TEXT SUMMARIZATION WITH USING MULTI-NEWS DATASET REPORT

FINAL PROJECT REPORT

2025W-T3 AML 3104 - Neural Networks and Deep Learning 01 (DSMM Group 1)



Presented by:

Jashanpreet Kaur (C0928354)

Ashish Kathrotiya (C0924786)

Devansh Patel (C0928483)

Govind Dogra (C0929421)

Shlok Shah (C0925532)

Submitted to:

Ishant Gupta

1. Introduction

The Text Summarisation Model developed with Keras/TensorFlow is explained in detail in this document. The model uses a sequence-to-sequence (Seq2Seq) architecture with LSTM-based encoder-decoder components to produce succinct summaries from news items.

Objective

- Input: A news article (text).
- Output: A short, coherent summary.

Dataset

 CNN/DailyMail Dataset (from Kaggle) containing news articles and their corresponding summaries.

2. Data Preprocessing

Data Loading & Filtering

- Pandas is used to load the dataset.
- Overlength articles and summaries (TEXT_LIMIT=1600, SUMMARY_LIMIT=500) are eliminated.
- Seaborn and Matplotlib are used to visualise length distributions.

Train-Test Split

- The dataset is divided into:
 - The majority of the dataset is used for training.
 - The last ten samples are the test data (for validation).

Preparing the Sequence and Tokenisation

- Text is transformed into sequences using the Keras tokeniser.
- Summaries now include special tokens (<start>, <end>, <PAD>.)
- To guarantee consistent sequence lengths, padding is used.

Lengths of Sequences and Vocabulary

- The encoder tokeniser is used to determine the size of the input vocabulary.
- The decoder tokeniser was used to determine the output vocabulary size.

• Maximum Lengths of Sequences:

- Max_input_seq_length is the input (Article).
- Max_output_seq_length is the output (summary).

3. Model Architecture

Encoder-Decoder with Attention

The model consists of:

Encoder (LSTM-based):

- Takes an input sequence (article).
- Produces hidden states (h, c) and encoder outputs.

Decoder (LSTM-based):

- Takes the encoder's hidden states and generates summaries.
- Uses Bahdanau Attention to focus on relevant parts of the input.

Attention Mechanism:

• Computes a context vector to weigh encoder outputs dynamically.

Key Components

| Components | Description |
|------------|------------------------------------|
| Encoder | Embedding + LSTM |
| Decoder | Embedding + LSTM + Dense (Softmax) |
| Attention | Dense layers + Softmax weighting |

Training Process

• **Loss Function:** Sparse Categorical Crossentropy (since outputs are sequences).

Optimizer: Adam.Batch Size: 32.

• **Epochs:** 5 per training cycle (total 25 epochs).

4. Model Performance

Training Metrics

| Epoch | Training | Validation | Training | Validation |
|-------|-------------------|------------|----------|---------------------|
| | Accuracy | Accuracy | Loss | Loss |
| 1-5 | ~59% → 66% | ~62% → 66% | ~2.38e-5 | ~2.98 → 2.53 |
| 6-10 | ~67% → 71% | ~62% → 66% | ~2.38e-5 | ~2.52 → 2.57 |
| 11-15 | ~73% → 87% | ~62% → 66% | ~2.38e-5 | ~2.60 → 3.20 |

Observations

- **Training Accuracy** improves significantly (59% → 87%).
- Validation Accuracy plateaus at ~66%, indicating overfitting.
- **Loss** increases on validation data, suggesting the model struggles to generalize.

5. Inference & Testing

Summary Generation

Summaries are produced by the model using:

- At each stage, Greedy Search chooses the word with the highest likelihood.
- When the token is anticipated, it stops.

Example outputs

Example 1 (Index 1116):

Input Text:

"Rescue workers have pulled a body from underneath the rubble of a collapsed apartment building in Cologne, Germany..."

Generated Summary:

"New the death toll rises to 931 according to Bangladesh's national weather service..."

X Incorrect facts (hallucination).

Reference Summary:

"Rescue workers pull body from rubble of collapsed building. One person still missing..."

Example 2 (Index 100):

Input Text:

"Michael Jackson's brothers are working on a reunion tour to perform their old Jackson 5 songs..."

Generated Summary:

"Timothy Tracy was accused of fomenting unrest in Venezuela..."

X Completely unrelated summary.

Reference Summary:

"Jermaine Jackson says the brothers are meeting Monday to plan a new tour..."

6. Issues & Improvements

Identified problems

- **Overfitting:** High training accuracy but stagnant validation accuracy is known as overfitting.
- Hallucinations: The model produces inaccurate or irrelevant summaries.
- Limited Generalisation: Faces challenges while dealing with unknown data.

Possible Solutions

| Problem | Solution |
|----------------|---|
| Overfitting | Add Dropout, Regularization, or Early Stopping. |
| Hallucinations | Use Beam Search instead of greedy decoding. |
| Generalization | Increase dataset size or use pre-trained embeddings |
| Training | Adjust learning rate or use gradient clipping. |
| Instability | |

7. Web Application

Objective

The purpose of this app is to generate concise summaries from longer news articles using a trained sequence-to-sequence model with attention. The app is built using Streamlit, making it interactive and user-friendly.

Key Functionalities

Model and Tokenizer Loading:

- The function load_model_and_tokenizers() is used to load the trained Keras model (Teacher_Model.keras) and the associated encoder_tokenizer and decoder_tokenizer from pickle files.
- It uses @st.cache_resource to ensure that the model and tokenizers are loaded only once, improving performance.

Summary Generation Logic:

- The function generate_summary(text) takes in an article as input and performs the following:
 - Tokenizes and pads the input article.

- Passes it through the encoder to get hidden and cell states.
- Uses these states to initialize the decoder.
- Iteratively generates tokens one by one until the end token is predicted or the maximum length is reached.
- Decoded token IDs are converted back to words using index_to_word mapping to produce the final summary.

User Interface:

- The Streamlit app includes a simple interface:
 - A text area for users to paste or type the news article.
 - A button to trigger summary generation.
 - A loading spinner for user feedback while the summary is being generated.
 - A result section displaying the generated summary once it's ready.
- It uses st.set_page_config() to configure the layout and title of the app.

Technologies Used

- Streamlit: For building the web interface.
- TensorFlow / Keras: For the deep learning model used in summarization.
- **Pickle:** To load pre-trained tokenizers.
- Numpy: For array manipulation.

8. Conclusion

- Despite overfitting and hallucinations, the model is able to learn to produce summaries.
- Upcoming enhancements:
 - Improved attentional systems (based on transformers).
 - larger dataset or improving data specialised to a given domain.
 - post-processing (optimisation of ROUGE scores).

Next Steps:

- Hyperparameter tuning (LSTM units, embedding size)
- Try out different Transformer models, like as T5 and BART.
- Implement as a real-time summarisation API.