CSE 676 (Summer 2023): Deep Learning Final Project

Machine Language Translation with DL

Team 13

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Project Description

The major objective of this project is create a machine translator that takes prompt from language A and translates into language B where A and B are languages we train our model on. Our goals is to have fluency and naturality of the translated texts and the output must be as a sentence generated by a human who is fluent in the language.

We will then compare the accuracies of various architectures in solving the above task of translating from English to French.

Background

- *Sequence to Sequence Learning with Neural Networks by Sutskever et al. (2014)* – Basic Architecture for Seq2Seq Learning with LSTM
- *Neural Machine Translation by Jointly learning to Align and Translate by Bahdanau et al. (2015)* – Introduces Attention Mechanism so as to effectively translate longer sentences
- Effective Approaches to Attention-based Neural Machine Translation by Luong et al. *(2015)* – Different effective ways to introduce attention to the model architecture

Dataset

The data is taken from the parallel language corpus available in Kaggle. DGT-TM is a translation memory (sentences and their manually produced translations) in 24 languages.

We further selected a dataset for English to French translations.

In total we are using around 135,000 sentences of upto 25 word length for training and test.

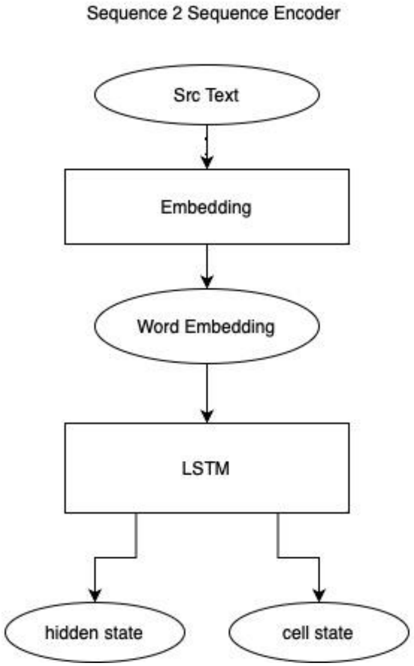
Dataset Preprocessing

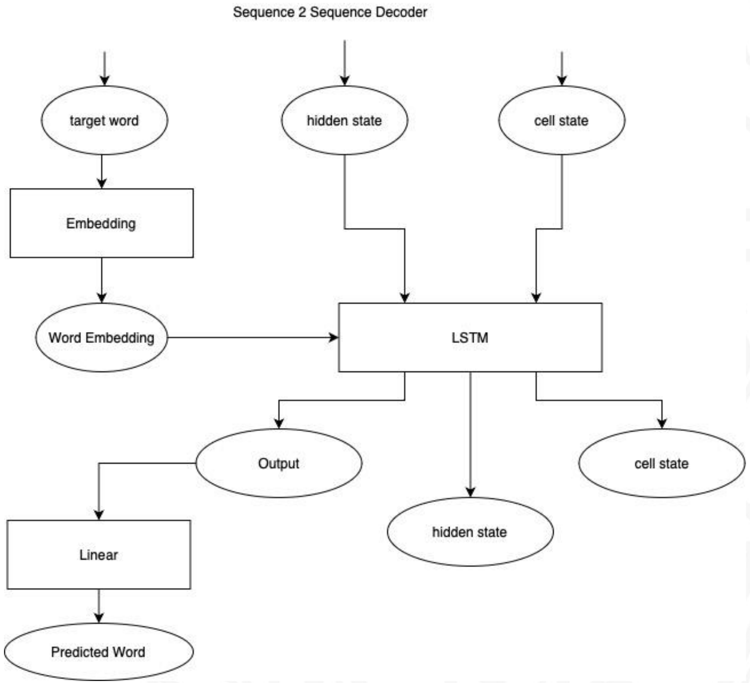
- We used spacy, torchtext and NLTK libraries for preprocessing
- Before tokenization we converted sentences to lower case and then removed special characters and digits
- We then tokezined and added <sos> and <eos> tags at the start and end.
- We then built vocabularies for English and French feeding the training data to Spacy models.

Dataset Preprocessing - Challenges

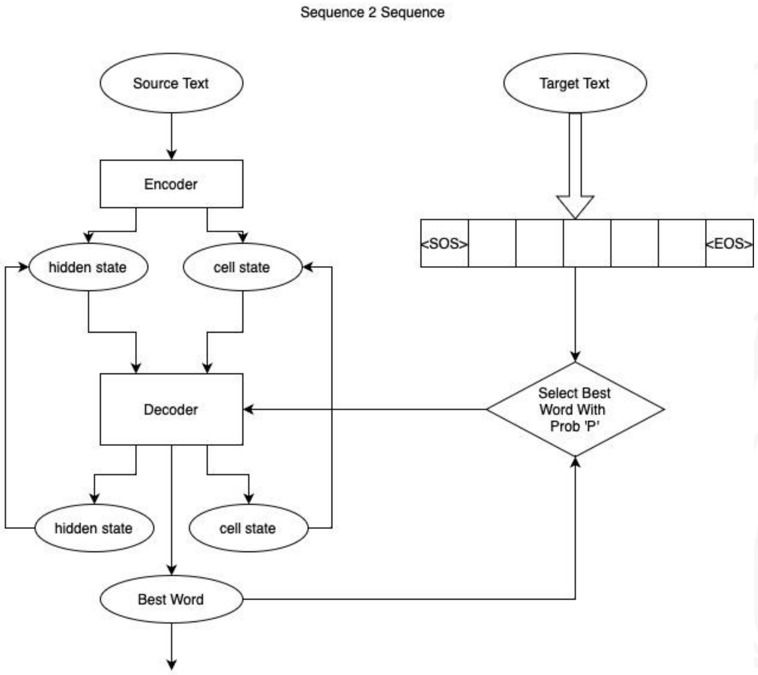
- Excessive Padding:
  - If we padding the entire corpus with maximum sentence length, training might not happen.
  - To overcome this we are using sorting and batch padding techniques.
  - It also improves training time and decreasing the computational expenses.
- Word Embedding:
  - We are using a custom Embedding layer to do this.

Vanilla Seq2Seq DataFlow

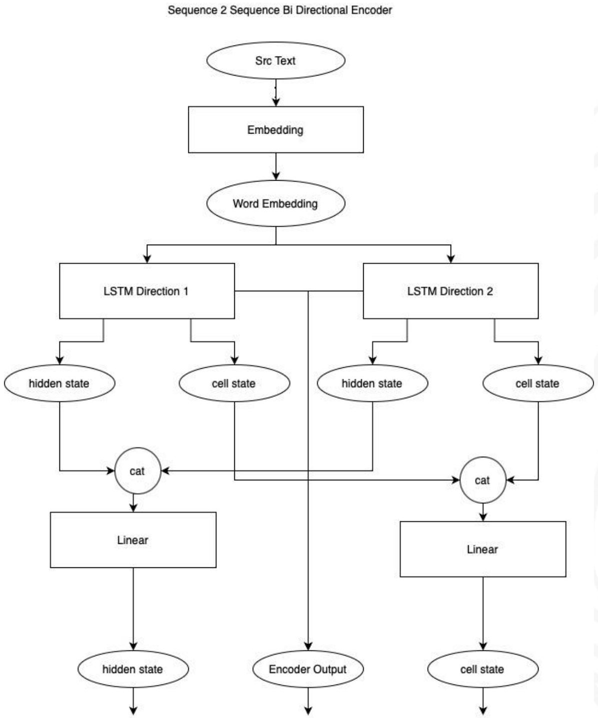




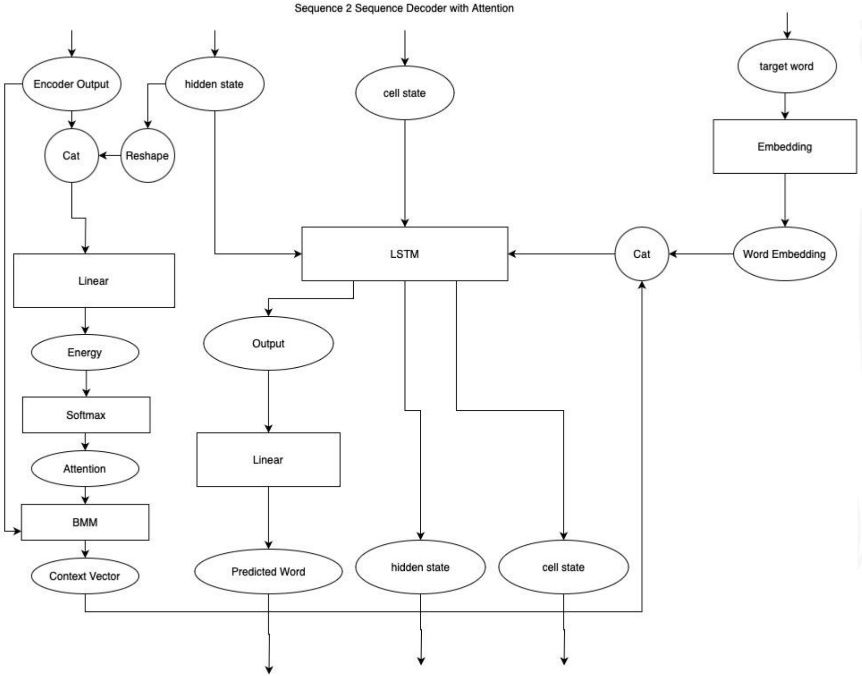
Vanilla Seq2Seq DataFlow



Bidirectional Encoding DataFlow

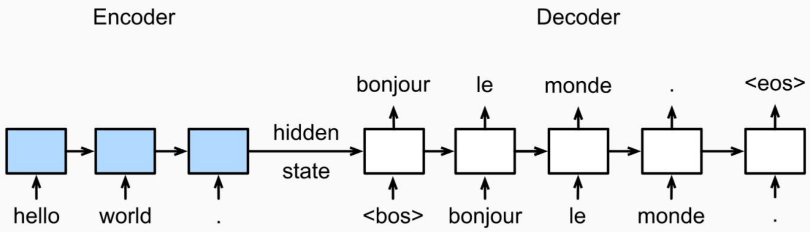


Seq2Seq with Attention DataFlow



Implementation - Vanilla Seq2Seq model

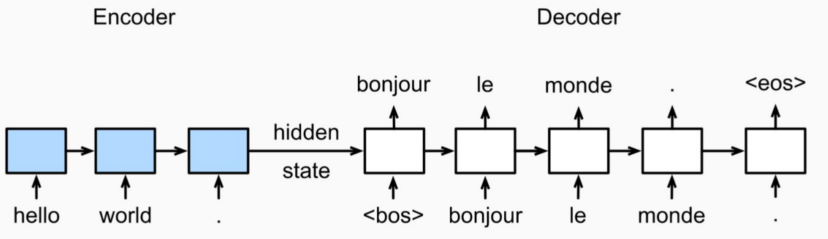
- Hyperparameters
  - Learning Rate = 3e-4
  - Number of epochs = 50
  - Batch Size = 64
  - Encoder and Decoder Dropout = 0.5
  - Encoder and Decoder Embedding Size = 300
  - Teacher Force Ratio = 0.6
  - LSTM Number of layers = 2
  - Optimizer = Adam



The sequence to sequence model architecture.

Implementation - Seq2Seq with Bidirectional LSTM

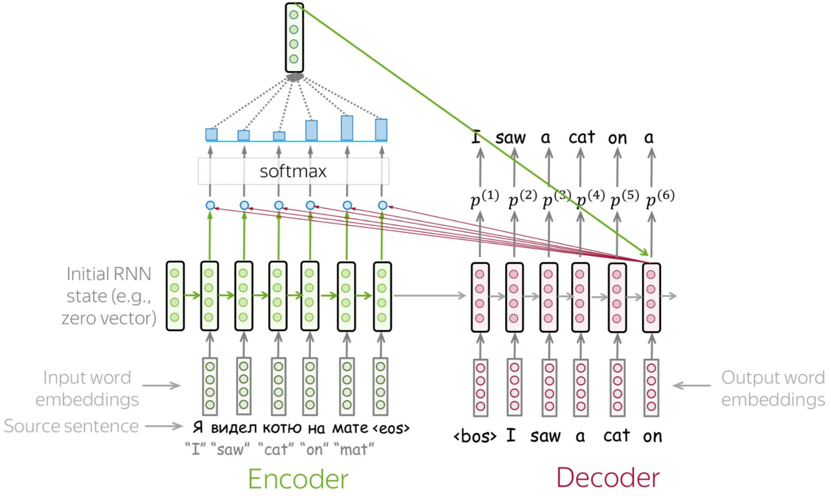
- Hyperparameters
  - Learning Rate = 3e-4
  - Number of epochs = 50
  - Batch Size = 64
  - Encoder and Decoder Dropout = 0.5
  - Encoder and Decoder Embedding Size = 300
  - Teacher Force Ratio = 0.6
  - LSTM Number of layers = 2
  - Optimizer = Adam



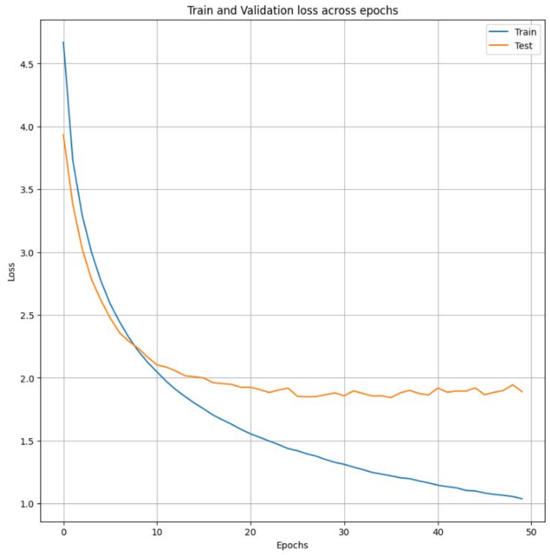
The sequence to sequence model architecture.

Implementation - Seq2Seq Model with Attention

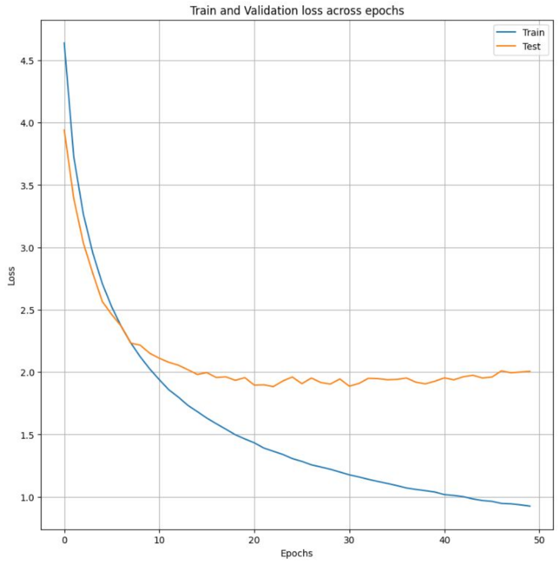
- Hyperparameters
  - Learning Rate = 3e-4
  - Number of epochs = 50
  - Batch Size = 64
  - Encoder and Decoder Dropout = 0.6
  - Encoder and Decoder Embedding Size = 300
  - Teacher Force Ratio = 0.6
  - LSTM Number of layers = 1
  - Optimizer = Adam



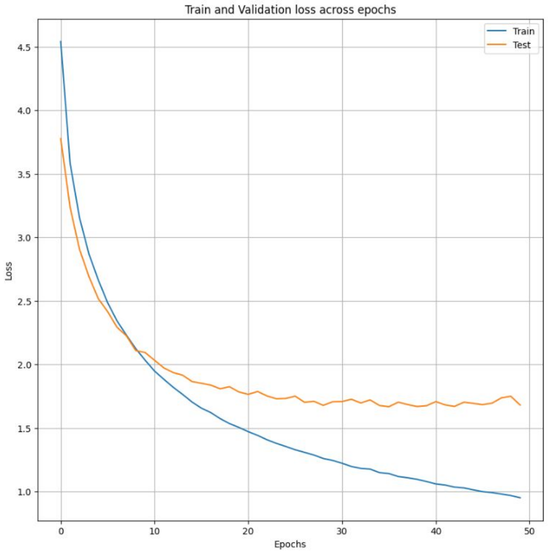
Results - Loss Plots



Seq2Seq

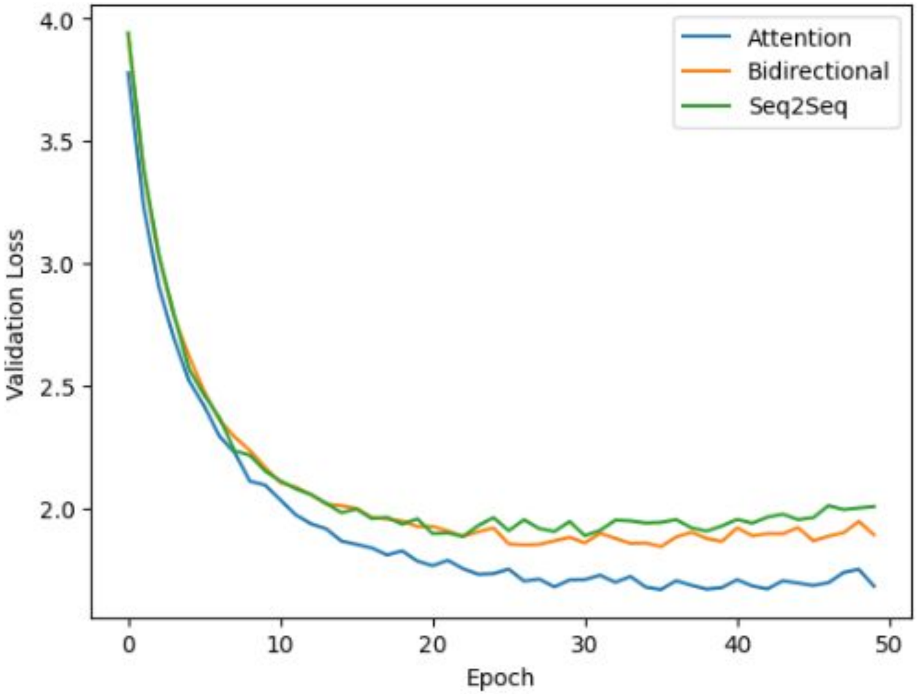


Bidirectional



Seq2Seq with Attention

Results - Validation Loss Comparison



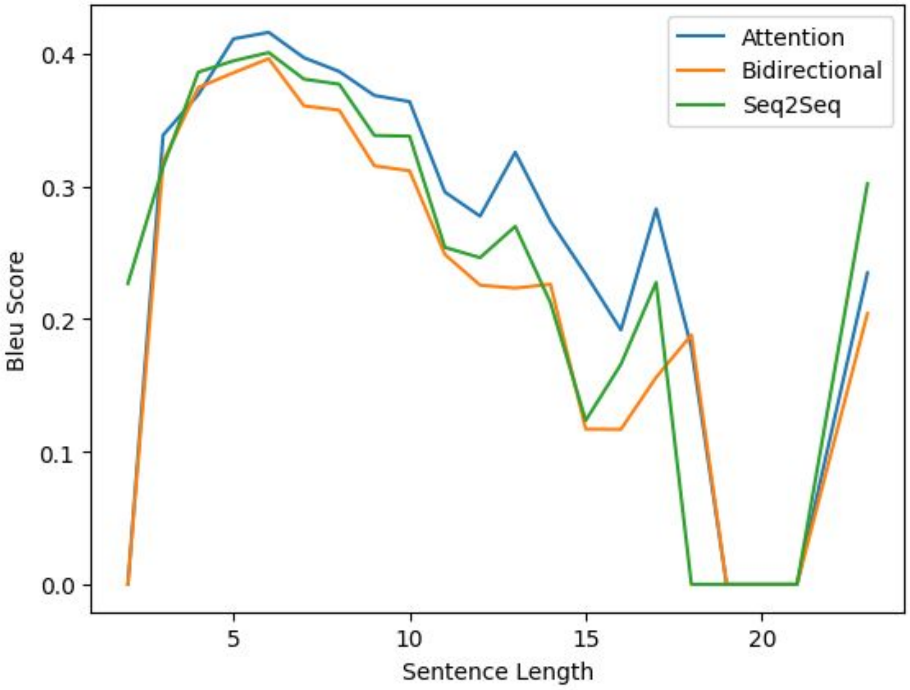
BLeU(BiLingual Evaluation Understudy) Score

- BLeU Score is a metric for automatically evaluating machine-translated text. It is a number between zero and one that measures the similarity of the machine-translated text to a set of high quality reference translations.
- A value of 0 means that the machine-translated output has no overlap with the reference translation (low quality) while a value of 1 means there is perfect overlap with the reference translations (high quality).

BLEU Score	Interpretation
< 10	Almost useless
10 - 19	Hard to get the gist
20 - 29	The gist is clear, but has significant grammatical errors
30 - 40	Understandable to good translations
40 - 50	High quality translations
50 - 60	Very high quality, adequate, and fluent translations
> 60	Quality often better than human

Evaluation - BLeU Score Comparison

- Seq2Seq - 0.365
- Bidirectional - 0.369
- Seq2Seq with Attention - 0.406



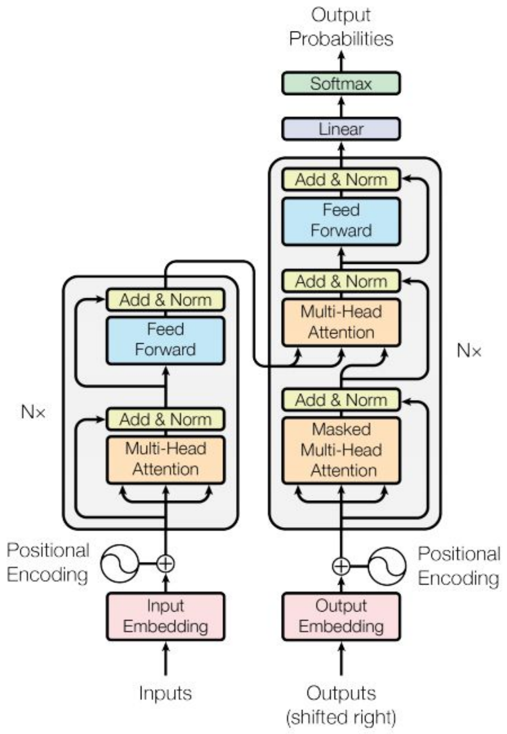
Demo

Key Takeaways

- We observed we had slightly better loss values for Seq2Seq with Bidirectional Encoding over Vanilla Seq2Seq. And Seq2Seq with Attention had significantly better loss value than other two models.
- We also observed that Seq2Seq with Attention had an better overall BLeU Score as well as slightly better BleU score over longer sentences.
- Hence, Attention is all you need.

Further Improvements

- Transformer based Architecture: Uses self attention mechanism to capture dependencies between words in a sentence effectively
- Larger dataset with longer sentences
- Data Augmentation: Use techniques such as word swapping, sentence shuffling etc.



Contribution

Name	Part	Contribution
Sailesh Reddy Sirigireddy	Vanilla Seq2Seq	35%
Chandini Kondinolu	Bidirectional Encoding	30%
Shri Harsha Adapala Thirumala	Seq2Seq with Attention	35%

Thank You