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Abstract

This is the place to put the English version of the abstract.

Zusammenfassung

Und hier sollte die Zusammenfassung auf Deutsch erscheinen.

Acknowledgement

I want to thank X, Y and Z for their precious help. And many thanks to whoever for proofreading the present text.

Phillip Ströbel from the CL institute at the UZH for his help with the OCR technologies. Lysander Jakobi for writing the Hebrew transcription. Florina Vogel for helping with the Farsi transcription. Si-En? Tanzil?

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List of Acronyms

IPA	International Phonetic Association
IPA	International Phonetic Alphabet
WER	word error rate
CER	character error rate
PER	phone error rate
G2P	grapheme-to-phoneme
FST	finite-state transducer
EM	Expectation-Maximization
seq2seq	sequence-to-sequence
SIGMORPHON	Special Interest Group on Computational Morphology and Phonology
NLP	natural language processing
PoS	Part-of-Speech
UZH	University of Zurich
WALS	World Atlas of Language Structures
ASR	automatic speech recognition
TTS	text-to-speech
HTR	Handwritten Text Recognition
NWS	The North Wind and the Sun
RNN	reccurent neural network

1 Introduction

With the advent of technologies that can process huge amounts of data, many linguistic tasks that were originally very tiresome and expensive to do, can now be accomplished much faster. Well known examples for this branch called natural language processing (NLP) are machine translation or search engines. A lot of available tools and consequently research done in this area is concerned with written text. For many scenarios like machine translation large corpora of written text in many languages are collected that are used to train such models. Following, there is an ever-growing set of models that are trained on written text and are used to accomplish those text-based tasks. Often the goal is to reach or outperform human solutions to those various tasks. It is necessary that this training data represents language well enough for a machine to reach that performance. From a linguistic point of view, the questions comes up if focusing on written language only can ever represent human language adequately. Most of communication and daily language use happens through speaking. This is a first potential limitation to many (written-)language technologies. Another possible limitation is the concern if written text represents language in general well enough to draw significant conclusions. It is not easy to find out what characteristics of a language can be observed in written representations. There are technologies like automatic speech recognition (ASR) or text-to-speech (TTS) that require the mapping of written to spoken language. Spoken language in those cases is mostly represented as phonetic transcriptions as those are easier to process. Those research foci do contribute to the questions how spoken and written language relate. But this still does not answer the question of how well written language represents language in general. The representative power of written text is much less studied. This is where this current thesis connects to cutting-edge research. I am going present my attempt of studying a multilingual phonetic corpus and comparing it to its written-text version. I will try to answer the following question: **Is it essential for the study of multilingual corpora to perform analyses on phonetic text (i.e. speech representations) rather than only written text?** It becomes clear, when looking at these considerations, that there are a few huge topics addressed. None of these is trivial and can be answered easily. While this thesis cannot possibly discuss everything from the use of phonetic transcriptions up to the nature of human language use, the aim is to make a step into the direction of quantifying the representative power of written text.

1.1 Research questions & goals

The text group of the Language and Space lab at the University of Zurich maintains a project that provides a multilingual corpus consisting of 100 language text samples [SPUR project]. Those 100 languages are meant to be representative for all the world's languages which is explained in more detail in section 2.4. It is therefore meant to give insight on relations, similarities, differences or properties of individual languages or language families. Specifically, their goal is to use quantitative methods like statistical modelling, machine learning and information theory to study language variation and compare languages. The goal is now to collect phonetic transcriptions of the corpus. The same analyses that are performed on the original written corpus can be performed on the phonetic texts and both can be compared. In order to add a phonetic corpus to the already existing one, various steps need to be performed which are outlined below:

1. **Data collection:** The given dataset contains no phonetic transcriptions of those 100 languages. The first step is to find already existing data.
2. **Phonetic transcriptions:** As existing data will not be available in sufficient amounts to perform meaningful analysis, the next step is to actually create phonetic transcriptions of as many languages as possible of the corpus.
3. **Calculations and Analysis:** Once the transcriptions have been obtained, the newly created phonetic corpus can be analysed and calculations can be performed.

By performing these steps I am aiming at answering the following two questions:

1. Is there any significant difference in comparing spoken or written languages?
2. Does written text represent language well enough to justify text-based research only?

1.2 Thesis structure

The thesis is subdivided into six chapters including a final conclusion. Chapter 3 sets the boundaries of the theoretical background. It presents the linguistic foundation of phonetics and phonology, an introduction to corpus linguistics or rather corpus phonetics and finally an overview of the possibilities for automated creation of phonetic transcriptions. Chapter 4 introduces to the struggle of data collection. It explains the various data types and how those can be used. Chapter **??** dives deeper into the possibilities for creating phonetic transcriptions and what models can be used to create those. Chapter 5 presents my own experiments to create phonetic transcriptions of the corpus.

2 Linguistic Background

This chapter sets out the linguistic background needed in order to get a better understanding of how spoken and written language relate. It covers the basics of phonetics and phonology, writing systems and the relatively new field of corpus phonetics. After setting this foundation I will have a look at the relation of spoken and written language.

2.1 Phonemes and syllables

Given that phonetics and phonology is a sub-area of traditional linguistics and often only touched on superficially in computational linguistics, I will summarise the most important assumptions and terms concerning said field. A very important terminological distinction is between phonetics and phonology. While phonetics refers to the study of actual sounds, phonology refers to the study of sound *systems*. In phonetics, it is not so much important what the different sounds mean, but how they are produced and perceived and what different sounds a human being can produce and perceive at all. When it comes to human communication using spoken language, many of these sounds are not actually used to produce distinguishable meaning. This is why on the other hand phonology is important to describe the set of distinguishable sounds that make up a language. For example: the letter /r/ in English can be pronounced in many different ways in a specific word like ‘request’. I can roll the /r/ like it is common in Spanish or I can pronounce it like an /r/ in German. None of those pronunciations produces a change in meaning. Others might say I have an accent or I speak a dialect but usually people will understand. This means that there exist many different *phonetic* sounds but only one *phonological* or *phonemic*. Those sounds are referred to as phone and phoneme respectively. While there are infinitely many phones, there are only finitely many phonemes in a language. Also, in one language there is typically a set of phones that is used by the majority of speakers of this language that can replace phonemes and does not change the meaning. Sounds that can replace another sound without changing the original meaning are referred to as ‘allophones’. Each language has therefore a set of phonemes, a phoneme inventory, and a set of allophones. How phonemes and allophones are used depends a lot on the dialect and idiosyncratic language use.

Not all different possible sounds are actually considered qualitatively ‘good’ sounds of a language. Usually there is a subset of all possible phones that is accepted as ‘good quality sounds’ within all different dialects of a language [Kracht, 2007]. An obvious example being loudness: Although very silent speech produces correct phones, these are not ‘good quality’ as they simply cannot be understood. Or speaking in English with hardly any mouth and tongue movement. Although this produces understandable sound, it is not generally considered good speech.

It is important to note at this point that the terms phonetic and phonemic respectively phone and phoneme are sometimes used interchangeably. Their linguistic definition as given above is clear while the definition on the computational side is often less strict. Strictly speaking phonemic transcriptions are not allowed to contain allophones but should write the respective phoneme. This will not always be the case when it comes to data used in language technology [Lee et al., 2020].

Vowels and consonants Each phone can be described based on different categories. A well-known distinction is that between vowels and consonants. Both of these are again categorized differently. The schema for vowels and consonants is inspired by the human vocal cavity. The terms to describe vowels sounds are based on the position of the tongue in the mouth and if the lips are rounded or not. Using those two categories enables us to distinguish every possible vowel. Figure 2 shows the vowel chart how it is usually represented in the International Phonetic Alphabet (IPA). More on this special alphabet and writing systems in general follows in section 2.3. Consonants are defined by the place and the manner of their production. The place, again, refers to the position of the tongue in the mouth and the overall form of the vocal tract. The vocal tract is used to block the air and make it flow in a specific way. The manner, on the other hand, describes the way the air is lead through the mouth or how it is blocked to produce a sound [CrashCourse, 2021a]. For dental sounds, the tip of the tongue is moved to the upper middle teeth. For palatal sounds, the body of the tongue is pressed against the hard palate in the back of the mouth cavity. These are examples for places of articulation. Examples for the manner are plosive or trill. A trill makes the tongue move in a vibrating way which consequently makes the air vibrate. A plosive first completely blocks the air and then pushes the air out of the mouth in a fast manner, a bit like an explosion, therefore the name. As well as for vowels, also consonant categorization is rather intuitive and pictorial. The complete consonant chart is depicted in figure 2. The exact description of each phone will later become important when we talk about representing phonemes for G2P models in section ??.

Syllables Phonemes, or letters, can be grouped into larger units called *syllables*. Syllables can be an entire word or a part of a word. English syllables typically consist of a group of consonants followed by a group of vowels or a diphthong followed by a group of consonants again. These parts are called *onset*, *nuleus* and *coda* respectively. For every syllable in every language it is true that the nucleus cannot be empty. The onset and the coda can be empty. Other than that, syllables are organized very differently in different languages. [Kracht, 2007]

Tones In some languages tones are used to distinguish meaning. Tones are a specific type of intonation that are used in some languages in addition to other sounds. Tones can be written but often they are not included in everyday texts.

Monophthongs and diphthongs

Suprasegmentals

2.2 Mappings of written and spoken language

Unlike spoken language that was a part of human interaction all the time, writing systems only developed over time. There are different writing systems that developed in different places at different times. The structure of the spoken language, the cultural context or the tools that were at hand to write are a few of many factors that influenced the emergence of a specific writing system. In General, we can think of writing systems as mappings from spoken language to written language. The systems used to represent sounds in different languages do not uniquely map a letter to one specific phoneme. Most of the time, there is a standard pronunciation of each letter that is trained by reciting the alphabet. However, in reciting the alphabet there is a vowel added to the consonants in order to pronounce them more easily. These explanations make clear that the mapping of written text to spoken text in various languages is complex. When taking a step back, we can see that a single grapheme can represent either a phoneme, a syllables or words. The history and development of writing systems is an entire independent study area. For this thesis it is mostly important to be aware of the independently developing systems.

Not all scripts can be treated the same and this most certainly has implications on models to create phonetic transcriptions. Each major mapping will be presented below.

ALPHABET When a grapheme maps to a phoneme, we call this an alphabet. In German, for example, the writing system consists of the Latin alphabet. The Latin alphabet is used for many different languages in western Europe and those languages that were influence by colonisation. There are other alphabets like the Cyrillic or the Greek alphabet. Having an alphabet does not mean that each grapheme, or letter in this case, maps to exactly one phoneme. In fact, one grapheme can have many different realizations as example 2.1 shows.

(2.1) The examples show the different realizations of the English grapheme sequence ‘ough’ [CrashCourse, 2021a]

(a) tough [tʌf]

(b) cough [kɒf]

(c) though [ðəʊ]

(d) through [θruː]

(e) bough [baʊ]

(f) brought [brɔːt]

The above examples show that it is not possible to have a one-to-one mapping from one grapheme or a sequence of graphemes to one phoneme or a sequence of phonemes with in the English language. Let alone within all languages that use the Latin alphabet. In addition, alphabets typically have diacritic marks that can be used to extend the main letters. Just as with single graphemes, also diacritic marks cannot simply be mapped to a phoneme.

ABJAD A special variant of an alphabet-language is abjad. Abjad represents only consonants and no vowels. This means that consonants need to be added while reading. Again, this means that there is a lot of ambiguity as it is not always clear which vowel should be added if there is no context. Semitic languages like Hebrew or Arabic make use of abjad.

(2.2) Hebrew examples that are first mapped to Latin alphabet then to the Latin alphabet including vowels.

(a) בצלם bzlm bzelem

(b) בצלם bzlm bzalam

Example 2.2 shows that each grapheme maps to a consonant but it can be completed with different vowels that change the meaning.

Syllabary In syllabaries, a grapheme represents a syllable instead of a single sound. Examples are the Japanese Hiragana and Katakana. Both of these examples do not have any internal ambiguities in their pronunciation as one grapheme maps to exactly one phoneme. However, in the case of Japanese, in addition to the syllabaries they use a logographic system as well which is ambiguous.

Logographic systems Logographic systems represent entire words or morphemes as graphemes. Chinese is an example for a logographic system. We cannot break down Chinese signs into single morphemes or letters. Similarly to an alphabet, also logographic systems are ambiguous in their pronunciation. The same sign in a different context is not always pronounced in the same way.

What all of these mappings have in common is that they are no reliable source of pronunciation as the examples above show [Kracht, 2007]. Many of the pronunciation rules of a language are based on convention. Speakers of a language just *know* how to pronounce a word. Still, there can arise heated debates about the correct pronunciation of certain words. Just think of Swiss German dialects. Apart from these conventions, spoken and written languages change differently over time. Spoken languages are typically more flexible and ready to change while their written representation often stays the same [Moran and Cysouw, 2018]. This can lead to official governmental interventions like the German orthography reform of 1996 that intended to adapt the German spelling to represent the German pronunciation more adequately. Also, major inventions like printing machines gave rise to standardization of writing systems as reading and writing became more common.

2.3 The International Phonetic Alphabet (IPA)

An exception to the above explained characteristics of an alphabet are phonetic alphabets like the IPA where each grapheme is intended to represent exactly one phone [CrashCourse, 2021b; Kracht, 2007]. As usual, reality is more complex than what we wish it to be. Even with the IPA there are inconsistencies. Figure 2 shows the full IPA chart including all characters that the International Phonetic Association (IPA) decided to use. Although the IPA seems very complete there are still sometimes sounds that cannot be represented using the IPA. The IPA has many conventions and covers a lot of sounds, but there are still some cases where a specific sound might not be covered. This becomes clear when, for example, looking at the vowel chart (see figure 2). The tongue does not 'click into place' for the vowels on the chart. Vowel characterisation happens on a continuum. This means that it is always possible to characterize a vowel as in between two vowels on the chart. The IPA is not the only transcription convention but by far more common (at least in this present research setting).

Apart from different character sets there are different levels of detail. Not all transcriptions represent the phonetics in equal detail. Generally, there is the distinction of broad and narrow transcription. These two go back to the linguistic distinction of phone and phoneme. Broad refers to a phonemic description. Following the linguistic definition in chapter 4, this means that the transcription does not transcribe speaker specific pronunciations or dialectal variations. This kind of transcription is therefore less complex and usually easier to create and understand. Narrow transcriptions are phonetic. They present every speaker individual or dialectal sounds as exactly as possible. Although the spoken text in narrow and broad transcription sounds only minimally different, the two texts can diverge greatly. It is important to treat broad and narrow transcriptions as two different kinds of transcriptions.

(2.3) pɪˈkʊ kɘˈʐɘf

(2.4) pɪˈkʰʊ kʰɘˈʐɘf

Example 2.4 is a narrow (phonetic) transcription of the beginning of the Mapudungun version of the short story *The North Wind and the Sun.* The same text is transcribed broadly (phonemic) in example 2.3. As becomes clear in this example, the narrow transcriptions is longer as it contains more different characters. In this case it is only the superscript h that is different. The problem, with especially the narrow transcriptions, is that the transcriber still needs to define what narrow means in a specific case. This becomes tricky when given a task to automatically transcribe text, the training data might employ one definition of narrow, while there are texts in the test set that might follow another definition. However, in practice data is very rare, so in the end you would probably just use any data you can get.

2.4 The corpus

As mentioned in the introduction, the basis of the data used in this thesis is a corpus provided by the SPUR lab at the University of Zurich (UZH). The corpus contains 100 languages which are proposed by Comrie et al. [2013]. This online book contains different chapters each of which shows a different linguistic feature including a map which shows the distribution of that feature over the world's languages. While the number of languages presented on the individual maps depends on the amount of research done in a specific area, the sum of all maps gives quite an impressive overview on the structure of nearly half of the world's languages. Out of the 2676 languages a sample of 100 languages was chosen. This sample does not contain too many languages from one area, neither does it contain too many languages from one family. Not considering the aforementioned criteria of maximizing genealogical and areal diversity can lead to misleading results. Figure 1 shows the distribution of the corpus on a world map. The different icons show the genus of the languages which is a classification of languages defined by the World Atlas of Language Structures (WALS) team that maintains the language description collection. The interactive map can be viewed online [100-language-sample]. Table 6 in the appendix A shows all languages that are in the 100 language corpus. None of the text samples are provided by WALS. The entire corpus is provided by the SPUR team that collected the corpus over the last few years and is continuously working on and with it.

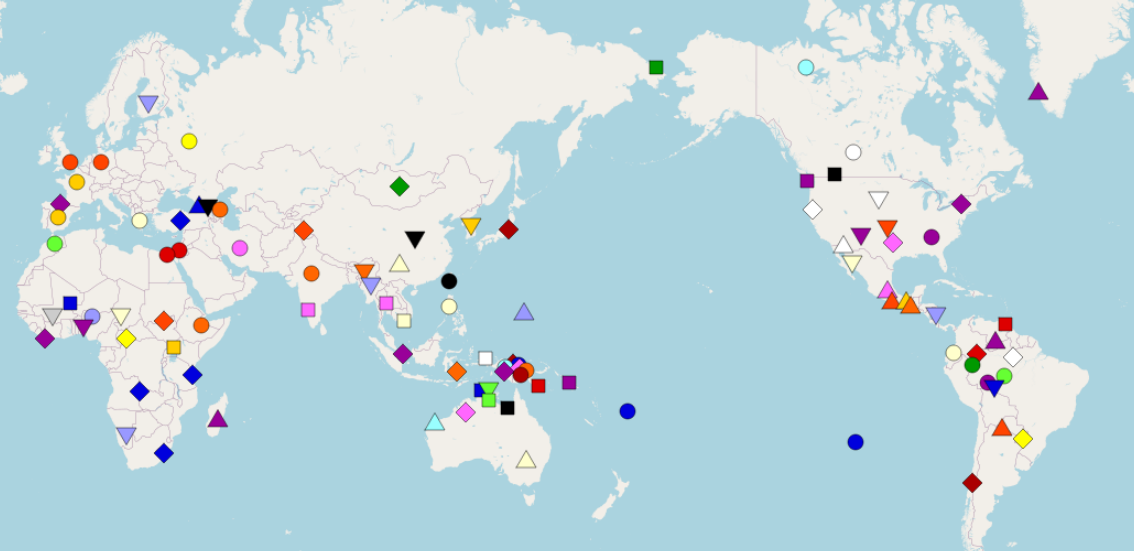


Figure 1: WALS - Map that shows the 100 Languages

2.5 Corpus phonetics

Due to recent technological advancement it has become possible to store large digital collections of speech recordings and their aligned transcriptions. These possibilities gave rise to a wider acknowledgement of corpus phonetics. Corpus phonetics deals with an abundance of linguistic variation. In addition to language, style or vocabulary variation, there are differences in dialect and idiolect, physiological state of the speakers and their attitude [Liberman, 2019; Chodroff, 2019]. Many methods and tools used in corpus phonetics are based on ASR algorithms or simple programming [Chodroff, 2019].

A way to analyse or use phonetic corpora is to use phonetic features to represent each phoneme. These features are a list of properties that are overlapping with the phonetic description of each phoneme. It is a minimal list that can be used to describe unique phones.

2.6 Representing language

Elaborated writing systems like we are used to nowadays came only much later compared to language in general. Can they capture language as such well enough? Computational linguistics deals mostly with written languages, but what does traditional linguistics say about the relation of written and spoken language? Whenever we study language we look at samples of that language. It is simply impossible to study an *entire* language as we would need all texts that were ever produced in that language. Consequently, we need to ask ourselves how much and what material of a language is enough to study it properly [Baird et al., 2021]. Both written and spoken language are representations of a language. As we have seen earlier in in this chapter mapping a spoken language to its written representation is far from easy and never perfect. Baird et al. [2021] focus on answering the question how much phonetic data is needed to represent a language well. We know that each language has specific sounds, its phoneme inventory, that are frequently used. The question is now how much data is needed to cover this entire phoneme inventory of a language. In order to answer that question Baird et al. [2021] study The North Wind and the Sun (NWS) corpus. I will elaborate more on that corpus later in the data collection section (see section 4.2).

corpus linguistics and quantitative analysis.

2.7 Dataset collection

The first practical part of this thesis is concerned with data collection. Although phonetics is an important sub-area in linguistics, phonetic transcriptions are hard to find. If there are any transcriptions available, there are various hindrances that prevent it from being used as is. The following chapter outlines the different data types which are available and the different strategies that are used to convert the data into one well-formatted corpus. Apart from hindrances concerning sources and format, there are issues concerning the data itself. There are generally many more different pronunciations of a word than there are spellings. It is thus important to specify clearly what dialect or pronunciation convention a phonetic transcription follows.

2.8 Transcription Sources & Formats

Phonetic transcriptions of various languages are available from different sources in different formats. In order to use those, they have to be converted into simple text format in appropriate encoding that can easily be read and processed by a machine. The following subsections list the different data types and how they are used.

2.8.1 Full Text

For the task at hand, phonetic transcriptions in the form of fully transcribed texts would be ideal. As became clear, it is hardly possible to find those. There is plenty of material describing how different languages can be transcribed but those rarely contain fully transcribed text. If they do, it is mostly limited to one or a few sentences. The JIPA continuously published different phonetic transcriptions of a short story called “The North Wind and the Sun". A collection of those is available in a handbook of the JIPA which is only available as a pdf scan of the original book [Press, 2010]. While OCR is technically possible it turns out to be very difficult for IPA characters. The tools that exist do sometimes include IPA character recognition like the ABBYY FineReader which can be acquired for a fee. The CL institute at the UZH owns a version of the ABBYY tool but this version does not include the IPA module although ABBYY generally supports IPA character recognition. This ABBYY version was run on a JIPA pdf containing said phonetic transcriptions but the result could not be used. Mostly diacritics and special phonetic symbols were not correctly transcribed. There are also open source tools. One of which is called tesseract. tesseract does not include the IPA alphabet. It is possible to train the model to include the IPA alphabet but this would need appropriate training data. Add quote

Iso639-3	Type	Variation	Language
arn	broad and narrow		Mapudungun
cmn		Pekinese	Mandarin Chinese
deu	broad and narrow	North German	German
ell			Modern Greek
eng	broad and narrow		English
eus	broad and narrow	Goizueta	Basque
hau	narrow		Hausa
heb			Modern Hebrew
hin	narrow		Hindi
ind			Indonesian
kat	broad and narrow		Georgian
kor			Korean
mya			Burmese
pes			Western Farsi
spa	broad and narrow	Castilian	Spanish
tha			Thai
tur	broad	Istanbul	Turkish

Table 1: The table shows a list of all the short stories “The North Wind and the Sun" that are available as phonetic text and whose languages are in the corpus.

Additionally, some texts include short descriptions where certain pronunciations rules are explained which are not included in the transcriptions (especially stress).

2.8.2 Pronunciation Dictionaries

Another data type that is found quite often are lists of words' pronunciation. Those are sometimes referred to as pronunciation dictionaries. However, these often mean that there are words mapped to an audio representation which is not what is meant in this present case. Pronunciation dictionary in this present case refers to the mapping of an orthographic word to its pronunciation using phonetic symbols. Although such lists are very handy, especially as they can easily be used to train a transcription model, transcriptions of individual words and of entire texts are not exactly the same. There are two major problems:

- Pronunciation depends on the context of the word in question. Word forms are ambiguous and sometimes their pronunciation differs given on their specific context. add example

- Phonetic boundaries are not always equivalent with word boundaries. Spoken language sometimes merges certain words which leads to one phonetic unit. There are phonetic symbols to represent such merging which often happens in, for example, French.

2.8.3 Data used for this thesis

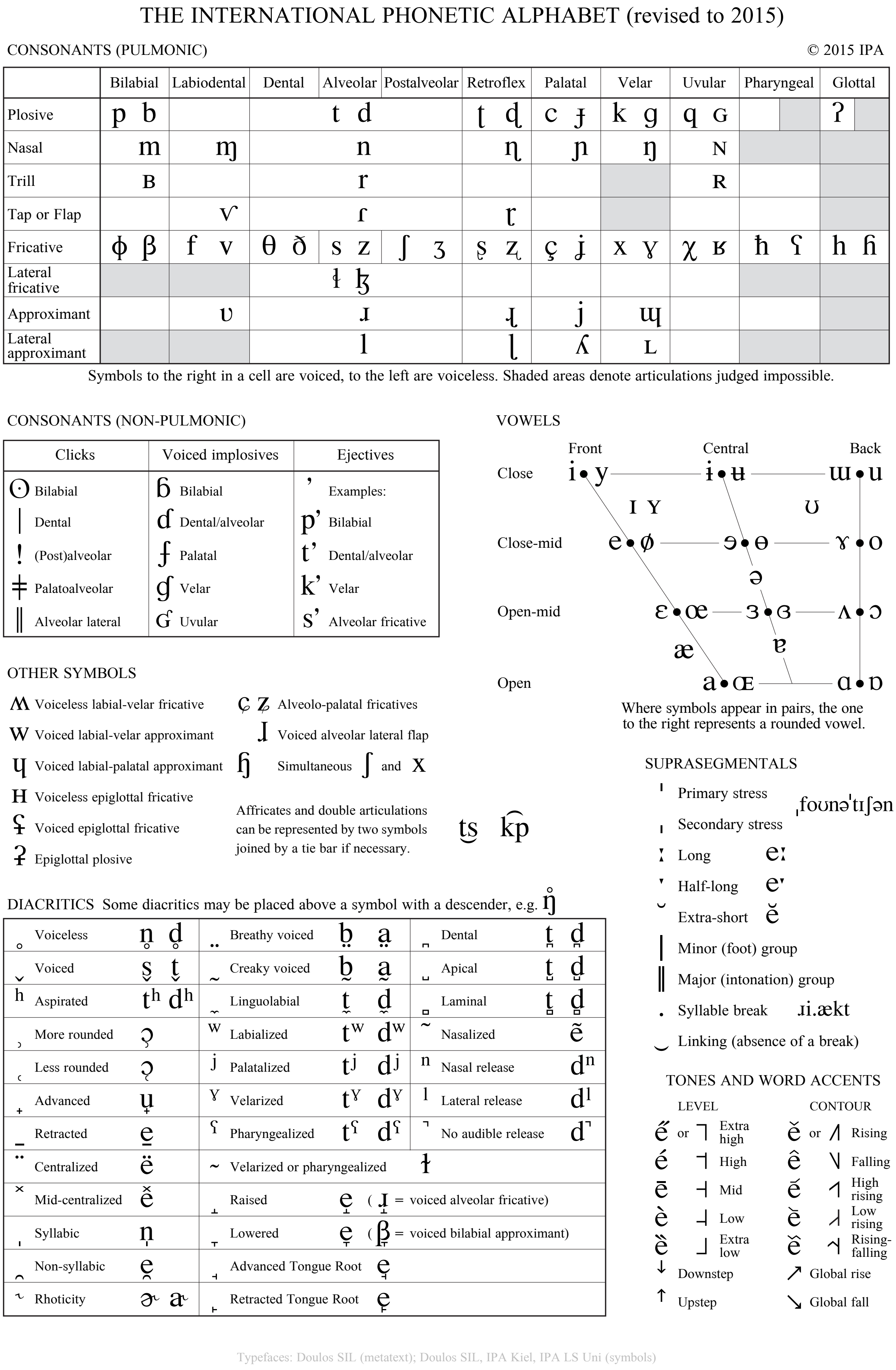
The data which I will use for my experiments in this

2.8.3.1 WikiPron

There exist databases of pronunciation dictionaries. Many of those do not release the mining software used to extend the database with more languages [Lee et al., 2020]. A very recent project that publishes pronunciation lists is WikiPron. The WikiPron project [Lee et al., 2020] is an open-source Python mining tool to retrieve pronunciation data from Wiktionary. Their database contains 1.7 million word/pronunciation pairs in 165 languages. Both, the database and the tool, are freely available online. Apart from the mining tool and the database, WikiPron can be used for grapheme-to-phoneme modelling. More on this subject will be discussed in chapter ??. In both G2P shared tasks organized by SIGMORPHON (see ??, data provided by WikiPron was used. For the 2021 task, WikiPron was improved and additional scripts were added based on feedback and findings in the 2020 task. One major improvement was concerned with languages written in different scripts. WikiPron supports now the detection of different scripts and languages can be sorted according to those scripts.

2.8.3.2 The North Wind and the Sun

Quite a well-known phonetic corpus is a collection of short stories 'NWS'. The story is a fable said to be written by Aesop and has been translated in many languages. Additionally, for many languages there exits a phonetic transcription. Some transcriptions have been published in separate issues as part of a collection of articles called "Illustrations of the IPA". While some of them are available in plain text format most of them are only available as pdfs or even images in text books. It is of course possible to manually type-write those which is what I did. More on how this is best done is explained in chapter 5 on experiments. Table 2 shows the languages for which the short story is available and which are also in the corpus. [Baird et al., 2021]



THE INTERNATIONAL PHONETIC ALPHABET (revised to 2015)

CONSONANTS (PULMONIC)

	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k ɡ	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Symbols to the right in a cell are voiced, to the left are voiceless. Shaded areas denote articulations judged impossible.

CONSONANTS (NON-PULMONIC)

Clicks	Voiced implosives	Ejectives
ʘ Bilabial	ɓ Bilabial	ʼ Examples:
ǀ Dental	ɗ Dental/alveolar	pʼ Bilabial
ǃ (Post)alveolar	ʄ Palatal	tʼ Dental/alveolar
ǂ Palatoalveolar	ɠ Velar	kʼ Velar
ǁ Alveolar lateral	ʛ Uvular	sʼ Alveolar fricative

VOWELS

	Front		Central		Back
Close	i • y		ɨ • ʉ		ɯ • u
		ɪ ʏ		ʊ	
Close-mid	e • ø		ɘ • ɵ		ɤ • o
			ə		
Open-mid		ɛ • œ	ɜ • ɞ		ʌ • ɔ
		æ	ɐ		
Open		a • ɶ			ɑ • ɒ

Where symbols appear in pairs, the one to the right represents a rounded vowel.

OTHER SYMBOLS

ʍ Voiceless labial-velar fricative

w Voiced labial-velar approximant

ɥ Voiced labial-palatal approximant

ʜ Voiceless epiglottal fricative

ʢ Voiced epiglottal fricative

ʡ Epiglottal plosive

ɕ ʑ Alveolo-palatal fricatives

ɺ Voiced alveolar lateral flap

ɧ Simultaneous ʃ and x

Affricates and double articulations can be represented by two symbols joined by a tie bar if necessary. t͜s k͡p

DIACRITICS Some diacritics may be placed above a symbol with a descender, e.g. ŋ̊

˳	Voiceless	n̥ d̥	¨	Breathy voiced	b̤ a̤		Dental	t̪ d̪
ˬ	Voiced	s̬ t̬	˷	Creaky voiced	b̰ a̰		Apical	t̺ d̺
ʰ	Aspirated	tʰ dʰ		Linguolabial	t̼ d̼		Laminal	t̻ d̻
˒	More rounded	ɔ̹	ʷ	Labialized	tʷ dʷ	˜	Nasalized	ẽ
˓	Less rounded	ɔ̜	ʲ	Palatalized	tʲ dʲ	ⁿ	Nasal release	dⁿ
˖	Advanced	u̟	ˠ	Velarized	tˠ dˠ	ˡ	Lateral release	dˡ
ˍ	Retracted	e̠	ˤ	Pharyngealized	tˤ dˤ	˺	No audible release	d̚
¨	Centralized	ë	~	Velarized or pharyngealized	ɫ			
˟	Mid-centralized	e̽	˔	Raised	e̝ (ɹ̝ = voiced alveolar fricative)			
ˌ	Syllabic	n̩	˕	Lowered	e̞ (β̞ = voiced bilabial approximant)			
	Non-syllabic	e̯		Advanced Tongue Root	e̘			
˞	Rhoticity	ɚ a˞		Retracted Tongue Root	e̙			

SUPRASEGMENTALS

- ˈ Primary stress ˌfoʊnəˈtɪʃən
- ˌ Secondary stress
- ː Long eː
- ˑ Half-long eˑ
- ̆ Extra-short ĕ
- | Minor (foot) group
- ‖ Major (intonation) group
- . Syllable break ɹi.ækt
- ‿ Linking (absence of a break)

TONES AND WORD ACCENTS

LEVEL			CONTOUR		
e̋ or	˥	Extra high	ě or	˩˥	Rising
é	˦	High	ê	˥˩	Falling
ē	˧	Mid	e᷄	˧˥	High rising
è	˨	Low	e᷅	˩˧	Low rising
ȅ	˩	Extra low	e᷈	˧˦˧	Rising-falling
↓		Downstep	↗		Global rise
↑		Upstep	↘		Global fall

Typefaces: Doulos SIL (metatext); Doulos SIL, IPA Kiel, IPA LS Uni (symbols)

Figure 2: This is the full IPA chart, last updated in 2015

3 Technical Background

This chapter presents the technical background that is needed for this thesis. It explores everything around automated models that can be used to create phonetic transcriptions. I will first set the basis and dive into evaluation metrics and general architectures and frameworks that are commonly used and then present current state-of-the-art models. Table 1 shows the state-of-the-art models for G2P modelling.

3.1 Evaluation metrics

The evaluation of phonetic transcriptions depends on whether the system output and the reference are sentences or single words, i.e. character sequences. The most common metric to evaluate the former is the word error rate (WER). The lower the score, the better the model. If the WER is 0, this means that the texts are exactly the same. The following formula is used to calculate WER:

$$WER = \frac{S + I + D}{N} \tag{3.1}$$

In equation 3.1 the S stands for substitution, I for insertion, D for deletion and N denotes the total number of words in the reference sequence. Those numbers can be calculated by using an algorithm to get the edit distance. The idea behind the score is that we can capture the cost that it takes to transform the system output into the reference phoneme sequence. If you want the percentage, the number needs to be multiplied with 100. Note that the WER can be more than 100%. This happens if, for example, the are a lot of additional insertions or deletions in the system text. If the system output and reference are character sequences, the score is called character error rate (CER). It is calculated in the exact same way as the WER, but instead of words everything is calculated on character basis. In the phonetic transcriptions setting, the CER is typically replaced by the phone error rate (PER) to match the correct terminology. The calculations are not changed. In a multilingual setting,

Author	Model Architecture	ISO 639-3	WER
SIG21: Clematide and Makarov [2021] Link	CLUZH models 1-7. LSTM-based neural transducer with pointer network-like monotonic hard attention trained with imitation learning. All models 1-7 are majority-vote ensembles with different number of models (5-30) and different inputs (characters or segments). Achieved good results in nld (14.7), ice (10), jpn (5.0), fra (7.5) and vie (2.0) but not better than SIG20.	medium (10,000 pairs)	
		hye (arm_e)	6.4
		hun	1.0
		kat (geo)	0.0
		kor	16.2
		low (800 train pairs)	
		ell (gre)	20
		ady	22
		lav	49
		mlt_ltn	12
		cym (wel_sw)	10
SIG21: Lo and Nicolai [2021] Link	UBC-2 outperforms the baseline. They analysed the errors of the baseline and extend it by adding penalties for wrong vowels and wrong diacritics. Errors on vowels actually decreased. Best macro average (low -resource).	ady	22
		khm	28
		lav	49
		slv	47
SIG21: Gautam et al. [2021] Link	Dialpad-1: Majority-vote ensemble consisting of three different public models (weighted FST, joint-sequence model trained with EM and a neural seq2seq), two seq2seq variants (LSTM and transformer) and two baseline variations.	high (32.800 train pairs)	
		eng (eng_us)	37.43
SIG20: Peters and Martins [2020] Link	DeepSPIN-2,-3,-4: Transformer- or LSTM-based enc-dec seq2seq models with sparse attention. Add language embedding to enc or dec states instead of language token.	3.600 train pairs	
		jpn (jpn_hira)	4.89
		fra (fre)	5.11
		rum	9.78
		vie	0.89
SIG20: Yu et al. [2020] Link	IMS: Self training ensemble of one n-gram-based FST and 3 seq2seq (vanilla with attention, hard monotonic attention with pointer, hybrid of hard monotonic attention and tagging model).	hin	5.11
		nld (dut)	13.56

Table 2: This table presents the state-of-the-art G2P models. Models that are important for this thesis will be explained in more detail. The language code in parenthesis is the code used in the respective paper.

it is sometimes necessary to have a score for the entire system covering more than one language. In such cases it is custom to use a macro-averaged WER or CER. This means that the sum of the scores for each language is divided by the number of languages [Leung, 24.6.2021].

In the case of G2P conversion, the WER actually just reflects the rate of wrongly predicted words, as one sequence consists of only one word.

3.2 Automated phonetic transcription

In this section I set the stage for understanding the technical background of G2P models. Today's technologies allow to build models that create phonetic transcriptions automatically given an original text. There are several approaches which I will discuss below. Creating phonetic transcriptions is essentially a sequence-to-sequence (seq2seq) task. Like other NLP tasks its goal is to transform a sequence of characters into another sequence of characters. In particular, it is very similar to machine translation which is such a task as well [Rao et al., 2015]. In the present case, the input sequence is a sequence of graphemes. These can look very differently depending on the script (see section 2.2). The output sequence is a sequence of phonemes[1]. This process is typically referred to as G2P. There are a few problems and characteristics of the G2P task that are important:

- The input and output sequences are not always of the same length. It is difficult to align input and output. Not all systems rely on aligning input and output but often it is needed to analyse the results (for example to create confusion matrices).
- Due to the open-vocabulary situation and the impossibility to cover all possible words, all systems must be able to deal with rare and unseen words [Rao et al., 2015; Bisani and Ney, 2008].
- Most of the research done in this area is limited to the English language. This is not uncommon in NLP research. The availability of English data resources and the unavailability and struggles to find data in other languages heavily influences this research. Ashby et al. [2021] report that the SIGMORPHON (Special Interest Group on Computational Morphology and Phonology) G2P tasks in 2020 and 2021 are the first attempt to tackle multilingual G2P.

In the following, I explain the most important model types. Often, those different types are used in combination as the different models have different advantages which can be used very well in combination.

[1] Please refer to section 2.1 in order to understand the terminological implications of phoneme. As it is common in research, I will stick to the term *phoneme* although strictly speaking it is not always correct. Phoneme in this case just refers to any symbol that is used to represent a sound.

3.2.1 Look-up dictionary

The simplest version of a G2P model is a look-up table where a grapheme sequence is stored together with its phonetic transcription. Such a dictionary is expensive to create and needs a lot of storage and has a very limited coverage. Although such a system is no longer useful on its own it can still be used in addition to other, for example, statistical models [Bisani and Ney, 2008].

3.2.2 Rule-based models

The first systems to create phonetic transcriptions of text were rule-based systems. Although rule-based systems are outperformed by more recent neural models [Ashby et al., 2021; Gorman et al., 2020], I will introduce them as they were an important step towards G2P modelling. Additionally, rule-based models can be used together with other models to reach a better performance. Rule-based transcriptions models are built using linguistic pronunciation rules. In order to be able to create such a system, one needs to collect pronunciation rules first. While there are only few languages where such rules are ready and available for the general public there are many languages where those rules need to be created first. In order to create the rules in the first place, a lot of linguistic expertise is needed. Apart from this initial effort to create the rules, a problem with rule-based approaches is the maintenance of the systems. To maintain the system, experts need to keep track of language change which is time consuming and expensive. Most languages are irregular in their pronunciation and those irregularities need to be tracked as well. Another drawback of such systems is that they might fail when presented with unseen or rare words [Bisani and Ney, 2008]. Many earlier systems published considered only one language and were not multilingual (see e.g. Toma and Munteanu [2009]).

Epitran Epitran is an example of a relatively new rule-based system. It makes use of the fact that there are languages that are more or less regularly pronounced and presents a rule-based system for G2P conversion for mostly low-resource languages. The system has the ability to provide a solution for every possible word and is consistent within its transcriptions. Epitran for all languages except English and traditional Chinese works with a map file that allows to map graphemes to phonemes. Additional pre- or post-processing can be applied that follow context specific rules [Mortensen et al., 2018].

3.2.3 N-gram Models / Statistical models

N-gram models, statistical models or joint-sequence models were used before neural models took over the field. These are sometimes referred to as traditional models. One reason why they were outperformed by neural models is that it is necessary to construct alignments between grapheme and phonemes. This is needed because one grapheme can be realized as multiple phonemes or vice versa. It is not possible to simply have a one-to-one alignment. Joint-sequence models were often used with different versions of the Expectation-Maximization (EM) algorithm [Lo and Nicolai, 2021]. The main intuition about those models is that they, in some way or other, try to statistically model the relationship between graphemes and phonemes. Typically, those models consist of two parts: first an alignment model. Second, a model that captures the relationship between graphemes and phonemes using clearly defined statistical methods. A very common model is the joint-sequence model.

Joint-sequence model The term *joint-sequence* hints already at the underlying architecture of those models: the idea is to process *joint* sequences of input and output symbols. In order to do that they must be aligned. We can then concatenate those alignments, which means to concatenate the grapheme and the phoneme which it is mapped to, and receive what is called a graphone. Using the concept of FST, we can build a model. FSTs are similar to finite-state automatons. But instead of just telling whether a certain sequence belongs to a certain language (which is pattern matching), they can output none or many symbols at every step as well. This means that in the process of iterating over the sequence, they produce another sequence. Knowing that, it is easily understandable that this works well for our given G2P task. The idea is now, that we model the joint-probability of the input graphemes and output phonemes or rather our graphones. Doing this we can use the EM algorithm to find a mapping of graphemes to phonemes that is most probable. As those graphones consist of n-grams of both the input and output sequence, they themselves can be considered a n-grams which is why those models are sometimes referred to as n-gram models [Bisani and Ney, 2008; Lo and Nicolai, 2021].

3.2.4 Neural models

Neural G2P models have been reported to outperform most other models [Lee et al., 2020]. Many researchers experiment with different variants of LSTM models [Lee et al., 2020; Hammond, 2021; Gautam et al., 2021; Rao et al., 2015]. But there are also other models that have been used. The most important of those will be introduced in the following.

Sequence-to-sequence seq2seq is not a model type as such but rather an architecture. seq2seq models include an encoder and a decoder or more than one of each depending on the exact implementation. Both encoder and decoder can be the same model type or different ones but all of them are reccurent neural networks (RNNs) or some variant of it. The output of the (last) encoder RNN is used as input for the decoder RNN. What makes such a model architecture powerful is that they can map an input sequence to a output sequence of a different length and different type. Generally, there is a difference between models that assume conditional independence between each output step (e.g. Hidden Markov Models) and there are models that do not make this assumption but condition the current output on the entire sequence before. Depending on what model type is used as encoder or decoder considering the entire preceding input can get tricky if the input sequence is really long. This is true especially for RNN models. Apart form that, seq2seq models have to wait until the full input sequence is processed before they can start decoding. This does not work well for input that gets continuously longer [Kostadinov, 02.05.2019; Sutskever et al., 2014].

RNN The important intuition about RNNs is that they process each unit of an input sequence one unit at a time. In our case, we can think of one unit as one grapheme in the input sequence. Instead of only outputting something at each time step, a hidden representation is passed on to be processed in the next time step. This sequential processing is crucial as it means that each unit gets information about the units preceding it. This makes sure that information about the preceding context is included. The output of such an RNN is therefore a manipulated version of the input sequence of the same length. A special kind of RNN is the LSTM. LSTM means long short-term memory. As their name suggests they include what we could call a memory. Instead of just adding some representation of the preceding units at each time step, LSTMs can more flexibly decide what information is added and what information should be forgotten [Olah, 29.01.2022; Kostadinov, 12.02.2017]. Many earlier neural LSTM models use a connectionist temporal classification layer to include alignment information [Lo and Nicolai, 2021]. This is a special methodology that can deal with n-to-m alignments which is the case in G2P modelling.

Transformer Transformers are seq2seq models as well. A central concept and what makes transformers powerful models is their self-attention mechanism. Also, they can process the entire input sequence in one go such that each unit is processed by a separate part of the model instead of just using the same cell for every unit. This allows to have dependencies between the different input units which means that we can model any dependencies within a sentence or a grapheme sequence. This is the reason why we call it *self*-attention as the attention is focused on other parts of the input sequence, but still on the sequence itself [Alammar, 03.01.2022].

Neural Transducer Neural transducers, as presented by Jaitly et al. [2016], extend previously used seq2seq models. They can treat more arriving input without having to redo the entire calculation for the entire updated sequence. At each time step, the neural transducer can output zero to many output symbols.

ISO396-3	**BS20**						**DeepSPIN20**		**IMS20**		**BS21**	**CL21**	**UBC21**		**DP21**
	LSTM		**transformer**		**pair n-gram**							CL	UBC-1	UBC-2	
	WER	PER	WER	PER	WER	PER	WER	PER	WER	PER	WER	WER	WER	WER	
ady^{B}	28.00	*6.53*	28.44	*6.49*	32.00	*7.56*	24.67^{3}		25.00	*5.79*	**22.00**	**22.00**^{23}	25.00	**22.00**	
bul^{A}	31.11	*5.94*	34.00	*7.89*	41.33	*9.05*	-		22.22	*4.85*	**18.30**	18.80^{6}			
cym (wel)^{B}											**10.00**	**10.00**^{1}	13.00	12.00	
ell (gre)^{B}	18.89	*3.30*	18.89	*3.06*	21.78	*4.05*	-		**18.67**	*2.97*	21.00	20.00^{13}	22.00	22.00	
eng(_us)											41.94				**37.43**
fra (fre)^{A}	6.22	*1.32*	6.89	*1.72*	13.56	*3.12*	**5.11**^{3}		6.89	*1.60*	8.50	7.50^{456}			
hbs^{A}											**32.10**	35.3^{7}			
hin	6.67	*1.47*	9.56	*2.40*	12.67	*4.05*	-		**5.11**	*1.20*					
hun^{A}	5.33	*1.18*	5.33	*1.28*	6.67	*1.51*	-		5.11	*1.12*	1.80	**1.00**^{67}			
hye (arm)^{A}	14.67	*3.49*	14.22	*3.29*	18.00	*3.90*	-		12.67	*2.94*	7.00	**6.40**^{7}			
ice^{B}	10.00	*2.36*	10.22	*2.21*	17.56	*3.62*	-		**9.33**	*2.04*	12.00	10.00^{13}	13.00	11.00	
ita^{B}											**19.00**	31.00^{3}	20.00	22.00	
jpn(_hira)^{A}	7.56	*1.79*	7.33	*1.86*	9.56	*2.07*	**4.89**^{4}		5.33	*1.26*	5.20	5.00^{7}			
kat (geo)^{A}	26.44	*5.14*	28.00	*5.43*	37.78	*6.48*	-		24.89	*4.57*	**0.00**	**0.00**^{4567}			
khm^{B}											34.00	32.00^{13}	31.00	**28.00**	
kor^{A}	46.89	*16.78*	43.78	*17.50*	52.22	*15.88*	24.00^{13}		26.22	*4.38*	16.30	**16.20**^{4}			

lav^{B}											55.00	**49.00**^{23}	58.00	**49.00**
lit	**19.11**	*3.55*	20.67	*3.65*	23.11	*4.43*	-		20.00	*3.63*				
mlt(_ltn)^{B}											19.00	12.00^{1}	19.00	18.00
nld (dut)^{A}	16.44	*2.94*	15.78	*2.89*	23.78	*3.97*	-		**13.56**	*2.36*	14.70	14.70^{7}		
rum^{B}	10.67	*2.53*	12.00	*3.62*	11.56	*3.55*	**9.78**^{3}		10.22	*2.23*	10.00	12.00^{3}	14.00	10.00
slv^{B}											49.00	50.00^{1}	56.00	**47.00**
vie^{A}	4.67	*1.52*	7.56	*2.27*	8.44	*1.79*	**0.89**^{2}		1.56	*0.48*	2.50	2.00^{57}		
macro	16.84	*3.99*	17.51	*4.30*	22.00	*4.92*	14.15	*2.92*	13.81	*2.76*				
macro low											25.10		27.10	24.10
macro medium											10.60			

Superscript numbers denote model numbers. Numbers in bold denote best model for one language (only WER). Languages in bold are in the 100LC corpus. ^{A}: medium resource languages in 2021. ^{B}: low resource languages in 2021

BS20: Link
DeepSPIN: Transformer- or LSTM-based enc-dec seq2seq models with sparse attention. Add language embedding to enc and dec states instead of language token. The WER scores are not available for all languages. Neither are the PER scores available. Link
IMS: Self training ensemble of one n-gram-based FST and 3 seq2seq (vanilla with attention, hard monotonic attention with pointer, hybrid of hard monotonic attention and tagging model) Link
BS21: similar to CL21 Link
CL21: LSTM-based neural transducer with pointer network-like monotonic hard attention trained with imitation learning 7 different, but still very similar ensembles of one model. Link
UBC21: UBC-2 baseline variant with vowel error punishment. UBC-1 baseline variant with syllable prediction. Link
DP21: Majority-vote ensemble consisting of 7 different models Link

Figure 3: The table lists the SOTA models from the SIGMORPHON tasks in 2020 and 2021.

3.3 State-of-the-art G2P models

As I have to decide what model I will use to train on my language set, I will now have a look at the state-of-the-art models that can be used for G2P conversion. The Special Interest Group on Computational Morphology and Phonology (SIGMORPHON) [Sigmorphon, 2021] regularly organizes shared tasks concerned with morphology and phonology. For the years 2020 and 2021 they organized a G2P conversion task [Ashby et al., 2021; Gorman et al., 2020]. The tasks represent a first attempt at creating benchmarks for multilingual G2P conversion. Although there is other research on G2P, many recent publications have been made within the SIGMORPHON shared tasks. In the next sections, I will summarize the results and insights from G2P research.

3.3.1 Model architectures

An essential part of G2P modelling is the actual model. In section 3.2 I explained the most important theoretical basics. For this part here, I familiarized myself a bit more with strategies that work well in practice and what some concrete problems are. The methodologies mentioned below are to the most part task-agnostic. This means that they often improve results on most NLP tasks and are not specifically developed for the G2P task. Still, I think it is insightful to be aware of the great variety of approaches that nowadays technology offers.

Ensembles Many models that are used and achieve peek performance for G2P modelling are ensemble models. An ensemble is essentially just a pool of different models that are trained on the data with different settings or they are completely different models. The way such a model can be used for inference is that all of the models process the input and present their predicted results. Out of all possibilities, one prediction will be chosen that is then the final model output. In order to get the final output, an ensemble needs some kind of decision algorithm to output the best result. A disadvantage of ensembles is that the models need a lot of storage. Also, it is to some extent a bit of a *brute-force* approach as it could lead to preferring quantity over quality.

Learning edit actions Instead of learning the output phoneme sequence, a model can also learn how to edit the input sequence in order to get the output sequence. Such a model would then output an edit sequence which can be applied to the input sequence in order to obtain the final phoneme output. The model therefore learns to create sequences of edit actions. The problem with this approach is that there are many possible sequences of edit actions that produce the same result. For example, it is always correct to delete every unit in the input sequence and then insert every unit from the output sequence. But this does not tell us anything about how graphemes and phonemes relate. To this end, we would also want to use substitution actions to see whether one grapheme is always substituted by the same phoneme. Imitation learning is proposed as a solution for this problem. Easily put, imitation learning is a variant of reinforcement learning. The idea is that the model learns to imitate the behaviour of an expert (for example, a human expert that provides correct samples of the task in question) [Ai, 19.9.2019].

Multi-task learning What has worked well for G2P models is to use multi-task learning. This means that the model is not only trained on one task but on multiple tasks that are related. In the present case, a model was trained on phoneme-to-grapheme conversion as well [Gorman et al., 2020].

Neural models Not surprisingly, models that achieve peek performance are almost exclusively neural models [Gorman et al., 2020]. Due to their ability to process increasingly longer sequences and the above discussed techniques like attention, the are ideal for almost all NLP tasks. What type of neural model is chosen also depends on the amount of data available. Transformers are suggested to work better for larger datasets, while they are outperformed by LSTMs on medium-size datasets (a few thousand training pairs) [Gorman et al., 2020].

Reduce vocabulary size Some syllabary languages like Korean allow the decomposition into smaller units that make up the signs. Many other languages that do not use the Latin alphabet allow to be written with Latin letters. If a reduction of the vocabulary size is possible in one of these ways, it almost always improves performance as smaller vocabulary sizes are easier to handle for models [Gorman et al., 2020].

3.3.2 Data manipulation

A model is only as good as the data that is used to train it. While this is a very basic paradigm, in reality assuring data quality is not always easy. In this section I list a few strategies that are used to preprocess and prepare G2P data and how to deal with too little available data.

Data quality Authors mostly include a section about their preprocessing and what should be done to ensure high quality datasets. The list given below is an incomplete list of potential problems and measures taken in different settings for G2P data:

- **Exclusion of words with less than two Unicode characters or less than two phone segments** [Ashby et al., 2021]
- **Separation by script** [Ashby et al., 2021]: It is very straightforward why this is done. There is no obvious connection between the different scripts of a language and its pronunciation. It makes sense to treat different scripts as different languages.
- **Exclude foreign words with foreign pronunciations** [Ashby et al., 2021]: Foreign words in a language with their original pronunciation can add phonemes that are not in that language's phoneme inventory. If they were to be included it would make sense to include a pronunciation adapted to the actual language.
- **Words with multiple pronunciations in word lists**: Ashby et al. [2021] excluded those words, however, it might also be possible to add Part-of-Speech (PoS) tags or other linguistic information to distinguish these words.
- **Consistent broad transcriptions** [Ashby et al., 2021]: With broad transcriptions it is important to be consistent and not use allophones. Ashby et al. [2021] did this specifically for Bulgarian.
- **Linguistic variation and processes** [Ashby et al., 2021]: Some transcriptions include examples for monophthongization or deletion which are ongoing linguistic processes but should not be part of a dataset representing a standard variation. Ashby et al. [2021] dealt with monophthongization by choosing the longer to two transcriptions as this logically exclude the monophthonged version. This does of course only work if there are more than one pronunciations available.
- **Tie bars**: Ashby et al. [2021] notice that some languages (English and Bulgarian) have inconsistent use of tie bars. This can be correct by replacing all inconsistencies by the tie-bar-version.
- **Errors in the transcriptions**: Gautam et al. [2021] noticed many errors

> in the WikiPron English data. They identified errors by looking at the least frequent phones and then check the word-pronunciation pairs where those phones occurred in. As the number of phones in a language is often known this can be used to check the phones in the datasets and identify uncommon ones.

Especially the task of finding errors in the transcriptions is quite tricky. It requires a lot of knowledge about the phonology and phonetics of a specific language.

Low-resource setting Apart from a few well-studied examples, for most languages there is only little data available. It is therefore highly interesting and important to find solutions of how to deal with lack of data. Hammond [2021] submitted a system to the 2021 SIGMORPHON edition focusing on data augmentation methods. The primary goal of their approach was to test how successful a minimalist data augmentation model would be, knowing it would most probably not outperform any of the other models. They identified two approaches that might improve low-resource models. The first one is to use as much as possible of the development set for training. The second, to train all languages together differentiating the languages only by a tag added to the word representations. The model they used was purposefully a very simple model that does not use a lot of resources. They used a seq2seq neural net with a LSTM decoder and encoder. Both LSTMs have two levels.

Yu et al. [2020] propose a data augmentation model for low-resource settings. The methodology applied in their approach is ensemble learning combined with a self-learning strategy. They use their ensemble to make predictions on unlabelled data. This newly created data is then added to the training data and the models are trained for another epoch on the extended data. This strategy worked well and produced good results.

Results in a low-resource setting are still bad when only using 800 samples for training. More research needs to be done in data augmentation techniques and improving the systems to cope with only little available data.

3.3.3 Error and result analysis

In this section I will list different types of analysis that have been performed on a trained model to improve future research.

Broad and narrow transcriptions In the SIGMORPHON tasks, there are great differences in the performance of models for different languages. One possible explanation is that the datasets were a mix between broad and narrow transcriptions. As narrow transcriptions contain much more detail, it can be argued that this is more difficult for any system [Ashby et al., 2021]. This assumption still needs to be analysed more closely. This differing performance for various languages calls for the questions what makes a language hard to pronounce. Especially as for Georgian all models from the SIGMORPHON task reached a WER of 0.0. Interestingly enough, the WER for the language in the high-resource setting, English, reached one of the highest WERs.

Linguistic error analysis Lo and Nicolai [2021] chose to perform an error analysis and try to minimize the frequent errors of a model in a multilingual low-resource setting. The analysis showed that often the model gets vowels and diacritics wrong. They extended the model in a way such that wrong vowel and diacritics predictions are punished more than other errors. Compared with the unchanged model, this extended model reached a better performance for some languages. The predictions with their model shows an improvement in vowel prediction. A further analysis showed that many errors still happen with vowels. Vowels get often confused with similar vowels. Their conclusion is that many of these errors make sense in a linguistic sense. They also tested augmenting the input data with syllable boundaries which did not improve the results.

Another type of linguistic analysis that can be performed is to analyse the data and check for uncommon pronunciations or language internal ambiguities. If a model produces a lot of wrong output because of ambiguities or uncommon data, then this is not necessarily the models fault but just a language inherent inconsistency. As languages are generally ambiguous, this type of analysis is very insightful to find out about *real* errors of the model. These are errors that could be derived from the data, but the model did not get there. Ashby et al. [2021] did such an analysis for the SIGMORPHON 2021 task which showed that many errors are due to language internal ambiguities.

Include linguistic information What has been suggested by Gorman et al. [2020], is to make use of phonetic resources or rule-based systems to improve the quality of current models. The advantage of such an approach is that it is specifically tailored to the problem at hand and not at all task-agnostic. Makarov and Clematide [2020] confirm this suggestion as they performed an error analysis which showed that including linguistic information such as PoS-tags might be useful.

As is always the case with such research there are many different aspects that can be tuned in order to improve model results. For my thesis I will have a closer look at how we can use phonetic features to improve models.

3.4 CMUSphinx

For my personal experiments, I decided to use the CMUSphinx seq2seq G2P model. This model has been used in the SIGMORPHON task. It was not used on many languages but promised a good performance which is why I decided to use this model for this present thesis. the CMUSphinx model is a transformer-based acas2s model implemented with tensorflow. There exists a pre-trained version of the model for acg2p, however, they use a transcription format other than IPA which means it cannot be used for our dataset [GitHub, 03.02.2022].

3.5 Unicode and the International Phonetic Alphabet

When it comes to representing characters in a machine-readable format things get very tricky, very quickly. In order to understand this fundamental problem it is necessary to understand the basic concept behind unicode and encodings in general. Moran and Cysouw [2018] present a neat overview in their book. As discussed in chapter 2, there are many different kinds of what we typically call letters, graphemes, characters or signs[2]. Just as a human writer must be able to uniquely identify each different graphemes, so must a computer. The most widely spread standard to represent scripts is called Unicode. Graphemes are mapped to unique numbers that can be rendered differently depending on the font and the context. There are different stages of representation until a graphemes can be represented on screen:

CODE POINT A unique numerical, non-negative value usually expressed as a hexadecimal number (U+0000). Allows one-to-one mapping between letters and codes. Each code point has a set of properties attributed to it. Properties like the script, uppercase or not, etc.

[2] Please note that I will from now on use grapheme to denote the smallest meaningful element of any writing system. Grapheme does not imply any specific writing system nor does is take the Unicode background into consideration. If I wish to distinguish the Unicode specifications I will use the correct Unicode term as described in this section.

Character An abstract representation of the shape of the grapheme. Can in theory not be represented visually, as this includes a font. A Unicode character is *not* the same as what we would call a grapheme in different writing systems.

Glyph The rendered and therefore visual representation of one or more Unicode characters that can be identified by its code point(s). A glyph is rendered in a specific font in a specific context. No matter how different it looks to the user, for Unicode all different representations of one code point are exactly the same. Sometimes one character is represented as two glyphs. It is important to note here, that the exact visual representation of a glyph is not at all defined by its code point. This means that the exact same glyph can represent more than one code points. This happens sometimes in the IPA. An example is the post-alveolar click:

- ! : this glyph represents an exclamation mark with unicode code point U+0021.
- ǃ : this glyph represents an post-alveolar click with unicode code point U+01C3.

It is striking that these two look exactly the same. Things like this become important when, for example, I want to count the different characters in a text.

Unicode code points are often organized in blocks. A block can, for example, contain all letters of the Latin script. Those blocks are helpful although not always consistent. The IPA is represented in a basic block but many IPA symbols are actually found in other blocks. Confusion often arises from the fact, that one human-perceived grapheme is sometimes represented as more than one code point.

Grapheme clusters A grapheme cluster is one visual letter that is represented in Unicode as more than one code point. This is the case for diacritic marks. A problem with grapheme clusters is that some diacritic marks, so marks that cannot really exists without any base character are underspecified. This means that when we want to split into clusters, we do not know if that character belongs to the left or the right base character. This is the case for many characters in the IPA. Unicode does not specify these but leaves it to the user to create tailored grapheme clusters.

Precomposed characters Note that sometimes, grapheme clusters can be precomposed and the combination of those two or more characters is assigned a new number. These clusters can be problematic if in a specific context, the graphemes should not be clustered but read separately. An example is the German ‘ä’.

Additional complexity is added through the possibility of Unicode to create Unicode locales. These allow users to specify language- or writing-system-specific cases. An additional challenge is that of picking the right font. Our standard font format can only contain about half of all the Unicode code point. It is therefore simply not possible to display the entire set of Unicode characters with one font. Many problems encountered with displaying writing systems are somehow connected to the font rather than Unicode itself [Moran and Cysouw, 2018]. Moran and Cysouw [2018] list a few more ‘pitfalls’ that one might encounter when dealing with Unicode.

For the present thesis, this topic is relevant for multiple reasons:

1. The IPA contains many special characters and many diacritics.
2. The language data is available in many different scripts.

It is crucial that all data files, be it phonetic or ‘normal’ scripts, are formatted and read correctly. Or rather that the encoding and processing is made transparent as often there is not one correct way of how to treat IPA characters.

3.5.1 Unicode normalization forms

The above explanations make clear that there are considerable differences in what a human reader perceives and in what happens in the background. Unicode therefore provides normalization forms that can help to process written data. Unicode publishes extensive explanations along with their standards which also includes those normalization forms. I will therefore not explain everything in full detail as this is done so already online [**?**]. What is important is that each normalization form results in very different behaviour if a text is processes. There are two important aspects to normalization. One is that we can have decomposed or composed characters. The second is that we have a compatibility form and a non-compatibility form. In a decomposed string, we split the characters into their individual components. This means that characters with diacritics are split up into two or more characters. This means that a characters that had originally assigned one code point can in a decomposed form have more than one code points. In a composed normalization usually precomposed forms are kept. This means that some parts can be similar or the same to the decomposed version but if for a character there exists a precomposed version, this one is usually used. If a normalization is according to compatibility decomposition, this means that any formatting is removed such that we receive the underlying character in its original form. Superscript characters are then shown normal. How exactly these normal forms work is not always equally important, but what is absolutely crucial to make sure that when characters are compared or counted, the same normalization form is used. The names for these normalization form are as follows:

NFD : Canonical Decomposition

NFC : Canonical Decomposition, followed by Canonical composition

NFKD : Compatibility Decomposition

NFKC : Compatibility Decomposition, followed by Canonical Composition

3.6 Random background

I put things here that I had to look up working on this thesis but that might no end up in the final thesis. I might put in into the glossary if it makes sense... Monte Carlo simulation: a simulation that evolves randomly. We can, for example, estimate pi with a Monte Carlo simulation. The most basic intuition is that I can estimate something from random samples. The important thing is that the selection of the samples must be random and cannot be biased. A second factor that influences the reliability of the results is that the sample size must be large enough. According to the law of large numbers this is a common rule when estimating numbers. The Monte Carlo simulation can be used in situations where it is not possible to explore all possible combinations that are needed to produce a certain outcome (e.g. measuring the hight of all people living on this planet to obtain the average). In such cases we can pick a large enough sample randomly.

source

Student's t-test: This is a statistical test that tells us something about the significance of the difference between one result compared to another. If I have two averages over two related (paired) or unrelated (unpaired) groups, the t-test tells me if the change from one average to the other is statistically significant. If not, the change can occur just as well by chance.

There are systems that can produce speech directly from orthography and question the necessity of phonetic transcriptions. When only little data is available, the training data might not be enough to train a orthography-to-phoneme system, making phonetic transcriptions necessary. Another reason for creating phonetic transcriptions is that it usage is not limited to speech applications [Mortensen et al., 2018]. They might also be used to compare languages on speech basis. In order to do that, there needs to be a lot of knowledge about how language works. Comparing languages and studying their similarities and differences is part of a well-established branch of traditional linguistics called comparative linguistics. The analysis of large amounts of text in any language is commonly referred to as corpus linguistics. Corpus linguistics allows for both qualitative and quantitative analysis of text. Although text can refer to written or spoken language, most corpora contain written text [McEnery and Hardie, 2011]. Multilingual corpora can be used to compare languages. If all of these different approaches are combined, we end up by what we could call comparative corpus phonetics.

Add quick intro into corpus linguistics, quantitative analysis, this is essentially what is done with the corpus. [McEnery and Hardie, 2011]

Introduction to comparative linguistics at some place. [Hock and Joseph, 2019]

4 Experiments

This chapter presents the experiments and practical explorations that I conducted for this thesis. The previous chapters listed the different steps and problems that arise when trying to create and analyse a phonetic corpus.

4.1 Typewriting pdf phonetic transcriptions

In order to make use of as much data as possible, I used a software to manually transcribe the pdf scans. The software allows to make use of neural Handwritten Text Recognition (HTR) models. There exists no pre-trained IPA model but I trained my own while transcribing the documents. On the website they mention that ideally training needs 5,000 - 10,000 words already transcribed. Although my available data is not nearly enough to train a reliable model, it was a great help to transcribe. As the scans where not handwritten text, the model still reached a surprisingly good quality. For the Hebrew transcription, the model reached a WER of 34.52% and a CER of 6.11%. The two main mistakes were made for two characters that were not even in the training data. The quality of the scans differed quite a lot which had an influence on the performance of the model as well. After transcribing another document I trained the model again and transcribed the remaining documents. The transcriptions got continuously better such that in the end for the last documents I did not take me nearly as much time as in the beginning. Most of the errors resulted from characters that had not been in the previously described documents. I did not run a closer analysis so this is only my intuition.

Transkribus allows to use public models and share their own. Technically, I can share my model as well. It needs to be clarified whether it is actually possible as there is not a lot of training data involved and the models performance differs.

potentially add short table for WER and CER values for a few languages

4.2 Pronunciation dictionary coverage

In order to get an understanding of how many words are covered in the word lists, I created a script to calculate the coverage, the WER and the CER. I replaced the words in the texts with the words in the word list and compared it to the reference transcription. While dealing with the full texts and the word lists, I noticed several things that are important when dealing with those texts.

- The pronunciation dictionaries sometimes included duplicates with different pronunciations. This is not surprising but still it needs to be handled well. A solution is to simply delete duplicate words. A close examination also showed that sometimes, the duplicate pronunciations are wrong. As it is the case with the English word "would". add this example indented

- For some full texts it is not clear whether their transcription is narrow or broad. On the other hand, sometimes there is no broad or narrow word list available for a specific language but only one of those. In order to find out how similar broad and narrow texts and word lists are, the calculations were run for every possible combination of each language. For languages that had both types of text and both types of word lists, the calculations were run four times.

- The IPA allows to transcribe intonation segments. In German, those correspond mostly to punctuation marks like end of sentence symbols or commas. But this must not be true for every case. It needs to be decided if those should be kept or potentially deleted.

- In order to do this very simple experiment, it is necessary to tokenize the texts. This works well for languages using the Latin script. For languages like Chinese or Korean this is more difficult to accomplish. However, this issue needs to be tackled to create G2P models anyway. I will therefore not explore this issue here.

- WikiPron filtered some datasets for the SIGMORPHON shared task. verify that. whenever available I used the filtered version.

The results from this experiment are summarized in table 3. Generally it is good to see, that most texts are at least partially covered by the pronunciation dictionary. A closer examination of the results shows a few language specific issues that might be relevant in further experiments.

Chinese Although the Chinese coverage is rather high, the WER is very bad. This is due to the fact, that in the lists the tones are represented differently than in the reference text. It needs to be analysed if one of these formats can be converted into another format. check the different tone transcriptions

Hebrew The only language that is not covered at all is Hebrew. A closer examination showed that the words in the text have many diacritics, while the words in the list do not have many diacritics. Additionally, the list is very short.

Whenever there were four experiments per language, the combination of the broad reference text written with the broad list had the best WER and CER or in the case of English the best WER and a slightly worse CER. However, this finding needs to be analysed with caution as the narrow word lists contain always less words than the broad ones. Interestingly enough, sometimes it does not matter if the text written with the broad word list is compared to the narrow transcription or the broad. In fact, for English, the text written with the broad list compared to the narrow reference shows a better CER. This suggests that the differences in broad and narrow transcriptions are not great. For languages where the type of the transcriptions was unclear but two lists for available, the broad list produced the better results if there was any difference.

4.3 Automatic grapheme-to-phoneme

The model that I am using for my G2P experiments is explained in section 3.4. Setting it up was not very easy as there were issues with the tensorflow version and some other dependencies. Also, they do have a pre-trained model, but this uses a completely different transcription convention than IPA. So we cannot use this model. But to test the model and have a baseline, we trained in on the data we have, to see how it performs. As there is only very little data available as full texts, we decided to use the short stories as test set for the experiments with G2P models. Those texts are all manually created and are specifically created by linguists for the purpose of studying phonetics of many languages.

4.3.1 Training settings

There are different settings which I will use to train the models and analyse their performance.

Iso 639-3	Coverage	WER	CER	Type ref	Type list	Num words list
cmn	87.5	2.3	0.84		broad	133 686
deu	75.0	0.77	0.52	broad	broad	34 145
deu	22.22	0.98	0.82	narrow	narrow	10 984
deu	75.0	0.85	0.52	narrow	broad	34 145
deu	22.22	0.98	0.83	broad	narrow	10 984
ell	6.14	1.0	0.9		narrow	408
ell	22.81	0.94	0.85		broad	10 547
eng	92.04	0.92	0.38	broad	broad	57 230
eng	7.08	1.01	0.83	narrow	narrow	1 633
eng	7.08	1.0	0.83	broad	narrow	1 633
eng	92.04	0.92	0.36	narrow	broad	57 230
eus	5.75	0.97	0.85	broad	broad	1 742
eus	0.0	1.0	0.92	narrow	narrow	186
eus	0.0	1.0	0.89	broad	narrow	186
eus	5.75	0.98	0.89	narrow	broad	1 742
heb	0.0	1.28	0.92		broad	1 439
heb	0.0	1.28	0.92		narrow	146
ind	22.22	0.97	0.8		broad	1 555
ind	1.85	1.0	0.91		narrow	2 637
kat	43.66	0.86	0.66	broad	broad	15 123
mya	7.14	0.98	0.93	broad	broad	4 631
spa	64.95	0.51	0.41	broad	broad	60 677
spa	35.05	0.99	0.69	narrow	narrow	52 190
spa	35.05	1.0	0.62	broad	narrow	52 190
spa	64.95	0.84	0.56	narrow	broad	60 677
tha	20.0	1.0	0.98		broad	15 050
tur	18.46	1.0	0.91		broad	1 789
tur	6.15	1.0	0.96		narrow	1 812
hin	31.78	1.03	0.69		narrow	9 563
hin	57.36	0.93	0.52		broad	10 812
kor	18.64	1.0	0.96		narrow	14 141
pes	50.0	1.09	0.75		broad	6 128
pes	18.0	1.1	0.91		narrow	1 922

Table 3: The table shows the coverage, WER and CER when the pronunciation dictionaries are used to write “The North Wind and the Sun".

put the high, low resource list in the appendix and explain the distinction

Setting 1: Baseline Small Test all languages with the CMU model where we have data available. We want to have a baseline for all languages. All models are trained separately. Broad and narrow transcriptions are treated as separate languages and thus trained separately as well. The same is true for dialects if there is any information available. American and British English are trained in different models. I used the WikiPron pronunciation dictionaries to train the model. While some of the data has been down-sampled in the shared task, I used all that was available. Whenever a filtered version used in the SIGMORPHON task was available I used that one. The model is trained with the least amount of effort. Default settings are used and no hyperparameters are changed. The model is trained for the minimum number of steps which is 10,000 in this case. First, I trained it on those languages where I have results from the SIGMORPHON 2021 challenge. The results are compared in table 6.

Setting 2: Baseline Large This setting is similar to setting 1 except that the model is trained as long as possible for each language. All models have been trained for 200,000 steps and the default settings.

Setting 3: WikiPron clean I will train another model that is the same like the Baseline Large, but I will use the cleaned WikiPron data. What I will clean is described below (section 5.3.2).

Setting 4: Feature input The final experiment will be with the features as input.

4.3.2 Preprocessing

I will be working with WikiPron data and with the small NWS corpus. For my experiments I will replace the phonemes by their features from PHOIBLE. In order to make sure that this works well, I will clean the data and check that the phonemes are in PHOIBLE. In section 2.3 I talked about the incompleteness and difficulties of transcribing using the IPA. How exactly a sound is mapped to a IPA symbol also depends on whoever transcribes a particular text. The WikiPron data has been put together by many different people. That said I will carefully examine and clean the dataset.

NWS corpus Before any of the data can be used, it needs to be preprocessed. As I am going to use the WikiPron data which consist of single words per line with their pronunciation, the full texts need to be prepared like that as well. I did the following steps to convert the full short story texts into pronunciation dictionaries:

- Conversion of || to ‖. Some transcriptions include the double vertical line to mark a major intonation groups in the text. In some transcriptions this is a written as two single vertical lines. Those were replaced by the former to be consistent.
- Removal of ties bars in the phonetic transcriptions. Tie bars are not adding any valuable information. get quote for this!
- Removal of suprasegmentals, except long and half long mark, and the extra short mark.

WikiPron Some of the WikiPron data has already been filtered as has been explained in section 3.3.2. However, as I am not only using their filtered data I will have to do some preprocessing as well and also make some additional changes also to the filtered versions. Table 4 shows a list of all those phonemes that are used in at least one of the WikiPron datasets for a language but are not in PHOIBLE. While it is possible that a correctly used phoneme is not in PHOIBLE, it still gives a good overview of potential ambiguities in transcription or mistakes.

As the model expects the graphemes no to contain any whitespace, I replaced any whitespace in the input with underscores. This was necessary only for Vietnamese. The alternative to removing the white space would have been to splitting the grapheme at white space and align the phonemes. However, this is firstly much more work as it is not clear where to split the phonemes and it might be that the word on its own is pronounced differently.

jpn In Japanese there is the superscript letter b. This actually means compression, it is a type of rounding. This is not official, but we should actually leave it.

4.3.3 Results

4.4 Things to include and sort out later

Data Stats In order to get a feeling of the data and what it covers, I collected phoneme and grapheme profiles of the data and compared it to the Phoible dataset. For each language that I am working with, I have two different types of data: first the short story and second the WikiPron G2P dictionary. For each language and each data type I got three lists:

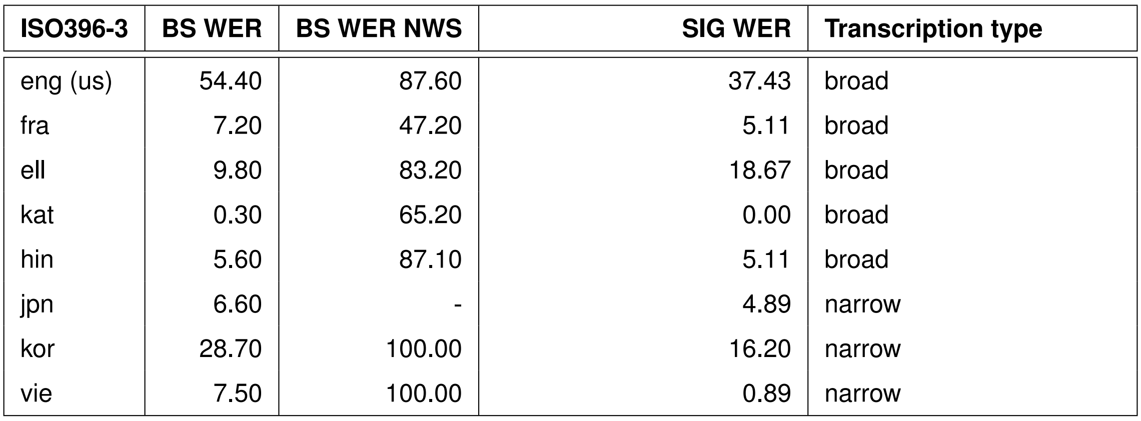
- Grapheme list: contains all graphemes in that language. Characters that need

Phon.	Unicode name	Repl.	Explanation
ˈ ˌ | ‖ . ‿	MODIFIER LETTER VERTICAL LINE MODIFIER LETTER LOW VERTICAL LINE VERTICAL LINE DOUBLE VERTICAL LINE FULL STOP UNDERTIE	NULL NULL NULL NULL NULL NULL	These are all IPA suprasegmentals except the long and half long marker and the extra short (ː ˑ ˘). The reason why these were excluded is that they don't carry any meaning on the character level. The vertical lines, for example, mark intonation groups which only matter in a larger sentence or text context. There are a few rare occurrences of COMBINING VERTICAL LINE ABOVE which is probably meant to be MODIFIER LETTER VERTICAL LINE as they look similar. It is excluded as well.
͡	COMBINING DOUBLE INVERTED BREVE	NULL	add explanation
͜	COMBINING DOUBLE BREVE BELOW	NULL	add explanation
ɝ	LATIN SMALL LETTER REVERSED OPEN E WITH HOOK	ɚ	add explanation
ɡ	LATIN SMALL LETTER G	g	The IPA 'g' has a different code point and is a different character than the typical keyboard small Latin 'g'. This is just an IPA decision. For some fonts the two characters do not look different, for some they do.
⁓ , ṽ ᵊ	SWUNG DASH COMMA TILDE MODIFIER LETTER SMALL SCHWA	NULL NULL NULL NULL	All of characters make out less than 1% of their respective dataset, most of the time it is less than 0.1%. A close examination of the dataset and the Wiktionary transcription conventions for the respective language did not show any reason why to keep the phoneme. Note that the 'v' for the tilde is only there to show character correctly.
ˣ	MODIFIER LETTER SMALL X	ʔ	The ˣ only occurred in the broad Finnish transcription and is used to denote possible gemination. In the narrow transcriptions there is a glottal stop instead. The occurrence of glottal stops and gemination follows the same rules. Therefore, for consistency, the gemination ˣ is mapped to a LATIN LETTER GLOTTAL STOP.
( )	(SUPERSCRIPT) [LEFT | RIGHT] PARENTHESIS	NULL	Parentheses are used to denote optionality for phonemes or tones. WikiPron actually discards those but keeps the content (add GitHub reference). I will do the same for all parenthesis found.

Table 4: The table shows what phonemes where changed or excluded and what the reason is for this preprocessing. All characters that were excluded are replaced by a NULL value.

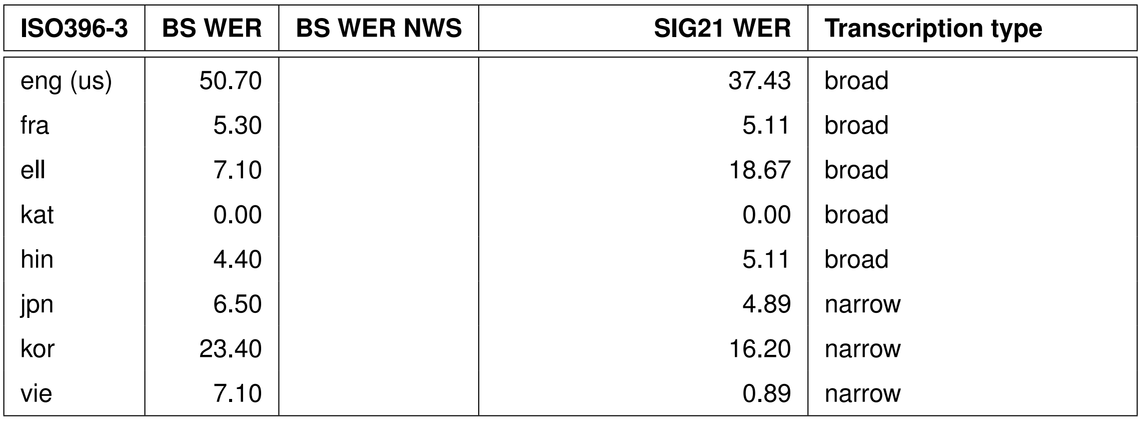
a base character like diacritics are shown together with their base character.

- Phoneme list: contains all phonemes in that language. Again, diacritics and similar characters are shown with their base characters.



ISO396-3	BS WER	BS WER NWS	SIG WER	Transcription type
eng (us)	54.40	87.60	37.43	broad
fra	7.20	47.20	5.11	broad
ell	9.80	83.20	18.67	broad
kat	0.30	65.20	0.00	broad
hin	5.60	87.10	5.11	broad
jpn	6.60	-	4.89	narrow
kor	28.70	100.00	16.20	narrow
vie	7.50	100.00	0.89	narrow

Table 5: Baseline CMUSphinx results compared with SIGMORPHON 2020 and 2021 results. For each language the best score is reported no matter what year or what model. The table shows the results for setting 1. CMUSphinx provides a WER implementation which has been used to evaluate the models.



ISO396-3	BS WER	BS WER NWS	SIG21 WER	Transcription type
eng (us)	50.70		37.43	broad
fra	5.30		5.11	broad
ell	7.10		18.67	broad
kat	0.00		0.00	broad
hin	4.40		5.11	broad
jpn	6.50		4.89	narrow
kor	23.40		16.20	narrow
vie	7.10		0.89	narrow

Table 6: Baseline CMUSphinx results compared with SIGMORPHON 2020 and 2021 results. For each language the best score is reported no matter what year or what model. The table shows the results for setting 2. CMUSphinx provides a WER implementation which has been used to evaluate the models.

- Phoneme cluster list: Phonemes can be clustered into bigger sound groups. How to do this, is an ongoing discussion, but I used the segments library to get the clusters (compare Moran and Cysouw [2018])

Having those overview for the characters for each language allowed me to compare the character vocabulary to the characters or character clusters available in the Phoible dataset. This comparison showed that quite a few characters are missing that are included in the WikiPron data and the short stories. Some problems and potential strategies to solve it:

- No real IPA: There are sometimes characters included that are no part of the IPA. There might be a reason why the authors of the transcriptions decided to use this special character to denote a particular sound, but this is not always known. A possibility is to try and map it to a character that is available in Phoible and that represents a similar sound (or even the same sound actually).
- Tie bars: The creators of Phoible decided to exclude tie bars because they add no real value to the transcriptions. add source for this?
- Stress marks: Stress marks are not represented in Phoible as they do not represent a sound.
- Tones: Even within the IPA there exist different conventions of how to represent tones. Some are better suited for different languages. Apart from different ways of representing tones, it is not always sensible to have tones represented. Mostly, tones are not written as speakers of that language know how to pronounce the tones. So, the questions is whether it is necessary to include the tones at all. When looking at the written representation it does not matter what the tones are as the basic phonemes do not change. This is of course different when the phonetic representation is mapped to a spoken representation. add more on that, maybe in background chap

5 Conclusion

5.1 What now?

Non surprisingly, apart from the many exciting things I *could* do, there are many others that would have gone beyond the scope of this thesis. I would like to list a few entry points on where further research could start.

- **Data preprocessing**: Ashby et al. [2021] cleaned broad transcriptions for Bulgarian and replaced allophones by their standard phoneme. This could further improve model quality by having consistent broad transcriptions.
-

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A Tables

Table 7: The table shows a list of the 100 languages in the corpu
mation on the language families.

Iso639-3	Name WALS	
39-3abkWALSAbkhazWALSNorthwest Caucasian6639-3	–WALS	
6639-3	–WALS	–W
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–WAL
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	–WALS39-3
6639-3	–WALS	
6639-3	–WALS	–WALS
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	–WA
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	

Iso639-3	Name WALS	
6639-3	–WALS	–W
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	–WALS39
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–WALS39-
6639-3	–WALS	–W
6639-3	–WALS	–WALS39-3dniWALSD
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	–WALS39
6639-3	–WALS	–WALS
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	

Iso639-3	Name WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–WALS39-3m
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–V
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	–V
6639-3	–WALS	–V
6639-3	–WALS	–WA
6639-3	–WALS	
6639-3	–WALS	–W
6639-3	–WALS	
6639-3	–WALS	–
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	
6639-3	–WALS	

Iso639-3	Name WALS
6639-3	–WALS

Iso639-3	Name WALS	
39-3abkWALSAbkhazWALSNorthwest Caucasian6639-3	–WALS	–WALS39-3amp
6639-3	–WALS	–WALS39-3aeyWALSAm
6639-3	–WALS	–WALS39-3apuW
6639-3	–WALS	–WALS39-3bmiWALSBa
6639-3	–WALS	–WALS39-3bsnWA
6639-3	–WALS	–WALS39-3gryWA
6639-3	–WALS	–WALS39-3eus
6639-3	–WALS	–WALS39-3apeWALSArape
6639-3	–WALS	–WALS39-3bskWALSI
6639-3	–WALS	–WALS39-3ramWALSCa
6639-3	–WALS	–WALS39-3tzmWALSBerber (Mi
6639-3	–WALS	–WALS39-3chaWALSC
6639-3	–WALS	–WALS39-3cktWALSChukchiV
6639-3	–WALS	–WALS39-3zocWALSZoque (C
6639-3	–WALS	–WALS39-3
6639-3	–WALS	–WALS39-3haeWALSOror
6639-3	–WALS	–WALS39-3arzWALSArabic
6639-3	–WALS	–WALS39-3fijWA
6639-3	–WALS	–WALS39-3
6639-3	–WALS	–WALS39-3gniWAL
6639-3	–WALS	–WALS39-3kl
6639-3	–WALS	–WALS39-3hauW
6639-3	–WALS	–WALS39-3hebWALSHebrew
6639-3	–WALS	–WALS39-3hinWAL
6639-3	–WALS	–WALS39-3hixWA
6639-3	–WALS	–WALS39-3hnjWALSHm
6639-3	–WALS	–WALS39-3qviWALSQuechua
6639-3	–WALS	–WALS39-3im
6639-3	–WALS	–WALS39-3indWALSIn
6639-3	–WALS	–WALS39-3kalWALSGreenland
6639-3	–WALS	–WALS39-3
6639-3	–WALS	–WALS39-3gydW
6639-3	–WALS	–WALS39-3kioWAL
6639-3	–WALS	–WALS39-3ckuWA
6639-3	–WALS	–WALS39-3kc
6639-3	–WALS	–WALS39-3sesWALSKoy
6639-3	–WALS	–WALS39-3k
6639-3	–WALS	–WALS39-3ku
6639-3	–WALS	–WALS39-3lk
6639-3	–WALS	–WALS39-3lajWALSL
6639-3	–WALS	–WALS39-3lvkWALSLavukaleveW
6639-3	–WALS	–WALS39-3lezWALSLezgia
6639-3	–WALS	–WALS39-3dniWALSDani (Lower Grand Val