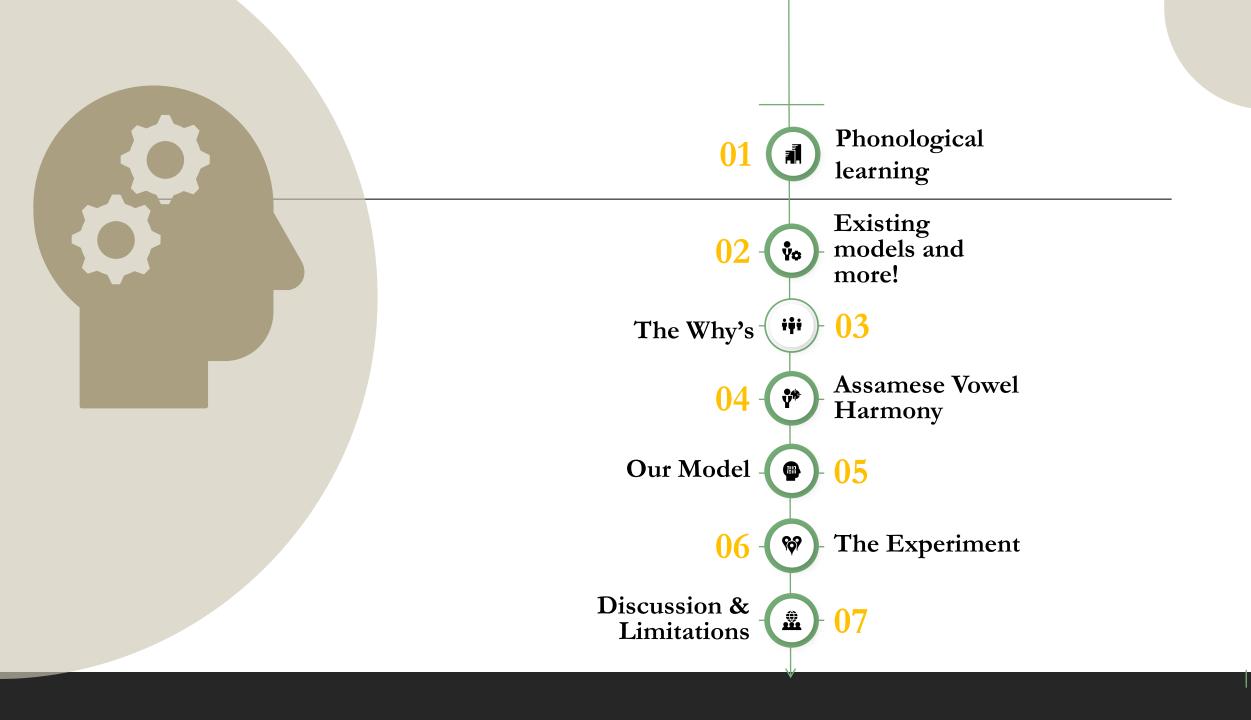
### Modeling Regressive Vowel Harmony from Continuous Speech Stream

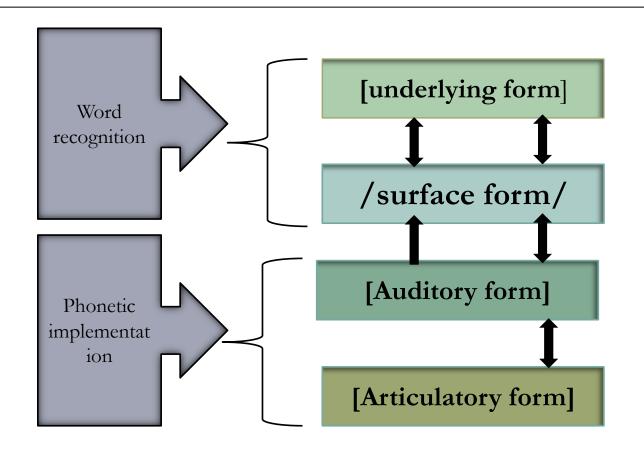
Sneha Ray Barman, Shakuntala Mahanta Indian Institute of Technology Guwahati, India sneha.barman@iitg.ac.in, smahanta@iitg.ac.in







#### Phonological learning



Phonological production

Prelexical perception

#### Existing models and more!

Approach	Author(s)	Common Factor	
Optimality Theory	Prince and Smolensky (2004)	Curated <b>text</b> data;	
Harmonic Grammar	Legendre et al. (1990)	Supervised and/or semi- supervised training.	
Maximum Entropy Grammar	Goldwater & Johnson (2003); Hayes & Wilson (2008)		
Computational Models	Kirove & Cotterell (2018); Mayer & Nelson (2020); Prickett et al. (2022)		

# Unsupervised Modeling of Vowel HarmonyWHY?

- Vowel harmony is widespread yet nowhere near universal.
- Involves learning crucial factors like features, domains, directionality, iterativity, and opacity (Archangeli & Pulleybank 2007).
- Regular patterns while also accommodating exceptions.
- Raw speech ~ The input received by a child (approx.)
- Unsegmented, unlabeled.
- Probably easy to infer phonology from readily available language data.



#### Assamese

- An Indo-Aryan language spoken across the state of Assam
- Spoken by 15 million people, according to 2011 Census of India
- °20 consonants and 8 surface vowels.

#### Phonemic inventory of Assamese

Consonants:	Bil	abial	Alv	veolar	Palatal	Vel	lar	Glottal
Stops	p	b	t	d		k	g	
	ph	b <u>b</u> <sup>h</sup>	th	$d^{h}$		$\mathbf{k}^{\mathrm{h}}$	$g^h_{\!n\!$	
Nasals		m		n			ŋ	
Fricatives			s	Z		x		h
Approximants				Ţ	j		w	
Lateral approximant				1				

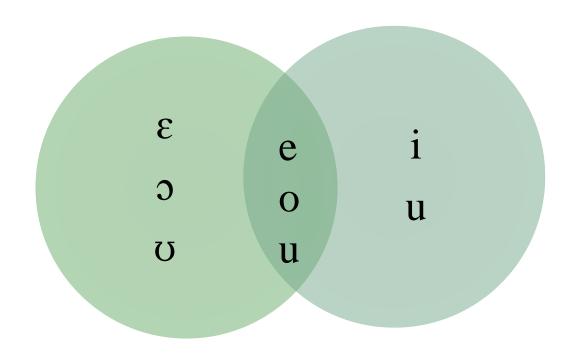
Fig 1. Consonants in Assamese (Mahanta 2007)

Vowels:	Front	Back		ATR
High	i		u	+ATR
			Ω	-ATR
Mid	e		o	+ATR
	ε		э	-ATR
Low			a	-ATR

Fig 2. Vowels in Assamese (Mahanta 2007)

#### Assamese Vowel Harmony

- Feature
- Domain
- Directionality
- Iterativity
- Opacity



#### Features

- Target: The vowel that changes its vocalic properties
- Trigger: The vowel that induces the change
- Example:
- [-ATR] vowels become [+ATR] when followed by [+high, +ATR] vowels.

$$\operatorname{p}_{\mathcal{E}}^{oldsymbol{\epsilon}}$$
t 'belly'  $ightarrow$  p $_{\mathcal{E}}$ t - $\operatorname{u}$  'pot-bellied'

pet 'belly' 
$$\rightarrow$$
 pet u 'pot-bellied'  
pagol -i 'mad-F'

Vowels:	Front	Back		ATR
High	i		u	+ATR
			Ω	-ATR
Mid	e		o	+ATR
	ε		э	-ATR
Low			α	-ATR

Fig 2. Vowels in Assamese (Mahanta 2007)

#### Directionality

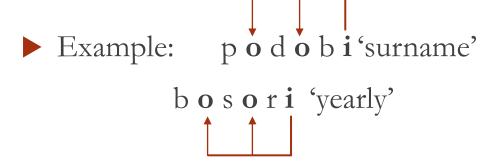
- ► **Regressive:** Righ-to-left harmony
- **Examples:**

```
kobita 'poem'

pagol'mad-M' pagol-i 'mad-F'
```

#### Domain

Non-local harmony: Trigger vowels target all the vowels.



#### Iterativity

- ► Long-distance iterative harmony
- Examples:
  p o d o b i 'surname'
  b o s o r i 'yearly'

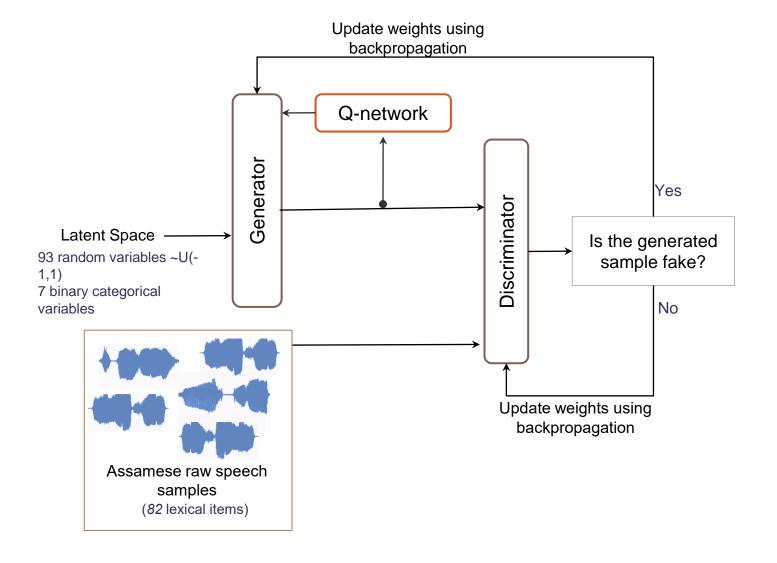
#### Opacity

- $\blacktriangleright$  / $\alpha$ / [-high, -ATR] blocks harmony.
- Examples:

```
z v n a k 'firefly-M' *z u n a k -i z v n a k -i 'firefly-F'
b ɛ p a r 'trade' *b e p a r -i b ɛ p a r -i 'trader'

Exception:
a l a x 'luxury' a l o x -u w a 'pampered' *a l a x u w a
m i s a 'lie' m i s o -l -i j a 'liar' *m i s a -l -i j a
```

# Featural InfoWaveGAN for Vowel Harmony



FiwGAN architecture (Beguš 2021; Beguš and Zhou 2022) trained on Assamese

#### Experiment

#### ► Research questions:

- 1. Can we model Assamese vowel harmony, especially iterative long-distance patterns, using fiwGAN?
- 2. How far can the model learn the discrete categories related to harmony?

#### Participants:

- 1. 15 native Eastern Assamese speakers from the campus. 8 females and 7 males between 18-35 years. All of them were educated in vernacular medium.
- 2. Recorded at the Phonetics and Phonology lab at IIT Guwahati with a DR-100 MKII recorder.

#### Data

English	Assamese	Recorded Sentence
(will) Tell	kobo	মই <u>ক'ব</u> বুলি ক'লো
Something worth mentioning	kobologija	মই <u>ক'বলগীয়া</u> বুলি ক'লো
To tell (you)	koboloi	মই <u>ক'বলৈ</u> বুলি ক'লো
Tell (me)	koba	মই <u>ক'বা</u> বুলি ক'লো
Meanwhile	EnEtE	মই <u>এনেতে</u> বুলি ক'লো

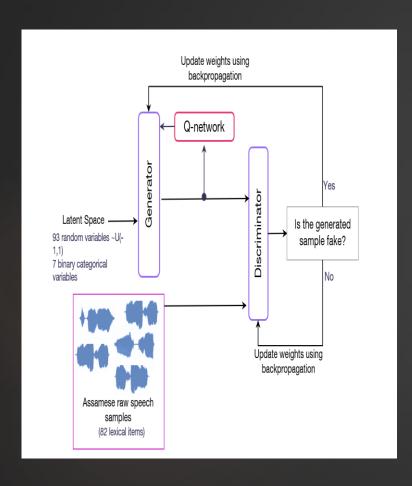
- 82 words harmonic and nonharmonic words in total.
- Each word was in a carrier sentence মই <u>X</u> বুলি ক'লো in Assamese; 'I say X' in English.
- Each sentence was repeated at least 4 times.
- 5000 tokens in total. 4789 tokens used for the training.

#### Data

English	Assamese	Recorded
		Sentence
(will) Tell	kobo	भरे <u>क'व</u> वूनि
		ক'লো
Something	kobologija	
worth		<b>म</b> इ
mentioning		ক'বলগীয়া বুলি
		ক'লো
To tell (you)	koboloi	মই <u>ক'বলৈ</u> বুলি
		ক'লো
Tell (me)	koba	মই <u>ক'বা</u> বুলি
		ক'লো
Meanwhile	επετε	गरे शतक दनि
		মই <u>এনেতে</u> বুলি
		ক'লো

Stem	Suffix	Surface	Category
dile	-i	dilei	Harmonic
nokorilε	-u	nokorileu	Harmonic
gorom	- <b>ɔ</b> -t	gərəmət	Non- harmonic
bεpar	-i	bεpari	Non- harmonic

#### Model Implementation



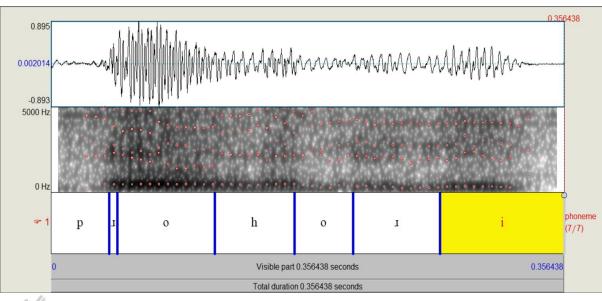
- Latent space has 93 uniformly distributed random variables (z).
- ► 7 binary latent codes (φ) accommodate 82 unique lexical items.  $2^7$  = 128 lexical classes.
- Each word is represented as a one-hot vector [1,0,0,0,0,0,0; 0,1,0,0,0,0,0 etc.].
- $\blacktriangleright$  Batch size = 64.
- ► Generator and Discriminator Adam optimizer.
- ▶ Q-network- RMSProp Algortihm.
- ▶ The model was trained for 960 epochs.
- ► Each epoch generated 100 outputs.
- ▶ 64 out of 100 outputs were analyzed.

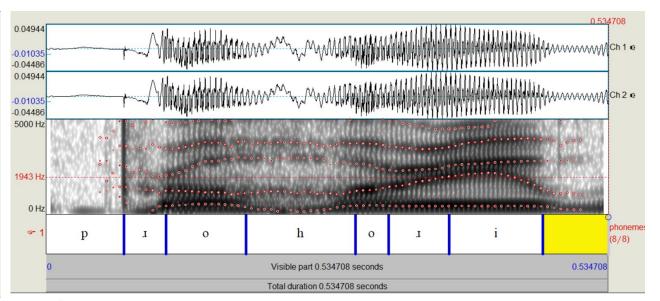
#### Method

- ▶ The recorded data was sliced in PRAAT (Boersma & Weenick 2009).
- ▶ Recorded data sampling rate 48 kHz with 16-bit quantization.
- ▶ Downsampled the data at 16 kHz using the Sox program. Converted to single-channel .wav files.
- ► Training dataset contained 3169 harmonic and 1620 non-harmonic words.
- ▶ At least 60 data points for each lexical element.
- ► The PyTorch version of the model was used.
- ▶ The model ran on the CLST lab's GPU for 3 consecutive days.

#### Results

#### Results at 960 epochs (Identical)





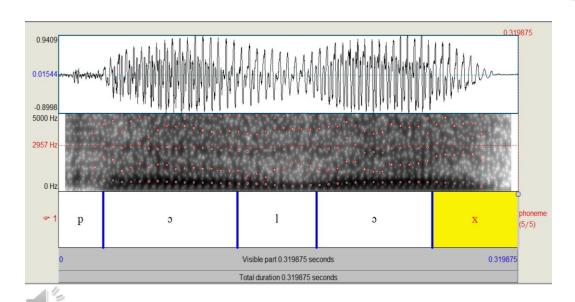


Generated item

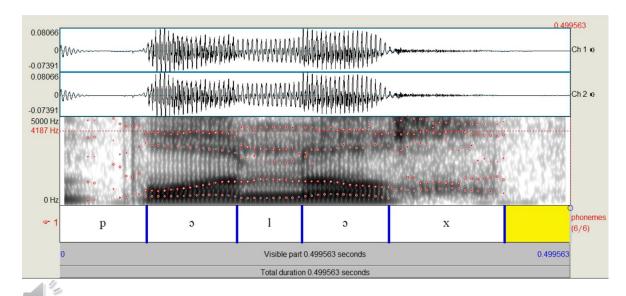


Training item

#### More identical outputs...

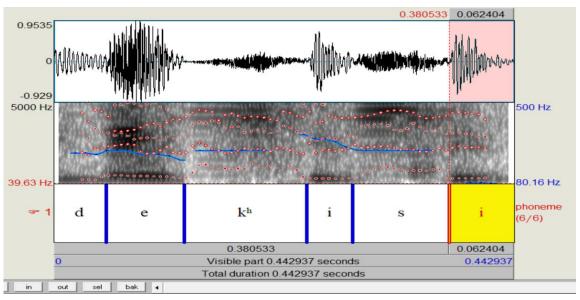


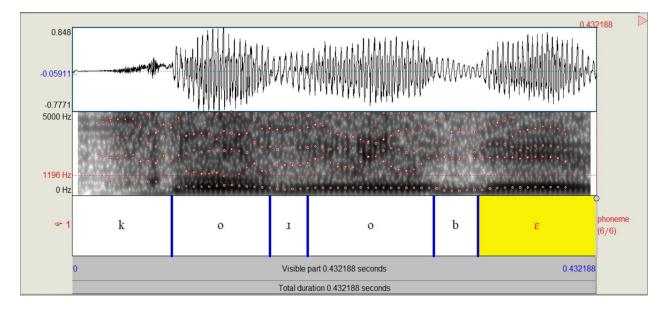
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Training item

#### Results at 960 epochs (Innovative)





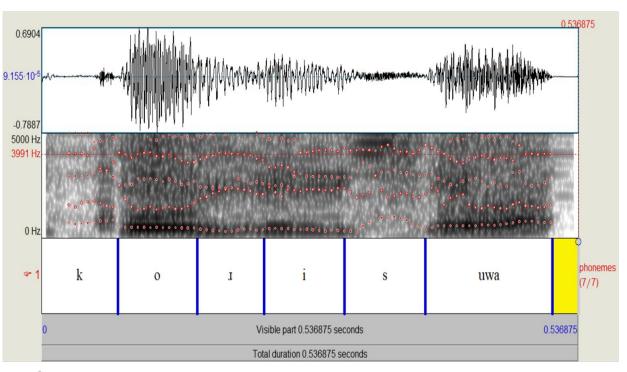


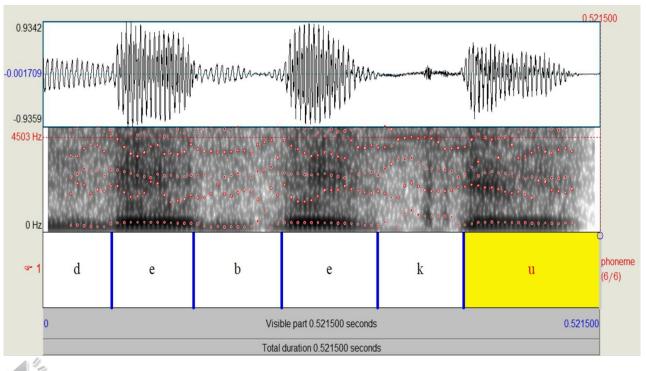
Generated item



Generated item

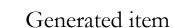
#### More innovative outputs...



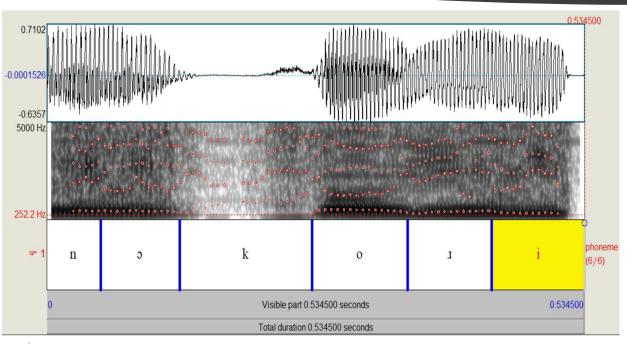


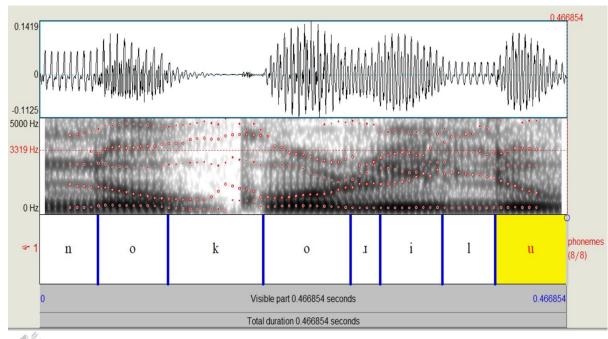


Generated item



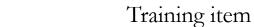
#### Results at 960 epochs (Shortened)



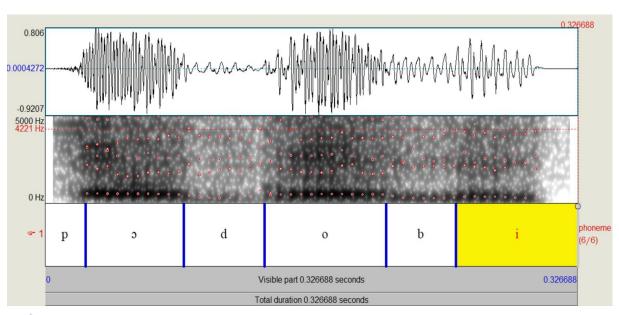


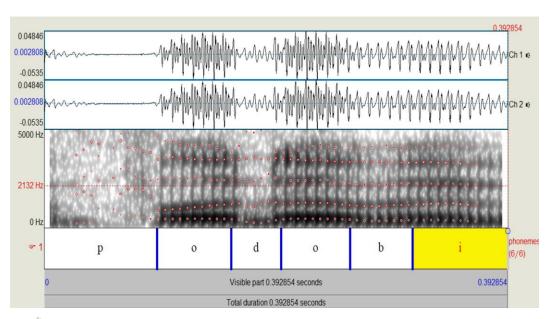


Generated item



#### Ungrammatical outputs







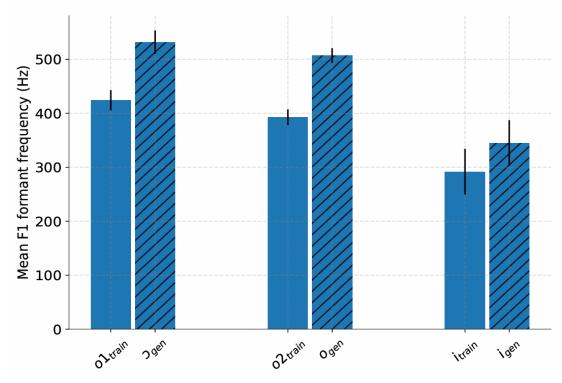
Generated item



Training item

#### Analysis

- The outputs were manually annotated in PRAAT; and collected F1, F2, F3 values at 10-time points.
- The mean first formants of the vowels in training and generated data to quantify the presence of ATR vowel harmony in PRAAT.
- Regression analysis in R (R Core Team 2021) to assess the presence of directionality.



F1 comparison of [podobi] (training data; shown in bars) and [podobi] (generated data; shown in hatched bars). Here, o1 and o2 denote the first and second vowel and i denotes the third vowel, in the input training data "podobi".

Table 4: LMER model for the training dataset

Data	Directionality	Fixed effects	DF	$\chi^2$	р
Whole	right-to-left	$F1V1\sim V1+V2$	13	33.062	< 0.001
	left-to-right	$F1V2\sim V2+V1$	10	6.5156	0.77
Only [+ATR]	right-to-left	F1V1~V1+V2	7	27.829	< 0.001
	left-to-right	$F1V2\sim V2+V1$	2	1.6522	0.43

Table 5: Linear regression model for machine-generated items

Data	Estimate	t-value	p-value
Whole	605.25	7.793	< .001
only V2[i] coefficient	-279.11	3.376	.01

#### Discussion

- Computation of long-distance iterative vowel harmony.
- Feature learning.
- ► Emergence of lexical learning.
- ▶ Ungrammatical outputs with local harmony.
- Lack of results with opaque vowel /α/. Difficult to learn non-frequent/irregular items? (Marcus et al. 1995; McCurdy et al. 2020)

#### **Future Direction**

- Need more outputs to assess the learnability
- How does this learning take place? What are the cues? Latent space analysis.
- More epochs than previous experiments in English aspiration and French nasality.
- Can the model learn trans-word utterances?

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#### Dataset and codes available at:

https://github.com/sneha2599/Fiw

GAN-Assamese.git

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# THANK YOU!

#### Ungrammatical outputs

