# Part-Of-Speech Tagging for Gujarati Language

Group Members: Dharmeshgiri 2019201025 Smitkumar 2019201021

> Project Mentor: Ujwal Narayan

## **Project Definition**

- POS Tagging is a process that attaches each word in a sentence with a suitable tag from a given set of tags..
- Given table contains example of different tag and it's meaning in part of speech tagging.

Tag	Meaning	English Examples
ADJ	adjective	new, good, high, special, big, local
ADP	adposition	on, of, at, with, by, into, under
ADV	adverb	really, already, still, early, now
CONJ	conjunction	and, or, but, if, while, although
DET	determiner, article	the, a, some, most, every, no, which
NOUN	noun	year, home, costs, time, Africa
NUM	numeral	twenty-four, fourth, 1991, 14:24
PRT	particle	at, on, out, over per, that, up, with
PRON	pronoun	he, their, her, its, my, I, us
VERB	verb	is, say, told, given, playing, would
	punctuation marks	.,;1
X	other	ersatz, esprit, dunno, gr8, univeristy

## Project Timeline

- 1. Implementation of Pos tagger using HMM & CRF
- 2. Testing and Improvement
- 3. Evaluation Metrics

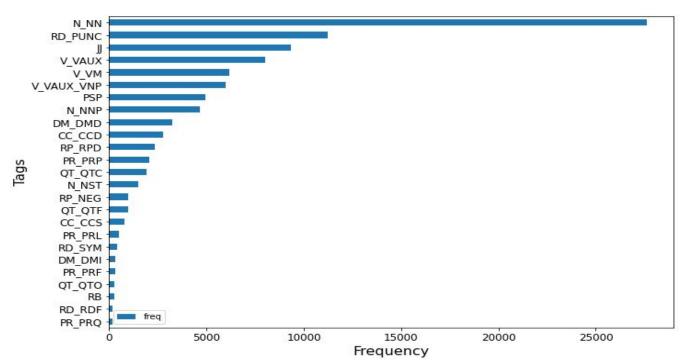
- 1. Implementation of Pos tagger using Neural
- 2. Training Testing
- 3. Evaluation Metrics
- 4. Report

MID EVALUATION FINAL EVALUATION

## **Dataset Details**

Index	Dataset	Size (No. of sentences)	Size (No. of words)	Train (No. of sentences)	Test (No. of sentences)
D1	guj_art and culture_sample1.txt	1000	16050	800	200
D2	guj_economy_sample2.txt	1000	12467	800	200
D3	guj_entertainment_sample3.txt	1000	11879	800	200
D4	guj_philosophy_sample4.txt	1000	12904	800	200
D5	guj_religion_sample5.txt	1000	12247	800	200
D6	guj_science and technology_sample6.txt	1000	16857	800	200
D7	guj_sports_sample7.txt	1000	14836	800	200

## **Dataset Details**



- 1. Hindi POS Tagger Using Naive Stemming: Harnessing Morphological Information Without Extensive Linguistic Knowledge
  - a. <a href="https://www.cse.iitb.ac.in/~pb/papers/icon08-hindi-pos-tagger">https://www.cse.iitb.ac.in/~pb/papers/icon08-hindi-pos-tagger</a>
  - b. In this paper, They present a simple HMM based POS tagger, which employs a naive (longest suffix matching) stemmer as a pre-processor to achieve reasonably good accuracy of 93.12%. This method does not require any linguistic resource apart from a list of possible suffixes for the language.

- 2. POS Tagging For Resource Poor Indian Languages Through Feature Projection
  - a. <a href="https://www.researchgate.net/publication/323174678">https://www.researchgate.net/publication/323174678</a> POS Tagging For Resource Poor Indian Languages Through Feature Projection
  - b. They used feature transfer from a resource rich language to resource poor languages. Across 8 different Indian Languages, they achieved encouraging accuracies without any knowledge of the target language and any human annotation. For Indian Languages, they considered the following morph features The prefix characters up to 7 characters, The suffix characters up to 4 characters, Length of the word, Context Window size of 3 (Previous word, Current word and Next word)

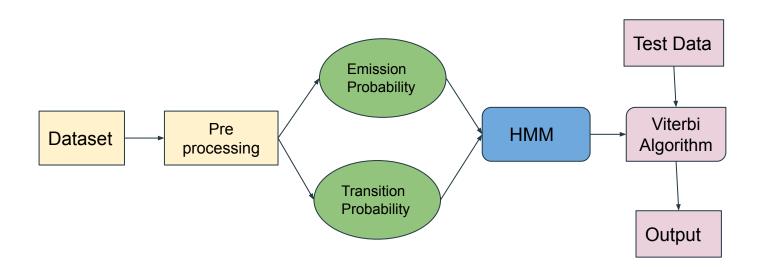
- 3. Character-level Supervision for Low-resource POS Tagging
  - a. <a href="https://pdfs.semanticscholar.org/a93a/3799ba977aa2393cad8cd260d6f778a">https://pdfs.semanticscholar.org/a93a/3799ba977aa2393cad8cd260d6f778a</a>
    <a href="495e0.pdf?\_ga=2.249332687.936938462.1614443610-381175129.16144436">495e0.pdf?\_ga=2.249332687.936938462.1614443610-381175129.16144436</a>
    <a href="https://pdfs.semanticscholar.org/a93a/3799ba977aa2393cad8cd260d6f778a">https://pdfs.semanticscholar.org/a93a/3799ba977aa2393cad8cd260d6f778a</a>
    <a href="https://pdfs.semanticscholar.org/a93a/3799ba97aa2393cad8cd260d6f778a">https://pdfs.semanticscholar.org/a93a/3799ba97aa239cad8cd260d6f778a</a>
    <a href="https://pdfs.semanticscholar.org/a93a/3799ba97aa239a</a>
    <a href="https://pdfs.semanticscholar.org/a93a/3799ba97aa239a</a>
    <a href="https://pdfs.semanticscholar.org/a93a/3799ba97aa239a</a>
    <a href=
  - b. In this paper experiment with three auxiliary tasks: lemmatization, character-based word autoencoding, and character-based random string autoencoding. They have used bidirectional LSTM.

- 4. Part-Of-Speech Tagging for Gujarati Using Conditional Random Fields
  - a. <a href="https://www.aclweb.org/anthology/108-3019.pdf">https://www.aclweb.org/anthology/108-3019.pdf</a>
  - b. They used dataset where where the training corpus is of 10,000 words and the test corpus is of 5,000 words in Gujarati. The algorithm has achieved an accuracy of 92%. The machine learning part is performed using a CRF model.

## Baseline: Hidden Markov Model (HMM)

- HMM (Hidden Markov Model) is a Stochastic technique for POS tagging.
- HMMs are a standard generative probabilistic model for sequence labeling that allows for efficiently computing the globally most probable sequence of labels and supports supervised, unsupervised and semi-supervised learning.
- HMM approach was used for this task since it does not need detail linguistic knowledge of the language as rule based approach.
- Hidden Markov models are known for their applications to reinforcement learning and temporal pattern recognition such as speech, handwriting, gesture recognition, musical score following, partial discharges, and bioinformatics.

## Baseline: Hidden Markov Model (HMM)

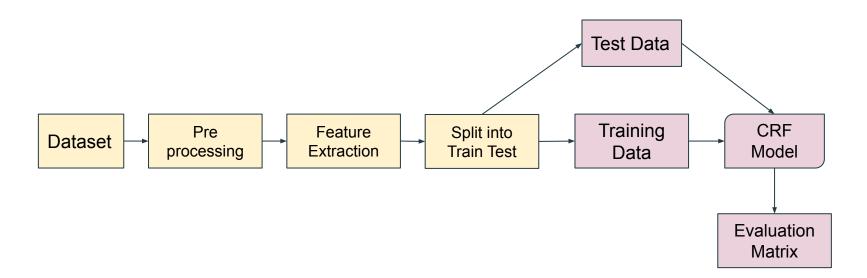


## Baseline: Conditional Random Field (CRF)

- A **Conditional Random Field (CRF)** is a sequence modeling algorithm which is used to identify entities or patterns in text, such as POS tags.
- This model not only assumes that features are dependent on each other, but also considers future observations while learning a pattern.
- Since these models take into account previous data, we use features which are modelled from the data to feed into the CRF.
- CRF is described as:

$$P_w(y|x) = \frac{1}{Z_w(x)} exp\Big(\sum_{j=1}^n \sum_{i=1}^m w_i f_i(y_{j-1}, y_j, x, j)\Big)$$
where  $Z_w(x) = \sum_{y \in Y} exp\Big(\sum_{j=1}^n \sum_{i=1}^m w_i f_i(y_{j-1}, y_j, x, j)\Big)$ 

## Baseline: Conditional Random Field (CRF)



#### **Feature Selection**

- 'word' : Word
- 'is\_first': Is it first word of sentence? (True / False)
- 'is\_last' : Is it last word of sentence ? (True / False)
- 'prefix-1': Prefix of word of sizes 1
- 'prefix-2': Prefix of word of sizes 2
- 'prefix-3': Prefix of word of sizes 3
- 'suffix-1': Suffix of word of sizes 1

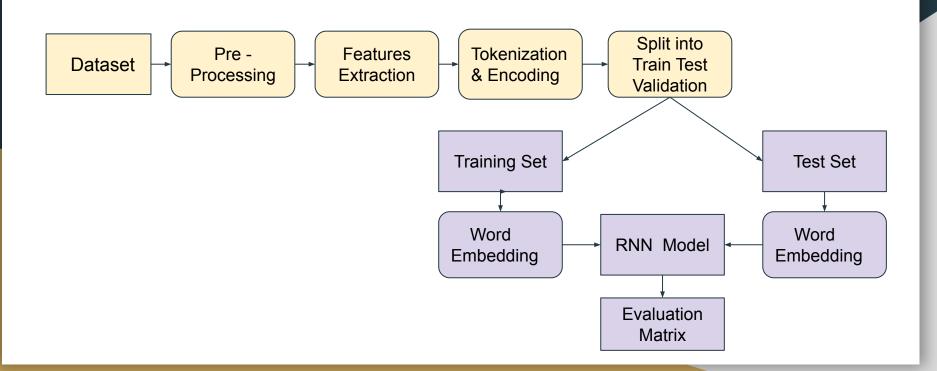
#### Feature Selection

- 'suffix-2': Suffix of word of sizes 2
- 'suffix-3': Suffix of word of sizes 3
- 'prev\_word' : Previous word
- 'pprev\_word' : Previous of previous word
- 'next\_word' : Next word
- 'nnext\_word' : Next to next word
- 'Is\_numeric' : Is it numeric ? (True / False)

## Neural Part

- Recurrent neural networks, or RNNs, are a type of artificial neural network that add additional weights to the network to create cycles in the network graph in an effort to maintain an internal state.
- The promise of adding state to neural networks is that they will be able to explicitly learn and exploit context in sequence prediction problems, such as POS Tagging.
- Neural Based Models used for PoS Tagging.
  - o RNN
  - LSTM
  - Bidirectional LSTM

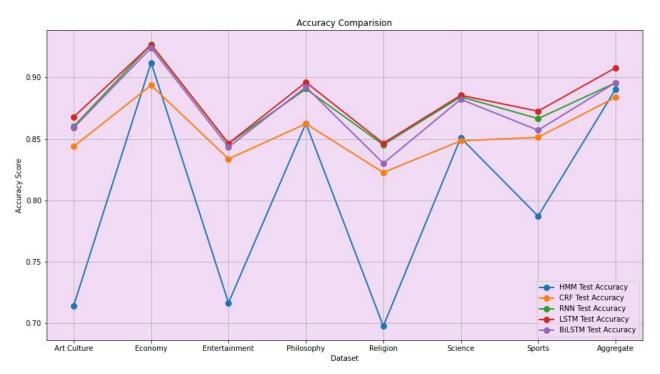
## Architecture



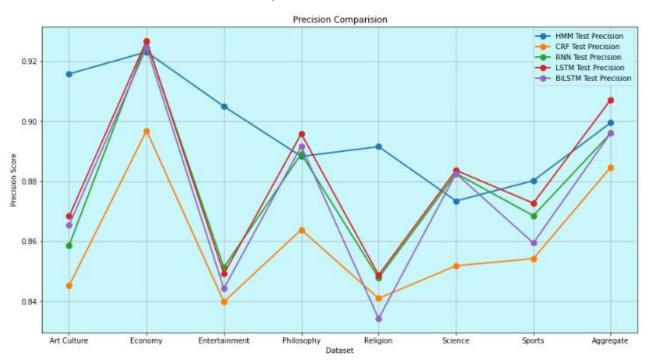
## Architecture

- Preprocessing: Data cleaning, Remove non useful characters, words and output list of sentence
- Feature Selection: convert each word into feature
- **Tokenization & Encoding :** encoding of features of using inbuilt Tokenizer of nltk
- Split into Train Test Validation: 65 20 15 ratio
- Word Embedding: More meaningful vector representation for neural model
- RNN Model: RNN, LSTM and Bidirectional LSTM
- Evaluation Metrics : Accuracy, F1-score

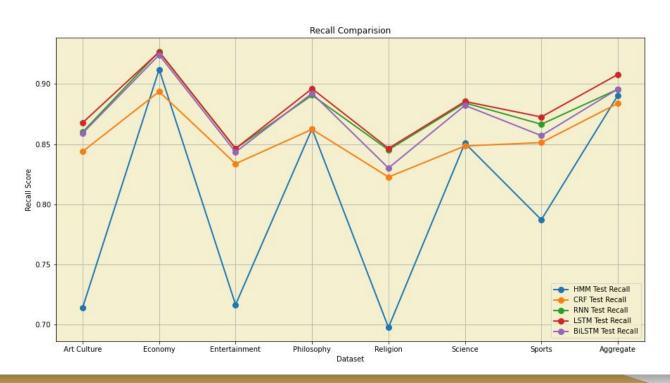
# Results & Comparisons : Accuracy



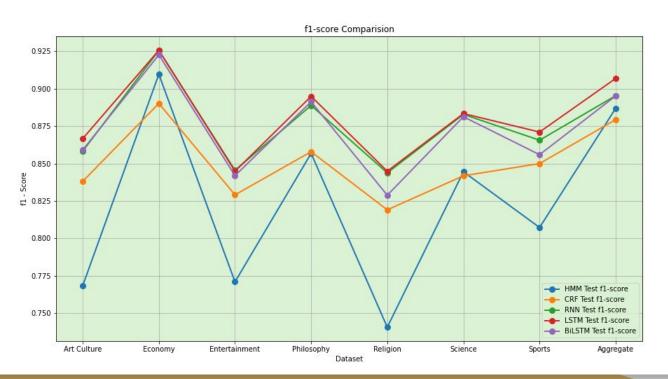
## Results & Comparisons: Precision



# Results & Comparisons : Recall



## Results & Comparisons: F1-score



# Error Analysis - HMM

Original Tag	Assigned Tag	Error Count	
N_NNP N_NN		481	
JJ	JJ N_NN		
V_VAUX_VNP	N_NN	290	
V_VM	N_NN	173	
Qт_Qтс	QTC N_NN		
PR_PRP	DM_DMD	70	
V_VAUX	V_VM	67	

# Error Analysis - CRF

Original Tag	Assigned Tag	Error Count	
N_NNP		427	
		334	
V_VAUX_VNP	N_NN	123	
N_NN	JJ	122	
PR_PRP	PR_PRP DM_DMD		
N_NN	N_NNP	63	
V_VM	N_NN	54	
	V		

# Error Analysis - LSTM

Original Tag	Assigned Tag	Error Count
N_NN	N_NNP	252
N_NN	JJ	182
N_NNP	NNP N_NN	
JJ	N_NN	157
V_VAUX_VNP	JX_VNP V_VM	
N_NN	V_VAUX_VNP	70
V_VM	V_VAUX	57
PR_PRP	DM_DMD	56

## Conclusion

- HMM model has more precision but less recall compare to other models.
- CRF accuracy does not fluctuate much with change in dataset.
- LSTM model has good Accuracy and F1 score compare to other models.
- An adjective (JJ) is tagged as a noun (N\_NN) with a high error count because, in Gujarati language, adjectives may or may not occur before the nouns.
- All models are struggling to make differences between common(N\_NN) and proper noun (N\_NNP).

## THANK YOU