Abstractive Summarization of Nepali News Articles

1. Dataset/Corpus

For this project, I scraped different online Nepali news portals and extracted headlines and news articles across different categories. The dataset consists of around 372,000 entries. Because each entry consists of the news article, headline, and news category, the dataset could be further used for classification tasks and also for training large language models.

Fig 1: News articles across different categories

Fig 2: Sample news from the dataset

2. Data Cleaning and Preprocessing:

- Removed special characters. (.,/";\[{ …) except for (. and %) since they are used in numbers,
- Replace arabic numerals(0-9) to Nepali numerals(०-९)
- Removed English characters (Aa-Zz), emails, HTML elements, Emojis, and other unwanted non-Devanagari characters.
- Removed all the articles with news < 16 words.
- Removed all the articles with titles < 2 words or > 11 words

3. Tokenizer:

For tokenization, Sentencepiece tokenizer based on the Byte Pair Encoding(BPE) algorithm was used, with a vocabulary size of 50 K.

4. Models

4.1. Attentive Seq2Seq Model

The model follows the Encoder-Decoder architecture with the following specification:
- **Encoder:**
    - Embedding Layer
    - Bi-LSTM
- **Decoder:**
    - Embedding Layer
    - LSTM
    - Bahdanau Attention
    - Concat → Context Vector and Decoder Hidden State
    - Dense
    - Softmax

4.1.1 Hyperparameters

Hyperparameters	Value
Vocab Size	50K
Encoder Sequence Length	256
Decoder Sequence Length	12
Embedding Dimension	100
Encoder Latent Dimension	128
Decoder Latent Dimension	256
Dropout	0.3
Batch Size	128
Epochs	18
L2 Regularization	0.01
Teacher Forcing Ratio	0.5
Coverage Weight	1.0

Table 1: Hyperparameters used for training the Seq2Seq Model

4.1.2 Attention Mechanism

The model uses the Bahdanau Attention also known as Additive Addition along with the Coverage Mechanism as discussed in the paper Get to the Point Summarization

4.1.3 Loss Function

The model uses a combination of Cross Entropy and Coverage Loss as discussed in the paper Get to the Point Summarization

4.2. Transformer

This model replicates the original Transformer architecture.

4.2.1 Hyperparameters

Hyperparameters	Value
Vocab Size	50K
Encoder Sequence Length	256
Decoder Sequence Length	12
Embedding Dimension (d_model)	256
Attention Heads (h)	8
Feed Forward Dim (d_ff)	2,048
Dropout	0.2
Encoder Layers	6
Decoder Layers	6
Batch Size	128
Learning Rate	1e-4
Epochs	20
L2 Regularization	0.01
Label Smoothing	0.1

Table 2: Hyperparameters used for training the Transformer Model

4.1.2 Loss Function

The model uses the Cross Entropy Loss function.

5. Training Methodology

- **Attentive Seq2Seq**: 50% Teacher Forcing (50% of the time, ground truth label was provided)
- **Transformer**: Full Teacher Forcing

6. Inference

- Greedy Decoding

- [Normalized Beam Search Decoding](#)

7. Evaluation Metric

- [BLEU](#)
- [Rouge](#)

8. Results

Because the inference takes a very long time, Kaggle kernel could not handle it, so I have sampled a random 1000 news headline pairs and computed the metrics for that sample. Greedy Search actually performed better on Attentive Seq2Seq, while Beam Search outperformed Greedy Search in Transformer

Model	BLEU	Rouge-1	Rouge-2	Rouge-L
Attentive Seq2Seq	3.17	19.15	4.9	18.68
Transformer	5.37	23.83	8.35	23.25
Dhakal and Baral (2024)[8]	-	35.9	19.99	34.88
Paudel (2022)[9]	-	15.74	3.29	15.21
Mishra et al. (2020)[10]	22.1	-	-	-
Thapa et al. (2024)[11]	-	20.42	15.89	17.76

Table 3: BLEU and Rouge comparision

9. Future Enhancements

- Experiment with Large Language Models.
- Use Beam Tree pruning methodologies to speed up the decoding process..

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