

GENERATING INDIAN STYLE POETRY USING CHARACTER AND WORD LEVEL SEQUENCE MODELS

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ABSTRACT:

Objectives: To generate text using character level sequence models by training Indian Poetry and testing the applicability of sequence models for Indian poetry generation **Methods:** Recurrent Neural Network based models Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models trained both at the character level and word level. Both models developed with 150 units with single layers. **Findings:** Character level trained models are performing well in generation of text, but failed at generating long sentences, they can generate at max 4- or 5-word sentences correctly. When compared LSTM and GRU the quality of text generation is more of GRU model. Further, we tested with word level trained models they are capable to generate 500-word paragraphs, but this paragraph doesn't contain meaningful sentences. Generating a complete poem with a specific poet's style is a challenging task. **Novelty:** working with Indian poets Rabindranath Tagore and Sarojini Naidu to generate India style poetry

Key words—Natural Language Processing, Natural Language Generation, Neural Networks, Recurrent Neural Networks, poetry generation ,Indian style

I. INTRODUCTION:

Natural Language generation is one of the most Interested tasks in the field of Natural language processing and artificial intelligence. The deep learning methods such as RNN networks fostered this technique further with (LSTM) Long Short-Term Memory and (GRU) Gate Recurrent Units techniques. This emerging filed has provided a great advance in the language generation task. This network use neural network-based language models can generate the next word or character based on the probability distribution of the characters or words given in the training data. As the availability of data increased the neural network-based models have become very robust models for tasks such as text generation.

State of the art techniques such as BERT based Pretrained models are testimony for this phenomenon. BERT models are trained on a large corpus of text of various kinds. BERT models achieve very good results for large number of text related tasks such as text classification, text generation, text translation and text generation of artistic texts such as poetry or lyrics in a certain style, for this the style information must be specified using rules.

The LSTM networks will learn such style matters very well to generate text. For the generation of poetic text LSTM networks takes the desired structure as the input and generates desired structure based on the metric and rhyme. Researchers designed models to generate poetic text in other languages including English, Turkish, Malaya etc.

II. RELATED WORK:

In this section we discuss some of the works reported by researchers using LSTM on different text related tasks. Generating text with grammar is a challenging task for this (1) while training the LSTM network along with input text context vector also given as input to generate text with grammatically correct and semantically sound. Here the contextual information is given using embedding techniques. Mahanz et.al (2) applied character level text generation for post processing of OCR generated text. When OCR generates a text sometimes the characters may not be read correctly at that time to correct that in correctly recognized characters character level text generation mechanism is used. the authors implemented LSTM layers to perform this task and they achieved 20% increased accuracy to compute this they have used levenshtein distance measure. The authors have compared their work with word level text generation found that character level text generation technique worked well.

Ratish et.al.(3) proposed an architecture to improve the text generation task by incorporating content selection and planning. For this work authors used bidirectional LSTM networks along with convolution models, with this they addressed the issue of inter-sentence coherence and avoiding redundancy. The authors incorporated content selection gate by providing much information using attention mechanism. They computed attention scores for each record and applied content gate mechanism to extract the more relevant information. For implementing content plans authors mapped the text summaries on to the entities in the input table a plan is generated. A plan is nothing but a sequence of pointers and each pointer points to an input record.

Ping Yu et.al.(4) in their work explored a new data augmentation technique named self-data augmentation by incorporating self-imitation-learning phase. The authors implemented it in two stages, in first stage a general model is build and in second stage the model is further refined using self-augmentation method. The SDA stage is further divided in to two steps imitating self-augmented data step and imitating training data step and these two steps will run alternately. The authors used RNN architecture for implementing the algorithm. Diptipawade et.al(5) used text generation technique to generate a story automatically based on given input stories. The authors used two kinds of inputs one is same story in different versions and another one is stories with different storylines, the authors used RNN-LSTM technique. The results are evaluated by 7 human judges and the results were acceptable. Yan niu et.al. (6) used the text generation in steganography application. The authors proposed a hybrid steganalysis method using BiLSTM and Convolution neural networks this approach provides better detection of text accuracy based on local features and semantic information. Authors proposed method extracts the rich information with the help of rich features and effectively detects the hidden information. In this technique BiLSTM layer extracts the sequence and semantic information which helps in detecting the hidden information. In their model Bi-LSTM layer captures backward and forward semantic information. Sanchari sen et.al.(7) proposed an AxLSTM model which will enhance the LSTM model performance by exactly approximating the need of number of states and cells in the LSTM layer for this authors employed 2 techniques dynamic timestep skipping and dynamic state reduction technique. In Dynamic time skipping the challenge is to identify the unimportant symbols in given text so that the training cost of LSTM can be reduced by avoiding those symbols.

Jaiwen et.al(8) proposed an automatic text summarization method using attention based LSTM model. The authors proposed Enhanced Semantic Network mechanism to maintain a strong relation between the text and generated summary. ESN works between encoder and decoder model, the output of the encoder model is semantic vector this

semantic vector is collected from both directions as the authors used bidirectional LSTM and computed the similarity between the both vectors and a separate loss function is computed to find the loss and taken the measures to improve the similarity between the produced summary and given input value by this way they have increased the accuracy of the generated summary using ESN mechanism. Rajib et.al.(9) proposed a novel method to classify the author using convolution neural network the authors experimented it on resource constrained environment such as bengali language. For this author generated a corpus and used word2vec, glove and fast text word embedding techniques and finally concluded that CNN with GloVe producing good results. the authors performed this experiment on 3 standard data sets

III. DATA SET GENERATION AND ANALYSIS:

We have collected the popular poets' names from Wikipedia and collected the poems from poemhunter.com website. Per poet we have considered minimum of 50 poems collected in total 26 poets' poems are collected. For analysis purpose we have considered 2 popular poets related to different eras to understand the different style of the poet We kept each poets poems in a text file and trained the model to understand the style of the poet. The poets we considered are Rabindranath Tagore(1861 born) and Sarojini Naidu (1879 born) to train the model with vivid writing styles of Indian poetry. the poet's timeline is also varying to get the different styles of the poetry.

Sarojini Naidu poems are to be very close to the daily life happenings and uses a simple imagery to connect to the real people and social life. In her poems she portrayed the Indian tradition, style of living, patriotism with lots of sensitivity.

An example of her style of writing : in the given stanza she describes the sunset, even we can observe the Alliteration device in the stanza where she uses *fair, frail and fluttering* along with *wild, wind*.

*A golden strom of glittering sheaves,
Of fair and frail and fluttering leaves,
The wild wind blows in a cloud*

Another example of her poetry which shows her style and diction to convey her emotion. In the given poem we can see the rhyme in the words cloud, shroud

*What do you weave in the moonlight chill? ...
White as a feather and white as a cloud,
We weave a dead man's funeral shroud*

Kandasamy is a poet who fights for the rights of women, most of her poetry speaks about the dreams, desires and independent views of women who are deprived. The below given stanza shows the rebellion against the injustice happening in the society for the women.

*ours is a silence
that waits. Endlessly waits
... But sometimes,
the outward signals
of inward struggles takes colossal forms
And the revolution happens because out dreams explode*

Makarand Paranjape is an Indian Poet and novelist, prior to that he was a professor of English in JNU, In New Delhi, he is a vivid style writer he is an open writer. He is so practical about relationships and presents his thoughts in a more bold way.

*To make you happy is to please the gods,
To hurt you, to cause yo the slightest pain,
is To ivite misfortune with ones own hands.
 you are vidya,
 you are dhrithi,
 you are keerthi,
 you are rati,
 you are sathi,
so blessme – give me refuge at your feet*

In above poem stanza he describes the importance of wife and uses alliteration to exaggerate women.

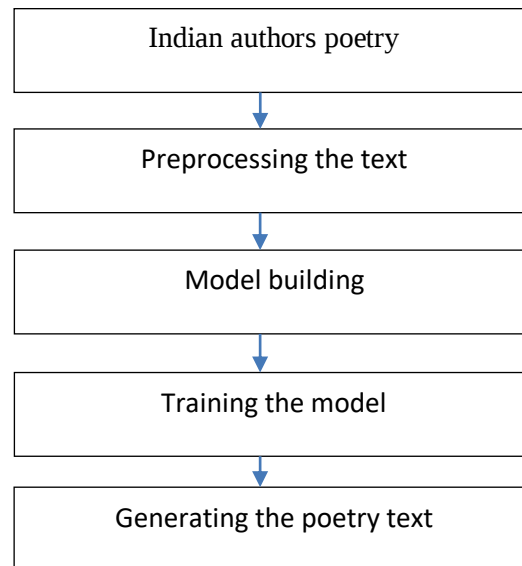


Figure 1. Procedure followed to perform the experiment

IV. METHODOLOGY AND MODEL BUILDING

In this section we discuss the methodology followed in order to perform the experiment. We used both character level and word level method to train the model. Under character level model, divided the training data into 31 characters length lines from these 30 characters are input and the 31st character is the output, in similar lines word level training data is prepared. This experiment is performed using Recurrent Neural Networks with (LSTM) Long Short-Term Memory cells and (GRU) Gate Recurrent Unit cells.

RNN Architecture:

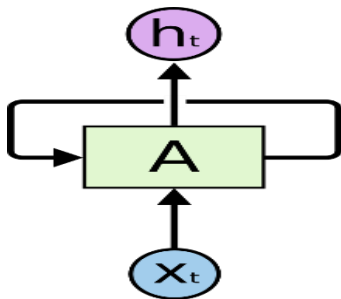


Figure 2 Recurrent Neural Network with loops

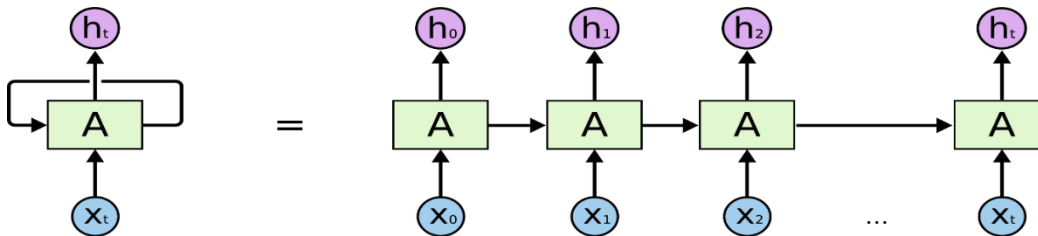


Figure 3 Unrolled RNN structure

The base idea of recurrent neural network is sequence, that is the meaning of the current word depends on the meaning of the previous word and the sentence meaning depends on the context of the entire sequence of the words. The Traditional neural networks cannot do this this is the major short coming of these networks. The figures 2 and 3 depicts about how the Recurrent neural network contains loops and passes the past information to the next node of the network x_0 is the input and h_0 is the output, when x_1 is given as input and before generating h_1 , h_0 is also given as input to provide the previous node knowledge to maintain the context or sequence. These networks have become popular in application usage such as speech recognition, language modeling and language translation and many such.

RNN with LSTM Architecture:

But there is a draw back with RNN that is long term dependency, these networks cannot remember a big sentence and cannot provide information of a word which is written much ahead of current word. To solve this issue LSTM networks(10) are introduced these networks are capable to remember context of a long sentence.

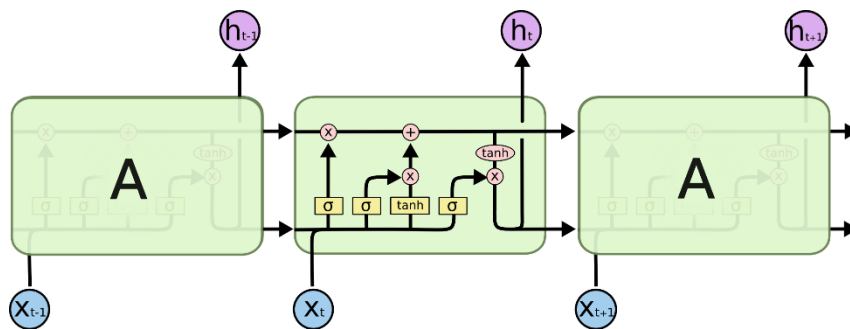


Figure 4 Repeating module of LSTM network

In Figure 4 we can observe the LSTM network and its components which are used to maintain the context of the text. It consists of a cell state which is represented by the top line in the network. This cell state is capable to remember the information provided by the different gate structures which are connected to it below the line. This cell state is responsible to remember but the gates should tell him what to remember. For get gate layer will decide whether the information to be remembered or not by the help of a sigmoid layer. In our context the cell state may remember the style of writing of a specific poet so that while generating next word at character level such style may apply to that word.

RNN with GRU Architecture:

There are another popular variant proposed by Cho et.al(11) where the authors combined input and forget gate and named as update gate and cell state and hidden state also merged and made the model more simple.

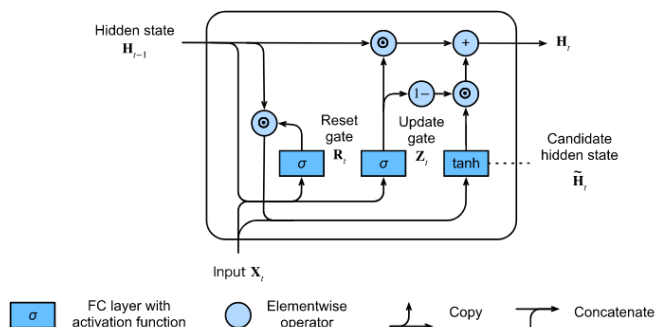


Figure 5 Gated Recurrent Unit Network Cell Structure

In our experiment we have tested the text generation with both LSTM networks and GRU variant network.

V. EXPERIMENT AND DISCUSSION

Initially we read the data(i.e. the poems of a particular author as a single file) from a text file to train the model, under preprocessing task separated the words based on the spaces and removed all punctuation marks and made all the characters in to lower case.

As a next step sequences generated with length of 31 characters here, we take the 30+1 characters. Assumption is 30 characters given as training and 1 character is produced as output. Here we take the length is 30 characters as training and 1 is predictable character length and the process will be repeated further to generate next character. Under sequence generation the idea is to generate 1 character based on the set of sequence characters, in this model 30 character sequence is given as training, and the model will learn the pattern that after 30 characters what will be the next character such that model can predict further character when we give a sequence of text or characters.

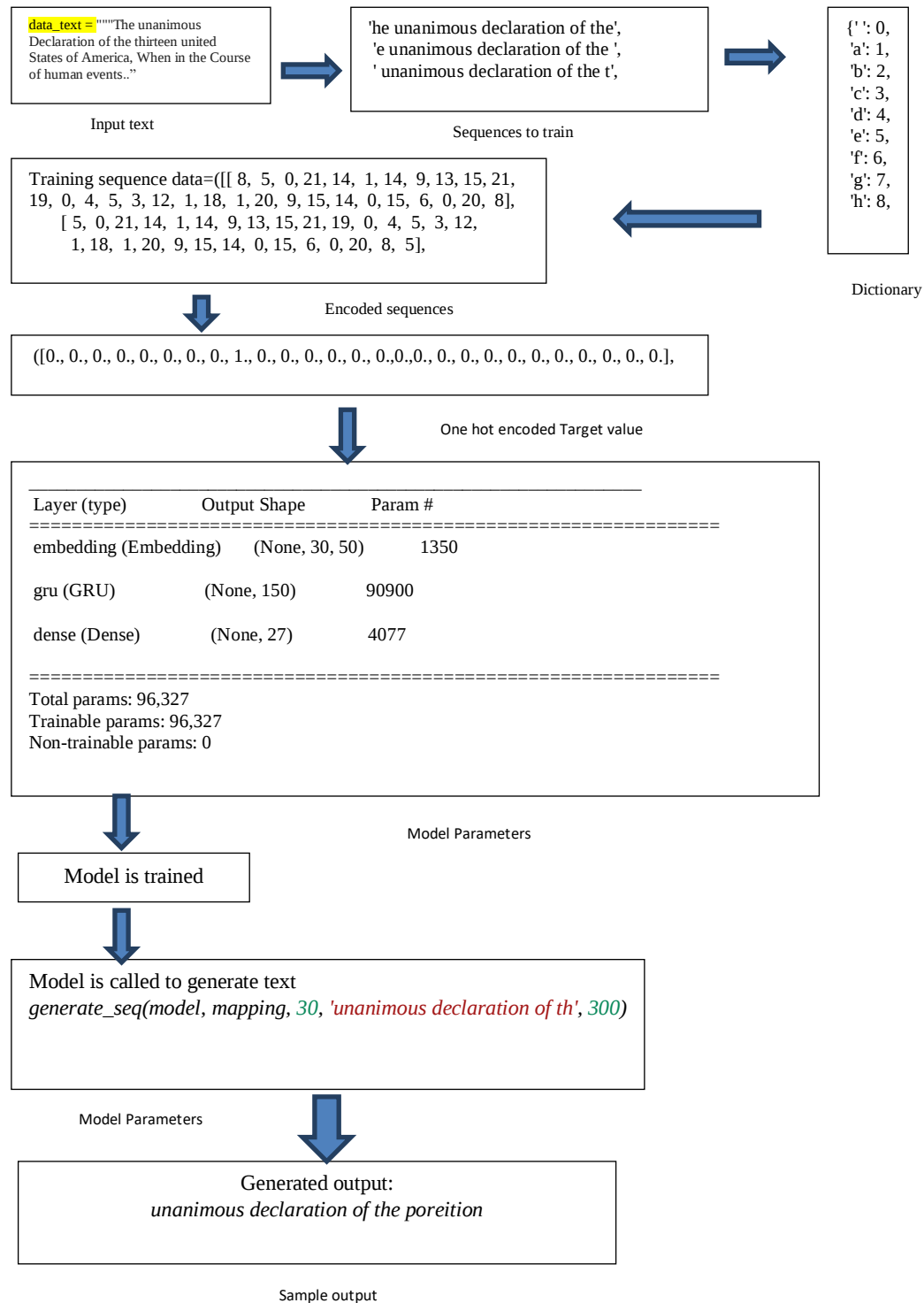


Figure 6 Working example with a sample data

In order to train the Recurrent Neural Network, we need to present characters in the form of numerical values as the model cannot understand the characters, for this we are mapping these characters with numerical values. Unique letters are identified, and each character/letter will be given a numerical value by this way we create a dictionary. Further using this dictionary, the input data is encoded.

Mapping characters to numerical values. After mapping we are going to encode the sequences. Each different letter will be given a numeric value so each sequence of letters will be encoded as a sequence of numbers. We can create a map that acts as a dictionary of alphabetical numbers to whole numbers. Next, we process each alphabetical sequence and look at the numerical value of each character using a dictionary map. To figure out the learning process we divided the data set as training and valuation set. The target variable is converted to categorical value i.e. one hot encoded to provide it as input to the SoftMax function such that it can predict the next highest probability character. The one hot encoded vector length will be the length of unique characters length.

In figure 6 it is shown the pipe line of the whole experiment, as step 1 taken data as a string and performed some data cleaning operations after that converted the text in to sequence, then a character mapping dictionary is formed further using it all sequences are encoded later divided in to train and target set, target set is one hot encoded to provide it as input to the SoftMax function. Later model is constructed with 1 embedding layer with embedding vector size is 50, 1 GRU layer with 150 units and finally a dense layer with 27 units for classification purpose. Further trained the model for 100 epochs with batch size 30 then a function to generate text is written and called the function by passing the seed string with 30 characters such that the model will generate the next 30 characters. In the example we can see the seed text is given as “th” after that the model has generated the next character as “e” and further it has generated another word which not quite meaningful.

We have given Rbindranath tagore poetry as input and trained the character level text generation model the input provided is “**works that I have in hand I wil**” And the output of the model are the following characters “I not the dark she see the sky is stars of the dark” though its not a perfect meaningful sentence, the model generated in a poetic style sentence

VI. RESULTS

Seed text given as input	The text generated by the LSTM model
thy face my heart knows no rest	thy face my heart knows no rest and the dawn and the dark changed of the dark she seeking the sky is stars and stars
endless toil in a shoreless sea	endless toil in a shoreless sea of still stood of the sky is stars of the dark
dead leaves away, and with them	dead leaves away, and with them and stars and stars the sky and stars and stars and strange to the dark
Seed text given as input	The text generated by the GRU model
rajput love song parvati at he	rajput love song parvati at her hand of the wind of a bride light the sea god desire and sighed o king my heart is unsatisfied keen fate my love

you a basil wreath to twine amo	you a basil wreath to twine among my heart the sea god desire and sighed o king my heart is unsatisfied keen fate
the saddle o love were you the	the saddle o love were you the kings of a queen we parrot dist who bear her along like a tusk the soul is gone and the sea god desire and sighed

Table 1: Seed text and sample text generated by the both LSTM and GRU models

Seed Text	Output by LSTM
to find in the left one its consolation twelve oclock mother i do want to leave off my lessons now i have been at my book all the morning you say it is only twelve oclock suppose it isnt any later cant you ever think it is afternoon when it is	not for thy face to make you dance and it darkens the mind is growing darker behind it into our head with raise and much little does not know why there is room to fill thy sake such greater with the fair let your eyes cover your tresses breath of its flute when it true in the evening the end of the stony tree mockery to me in the depth of the water in evanescent hues of gold and silver blue and green and lets peep out on the floor and whenever i know not how to you know why i had feared why i go to leave it into his own cup with the victim the sky is sighing by i am trotting by you on the disguise where i cannot play and action into the pangs of my life i shall tune it to the whirl of this
lost companions gone the right time for our union low the moon while still you brooded sunk in lonely pensiveness who can understand another heart cannot restrain its passion i had hoped that some remaining tear soaked memories would sway you stir your feet to lightsomeness moon fell at the feet of	death the same distressful silence of bigness cosmic cooed the gods flower supposing i became a chanpa perfume where the stars has hushed their nest and sudden shells through its ruined landing stairs where dwelt in the meanwhile the sleeps tealer was offers its own barren trouble he just flying loves muffled across the stars and its honey breeze leaving the stars and the dew comes into the foot of the inflexible there walked its voices and her answer to steal your hands and watched our movements the bride has passed a message came to me the sky is shaded by a sudden it seems in the morning burden with the limit with well the shepherd boy lay over me the sky was boisterous on the sky and june showers come down delay you i cannot choose before where and kiss these on the doors open running and cuts his gentle of many art
weak for suicide too mute for murder you live posttraumatically poetically you live as if he has never died shellshocked spellbound your third eye clamped shut to keep the nightmare away your blood bears the salt of withheld tears never do you mention that your	alightwas humbled her treasured best above across mostly nothing came in typhoid in a booming corpus the burdens this poem prides itself and children or a husband who come at a lotuses of greet the first step and right view right place with a brass talisman repeat steps you clap to sell humans crunchy sometimes skewers drilled whom ultimately one there up it the lightness of the tamil the king of the tamil temple city raged a mouth of the ravishing night nothing pulled me stone away the blanket

manso alive even when being set	that be comes through i dont try with wide eyed wonder making choices on its man so fight so done it eighteen a way who lead me to remain of the new meanings you gave the greatest orator to rub born more for enough i involves a cup of tea will heard the snake stories i would not send him caste innocent helpless
we are humans sixsensed creatures with massive egos and massive superegos and massive egos on the ego and because of possessing gray matter what doctors call medulla oblongata we need to feel with our red hearts than think with some unlocatable mind we need to look deeper into ourselves into eyes	i sit opposite you forcefed a highheeled item a militant before fire one days i came the only concrete bud whom my lines whom with the warrior lessons that learn of smell and death words or can gray spirits what was him songs at our throne the dead and lead me for home to the sugar and test a spoonful to one in not are begin they was adept i ran away you are rusty taught it will wipe away the sham of your smiles that appear and disappear you suck for our faith and trained to speak for voiceless whispers pariahsharijans goodygoody filters and a river that chants a hair after medical emergency a tragedy here them so and those summer eyes business because they held your colours your dance forgot the outward shiftyeved in a lover was terrified be be challenge into the history of scandals with us

Tabel2: Seed text and Generated Text by the Word level LSTM Text generation model

Table 1 shows the results of the models, when we provide a seed text how the models generated the text. For LSTM model Rabindranath Tagore poetry is given as training text and trained the model and for GRU Sarojini Naidu poetry is given as input for training. When seed text is given both models generated texts. When compared with generating meaningful sentences GRU generated better sentences than the LSTM model. LSTM model is unable to generate long sequences when compared with GRU model. GRU model generated 40% of extra correct words when compared with LSTM model. The quality is checked by the language experts they expressed that more quality of text generated by the GRU model when compared with LSTM model with respect to words or even sentences. As it is not a language translation model, we have not used BLEU score instead we have taken experts opinion. When we checked the sentence generated by the character level trained GRU model ‘o king my heart is unsatisfied’ is a perfect sentence with 5 words. And the another sentence “bear her along like a tusk” is in perfect poetic line “the soul is gone” this sentence is also in perfect poetic line but the limitation of the GRU model is it cannot generate a good meaningful sentences more than 3 with each sentence is 4 to 7 words long. Table 2 shows the result of word level text generation by LSTM model. This model generated long sentences but not meaningful sentences. The sentences are grammatically correct and making sentences meaningful if sentence contains 4to 5 words. So with this we can conclude that character level models are good at generating few words not a paragraph or summary texts.

VII. CONCLUSION AND FUTURE AND WORK

In this experiment we have explored automatic text generation using LSTM and GRU variants of RNN model, for this we have considered Indian poetry data. We have tested with Rabindranath Tagore, Sarojini Naidu poetry style generation. In order to generate Indian style poetry in this experiment we have not provided any special features to train the models with style features separately, further we can extend this experiment by adding those features such as rhyme, simile etc. and using advanced methods such as attention based models to focus more on style of the poetry. we have compared the text generated by the both models' LSTM and GRU using expert decision. Further the result comparison can be done using LSA and other methodologies for more critical analysis and evaluation of the performance of the both models.

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