Reduce and Reconstruct: ASR for Low-Resource Phonetic Languages

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Introduction

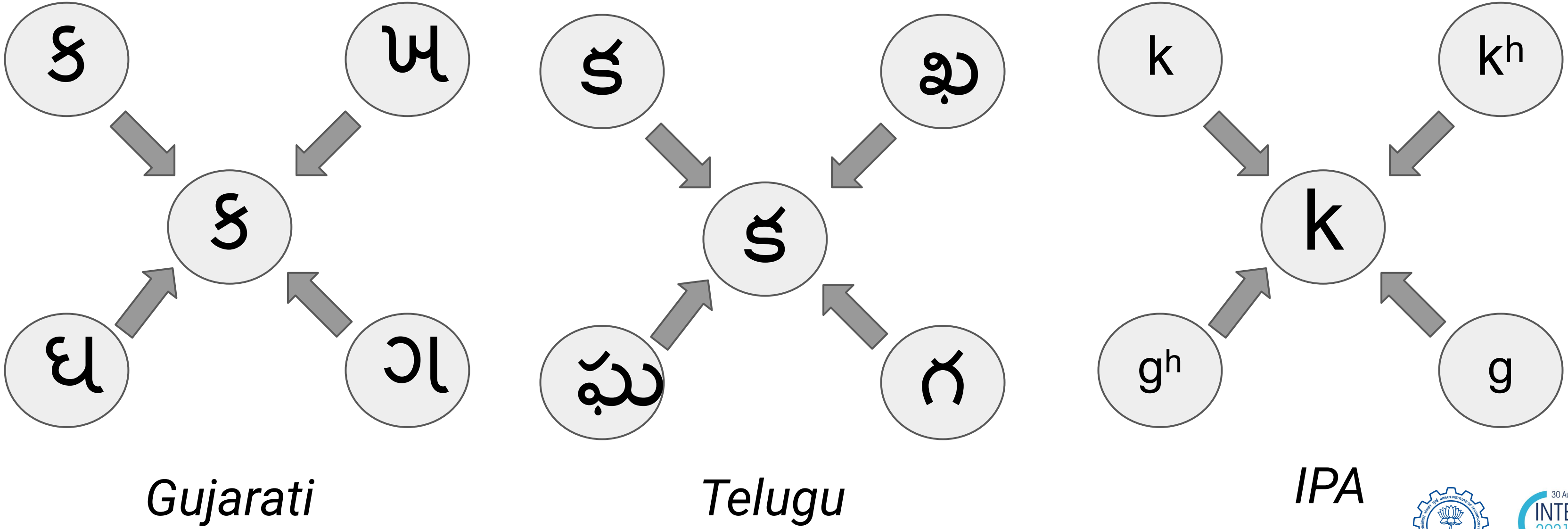
- A seemingly simple but effective technique to improve E2E ASR systems for low-resource phonetic languages.
- E2E ASR is an attractive choice since speech is mapped directly to graphemes or subword units derived from graphemes.
- However, it is also very data-intensive and tends to underperform on low resource languages.

Introduction

- In our approach, we train two modules:
    a. an ASR system with a linguistically-motivated reduced output alphabet. For the ASR model, it is easier to learn and less data-intensive. (***reduce***)
    b. an FST-based reconstructor that recovers sequences in the original alphabet. (***reconstruct***)
- We run experiments on two Indian languages, Gujarati and Telugu.
- With access to only 10 hrs of speech data, we obtain relative WER reductions of up to 7% compared to systems that do not use any reduction.

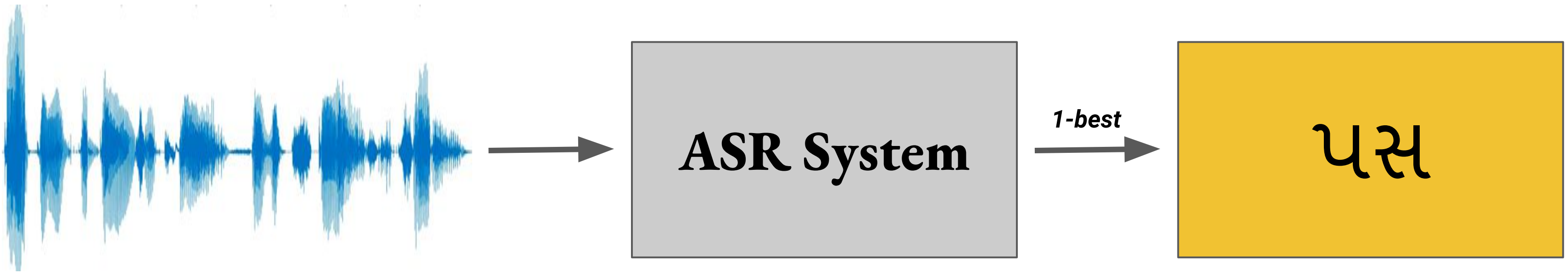
Our Approach

1. **Devise** a **reduced vocabulary** that merges acoustically confusable and linguistically discriminative graphemes.



Our Approach

2. Given labelled speech data, **transform transcriptions** using the reduction.
3. **Train** an **ASR system** that maps the original speech to the reduced transcriptions.



Sound wave saying
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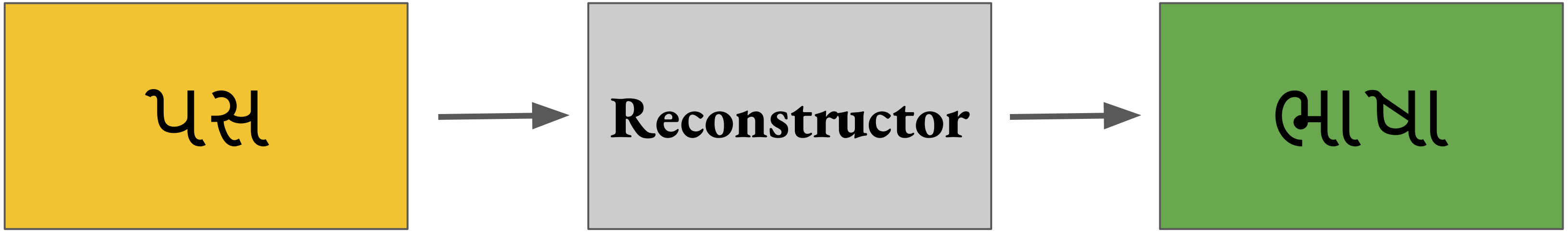
Our Approach

4. **Train** a **reconstructor** to reconstruct the original grapheme sequence from the reduced grapheme sequence.



Our Approach: FST-based Reconstructor

- **Input:** reduced-grapheme hypothesis from ASR system.
- Represent as a linear acceptor, **H**.

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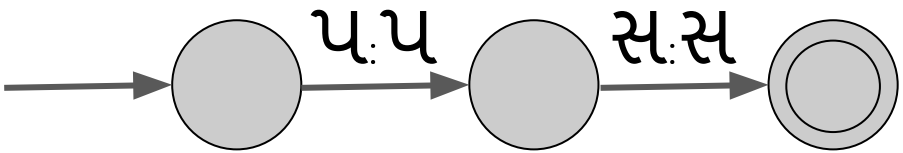
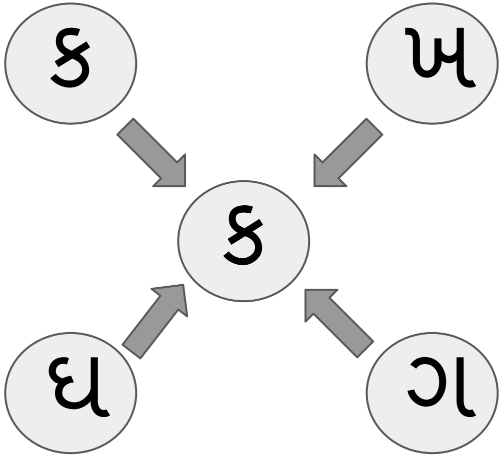
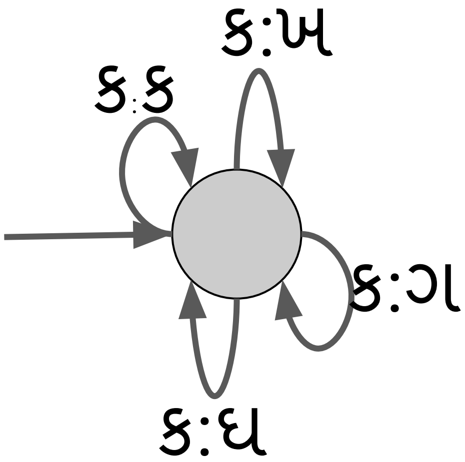


Our Approach: FST-based Reconstructor

- Compose with the **Reduction FST**, S.
- S is a single-state FST that takes reduced graphemes as input and produces original graphemes as output.
- For example,



is represented as



Our Approach: FST-based Reconstructor

- Further compose with the **Edit Distance FST**, E.
- E is an FST that that takes a grapheme sequence as input. It produces as output all grapheme sequences that satisfy the constraint that every word in the output is within an edit distance of ***d*** from each word in the input. The allowable edits are substitutions, insertions and deletions.
- Each edit incurs an additive cost $\boldsymbol{\lambda}$.
- ***d*** and $\boldsymbol{\lambda}$ are hyperparameters.

Our Approach: FST-based Reconstructor

- Further compose with the **Dictionary FST**, L.
- We fix a vocabulary; in this case, the set of all ASR training set words.
- L simply maps a sequence of graphemes to a sequence of words (each word is internally represented as an index in the aforementioned vocabulary).
- Out-of-vocabulary words are mapped to a special `<unk>` word.

Our Approach: FST-based Reconstructor

- Further compose with the **Language Model FST**, G.
- G is an n-gram language model trained on ASR training set transcriptions.
- $H \circ S \circ E \circ L$ contains all possible reconstructions. Composing this with G rescores the reconstructions, giving higher scores to meaningful sentences.
- These operations are efficient owing to highly-optimized FST libraries.

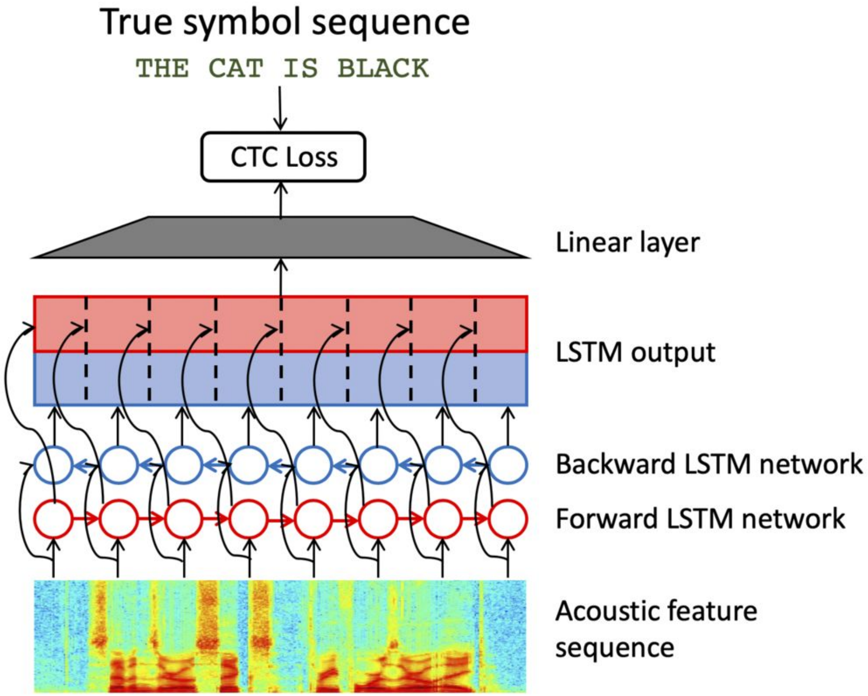
Our Approach: FST-based Reconstructor

- Finally, obtain output O, the best reconstructed sequence, by running a shortest path FST algorithm on the composed FST $H \circ S \circ E \circ L \circ G$.
- These operations are efficient owing to highly-optimized FST libraries.

Experiments

- **2 Indian languages**: Gujarati, Telugu
- **ASR architecture:** biLSTM (without and with RNNLM)
- **2 Training Durations:** Full and 10-hr
- Gujarati 10-hr experiments on the advanced Conformer ASR architecture

Experimental Setup: BiLSTM (without RNNLM)



biLSTM Architecture for Speech Recognition

We use the ESPNet toolkit to train hybrid CTC-attention biLSTMs

Major hyperparameters:
4 encoder layers: **512** units for Guj, **768** units for Tel
1 decoder layer: **300** units for Guj, **450** units for Tel
0.8 CTC, 0.2 Attention

Reference:
K. Audhkhasi, G. Saon, Z. Tüske, B. Kingsbury and M. Picheny, "Forget a Bit to Learn Better: Soft Forgetting for CTC-Based Automatic Speech Recognition," in Interspeech, 2019.

Experimental Setup: FSTs

- All FSTs were implemented using the OpenFST toolkit.
- The LM FST, **G**, is a 4-gram LM with Kneser-Ney discounting for order 4. It is implemented using SRILM.
- Best tuned values: d=3, λ=5.

Results: Pre-Reconstruction ASR Experiments

Duration	Reduction	r-WER (Guj)		r-WER (Tel)	
		Dev	Test	Dev	Test
Full	identity	41.5	43.2	44.1	46.8
	ρ_1	36.5	39.6	39.3	42.8
	ρ_1-rand	41.3	42.3	44.2	47.9
10 hr	identity	60.2	68.6	64.1	71.4
	ρ_1	53.9	63.6	56.9	66.5
	ρ_1-rand	63.2	71.8	60.8	69.4

Reduced Word Error Rate (r-WER)
(WERs computed between ASR hypothesis and *reduced* ground truth text)

Identity: Baseline with no reduction
ρ_1: Our reduction
ρ_1-*rand*: Randomized reduction

Results: Pre-Reconstruction ASR Experiments

Duration	Reduction	r-WER (Guj)		r-WER (Tel)	
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10 hr	identity	60.2	68.6	64.1	71.4
	ρ_1	53.9	63.6	56.9	66.5
	ρ_1-rand	63.2	71.8	60.8	69.4

- Lower r-WERs for ρ_1 show that reduction **simplifies** the ASR task
- ρ_1 vs ρ_1-rand shows that a **principled reduction** is important

Results: Post-reconstruction

d	λ	Reduction	WER (Guj) Dev	WER (Guj) Test	WER (Tel) Dev	WER (Tel) Test
		Baseline	41.5	43.2	44.1	46.8
0	5	identity	41.8	43.4	45.1	47.7
		ρ_1	40.4	41.9	42.1	45.7
3	5	identity	37.9	37.8	40.6	42.5
		ρ_1	**37.8**	**36.5**	**38.5**	**41.2**

(a) *Full training duration.*

d	λ	Reduction	WER (Guj) Dev	WER (Guj) Test	WER (Tel) Dev	WER (Tel) Test
		Baseline	60.2	68.6	64.1	71.4
0	5	identity	60.3	68.6	64.4	71.6
		ρ_1	56.2	64.9	58.4	67.8
3	5	identity	56.8	64.9	59.2	66.1
		ρ_1	**53.2**	**61.2**	**54.3**	**63.6**

(b) *10-hr training duration.*

Word Error Rate (WER)
for different values of *d* and *λ*

ρ1 is **our approach.**

Results: FST Reconstruction

d	λ	Reduction	WER (Guj) Dev	WER (Guj) Test	WER (Tel) Dev	WER (Tel) Test
		Baseline	41.5	43.2	44.1	46.8
0	5	identity	41.8	43.4	45.1	47.7
		ρ_1	40.4	41.9	42.1	45.7
3	5	identity	37.9	37.8	40.6	42.5
		ρ_1	**37.8**	**36.5**	**38.5**	**41.2**

(a) *Full training duration.*

d	λ	Reduction	WER (Guj) Dev	WER (Guj) Test	WER (Tel) Dev	WER (Tel) Test
		Baseline	60.2	68.6	64.1	71.4
0	5	identity	60.3	68.6	64.4	71.6
		ρ_1	56.2	64.9	58.4	67.8
3	5	identity	56.8	64.9	59.2	66.1
		ρ_1	**53.2**	**61.2**	**54.3**	**63.6**

(b) *10-hr training duration.*

- For *d=0* (exact reconstruction), reduction **outperforms** identity and baseline
- Increasing *d* **improves all** WERs as expected; reduction still **outperforms** the other two
- Improvements are more pronounced in the **low-resource** 10-hr setting

Experimental Setup: biLSTM (with RNNLM)

- **2 RNNLM** layers with **1500** units
- Trained on transcriptions of **full** speech data

Results: With RNNLM

Duration	Reduction	WER (Guj)		WER (Tel)	
		Dev	**Test**	**Dev**	**Test**
Full	Baseline	37.4	34.0	37.9	40.0
	identity	**36.2**	**31.8**	37.7	39.2
	ρ_1	37.1	32.2	**36.5**	**38.1**
10-hr	Baseline	56.2	63.2	56.9	63.8
	identity	55.5	62.3	56.2	62.5
	ρ_1	**52.0**	**58.2**	**51.2**	**59.1**

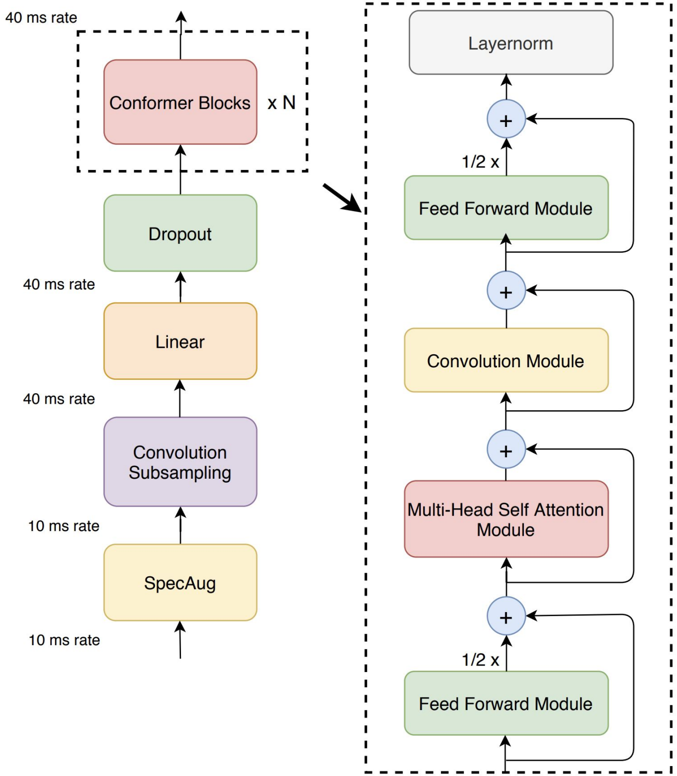
Word Error Rate (WER)
using reconstructor with d=3, λ=5
on ASR with RNNLM rescoring

Results: With RNNLM

Duration	Reduction	WER (Guj)		WER (Tel)	
		Dev	**Test**	**Dev**	**Test**
Full	Baseline	37.4	34.0	37.9	40.0
	identity	**36.2**	**31.8**	37.7	39.2
	ρ_1	37.1	32.2	**36.5**	**38.1**
10-hr	Baseline	56.2	63.2	56.9	63.8
	identity	55.5	62.3	56.2	62.5
	ρ_1	**52.0**	**58.2**	**51.2**	**59.1**

- Baseline with RNNLM is **better** than baseline without RNNLM
- Reduction significantly **outperforms** identity in the 10-hr setting, doesn't do as well in the Full setting for Guj

Experimental Setup: Conformer



Conformer Architecture for Speech Recognition

We use the [ESPNet] toolkit to train hybrid CTC-attention Conformers

Major hyperparameters:
2 encoder layers: **350** units, 4 att heads
1 decoder layer: **350** units, 4 att heads
0.3 CTC, 0.7 Attention

Reference:
A. Gulati, J. Qin, C-C. Chiu, N. Parmar, Y. Zhang, J. Yu, W. Han, S. Wang, Z. Zhang, Y. Wu and R. Pang, “Conformer: Convolution-augmented Transformer for Speech Recognition” in Interspeech, 2020.

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Results: Conformer on Guj 10-hr

d	λ	Reduction	WER (Guj)	
			Dev	**Test**
		Baseline	57.7	61.1
0	10	identity	57.7	61.1
		ρ_1	57.9	60.4
3	10	identity	**57.1**	60.5
		ρ_1	57.6	**59.9**

Similar trends as for other experiments

Discussion

- **Choice of reduction**: We show in the paper that our reduction is superior to randomized/less compressive reductions.
- **Reduction function corrects ASR errors:** 16.29% (for Gujarati) and 16.92% (for Telugu) of identity substitutions errors corrected by the reduction.
- **Test-set perplexities:** Reduction function decreases LM perplexity. Larger drop for Telugu corresponds to larger improvements observed for Telugu.

Reduction	Test ppl (Guj)	Test ppl (Tel)
identity	115.05	768.66
ρ_1	108.13	706.32

Discussion

- **Examples**:

R: સપાના તેજ પ્રતાપ યાદવે જીતી છે

(səpa:na: te:ɟ pɾəta:p ja:dʌʋe: ɟi:ti cʰe:)

I: સપા માટે તે પ્રતાપ યાદવ લીધી છે

(sʌpa: ma:ʈe: te: pɾəta:p ja:dʌʋ li:dʰi cʰe:)

p_1: સપાના તેજ પ્રતાપ યાદવે જીતી છે

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R: ఈతకు వెళ్లి బాలుడి మృతి

(i:taku ʋeɭɭi ba:luɖi mruti)

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(inka: ʋeɭɭi bo:lɖ mruti)

p_1: ఈతకు వెళ్లిన బాలుడి మృతి

(i:taku ʋeɭɭina ba:luɖi mruti)

Future Work

- Automatically learning a **data-driven** reduction mapping.
- Training more powerful sequence-to-sequence reconstruction modules
- **Combine** the two modules into one using a bottleneck layer and multitask learning.
- Instead of the ASR 1-best hypothesis, use the ASR **decoding lattice**.

Conclusion

- We propose a simple reduce-and-reconstruct technique and demonstrate its utility for two Indian languages.
- We show that as the available training data decreases, our approach yields greater benefits, making it well-suited for low-resource languages.

Short Presentation Slides

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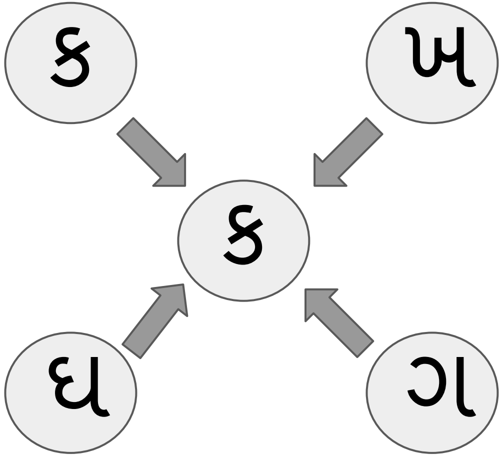
Reduce and Reconstruct (**RnR**)

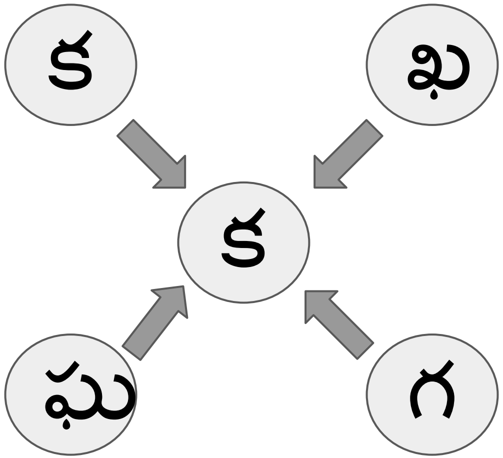
- Technique to boost end-to-end (E2E) ASR performance on low-resource languages:
    a. Train an E2E ASR system with a linguistically-motivated reduced output alphabet (***reduce***)
    b. Train a standalone FST-based reconstructor that recovers sequences in the original alphabet (***reconstruct***)
- Experiments on Gujarati and Telugu.
- With access to only 10 hrs of speech data, we obtain relative WER reductions of up to 7% compared to baseline systems.

Our Approach

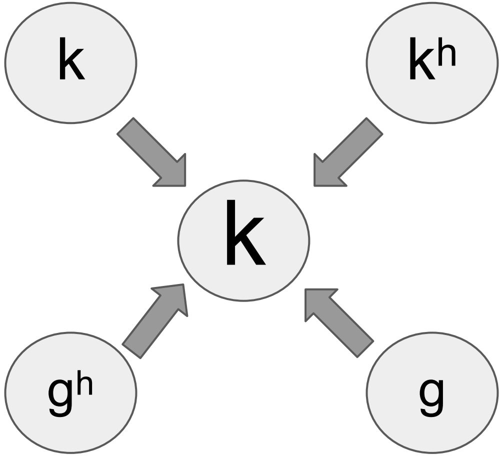
1. **Devise** a **reduced vocabulary** that merges acoustically confusable and linguistically discriminative graphemes.



Gujarati



Telugu



IPA

Our Approach

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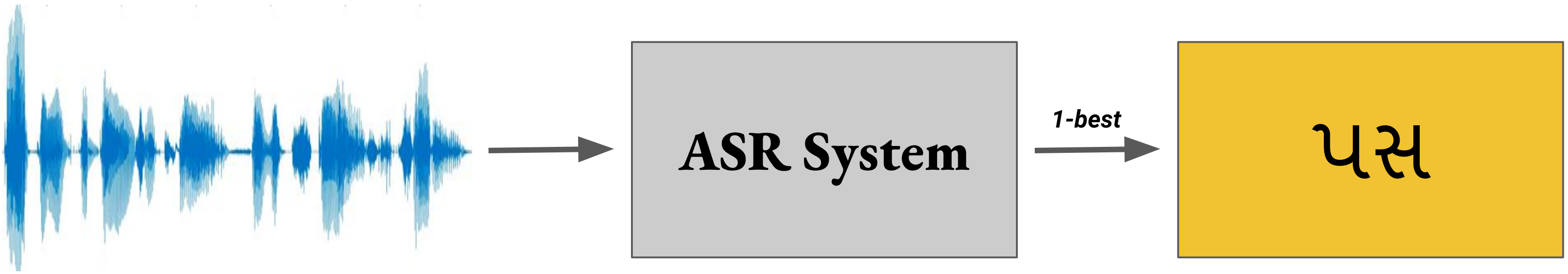
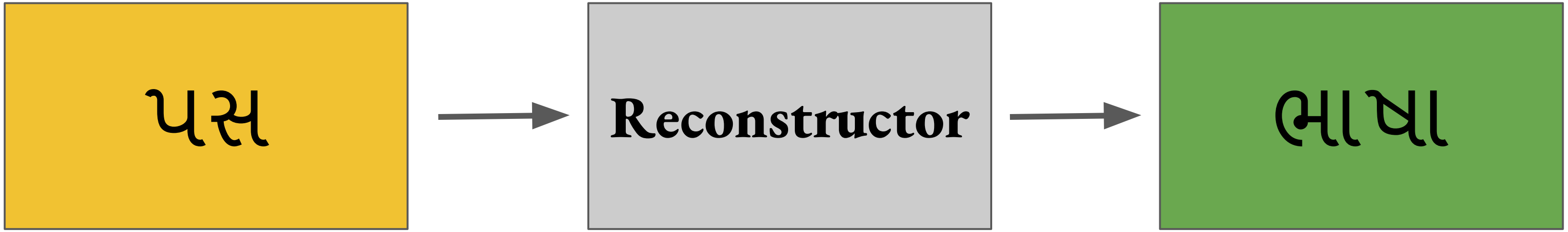
3. **Train** an **ASR system** that maps the original speech to the reduced transcriptions.



Sound wave saying ભાષા

Our Approach

4. **Train** a **reconstructor** to reconstruct the original grapheme sequence.



Our Approach: FST-based Reconstructor

- **Input:** Represent as a linear acceptor, **H**.
- Compose with a cascade of FSTs: **S, E, L, G:**
  - Using the reduction, **S** is able to reconstruct all possible sequences.
  - **L** and **G** constrain, rank these sequences using language-model scores.

Our Approach: FST-based Reconstructor

- **Input:** reduced-grapheme hypothesis from ASR system.
- Represent as a linear acceptor, **H**.

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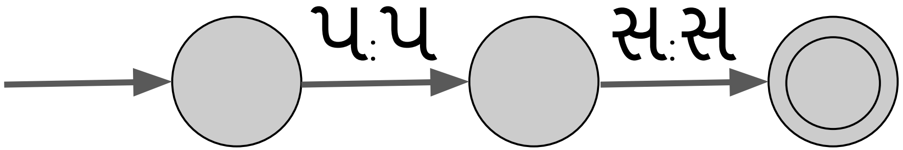

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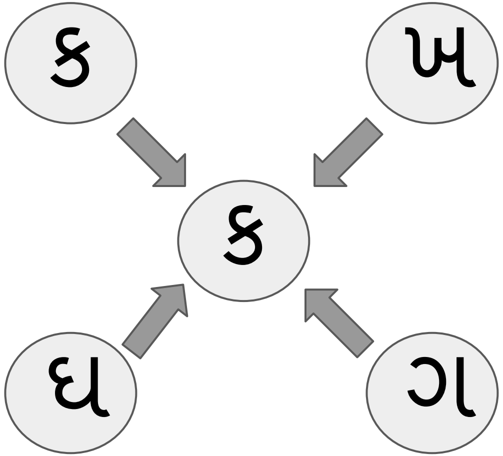
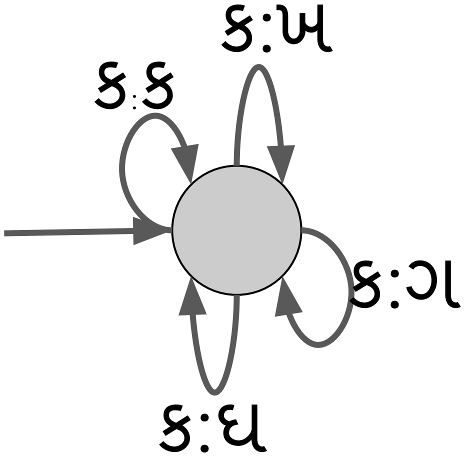


is represented as



Our Approach: FST-based Reconstructor

- Further compose with the **Edit Distance FST**, E.
- E is an FST that that takes a grapheme sequence as input. It produces as output all grapheme sequences that satisfy the constraint that every word in the output is within an edit distance of ***d*** from each word in the input. The allowable edits are substitutions, insertions and deletions.
- Each edit incurs an additive cost $\boldsymbol{\lambda}$.
- ***d*** and $\boldsymbol{\lambda}$ are hyperparameters.

Our Approach: FST-based Reconstructor

- Further compose with the **Dictionary FST**, L.
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Our Approach: FST-based Reconstructor

- Finally, obtain output O, the best reconstructed sequence, by running a shortest path FST algorithm on the composed FST $H \circ S \circ E \circ L \circ G$.
- These operations are efficient owing to highly-optimized FST libraries.

Experiments

- **2 Indian languages**: Gujarati, Telugu
- **ASR architecture:** Bi-LSTM (without and with RNNLM)
- **2 Training Durations:** Full and 10-hr
- Gujarati 10-hr experiments on the advanced Conformer ASR architecture

Results

ASR Architecture	Training-set Duration	Reduction	Gujarati Test WER	Telugu Test WER
biLSTM	Full	none (baseline)	43.2	46.8
		identity	37.8	42.5
		our reduction	**36.5**	**41.2**
	10-hr	none (baseline)	68.6	71.4
		identity	64.9	66.1
		our reduction	**61.2**	**63.6**

- Reduction **outperforms** identity and baseline
- Improvements are more pronounced in the **low-resource** 10-hr setting

Results

ASR Architecture	Training-set Duration	Reduction	Gujarati Test WER
Conformer	**10-hr**	none (baseline)	61.1
		identity	60.4
		our reduction	**59.9**

Results

ASR Architecture	Training-set Duration	Reduction	Gujarati Test WER	Telugu Test WER
biLSTM **(with RNNLM)**	**Full**	none (baseline)	34.0	40.0
		identity	**31.8**	39.2
		our reduction	32.2	**38.1**
	10-hr	none (baseline)	63.2	63.8
		identity	62.3	62.5
		our reduction	**58.2**	**59.1**

- Reduction is significantly **better** in the 10-hr setting
- Reduction doesn’t do as well in the Full setting for Gujarati

Analysis

- **Choice of reduction**: We show in the paper that our reduction is superior to randomized/less compressive reductions.
- **Reduction function corrects ASR errors:** 16.29% (for Gujarati) and 16.92% (for Telugu) of identity substitution errors corrected by the reduction.
- **Test-set perplexities:** Reduction function decreases LM perplexity.

Reduction	Test ppl (Guj)	Test ppl (Tel)
identity	115.05	768.66
our reduction	108.13	706.32

Discussion

- **Examples**:

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(səpa:na: te:ɟ pɾəta:p ja:dʌʋe: ɟi:ti cʰe:)

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(sʌpa: ma:ʈe: te: pɾəta:p ja:dʌʋ li:dʰi cʰe:)

p_1: સપાના તેજ પ્રતાપ યાદવે જીતી છે

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(inka: ʋeɭli bo:lɖ mruti)

p_1: ఈతకు వెళ్లిన బాలుడి మృతి

(i:taku ʋeɭlina ba:luɖi mruti)

Conclusion and Future Work

- We propose a simple reduce-and-reconstruct (RnR) technique for E2E ASR systems and demonstrate its utility for two phonetic languages.
- As the available training data decreases, RnR yields greater benefits, making it well-suited for low-resource languages.
- Future work includes:
  - Training more powerful sequence-to-sequence reconstruction modules
  - Automatically learning a mapping from the original alphabet to the reduced alphabet