

Automatic Speech Recognition in Sanskrit: A New Speech Corpus and Modelling Insights

Devaraja Adiga^{1*}
pdadiga@iitb.ac.in

Rishabh Kumar^{1*}
krrishabh@cse.iitb.ac.in

Amrith Krishna²
ak2329@cam.ac.uk

Preethi Jyothi¹
pjyothi@cse.iitb.ac.in

Ganesh Ramakrishnan¹
ganesh@cse.iitb.ac.in

Pawan Goyal³
pawang@cse.iitkgp.ac.in

¹IIT Bombay, Mumbai, India; ²University of Cambridge, UK; ³IIT Kharagpur, WB, India

Abstract

Automatic speech recognition (ASR) in Sanskrit is a challenging task, owing to the various linguistic peculiarities present in the language. The language is lexically productive, undergoes euphonic assimilation of phones at the word boundaries and exhibits variations in spelling conventions and in pronunciations. In this work, we propose the first large scale study of automatic speech recognition (ASR) in Sanskrit, with an emphasis on the impact of unit selection in Sanskrit ASR. In this work, we release a 78 hour ASR dataset for Sanskrit, which faithfully captures several of the linguistic characteristics expressed by the language. We investigate the role of different acoustic model and language model units in ASR systems for Sanskrit. We also propose a new modelling unit, inspired by the syllable level unit selection, that captures character sequences from one vowel in the word to the next vowel. We also highlight the importance of choosing graphemic representations for Sanskrit and show the impact of this choice on word error rates (WER). Finally, we extend these insights from Sanskrit ASR for building ASR systems in two other Indic languages, Gujarati and Telugu. For both these languages, our experimental results show that the use of phonetic based graphemic representations in ASR results in performance improvements as compared to ASR systems that use native scripts.¹

1 Introduction

Sanskrit is a classical language, with fairly advanced disciplines of phonetics (*Śikṣā*), prosody (*Chandas*), and grammar

(*Vyākaraṇa*), in existence for the past 2,500 years (Scharf, 2013). The language has a rich oral tradition and it tends to follow a phonemic-orthography resulting in systematic grapheme-phoneme correspondences. The closest proximity of letters gave rise to *Sandhi*, a phenomenon by which utterances caused by connected speech is preserved in writing as well. Sandhi is defined as the euphonic assimilation of sounds, *i.e.*, modification and fusion of sounds, at or across the boundaries of grammatical units (Matthews, 2007, p. 353). Phonemic orthography is desirable for a language, when it comes to designing automatic speech recognition Systems (ASR), specifically for unit selection at both the Acoustic Model (AM) and Language Model (LM) levels.

Regardless of the aforementioned commonalities preserved in both the speech and text in Sanskrit, designing a large scale ASR system raises several challenges. The Unicode encoding for the native scripts in Sanskrit, both in Roman and Devanāgarī, does not preserve the correspondence with the phonemic encoding. Further, mapping the graphemes in Unicode to the corresponding phonemes either leads to ambiguity and redundancy or often requires multi-grapheme combinations.

The language is lexically productive, which results in long compound words with multiple components in usage. This results in the speakers segmenting the compounds at arbitrary lexeme boundaries of the compound, as it need not always be possible to utter the compound in one breath and also to convey the meaning clearly. Similarly, such arbitrary segmentations at the word boundaries are possible in utterance of long text sequences where multiple lexical items are fused

* Joint first author

¹Dataset and code can be accessed from <https://bit.ly/31zzTGf>.

together via Sandhi. These segmentations are accompanied with the corresponding Sandhi based transformations, resulting in a new phonetic sequence different from the original sequence. Finally, Sanskrit might be one of those rare natural languages where the number of non-native proficient speakers are manifold in comparison to the native speakers (Krishna et al., 2020). This makes the ASR task further challenging, as the speakers are prone to carry their influence from their corresponding mother tongues into the Sanskrit utterances as well.

While there exist several computational models for processing Sanskrit texts (Kulkarni, 2013; Kumar et al., 2010; Shukla et al., 2010; Kulkarni et al., 2010a,c; Mishra et al., 2013; Saluja et al., 2017; Anoop and Ramakrishnan, 2019), large scale systems for processing of speech in Sanskrit, are almost non-existent. First, we present a new dataset, with 78 hours of speech covering about 46,000 sentences, for ASR in Sanskrit. Keeping the rich and long cultural heritage the language carries, we prepare our dataset to be diverse both chronologically and in terms of the domain coverage. Further, the dataset contains utterances from 27 different speakers, representing 6 different native languages. The dataset splits have disjoint speakers, with 12 in the training and 5 each in the validation, test and out-of-domain test data sets. Further, we explicitly mark the segmentation decisions made by a speaker to segment long compound words and fused phrases and include the corresponding transformations due to sandhi.

Using this dataset, we propose a new, large-vocabulary Sanskrit ASR system, which, to the best of our knowledge, is the first such system for Sanskrit. The phonemic orthography followed in Sanskrit has influenced our design choices in terms of unit selection at the level of the acoustic and language models. We investigate three different encoding schemes used to model LM tokens, namely, word-based encoding, byte pair encoding (BPE) and a new vowel split encoding inspired by existing linguistic theories of syllabic structure popularly used within text-to-speech systems (Kishore and Black, 2003), (Mishra et al., 2013). Further, to address the redundancy issues in Unicode

representations, we make use of the Sanskrit Library Phonetic (SLP1) encoding scheme proposed by Scharf and Hyman (2011). SLP1 is designed such that it preserves the phonemic orthography. Building on the study by Scharf and Hyman (2011), we focus on two graphemic representations only, *viz.*, native script (Devanagari) and SLP1.

Finally, we extend our insights to model ASR systems for two more Indian languages, *viz.*, Telugu and Gujarati. We extend the SLP1 to include graphemes relevant for these languages and are missing from Sanskrit. We report the performance of these ASR systems on two publicly available ASR datasets.

Our main contributions in this work are:

- 1) We present (in Section 2) a new, large vocabulary Sanskrit ASR system and the first ever ASR-based study for Sanskrit using a new, large and diverse, labeled speech corpus वाक्सञ्चयः (/Vākṣaṇcayaḥ/).
- 2) We investigate (in Sections 3 and 4) different modeling choices for both acoustic models and language models in Sanskrit ASR systems, along with different graphemic representations. We propose a new word segmentation technique based on splitting at vowels that can be used with both the acoustic model and the language model.
- 3) We also contextualize our findings for Sanskrit by providing comparisons on ASR systems built for two other Indian languages, *viz.*, Gujarati and Telugu.

2 A new Sanskrit Speech Corpus: वाक्सञ्चयः (/Vākṣaṇcayaḥ/)

Our corpus वाक्सञ्चयः (/Vākṣaṇcayaḥ/), has more than 78 hours of data with an overall vocabulary size of 91,000 words and recordings of about 46,000 sentences, each with a sampling rate of 22 KHz. The contents span over

Dataset	Speakers	Hours	Utterances
Train	12	56	34,309
Validation	5	8	33,37
Test	5	10	5,531
Out-of-domain Test	5	5	2,618

Table 1: Overview of Sanskrit speech corpus.

3 time periods categorised into pre-classical literature (1,500 BCE -100 BCE), classical literature (300 CE - 800 CE) and modern literature (900 CE to now). The corpus is intended to address the challenges in interfacing the speech and the text covered by the disciplines of phonetics (*śikṣā*), and grammar (*vyākaraṇa*). Hence, we confine our corpora to those written only in prose (गद्य)². In Sanskrit literature frequency of commonly used words changes from one *Śāstra*(branch of learning) to another (Adiga et al., 2018). Our corpus contain samples from diverse domains, including philosophy, literature, commentary on poetry, grammar, spiritual discourse and radio program/podcast, so that collecting a wide range of Sanskrit vocabulary.

The recordings were primarily collected with the help of volunteers, recording their speech by using the Recorder app on Android phones and the Audacity platform, and from various sources available online.³ oTranscribe³ was used to transcribe the audio files. We had a total of 9 volunteers for recording and 18 unique speakers for the content collected online. Each of these speakers are proficient Sanskrit speakers, with at least an undergraduate or equivalent degree in Sanskrit. These speakers are native speakers of one of the 6 following Indic languages, Hindi, Kannada, Malayalam, Marathi, Tamil and Telugu. In Table 1, we provide the details of the training/validation/test splits for our corpus, वाक्सञ्चयः (/Vākṣaṇṇaya/). The speakers in all these 4 splits, train, validation, test, and out-of-domain test sets are disjoint. The out-of-domain test dataset is a stratified sampled dataset, consisting of speech samples from 5 unique speakers. Two of these were added to include utterances in Sanskrit from speakers with more pronounced influence of their native languages (in Hindi and Tamil). The domain of the training dataset primarily is a speech collection of readings from various well known texts. Further, the speech in the training data is in accordance with the traditional phonetic

prescriptions of Sanskrit (*Śikṣā*). Hence, the remaining three in the out-of-domain test set were added to include utterances from different speech domains, extempore discourse, lecture and radio program, differing from the speech domain in the training set. The radio program is studio produced, while the other two are live recorded.

2.1 Challenges in Sanskrit ASR

In this section, we describe various linguistic phenomena that are important to consider when preparing datasets and building ASR systems for Sanskrit with the help of illustrative examples.

Word Length: Word length in Sanskrit, can become very large owing to “Sandhi” and the lexically productive process of compounding (“Samāsa”). For example, after combining the three Sanskrit words वाक्, अर्थ, प्रतिपत्ति (/vāk, artha, pratipatti/), by applying Sandhi and Samāsa rules, the word वागर्थप्रतिपत्तये (/vāgarthapratipattaye/) is formed, which has 19 characters (SLP1 representation is vAgarTapratipattaye). In Figure 1, we present the distribution of the number of characters (in SLP1 format) per word across the three languages that we experimentally analyse in this work, viz., Sanskrit, Telugu and Gujarati. The plots are normalized with respect to the size of the vocabulary. The average word length is much higher in Sanskrit (10.75) compared to Gujarati (7.79) and Telugu (9.35). Table 2 compares the distribution of number of characters (*wrt* SLP1) per word in the training vocabulary of three ASR datasets. More than 26% of the words in Sanskrit have length exceeding 12 characters.

Char count(N)	Sanskrit	Telugu	Gujarati
N≤6	13.79%	21.27%	34.11%
6<N≤12	59.56%	61.60%	61.82%
N>12	26.65%	17.13%	4.07%

Table 2: Distribution of Number of characters (*wrt* SLP1) per word in three ASR datasets

²We do not include verses in our current dataset, as modelling ASR systems for verses would require additional resources on both the acoustic model and the language model fronts.

³ The URLs of the tools and the list of the texts we use are available in the supplementary material.

Sandhi: Sandhi can occur between successive words in a phrase or between the lexemes in a compound, or between the mor-

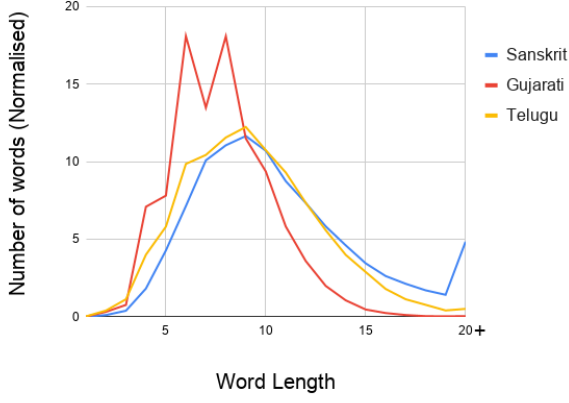


Figure 1: Distribution of Number of vowel split units per word across Sanskrit, Telugu and Gujarati

phemes of the same word. While recognising longer sequences due to sandhi and compounding is a challenge in itself, the external sandhi gives rise to the issue of arbitrary points of segmentation performed by speakers at the time of utterance. Figure 2a shows text-sequence where the sequence contains a compound *nityaḥ* and *śabdārthasambandhaḥ* fused together via Sandhi. Further, *śabdārthasambandhaḥ* is a compound with *śabda*, *artha* and *sambandha* as its components. While it is expected to be uttered without any pause after considering *Samhitā* (Aṣṭādhyāyī-1-4-109), a speaker may choose to segment at the lexical boundaries as shown in 2c and 2d. However in doing so, a proficient speaker would prefer a sequence similar to 2a or 2b, rather than 2c or 2d. This is because, the former two, though results in phonetic transformations, preserves the syntactic and semantic validity of the sequence. However, the latter does not preserve the syntactic and semantic validity of the sequence. Similarly, there are cases where there can be phonetic transformations between the bound morphemes and the free morpheme of a word. These transformations do not result in any modification to the word, other than phonetic variations. However, this makes it challenging for an ASR system. The case of Diphthongs is the quite prevalent under these cases.

In Diphthongs, which can occur both at internal or external sandhi, the independent vowel can only occur at the start of a word. Any vowel appearing in the middle of a word

- a) *nityaśśabdārthasambandhaḥ*
- b) *nityaḥ śabdārthasambandhaḥ*
- c) *nityaḥ śabdārtha sambandhaḥ*
- d) *nityaśśabdārtha sambandhaḥ*

Figure 2: a) Utterance of a sequence without any pause b) Sandhi split at word boundary c) Sandhi based segmentation d) utterance splits without sandhi

either gets converted to a dependent vowel or a diphthong. When a word ending with “ए(/ē/) or ओ(/ō/)” and followed by any vowel, then ending will be changed to either “अय्(/ay/) or अव्(/av/) respectively” or “अ(/a/)”. For example विष्णो+ इह(/viṣṇo+iha/) will get converted to विष्णइह(/viṣṇaiha/) or विष्णविह(/viṣṇaviha/).

Unicode encoding: The Unicode encoding for the native scripts in Sanskrit, similar to several indian languages, does not preserve the correspondence with the phonemic encoding. Further, mapping the graphemes in Unicode to the corresponding phonemes either suffer from ambiguity and redundancy or often require multi-grapheme combinations. For instance, consider the word वागर्थविव(/vāgarthāviva/) in Sanskrit. Here the graphemes in Devanagari ‘वा ग र् थ ा व ि व’ and Roman (v ā g a r t h ā v i v a) do not exhibit a one-to-one mapping with the phonemes. For instance, a single grapheme (e.g., ण) may correspond to 2 phonemes while two graphemes (e.g., र् ण in devanagari, ‘t h’ in roman) may correspond to a single phoneme.

3 Unit Selection Alternatives for AM and LM

In this section, we discuss different alternatives for identifying units of the language model and the acoustic model that we subsequently employ in our experimental evaluation and analysis.

3.1 Alternatives for Graphemic Representation

The Unicode standard for native scripts of Sanskrit : Devanagari, Gujarati and Telugu faces challenge for computational language processing due to redundancy in mappings between phonemes and graphemes as previously discussed. So for Sanskrit, we use San-

skrit Library Phonetic encodings (SLP1) designed by Peter Scharf and Hyman, described in (Scharf and Hyman, 2011). This encoding gives unique one-to-one mapping to the phoneme. However Gujarati possess extra native characters such as $\text{अँ}(/e/)$, $\text{ओँ}(/o/)$ and in Telugu also such as $\text{ఎ}(/e/)$, $\text{ఓ}(/o/)$, and $\text{ఊ}(/r/)$. So we extend SLP1 to fit to the character set of Gujarati and Telugu in our experiments.

3.2 Alternatives for Sub-word units

One possibility for deriving subword units for the language modeling is to segment words in Sanskrit based on Sandhi rules. However, Sandhi splitting can change some phonemes corresponding to the words in almost all cases. Consider the word $\text{रामायेदम्} = \text{रामाय} + \text{इदम्}$ ($/rāmāyēdam/ = /rāmāya/ + /idam/$), wherein the vowel $\text{ए} (/e/)$ is changed into $\text{अ} + \text{इ}$ ($/a/ + /i/$) after performing Sandhi-based splitting. This leads to a mismatch between the speech transcript and the speech audio, potentially creating further complications for ASR.

3.2.1 BPE-based Word Segmentation

Byte pair encoding (BPE) is a simple data compression algorithm that iteratively replaces the frequently occurring subword units with a single unused byte (Gage, 1994). This technique was first adopted to model rare words using subword units in neural machine translation (Sennrich et al., 2016). Interestingly, BPE has been explored for learning new vocabulary for poetry to prose conversion in Sanskrit (Krishna et al., 2019). We consider the benefits of using BPE as a subword unit for Sanskrit ASR.

While BPE is a purely data-driven segmentation strategy, we next present a linguistically motivated segmentation approach that might be aligned with finding syllable units for ASR that are more phonetically compliant. We refer to this technique as *vowel segmentation*.

3.2.2 Vowel Segmentation

Splitting the words based on vowels and adjacent consonants is inspired by the *Laghu-Guru* mapping of syllables of the words for identifying the meters of Sanskrit verses. Here, every short vowel is referred to as *Laghu* (represented by the symbol ।) and every long vowel is referred to as *Guru* (represented by the

ALGORITHM 1: Vowel segmentation algorithm for Indian languages

Input: *word* in Indian language
Output: Vowel segments in OUTPUT
 OUTPUT = “”;
for each graphemic unit c_i in word **do**
 if c_i is *V* **then**
 if c_{i+1} is *V* **then**
 OUTPUT += c_i + “ ”;
 else if c_{i+1} is *C* and c_{i+2} is *C* **then**
 OUTPUT += c_i ;
 else if c_{i+1} is *C* and c_{i+2} is *V* **then**
 OUTPUT += c_i + “ ”;
 else
 if c_{i+1} is *V* **then**
 OUTPUT += c_i ;
 else if c_{i+1} is *C* and c_{i+2} is *C* **then**
 OUTPUT += c_i ;
 else if c_{i+1} is *C* and c_{i+2} is *V* and c_{i+2} is first vowel of the word **then**
 OUTPUT += c_i ;
 else if c_{i+1} is *C* and c_{i+2} is *V* **then**
 OUTPUT += c_i + “ ”;

symbol ऽ). Also, when a short vowel is followed by a conjunct consonant or Anusvāra (nasal sound $/m/$) or Visarga (voiceless glottal fricative $/h/$) the short vowel now becomes *Guru*. E.g., the *Laghu-Guru* mapping of “अन्यानि संयाति($/anyāni saṃyāti/$)” is “ऽऽ। ऽऽ।”. In prior work involving Indian languages for TTS, (Kishore et al., 2002) proposed various syllabification rules for words. Herein (with a few exceptions), if a vowel is followed by 3 or more consonants, only the first following vowel is grouped with the preceding vowel to form the subword unit.

Our proposed algorithm for vowel segmentation (VS) is outlined in Algorithm 1. We propose segmenting words at vowel boundaries to extract the units for which alignment with speech is learnt within the ASR system. For acoustic models, an effective unit of a word for ASR would arguably be the syllable (Lee et al., 2013). Representing a word in terms of syllables demands the mapping of a word

from graphemes to phonemes. To create syllable units, phonemes are then combined together based on the *sonority sequencing principle* (Clements, 1990). Absence of accurate syllabifiers for Indian languages restrict the use of syllables as units for learning alignment. Our approach produces units which can be viewed as a rough approximation to a syllable. A syllable is composed of three parts *viz.*, onset, nucleus and coda, where nucleus has the highest sonority and is always a vowel. In our approach, the onset is always one or zero consonants and the coda is zero or $n-1$ consonants if the nucleus is followed by n consonants. It is also observed in the pronunciation of conjunct consonant by professional speakers that the beginning part of conjunct consonant gets associated more with the preceding vowel than the following. We consider nasal Anusvāra (ँ), Chandrabindu (ँ or ॡ), and Visarga (ः) to be part of the consonant set. For example, in Sanskrit, the units for a word उद्यानः (udyānaḥ, park) will be ‘उद् या नः(/ud yā naḥ/)’ and subword units of the Telugu word తల్లితండ్రులు(/tallitaṁḍrulu/) will be ‘తల్లి తండ్రి లు(/tal li taṁḍ ru lu/)

3.3 Summarizing unit choices for AM and LM

For each choice of graphemic unit (*viz.* native script and SLP1) described in Section 3.1, we study three different units for the acoustic modeling (AM) in ASR, *viz.*, graphemic unit, BPE and vowel segmentation across Sanskrit and the two other representative Indian languages. *viz.*, Gujarati and Telugu. The number of units that need to be aligned defines the vocabulary size of the acoustic modeling (AM) task. Smaller the vocabulary, lesser is the data requirement for alignment learning. As the vocabulary size increases, more training examples are required to learn the corresponding alignments. In Figure 3, we report the vocabulary size based on each of these *three* different unit selections and contrast the sizes with that of two extreme hypothetical systems - one that considers the entire word as a single unit for AM and the other that treats the phoneme as a single unit for AM. Note that while phoneme annotations are available in the ground truth datasets for Telugu and Gujarati, our dataset does not have phonetic an-

notations. We present the variation in vocabulary size as a function of the graphemic unit (native script vs. SLP1). In both Gujarati and Telugu, we point out that the number of SLP graphemic units almost coincide with the number of phonemes, while the native script-based graphemes are much larger in number compared to phonemes.

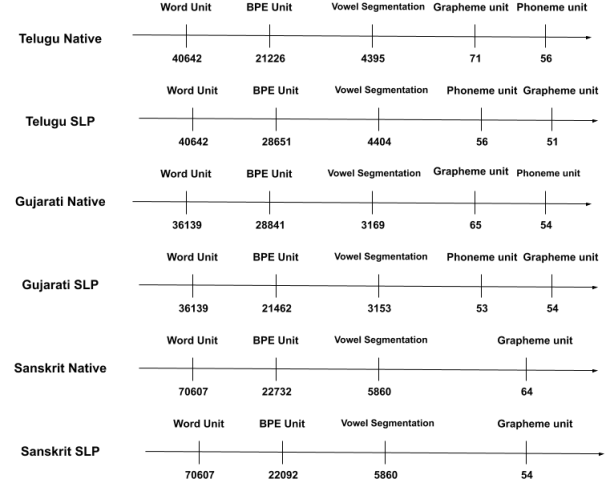


Figure 3: Variation in vocabulary size as a function of the Graphemic unit (native script vs. SLP1) depicting the vocabulary sizes of the whole word units, vowel segment units, BPE units, phonemes and graphemes for ASR data across the three languages including our new Sanskrit ASR data

We can also roughly estimate the extent of data sparsity in terms of vocabulary size in each setting - larger the vocabulary size, higher is the chance of data sparsity. We note that data sparsity is minimal for graphemes and highest for a hypothetical system where whole words are the unit of selection.

4 Experiments and Results

Description of Datasets. In addition to reporting ASR results on the carefully created वाक्सञ्चयः (/Vākṣaṁcayaḥ/) dataset (described in Section 2), we also contrast through experimental analysis on two other Indian languages, *viz.*, Telugu and Gujarati. For Telugu and Gujarati, we used the publicly available speech corpora released by Microsoft (Srivastava et al., 2018) that contains 36.2/8.7 hours and 33.2/5.8 hours of training/test speech in Telugu and Gujarati, respectively. We use a new train-test split for the Gujarati and Telugu datasets because the original split had

Sr.	Script	LM Unit	AM Unit	WER
1	Native	Word	Gr.	40.06
2	SLP1	Word	Gr.	40.57
3	Native	VS	Gr.	22.55
4	SLP1	VS	Gr.	22.59
5	Native	BPE	Gr.	21.99
6	SLP1	BPE	Gr.	21.94
7	Native	Word	Gr.+VS	42.05
8	SLP1	Word	Gr.+VS	41.36
9	Native	VS	Gr.+VS	24.04
10	SLP1	VS	Gr.+VS	24.98
11	Native	BPE	Gr.+VS	23.58
12	SLP1	BPE	Gr.+VS	24.15

Table 3: WERs on Sanskrit test set. (Native=Devanagari, VS=Vowel-Split, Gr.=Grapheme)

overlapping speakers in their train and test. Our new split ensures that the train-test split have disjoint speakers. Transcripts of this corpora was cleaned for orthographic errors. Corpora in these two languages were accompanied by pronunciation lexicons, which we used to build phoneme-based ASR systems to compare against our grapheme-based systems.

Experimental Setup. We use the Kaldi toolkit (Povey et al., 2011) for all our ASR experiments. Our acoustic model is implemented using Time Delay Neural Networks (TDNNs) (Peddinti et al., 2015) containing 14 layers. We use 40-dimensional MFCCs as our input features along with 100-dimensional i-vector based speaker embeddings (Saon et al., 2013). We used ngram language models with Kneser-Ney smoothing implemented using the SRILM toolkit (Stolcke, 2002). The language models were trained using both training transcripts from the speech data, as well as additional textual data derived from the Leipzig Corpora Collection for Gujarati and Telugu (Goldhahn et al., 2012) and the Digital Corpus of Sanskrit (Hellwig, 2010) for Sanskrit. The word vocabulary sizes in the lexicons for Sanskrit, Telugu and Gujarati are 76K, 43K and 48K, respectively.

Results: In Tables 3, 4 and 5, present the WERs from ASR systems built using different choices of AM and LM units using both the

Script	LM Unit	AM Unit	WER
Native	Word	Phn.	18.63
Native	Word	Gr.	19.17
Native	BPE	Gr.	24.49
SLP1	Word	Gr.	18.27
SLP1	Word	Gr. + VS	19.81
SLP1	BPE	Gr.	23.97
SLP1	BPE	Gr. + VS	25.08
SLP1	VS	Gr.	26.33
SLP1	VS	Gr. + VS	26.18

Table 4: WERs on Gujarati test set. (Gr.=Grapheme, Phn.= Phoneme)

graphemic representations (Native and SLP1) for Sanskrit, Gujarati and Telugu, respectively. From Table 3, we see that BPE units and vowel segment units are far superior compared to words as an LM unit for Sanskrit. This is unsurprising given the fat tail of the word vocabulary in Sanskrit (shown in Section 2.1). We observe that purely grapheme-based acoustic models outperform grapheme+vowel segment-based acoustic models. With the consistent mapping between graphemes and phonemes and the absence of schwa deletion, it is intuitive that grapheme-based models would be most appropriate for Sanskrit.

In contrast to Sanskrit, from Tables 4 and 5, we find that both BPE-based models and vowel segment-based models deteriorate in performance when compared with word-based models for Gujarati and Telugu. We conjecture that this deterioration could be attributed to word length and conjunct consonant ratios. Both Gujarati and Telugu have shorter word lengths on average and shorter tails in their vocabulary distributions compared to Sanskrit, thus favouring word-based LMs more. The number of words with conjunct consonants is much higher in Sanskrit compared to Gujarati and Telugu; this could be another reason why subword-based LMs do not help improve over word-based LMs in the latter set of languages.

Table 6 shows the distribution of words with 1-4 continuous consonants in all three languages. For Telugu, even though the number of conjunct consonants with $N = 2$ is higher than in Sanskrit, we found on inspect-

Script	LM Unit	AM Unit	WER
Native	Word	Phn.	21.12
Native	Word	Gr.	21.25
Native	BPE	Gr.	26.68
SLP1	Word	Gr.	20.75
SLP1	Word	Gr. + VS	22.13
SLP1	BPE	Gr.	25.07
SLP1	BPE	Gr. + VS	26.3
SLP1	VS	Gr.	33.68
SLP1	VS	Gr. + VS	36.57

Table 5: WERs on Telugu test set. (Gr.=Grapheme , Phn.= Phoneme)

ing the audio data that such conjunct consonants are often not enunciated clearly. For example స్వాతంత్ర్యమ్ (/svātantryam/) is pronounced as స్వాతంత్రమ్ (/svātantram/). However, in Sanskrit, conjunct consonants having 5 consonants together such as कार्त्स्न्यम् (/kārtsnyam/) are enunciated very clearly and all consonants appear articulated in its pronunciation.

We also find that ASR performance using phonemes is comparable to graphemes for Gujarati and Telugu. And, SLP1 as a graphemic representation is better than the use of native scripts for both the languages. In Sanskrit, BPE based model with the SLP1 as a graphemic representation (Sr. 6 in Table 3) report the best result. In some cases Devanagari as a graphemic representation outperforms the SLP1, the model that uses SLP1 script outperforms the other in terms of character error rate.

In Sanskrit the pause given between the constituent words of a compound word and in between two words varies depending on the fluency of the speaker and the complexity of the text, which can deteriorate the WER. The utterance for ‘महान् प्राकारः’ /mahān

N	Sanskrit	Telugu	Gujarati
1	77.30%	75.77%	89.37%
2	21.41%	23.27%	10.06%
3	1.26%	0.96%	0.56%
4	0.03%	0%	0%

Table 6: Number of continuous consonants (N) distribution in three ASR datasets

prākārah/ may get recognised as ‘महान्प्राकारः’ /mahānprākārah/, where two correctly recognised words will be evaluated as one *deletion* and one *substitution* by the evaluation model. Similarly if the audio of ‘शोभमानमासीत्’ /śobhamānamāsīt/ gets recognised as ‘शोभमानम् आसीत्’ /śobhamānam āsīt/, then it will be considered as one *insertion* followed by one *substitution*. After negotiating these two particular errors, we will get 17.79% as the WER for our best model of Sanskrit (Sr. 6 of Table 3). Given the OOVs at word level are 44.16%, 11.46% and 18.63% for Sanskrit, Telugu and Gujarati respectively, we achieved remarkable results for Sanskrit.

#	WER	Speech Description
1*	37.79%	Tamil influenced accents
2*	37.60%	Hindi influenced accents
3*	46.27%	Radio Program
4	46.62%	Extempore Discourse
5	51.52%	Live Lecture

Table 7: Test results for the Out-of-domain Dataset (* readings from books and transcripts)

Out-of-domain test set. Table 7 presents results on the out-of-domain test set described in Section 2. It shows the WERs we can expect from our models when the speakers and content largely vary in domain from our dataset. This test set was sampled for specific speakers and content that qualify as being out-of-domain. These test utterances were evaluated using our best performing Sanskrit ASR models. Speakers #1 and #2 were included, as their utterances show more pronounced influence of their native languages, Tamil and Hindi respectively. It is observed that speaker #1, does not often attempt to distinguish between the pronunciation of the phoneme pairs such as /ta/ and /da/, /ka/ and /ga/, etc. This is in congruence with the orthography followed in Tamil, the speaker’s native language. Speaker #2’s reading was influenced by schwa deletion, i.e., the phenomena of deleting vowel markers accompanying consonants at certain contexts (elaborated in the supplementary material) which is dominant in Hindi. For example, गतवान् /gatavān/ is pronounced as /gatvān/ by this speaker and the ASR sys-

tem correctly predicts it as /gatvān/. Here, the acoustic model clearly dominates the language model. Speaker #3’s utterances are the Sanskrit translation of the Indian government’s public outreach program known as ‘मन की बात’ /man kī bāt/. This widely differs from the training speech dataset and vocabulary of the LM that is used. Similar observation can be made for speakers #4 and #5, albeit for different reasons. Speaker #4 in the discourse tends to use rare words, especially domain-specific proper nouns and derivational verbs, both of which are scarce in our LM vocabulary. Speaker #5 tends to deviate from conventional speech patterns, by providing emphasis on specific words, for the purpose of pedagogy.

5 Conclusion

We presented a new Sanskrit speech corpus वाक्सञ्चयः (/Vākṣaṇḍayah/) along with a new large-vocabulary ASR system. We explored different unit selection alternatives for both AM and LM, along with a new segmentation approach. We observe that SLP1, when used as the script instead of the native scripts generally results in better performances for Gujarati and Telugu. For Sanskrit, SLP1 based model results better character error rate. Similarly, we observe that vowel split based segmentation consistently yields better performance than other configurations. Our current dataset and the model are specifically designed to handle data in prose. The inclusion of poetry data would require substantial changes to the system, which we plan to address in the near future. For instance, the poetry data would greatly benefit from insights from Sanskrit prosody. More importantly, the degree of free word orderliness in prose and poetry greatly varies in Sanskrit, so much so that an n-gram LM will not be effective (Krishna et al., 2018).

Acknowledgments

We would like to thank Prof. K. Ramasubramanian, IIT Bombay, for supporting the creation of Sanskrit speech corpus. We express our gratitude for the volunteers who have participated in recording various texts and all other people who recorded the reading of classical Sanskrit texts and made available for public.

References

- Devaraj Adiga, Rohit Saluja, Vaibhav Agrawal, Ganesh Ramakrishnan, Parag Chaudhuri, K Ramasubramanian, and Malhar Kulkarni. 2018. [Improving the learnability of classifiers for sanskrit ocr corrections](#). In *The 17th World Sanskrit Conference, Vancouver, Canada. IASS*, pages 143–161.
- CS Anoop and AG Ramakrishnan. 2019. [Automatic speech recognition for sanskrit](#). In *2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT)*, volume 1, pages 1146–1151. IEEE.
- G. N. Clements. 1990. [The role of the sonority cycle in core syllabification](#). *Papers in Laboratory Phonology*, pages 283–333.
- Philip Gage. 1994. [A new algorithm for data compression](#). *C Users Journal*, 12(2):23–38.
- Dirk Goldhahn, Thomas Eckart, and Uwe Quasthoff. 2012. [Building large monolingual dictionaries at the Leipzig corpora collection: From 100 to 200 languages](#). In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC’12)*, pages 759–765, Istanbul, Turkey. European Language Resources Association (ELRA).
- Oliver Hellwig. 2010. [DCS-the digital corpus of Sanskrit](#). *University of Heidelberg: Department of Classical Indology*.
- S Prahallad Kishore and Alan W Black. 2003. [Unit size in unit selection speech synthesis](#). In *Eighth European Conference on Speech Communication and Technology*.
- SP Kishore, Rohit Kumar, and Rajeev Sangal. 2002. [A data driven synthesis approach for indian languages using syllable as basic unit](#). In *Proceedings of Intl. Conf. on NLP (ICON)*, pages 311–316.
- Amrith Krishna, Bishal Santra, Sasi Prasanth Bandaru, Gaurav Sahu, Vishnu Dutt Sharma, Pavankumar Satuluri, and Pawan Goyal. 2018. [Free as in free word order: An energy based model for word segmentation and morphological tagging in Sanskrit](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2550–2561, Brussels, Belgium. Association for Computational Linguistics.
- Amrith Krishna, Vishnu Sharma, Bishal Santra, Aishik Chakraborty, Pavankumar Satuluri, and Pawan Goyal. 2019. [Poetry to prose conversion in Sanskrit as a linearisation task: A case for low-resource languages](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1160–1166, Florence,

- Italy. Association for Computational Linguistics.
- Amrith Krishna, Shiv Vidhyut, Dilpreet Chawla, Sruti Sambhavi, and Pawan Goyal. 2020. [SHR++: An interface for morpho-syntactic annotation of Sanskrit corpora](#). In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 7069–7076, Marseille, France. European Language Resources Association.
- Amba Kulkarni. 2013. [A deterministic dependency parser with dynamic programming for sanskrit](#). In *Proceedings of the Second International Conference on Dependency Linguistics, DepLing 2013, August 27-30, 2013, Prague, Czech Republic*, pages 157–166. MATFYZPRESS Publishing House of the Faculty of Mathematics and Physics Charles University in Prague / ACL.
- Amba Kulkarni, Sheetal Pokar, and Devanand Shukl. 2010a. [Designing a constraint based parser for sanskrit](#). In *Sanskrit Computational Linguistics - 4th International Symposium, New Delhi, India, December 10-12, 2010. Proceedings*, volume 6465 of *Lecture Notes in Computer Science*, pages 70–90. Springer.
- Malhar Kulkarni, Chaitali Dangarikar, Irawati Kulkarni, Abhishek Nanda, and Pushpak Bhattacharyya. 2010b. [Introducing sanskrit wordnet](#). In *Proceedings on the 5th global wordnet conference (GWC 2010)*, Narosa, Mumbai, pages 287–294.
- Malhar Kulkarni, Irawati Kulkarni, Chaitali Dangarikar, and Pushpak Bhattacharyya. 2010c. [Gloss in sanskrit wordnet](#). In *Sanskrit Computational Linguistics - 4th International Symposium, New Delhi, India, December 10-12, 2010. Proceedings*, volume 6465 of *Lecture Notes in Computer Science*, pages 190–197. Springer.
- Anil Kumar, Vipul Mittal, and Amba Kulkarni. 2010. [Sanskrit compound processor](#). In *Sanskrit Computational Linguistics - 4th International Symposium, New Delhi, India, December 10-12, 2010. Proceedings*, volume 6465 of *Lecture Notes in Computer Science*, pages 57–69. Springer.
- Chia-ying Lee, Yu Zhang, and James Glass. 2013. [Joint learning of phonetic units and word pronunciations for ASR](#). In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 182–192.
- P.H. Matthews. 2007. *The Concise Oxford Dictionary of Linguistics*. Oxford Paperback Reference. OUP Oxford.
- Diwakar Mishra, Kalika Bali, and Girish Nath Jha. 2013. [Syllabification and stress assignment in phonetic sanskrit text](#). In *2013 International Conference Oriental COCOSDA held jointly with 2013 Conference on Asian Spoken Language Research and Evaluation (O-COCOSDA/CASLRE)*, Gurgaon, India, November 25-27, 2013, pages 1–4. IEEE.
- Vijayaditya Peddinti, Daniel Povey, and Sanjeev Khudanpur. 2015. [A time delay neural network architecture for efficient modeling of long temporal contexts](#). In *INTERSPEECH*.
- Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukás Burget, Ondrej Glembek, Nagendra Kumar Goel, Mirko Hannemann, Petr Motlíček, Yanmin Qian, Petr Schwarz, Jan Silovský, Georg Stemmer, and Karel Veselý. 2011. [The kaldi speech recognition toolkit](#). In *IEEE 2011 workshop on automatic speech recognition and understanding*. IEEE Signal Processing Society.
- Manomohan Ghosh Pāṇini. 1938. *Pāṇinīya Śikṣā or The Śikṣā Vedāṅga, Ascribed to Pāṇini*. University of Calcutta.
- Richard G Salomon. 1996. [Brahmi and kharoshthi](#). *The world’s writing systems*, pages 373–383.
- Rohit Saluja, Devaraj Adiga, Parag Chaudhuri, Ganesh Ramakrishnan, and Mark Carman. 2017. [Error detection and corrections in Indic OCR using LSTMs](#). In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*, volume 1, pages 17–22. IEEE.
- George Saon, Hagen Soltau, David Nahamoo, and Michael Picheny. 2013. [Speaker adaptation of neural network acoustic models using i-vectors](#). *2013 IEEE Workshop on Automatic Speech Recognition and Understanding*, pages 55–59.
- Peter M Scharf. 2013. [Linguistics in India](#). *The Oxford handbook of the history of linguistics*, pages 227–257.
- Peter M. Scharf and Malcolm D. Hyman. 2011. [Linguistic Issues in Encoding Sanskrit](#). The Sanskrit Library.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. [Neural machine translation of rare words with subword units](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.
- Preeti Shukla, Devanand Shukl, and Amba Kulkarni. 2010. [Vibhakti divergence between sanskrit and hindi](#). In *Sanskrit Computational Linguistics - 4th International Symposium, New Delhi, India, December 10-12, 2010. Proceedings*, volume 6465 of *Lecture Notes in Computer Science*, pages 198–208. Springer.
- Richard Sproat. 2003. [A formal computational analysis of Indic scripts](#). In *International symposium on Indic scripts: past and future*, Tokyo.

Brij Mohan Lal Srivastava, Sunayana Sitaram, Rupesh Kumar Mehta, Krishna Doss Mohan, Pallavi Matani, Sandeepkumar Satpal, Kalika Bali, Radhakrishnan Srikanth, and Niranjana Nayak. 2018. [Interspeech 2018 low resource automatic speech recognition challenge for Indian languages](#). In *SLTU*.

Andreas Stolcke. 2002. [SRILM - an extensible language modeling toolkit](#). In *INTER_SPEECH*.

A Differences between Sanskrit and other Indic languages for ASR

Many Indian languages are known to be derived from Sanskrit (Kulkarni et al., 2010b) and their scripts derived from the Brahmi script (Salomon, 1996; Sproat, 2003), which leads to grapheme-based similarities amongst them. In Figure 4, we illustrate through an example, the spectrum of mapping the native character/grapheme (units) in words across languages; at one end of the spectrum is राम(/rām/) in Hindi mapped to రామ(/rāma/) in Telugu as an example where direct correspondence with the native character exists. Going further in the spectrum are examples for which direct character correspondence does not exist. सीता(/sītā/) in Hindi going to ಸೀತೆ(/sīte/) in Kannada is an instance where there is a change in the ending vowel.

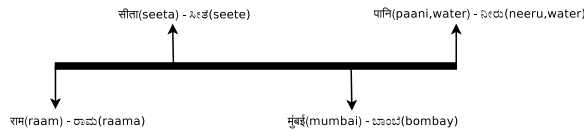


Figure 4: Spectrum of mapping native character/grapheme (units) in words across Indian languages

Schwa Deletion The schwa deletion phenomenon plays a crucial role in the north Indian languages. Every consonant by itself includes a short /a/ vowel sound (referred to as “schwa”) unless otherwise specified. For example, the letter ‘त’ in Hindi is pronounced as /ta/. This sound can be associated with any other vowel sound by the use of “Mātras”. Mātras are dependent forms of vowels. Schwa is the default vowel for a consonant and hence does not require any explicit Mātra to represent it. Schwa deletion is a phenomenon

where implicit schwas of a word are deleted during pronunciation. For example, in Hindi, the proper noun, ‘अर्जुन’ (/arjun/, the name of a person) has schwa deletion after the consonant ‘ज’ and is pronounced as Arjun. This phenomenon is not observed in the South Indian languages. For instance, in Kannada it is pronounced as ‘Arjuna’. There is no implicit schwa deletion in Sanskrit as well as in the traditional use of South Indian languages such as Kannada. North Indian languages observe schwa deletion not only at the end of the word, but also in the middle of a word in some cases. For example, the word ‘गलती’ (/galtī/ meaning mistake) in Hindi observes implicit schwa deletion after the consonant ‘ल’ (/la/).

ASR becomes challenging because of this phenomenon since the occurrence of schwa deletion is not always explicitly specified in the orthography. For example, the name रामबाबु (/rāmbābu/) has two basic words concatenated to form a name. In Hindi, this name has an implicit schwa deleted at म (consonant sounding ‘ma’) of राम (/rām/). While constructing phonetic representations for ASR, such deletions introduce ambiguities in pronunciation which could be alleviated by enforcing more consistency between graphemes and phonemes. This same word रामबाबु written in Telugu would be phonetically represented as రామ్బాబు (/rāmbābu/) instead of రామబాబు (/rāmabābu/) which is intuitive. Note that in the former case, there is an addition of ‘^h’ (halant: an explicit schwa deletion marker) at మ (/ma/). This forces the consonants మ (/ma/) and బ (/ba/) to combine and form a conjunct. In the latter case there is a grapheme consistency across both Hindi and Telugu languages but there is a variation in their pronunciation due to the schwa deletion phenomenon. In contrast, in the case of Sanskrit, since pronunciation is strictly governed by the शिक्षा (/śikṣā/) (Pāṇini, 1938), a treatise on phonetics, schwa deletion is not observed.

B List of works used in the speech corpus

- Mallinātha’s commentary on KumāraSambhavam
- Mallinātha’s commentary on Raghu-vamśam

- Ādiśaṅkara's Bhaṣyam on Kaṭhōpaniṣat
- Ādiśaṅkara's Bhaṣyam on Bhagavadgītā (Chapters 1-9)
- Ādiśaṅkara's Bhaṣyam on Brahmasūtram
- Yogasūtram Vyāsabhāṣya-sahitam
- R̥ṇvimuktiḥ by SaṃskṛtaBhāratī
- Āñjaneya-Rāmāyaṇam by SaṃskṛtaBhāratī
- Kathālaharī by SaṃskṛtaBhāratī
- Bālamodinī stories from SambhāṣaṇaSandēśa by SaṃskṛtaBhāratī
- Samarthaḥ Svāmī Rāmadāsaḥ by SaṃskṛtaBhāratī
- Yugāvatāraḥ by SaṃskṛtaBhāratī
- Prāstāvikam of Svāmī Aḍgaḍānanda's commentary on Bhagavadgītā
- ViśuddhaVedāntaSāraḥ by SaccidāndendraSarasvatī
- Man-Kī-Bāt Sanskrit translation
- Lecture on Lilāvatī
- Extempore Discourse

B.1 Sources of Recorded Audios

- vedabhoomi.org
- <https://archive.org/details/Anjaneya-rAmAyaNam>
- <https://archive.org/details/geethasb>
- <https://archive.org/details/bAlamodinI-01>
- <https://archive.org/details/kathA-laharI>
- <https://www.youtube.com/watch?v=LJGjfHHHBoQ>
- <https://sanskritdocuments.org/sites/manogatam/>
- <https://archive.org/details/YatharthGeetaSanskritAudio>

B.2 Sources of Tools used for Recording, Cleaning and Transcribing the Audios

- ASR Voice Recorder <https://play.google.com/store/apps/details?id=com.nll.asr>
- Audacity <https://www.audacityteam.org/>
- oTranscribe <https://otranscribe.com/>

C Computing Infrastructure

- GPU Model Name : GeForce GTX 1080 Ti
- GPU RAM : 12 GB
- CPU Model Name : CPU Intel(R) Xeon(R) Gold 5120 CPU
- Processor Speed : 2.20GHz
- System Memory : 256 GB
- CPU Cores : 56