique during the backpropagation phase, leveraging the computed loss. The training process continues through multiple iterations of these forward and backward passes until the model converges.

In response to the challenges posed by the distinctive variations in children's speech, novel adaptations of this training pipeline have been proposed. Noteworthy among these is transfer learning, which leverages efficient pre-trained DNN models. Additional, multi-task learning has been explored to capture shared representations across related tasks, while self-supervised learning has emerged as a promising paradigm that enables the model to glean information about speech without relying on labeled data.

2.3.6.A Transfer learning

When confronted with a new problem, humans exhibit the ability to draw upon information from prior tasks as an inductive bias. This cognitive capacity enables individuals to avoid starting the learning process entirely from scratch by leveraging knowledge acquired from past tasks. This ability, often referred to as transfer learning, may be defined as the capacity to identify and use knowledge from previous tasks as a foundation for approaching new tasks.

In contrast, in the context of machine learning, algorithms are generally developed from scratch on a specific task, lacking the inherent capability to transfer knowledge. Therefore, the concept of transfer learning (TL), or parameter transfer, has emerged as a pivotal bridge between artificial and biological



(a) Acoustic adaptation **(b)** Pronunciation adaptation

Figure 2.10: Transfer learning approaches. Figures from [6]

intelligence. In this paradigm, a model's parameters are initialised with values derived from another well-resourced model trained on a related source task. Subsequently, the model's parameters are adapted, also called fine-tuned, with data from the new domain, adjusting parameters to better align with the target task. This knowledge transfer allows the model to leverage underlying characteristics acquired from the source task, contributing to enhanced performance when applied to the target task.

Furthermore, a notable advantage of TL is its ability to require a reduced amount of training data for adaptation. By building upon a pre-trained model, it leverages the knowledge acquired during the initial training on a source task. The target model can exploit the informations encapsulated in the pre-trained parameters, mitigating the demand for an extensive dataset in the target domain. This makes transfer learning particularly advantageous in scenarios where labeled data is difficult to obtain, such as children's speech.

A common assumption in deep learning TL is that the lower layers, situated closer to the input, tend to capture more signal-specific characteristics, whereas the higher layers, in proximity to the output, capture more task-specific information [148, 149]. This hierarchical organisation within neural networks aligns with the notion that lower layers are learning general representations of input data, or low-level features, while higher layers specialise in extracting intricate patterns that are specifically relevant to the task at hand.

In recent years, TL has emerged as a highly successful technique across various applications, particularly effective for low-resource tasks, in domains such as as language understanding [62], character recognition [150], and dysarthric speech recognition [151], among others. The successes in these domains have motivated interest in exploring the utility of transfer learning for children's speech recognition. In particular, given the prevalence of large adult speech corpora, acoustic models trained on adult are in-

creasingly efficient and contain many acoustic and phonetic informations that can be used for efficient adaptation to children's speech. Since children's speech variabilities are present in both acoustics and linguistics, [6] proposed investigating three distinct transfer learning methods to assess the contributions of acoustic adaptation, pronunciation adaptation, and their combination in the context of children's speech recognition.

Acoustic adaptation targets the lower-level layers, leveraging the established notion that these layers capture acoustic properties. The methodology involves freezing the weights of the top-level layer and applying transfer learning to the lower-level layers, as depicted in Figure 2.10(a). In experiments conducted by [6] and [152], acoustic transfer learning from an adult model to children's speech, by retraining only the first layers, yielded substantial relative WER improvements of 38% and 26%, respectively, compared to the performance of adult models. Impressively, the acoustic adaptation outperformed a randomly initialised acoustic model trained on the same children's data, achieving a 4.9% relative WER improvement.

Pronunciation adaptation, based on the idea that higher-level layers capture task-specific information, focuses on adapting these layers while keeping lower-level layers frozen. As illustrated in Figure 2.10(b), [6] conducted experiments applying pronunciation adaptation to the last layers of the model, resulting in a significant 31% relative WER improvement compared to the performance of the adult model. However, when compared to a randomly initialised acoustic model trained with the same children's data, pronunciation adaptation degrades by 5.6% relative WER.

In recent years, transfer learning (TL) has emerged as a highly successful technique across various applications, particularly proving effective in low-resource tasks such as language understanding [62], character recognition [150], and dysarthric speech recognition [151], among others. The achievements in these domains have spurred interest in exploring the utility of transfer learning for children's speech recognition, a domain often characterized by limited labeled data.

Given the prevalence of large corpora derived from adult speech, recent acoustic models trained on adult data have demonstrated high efficiency and encapsulate rich acoustic and phonetic information. Motivated by these successes, [6] proposed investigating three distinct transfer learning methods to assess the contributions of acoustic adaptation, pronunciation adaptation, and their combination in the context of children's speech recognition.

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Pronunciation adaptation, premised on the idea that higher-level layers capture task-specific infor-

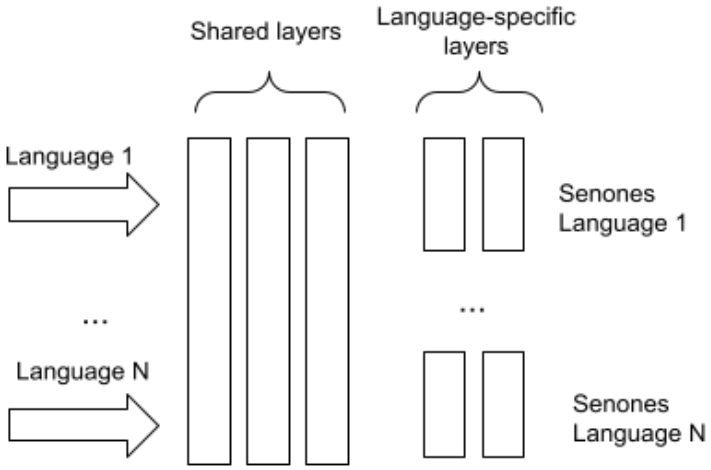


Figure 2.11: Multilingual approach using each language as a task in a multi-task learning context.

mation, focuses on adapting these layers while keeping lower-level layers frozen. As illustrated in Figure 2.10(b), [6] conducted experiments applying pronunciation adaptation to the last layers of the model, resulting in a significant 31

Finally, the combination of acoustic and pronunciation adaptation, achieved through fine-tuning the entire network, demonstrated outperforms performances compared to individual adaptations. This aligns with recent observations in end-to-end models, where transfer learning from an adult pre-trained model outperformed training from scratch using only children's data only [118, 119]. These findings underscore the efficacy of transfer learning strategies for optimising acoustic and pronunciation adaptation in children's ASR.

2.3.6.B Multi-task learning

Multi-task learning (MTL), like to transfer learning, draws inspiration from biological intelligence. In contrast to transfer learning, MTL does not train solely on source and target tasks in a sequential manner, here MTL simultaneously train on multiple tasks at the same time. The fundamental objective of MTL is to discover shared representations among related tasks. In general, a typical MTL model consists of two distinct components. The first part is a sub-network shared by all tasks, while the second part consists of task-specific output sub-networks, as illustrated in Figure 2.11. The shared layers facilitate the learning of a joint representation that is more robust, enhancing the model's reliability across diverse tasks.

More formally, for any task i the corresponding output of the forward pass will be:

$$f(X_i; \{M_i, M_c\}) = f_i(f_c(X_i, M_c); M_i) \tag{2.12}$$

where X_i is the data associated with the task i, M_i represents the task-specific parameters of the model, and M_c corresponds to the parameters that are shared (or common) across all tasks.

In consequence, the performances of MTL is intricately tied to the degree of relatedness among tasks used during training. Indeed, its efficacy diminishes when confronted with outlier tasks that are unrelated to the majority of the other tasks. This sensitivity is due to the inherent challenge of learning common representations for tasks that lack substantial relatedness to one another [153]. This task-relatedness consideration underscores the importance of thoughtful task selection when using MTL techniques.

Moreover, MTL has been used effectively in a variety of areas, including natural language processing [154], computer vision [155] and bioinformatics [156]. MTL has been naturally applied in the field of automatic speech recognition [157] with directly application to low-resource ASR [158]. Given that ASR for children represents a resource-limited task, MTL has been proposed as a strategy to mitigate the issue of data scarcity. Notably, studies such as [152] and [159] successfully applied MTL to Mandarin and English-speaking children, with a 16.96% relative improvement in WER for the English children.

2.3.6.C Self-supervised Learning

A first step towards self-supervised learning (SSL) was the introduction of semi-supervised techniques, such as pseudo-labeling. Semi-supervised appraoches were a dominant training strategies for using unlabeled data. In particular, The pseudo-labeling starts with the training of a "teacher" model on a set of supervised data. Subsequently, pseudo-labels are generated for unlabeled data by leveraging the predictions of the trained teacher model. Following this, a "student" model is trained using a combined dataset comprising both supervised and pseudo-labeled data. Importantly, the pseudo-labeling process can be iteratively repeated multiple times to enhance the quality of teacher-generated labels [160, 161]. It is noteworthy that, as of today, some of the most effective ASR models, such as the Whisper model, leverages pseudo-labeling as a crucial component of its training strategy [30]. However, the performances of semi-supervised, and particularly pseudo-labeling, has been found to be highly dependent on the quality of the teacher model, prompting the need for more robust and sophisticated training strategies.

In this context, SSL has emerged as a paradigm designed to acquire general data representations direclty from unlabeled examples, subsequently allowing transfer learning on a small amount of labeled data. This approach has proven particularly successful in the domain of natural language processing [162] and computer vision [163]. One notable first attempt to bring SSL to the speech domain was made by the introduction of the problem-agnostic speech encoder (PASE) and its extension, PASE+. These innovations demonstrated the capability to learn meaningful speech information such as speaker identities, phonemes, and emotions. The PASE framework operates by encoding raw speech waveforms into a representation, which is then input to multiple regressors and discriminators. The regressors within PASE are standard features computed from the input waveform. While the discriminators focus on positive or

negative samples and are trained to effectively separate them. Both the regressors and discriminators play a crucial role in incorporating prior knowledge into the encoder, a key factor for deriving meaningful and robust representations.

Recently, self-supervised systems have obtained remarkable results with the introduction of models employing BERT-like training methodologies, such as Wav2vec2 [164] and HuBERT [165]. Notably, the success of these models can be attributed to the conjunction use of masking, discrete speech units, contextualized representations, and contrastive loss. The integration of masking techniques allows these models to effectively learn contextualised representations by masking certain portions of the input data and predicting them based on the remaining context. The use of discrete speech units enable the model to be more robust to variations, while the contrastive loss functions enhances the discriminative power of these models by encouraging the model to differentiate between positive and negative samples. Motivated by the successes of SSL methods in overcoming challenges in low-resource ASR tasks, such as low-resource languages [166], noisy speech [167], and accented speech [168], the integration of SSL for children's ASR marked its debut in 2021, with a first place in a non-native children's speech recognition challenge [169]. Subsequent to this notable success, the application of SSL for children's ASR has gained increased attention, especially with the use of models like Wav2vec2 [170–172]. A concise analysis of various SSL approaches for children ASR has been conducted within the context of this thesis, and the findings are presented in Annex (PUT ANNEX REF HERE).

2.4 Children Corpora

As described in Chapter 2.1.3, notwithstanding recent efforts to assemble dedicated databases for children's speech, the quantity of available data remains lower compared to that for adults. Collecting speech data from children is challenging in many ways, from factors such as limited attention spans, frequent mispronunciations, ungrammatical expressions, and the use of non-standard vocabulary. These difficulties involved in capturing high-quality child speech data contribute to the scarcity of publicly accessible child speech corpora. The relatively modest sizes of these datasets present obstacles to research efforts and impede progress in developing reliable ASR systems for children.

Table 2.1 presents a compilation of existing corpora of children's speech. Notably, approximately one-third of the available corpora are in English. Likewise, a comparable proportion is specifically oriented towards children under the age of 4. It is crucial to acknowledge the inherent trade-offs in these corpora, involving considerations of speaker diversity, total duration, and the number of utterances.

Subsequently, the remainder of this section will go through an examination of the children's speech corpora employed in this thesis.

Corpus	Languages	# Spkrs	# Utt	Dur.	Age Range	Date
Providence Corpus [173]	English	6		363h	1-3	2006
Lyon Corpus [174]	French	4		185h	1-3	2007
CASS_CHILD [175]	Mandarin	23		631h	1-4	2012
Demuth Sesotho Corpus [176]	Sesotho	4	13250	98h	2-4	1992
NITK Kids' Speech Corpus [177]	Kannada	160		10h	2-6	2019
CHIEDE [178]	Spanish	59	15,444	8h	3-6	2008
CUChild [179]	Cantonese	1,986			3-6	2020
EmoChildRu [180]	Russian	100	20,000	30h	3-7	2015
CNG Portuguese children [181]	Portuguese	510		21h	3-10	2013
AusKidTalk[1] [35]	English	750		600h	3-12	2021
UCLA JIBO kids [182]	English	130			4-7	2019
PF-STAR-SWEDISH [183]	Swedish	198	8,909	6h	4-8	2005
SLT 2021 [184]	Mandarin	981		58h	4-11	2021
PF-STAR Children British [38, 183, 185]	English	158		14.5h	4-14	2006
AD-child. RU [186]	Russian	278			4-16	2019
TBALL [187]	English	256	5,000	40h	5-8	2005
SPECO [188]	Hungarian	72		12h	5-11	1999
UltraSuite [189]	English	86	14,456	37h	5-14	2019
CID read speech corpus [190]	English	436			5-18	1996
Persian Kids Speech Corpus [191]	Persian	286	162,395	33h	6-9	2022
Letsread[2] [192]	Portuguese	284	4,629	14h	6-10	2016
CMU kids Corpus [36]	English	76	5,180		6-11	1997
CFSC [193]	Filipino	57		8h	6-11	2012
IESC-Child [194]	Spanish	174	19,793	34h	6-11	2020
CU Children's read and prompted [195]	English	663	66300		K-G5	2001
Chorec[2] [196]	Dutch	400	3,065	25h	6-12	2008
ChildIt2 [197]	Italian	96	4,875	9h	6-14	2016
TIDIGITS [198]	English	101			6-15	1993
CSLU Kids' Speech Corpus [37]	English	1,100	1,017		K-G10	2007
SingaKids-Mandarin [34]	Mandarin	255	79,843	125h	7-12	2016
ChildIt corpus [199]	Italian	171			7-13	2007
VoiceClass Database [200]	German	170			7-14	2010
Deutsche Telekom telephone [200]	German	106			7-14	2010
Jasmin [201]	Dutch			63h	7-16	2008
Tgr-child corpus [199]	Italian	30			8-12	2007
SponIt corpus [199]	Italian	21			8-12	2007
Swedish NICE Corpus [202]	Swedish	75	5,580		8-15	2005
CHIMP spontaneous speech [27]	English	160			8-14	2002
SpeeCon corpus [203]	20 Languages				8-15	2002
Rafael.0 telephone corpus [108]	Danish	306			8-18	1996
Boulder Learning - MyST [33]	English	1,371	228,874	384h	G3-G5	2019
CU Story Corpus [195]	English	106	5,000	40h	G3-G5	2003
ETLT[2] [204]	L2 German		1,674	6h	9-16	2020
Lesetest corpus [205]	German	62			10-12	2000
FAU Aibo Emotion Corpus [206]	German	51	13,642	9h	10-13	2002
PIXIE corpus [207]	Swedish	2,885				2003
Takemaru-kun corpus [208]	Japanese	17,392				2007
CALL-SLT [209]	German		5,000			2014

[1] To this day, data collection for this dataset is not complete.

[2] Information displayed here correspond to a subset of the original data used in this proposal.

Table 2.1: Non-exhaustive comparison of children's speech corpora. This table has been sorted by age range. Blanks indicate unavailable information. Entries highlighted in bold correspond to the corpora used in the experiments presented in this thesis. K: Kindergarden. G: Grade

2.4.1 LETSREAD

LetsRead database [192] is a read-aloud speech database of European Portuguese from children aged 6 to 10, from 1st to 4th grade. This corpus is composed of a total of 284 children, 147 girls and 137 boys, whose mother tongue is European Portuguese. Children from private and public Portuguese schools were asked to carry out two tasks: reading sentences and a list of pseudo-words. The difficulty of the tasks varies depending on the school year of the child. For this proposal, we excluded all utterances from the pseudo-word reading task because we do not include pseudo-words in the language model and lexicon in our experiments.

2.4.2 PFSTAR_SWEDISH

The PFStar children's speech corpus [183] was collected as part of the EU FP5 PFSTAR project. It contains more than 60 hours of speech. This corpus is divided into two parts: native-language speech and non-native language part. The native-language speech part contains recordings of British English, German and Swedish children, from 4 to 14 years old. The non-native language part consists of speech by Italian, German and Swedish children speaking English. In this work, we only used the native language Swedish part, consisting of speech by 198 native Swedish children, between 4 and 8 years old recorded in the Stockholm area, imitating an adult who read the text from a screen.

2.4.3 ETLTDE

Extended Trentino Language Testing (ETLT) corpus [204] has been collected in northern Italy for assessing English and German proficiency of Italian children between 9 and 16 years old, by asking them to answer questions. The data collection was carried out in schools. On average the signal quality is good, but some background noise is often present (doors, steps, keyboard typing, background voices, street noises if the windows are open, etc). In addition, many answers are whispered and difficult to understand. For this thesis, we only used the German-transcribed subset (named ETLTDE), around 6h divided into training and test partitions.

2.4.4 CMU_KIDS

The CMU kids corpus [36] contains English sentences read aloud by children, 24 males and 52 females, from 6 to 11 years old. In total, 5,180 utterances were recorded with one sentence per utterance. This database was created to train the SPHINX II [210] automatic speech recognition system within the LISTEN project at Carnegie Mellon University (CMU).

2.4.5 CHOREC

The Chorec corpus [196] consists of 400 Dutch-speaking elementary school children, between 6 and 12 years old, reading words, pseudo-words and stories. The difficulty of the reading task was adapted to children with 9 different levels. Recordings were made in schools, leading to some environmental noises (school bells, children entering the playground etc.). For this thesis, similarly to the LETSREAD dataset, we discarded pseudo-word utterances.

2.4.6 MyST

My Science Tutor (MyST) Children Speech Corpus [33] is currently one of the largest publicly available corpora of English children's speech, with around 400 hours. This is about 10 times more than all other English children's speech corpora combined. It consists of conversations between children and a virtual tutor in 8 scientific domains. Speech was collected from 1,372 students in third, fourth and fifth grades. Partitioning of the corpus is already available, ensuring reasonably representation of each scientific domain and that each student is present in only one partition. However, only 45% of the utterances were transcribed at the word level. Furthermore, for the purposes of this thesis, we decided to remove all utterances shorter than one second and longer than 30 seconds. After this filtering, 81971 utterances from 736 speakers for a total of 151 hours remain.

2.5 Summary

In this chapter, we provided an overview of children's ASR, its inherent challenges, and the ongoing responses from the research community. The complexity of ASR in children arises primarily from the developmental nuances of the vocal apparatus, resulting in an acoustic mismatch with adult speech, although this mismatch gradually diminishes until around the age of 15. Despite sustained efforts, ASR for children remains ctive and challenging area of research.

Our examination in this chapter highlights that knowledge transfer approaches, such as transfer learning and multi-task learning, appear to be promising avenues for improving children's ASR. Additionally, the exploration of synthetic speech generation, using TTS systems, has captured our attention as a potential strategy for improvement. These methodologies will be applied and explored in-depth in the subsequent chapters of this thesis.

Moreover, we have presented a comprehensive comparison of children's speech corpora, which, to the best of our knowledge, stands as the most exhaustive compilation available. This analysis provides valuable insights into the landscape of available datasets for children's speech.

3

Hybrid models for children automatic speech recognition

Contents

3.1 Introduction

In Chapter 2, we saw how a HMM-GMM or HMM-DNN ASR system may integrate knowledge into the automatic speech recognition pipeline. It uses knowledge from language model, acoustic model, and vocabulary to reduce the amount of speech data required to generate appropriate results. According to the literature, these results can be further improved with inductive bias approaches such as transfer learning and multi-task learning [152]. For years, hybrid configurations have been a privileged setting for the children's ASR community. As a matter of fact, between 2009 and 2020, 80% of published research on children's speech recognition was based on hybrid systems, with 45% using HMM-GMM and 35% HMM-DNN. However, during the same period, 63% of published work was conducted for English [211]. As a result, it is uncertain how children's speech from other languages relates to the various approaches used in English, particularly transfer and multi-task learning.

This chapter will investigate these strategies in a variety of scenarios employing non-English data. First, we present transfer and multi-task learning using adult speech as an inductive bias, as is common in the literature. Second, because there is a lack of data for both adult and children's low-resource languages, we investigate the same methodologies using only children's speech. Finally, we present our approach, multilingual transfer learning, which combines transfer and multi-task learning to produce a more robust model for speech recognition in low-resource children setting.

3.2 Multi-task and Transfer learning using adult and children data

3.2.1 Methodology

Motivated by the success of knowledge transfer approaches for ASR children using adult data in the research [6, 152, 159], we intend to validate these findings using a low-resource language. Indeed, using adult data for pre-training makes sense since adult speech is more stable and less prone to variation. Using adult speech to train a speech recognition algorithm makes it simpler to extract and recognize intrinsic and meaningful speech patterns.

For this proposal, we assess children's speech recognition performances in four distinct configurations:

1. **Adult model**: Using a model trained from scratch with only adult data.

2. **Children model**: Using a model trained from scratch with only children data.

3. **Multi-task model**: Using a model trained jointly on adult and children data in parallel using multi-task learning.

4. **Transfer learning**: Using a model that has been fine-tuned on children data from the adult model of configuration 1.

3.2.2 Corpus

As stated in the introduction, we aim to evaluate the performance of children's speech in a low-resource language. To this end, we decided to use European Portuguese corpora. European Portuguese can be considered a low-resource language since most adult speech corpora do not exceed 100 hours [212]. In this experiment, we used LetsRead, a child corpus, described in section 2.4 and BD-PUBLICO as adult corpus. The statistics of all these two corpora are provided in the following table 3.1. The rest of this section provides further information about the BD-PUBLICO corpus.

Corpus name	Train	Test
BD-PUBLICO	8085 utt	412 utt
Adult	21h48	01h10
LETSREAD	3590 utt	1039 utt
Children	12h00	02h30

Table 3.1: Number of utterances and duration of the different corpora for multi-task and transfer learning experiments using adult and children data

BD-PUBLICO

The BD-PUBLICO database (Base de Dados em Português eUropeu, vocaBulário Largo, Independente do orador e fala COntínua) [213] consists of reading sentences extracted from Portuguese newspaper PÚBLICO. The sentences that are read correspond to a total of 6 months of news (equivalent to 10M words and 156k different forms). It is composed of 120 speakers, and graduate and undergraduate students from Instituto Superior Técnico (Lisbon). This corpus is considered an adult dataset since all students are between 19 and 28 years old. All recordings were performed in good noise condition, in a soundproof room at INESC-ID (Lisbon), at a sampling frequency of 16kHz and using a high-quality microphone. In addition, a pronunciation lexicon with citation phonemic transcriptions for each word was produced. Finally, manually corrections were applied to the automatically generated transcriptions.

We divided the BD-PUBLICO corpus into three unique sets with balanced gender partitioning: 1) A training set of 80 sentences by 100 speakers. 2) A development set of 40 sentences performed by a total of 10 speakers. Finally, a test set of 40 sentences by 10 speakers.

3.2.3 Experimental setup

All experiments were carried out using the Kaldi open-source toolkit [69]. First, for each corpus, an independent HMM-GMM acoustic model was trained to produce the necessary alignment for the HMM-

DNN model. Then, HMM-DNN acoustic models were trained using 40-dim filter-banks (fbanks) in addition to a 40-dim Spectral Subband Centroid (SSC) features [214]. These features are known to have similar properties to formant frequencies. Thus, we expect them to help vowel recognition and lead to better recognition of children's speech. The resulting 80-dim input features are then augmented by a 100-dim i-vector. Concatenating speaker embeddings to the input features helps to improve model speaker robustness [104]. For our experiments, we use an i-vector extractor trained on a set of pooled children data from different languages.

Data augmentation was applied to all training corpora by perturbing the speaking rate of each training utterance by 0.9 and 1.1 factors; as well as volume perturbation. This helps the network to be more robust to rate and volume variability on the test sets. To further improve the robustness of the model, Specaugment [145] was applied on top of the fbanks and SSC features by randomly masking time and frequency bands.

For all experiments, we kept the same HMM-DNN acoustic model architecture using lattice-free maximum mutual information (LF-MMI) objective with a learning rate of 2.0E-4. The acoustic model architecture is divided into two parts: i) six convolutional neural network layers and seven TDNN-F layers of dimension 1024 and followed by ii) two TDNN layers of dimension 450 and a fully-connected layer.

For the transfer learning experiments, only the first part of the network will be fine-tuned, while the second part will be dropped and replaced by randomly initialized ones. Similarly, for the multi-task learning experiment, the first part will be shared between the adult and the child, while the second part will be independent.

3.2.4 Results

Method	Adult WER ↓	Children WER ↓
Adult model	3.82%	102.83%
Children model	45.56%	26.88%
Multi-task model	4.59%	27.65%
Transfer learning	-	25.36%

Table 3.2: WER results using adult data for knowledge transfer methods

The WER scores for all settings are presented in table 3.2. In the first row, we notice that employing a model trained on adult data yields a WER of 102.83% on the children's test set. This model achieves 3.82% for BD-PUBLICO. This degradation in the children's compared to adults' scores demonstrates the presence of considerable variability in children's speech, which has a detrimental impact on the ASR scores. It supports the idea that an acoustic model designed exclusively for children is necessary because child speech is currently unusable with adult systems.

Training the acoustic model directly on the children's data, on the other hand, considerably improved the word error rate on the children's data to 26.88%. Since the model observes acoustic variability during training, it becomes more robust to it. While the model improved for children, it deteriorated adult speech recognition performance to 45.56 % WER. This confirms the acoustic mismatch between adult and children speech once more. We compare transfer and multi-task learning approaches using these two experiments as a baseline.

When the model was trained jointly utilising adult and children data in the scenario of multi-task learning, the recognition score of the adults and children decreased marginally when compared to the adult and child model baselines. Unlike in the adult and child models, where the mismatch significantly reduced the children's score in the adult model and the adult's score in the child model, both recognition scores in this multi-task learning scenario are comparable to their respective "trained from scratch" baselines. These results were achieved by including corpus-specific layers into the acoustic model architecture. Indeed, the model's shared component will learn the key characteristics of Portuguese speech, while the corpus-specific part will focus on how to apply them to adults and children, respectively.

In the fourth line, Training over children data with a pre-trained Portuguese adult model as initialization enhanced the result to 25.36% WER. When compared to weights random initialization, it is shown that the weights of the adult model are a beneficial starting configuration and allow the transfer learning model to learn relevant patterns for children. It avoids the need for the model to learn these patterns from scratch, using data from a highly variable source. As a result, transfer learning may be considered a viable strategy for improving the ASR performance for children's speech. This finding is consistent with the literature on hybrid models [6, 152].

3.2.5 Summary and discussion

In this study, we conducted a knowledge transfer technique analysis to improve the results of ASR systems for children. We corroborate the acoustic mismatch between adult and child speech and the importance of the model encountering child data and its variability. Our investigations revealed that the transfer learning approach is a promising way to improve low-resource children's speech recognition scores. Furthermore, multi-task learning was found to be helpful in the setting of mixed adult-child ASR acoustic modelling. However, in this study, we focus on the transfer from adults to children. It is not clear how such a system can work using only children's data.

3.3 Multi-task and transfer learning using multilingual children data

3.3.1 Motivation

In this section, we study whether the performance of children's ASR for low-resourced languages may be improved by combining children's resources from different languages. In many cases, there is limited or no data for both adults and children. Therefore, we propose using several small-sized corpora of children from various languages to overcome the substantial acoustic variability and data scarcity issues. The current study extends standard multilingual training and transfer learning for hybrid HMM-DNN ASR by combining them in a meaningful way to use knowledge from heterogeneous data. First, a multilingual model trained with a multi-task learning objective tries to optimise network parameters to the specific characteristics of children's speech in multiple languages/tasks simultaneously. Subsequently, this multilingual model is used to improve ASR for a target language –potentially different from those used in the multilingual training stage– by using transfer learning. We address the following research question: Does this two-step training strategy outperform conventional single language/task training for 's speech, as well as multilingual and transfer learning alone?

3.3.2 Proposed approach

We propose to combine transfer learning (TL) and multi-task learning (MTL) together for improved acoustic modelling of hybrid HMM-DNN ASR. The proposed approach consists of a two-stage procedure using both MTL and TL that extends the existing techniques since these are usually applied separately. First, a multilingual model trained with a multi-task learning objective attempts to optimize the network parameters to the particular characteristics of children's speech in multiple languages in parallel. In this work, the model is considered multilingual because all the tasks trained during multitask learning are a corpus of children from different languages. Secondly, we adapt this model for a specific children's corpus with TL. The motivation for using TL as a second stage is to take advantage of the robust pre-trained model trained during the MTL phase. Indeed, this pre-trained model has potentially learned cross-linguistic information about children's speech but has also seen more children's data than a model trained in a single language. For this purpose, the acoustic model is divided into two parts: the layers close to the input are shared across all languages and the top layers are language-specific. That is, there are as many output layers as there are languages, i.e. children corpora. Notice that one can incorporate a new language/task in this second stage by adding a new language-specific output, even if this new language/task has not been seen during MTL training (figure 3.1). Our hypothesis is that the more data has been seen by the acoustic model, the better the shared layers can capture the underlying characteristics of children's speech during the first stage of the procedure. These characteristics can be

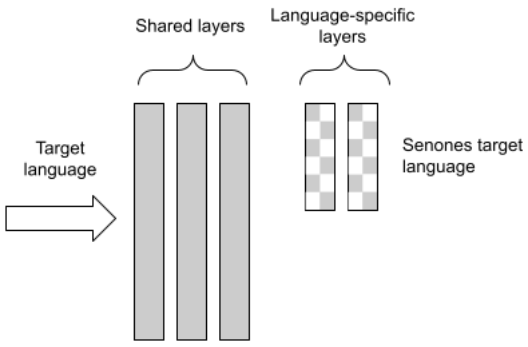


Figure 3.1: Multilingual transfer learning approach. Language-specific layers can be randomly initialized for a language not present during the MTL phase or use the corresponding pre-trained layers in case the target language was present during the MTL phase. Grey blocks are pre-trained during MTL phase.

used effectively, later, by the language-specific layers and during the second step of the procedure (figure 3.1).

Although the approaches adopted in this work have been used previously in other studies, for instance [152] and [159] where they successfully applied MTL using children speaking Mandarin and English, obtaining a relative improvement of 16.96% WER in the English children case, it is clear that successful performance of a methodological approach in the case of English cannot be expected to generalize to other contexts and languages. As we all know, English is a large-size, resource-rich pluricentric language which should be seen more as an exceptional case, rather than an average representative. Against this background, it is important to emphasize that there is a need for research that investigates whether methods that have already been tested for English also work in new contexts such as those of mid-sized languages with fewer resources than English, like Dutch, Portuguese, Swedish and German.

3.3.3 Setup

All experiments were conducted using five children corpora, each from a different language. Namely PFSTAR_SWE, ETLTDE, CMU, LETSREAD and CHOREC. All those datasets have been described in section 2.4.Table 6.1 presents statistics about the duration, number of utterances and language Notice that in this work we have only used small datasets to better reflect the average size of the available children's speech corpora.

We employ the same experimental design as the prior experiment with adult data from section 3.2.3 setup, where the acoustic model is divided in two. The first part is shared across all languages, whereas the second is language specific. Furthermore, each corpus, i.e. each language, uses an independent language model and lexicon that is constant throughout all experiments in order to assess solely the acoustic model contribution.

Corpus name	Language	Train	Test
PFSTAR_SWE	Swedish	6030 utt 04h00	2879 utt 01h48
ETLTDE	L2 German	1445 utt 04h41	339 utt 01h06
CMU	English	3637 utt 06h26	1543 utt 02h45
LETSREAD	Portuguese	3590 utt 12h00	1039 utt 02h30
CHOREC	Dutch	2490 utt 20h12	575 utt 04h42

Table 3.3: Statistics on the different corpora of children's speech.

3.3.4 Multilingual-transfer learning experiment

	PFSTAR_SWE	ETLTDE	CMU	LETSREAD	CHOREC
Language	*Swedish*	*German*	*English*	*Portuguese*	*Dutch*
Single language	54.36%	44.69%	21.26%	26.88%	25.15%
MTL	54.95%	42.46%	23.01%	27.45%	25.10%
TL from PFSTAR_SWE	-	42.23%	20.62%	26.47%	24.65%
TL from ETLTDE	53.60%	-	20.90%	26.61%	25.42%
TL from CMU	52.83%	41.54%	-	26.49%	24.58%
TL from LETSREAD	52.50%	41.77%	20.41%	-	24.60%
TL from CHOREC	52.20%	40.28%	19.77%	26.05%	-
TL Average	52.78%	41.46%	20.43%	26.41%	24.81%
TL Best	52.20%	40.28%	19.77%	26.05%	24.58%
MLTL	**51.67%**	**38.04%**	**19.33%**	**25.75%**	**23.78%**
MLTL-olo	**51.58%**	40.05%	**19.67%**	26.20%	**24.57%**

Table 3.4: WER results of multilingual-transfer learning and cross-lingual experiments. MTL: Multi-Task Learning, TL: Transfer Learning, MLTL: Multilingual Transfer Learning, MLTL-olo: Multilingual Transfer Learning one-language-out

Table 3.4 presents the WER results of the multilingual transfer learning (MLTL) approach compared to three different methods: baseline, trained on each corpus individually for 4 epochs; Multi-task Training (MTL) alone, trained jointly using all corpora for 4 epochs ; Transfer Learning (TL) alone, adapted for the target language using in turn one of the other 4 baseline models as a source, leading to 4 results per target language. In addition, for clarity, we summarise the transfer learning scores with the average of the 4 scores and the best of the 4 for each target.

Firstly, it is important to emphasise that the baseline scores correctly reflect the different tasks the children were asked to perform and the corresponding amount of data available for each corpus. The best WER score, 21.26% for CMU, can be explained by the reading-aloud-sentences task nature of this corpus. Thus, the language model can more easily compensate for the acoustic model errors. In addition, Chorec and LetsRead, as the largest corpora in our experiment, also yield relatively good results for children's

speech recognition. On the other hand, ETLTDE and PFSTAR_SWE show the worse WER results with 44.69% and 54.36% WER, respectively. This can be explained by the amount of data available and by the language model which does not compensate as much as the CMU model. Especially for ETLTDE, since it is the only corpus that does not contain scripted text, but spontaneous responses. In addition, the age range of PFSTAR_SWE children also plays a critical role in performance, since younger children generally yield worse performance scores [6].

Turning to multi-task learning, among all the approaches presented, only MTL fails to improve the baseline performance for almost all languages, which is in contradiction with [152]. However, it can be explained by the differences in terms of the size of the child's speech corpora used. The smaller the size of the corpora used, the more difficult it is to model the acoustic variation in the children's speech.

Concerning TL, all performance scores outperform their corresponding baseline, confirming that TL is an adequate method for children's ASR since it allows the system to be confronted with more children, thus with more variation. Precisely, table 3.4 shows that the best pre-trained model for knowledge transfer is Chorec. This makes sense since Chorec is the largest corpus, representing about 40% of the total data used in our experiments.

Finally, MLTL shows an average relative improvement in WER of 7.73% compared to the baseline, slightly higher than the average (TL Avg) and the best (TL Best) transfer learning performance, with an average relative improvement of 4.50% and 2.66%, respectively.

The strength of MLTL is that it can benefit both from MTL and TL, minimizing some of their associated weaknesses. Attending to our results, MTL does not improve single language training. We believe that the unbalanced amount of data, the significant differences among data sets and the use of segmental optimization (lattice-free MMI) can partially explain these results. Nevertheless, we hypothesize that the multi-task objective leans the network towards better optimization of the lower layers, rather than optimizing the upper language-specific layers, can still be beneficial for TL. Regarding TL, one can observe considerable performance variations depending on the pre-trained model used as the source model, probably due to a poorer initialisation of lower layers that is less efficient for TL. The MLTL experiments show that we can overcome these drawbacks by combining both MTL and TL, thus, validating the effectiveness of this approach for robust speech recognition of children.

3.3.5 Cross-lingual validation

In the previous section, we saw that the MLTL approach yields better results than separate multi-task and transfer-learning frameworks.

To further validate the hypothesis that the shared lower layers are able to learn meaningful information about children's speech characteristics, regardless of the language, we perform a cross-language experiment following a leave one-language-out cross-validation setting. In this experiment, we keep one

language out of the multi-task training and use it only during the TL phase to adapt the acoustic model parameters.

We repeated this procedure for each corpus in our experiment. As in the previous experiment, we used 4 epochs for each learning phase. The last row of Table 3.4 presents the results of the cross-language experiment.

For all corpora, the MLTL one-language-out (MLTL-olo) approach outperforms the baseline WER score with an average relative improvement of 5.56%. Improvements are more important for the small corpora ETLTDE and CMU, with a relative improvement of 14.88% and 9.07%, respectively. PFSTAR_SWE does not benefit as much, with only 5.05% relative improvement. This is mainly due to the age differences with the children in the other corpora used in the MTL phase. Indeed, the children in PFSTAR_SWE are much younger (see section 3.3.3 for more details). Therefore, we conclude that the shared layers have learned the underlying multilingual features of children.

It is also interesting to compare MLTL-olo with the results of transfer learning alone. In both cases, the pre-trained models used have never seen the target language data. We observe that the results between the MLTL-olo and TL Best are extremely close, with small improvement with the MLTL-olo, only the best transfer learning model on LetsRead is slightly better than MLTL. This means that during multilingual training the system learned, at least, the best representation of the available children's characteristics. This is consistent with our hypothesis of the important role of the multilingual training phase in our two-step procedure.

3.3.6 Summary and discussion

In this work, we addressed the following research question: Does the two-step training strategy we propose in the current chapter outperform conventional single language/task training for children's speech, as well as multilingual and transfer learning alone. Our results provide a positive answer to this question, by showing that the limitations of MTL and TL can be overcome by the multilingual transfer learning approach, even in a low-resource scenario, leading to an average relative improvement of 7.73%. Multilingual pre-training is also beneficial for transfer learning with an unseen language, with an average relative improvement of 5.56%. Multilingual transfer learning thus seems to be an appropriate method to address children's speech recognition in a challenging context.

3.4 Conclusion

In this chapter, we look at the current state of the art for a Hybrid HMM-DNN speech recognition system for children. We illustrated that transfer learning is the most promising strategy for addressing children's ASR variability because it makes efficient use of the knowledge contained in the pre-trained

source model. A pre-trained model that can be trained on both adults or children. The multi-task learning does not produce the greatest results alone, but we showed that the shared part of the model is capable of learning relevant information for all tasks jointly. Furthermore, we proposed in this chapter to combine these two approaches in our multilingual transfer learning system. Using the capacity of learning relevant information of the multi-task learning approach and the capabilities of efficient use of pre-existing knowledge from transfer learning.

4

End-to-End children automatic speech recognition

Contents

4.1 Introduction

The growing popularity of deep learning has witnessed numerous successful applications in ASR. NIt was only recently, that end-to-end models have shown their capability to outperform hybrid HMM-DNN systems for a variety of speech recognition tasks, including children's ASR. The primary advantage of end-to-end speech recognition systems lies in merging the entire training process within a single neural network, thereby eliminating potential behavioral incompatibilities that may arise between independently trained modules.

However, the application of the end-to-end paradigm for children's ASR is a relatively recent development and has not been extensively explored, mainly due to the challenge of data scarcity in the context of children's speech [118–121]. Additionally, end-to-end models often necessitate a larger number of parameters to achieve the desired robustness and flexibility. Consequently, training them on small datasets becomes increasingly challenging [215]. Despite these challenges, the exploration of end-to-end models holds promise for advancing the state-of-the-art in children's ASR.

As mentioned in section 2.2.3, the recent increased interest in end-to-end speech recognition, has led development the several architecture, encompassing recurrent neural networks [216], neural transducers [217], and the Transformer architecture [7]. Among these, the Transformer architecture stands out as it consistently delivers state-of-the-art results in large-vocabulary speech recognition, demonstrating its efficacy across both adult and children's speech domains [118].

This chapter will dives into more details of the Transformer design as well as the adapter transfer for children ASR, a parameter-efficient transfer for Transformer models that we have recently proposed.

4.2 Transformer model

Introduced in 2017 by Vaswani et al. [7], the Transformer architecture is a sequence-to-sequence encoder-decoder model that relies solely on self-attention mechanisms, completely discarding the use of recurrence and convolutions. This design choice addresses challenges such as vanishing gradient issues commonly associated with recurrent neural networks. Another notable difference with recurrent neural networks is that the Transformer computes the dependencies between each pair of positions simultaneously, rather than one by one, by directly encoding the position in the sequence. This enables more parallelisation and therefore a faster training process.

Since its introduction, the Transformer architecture had a tremendous impact across various domains, including Natural Language Processing (NLP) [62,63], computer vision [218], and speech processing [80]. The Transformer's capacity to capture intricate dependencies and patterns in sequences has established it as a popular architecture in the deep learning field, contributing to advancements and breakthroughs across various applications, such as ChatGPT [219] or Dall-E [220].

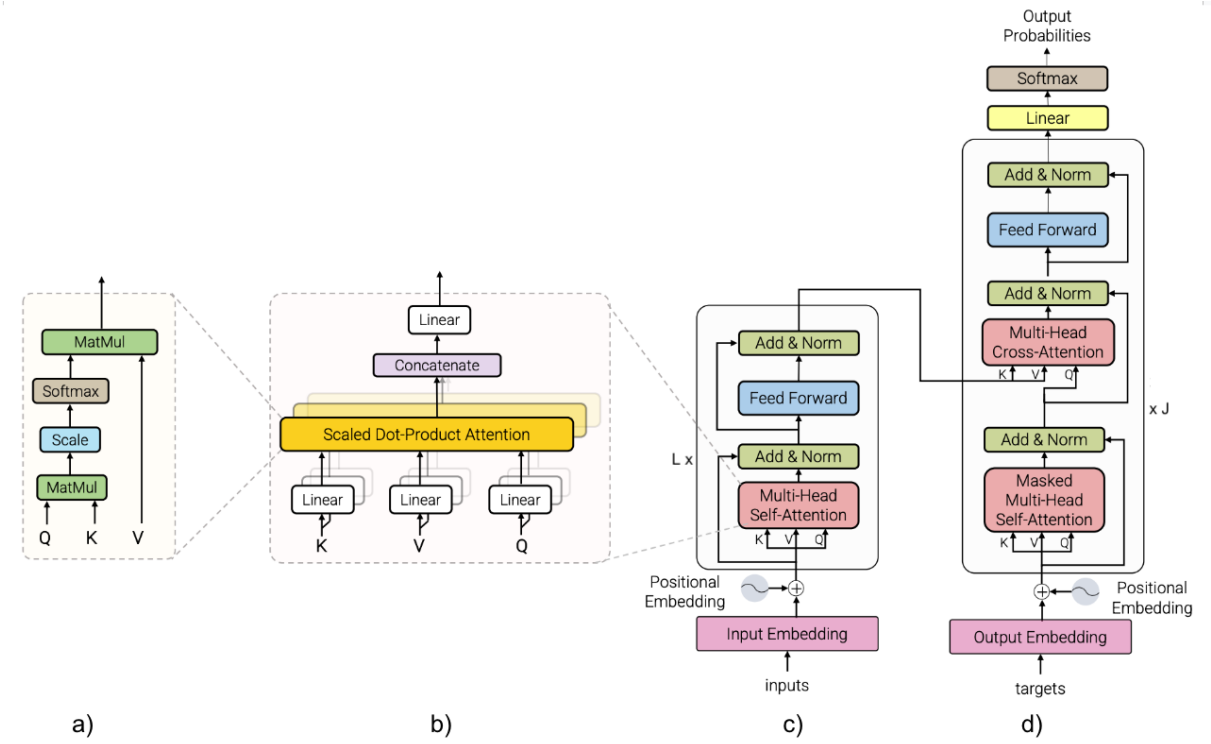


Figure 4.1: Architecture of the standard Transformer [7]. a) scaled dot-product attention, b) multi-head self-attention, c) Transformer-encoder, d) Transformer-decoder.

The Transformer encoder-decoder architecture, as depicted in Figure 4.1, consists of an encoder (c) and a decoder (d). Prior to entering the encoder or decoder, both inputs and targets undergo processing through an embedding layer. This involves the use of learned embeddings to convert input tokens and output tokens into vectors of dimension d_{model}. Since the transformer model contains no recurrence and no convolution mechanisms, information about the relative or absolute position of the tokens must be injected in the sequence to allow the model to make use of the order of the sequence. To achieve this, information about the relative or absolute position of the tokens is obtained through the summation of the input/output embedding and the positional embedding. While various alternatives for positional encodings were used , Vaswani et al. [7] proposed the use of sinusoidal and cosine functions with different frequencies, as follows:

$$PosEnc_{(pos,2i)} = \sin\left(pos/10000^{2i/d_{\text{model}}}\right) \tag{4.1}$$

$$PosEnc_{(pos,2i+1)} = \cos\left(pos/10000^{2i/d_{\text{model}}}\right) \tag{4.2}$$

Where pos is the current token or label position and i is the dimension.

The encoder's primary objective is to transform the input sequence $X = x_1, \ldots, x_T$ into a series of continuous representations $Z = z_1, \ldots, z_T$. The encoder is structured as a stack of L identical layers,

each comprising two sub-modules: the multi-head self-attention (MHSA) and the position-wise fully connected feed-forward network (FFN). Each of these modules are followed by a normalisation with a residual connection.

Subsequently, the continuous representations Z are fed into the decoder. The decoder is responsible for constructing an output sequence $Y = y_1, \ldots, y_N$ one element at a time. At each time step, the decoder receives both the encoder outputs and the last decoder output in an auto-regressive manner. Similar to the encoder, the decoder is composed of a stack of J identical layers. Nevertheless,in comparison to the encoder, the decoder encompasses a third sub-module, which performs multi-head attention (MHA) over the output of the encoder stack. The self-attention sub-module in the decoder stack is modified to prevent positions from attending to subsequent positions. This masking combined with a modified MHA prevents the attention to use subsequent positions, ensuring that the prediction at time-step i solely depends on the previous $< i$ time-steps.

The MHA module relies on scaled dot-product attention [7], as illustrated in Figure 4.1(a). Scaled dot-product attention focuses on determining how relevant a particular token is with respect to other tokens in the sequence and is defined as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4.3}$$

Here, the input consists of queries Q, keys K of dimension d_k, and values V of dimension d_v. The dot product of the query with all keys is divided by $\sqrt{d_k}$, and the result passes through a softmax function to obtain attention weights. The attention weights are then multiply with the values. When d_k is large, the scaling $\frac{1}{\sqrt{d_k}}$ restrains the dot product from growing large in magnitude. Note that the Multi-Head Self-Attention (MHSA) is a specific case of MHA where K, V, and Q are all the same input of the module.

Instead of performing a single scaled dot-product attention, the MHA module linearly projects h times K, V, and Q with different, learned, linear projections to dimensions d_k, d_k, and d_v respectively. The attention function 4.3 is then applied in parallel to each of the h projected versions. The output of each of the h attention functions, of dimension d_v, is concatenated and projected one final time, as depicted in Figure 4.1(b). Each of the h attention functions is called a head, while the overall is called Multi-head attention (MHA) or Multi-Head self-attention (MHSA) if K, V and Q are the same. More formally:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \tag{4.4}$$

where

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{4.5}$$

and the different projection matrices are $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$, and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

Furthermore, in addition to the attention modules, each layer within the encoder and decoder encompasses a FFN module. This network is applied to each position separately and identically, and it consists of two linear transformations with a Rectified Linear Unit (ReLU) activation in between. While attention capture interdependencies between the element of the sequence regardless of their position, the FFN non-linearly transform each input token independently:

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2 \tag{4.6}$$

With $W_1 \in \mathbb{R}^{d_{model} \times d_{ffn}}$, $b_1 \in \mathbb{R}^{d_{ffn}}$, $W_2 \in \mathbb{R}^{d_{ffn} \times d_{model}}$ and $b_2 \in \mathbb{R}^{d_{model}}$. Typically d_{ffn} is usually set to $4 \times d_{model}$.

4.3 Conformer model

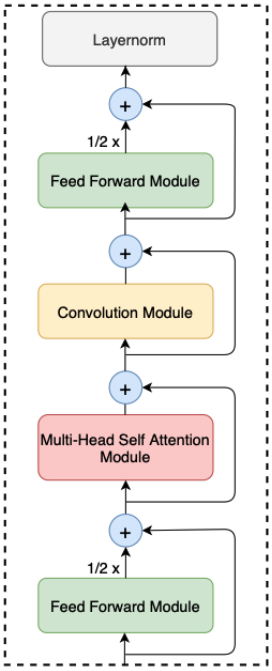


Figure 4.2: Architecture of a Conformer layer

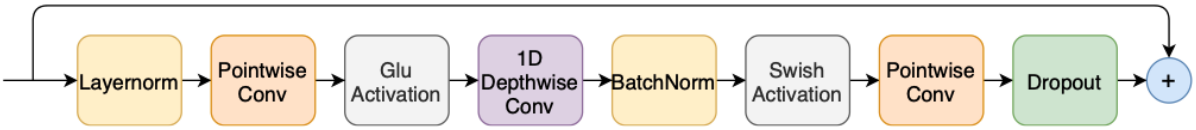


Figure 4.3: Convolution module in the context of a conformer layer

Transformers are recognised for their effectiveness in capturing global information within sequential tasks, thanks to the attention mechanism. Conversely, CNNs excel in capturing local features within data. To leverage the complementary strengths of both architectures, various approaches have been explored [221, 222], and the Conformer architecture [223] stands out as a notable combination of Transformers and CNNs.

This combination involves incorporating CNNs into the conventional Transformer architecture, as depicted in Figure 4.2. Specifically, a Conformer block comprises four modules arranged sequentially: a FFN module, a MHSA module, a convolution module, and a second FFN module. Notably, the Conformer block features two FFN modules sandwiching the MHSA module and the Convolution module. This design is inspired by Macaron-Net [224], which advocates replacing the original FFN in the Transformer block with two half-step FFN modules—one before the attention layer and one after. Similar to Macaron-Net, half-step residual weights is employed for the FFN modules. More formally, for an input x_i to a Conformer block i, the output y_i of the block is defined as follows:

$$\begin{aligned} \tilde{x_i} &= x_i + \frac{1}{2}FFN(x) \\ x'_i &= \tilde{x_i} + MHSA(\tilde{x_i}) \\ x''_i &= x'_i + Conv(x'_i) \\ y_i &= LayerNorm(x''_i + \frac{1}{2}FFN(x''_i)) \end{aligned} \tag{4.7}$$

More specifically,the convolution modules , inspired by [225] and illustrated in Figure 4.3., starts with a gating mechanism [226] involving a pointwise convolution and a gated linear unit (GLU). Subsequently, a single 1-D depthwise convolution layer is employed. Finally, this 1-D depthwise convolution is followed by a Batchnorm iand then a Swish activation layer.

4.4 Understand transfer learning efficacy for transformer based models

Motivated by the limited availability of children's speech data, TL emerges as a promising strategy to overcome this challenge in children's ASR. TL involves leveraging pre-trained models, typically trained on extensive out-of-domain datasets of adult speech, and adapting them to the specific characteristics of children's speech through a re-training phase using a smaller, in-domain dataset of children's speech. This approach has shown effectiveness in both traditional HMM-DNN approaches [105] and modern end-to-end ASR paradigms [118, 119]. In chapter 3, we presented the effectiveness of TL in improving HMM-TDNN-F models for both European-Portuguese and English children's speech.

While the end-to-end paradigm has become state-of-the-art for some children's datasets, particularly when adapted from pre-trained adult models using TL, it involves merging all components of traditional ASR (acoustic, pronunciation, and language models) into a single neural network. This unique neural network design leads to an increased number of parameters for end-to-end models. Therefore, there is a need to understand how these large pre-trained models behave when fine-tuned with limited downstream data. To address this, we propose to explore TL for children's speech using both Transformer models and the Conformer architecture, a variant of the Transformer specifically designed for speech tasks.

Investigating TL for large-size models is a crucial step in the development of robust children's ASR, given the widely acknowledged issue of overparameterisation in large Transformer-like models. For example, models like BERT [62] have been widely recognised as overparameterised in various studies within the Natural Language Processing (NLP) field [227, 228]. Overparameterisation occurs when models have more parameters than necessary for a given task. Notably, observations suggest that certain components or layers of the architecture can be removed without compromising performance and, in some cases, may even lead to slight performance gains [227–229]. This recognition has fueled successful compression studies, including pruning and distillation techniques [230, 231].

Furthermore, the acknowledgment of overparameterisation in Transformer-based models raises questions about the efficiency and computational cost of these architectures. Larger models tend to be more prone to overfitting, as demonstrated in a study where an ASR model was scaled up to 10 billion parameters [232]. Overfitting can be a concern when applying TL as using a overfitted pre-trained model could potentially leading to decreased performances. Therefore, there is a need for ablation studies, involving the systematic removal of components of the model, to understand which parts contribute significantly to the performances [233, 234]. These studies, predominantly explored in the field of computer vision [229], align with the Lottery Ticket hypothesis formulated by Frankle and Carbin [235]: *"A randomly-initialized, dense neural network contains a subnetwork that is initialized such that—when trained in isolation—it can match the test accuracy of the original network after training for at most the same number of iterations"*.

Understanding the contribution of the different components of the large-size model not only helps optimise model architectures for specific tasks but also reduces the computational demands of training and inference. This is particularly relevant in scenarios with resource constraints, such as limited computational power, memory, and training data.

While these ablation works have been extensively studied in NLP and computer vision, this approach remains under-explored for speech tasks. Specifically, the recent successes of distilation and pruning techniques for speech models [236–238], suggest that overparameterisation may also be present in ASR models. In the context of children's ASR, where data scarcity is a significant challenge, understanding and addressing overparameterisation could paves the way for the development of more tailored and efficient models, with improved performances. Notably, the Transformer and Conformer architectures have exhibited promising results in ASR applications, making them particularly compelling subjects for further investigation.

4.4.1 Partial Transfer learning

Our aim is to undertake a comprehensive exploration of TL, specifically on end-to-end ASR for children's speech. Notably, the previous research in this field has been focused on HMM-DNN models, as illustrated by the work of Shivakumar et al. [105]. It is noteworthy that the existing works on the end-to-end paradigm have only centered on the entire model fine-tuning, leaving a notable gap in the understanding of the impact of fine-tuning individual components.

Firstly, we perform a meticulous examination of the TL process, specifically isolating the effects on individual components of the Encoder and Decoder, in comparison to the fine-tuning of the entire model. The prevailing hypothesis asserts that the Encoder is capturing acoustic information, while the Decoder more linguistic informations. Considering the important presence of acoustic variability in children's speech, our investigation extended to discern which layers of the Encoder are more relevant for achieving effective TL.

Subsequently, our focus shifts to delineating the distinctive contributions of modules within both the Transformer and Conformer architectures during the fine-tuning process of adapting a pre-trained adult model to children's speech. Within the Transformer model, a granular analysis will be conducted to asses the roles of the MHSA module, the FFN, and the normalisation layers independently. Similarly, within the Conformer model, we evaluate the significance of the MHSA, FFN, normalisation, and convolution modules. This exhaustive examination is meticulously designed to identify the components that play a pivotal role in fine-tuning.

4.4.2 Experimental setup

4.4.3 Corpus

Training	Validation	Test
60897 utterances	10044 utterances	4079 utterances
566 speakers	79 speakers	91 speakers
113 hours	18 hours	13 hours

Table 4.1: My Science Tutor Children Speech Corpus statistics

In this experiment, we decided to used the Boulder Learning My Science Tutor (MyST) corpus, as detailed in section 2.4. This choice aligns with the nature of the task assigned to the children in the MyST corpus, which involves spontaneous speech. The the end-to-end paradigm, by encapsulating both the acoustic model and language model within the same network, requires careful consideration. Indeed, if the model is trained on a limited set of prompts, from a dataset focused on reading tasks for example, it may learn and overfit to those specific prompts, yielding unreliable results.

For the purposes of our experiments, we decided to remove all utterances shorter than one second and longer than 20 seconds and shorter than one second. Typically, utterances shorter than one second were found to predominantly contain silence alone, while those longer than 20 seconds were constrained by our GPU limitations. The details of the filtered corpora used in our work are presented in Table 4.1.

4.4.4 Implementation details

All experiments were conducted using the SpeechBrain toolkit [239]. The Transformer model encompasses 12 Transformer layers in the encoder and 6 Transformer layers in the decoder, all with a hidden dimension of 512. Similarly, the Conformer architecture featured 12 Conformer layers in the encoder and 6 Transformer layers in the decoder, with a hidden dimension of 512. Both configurations used 8 heads for all MHSA, a FFN hidden dimension of 2048, and a dropout rate of 0.1. These models were pre-trained on a large English adult speech corpus, specifically the LibriSpeech dataset [31], and are publicly available[1]. Furthermore, for all experiments, the same Transformer language model was employed, trained on 10 million words from LibriSpeech transcriptions. Our training involved 30 epochs with a learning rate of 8e-5. Furhtermore, in line with findings of [118], a combination of CTC and Seq2Seq losses was used, with respective weights of 0.3 and 0.7.

4.4.5 Encoder-Decoder Transfer learning

Table 4.2 summarises the results of the impact of isolating fine-tuning of the encoder and decoder components within Transformer and Conformer ASR models. For the Transformer model, using fine-tuning

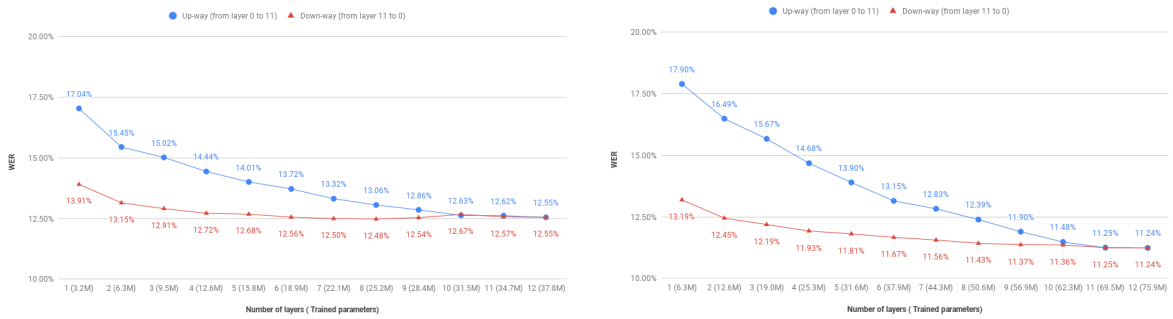
[1] https://huggingface.co/speechbrain/asr-transformer-transformerlm-librispeech
https://huggingface.co/speechbrain/asr-conformer-transformerlm-librispeech

Transformer	WER ↓	Trained parameters
Full model	12.99%	71.5M
Encoder only	**12.55%**	37.8M
Decoder only	15.95%	25.2M
Conformer		
Full model	12.28%	109M
Encoder only	**11.24%**	75.9M
Decoder only	16.94%	25.2M

Table 4.2: Encoder-Decoder experiment

then entire model exhibits a WER of 12.99% using 71.5 million parameters. Isolating the encoder component leads to a significant improvement in WER, with TODO% WER with a reduced parameter count of 37.8 million. Parallely, fine-tuning the decoder underperform compared to both full model and Encoder only fine-tuning by achieving a WER score of 15.95% training 25.2 million parameters.

Turning to the Conformer model, the full model achieves a WER of 12.28% with 109 million parameters updated. Isolating the transfer learning on the encoder component only yields a remarkable improvement, resulting in a WER of 11.24% with a parameter count of 75.9 million. Conversely, when the decoder only is fine-tuned the performances degrade with a higher WER of 16.94% using a parameter count of 25.2 million. Notably, the Conformer architecture consistently outperform the Transformer across all configurations, emphasising its effectiveness for speech related tasks. In addition, these results underscore the important role of the encoder in both Transformer and Conformer ASR models, highlighting its importance in capturing the inherent variabilities in children's acoustics. It confirms that the acoustics variabilities represent the most important source of variabilities as suggested by [6].



(a) Results of the transfer learning layer wise for the Transformer model

(b) Results of the transfer learning layer wise for the Conformer model

Figure 4.4: Layers-wise up-way and down-way transfer learning experiment for Transformer and Conformer architecture

Recognising the important role of the Encoder in the fine-tuning process for children ASR, our investi-

Transformer	WER ↓	Trained parameters
None	25.04%	-
Full model	12.99%	71.5M
Normalisation	17.00%	57.9K
MHSA	12.19%	25.2M
FFN	**11.84%**	37.8M
MHSA + FFN	12.39%	63.0M
Normalisation + FFN	12.19%	37.9M
Normalisation + MHSA	12.29%	25.3M
Conformer		
None	21.75%	-
Full model	12.28%	109M
Normalisation	15.61%	63.7K
MHSA	11.74%	28.4M
Convolution Module	11.67%	9.7M
FFN	**11.11%**	63M
↪ Module 1	11.44%	25.2M
↪ Module 2	11.48%	25.2M
↪ Up-linear (W_1)	11.47%	31.5M
↪ Down-linear (W_2)	11.40%	31.5M
FFN + MHSA	11.20%	91.4M
FFN + Convolution Module	11.11%	72.7M
FFN + Normalisation	11.15%	63.1M
MHSA + Normalisation	11.67%	28.4M
MHSA + Convolution Module	11.44%	38.0M
Convolution Module + Normalisation	11.62%	9.7M

Table 4.3: Modules fine-tuning experiment

gation further look to determine the specific layers that are the most relevant during this TL process. To this end, we adopt a meticulous approach of fine-tuning the Encoder incrementally, adding one layer at a time. This step-by-step TL procedure is executed in each directionally, one commencing from the input layer while the other one from the output layer of the encoder,the up-way and down-way respectively. In other words, the up-way, incremental fine-tuning begining with the input layer and progressively incorporating subsequent layers towards the output layer. While, the down-way initiates fine-tuning from the output layer, systematically integrating preceding layers towards the input layer.

4.4.6 Modules Transfer learning

The results of the transfer learning experiments, focusing on fine-tuning specific components of the Transformer and Conformer ASR models for children's speech, are presented in Table 4.3. In addition of the WER evaluation metric, we also display the number of trained parameters.

The baseline performance of the Transformer pre-trained model without any fine-tuning (corresponding to *None* line) yields a WER of 25.04%. In contrast, the fine-tuning of the full Transformer model exhibits a noteworthy improvement, achieving a WER of 12.99% with 71.5 million parameters trained.

The fine-tuning of specific components reveals valuable observations. Applying normalisation alone results in a modest improvement WER of 17.00% compared to keeping the pre-trained model, this using 57.9 thousand parameters. The MHSA module outperforms normalisation and full fine-tuning, achieving a WER of 12.19% with a parameter count of 25.2 million. However, the most important improvement is observed with the FFN module, which attains a remarkable WER of 11.84% with 37.8 million parameters. Remarkably, both MHSA and the FFN modules, when fine-tuned individually, already outperform the full model performance. This implies that the decrease in the number of parameters, coupled with the significance of these modules, may play a substantial role in the enhanced performances.

Turning to the Conformer model, the baseline WER without fine-tuning is 21.75%, with no additional parameters. The full fine-tuning of the Conformer model improved performance, yielding a WER of 12.28% with 109 million parameters.

Fine-tuning specific Conformer modules offers further granularity. First, the normalisation finetuning, in a similar way as observed in the Transformer configuration, yield a score of 15.61% WER, with 63.7 thousand parameters. Then, the MHSA module proves effective by already providing better result than the full full-tuning with a WER of 11.74%, this by fine-tuning 28.4 million parameters. The convolution modules outperform the MHSA with a WER of 11.67% with less parameters used, 9.7%. Howver, as in the Transformer model, the FFN module stands out prominently, demonstrating a WER of 11.11% with a parameter count of 63 million. Notably, the MHSA, convolution modules and FFN modules, when fine-tuned in isolation, surpass the performance of the full Conformer model.

As FFN, consistently proved to be the most relevant component to fine-tune for children ASR, no matter the configuration. We decided to delve deeper into the FFN submodule. There is two way to see this subdivision, first using the macaron style of the Conformer FFn layer, including two modules, one before the MHSA and one after the convolution module will be respectively called Module 1 and Module 2. The second approach to subdivde the FFN layers would be to only look at the up-linear and down-linear, respectively W_1 and W_2 equation 4.6. Module 1 and Module 2 achieve WERs of 11.44% and 11.48%, respectively, each by fine-tuning 25.2 million parameters. The Up-linear and Down-linear submodules exhibit WERs of 11.47% and 11.40%, respectively, with parameter counts of 31.5 million. The subdivision of the FFN modules do not allow to perform better than their coupled usage. This show the importance of the full FFN modules in Transformer based end-to-end models.

These comprehensive study not only highlight the importance of the various components within Transformer and Conformer ASR models but also underscore the effectiveness of fine-tuning only specific modules compared to the full model fine-tuning, especially the FFN module, in achieving improved performance.

4.5 Summary

We covered the state-of-the-art for end-to-end children's speech recognition in this chapter. Particularly, the usage of the Transformer architecture in conjunction with transfer learning. In a similar way as chapter **??**, to avoid a drop in performances attributable to an acoustic mismatch between children and adults, the end-to-end model should be trained with children's data. In contrast to previous work, we demonstrated that fine-tuning only a portion of the transformer modules, particularly the FFN sub-module, yields better results since it serves as a key-value memory. As a result, we placed our adapter subsequent to it. The adapter's role is to accomplish knowledge transfer, which is related to transfer learning. Rather than updating the complete model's weights, we just tweak an extra module, hence fewer parameters. This adapter transfer achieves almost identical results as the entire model fine-tuning. In addition, adapters are useful in the context of customized models, where training and storing a whole model for each age group or each child can be expensive and time-consuming.

In addition, we proposed the variational adapter, a variant of the traditional adapter based on variational auto-encoders. Compared to the adapter, which takes a bottleneck encoder-decoder structure with a linear layer as encoder and a linear layer as decoder, the variational adapter's encoder consists of two branches, μ and σ. The outputs of these two branches are used as the mean and variance vector to sample the input of the decoder. By doing so, we enforce the adapter's input variability to be contained in the σ branch. A branch which is suppressed during inference. As a result, we reduce input variability while maintaining the same size as standard adapters.

5

Exploring Parameter-Efficient Strategies in Transfer Learning for Child-Focused ASR Systems

Contents

5.1 Introduction

The use of increasingly larger models coupled with the abundance of massive datasets is driving rapid advancements in many domains of machine learning, encompassing NLP [63] and computer vision [220]. In the context of ASR, this trend of scalling up models is exemplified by state-of-the-art models such as Whisper [30] and HuBert [165], where the number of parameters exceeds 1 billion. Research has underscored the interconnected nature of the training dataset size and the number of model parameters, identifying them as mutual bottlenecks that influence the performances of machine learning models. This observation accentuates the significance of scaling these two dimensions in tandem for the development of more robust and effective ASR models [240]. Typically, to scalling up the model size a combination of an increased number of layers and an expansion of the model's hidden dimensions is used [232].

However, the challenge arises when only a limited amount of data is available, making it challenging to train these large models from scratch, as highlighted by recent studies [118, 119]. Hence, as discussed in the preceding chapter, transfer learning emerges as a well-established and effective paradigm to tackle to problematic of limited dataset. Nevertheless, despite its efficacy, we emphasised certain limitations that may potentially impede the performance of fine-tuning. Specifically, attempting to fine-tune these large models using a downstream dataset limited in size can be challenging. Indeed, in addition to be an expensive process, using small amount of data on such big model could potentially result in overfitting. This issue necessitates careful consideration, particularly in light of the recent evolution towards ever-growing pre-trained model sizes. Additionally, even following last chapter highlights where only specific parts of the model were fine-tuned, the different part of the model could be intricately linked to the overall model size. For example, FFN modules usually represent substantial portion, around 70% of the total number of parameters. This insight underscores the persistence of the challenge associated with model size, even when fine-tuning only specific components. Finally, TL on large amount of parameters is memory-storage-inefficient, especially when there is a need to store a replicas of the billion of parameters models for many different small tasks.

Consequently, there is a growing need for more parameter-efficient transfer learning (PETL) as lightweight alternatives. Among the approaches introduced by the research community, residual Adapter modules stand out as the most popular and promising [241, 242]. Specifically tailored for Transformer-based systems, Adapters integrate a compact set of additional layers into a pre-trained source model. This design enables Adapters to enhance computational efficiency, resulting in faster training and addressing the challenge of catastrophic forgetting. Diverging from conventional transfer learning methods, where the source pre-trained model's weights are entirely replaced, Adapter-transfer maintains the integrity of the backbone model. Therefore, when the Adapter modules are removed, the initial pre-trained model remains unchanged. This preservation of the backbone model is a crucial advantage as it offer increased flexibility. Furthermore, owing to their limited number of trainable parameters, Adapters demonstrate a

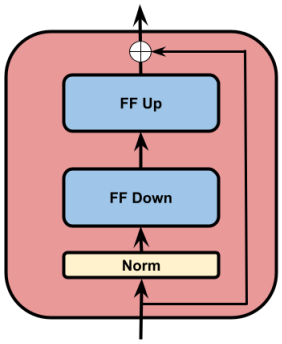


Figure 5.1: Residual Adapter architecture

decreased susceptibility to overfitting, thereby contributing to improved generalisation performance.

In this chapter, motivated by these promising characteristics, our investigation will delve into the use of Adapters in the specific context of children's ASR. We will explore different Adapter configurations within both Transformer and Conformer architectures. Additionally, as a comparative analysis to Adapters, we will explore the application of other PETL approaches in the context of children's ASR. Lastly, we will introduce a novel type of Adapter, referred to as shared-Adapters, taking advantage from the overparameterisation inherent in Transformer-based models.

5.2 Adapter tuning

Adapters were initially introduced in the NLP field to efficiently adapt large models, such as Transformers, using minimal amount of parameters for text classification [241]. As an alternative to full model fine-tuning, Adapter-transfer involves training an extra small number of task-specific parameters while keeping the original model frozen. This is done at each Transformer layer level by plugging them after the Multi-Head Attention (MHA) and Feedforward Neural Network (FFN) modules, a setup often referred to as the *Houlsby* configuration. Subsequently, [242] demonstrated that Adapters placed only after the FFN modules were sufficient for achieving efficient performances, referred to as the *Pfeiffer* configuration. Generally, Adapters employ a bottleneck architecture, consisting of a normalisation layer followed by a projection-down linear layer with a non-linear activation, and subsequently a projection-up linear layer. Finally, a residual connection is applied by summing the input of the Adapter with its output. The overall structure is illustrated in Figure 5.1. Research suggests that the hidden dimension, between the down and up projections, may not always benefit from a bottleneck structure, where $d_{hidden} < d_{model}$, and the optimal design may vary depending on the downstream task. In some tasks, an hidden dimension larger than the model size itself, in other words $d_{hidden} > d_{model}$, has been proven more effitive [172].

Some of the main advantages of Adapters are their parameter efficiency and modularity. This efficiency is particularly interesting when working with large pre-trained models, while the modularity is valuable

when a large number of tasks need to be trained. Mathematically, the structure of an Adapter can be expressed as follows:

$$adapter(x) = x + (W_{up}(f(W_{down}g(x) + b_{down}))) + b_{up}) \tag{5.1}$$

Where W_{down} and W_{up} denote the weights of the projection-down and projection-up linear layers, and b_{down} and b_{up} represent the corresponding biases. The function $f(\cdot)$ is a non-linear activation, while $g(\cdot)$ a layer normalisation or identity function. Finally, x corresponds the input given to the Adapter.

In terms of computation, Adapters offer the advantage of faster training, given that they update fewer parameters compared to fully fine-tuning models. However, there might be a slight processing delay during inference due to the addition of extra parameters introduced by the Adapters, this difference is generally minimal and can be well-managed [243].

Adapter-transfer has gained increased attention in the context of ASR tasks [244–246], particularly owing to its modular nature, which has proven advantageous in the context of multi-lingual ASR [247–249]. In these studies, distinct Adapters were trained for each language, contributing to enhanced performance compared to a monolingual model and mitigating certain challenges associated with transfer learning, such as overfitting. This modular approach provides a tailored solution, as each Adapter designed for a specific language can effectively capture the diverse acoustic characteristics unique to that language.

In addition, researchers have explored the use of Adapters in the context of SSL. In SSL, larger model are typically employed to capture a wide range of information from speech for application in a broad spectrum of tasks [172, 250]. However, the computational cost and scalability to multiple tasks can pose a challenge. Notably, once the model is fine-tuned for a specific task, the entire model is fixed for that task, and re-loading and re-training the base model are necessary for transferring to a different task. Therefore, the use of Adapters has proven effective in addressing these challenges by providing a modular and parameter-efficient task-specific adaptation.

Additionally, the effectiveness of Adapters has been demonstrated in addressing challenges related to low-resource and atypical speech recognition scenarios [251]

Finally, the effectiveness of Adapters has also been demonstrated in addressing challenges related to low-resource and atypical speech recognition scenarios [251]. In such scenarios, similarly to children's speech, there is limited availability of labeled data and atypical speech characteristics. As a result, Adapters provide a valuable solution by efficiently adapting large pre-trained models to these challenging tasks.

However, the application of Adapters in the context of children's ASR has received limited attention, with only one notable study by [172]. In this study, the authors proposed integrating and training Adapters within SSL models, followed by fine-tuning the entire model, including the adapter weights, for better modeling of children's speech. This represents a pioneering effort to leverage Adapters for

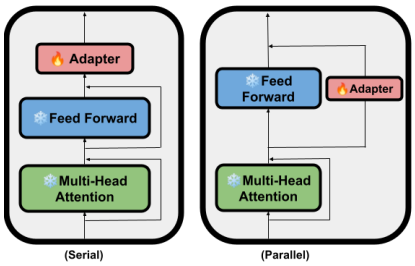


Figure 5.2: Transformer block with various residual adapter configurations. Normalisation layers are not display in this figure

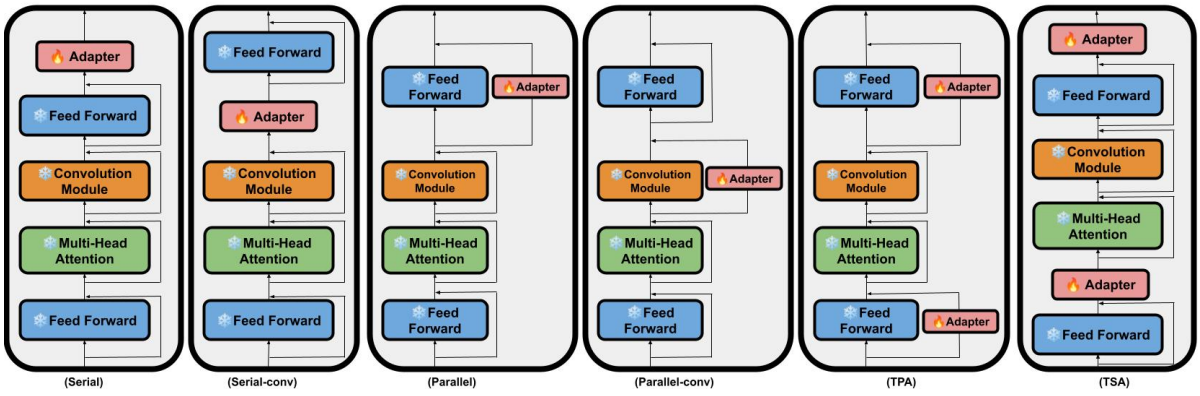


Figure 5.3: Conformer block with various residual adapter configurations. Normalisation layers are not display in this figure

adapting large-scale models to the unique characteristics of children's speech.

5.3 Investigating ASR for Child Speech with Adapters

In this section, we delve into the application of Adapter-transfer as PETL for both Transformer and Conformer architectures in the domain of children's ASR. Building upon our findings from the previous chapter, where we identified the FFN modules as the most relevant component to fine-tuning in a Transformer-based model, we opt to leverage Adapters for modifying the output of these FFN modules. Additionally, considering our results that underscore the significance of fine-tuning the Encoder, our primary emphasis will be on investigating the implementation of Adapters within the Encoder. Specifically, for the Transformer architecture, we investigate two integration methods: parallel and serial placement with the FFN component. Such configurations were used in prior work [252] and are depicted in Figure 5.2.

In the case of the Conformer architecture, we explore six distinct Adapter configurations, as illustrated in Figure 5.3. The initial two configurations mirror our Transformer investigation, involving both parallel

and serial placements, either after or in parallel with the second FFN layer [245]. Additionally, we assess a configuration that introduces an Adapter following the convolution module, denoted as the "serial-conv" setup used in [246]. Notably, although the FFN component has been identified as the most crucial for fine-tuning, promising results have also been observed by fine-tuning the convolution modules [245]. Furthermore, [245] introduces two variants of the parallel setup: "parallel-conv," where the Adapter operates in parallel with the convolution module, and "TPA," which deploys two adapters in parallel with both FFN modules in the Conformer layer. This comprehensive exploration of Adapter configurations within both architectures aims to discern the most effective adaptation strategies for children's speech in the context of ASR.

In the case of serial configurations, the integration of adapter information is performed with the preceding component denoted as P. The specific component P varies depending on the configuration and can be either FFN or convolution modules. This integration is realised through the following process:

$$output = Adapter(P(x)) \tag{5.2}$$

where x represents the input of component P.

For parallel configurations, the integration process varies slightly. In this scenario, the adapter's output is combined with the output of component P as follows:

$$output = x + 0.5 \cdot P(x) + (Adapter(x) - x) \tag{5.3}$$

where x is the input of component P.

To comprehensively explore all feasible configurations, we introduce two novel setups. The first one is referred to as "Two Serial Adapters" or "TSA," where two Adapters are sequentially positioned after each FFN component in all layers. The second configuration combines TPA and TSA, resulting in the integration of four Adapter modules both in parallel and serially at the two FFN modules level.

Moreover, we consider three distinct configurations where Adapters are placed in the Decoder. It is important to note that in the Conformer architecture, the decoder is a regular Transformer. Therefore, we evaluate the "Serial" and "Parallel" setups. Subsequently, we investigate the combination of the most effective encoder Adapter configuration with both Decoder configurations. To the best of our knowledge, there is no prior research that formally investigates the influence of Adapters within an ASR decoder.

Finally, motivated by the observed strong correlation between children's speech variability and age, we explore the possibility of training specialised Adapters. However, considering the high inter-speaker variabilities in children's speech, using age directly may not effectively capture children with similar acoustic characteristics. Additionally, in many children's speech datasets, precise age information is often not provided. To address this, we partition the training dataset into groups of speakers with similar

acoustic characteristics based on unsupervised clustering. In practice, we apply a k-means clustering algorithm on the x-vector representation [253] of all training utterances. Subsequently, distinct Adapters are trained for each speaker cluster separately. During the testing phase, the closest clusters of group of speaker is determined for each test utterance, and the corresponding Adapters specific to that group are employed for decoding.

The primary objective of these experiments is to investigate whether Adapters trained on comparable speech characteristics yield improvements over a general Adapter on the entire training set. Indeed, children's speech is inherently atypical and displays a significant degree of variability, making it imperative to assess the efficacy of existing methods. In prior work, different configurations were employed resulting in a lack of standardised evaluation.

5.4 Implementation details

All experiments were performed using the SpeechBrain toolkit [239]. We used 12 Transformer or Conformer layers for the encoder, for the Transformer and Conformer model respectively, and 6 Transformer layers for the decoder, all with dimensions 512. These models have been pre-trained using the LibriSpeech dataset [31] and are publicly available[1] [2]. Furthermore, for all of our experiments, we used the same Transformer language model, trained on 10 million words on the LibriSpeech transcriptions. The adapter architecture consists of a first linear layer projection to dimension 512 with a ReLu activation, followed by another linear layer projection to dimension 512 with a residual connection of the adapter input. For all Adapters, in the initialisation process, we set W_{down} to all zeros, and W_{up}, b_{down}, b_{up} are initialised using Xavier initialisation [254].

The use of a hidden-dimension size equal to the model size (instead of a bottleneck) was motivated by previous research exploring hidden-dimension size, that consistently demonstrated that larger dimensions tend to yield improved performance scores [245]. All models were trained for 30 epochs, with a learning rate of $8 \cdot 10^{-4}$ for Adapters experiments and of $8 \cdot 10^{-5}$ for fine-tuning the entire model. For the clustering experiments, we use the k-means clustering algorithm on the speaker-embedding of each utterance. The speaker embeddings were extracted using a publicly pre-trained ECAPA-TDNN model, trained on adult speech[3].

Table 5.1: Results of the different Adapters configurations in both Transformer and Conformer.

Method	WER ↓	Trained params
Transformer		
Frozen	25.04%	-
Full fine-tuning	12.99%	71.5M
Serial	12.78%	6.3M
Parallel	**12.62%**	6.3M
Conformer		
Frozen	21.75%	-
Full fine-tuning	12.28%	109.1M
Serial	11.76%	6.3M
Serial-Conv	11.78%	6.3M
Parallel	11.72%	6.3M
Parallel-conv	11.79%	6.3M
TPA	**11.58%**	12.6M
TSA	11.75%	12.6M
Serial (Decoder)	18.09%	3.2M
Parallel (Decoder)	17.76%	3.2M
TPA + Parallel (Decoder)	**11.47%**	15.8M

5.5 Results

5.5.1 Configurations

In this section, we present a comprehensive evaluation of Adapter configurations applied to both Transformer and Conformer models, assessing their performance based on Word Error Rate (WER), as presented in Table 5.1. First, we assess the Transformer model when no fine-tuning was applied (*Frozen*), resulting in a WER of 25.04%. Conversely, *Full Fine-Tuning* involved complete fine-tuning of the entire model, working as our baseline system , reducing the WER significantly to 12.99%, at the expense of 71.5 million trainable parameters. Turning to the Adapter setups, we investigate the "Serial" and "Parallel" configurations, both equipped with 6.3 million trainable parameters. The "Parallel"emerged as the best configuration, achieving the lowest WER of 12.62% compared to 12.78% for the "Serial". These results underscore the effectiveness of Adapter configurations within the Transformer architecture, as they both perform slightly better than the full-finetuning.

Next, we investigated the Conformer model, we once again explored *Frozen* and *Full Fine-Tuning*. In *Frozen* the pre-trained model remained untouched, yielding a WER of 21.75%. The Full fine-tuning, in a similar way as the Transformer, led to enhanced performance, reducing the WER to 12.28% with a total of 109.1 million trainable parameters. We can observe that given the same pre-training dataset, the

[1]https://huggingface.co/speechbrain/asr-transformer-transformerlm-librispeech
[2]https://huggingface.co/speechbrain/asr-conformer-transformerlm-librispeech
[3]https://huggingface.co/speechbrain/spkrec-ecapa-voxceleb

Table 5.2: Results of the clustering approach.

# of clusters	Average WER ↓
1	11.58%
2	**11.50%**
3	11.57%
4	11.51%

Conformer architecture outperforms the regular Transformers. Within the set of adapter configurations, "Serial" achieved a WER of 11.76%, while "Parallel" demonstrated slightly better performance with a WER of 11.72%. These results indicated that "Parallel" Adapters were more effective in improving WER in the Conformer model. When Adapters are placed after the convolution layer, with the "Serial-conv" and "Parallel-conv" configuration, both slightly under-perform compared to Adapters placed after the second FFN component with respective scores of 11.78% and 11.79%. Finally, we evaluated the "TPA" and "TSA" configurations. The "TPA" configuration emerged as the most promising, with a very remarkable WER of 11.58% using 12.6 million trainable parameters, while "TSA" achieved a WER of 11.75%, which is slightly under-performing compared to the "TPA" configuration.

In addition, we evaluated the use of Adapters in the decoder. As the decoder of the Conformer architecture is a regular Transformer, we only evaluate the "Serial" and "Parallel" setup, which respectively reached 18.09% and 17.76% WER with 3.2 million parameters. Results showed that Adapters are more relevant when plugged into the encoder. It confirms that acoustic variability plays a critical role in the degradation of children's ASR performance. Finally, combining "TPA" in the encoder layers with "Parallel" Adapters in the decoder outperforms Adapters in the encoder only, with 11.47% WER. Consequently, this configuration stands as the most effective model.

We performed statistical tests (Matched Pairs Sentence-Segment Word Error) across all Adapter setups in comparison to the full fine-tuning configuration using SCTK, the NIST Scoring Toolkit [4]. The results reveal that, in all scenarios, the p-value is less than or equal to 0.001. This observation denotes statistical significance, indicating evidence against the null hypothesis.

These results collectively illustrate the versatility and effectiveness of different Adapter configurations within the Transformer and Conformer model for the children's ASR task. "TPA" Adapters in the Encoder combined with "Parallel" Adapters in the Decoder showcased outstanding performance, highlighting their potential as a fine-tuning replacement in large model children ASR scenarios.

5.5.2 Unsupervised Clustering of utterances

In this section, we present the outcomes of our clustering approach, as summarised in Table 5.2. The investigation focused on the influence of varying the number of cluster on the ASR performance, ranging from 1 to 4 clusters, using the "TPA" configuration in an encoder-only setup. First, when the data remained unclustered (one cluster), the ASR system exhibited a WER of 11.58%. Notably, the two-cluster configuration outperformed the other setups, achieving a superior performance with a WER of 11.50%. This result suggests that partitioning the data into two distinct clusters allows the different Adapters to more effectively capture underlying patterns intricately linked to their respective clusters, consequently enhancing the recognition scores. Furthermore, we explored the impact of increasing the number of clusters to three and four, revealing only marginal differences in performance. Specifically, the three-cluster configuration yielded a WER of 11.57%, and the four-cluster configuration resulted in a WER of 11.51%. These findings underscore the role of data clustering in children's ASR systems by grouping shared speaker characteristics in different clusters.

In summary, our investigation underscores the significance of data clustering in children's ASR systems. The optimal performance was achieved with a two-cluster configuration, suggesting that this approach enables the Adapters to capture cluster-specific patterns effectively. The marginal differences observed with three and four clusters highlight a potential saturation point where further partitioning offers diminishing returns in terms of ASR performance improvement.

[4]https://github.com/usnistgov/SCTK/tree/master

6

Integration of synthetic speech for data augmentation

Contents

6.1 Introduction

As mentioned in Chapter 2, the ongoing advancements in deep learning, coupled with the availability of extensive training datasets, have undeniably improved the performances of ASR. However, despite these remarkable advancements, the recognition of children's speech remains a domain where performance lags behind that achieved for adult speech. Children's speech introduces distinct challenges owing to its inherent variability influenced by age, linguistic development, and articulatory differences. Therefore, there is a growing need acquiring a sufficiently diverse and extensive dataset for training children's ASR systems.

However, practical constraints, including ethical considerations, privacy concerns, the high cost of data collection, and the challenges posed by children's limited attention span and inconsistent adherence to prompts during reading tasks, hinder the creation of such datasets. In an effort to address this performance gap, researchers in [39] leveraged an in-house sizable dataset of children's speech, comparable in scale to an adult corpus, to train an ASR model. The outcomes showcased state-of-the-art performances, emphasizing the potential of ASR networks to effectively learn from diverse and variable children's speech data when provided with a substantial amount of training data.

As an answer to the challenges of collecting real childen's speech data, an alternative strategy emerged, involving the generation of synthetic datasets using a Text-to-Speech (TTS) model. TTS offers a solution to bypass to the challenges associated with collecting and annotating real children's speech data. While some studies have explored the application of TTS for ASR, either through direct use of synthetic speech for training or as a form of data augmentation [135,255], synthesising children's speech introduces a unique set of challenges. The inherent substandard and imprecise pronunciation in children's speech [136] poses a hurdle, raising concerns that using synthetic data directly may lead to a decrease in performance [136,256].

In this chapter, we introduce a novel technique known as "Adapter Double-Way Fine-Tuning" to enhance ASR models specifically tailored for children, even in scenarios where imperfect data augmentation is employed. Our approach involves the integration of additional Adapter modules into the existing ASR model during the fine-tuning process. As demonstrated in the preceding chapter, Adapters have proven to be efficient in transferring knowledge for children's speech, thereby serving as a parameter-efficient means of knowledge transfer. Building upon the efficiency of Adapters in the realm of children's speech, we hypothesise that these adapters can be further leveraged to mitigate the domain mismatch between real and synthetic data. We accomplish this through a two-step training procedure in a similar way as the methodology proposed in [172].

In the initial step, the Adapters are exclusively trained using synthetic data, while the pre-trained model remains frozen. This phase enables the adapters to specialise in handling the nuances introduced by synthetic data. Subsequently, in the second step, we perform fine-tuning, involving both the trained adapters and the entire model. During this fine-tuning process, a combination of synthetic and real

data is used. Notably, our approach introduces a crucial distinction between synthetic and real data throughout the fine-tuning process. Synthetic data traverses through the adapter layers, allowing the synthetic characteristics to be handle by the Adapters while still contribute to the full model, while real data bypasses these Adapters. We hypothesise that this meticulous differentiation could enables the effective use of imperfect synthetic data, ultimately leading to an enhancement in ASR performance tailored for children.

6.2 Enhancing ASR Performance through TTS Data Augmentation

The progression of TTS systems, achieving human-like quality, presents a valuable avenue for effective TTS-based data augmentation in ASR. This approach, as exemplified in studies such as [135], involves the generation of synthetic speech from text using TTS models. The synthetic speech is then combined with real speech during the training process, leading to notable performance enhancements. Importantly, this approach is not limited to well-resourced tasks and has demonstrated success even in low-resource scenarios, as illustrated in [257]. However, despite its efficacy, TTS-based data augmentation offers only modest improvements, primarily owing to the persistent challenge of domain mismatch between synthetic and real speech, indeed, even with human-like quality, some generated utterances suffer artefacs or wrong modelisation. The inherent differences between the characteristics of synthetic and real speech limit the extent to which the benefits of TTS augmentation as ASR data augmentation.

In order to mitigate the mismatch with real data and to reduce speaker dependency, the use of discrete intermediate representations both shared by the TTS and ASR systems instead of Mel-scale filterbanks, obtained with a VQ-wav2vec, has been proposed in [258]. This approach has demonstrated promising results. However, it is essential to note that implementing such a strategy necessitates training both the ASR and TTS systems from scratch. This requirement may pose challenges, particularly in the context of low-resource ASR scenarios

An alternative approach to address the domain mismatch between synthetic and real speech rely on data selection techniques, as proposed by [136]. This approach focuses on selectively choosing high-quality synthetic speech data to mitigate the challenges associated with imperfect data augmentation. The data selection process ensures that only the most reliable and accurate synthetic speech samples are incorporated during the augmentation process. One advantageous aspect of this work is that it does not necessitate more complex training for the TTS or ASR system. Instead, it operates as an off-the-shelf selection on top of the TTS system. This characteristic underscores the practicality and ease of it integration into existing TTS systems. In [136], they demonstrated the effectiveness of employing i-vector speaker-embedding cosine similarity between reference and generated utterances as a metric for

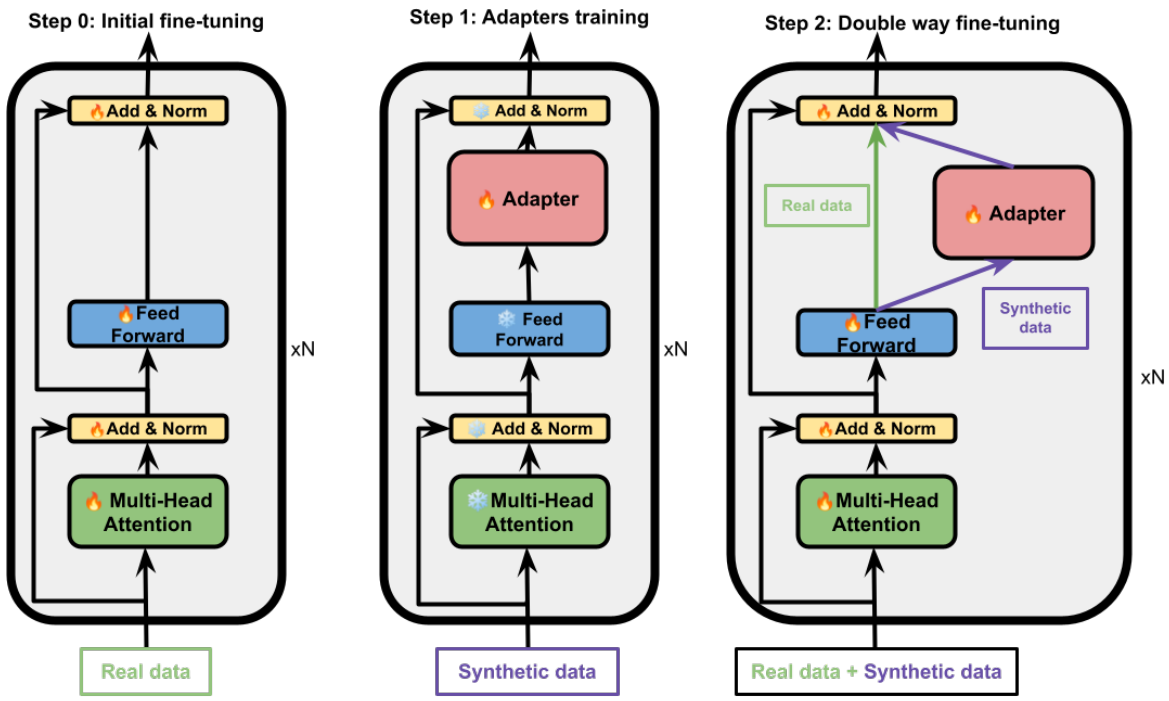


Figure 6.1: Overview of "Double way Adapter fine-tuning" within th context of an Transformer model

data selection. This metric was compared to other metrics such as error rate, acoustic posterior, and synthetic discriminator.

More recently, [256] introduced the Synth++ framework, which employs a similar data selection approach, called rejection sampling. This rejection sampling method relies on the output of a DNN, which is trained on a 5-dimensional features vector derived from a pre-trained ASR model. The goal of this DNN is to discriminate either the data is real or synthetic. To this end, the 5-dimensional features vector for each utterances encompass cross-entropy loss, CTC loss, WER, lengths of tokens in the predicted text and the length of tokens in the target text. In addition to rejection sampling, Synth++ introduces the use of separate batch normalisation for real and synthetic data. During the training process, when synthetic data is fed into the model, it undergoes distinct normalisation layers. The incorporation of this separated normalisation has been demonstrated to significantly reduce the mismatch between real and synthetic data during training, leading to notable improvements in WER scores.

6.3 Closing the synthetic and real mismatch gap with Adapters

The effectiveness of Adapters in the existing literature for both speech and NLP tasks has been well-documented [242, 259, 260]. Additionally, the positive results detailed in Chapter 5, where Adapter modules were proven effective for children's ASR, underscore their pivotal role in mitigating the mismatch between a source model and a target task. Proving that Adapters are capable of capturing task-relevant

information, while the frozen pre-trained model retains valuable insights about the source task.

In alignment with these findings, [172] introduced the Domain Responsible Adaptation and Fine-Tuning framework (Draft) for children's ASR. The authors aimed to reduce the mismatch between adult and children speech data in SSL models by incorporating Adapters and an additional adaptation phase. Leading to improved performances.

Motivated by the successes of the Draft framework and Synth++, our approach integrates Adapter modules as a substitute for the separate normalisation layers present in the Synth++ framework. Furthermore, we incorporate the multiple-step adaptation and the use of Adapters from the Draft framework. Finally, we employed filtered synthetic data, implementing a speaker-embedding cosine similarity metric to retain synthetic utterances that exhibited high-quality generation as pproposed by previous work on data selection for TTS data augmentation. This combination forms a novel strategy to address the domain mismatch in ASR for children's speech, called "Double-way Adapter tunning" (DWAT).

Our primary goal is to inject external knowledge of synthetic children's speech into a pre-trained ASR model using Adapters. This approach allows us to preserve the real children's speech knowledge acquired during pre-training while separately modeling the synthetic characteristics within the Adapter modules. Therefore, Adapters serves as a bridge, that can effectively reducing the domain mismatch between real and synthetic speech data during the training of ASR models for children using a combination of real and synthetic data.

In our DWAT methodology, as illustrated in Figure 6.1, we introduce two additional steps following the standard ASR model training with children's data (Step 0). Step 1 involves the standard training of Adapter modules, as explained in the previous chapter. While keeping the pre-trained ASR model parameters fixed, the Adapter weights are trained on the target data, here TTS utterances. These Adapter modules are strategically placed after the transformer layers' Feed-Forward Network (FFN) component. The goal is to learn a projection that aligns synthetic children's speech with real children's speech within each transformer layer. This approach allows the model to retain knowledge about children's speech, while the Adapters aim to capture the synthetic characteristics of the different TTS utterances. This step is crucial, as Adapter modules require this learning process. Without it, the subsequent fine-tuning in Step 2 could be more challenging and less effective. In Step 2, we fine-tune both the Adapters trained in Step 1 and the entire pre-trained ASR model using a mix of synthetic and real data. A pivotal aspect of our approach lies in how we handle data flow within the model. Real samples bypass the Adapter modules as they do not need further adjustments, directly passing through the original ASR model components. In contrast, synthetic data goes through the Adapters for necessary modifications to better align with real children's speech characteristics. This differential treatment of data optimises Adapter usage, potentially enhancing the overall performance of the ASR system. During the inference phase, the Adapter modules become unnecessary and are discarded since the test data only contains real

samples and the training is already complete. It is essential to note that Steps 1 and 2 can be iteratively repeated with newly generated synthetic data. However, it's important to highlight that this aspect is not thoroughly investigated in this work and serves as a subject for future research. The potential iterative repetition of these steps could provide insights into the adaptability and generalisation capabilities of the proposed Double-Way Adapter Tuning methodology.

In summary, our proposed approach use Adapter modules to enhance the performance of a pre-trained ASR model through the incorporation of synthetic data augmentation. This innovative methodology, known as DWAT introduces a two-step process involving the training of Adapter and subsequent fine-tuning with a mix of synthetic and real data in order to bridge the domain gap between real and synthetic children's speech.

6.4 Experimental settings

6.4.1 Transformer architecture for ASR

In our experiments, we employed the SpeechBrain toolkit [239] for the ASR component of our system, using a pre-trained Transformer model[1]. This model has trained on the LibriSpeech dataset [31] and comprises 12 encoder layers and 6 decoder layers, each with a dimension of 512. It is noteworthy, that is model is different from the ones used in previous Chapters. A mix of sequence-to-sequence and CTC loss where used with respective weight of 0.7 and 0.3. Additionally, we integrated a Transformer language model trained on a 10 million-word transcriptions of Librispeech.

6.4.2 Multi-speaker text-to-speech: YourTTS

In this work as TTS component, we used the pre-trained YourTTS model[2] proposed by [8] based on the Coqui toolkit. YourTTS is a zero-shot multi-speaker and multilingual TTS system that is built upon the Variational Inference with adversarial learning for end-to-end Text-to-Speech (VITS). It incorporates several novel modifications to enable zero-shot multi-speaker and multilingual synthesis. An overview of the YourTTS architecture is presented in Figure 6.2. YourTTS featuring a 10-layer Transformer-based text encoder with 196 hidden channels. This encoder, adaptable for multilingual use, employs a 4-dimensional language embedding concatenated with the embedding of each input character. However, for the purpose of our experiment, the model use exclusively the English language. The decoder comprises four affine coupling layers [261], each incorporating four WaveNet blocks [262] to ensure high-quality speech generation. The model also use the HifiGAN vocoder [263]. Notably, YourTTS adopts an end-to-end approach, connecting the vocoder to the TTS model through a variational autoencoder (VAE) [264].

[1] https://huggingface.co/speechbrain/asr-transformer-transformerlm-librispeech
[2] https://coqui.ai/blog/tts/yourtts-zero-shot-text-synthesis-low-resource-languages

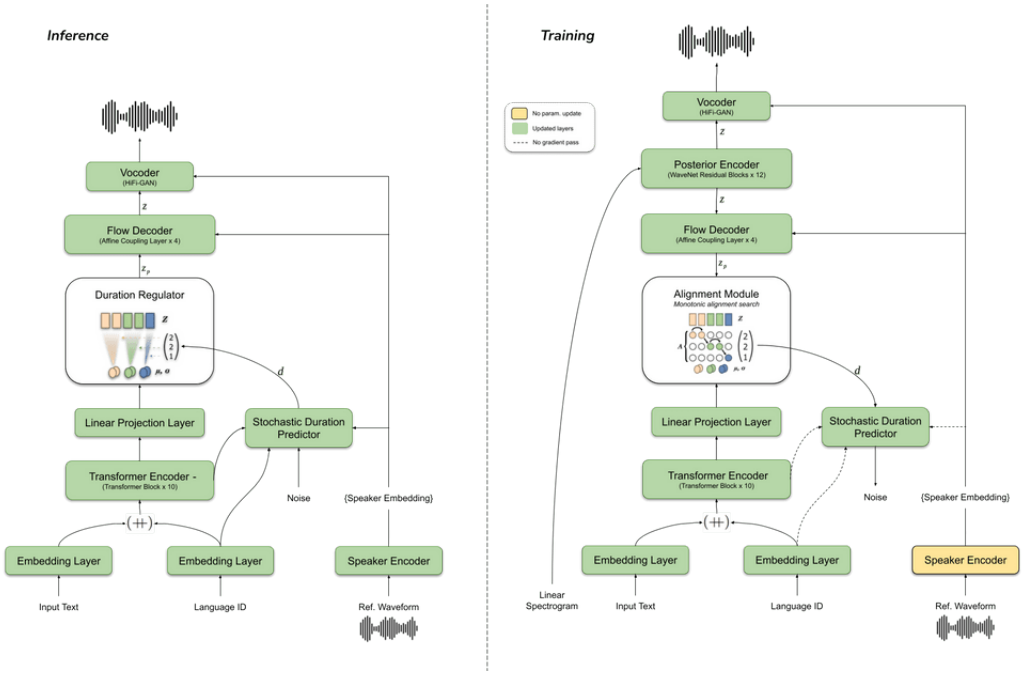


Figure 6.2: Architecture of the YourTTS model taken from [8]

To enhance its capabilities as multi-speaker and zero-shot TTS system, YourTTS integrates a speaker encoder, specifically the H/ASP speaker encoder [265], generating 512-dimensional speaker embeddings for each utterances. This speaker encoder models is compromising a CNN layers, followed by four Resnet layers [123], a attentive statistic pooling and a output linear layer. These embeddings serve as reference speakers for the model, enabling zero-shot multi-speaker capabilities. To give the model zero-shot multi-speaker generation capabilities, the authors conditioned all affine coupling layers of the flowbased decoder, the posterior encoder, and the vocoder on external speaker embeddings. Additionally, a speaker consistency loss (SCL) is added to the loss to further enhance the multi-speaker ability of the model. The SCL is formally expressed as follows:

$$L_{SCL} = \frac{-\alpha}{n} \cdot \sum_{i}^{n} cos\_sim(\phi(g_i), \phi(h_i)) \tag{6.1}$$

where let $\phi(\cdot)$ is the function outputting the speaker embeddings, cos_sim is the cosine similarity function, α is a positive real number controlling the influence of the SCL in the final loss, n is the batch size and g and h represent, respectively, the ground truth and the generated speaker audio.

The YourTTS model was trained using three languages: English with VCTK [266], Brazilian Portuguese with TTS-Portuguese Corpus [267], and French with the French set of the M-AILABS dataset [268]. This training corpus totaled 229 hours of speech data and involved 115 speakers. For a more in-depth understanding of the YourTTS architecture and training process, detailed information can be

found in the original paper [8].

6.5 Experimental setup

6.5.1 Real speech corpus

Table 6.1: My Science Tutor Children Speech Corpus statistics

	Training	Validation	Test
# of utterances	60897	10044	4079
# of speakers	566	79	91
# of hours	113	18	13

In this study, we used the My Science Tutor (MyST) Children Speech Corpus, referred to as the "Real" set. This corpus contains around 400 hours of speech collected from 1,372 students in grades three to five. It comprises conversations with a virtual tutor spanning eight scientific domains. Notably, only 45% of the utterances in the corpus are transcribed. For our experiments, we filtered out utterances shorter than one second and longer than 30 seconds due to GPU memory constraints. Additional details on the filtered corpora are provided in Table 6.1.

6.5.2 Synthetic data

To address the potential performance gap caused by the YourTTS model being trained solely on adult data and never exposed to children's data, we initiated the process by fine-tuning the YourTTS model using the MyST training set. In this study, two TTS systems were developed, each with distinct parameter settings, to examine their respective performances and outputs quality under varying conditions. Two TTS systems, TTS_1 and TTS_2, were developed with distinct parameter settings. The first model, called TTS_1, underwent fine-tuning for 250 epochs, focusing without incorporating the speaker encoder SCL loss. In contrast, the second system, labelled TTS_2, was fine-tuned for 50 epochs, incorporating the speaker encoder SCL loss. This incorporation should improve the alignment between the generated speech and the reference speaker embedding provided to the model. These variations in training strategies enable a thorough examination of the model's performance and output quality under varying conditions,

The first TTS model, TTS_1, was used to generate 300 hours of synthetic data referred to as $Synth_1$. The second TTS model, TTS_2, was employed to generate a larger volume of synthetic data, up to 1,000 hours, denoted as *Large* $Synth_2$. To compare the performance of TTS_1 and TTS_2, a subset of 300 hours was extracted from the *Large* $Synth_2$ dataset, called $Synth_2$. The full 1,000-hour set was exclusively used to evaluate the impact of different amounts of synthetic data, both with reduced and increased amount.

The speech synthesis process using the YourTTS model demands both a text transcription and a speaker-embedding vector to generate a synthetic utterance. Therefore, to generate each utterances in both *Synth*$_1$ and *Large Synth*$_2$, we randomly selected two utterances from the Myst training set, one designated for extracting the speaker embedding and the other exclusively used for its text transcription. The Myst training set, comprising a substantial 60,897 utterances, resulted in a vast pool of potential combinations, totaling 3,708,444,609. This extensive range of possibilities was strategically harnessed to introduce a deliberate mismatch between the selected speaker embeddings and their associated transcriptions. This intentional large range of possibilities served as a mechanism to infuse novel variability into the synthetic data, thereby introducing characteristics not present in the original real corpus.

The decision to use MyST transcriptions for generating synthetic data was driven by the aim to expose the TTS model to the unique transcription style present in the MyST dataset. This style encompasses elements such as "UM" hesitations. By adopting this strategy, we intended to enhance the model's ability to learn and reproduce the specific transcription characteristics of the MyST data.

To ensure the quality of the synthetic utterances in *Synth*$_1$ and *Large Synth*$_2$, we extended the approach proposed by [136], which involves using cosine similarity between the speaker embeddings of the reference and synthetic utterances as a data selection criterion. However, instead of using i-vector speaker embeddings, we opted for an x-vector approach and employed a different speaker embedding extractor than the one used by the YourTTS model (to prevent conflicts with the SCL loss). Specifically, we used a pre-trained x-vector extractor trained on VoxCeleb[3]. During the generation process, we applied a cosine similarity threshold of 0.75 to discard all poorly generated synthetic utterances. While exploring data selection mechanisms, we considered the rejection sampling method suggested by Synth++ [256] but found it unsatisfactory, ultimately opting for speaker-embedding similarity as the selection criterion. To comprehensively evaluate the impact of this data selection, we also created *Unfiltered Synth*$_1$ and *Unfiltered Synth*$_2$, two 300-hour corpora of synthetic data generated without using speaker embedding data selection, created with TTS$_1$ and TTS$_2$, respectively.

6.5.3 Experiments

We conducted a comprehensive evaluation of our DWAT approach through a series of experiments, comparing it with existing methods. We started the process with baseline models, fine-tuning an pre-trained adult model to children's speech using *Real* data for 20 and 25 epochs (referencing step 0 in Figure 6.1). Subsequently, we evaluated the performance of TTS models using only *Synth*$_1$ and *Synth*$_2$ data. To understand the impact of data filtering, we compared these models trained on filtered data with the unfiltered versions *Unfiltered Synth*$_1$ and *Unfiltered Synth*$_2$. Additionally, we considered the combination of these synthetic datasets with *Real* data. These models underwent training for 20 epochs.

[3]https://huggingface.co/speechbrain/spkrec-ecapa-voxceleb

Method	TTS_1	TTS_2
Real (20 epochs)	12.99%	
Real (25 epochs)	13.15%	
Real + Unfiltered *Synth*	13.41%	13.24%
Real + *Synth* [136]	13.09%	12.98%
Synth alone	40.58%	40.21%
Two step adaptation	13.49%	13.46%
Norm double-way (from adult)	12.89%	13.04%
Norm double-way (from children)	13.56%	13.87%
DWAT (Ours)	**12.42%**	**12.31%**

Table 6.2: Results of the different approaches (in WER).

We also explored the application of double-way normalisation, inspired by Synth++ [256]. In one scenario, we fine-tuned the adult model for 20 epochs using a mix of filtered synthetic and real data with double-way normalisation (*Norm double-way from adult* in Table 5.1). In another scenario, we trained the double-way normalisation model for 5 epochs with the baseline model as initialisation, referred to as *Norm double-way from children*.

Finally, we implemented our *DWAT* approach, training the models for 5 epochs with the baseline model as initialisation. Various hyper-parameter configurations will be explored in section 6.6.

6.6 Results and discussion

6.6.1 Comparison with existing approaches

Table 6.2 present the results of the various approaches. The baseline models, obtained by fine-tuning an adult model on children's speech using *Real* data, achieved a WER score of 12.99%. However, extending the training to 25 epochs resulted in an overfitting and a subsequent reduction in performance score with 13.15% WER. Moving to the impact of incorporating unfiltered synthetic data, denoted as *Unfiltered* $Synth_1$ and *Unfiltered* $Synth_2$, as opposed to their filtered counterparts $Synth_1$ and $Synth_2$, in conjunction with *Real*. We observed that the inclusion of filtering presented a notable 2% enhancement in WER when compared to the unfiltered counterparts. However, relying solely on filtered TTS speech (*Synth* alone) without any *Real* data, resulting in a substantial 40% WER on the *Real* test set for both TTS_1 and TTS_2. This discrepancy underscored the considerable domain mismatch between real and synthetic data, signaling the imperative need for further approaches to mitigate this gap. Furthermore, we delved into a two-step adaptation process where we initially fine-tuned the adult model using only *Synth* data, followed by a subsequent fine-tuning with *Real* data. However, the results indicated a slight decrease in performance in both cases, with WER scores of 13.49% and 13.46%, respectively. This decline could be attributed to the gap between the characteristics of TTS data which may be bigger than the original adult data.

Amount of TTS data	WER
0h	12.99%
10h	12.73%
50h	12.54%
100h	12.49%
300h	**12.31%**
600h	12.57%
1000h	13.14%

Table 6.3: Results of the different number of hours influence in our DWAT approach with *Large Synth*$_2$ data

During our experiments, the use of double batch normalisation proved ineffective in enhancing the baseline model's performance. Instead, it led to a 5% relative decrease in WER performance when evaluated with the baseline model as initialisation (from children). When training from the adult model, the results were consistent with the baseline models, with no observed improvement. These results underscore the limitations of double batch normalisation in addressing the domain mismatch between real and synthetic speech data within a Transformer model. This highlights the importance of exploring alternative strategies to effectively bridge the gap. Our proposed DWAT approach, initiated with the baseline model (step 0 in Figure 6.1), emerged as the most effective among all methods examined. It demonstrated a notable 4% and 5% relative improvement in WER over the baseline when evaluated on *Synth*$_1$ and *Synth*$_2$ respectively. This outcome highlights the efficacy of our approach compared to longer training on the *Real* set, showcasing its potential in mitigating the challenges posed by domain mismatch in the context of Automatic Speech Recognition systems.

6.6.2 Influence of synthetic number of hours

Given the potential of our approach to generate a theoretically "infinite" amount of TTS data, our primary objective is to conduct a comprehensive exploration of the impact of varying data quantities on the efficacy of the DWAT approach. To achieve this, we assess the influence of different quantities of synthetic data from *Large Synth*$_2$, as detailed in Table 6.3. The findings from our investigation reveal that utilising a small quantity of synthesised speech, ranging from 10 to 50 hours, results in limited improvements in ASR performance. Conversely, an excessive volume of TTS data, spanning from 600 to 1,000 hours, has the potential to introduce undesirable noise into the system. Consequently, achieving an optimal equilibrium, typically within the range of 100 to 300 hours, becomes crucial. This balance aims to enhance robustness in ASR performance while concurrently preventing the introduction of excessive noise, thereby maximising the effectiveness of the DWAT approach.

Location	Bottleneck size	5 epochs	20 epochs
Encoder	64	12.58%	12.24%
Encoder	128	12.31%	12.45%
Encoder	256	**12.25%**	12.32%
Encoder	1024	12.42%	**12.22%**
Encoder	2048	12.57%	12.47%
Encoder-Decoder	128	12.45%	12.48%
Skip step 0	256	12.30%	-
Skip step 0 and 1	256	13.28%	-

Table 6.4: Results of the different configurations of Adapter double-way approach on 300h of $Synth_2$

6.6.3 Impact of DWAT different hyper-parameters

To thoroughly evaluate the robustness of our approach, we conducted experiments with the DWAT in various configurations. This comprehensive analysis involved exploring different Adapters's bottleneck sizes, ranging from 64 to 2048, varying the number of training epochs (5 and 20), investigating the integration of Adapters in the decoder of the transformer model, and performing an ablation study by skipping step 0 and both step 0 and 1 in the DWAT process.

The summarised results in Table 6.4 provide insights into the optimal configuration, revealing that the most effective setup uses Adapters with a size of 1024 in the encoder only, coupled with 20 training epochs. This configuration resulted in a remarkable 6% relative WER reduction compared to the baseline. Notably, all configurations demonstrated superior performance to the baseline, underscoring the overall effectiveness of our DWAT approach.

Our observations indicate that extended training periods were particularly advantageous for larger Adapter bottleneck sizes, demonstrating no signs of overfitting. Moreover, the integration of Adapters into the decoder did not lead to a significant improvement in results. This outcome can be attributed to the higher acoustic variability and the fact that the same transcriptions from the Myst dataset were used for synthetic speech utterances. Lastly, skipping step 0 (pre-training) did not result in a significant degradation in performance. However, when both step 0 and step 1 (pre-training and Adapter pre-training) were skipped, performance degradation occurred, underscoring the critical role of Adapter pre-training phase (step 1) in achieving good performances.

6.6.4 Extension DWAT to the Conformer architecture

Building upon the favorable results observed in previous chapters, which indicated that the Conformer model outperformed the regular Transformer for ASR tasks, the effectiveness of Adapters in Conformer and considering that Synth++ [256] was originally designed for the Conformer architecture, we decided to evaluate our DWAT within the Conformer architecture. Given that the TPA configuration of Adapters proved to be the most effective, we chose to implement it in our DWAT for the Conformer architecture.

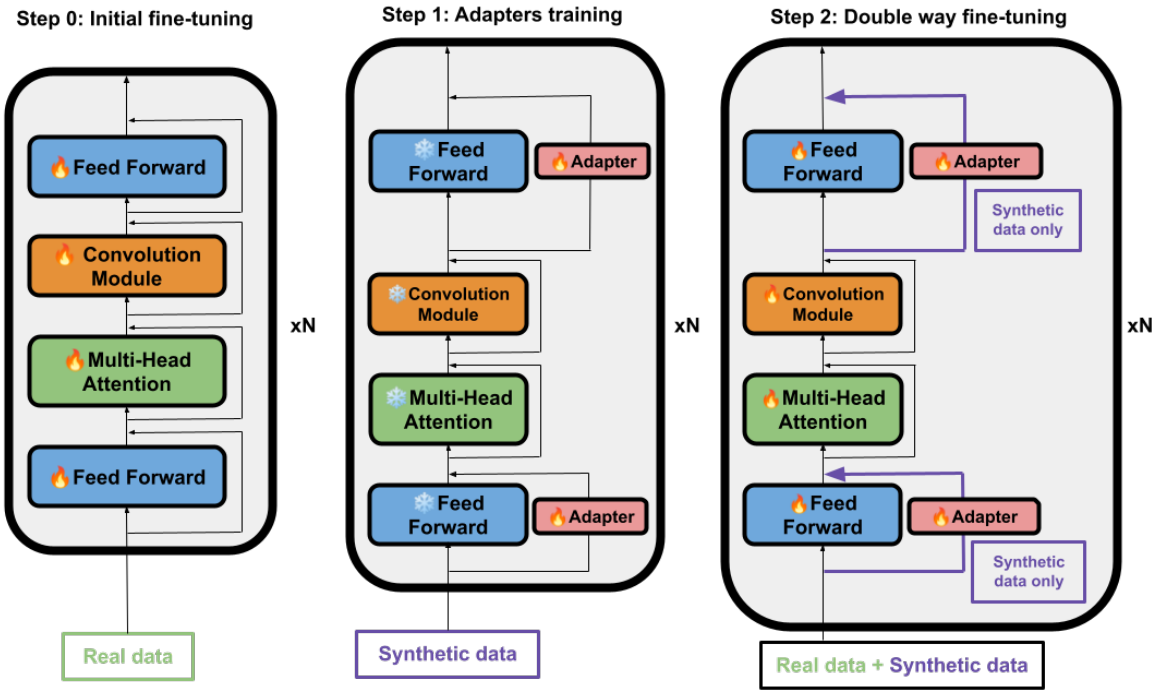


Figure 6.3: Overview of "Double way Adapter fine-tuning" within th context of an Conformer architecture

The DWAT with TPA is illustrated in Figure 6.3.

In this experiment, we employed the same pre-trained adult Conformer model used in previous chapters. This model comprises 12 layers of Conformer layers for the encoder, followed by 6 Transformer layers for the decoder, all with a hidden dimension of 512. The language model used is consistent with the experiments conducted with the Transformer model in the previous sections. Motivated by the insights gained from the exploration of hyperparameters in section 6.6.3, we opted for Adapters of size 512 in the Encoder only, using the TPA configuration. In term of training, Step 0 and step 1 were trained for 30 epochs while step 2 only used 10 epochs.

Method	WER Score ↓
Adult model	21.75%
Real only	12.28%
Unfiltered $Synth_2$	37.85%
Unfiltered $Synth_2$ + *Real*	12.30%
$Synth_2$ alone	31.72%
$Synth_2$+ *Real*	12.02%
Two step adaptation	12.51%
Synth++ (norm double way)	11.80%
DWAT	**11.64%**

Table 6.5: Scores for the different methods within the Conformer architecture

The results obtained from the extension of DWAT experiments using the Conformer architecture are

presented in Table 6.5. The frozen adult model, referred as the Adult model, achieved a WER score of 21.75%. When considering only real data (Real only), the WER score improved significantly to 12.28%. Which is already outperforming the best results of the Transformer.

When using unfiltered synthetic data alone (*Unfiltered Synth*$_2$) method, it resuted in a higher WER score of 37.85%, showcasing, once again, the mismatch between synthetic and real data. However, when combined with real data (*Unfiltered Synth*$_2$ + *Real*), the result are close to the real baseline with a WER score of 12.30%. Similarly, using the filterd *Synth*$_2$ alone resulted in a WER score of 31.72%, but when combined with real data (*Synth*$_2$ + *Real*), the WER score decreased significantly to 12.02%. This differ from the results observed in the Transformer architecture, as data filtering improved the WER score compared to the baseline. Similarly to the Transformer, the two-step adaptation method yielded a WER score of 12.51%.

Further insights into the performance of the more sophisticated methods are provided in the context of the Conformer architecture. Specifically, the Synth++ method, which incorporates separated batch normalisation within each Convolution module for TTS data, achieved a WER score of 11.80%. This contrasts with the results observed in the Transformer experiment, highlighting the efficiency of this approach specifically within Conformer models. In the other hand, the DWAT method consistently outperformed all other methods, showcasing a remarkable WER score of 11.64%. These findings emphasise the effectiveness of both the Synth++ and DWAT methods in enhancing the Conformer architecture's performance on the given task.

It is important to highlight that while both Synth++ and DWAT demonstrate efficacy within the Conformer setup, the DWAT approach consistently outperforms other methods in both Transformer and Conformer configurations. This consistent superiority underscores the relevance and robustness of the DWAT approach in improving the overall performance of the models across different architectures.

In summary, the experimental results demonstrate the effectiveness of leveraging synthetic data, real data, and advanced adaptation methods within the Conformer architecture. The DWAT method, in particular, stands out as the most successful approach in minimising the WER.

6.7 Conclusions and future work

We introduced the combined use of Adapters and synthetic data augmentation for children's speech recognition. Our two-step training procedure, involving training Adapter layers using synthetic data and subsequent fine-tuning of Adapters and the entire model with a combination of synthetic and real data, yielded improvements over the baseline and previous approaches in various configurations. or future work, we will explore an iterative approach with newly generated TTS data and varying the amount of real data used.

6.8 Ongoing and future work

In order to answer the following research questions: *Is it possible to develop an age-based, parameter-efficient automatic speech recognition model?; Is it possible to use children's synthetic speech to extend the amount of children's data? How can we control the quality and speakers's variability?; - Given that self-supervised representation based ASR for adults matches or surpasses current state-of-the-art, are these representation appropriate for children's speech?* , we want to pursue three research directions in the future work of this thesis: As a first direction, we want to keep exploring adapter transfer. For example, as proposed by Pfeiffer [269], employing multiple adapters trained on different age groups or children corpus and combining them with an attention mechanism. It may also be interesting to investigate the use of explicit speaker information for robust adapter transfer [270]. Furthermore, as explained in section **??**, Adapter module is structurally similar to an auto-encoder, thus it would be interesting to modify the structure of the adapter to follow the latest development in auto-encoder research. For instance, using neural discrete representations with the help of vector-quantized codebook [271] at the end of the adapter's down-projection.

As a second direction we want to investigate on the use of Text-to-speech (TTS) data augmentation. Indeed, as mentioned in section 2.1.3, one of the most significant obstacles in children automatic speech recognition is the lack of training data. One solution to this problem is voice conversion, in which the adult speech is transformed to child speech and then used for augmentation. However, the modified adult data can only capture a subset of the aspects of children's speech. As a result, it is important to generate children voice data directly from text [136]. A multi-speaker TTS system using speaker embeddings and text as input can be used to produce a synthesized utterance with the variability of child speaker. Indeed, the speaker embedding includes acoustic variability informations, which we want to find in the output utterance [134, 272]. One of the most challenging aspects of this approach is that the TTS model for children produces unequal quality speech due mainly to acoustic variability, and hence the ASR system suffers when trained with this additional synthetic data. Furthermore, because we intend to augment the original data with TTS data, there may be a domain shift that worsens the ASR performance. To address both of these concerns, a speaker embedding-based data selection method has been suggested, based on the computation of the cosine-similarity between the input speaker embedding and the speaker embedding obtained from the output utterance. [136]. More recently, in order to minimise domain shift, two separate normalisation layers have been employed, one for the original data and one for the TTS data. [256]. In our research, we want to combine these two approaches to maximise the contribution of TTS data during training. In addition, we want to investigate whether the use of a GAN [273], which could create an artificial children embedding, could alleviate the problem of the limited number of speakers during training.

7

Alternative approaches to parameter-efficient transfer learning

Contents

7.1 Introduction

In the previous chapters, we demonstrated the efficacy of Adapters, specifically residual Adapters, in diverse tasks related to Children's ASR. These tasks included their uses in PETL for children ASR and as domain mismatch reducer for TTS data augmentation. The success observed in these experiments has prompted a more in-depth analysis of potential alternatives to Adapters. Motivated by the literature where alternative approaches offer superior performances and more parameter-efficient solutions. Indeed, the gowing attention towards PETL from the research community has led the emergence of an array of novel architectures and methodologies. These alternatives extend beyond the conventional Adapters. These innovative approaches have been extensively explored in various domains such as NLP and image processing but remain relatively unexplored in the domains of speech processing and, even more in children's ASR.

The objective of this section is to analyse these emerging PETL methods specifically in the context of children's ASR. Drawing from our prior findings, which underscored the significance of fine-tuning FFN modules, we have curated a selection of PETL approaches designed to be integrated with FFN. Notably, we excluded PETL approaches centered around the MHSA modules, such as LORA, as well as any prompt-related PETL strategies like prompt tuning.

This chapter starts with a in-depth presentation of the selected PETL. Each chosen methodology is thoroughly described, elucidating its underlying principles, architectural intricacies, and key characteristics conpared to the traditional Adapter. Following, we assess the performances of these selected PETL methodologies in the specific context of children's ASR. The evaluation encompasses various dimensions, including performances compared to the full-finetuning and parameter-efficiency. By systematically benchmarking these alternative PETL methodologies against the conventional Adapter models, our objective is to not only understand the individual strengths and limitations of these approaches but also to evaluate their relative effectiveness in tackling the specific challenges presented by children's ASR.

7.2 Exploring literature alternatives

7.2.1 Scaled Adapters

Scaled or Gated Adapters extend the conventional residual Adapters by introducing a scaling mechanism to the output of the Adapter modules. The concept of scaled-Adapters was initially introduced by [274] and is formally expressed as:

$$adapter(x) = x + s \cdot (W_{up}(f(W_{down}g(x) + b_{down})) + b_{up}) \tag{7.1}$$

Here, $s \in \mathbb{R}$ is a tunable scalar hyperparameter. Notably, some research has proposed the to learn directly this scalar value during training as a gate mechanism [260]. The intuition behind this approach is to allow the network to gradually learn to assign weights to the target domain, achieving more fine-grained control of the Adapter activation or deactivation. The scaled learning process facilitates the regulation of contributions from the Adapters from differents layers, enabling the model to adapt and refine its responses based on the specific characteristics of the data encountered during training. Within the context of our experiments, we decided to use a trainable scalar associated to each Adapter modules. This scaling parameters and all Adapter modules were optimised through a 30 epochs training using a learning rate of 8×10^{-4}.

7.2.2 Convolution based Adapters

Convolutional Neural Networks have been widely recognised for their effectiveness in exploiting local information, particularly for computer vision tasks. These networks learn shared kernels based on position within localised windows, giving them the ability to capture features such as edges and shapes. This characteristic has also been demonstrated in the field of speech-related tasks, as demonstrated by the success of the Conformer architecture [223].

As a result of this success, CNNs have been naturaly incorporated into Adapter modules. This strategic fusion enables Adapters to leverage the spatial processing capabilities inherent in convolutional modules, thereby enhancing their capacity to capture and adapt to different patterns present in the data. The initial approach involved using CNNs as feature extractors, in conjunction with a linear transformation, as detailed by [275], we denoted this approach as Conv-Adapter. We experimented two version of Conv-Adapters, where a 1-dimensional CNN is used as replacement of either the first of second linear of the traditional Adapters. More formally, the $\textit{Conv-Adapter}_{down}$ expressed as followed:

$$\text{Conv-adapter}_{Down}(x) = x + (W_{up}(\text{CNN}_{1D}(x)) + b_{up}) \tag{7.2}$$

While $\textit{Conv-Adapter}_{up}$ is defined as:

$$\text{Conv-adapter}_{up}(x) = x + \text{CNN}_{1D}(W_{down}(x) + b_{down}) \tag{7.3}$$

We also investigated, the [276] Conv-Adapter where the CNN is integrated in between the Up and Down projection of the traditional Adapter, denoted $\textit{Conv-Adapter}_{Middle}$, mathematically expressed as:

$$\text{Conv-adapter}_{Middle}(x) = x + W_{up}(\text{CNN}_{1D}(W_{down}(x) + b_{down}) + b_{up}) \tag{7.4}$$

An alternative approach involves the use of a fully CNN-based Adapter known as ConvPass, which

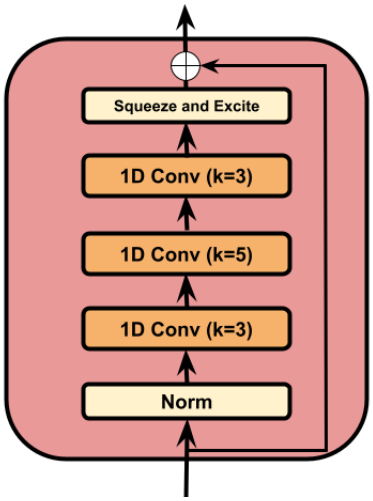


Figure 7.1: Th architecture of the ConvPass adapter. k is the kernel size of the 1D convolution. All Convoluation are depth-wise convolution.

has demonstrated effectiveness in computer vision tasks [277]. Diverging from conventional Adapters and the previously mentioned Conv-Adapter, ConvPass distinguishes itself by the removal of the up and down linear layers, replaced instead by three CNN layers. In [277], these layers comprise a 1×1 convolution, followed by a 3×3 convolution, and another 1×1 convolution. Notably, GELU activation functions are interposed between these convolutional layers.

For speech-related tasks, a comparable approach was introduced by [278]. The speech-specific ConvPass, illustrated in Figure 7.1, incorporates a layer normalisation layer, followed by three lightweight 1-dimensional CNN layers with kernel sizes of 3, 5, and 3, respectively. Additionally, a squeeze and excite module is integrated into the architecture. The squeeze and excite module, as proposed by [279], facilitates feature recalibration. It consists of a global pooling operation, followed by a linear layer, a Rectified Linear Unit (ReLU) activation, a second linear layer, and concludes with a Sigmoid activation.

During our experiments, all Conv-Adapters and ConvPass configurations were trained for 30 epochs with a learning rate of 8×10^{-4}.

7.2.3 BitFit

Bias-Term Fine-Tuning, known as BitFit, is a PETL method introduced by [280] for NLP tasks. The main idea behind BitFit is to fine-tune only the bias terms and the task-specific classification layer while keeping the rest of the model frozen. This approach aims to achieve efficient fine-tuning with reduced computational requirements in a similar way as our partial fine-tuning experiments in chapter **??**. The fine-tuning of bias terms can be seen as introducing a task-specific shift to the token representations.

The authors highlight three key properties of BitFit. Firstly, it matches of a fully fine-tuned model,

showcasing its ability to maintain comparable results while significantly reducing the number of parameters to be trained. Secondly, BitFit is designed to adapt to tasks arriving sequentially, eliminating the need for simultaneous access to all datasets. This adaptability enhances the model's versatility in handling diverse tasks with varying data distributions over time. Thirdly, BitFit exhibits parameter efficiency by fine-tuning only a small subset of the model's parameters.

In our experiment, the pre-trained model and children's ASR task shared the same output dimensions and character encoding. In consequence, we excluded the fine-tuning of the task-specific classification layer. The training process consisted of 30 epochs with a learning rate of 8×10^{-4}.

7.2.4 Scale and Shift features

Scale and Shift features (SSF) was introduced an PETL alternative approach by Lian and al. [281] for image classification. The primary objective of SSF is to establish a generalised method for efficient model fine-tuning without the introduction of task-specific inference parameters. Drawing inspiration from feature modulation techniques such as [282, 283], the SSF method modulate deep features extracted by a pre-trained model by scaling and shifting them to match the distribution of a target dataset. The intuition behind SSF comes from the inherent disparities in data distributions between upstream and downstream datasets. Directly applying model weights trained on an upstream dataset to a downstream dataset frequently leads to a performance degradation due to the disparities between the two datasets [284]. The SSF method addresses this challenge by introducing scale γ and shift β parameters, which could be considered as the variance and mean used to modulate the features extracted from the pre-trained model. This modulation ensures that the adapted features align with the characteristics of the upstream dataset. Formally, given an input x, the modulated output y is calculated by:

$$y = \gamma \odot x + \beta \tag{7.5}$$

Notably, the scale and shift parameters in SSF remain independent on any input and have a unified learnable parameter-space for different tasks. Another noteworthy advantage of SSF is its reliance on linear transformations, which can be seamlessly merged into the original pre-trained weights during model re-parameterization in the inference phase. This integration avoid the need for additional parameters removing the extra-computation time of other PETL such as Adapters.

In practical terms, SSF are introduced after each modules within the Conformer architecutre (FFNs, MHSA and Convolution modules). In the original paper, they also finetuned the Head-layers as the task is a image classification task, as our both upstream and downstream tasks, respectively adult and children ASR, share the same output dimension and character encoding, we do not finetune this extra layer and only use the SSF method.

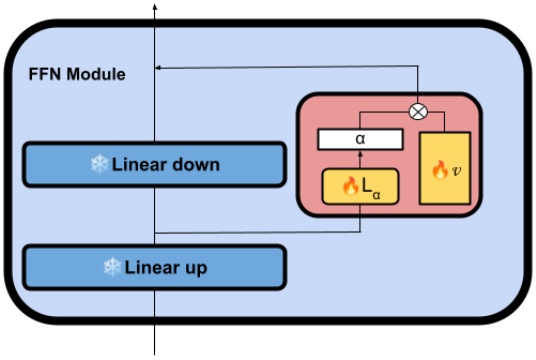


Figure 7.2: AdapterBias, consisting of a linear layer L_α and a vector $\mathcal{V}$, is added after the second feed-forward layer only in each FFN module.

In practice, the SSF modulation is integrated after each operations of the neural network. For our experiments, each operations corespond the different modules within the Conformer architecture, specifically the FFNs, MHSA and Convolution modules. It is noteworthy that, in the original paper, the authors also fine-tuned an Head-layer, as the output of the upstream and downstream image classification tasks are different. However, in our experiment, both the upstream and downstream tasks involve English ASR with shared output dimensions and characters encoding. Therefore,we did not include the head-layer fine-tuning and exclusively employed the SSF method. Our training compromise 30 epochs with a learning rate of $8 \cdot 10^{-4}$.

7.2.5 AdapterBias

Following the success of BitFit [280], which aims to introduce task-specific shifts to each output representation by selectively fine-tuning only the bias terms of a pre-trained model, recent research has suggested that certain tokens may hold more significance than others for specific tasks. While BitFit uniformly applies the same shift across all tokens regardless of their relevance to the task, [285] proposes AdapterBias to address this limitation.

AdapterBias comprises two essential modules: a vector $\mathcal{V}$ and a linear layer L_α. The vector $\mathcal{V}$ represents a task-specific shift added to the output of each FFN modules, acknowledging that tokens more closely related to the task should be assigned to larger representation shifts than others. On the other hand, the linear layer L_α generates a token-dependent weight vector $\alpha = [\alpha_1, \alpha_2, ..., \alpha_m]^T$, where α_i is the weight associated with the representation shift of the i^{th} token. By applying these token-specific weights to the task-specific representation shift $\mathcal{V}$, AdapterBias focuses on tokens which are more crucial to the task, allowing efficient and fine adaptation to various downstream tasks.

The output of AdapterBias is defined as the bias (B), represented as the outer product of $\mathcal{V}$ and the learned weights vector α. Mathematically, the output of AdapterBias is expressed as follows:

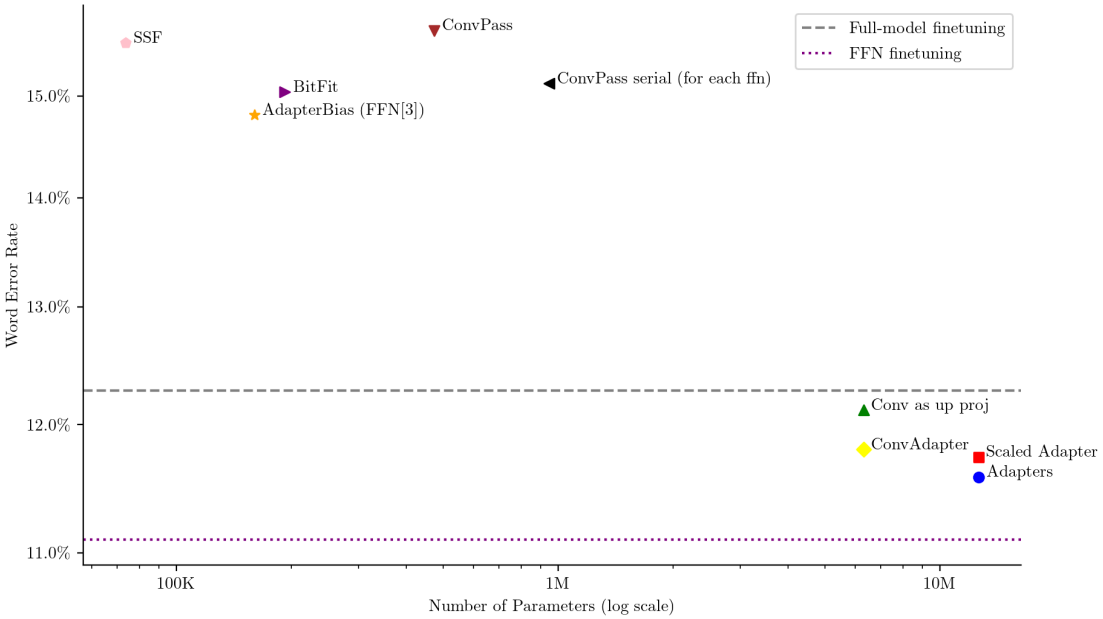


Figure 7.3: Different paramter efficent procedure for children ASR in conformer model

$$B = \mathcal{V} \otimes \alpha^T \tag{7.6}$$

Here, $\otimes$ denotes the element-wise multiplication of the task-specific shift vector $\mathcal{V}$ and the token-dependent weight vector α. In our experimental setup, we conducted the training for AdapterBias by integrating them into the second linear layer of each of the two FFN modules within the Conformer architecture. We trained AdapterBias for 30 epochs, employing a learning rate of 8×10^{-4}.

7.2.6 Results of the different PETL methods

The results of various PETL methods are summarised in Table 7.1. Notably, the traditional residual Adapter approach using the TPA configuration emerges as the most effective, achieving a 11.58% WER with 12.6 million parameters. The Scaled Adapter method exhibits a slightly reduced WER performance at 11.74%, while maintaining the same parameter count of 12.6 million.

Turning attention to convolution-based Adapters, the replacement of either linear layer (W_{down} and W_{up}) results in decreased performance, yielding WERs of 12.02% and 11.78%, respectively, using both 6.4 million parameters. Interestingly, introducing a convolutional layer between these two linear layers proves to be the best-performing convolutional system, approaching the scores of the regular Adapter with 11.62% WER and using a slightly increased amount of parameters of 12.7 million. It is noteworthy

Method	WER ↓	Trained Parameters
Adapter	**11.58%**	12.6M
Scaled Adapter	11.74%	12.6M
ConvAdapter(Down)	12.03%	6.4M
ConvAdapter (Middle)	11.62%	12.7M
ConvAdapter (Up)	11.78%	6.4M
ConvPass	15.13%	946.2K
BitFit	15.04%	192K
SSF	15.55%	73.7K
AdapterBias	14.81%	159.8K

Table 7.1: Model Performance and Parameters

that all these Conv-Adapter setups and the Scaled Adapters approach continue to outperform the fine-tuning of the entire model and are therefore valuable appraoches for children's ASR PETL. On the other hand, the ConvPass method, where all linear layers of the Adapter are replaced by convolution layers, does not surpass the full fine-tuning, yielding a WER of 15.13% with 946.2 thousand parameters.

Moving to bias shift methods, including BitFit, SSF, and AdapterBias, these approaches underperform compared to the entire model fine-tuning, with respective WERs of 15.04%, 15.55%, and 14.81%. However, it's important to note that these methods use significantly fewer parameters, with 192, 73.7, and 159.8 thousand parameters, respectively.

In summary, the traditional residual Adapter emerges as the most effective PETL approach for children's ASR. This finding aligns with recent research, as highlighted in studies such as [278] and [244], which also affirm the superior performance of Adapters in PETL for ASR tasks. Moreover, our findings highlight a noticeable trade-off between the number of parameters and the WER. Specifically, approaches employing fewer than a million parameters do not exhibit comparable performances to entire model fine-tuning, as illustrated explicitly in Figure 7.3. This trade-off emphasises the need for more research on the development of PETL methods that can effectively use fewer parameters while simultaneously maintaining or enhancing performance in the domain of children's ASR.

7.3 New type of Adapter: The Shared Adapter

7.3.1 Motivation

The primary objective of PETL is to either maintain or surpass the performance achieved through full fine-tuning of a pre-trained model, while minimising the number of parameters employed during training. In previous sections, the efficiency of residual Adapters has been underscored. Remarkably, using only 10% of the total number of parameters compared to the fine-tuning of the entire model, these residual Adapters exhibit superior performances in the context of children's ASR. In addition, our experiments

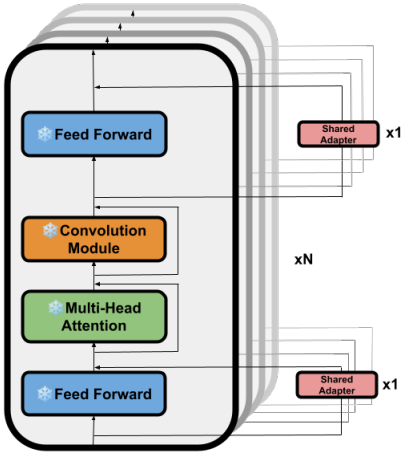


Figure 7.4: Shared-Adapter setup in a Conformer model

highlighted the drawback of overparameterisation present in Transformer-based models.

Leveraging this understanding, we propose a novel PETL methodology developed on the concept of sharing one residual Adapters across alll layers. The inspiration for this approach draws from the insights provided by the work of [286], which focus on the FFN modules. Despite representing a significant proportion of the model's parameters, the FFN was identified as highly redundant. This affirmation is confirmed by the work of [287], which establishes a connection between the FFN and attention mechanisms by proposing that the FFN corresponds to learnable key-value memories. In this conceptualisation, the weights of the first layer of the FFN represent the keys, while those of the second layer correspond to the values. These keys are proficient at capturing salient patterns at each layer. Interestingly, they observed that the classes of patterns tend to overlap between neighboring layers, indicating redundancy in the representation. This observation underscores the potential for optimising PETL methods by addressing and mitigating redundancy within FFN modules, ultimately contributing to more parameter-efficient transfer learning processes.

Building upon this observation, [286] modified the conventional Transformer architecture by sharing and dropping the FFN across different layers. Their investigation confirms the substantial degree of redundancy between the FFNs of the encoder and decoder components. Consequently, they successfully eliminate the decoder FFN while sharing a single FFN across the encoder, achieving a noteworthy reduction in model parameters without significant compromise to accuracy.

Formally, with N_{enc} denoting the number of encoder layers, the sharing of the FFN modules in the encoder can be expressed as follows:

$$\text{FFN}_i^{enc}(.) \overset{\text{tied}}{=} \text{FFN}_{all}^{enc}(.), \forall i : 1 \leq i \leq N_{enc} \tag{7.7}$$

In light of the success observed with the shared FFN in the encoder, we hypothesise that the presence of redundancy within the FFN might lead to a similar redundancy issue when employing one Adapter per FFN layer. In other words, employing separate Adapters plugged to redundant FFN modules for different layers might also exhibit redundancy. To address this concern, we introduced the *Shared Adapter* approach, wherein a single residual Adapter is used across all layers as shown in figure 7.5. This approach aims to use the redundancy present in FFN layers modules to reduce the total amount of parameters used in Adapter-transfer. The formal expression of the Shared Adapter is presented as follows:

$$\text{Adapter}_i(.) \overset{\text{tied}}{=} \text{Shared-Adapter}_{all}(.), \forall i : 1 \leq i \leq N_{enc} \tag{7.8}$$

7.3.2 Experimental setup

In our analysis, we focus on evaluating the performance of the Shared-Adapter using the same setting as the TPA configuration for traditional Adapters. Specifically, we assess the Shared-Adapter within a Conformer ASR model, where the two Shared-Adapters are directly integrated into the two FFN modules at each layer. The hidden dimension of the Shared-Adapters is set to 512. The Conformer model comprises 12 conformer layers followed by 6 Transformer layers, and for this experiment, we exclusively evaluate the Shared-Adapter in the Encoder. To quantify the reduction ofn umber of parameters used in the Shared-Adapter compared to the traditional Adapter, the following formula is used:

$$\text{Number of Parameters in Shared-Adapter} = \frac{\text{Number of Parameters of all traditional Adapters}}{\text{Number of Layers}} \tag{7.9}$$

For our experimental setup, the traditional A,dapter use approximately 12.6 million of parameters. Therefore, the number of parameters trained for the Shared-Adapter transfer is about 1.1 million. This corresponds to a significant reduction, as the Shared-Adapter use only 11% of the parameter count compared to the traditional Adapter, which already represented approximately 10% of the total parameters used in the entire model fine-tuning, therefore, compare to the entire model finetuning, the shared-adapter configuration use 1% of the amount of trainable parameters. For training the model, we use 30 epochs with a learning rate set to 8×10^{-4}.

7.3.3 Results

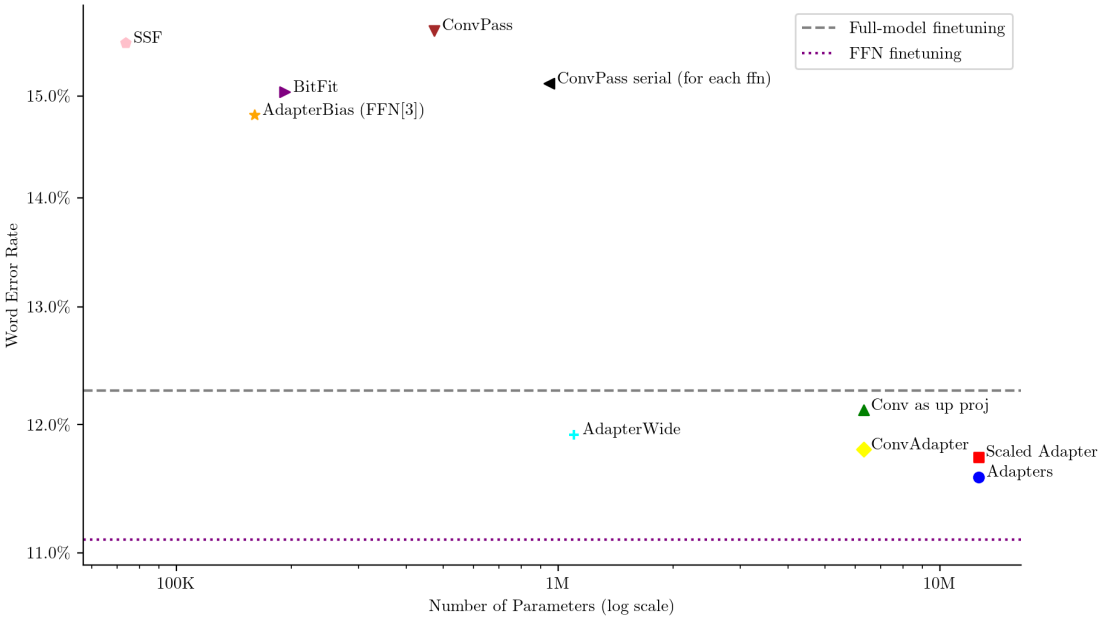


Figure 7.5: Different paramter efficent procedure for children ASR in conformer model with shared-Adapters

8

Conclusions

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A

Pathological speech detection through pre-trained models

A.1 Introduction

In the domain of speech therapy, and specifically paediatric speech therapy, advancements in speech and language technologies hold significant promise by providing automated tools for assessing pronunciation quality and identifying pathological conditions. While the primary focus of this thesis was to improve ASR for children, we also contributed into the identification of pathological conditions from speech. This annex provides a overview of these contributions.

A.2 Pathological speech detection using x-vector embeddings

A.2.1 Introduction

Speech has been proposed as a valuable biomarker for detecting various diseases, including neurological conditions, mood disorders, and respiratory diseases [288,289]. However, challenges such as temporal and financial constraints, lack of medical community awareness, ethical concerns, and patient privacy laws impede the acquisition of medical data, posing significant obstacles to the development of health-related speech-based classifiers, especially for deep learning models.

Most existing systems rely on knowledge-based (KB) features, often limited in capturing subtle symptoms and variations in disease severity. To address this limitation, some studies focus on speaker representation models, such as Gaussian Supervectors and i-vectors. For instance, [288] proposed i-vectors for Parkinson's disease classification, while [290] applied the i-vector paradigm to predict dysarthric speech evaluation metrics. The rationale behind using these representations lies in their ability to model speaker variability, which should also including disease symptoms [288].

X-vectors are discriminative DNN-based speaker embeddings, surpassing i-vectors in tasks like speaker and language recognition [253]. Despite initial doubts about the usability of such discriminative representations for disease detection as they have been trained on general datasets without diseased patients, recent studies have demonstrated their effectiveness. X-vectors have been successfully applied to paralinguistic tasks such as emotion recognition [291], obstructive sleep apnea detection [292], and as a complement to Alzheimer's Disease detection [293]. In our work [294], we investigate the hypothesis that speaker characteristics embedded in x-vectors, obtained from a single network trained for speaker identification using general data, contain sufficient information for the detection of multiple diseases. Furthermore, we aim to assess whether this information persists even in the presence of language mismatch, a phenomenon previously observed in speaker recognition [295]. Specifically, we employ the x-vector model as a feature extractor to train Support Vector Machines (SVM) for detecting two speech-affecting diseases: Parkinson's disease (PD) and obstructive sleep apnea (OSA).

A.2.2 Speaker embeddings: i-vector and x-vector

Speaker embeddings serve as fixed-length representations of variable-length speech signals, capturing essential information about the speaker. Traditional methods, such as Gaussian Supervectors [296] derived from MAP-adapted GMM-UBM [297] and i-vectors [298], have been fundamental in speaker recognition.

I-vectors, until recently considered state-of-the-art, extend the GMM Supervector approach by modeling total variability as a low-rank space through factor analysis. [288] observed that i-vectors, capturing total variability and speaker variability, also encompass information about speech disorders. For classification, they used reference i-vectors for healthy and PD populations.

In contrast, x-vectors, proposed as an alternative to i-vectors, aim to discriminate between speakers by modeling specific characteristics. Unlike i-vectors, x-vectors exhibit robustness to data variability and domain mismatches, requiring shorter temporal segments for optimal performance. Typically, the x-vector system comprises three main blocks: TDNN layers operating at the frame level, a statistical pooling layer for temporal aggregation (employing an attentive mechanism for importance weighting), and fully connected (Dense) layers for x-vector extraction.

A.2.3 Experimental setup

In our experiments, we used four corpora to determine the presence or absence of PD and OSA. With one of the European Portuguese corpus was employed to train the i-vector and x-vector extractors. For each disease-related dataset, we compared three representations: KB features, i-vectors, and x-vectors. All disease classifications were conducted using a SVM classifier using leave-one-speaker-out cross validation as an alternative to partitioning the corpora into train, development and test sets. Further details on the corpora, data representations, and classification method are provided below.

Our classification process operates at the segment level, assigning speakers a final classification through a weighted majority voting mechanism. In this approach, predictions obtained for each segment uttered by the speaker are weighted based on the corresponding number of speech frames.

A.2.3.A Corpora

In this section, we provide a description of the datasets employed in our study. The Speaker Recognition - Portuguese (PT-EASR) Corpus is a subset of the EASR (Elderly Automatic Speech Recognition) corpus [299]. It comprises recordings of European Portuguese read sentences and was used for training both i-vector and x-vector models for speaker recognition tasks. The dataset encompasses speakers aged 24 to 91, with 91% falling within the 60-80 age range. This specific age distribution was chosen with the intention of generating reliable speaker embeddings for this age group, particularly relevant to the diseases addressed in our study. The corpus was partitioned into training, development, and test sets in a ratio of 0.70:0.15:0.15, respectively. For PD Detection - Portuguese PD (PPD) Corpus, a subset of the FraLusoPark corpus [300] was employed. This subset includes speech recordings of both French and European Portuguese healthy volunteers and PD patients. The selected utterances consist of European Portuguese speakers reading prosodic sentences. The PD Detection - Spanish PD (SPD) Corpus corresponds to a subset of the New Spanish Parkinson's Disease Corpus, collected at the Universidad de Antioquia, Colombia [301]. For this experiment, we only used the read sentences subset. This corpus serves the purpose of investigating whether x-vector representations trained in one language (European Portuguese) can generalise effectively to another language, namely Spanish. The OSA Detection - PSD Corpus is an extended version of the Portuguese Sleep Disorders (PSD) corpus [289].

This corpus introduces tasks in European Portuguese, including reading a phonetically rich text, read sentences recorded during a cognitive load assessment task, and spontaneous descriptions of an image. All utterances were segmented into 4-second-long segments using overlapping windows with a 2-second shift. Further details about each of these datasets can be found in Table A.1.

Language	Task	Group	Speakers	Segments	Duration (h)
PT	Spk. Rcg.	-	919	290,690	171.81
	PD	Patient	75	1,838	1.24
		Control	65	1,527	1.07
	OSA	Patient	30	1,793	1.10
		Control	30	1,702	1.05
SP	PD	Patient	50	661	0.49
		Control	50	655	0.50

Table A.1: Description of Speakers and Segments

A.2.3.B Knowledge based features

For PD classification, the KB feature set proposed by Pompili et al. [302] comprises 36 features from the eGeMAPS [303], along with the mean and standard deviation (std) of 12 MFCCs and log-energy. Additionally, the set includes the first and second derivatives of these coefficients, resulting in a 114-dimensional feature vector.

In the case of OSA classification, the KB feature set, as proposed in [289], includes the mean of 12 MFCCs, along with their first and second order derivatives, and 48 linear prediction cepstral coefficients. The set also covers the mean and std of the frequency and bandwidth of formant 1, 2, and 3, as well as the mean and std of Harmonics-to-noise ratio, jitter, F0 at percentiles 20, 50, and 100, and mean and std values for all frames and only voiced frames of Spectral Flux. All KB features were extracted using openSMILE [304].

A.2.3.C Speaker embeddings

Layer	Contex	Total Contex	In × Out
TDNN1	$[t-2, t+2]$	5	$5F \times 256$
TDNN2	$\{t-2, t, t+2\}$	9	768×256
TDNN3	$\{t-3, t, t+3\}$	15	768×256
TDNN4	$\{t\}$	15	256×256
TDNN5	$\{t\}$	15	256×512
stats pooling	$[0, T)$	T	$512T \times 1024$
Dense 6	$\{0\}$	T	1024×512
Dense 7	$\{0\}$	T	512×512
softmax	$\{0\}$	T	$512 \times S$

Table A.2: X-vector network Description

In the i-vector system, 19 MFCCs plus log-energy are given as input with non-speech frames removed using energy-based Voice Activity Detection (VAD). Utterances are modeled with a 512-component full-covariance GMM, resulting in 180-dimensional i-vectors. The entire process is implemented using Kaldi [69] over the PT-EASR corpus.

For x-vectors, the network architecture is detailed in Table A.2, and x-vectors are extracted at the 6^{th} layer (Dense 6). Using 24-dimensional fbanks as input features. The non-speech frames were removed using energy-based VAD. This network was trained on the PT-EASR corpus for speaker identification, using 100 epochs, cross-entropy loss, a learning rate of 0.001, a learning rate decay of 0.05 with a 30-epoch period, a batch size of 512, and a dropout value of 0.001.

A.2.4 Results

		PD - Portuguese			OSA			PD - Spanish		
Features		Prec.	Recall	F1 Score	Prec.	Recall	F1 Score	Prec.	Recall	F1 Score
KB	Seg	64.5	64.6	64.5	64.8	64.9	64.8	**79.0**	**79.0**	**79.0**
	Spk	72.2	72.3	72.1	**82.0**	**81.7**	81.6	**87.1**	**87.0**	**87.0**
i-vector	Seg	66.6	66.6	66.6	65.6	65.6	65.6	75.7	75.7	75.7
	Spk	**75.6**	**75.7**	**75.6**	72.3	75.0	75.0	85.1	85.0	85.0
x-vector	Seg	**66.7**	**66.8**	**66.7**	**73.3**	**73.3**	**73.3**	77.2	77.2	77.1
	Spk	74.4	74.5	74.3	81.7	**81.7**	**81.7**	86.0	86.0	86.0

Table A.3: Results of the different tasks with KB and speaker embeddings

The results of the different task are summarised in Table A.3. For PD with Portuguese data, the findings indicate that speaker representations learned from out-of-domain data surpass the performance of KB features. This supports our hypothesis that speaker embeddings not only capture information about speech pathologies but also model symptoms of the disease that KB features may fail to include.

It is notable that x-vectors and i-vectors yield very similar results, with a slight advantage for x-vectors at the segment level and slightly better results for i-vectors at the speaker level. This observation suggests that while x-vectors offer stronger representations for short segments, i-vectors may perform better for longer segments. The application of a majority vote weighted by the duration of speech segments may favor the i-vector approach at the speaker level.

In the context of the OSA task, x-vectors demonstrate superior performance compared to all other approaches at the segment level. Notably, they significantly showed around 8% improvement over KB features, providing further support for our hypothesis. However, it is essential to highlight that both x-vectors and i-vectors perform similarly at the speaker level. Interestingly, i-vectors, in this scenario, perform less effectively than KB features. One possible explanation could be attributed to the fact that the PSD corpus incorporates tasks, such as spontaneous speech, which diverge from the read sentences included in the corpus used to train the i-vector and x-vector extractors. These tasks might be considered

out-of-domain, which would explain why x-vectors outperform the i-vector approach.

The objective of the PD Spanish experiment was to evaluate the efficacy of x-vectors trained in one language when applied to disease classification in a different language. Our findings reveal that KB features outperform both speaker representations, possibly due to the language mismatch between the Spanish PD corpus and the European Portuguese training corpus. However, it is noteworthy that, akin to the previous task, x-vectors demonstrate the ability to surpass i-vectors in an out-of-domain corpus.

To conclude, our experiments conducted on the European Portuguese datasets substantiate the hypothesis that speaker embeddings encompass pertinent information for disease detection. Notably, we identified evidence indicating that these embeddings capture information not represented by KB features, validating the efficacy of our approach. Additionally, the observations suggest that x-vectors outperform i-vectors in tasks where the domain does not align with the training data, such as verbal task mismatch and cross-lingual experiments. This underscores the potential of x-vector embeddings as formidable alternatives to KB feature sets for the detection of PD and OSA.

A.3 The INESC-ID Multi-Modal System for the ADReSS 2020 Challenge

A.3.1 Introduction

Later, in [305], we proposed to extend the aforementioned work by classifying Alzheimer's disease (AD). Indeed, existing studies have explored various approaches, including syntactic or semantic features, plain acoustic methods, and combinations of temporal speech parameters and lexical measures. However, the diversity in datasets and methodologies makes it challenging to compare these studies. To address this, the Alzheimer's Dementia Recognition through Spontaneous Speech (ADReSS) challenge was introduced, providing a common, statistically balanced, and acoustically enhanced dataset for researchers to test their approaches. In this work we introduced a the multi-modal system where both acoustic and textual feature embeddings were used for automatically distinguishing AD patients from healthy individual.

Initially, studies focused on hand-crafted temporal and acoustic parameters from speech or linguistic, or a fusion of both. For example, [306] analysed temporal speech features. [307] employed over 350 features to capture lexical, syntactic, grammatical, and semantic phenomena from transcriptions of a picture description task. Finally, [308] used in conjunction demographic, acoustic, and linguistic features.

More recently, a shift towards advanced architectures has been observed to overcome limitations in traditional methods. For instance, [309] used a gated CNN on acoustic data, while [310] explored linguistic impairments with CNN, RNNs, and a combination. Finally, [293] introduced a multi-modal feature embedding approach, based on N-gram, i-vector and x-vectors.

	Train		Test
	Control	AD	-
Audio Full	55min46s	1h14min	1h06min
Audio chunks	30min11s	26min31s	26min32s
# Words (unique)	6097 (567)	5494 (552)	5536 (602)

Table A.4: Statistical information on the ADReSS corpus

Our work differs from previous studies by using contextual embedding vectors for text data, feeding into two systems: one employing Global Maximum pooling and bidirectional LSTM-RNNs architectures, and the other based on statistical computation of sentence embeddings. This approach is simpler and does not require training deep architectures. For audio, we use DNN speaker embeddings extracted from pre-trained models. This is the first work which jointly use automatically learned representations for both audio and textual data.

A.3.2 Corpus

The ADReSS dataset comprises speech recordings and annotated transcriptions from 156 subjects, including 78 AD patients and 78 age and gender-matched healthy controls. The data is split into training (108 subjects) and test (48 subjects) sets. Participants provided descriptions of the Cookie Theft picture from the Boston Diagnostic Aphasia Examination [311]. Speech recordings were segmentated using Voice Activity Detection (VAD) and normalised [312]. The dataset contained both full enhanced audio, and normalised audio chunks. Our approach used both audio and transcriptions. The transcriptions were annotated with disfluencies, filled pauses, repetitions, and other complex events. The transcriptions contained 17,127 words, including 1,009 unique words. Additional details on the duration and size of the ADReSS dataset are provided in Table A.4.

A.3.3 Proposed system

Our multi-modal framework, illustrated in Figure A.1, is based on the independent generation of acoustic and textual feature embeddings. Subsequently, we conduct an early fusion of the output of the two systems to create a singular feature vector encapsulating a condensed representation of both speech and language characteristics. The final classification is carried out using an SVM classifier with a linear kernel. Further details on the two systems are provided in the subsequent sections.

A.3.3.A Acoustics modality

The acoustic system incorporates i-vectors and x-vectors. Taking into consideration the small size of the ADReSS dataset, we preferred to exploit already existing pre-trained models to produce our acoustic feature embeddings, rather than training them using in-domain challenge data. For the x-vectors framework,

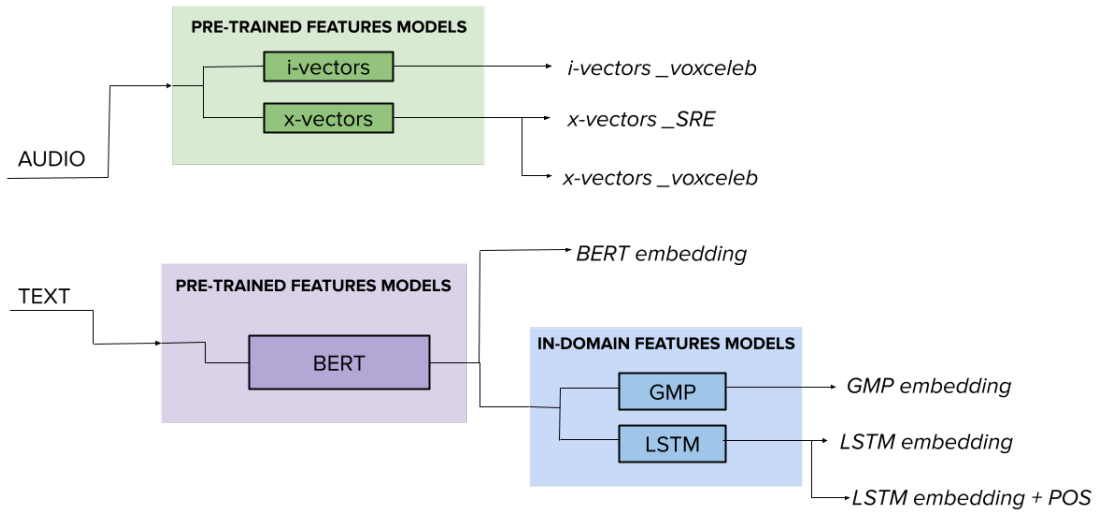


Figure A.1: Overview of the multimodal system based on embeddding appraoches

both the SRE and Voxceleb models were employed. The SRE model was primarily trained on telephone and microphone speech using data from the Switchboard corpus, Mixer 6, and NIST SREs [253]. The Voxceleb model was trained on augmented VoxCeleb 1 and VoxCeleb 2 datasets, encompassing speech from speakers with diverse ethnicities, accents, professions, and ages [253, 313]. This dataset was also used to build the i-vectors pre-trained model.

Inputs to these pre-trained models included 23 and 30-dimensional MFCCs extracted with Kaldi [69] and non-speech frames were filtered out using VAD. For x-vectors, a 512-dimensional embedding was extracted, while i-vectors, based on GMM-UBM, with a 400-dimension.

A.3.3.B Linguistic modality

We pursued two distinct methods to obtain textual feature embeddings. Firstly, we explored training deep architectures on the relatively small corpus with dimension like the one use in this challenge. Then, we compare this approach with a less data-intensive method based extracting sentence embeddings using a pre-trained model. Both strategies use contextual word embeddings as input but produced different types of learned representations as output. To integrate information from linguistic and acoustic systems, trained architectures were employed to extract linguistic features before the final classification layer, resulting in a single 768-dimensional feature vector for an entire description. In contrast, the sentence embedding approach yielded a 768-dimensional vector for each sentence in a description.

For both approaches, the initial pipeline step involved normalising the data in the ADReSS dataset. Clean transcriptions were encoded into 768-dimensional context embedding vectors using a pre-trained English BERT model with 12 layers and 768 hidden units. The first system, derived from the Com-

	Accuracy	Precision	Recall	F1 Score
x-vectors_Vox	0.6818	0.6834	0.6919	0.6812
x-vectors_SRE	**0.7273**	**0.7273**	**0.7273**	**0.7273**
i-vectors_Vox	0.6818	0.7292	0.6818	0.6645
i-vectors_Vox_x-vectors_Vox	0.7273	0.7273	0.7273	0.7273
i-vectors_Vox_x-vectors_SRE	0.7273	0.7351	0.7273	0.7250

Table A.5: Results of different acoustic approaches on the development set

	Accuracy	Precision	Recall	F1 Score
Global Max Pool.	0.7727	0.7947	0.7728	0.7684
LSTM-RNNs	0.8182	0.8182	0.8182	0.8182
LSTM-RNNs Pos	0.8636	0.8667	0.8637	0.8634
GMax/LSTM-RNNs/LSTM-RNNs-Pos	**0.9091**	**0.9091**	**0.9091**	**0.9091**
Sentence emb. - maj. vote	0.7727	0.7947	0.7728	0.7684

Table A.6: Results of different linguistic approaches on the development set

ParE2020 Elderly Challenge baseline [314], involved training three neural models on top of contextual word embeddings: (i) a Global Maximum pooling, (ii) a bidirectional LSTM (biLSTM) with an attention module, and (iii) the second model augmented with part-of-speech (POS) embeddings. The loss was evaluated during training on the development set.

The second system, do not require additional training phase, as representations are extracted from a pre-trained model to directly characterise linguistic deficits in AD. Contextual word embeddings obtained for each word were used to compute fixed-size embedding vectors for each sentence by averaging the second to twelfth hidden layers of each word.

A.3.4 Results

The results obtained using the different acoustic feature embeddings are summarised in Table A.5. Different independent models were explored, and an early fusion of the best acoustic results was performed. The x-vectors Voxceleb model generally achieved lower classification accuracy; however, when combining i-vectors and x-vectors extracted from this model, the fused accuracy was comparable to x-vectors trained on the SRE corpus, representing the best result on the development set. These outcomes are slightly lower than those reported in similar works in the literature [293, 309]. However, our approach, distinct from these previous studies as we uses a smaller dataset and do not rely on DNN training. To validate these results on the test set, we select the acoustic feature embeddings extracted from the pre-trained x-vectors SRE model for evaluation.

The results obtained with our various linguistic systems are shown in Table A.6, presenting the performance for features trained with three neural models, their fusion, and the sentence embeddings approach. For the sentence embeddings approach, the accuracy use a majority voting strategy over the

	Class	Accuracy	Precision	Recall	F1 Score
Fusion of system	AD	**0.8125**	0.9412	0.6667	0.7805
	non-AD		0.7419	0.9583	0.8364
Sentence embedding	AD	**0.7292**	0.8235	0.5833	0.6829
	non-AD		0.6774	0.8750	0.7636
x-vectors_SRE	AD	**0.5417**	0.5417	0.5417	0.5417
	non-AD		0.5417	0.5417	0.5417

Table A.7: Results of different acoustic and linguistic approaches on the test set

entire description. Our best classification result attained an accuracy of 90.91% on the development set using the fusion of the linguistic features sets generated by the three neural models. Comparing this result with the one obtained by sentence embeddings, we acknowledge that neural models outperform simpler strategies even with constrained training data. This was somehow surprising and in contradiction with similar experiments performed with the acoustic system. We hypothesise that the large amount of contextual information provided by the Bert model is helpful in overcoming the limited size of the ADReSS dataset. Nevertheless, we suspect that the high accuracy attained with neural models may be too optimistic, due to the fact of having used the development set both for testing and evaluating the model's loss. Thus, in spite of their lower outcome, the sentence embeddings approach is selected as one of the systems to be evaluated on the test set. In fact, on the one hand, we think that they may represent a more reliable system, since do not require additional training. On the other hand, we also observe that they achieve higher classification scores, when compared with a similar approach based on GloVe embeddings [38], thus corroborating our decision.

For a comprehensive evaluation of speech and language impairments in AD, we performed an early fusion of the best results from both the acoustic and linguistic systems. This involved merging x-vectors with linguistic feature sets from three neural models. However, results on the development set using this extended feature set did not yield additional improvements. Despite this, we selected the combined system as our primary choice for evaluation.

For the evaluation, three systems were submitted: (i) a fusion of the best results from linguistic and acoustic systems, (ii) sentence embeddings, and (iii) the best acoustic system. Results on the test set, presented in Table A.7, showed a consistent drop in performance compared to the development set, even for systems not requiring a training phase. The first system achieved the best result with an accuracy of 81.25%, indicating the capability of deep architectures with contextual word embeddings to overcome dataset limitations. The acoustic system alone yielded the lowest accuracy at 54.17%, suggesting room for improvement in adapting acoustic pre-trained models, for example, to better model elderly speech characteristics.

A.4 Transfer Learning-Based Cough Representations for Automatic Detection of COVID-19

A.4.1 Introduction

Finally, we further extend the idea of using pre-trained representation to automatically detect COVID-19 from cough recordings. Indeed, the COVID-19 respiratory disease was declared a pandemic by the World Health Organisation on March 2020, with profound personal, societal, and economic consequences. Clinical diagnosis primarily relies on RT-PCR and antigen tests, but these methods have drawbacks such as significant costs, intrusive sample collections, and delays in diagnosis due to laboratory saturation. To address these challenges, there is a growing interest in developing reliable, cost-effective, immediate, and user-friendly tools to optimise screening campaigns for health care operators, institutions, and companies.

In our work [315], we contributed to the ComParE 2021 COVID-19 Cough Sub-challenge [316]. Firstly, we employ transfer learning to develop COVID-19 classification subsystems using deep cough representation extractors, including TDNN-F and CNN embeddings, as well as PASE+ features. Secondly, we integrate individual decisions from the three experts into a calibrated decision-level fusion system. This ensemble of expert subsystems, relying on cough representations, aims to generate well-calibrated log-likelihood scores across various operating points. The resulting output can be readily interpreted by human experts and seamlessly incorporated into the decision-making process.

Current research on the automatic detection of COVID-19 from speech or respiratory sounds builds on prior studies demonstrating the distinct effects of various respiratory diseases on these sounds. This approach has proven effective in detecting pertussis, asthma, pneumonia, tuberculosis, among others [317]. While conclusive evidence is still pending for COVID-19, preliminary findings suggest specific signatures of COVID-19 in coughs and speech that could potentially enable detection even in apparently asymptomatic individuals and differentiate it from other common respiratory illnesses. Given the limited availability of labeled COVID-19 data, many approaches rely on transfer learning, data augmentation, and class balancing techniques.

The majority of previous work in this domain relies on CNNs. For instance, a pre-trained VGGish model [318]is employed as a generic audio feature extractor in [319]. Other works fine-tune CNNs initially trained for cough detection for the purpose of COVID-19 detection [320, 321]. Ensemble models incorporating both DNNs and CNNs, directly trained from scratch for COVID-19 detection, have also been proposed [322]. Additionally, certain studies [323] leverage information about self-reported symptoms, encoding them as one-hot vectors and combining them either at the feature- or decision-levels with traditional speech features.

A.4.2 Corpora

In this work, we used two datasets: the COVID-19 COUGH (C19C) corpus, provided in the ComParE 2021 COVID-19 Cough Sub-Challenge [319, 323] for evaluation, and the COUGHVID corpus [324], employed for training and fine-tuning transfer learning-based cough representation extractors. Silence segments were eliminated from both datasets.

The COVID-19 COUGH (C19C) corpus is a subset of the Cambridge COVID-19 Sound database [319, 323], consisting of 725 cough recordings from 397 participants with self-reported COVID-19 status labels (positive/negative). The corpus is distributed into train (71 positives/215 negatives), development (48 positives/183 negatives), and a blind test set (208 samples) with gender-balanced subsets.

In our preliminary analysis, it was observed that some files had a reduced bandwidth of 4 kHz, potentially corresponding to samples originally recorded at 8 kHz. Namely, 13, 8 and 8 narrow-band files were detected in the train, development and test subsets, respectively. This condition certainly reflects the reality of many real-world applications. However, we noticed that all the narrow-band recordings in the train and development subsets correspond to the COVID-19 positive class To address this, a second version of the dataset, denoted as "C19C$_{fullband}$", was created by removing narrow-band recordings from the original train and development subsets. This resulted in 273 samples in the train subset (58 positives/215 negatives) and 223 in the development subset (40 positives/183 negatives), while the test subset remained unchanged for consistent challenge evaluation conditions.

The COUGHVID corpus [324] is a publicly open dataset consisting of non-curated recordings performed using lossy codification. The dataset includes a variety of conditions such as sampling rate, bandwidth, number of channels, and quality. Volunteers recorded their coughs and reported their COVID-19 status (positive/symptomatic/healthy), age, gender, and medical condition. The dataset comprises 27,550 recordings, with 15,125 classified as coughs by an automatic cough detector. Of these, 10,763 have self-provided gender and COVID-19 status annotations, including 680 COVID-19 positives (395 male/285 female), 8,270 healthy (5,632 male/2,638 female), and 1,813 symptomatic (1,114 male/699 female). Additionally, a small fraction of the dataset was annotated by expert pulmonologists with information on various aspects, such as type of cough, presence of audible symptoms, diagnosis, and severity.

A.4.3 Proposed system

A.4.3.A TDNN-F embedddings

X-vector embeddings are currently regarded as state-of-the-art speaker representations, surpassing other proposed representations like d-vectors and i-vectors. Motivated by the results of the two previous works mentioned in this annex, this study explores the applicability of x-vector-like embeddings to coughs, aiming to encode relevant information about the cough signal for medical insights. The X-vector extractor

is implemented using TDNN-F as proposed for speaker recognition in [325]. Cough embeddings are 128-dimensional vectors obtained at the output of the final dense layer. The network undergoes two-stage training: initially an age estimation and gender classification using a subset of the COUGHVID dataset was performed, and subsequently fine-tuning with expert-annotated data for tasks closely related to COVID-19 classification. These tasks include cough type, presence of dyspnea, presence of wheezing, diagnosis, and severity. The reason behind this fine-tuning step is the fact that these tasks are much closer to COVID-19 classification than age and gender. Input features consist of 30 MFCCs computed every 10 ms from 25 ms-length frames, following the egs/voxceleb/v2 Kaldi recipe [69].

A.4.3.B CNN embedddings

CNN-based approaches for COVID-19 detection suffer from some limitations such as the use of CNNs as generic audio feature extractors without task-specific tuning or relying on relatively small datasets for training. In contrast, our work addresses these limitations by leveraging transfer knowledge from the VGGish model, originally trained on a vast corpus for audio classification, and subsequently fine-tuning it for COVID-19 detection using the COUGHVID dataset.

The VGGish model [318], is an adaptation of the VGG network [326] for audio classification. It consists of four blocks with convolutional and pooling layers, followed by fully-connected layers and an output layer. In this work, a simplified version of the model is used and was pre-trained using 5.4 million hours from YouTube data. For our experiments, we used two different settings. In the first setting, the model serves as a pre-trained generic feature extractor with weights directly loaded from the original model. In the second setting, the model is fine-tuned for COVID-19 detection using a balanced subset of the COUGHVID dataset. The input to the VGGish network is log Mel-spectrogram features computed every 0.24 s from 0.96 s-length segments amd the resulting embeddings are 256-dimensional vectors.

When fine-tuning, layers 9 and 10 are included to facilitate training with limited data, with their weights initialized randomly. The entire CNN is fine-tuned for 150 epochs using cross-entropy loss, the Adam optimizer with a learning rate of 10^{-5}, and a batch size of 64. The fine-tuning is conducted on a balanced subset of the COUGHVID dataset, consisting of 680 positive and 680 negative cough recordings, with 80% used for training and 20% for development.

A.4.3.C PASE+ embedddings

The study incorporates the problem-agnostic speech encoder model, PASE+ [327,328], g where targets are learned directly from the signal. PASE+ features are derived from a shared encoder with a SincNet-based layer [90], seven convolutional blocks, and a Quasi-RNN layer. The encoder output is connected to twelve workers, each designed for specific tasks like reconstruction of waveform, log power spectrum (LPC), MFCCs, prosody, filter banks (fbanks), gammatone, and binary discrimination tasks. Two PASE+

System	*dev*	$dev_{fullband}$	*test*
ComParE 2021 CCS Sub-challenge Baseline			
openSMILE	61.4	53.0	65.5
openXBOW$_{2000}$	64.7	56.5	72.9
DeepSpectrum+SVM	63.3	57.3	64.1
auDEEP$_{\text{-60 dB}}$	67.6	57.3	67.6
End2You	61.8	-	64.7
Fusion of Best	-	-	73.9
TDNN-F Embeddings			
Trained COUGHVID$_{\text{Step1}}$	68.8	63.6	-
Fine-tuned COUGHVID$_{\text{Step2}}$	68.1	62.3	-
CNN Embeddings			
Pre-trained YouTube	66.9	62.4	-
Fine-tuned COUGHVID	71.2^{+}	65.6	62.3^{+}
PASE+ Features			
Trained Librispeech	63.1	61.7	-
Trained COUGHVID	67.4	$\mathbf{66.8}^{+}$	64.1^{+}
Calibrated Fusion			
Fusion of experts	$\mathbf{72.3}^{+}$	66.1	69.3^{+}

Table A.8: Performance results (unweighted average recall-UAR) on the COVID-19 COUGH (C19C) corpus

extractors were used: one pre-trained on Librispeech and another trained from scratch on COUGHVID data. Both are trained for 150 epochs, creating 256-dimensional feature vectors for each frame every 10 ms.

A.4.3.D COVID-19 condition classification

The study employs transfer learning to address the limited COVID-19 data for training. Three SVMswe used on TDNN-F embeddings, CNN embeddings, and PASE+ features, respectively, for expert decisions. TDNN-F embeddings are directly input to the SVM. CNN-based embeddings are derived from cough segments and subjected to majority voting for the final decision. PASE+ features are averaged across the sequence and fed to the SVM classifier. The SVMs are trained on both the C19C and C19C$_{fullband}$ datasets, exploring various kernels, data normalisations, and class balancing methods. Hyperparameters are optimised through grid-search on development subsets, and linear logistic regression is applied to combine system decisions with scaling factors. The regression approximates log-likelihood ratios, thus, a theoretically determined decision threshold can be used for making hard decisions.

A.4.4 Results

Table A.8 shows the comparison between ComParE 2021 CCS baselines and our proposed system. All systems were separately trained on both the C19C and C19C$_{fullband}$ subsets, and evaluations were conducted on the corresponding dev and dev$_{fullband}$ subsets. The reported test results are based on the best

individual systems trained on the C19C and C19C$_{fullband}$ datasets (marked with +), presented in terms of unweighted average recall (UAR).

The proposal demonstrates competitive performance compared to baseline systems. The TDNN-F x-vector embeddings-based expert, trained initially on gender classification and age regression tasks using COUGHVID data, achieves a UAR of 63.6% on devfullband. However, fine-tuning in step 2 using a multi-task setting does not significantly enhance cough representations, suggesting potential overfitting for some subtasks with limited data.

The CNN embeddings pre-trained on YouTube videos exhibit reasonable performance, improving to 65.6% UAR after fine-tuning with COVID-19-specific data. The PASE+ features, trained with COUGHVID data, yield the best performance among the three expert systems, with a development UAR of 66.8% and a test UAR of 64.1%. Notably, the PASE+ extractor trained on the larger Librispeech dataset achieves a 5.1% absolute improvement in UAR when trained with COVID-19-specific data, indicating the significant benefit of such data.

The fusion of the best x-vector (Trained COUGHVIDStep1), CNN (Fine-tuned COUGHVID), and PASE+ (Trained COUGHVID) experts yields a UAR of 72.3% on development (1.1% absolute improvement from the best expert) and 69.3% on test when trained on the C19C datasets. The underperformance on the C19C$_{fullband}$ subset warrants further analysis but may be attributed to the low number of COVID-19 positive examples.

A.5 Conclusion and future work

In the three distinct research works done within the context of this thesis, we employed pre-trained embedding extractors as tools for detecting pathologies. These embeddings can be used in two different way: functioning either directly as feature extractors or undergoing fine-tuning for specific tasks. Our findings in these works present promising results, indicating that embeddings trained on substantial amounts of data may contain valuable health-related information.

We began by exploring the replacement of knowledge-based features with task-agnostic speaker representations in multiple disease detection. Focusing on x-vector embeddings trained with elderly speech data, our experiments with European Portuguese datasets supported the hypothesis that discriminative speaker embeddings, particularly x-vectors, contain relevant information for disease detection that knowledge-based features may fail to represent. Notably, x-vectors proved more suitable than i-vectors for tasks with domain mismatches, such as verbal task mismatches and cross-lingual experiments. Future endeavors include training the x-vector network with augmented and multilingual datasets, extending the approach to other diseases and verbal tasks, and replicating experiments with in-the-wild data collected from online multimedia repositories.

Moving to the context of AD classification, we adopted a multi-modal approach, leveraging automat-

ically learned feature representations. Our investigation covered both acoustic and linguistic, exploring feature embedding vectors from pre-trained models and training deep neural architectures. By combining these approaches, we achieved an accuracy of 90.91% and 81.25% on the development and test sets, respectively. Notably, acoustic systems demonstrated a greater need for data to improve predictive ability, especially in the presence of potential ASR errors. Future work may involve analysing the impact of ASR errors, exploring robust acoustic methods tailored to AD speech characteristics, and delving into the implications of atypical speech.

Lastly, our focus shifted to the ComParE 2021 COVID-19 Cough Sub-challenge. Leveraging transfer learning, we developed three expert classifiers: TDNN-F embeddings, CNN embeddings, and PASE+ features. While our results demonstrated competitive performance compared to baseline systems, caution is warranted due to the limited data. To enhance the reliability of COVID-19 screening tools, larger datasets are recommended for better learning of cough representations, coupled with more suitable back-end classifiers. Future exploration could includes recurrent neural networks with attention mechanisms to capture temporal dynamics, SSL, multi-task TDNN-F network-based cough embeddings, and assessing the suitability of PASE+ features as an alternative input representation.

Collectively, these contributions showcase the diverse applications of advanced technologies in addressing challenges in health-related tasks using pre-trained representations, ranging from COVID-19 screening through cough analysis to AD classification and beyond, ultimately paving the way for impactful advancements in SLT.

B

Sefl-supervised learning as feature extractor for children's ASR

B.1 Introduction

In light of the increasing availability of large amount of unlabeled speech data, there has been a need to efficiently extract general-purpose knowledge from it. Consequently, SSL has experience notable advances and has gained substantial attention in recent years especially in the context of low-resource tasks. SSL refers to a training paradigm where a model learns representations from unlabeled speech data without relying on explicit labels or annotations. This approach yields discernible enhancements in performance across various applications such as speech recognition, speaker identification, and emotion recognition [164]. Traditionally, SSL models can be used in two manners: firstly, as a feature extraction to replace human-designed features [329, 330], and secondly, as a model initialisation accomplished by concatenating prediction layers and fine-tuning the entire model [168, 170, 172, 234].

In recent years, an incrase number of research focus on using SSL models for children ASR. One notable

avenue observed in the literature involves the fine-tuning of SSL models exclusively using children's data [] or through a combination of adult and children's data []. These efforts have yielded improved performances, showcasing the adaptability of SSL models to the nuances inherent in the speech patterns of children. Conversely, an alternative strategy has emerged by using Adapters to adapt SSL models specifically to children's speech characteristics subsequently followed by the full model, Adapters included, fine-tuning [172]. This initial training, allow to reduce the complexity associated with the conventional process of fine-tuning the entire model directly with children speech. The observed successes of SSL as an initialisation for fine-tuning in the context of children's ASR underscore its efficacy as a new training paradigm. However, the exploration of SSL models as front-end feature extractors, compared to the conventional hand-crafted features, despite its use and success for adult speech [329, 330] remains unexplored for childen's ASR. Motivated by these considerations, this chapter undertakes a comprehensive review of various SSL models, evaluating their potential as novel feature extractors in the domain of children's ASR.

B.2 Self-supervised pre-trained models

Method	Architecture	#Params	Stride	Input	Corpus
FBANK	-	0	10ms	waveform	-
APC [7]	3-GRU	4.11M	10ms	FBANK	LS 360 hr
VQ-APC [32]	3-GRU	4.63M	10ms	FBANK	LS 360 hr
NPC [33]	4-Conv, 4-Masked Conv	19.38M	10ms	FBANK	LS 360 hr
Mockingjay [8]	12-Trans	85.12M	10ms	FBANK	LS 360 hr
TERA [9]	3-Trans	21.33M	10ms	FBANK	LS 960 hr
wav2vec 2.0 Base [14]	7-Conv, 12-Trans	95.04M	20ms	waveform	LS 960 hr
wav2vec 2.0 Large [14]	7-Conv, 24-Trans	317.38M	20ms	waveform	LL 60k hr
HuBERT Base [35]	7-Conv, 12-Trans	94.68M	20ms	waveform	LS 960 hr
HuBERT Large [35]	7-Conv, 24-Trans	316.61M	20ms	waveform	LL 60k hr

Table B.1: Overview of different SSL architectures used in this chapter

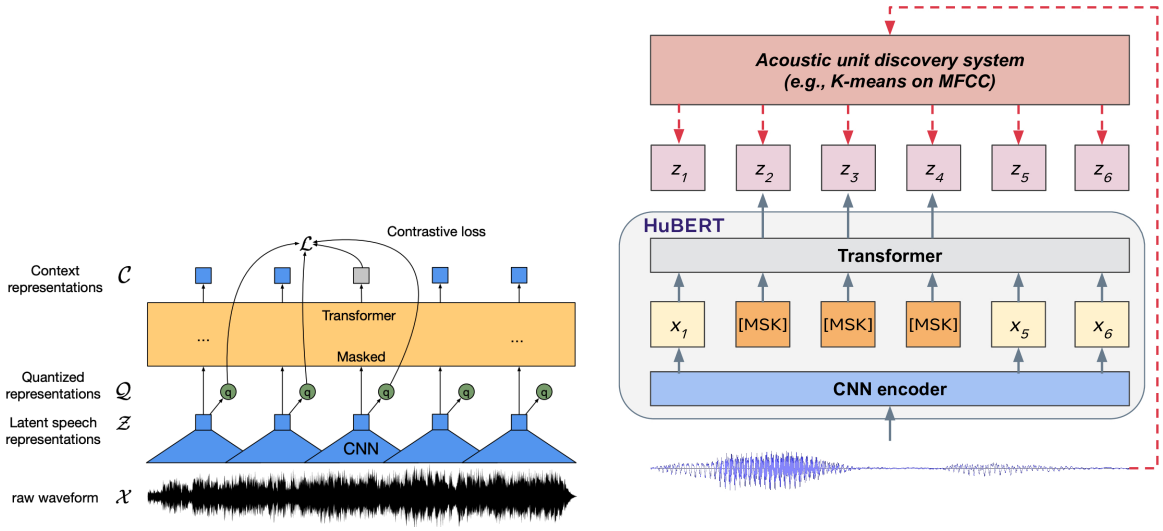
Traditionally, SSL models can be categorised into two distinct approaches: generative modeling and discriminative modeling. In this section, we will focus on summarising a selection of SSL models, presented in Table B.1, with a particular emphasis on their differences.

B.2.1 Generative modeling

Generative modeling has emerged as a prevalent approach for learning speech representations for SSL. Generally, generative models are trained to generate speech frames based on their learned speech representations with or without the help of context. For instance, the Autoregressive Predictive Coding (APC) model adopts a language model-like training paradigm, where a Recurrent Neural Network (RNN) gener-

ates future frames predicted from the past frames. Building upon this foundation, the Vector-Quantized APC (VQ-APC) model enhances the generative process by incorporating vector-quantization layers for more compact representations. The Mockingjay model takes inspiration from BERT-like pretraining techniques by masking input acoustic features along the time axis and subsequently regenerating the masked frames. Expanding upon this concept, the Temporal Encoder Representations from Acoustics (TERA) model introduces an additional layer of complexity by masking bins in the frequency axis alongside the temporal axis. Finally, the Non-autoregressive Predictive Coding (NPC) model combines elements from both APC and Mockingjay by substituting the RNN in APC with a CNN layers and modifying the future frames generation process into a masked reconstruction.

B.2.2 Discriminative modeling



(a) Illustration of the Wav2vec2 architecture taken from [164]

(b) Illustration of the HuBert architecture taken from [165]

Figure B.1: Overview of the discriminative SSL Wav2vec2 and HuBert models

The success of discriminative modeling has been notably pronounced with the introduction of the contrastive loss, a technique where the model discerns between correlated positive samples and negative samples. The underlying intuition is that positive samples should exhibit closer representations in comparison to their negative counterparts. A prominent exemplar of this approach is evident in the Wav2Vec2 model, which has demonstrated promising potential in learning speech representations. The Wav2Vec2 model achieves this by masking latent representations of the raw waveform and formulating a contrastive task over quantized speech representations. A more detailed representation of Wav2Vec2 architecture is displayed in figure B.1(a). Later, moving away from the contrastive loss, the work of [] proposed the

HuBert model. This model introduces a novel methodology by incorporating BERT's token prediction via offline clustering on representations. Specifically, the HuBert model use a BERT-like training that consumes masked continuous speech features to predict pre-determined cluster assignments. The labels assigned to the masked locations during clustering serve as the predicted targets. Importantly, the predictive loss is selectively applied solely over the masked regions, compelling the model to learn robust high-level representations of unmasked inputs in order to accurately infer the targets of the masked ones. The HuBert architecture is shown in figure B.1(b).

B.3 Experimental setup

In our experimental setup, we used the Self-Supervised Speech Pre-training and Representation Learning (s3prl) toolkit[1]. The s3prl allow the modular use of pre-trained SSL models, called upstream, to perform various downstream tasks. In order to evaluate the efficiency of different SSL models as features extractor for children's ASR, we froze the pre-trained models's weight to extract embedding representation of the speech signal as new acoustic features. All the differents SSL upstream models used in our experiments are listed along with detailed informations regarding their architectures in table B.1. Notably, each of these models underwent self-supervised pre-training on either 360 or 960 hours of LibriSpeech [31] (denoted as LS 360hr and LS 960hr, respectively) or on an extensive 60 thousand hours of LibriLight data [331] (referred to as LL 60k hr) . The ASR downstream task was conducted using a 2-layered Bidirectional Long Short-Term Memory (BiLSTM) architecture with 1024 units, optimised with a CTC loss. The training spanned 800 thousand iterations, with a learning rate set at $1.0\dot{1}0^{-4}$. Additionally, a dropout rate of 0.2 was applied to the BiLSTM architecture to increase robustness. Limited by the large size of some SSL model, we decided to used a subset of the Myst [33] dataset, using 77 hours of speech for training, by removing the longest utterances in the train and validation sets. A detailed description of the filtered Myst data is provided in table B.2.

Table B.2: My Science Tutor Children Speech Subset Corpus statistics

	Training	Validation	Test
# of utterances	23594	3959	4079
# of speakers	559	79	91
# of hours	77	12	13

Additionally, we evaluated the

SSL upsteam	UER ↓	WER ↓
Fbanks	12.29%	35.14%
TERA [332]	11.31%	31.80%
Audio Albert [333]	12.28%	34.69%
Wav2Vec2.0 Base	7.37%	19.76%
Wav2Vec2.0 Large	7.00%	18.76%
Distill HuBERT [237]	9.22%	25.75%
HuBERT Base	7.40%	19.77%
HuBERT Large	**6.03%**	**15.41%**

Table B.3: Results without language model of different Self-supervised models as feature extractors

B.4 Results

Table B.3 present the results of the comparaison between various SSL pre-trained model as feature extractors for children's ASR. We provide Unit error rate (UER) as well as WER. Fbanks are established as a baseline, yielding a UER of 12.29% and a WER of 35.14%. In terms of generative SSL models, TERA [332] and Audio Albert [333] surpass Fbanks, exhibiting improvements in both UER ,11.31% and 12.28% respectively and WER with 31.80% and 34.69% respectively. Turning to discriminative SSL, the Wav2Vec2.0 Base and Wav2Vec2.0 Large demonstrate substantial enhancements in performance, achieving UER values of 7.37% and 7.00%, and WER of 19.76% and 18.76%, respectively. The distilled version of HuBERT [237] outperforms Fbanks but falls behind the Wav2Vec2.0 models in terms of both UER and WER with 9.22% UER and 25.75% WER. Finally, HuBERT Base and HuBERT Large emerge as the top-performing SSL models, boasting the lowest UER with respectively 7.40% and 6.03% and WER of 19.77% and 15.41%. We observed that the best performing models are the large discriminative pre-trained on a large amount of speech data.

The results suggest that large Discriminative models, particularly HuBert Large, demonstrate superior performance compared to other SSL models and Fbanks as featuress extractor for children ASR. Notably, even though no language model where used in this experiment, the results are of the same order as those reported in previous the different chapters of the thesis obtained with a transformer and a transformer language model. Showing the benefic of using frozen pre-trained SSL models as feature extractor for children ASR.

B.5 Analysis of the extracted features

In this section, we delve in more detail into the distinct features extracted from various models, aiming to better understand the notable performance differences observed between Wav2Vec 2.0 and HuBERT, in contrast to generative models like TERA and traditional filterbanks. In a first step we aligned our children's speech data to obtain phoneme alignments using the Montreal Forced Aligner [334].

[1] https://github.com/s3prl/s3prl

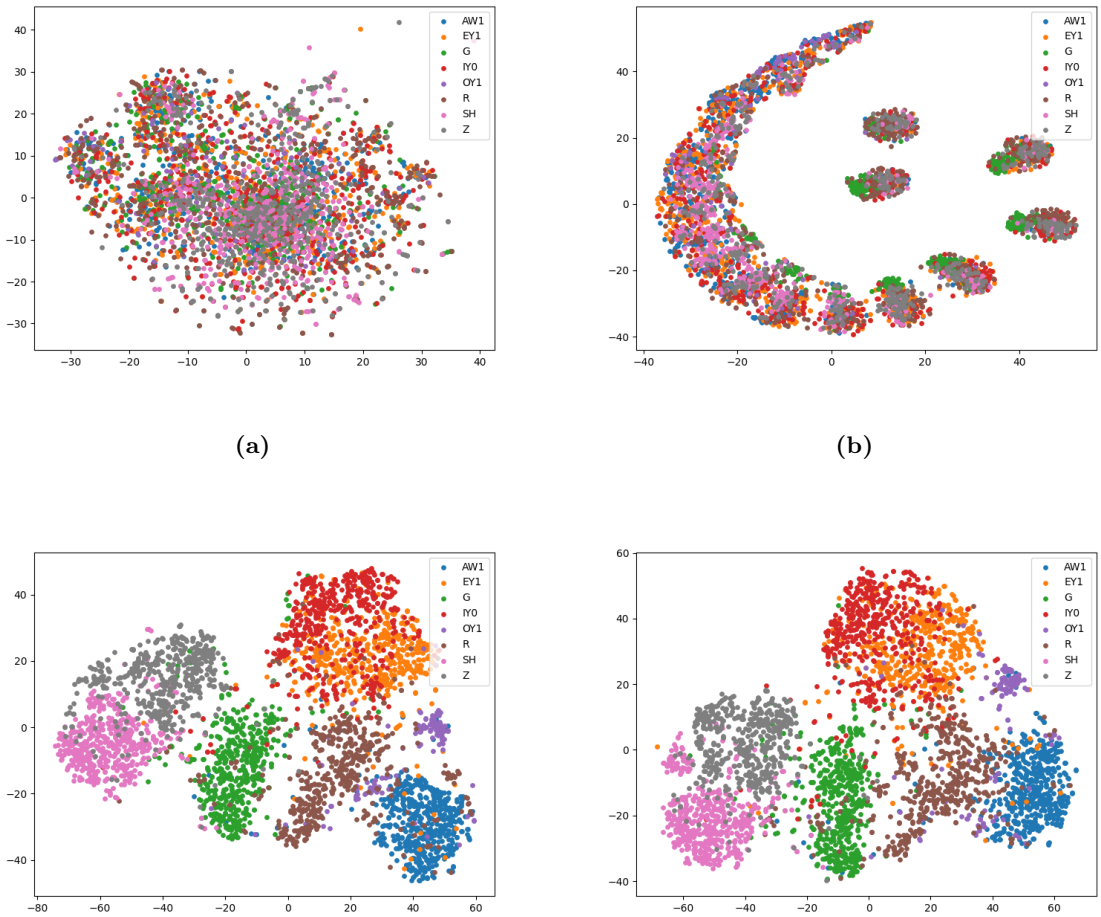


Figure B.2: (a) Fbanks (b) TERA (c) Wav2Vec 2.0 (d) HuBERT
T-SNE plot of the different extracted features using the same speech data using phoneme labels

Therefore, for each phonemes present in a utterance we obtained a variable-length feature sequences corresponding the extracted features for the different frames where the phoneme has been aligned. In order to get a single vector for each phoneme, we average these sequences. It is noteworthy that silence frames have been excluded. This operation is repeated for a subset of one thousand utterances of children speech in order to gather different exemple of the same phoneme from different speaker and different context. Subsequently, t-SNE (t-Distributed Stochastic Neighbor Embedding) plots are generated for each of the studied models.

The t-SNE plots are depicted in Figure B.2. We observe that traditional filterbanks features form a cloud points witn no structure. This lack of structure suggests that the fbanks features do not inherently exhibit phoneme-related information. Moving on to the t-SNE plot for TERA features, clusters are observable, but these clusters do not align with phoneme. This observation indicates that while TERA features capture information from speech, they not encode phoneme-specific information, as evidenced by the presence of mixed phonemes within the different clusters. In contrast, both Wav2Vec 2.0 and HuBERT exhibit highly similar plots, wherein distinct clusters corresponding to different phonemes are evident. This finding suggests that the features extracted from Wav2Vec 2.0 and HuBERT inherently capture phonemic information, even though no explicit phoneme annotations were provided during training. The presence of these phoneme-related clusters indicates that the usage of these features facilitate the ASR task by implicitly encoding phoneme information.

B.6 Conclusions and future work

However, it is crucial to emphasise that the outcomes and findings of our experiments are highly dependent on the language used. Specifically, all the SSL models were pre-trained using English language, which align with the language of the children dataset used in this experiment. Consequently, the generalisability of our results may be limited when applied to different languages. Using a different language could potentially result in decreased performances, as the SSL models may not be as adept at capturing the linguistic nuances and acoustic characteristics specific of that particular language [335]. To address the language-dependent nature of our results, future work could explore the efficacy of employing multi-lingual SSL models, such as XLS-R [336].