Transliteration of Sanskrit text

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Objective

- To develop a Transliteration mechanism for Roman to Devanagari and vice versa.
- Transliteration is changing words from one script to another, more commonly the words are proper nouns.
- Sometimes it also means changing sounds from one language to another. For example:

h a j a g i r e e

ह ज ग ि र ी

- This system is basically designed to help in retrieving old Sanskrit documents and manuscripts using different information retrieval techniques.

Objective

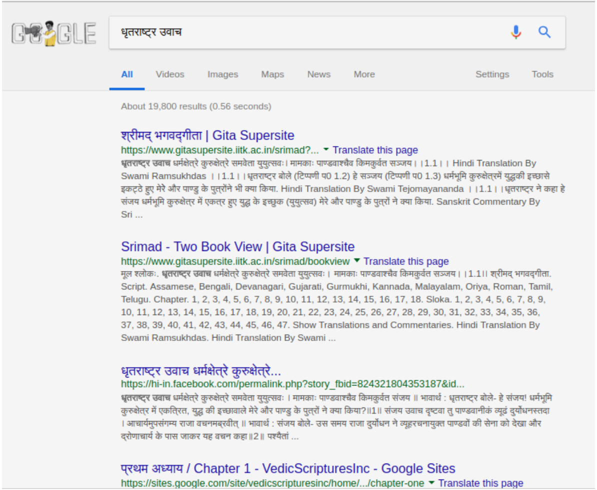
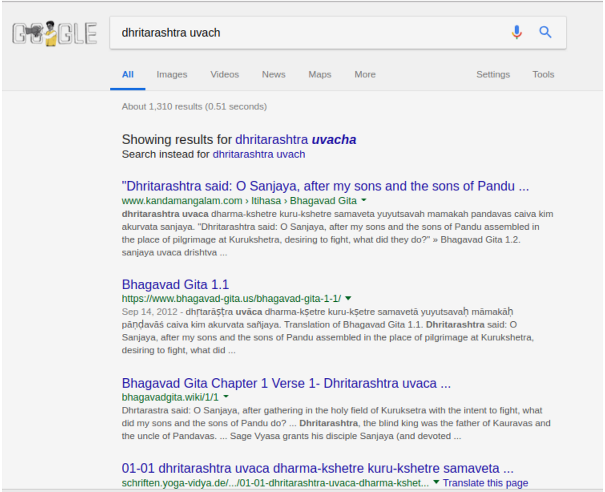


Figure: Google search results for Sanskrit query.

Objective



dhritarashtra uvach

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Showing results for dhritarashtra ***uvacha***
Search instead for dhritarashtra uvach

"Dhritarashtra said: O Sanjaya, after my sons and the sons of Pandu ...
www.kandamangalam.com › Itihasa › Bhagavad Gita
dhritarashtra uvaca dharma-kshetre kuru-kshetre samaveta yuyutsavah mamakah pandavas caiva kim akurvata sanjaya. "Dhritarashtra said: O Sanjaya, after my sons and the sons of Pandu assembled in the place of pilgrimage at Kurukshetra, desiring to fight, what did they do?" » Bhagavad Gita 1.2. sanjaya uvaca drishtva ...

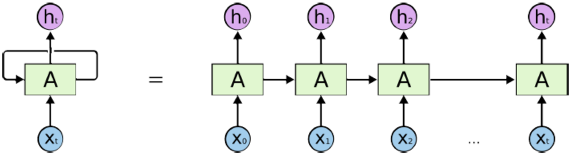
Bhagavad Gita 1.1
https://www.bhagavad-gita.us/bhagavad-gita-1-1/
Sep 14, 2012 - dhṛtarāṣṭra **uvāca** dharma-kṣetre kuru-kṣetre samavetā yuyutsavaḥ māmakāḥ pāṇḍavāś caiva kim akurvata sañjaya. Translation of Bhagavad Gita 1.1. **Dhritarashtra** said: O Sanjaya, after my sons and the sons of Pandu assembled in the place of pilgrimage at Kurukshetra, desiring to fight, what did ...

Bhagavad Gita Chapter 1 Verse 1- Dhritarashtra uvaca ...
bhagavadgita.wiki/1/1
Dhrtarastra said: O Sanjaya, after gathering in the holy field of Kuruksetra with the intent to fight, what did my sons and the sons of Pandu do? ... **Dhritarashtra**, the blind king was the father of Kauravas and the uncle of Pandavas. ... Sage Vyasa grants his disciple Sanjaya (and devoted ...

01-01 dhritarashtra uvaca dharma-kshetre kuru-kshetre samaveta ...
schriften.yoga-vidya.de/.../01-01-dhritarashtra-uvaca-dharma-kshet... Translate this page

Figure: Google search results for Sanskrit query.

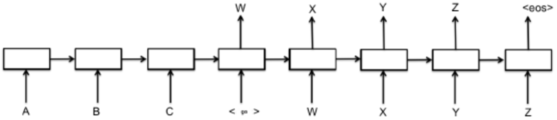
- RNN are a type of Neural network which contains loop in them, which basically allows information to persist.



- RNN emerged because of the need to address the issue of long term dependencies.
- A recurrent Neural Network can be considered as a repetition of the same network with each one of them passing message to its successor.

Seq2Seq Model

- Consists of two recurrent neural networks (RNNs).
- One of them is the encoder that processes the input given to it and the another one is the decoder that generates the output.



- The output of the decoder at time t is fed back to the algorithm and it becomes an input for the algorithm at time t+1.

Our Approach

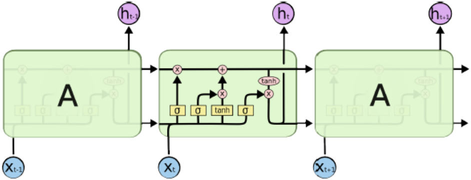
- Main problem faced by us in this task was to gather enough data so that our model could be trained efficiently.
  - To handle this problem we first converted Sanskrit text to Itrans notation.
  - This Itrans notation was then converted to Roman script by creating all possible mapping from Itrans to Roman characters which was created manually based on the phoneme that the Itrans was capturing.
  - The main advantage of this technique was that our data set was enriched with multiple ways of writing a given word in Roman script.Finally we trained our model on 1,52,000 words and cross-validated it on 38,000 words to fine tune the parameters and tested it on 10,000 words.

Our Approach

- To build our model we have used Seq2Seq model and then while decoding an unknown input sequence we go through a slightly different process.
  - Encode the input sequence into state vectors.
  - Start with a target sequence of size 1 (just the start-of-sequence character).
  - Feed the state vectors and 1-char target sequence to the decoder to produce predictions for the next character.
  - Sample the next character using these predictions (we simply use argmax).
  - Append the sampled character to the target sequence.
  - Repeat until we generate the end-of-sequence character or we hit the character limit.

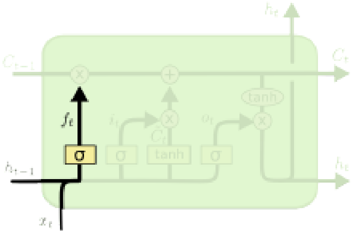
Why use Long Short Term Memory

- Long Short Term Memory networks usually just called LSTMs are a special kind of RNN, capable of learning long-term dependencies.



- In normal RNNs the repeating module generally have a simple structure like a tanh layer but in LSTMs the repeating module has four neural network layers instead of one which interact with each other in a very trivial way.
- There are basically 4 steps to reach the output of a particular cell:
  - Deciding what information to throw away.
  - Deciding what information to store.
  - Updating the cell state.
  - Giving the output.

Deciding what information to throw away

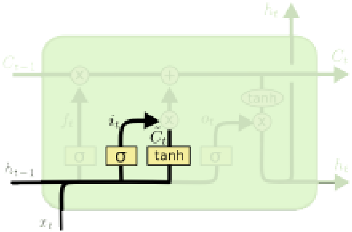


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Figure: Forget Gate Layer.

- For this purpose, the "forget gate layer" is used.
- It is a sigmoid layer that looks at previous output(h_{t-1}) and the input for this layer(x_t) and generates a number between 0 and 1 that decides how much to keep and how much to throw away.

Deciding what information to store

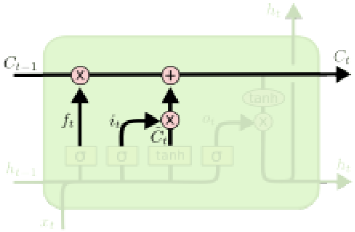


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Figure: Input Gate Layer.

- To store in formation in a cell state, our second sigmoid layer "input gate layer" along with a tanh layer is used.
- First, the sigmoid layer chooses which information is to be added to cell state then the tanh layer prepares a vector(C_t) which can be combined with the above result to update the cell state.

Updating the cell state



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Figure: Updating C_{t-1} to C_t.

- To update the cell state from C_{t-1} to C_t we multiply the old state by output from forget layer $f_t$to forget the old information and add it to the multiplication of it(what information to add) and C_t(the vector for new candidates). So the new state C_t becomes the above mentioned

Giving the output

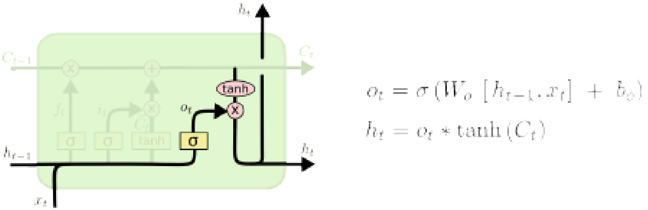


Figure: Output layer.

- The output we give is not the cell state but a filtered version of it because to predict the next thing maybe only some part of the information updated is required.
- This is done by another sigmoid layer known as "output layer" which controls which information should be passed ahead.
- This output o_t is multiplied to tanh of the cell state(to reduce it to [-1,1]) to give the output.

Results

- We have experimented our model by taking different test-sets. BLEU score, Word-error rate and accuracy were different metrices that we used to capture the quality of the system developed.
  - **BLEU (bilingual evaluation understudy)** is an algorithm for evaluating the quality of text which has been machine-translated from one natural language to another.
  - **Word error rate (WER)** is a common metric of the performance of a speech recognition or machine translation system.

Results

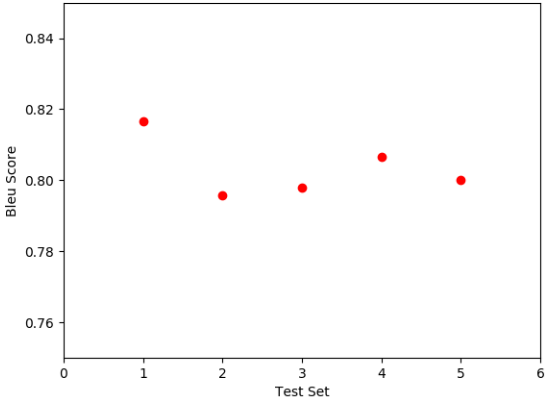


Figure: BLEU score vs Test-set

Results

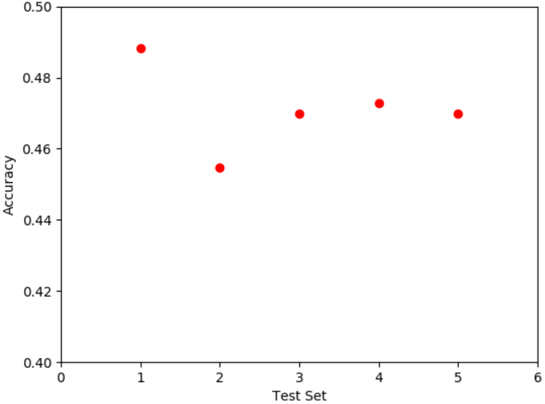


Figure: Accuracy vs Test-set

Results

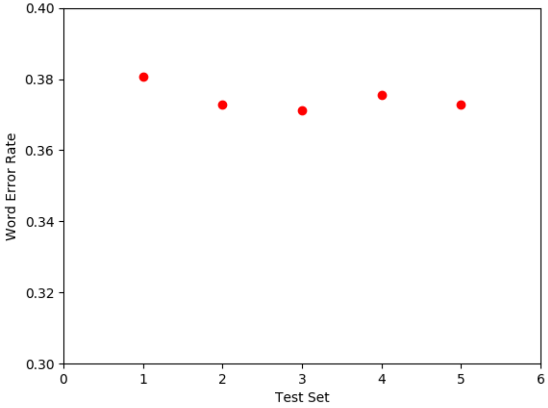


Figure: Word Error-Rate vs Test-set

Conclusions

- We have achieved an overall accuracy of 47.11% and a BLEU score of 80.34 .
- We believe that if we train the model with better data-set, there is a good hope of getting our accuracy improved.
- The accuracy is low because it is calculated by matching the whole word with one another, so for a better measure we calculated BLEU score and word-error rate. The overall word-error rate was found to be 37.43%.
- We plan to extend our model for cross-lingual information retrieval and apply information retrieval techniques on both, the transliterated and the original query in order to retrieve the set of relevant documents of the both the source and target language.

Thank You