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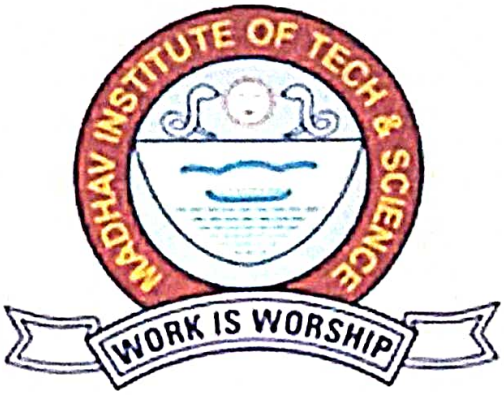

Project Report

on

Text Summarization

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CERTIFICATE

This is certified that **Aditya Chauhan** (0901am211004) and **Pravi Saxena** (0901am211040) has submitted the project report titled **Text Summarization** under the mentorship of **Dr. Sunil Kumar Shukla**, in partial fulfilment of the requirement for the award of degree of Bachelor of Technology in **Artificial Intelligence and Machine Learning** from Madhav Institute of Technology and Science, Gwalior.

23/11/2023

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DECLARATION

I hereby declare that the work being presented in this project report, for the partial fulfilment of requirement for the award of the degree of Bachelor of Technology in **Artificial Intelligence and Machine Learning** at Madhav Institute of Technology & Science, Gwalior is an authenticated and original record of my work under the mentorship of **Dr. Sunil Kumar Shukla**, Assistant Professor, Centre for Artificial Intelligence

I declare that I have not submitted the matter embodied in this report for the award of any degree or diploma anywhere else.

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ABSTRACT

This project explores the implementation of a text summarization system utilizing Sequence-to-Sequence (Seq2Seq) models. The Seq2Seq architecture, known for its success in natural language processing tasks, forms the core of our summarization model. Leveraging transfer learning principles, the model is initialized with pre-trained weights to capitalize on knowledge acquired from extensive language modelling.

The methodology encompasses comprehensive data pre-processing, model configuration, and hyper-parameter tuning, addressing challenges such as document length and abstractive summarization nuances. The evaluation phase employs metrics like ROUGE to assess the system's performance, acknowledging limitations related to handling long documents and potential biases.

Integration with external libraries enhances natural language processing capabilities, while scalability consideration ensure adaptability to evolving requirements. The system, designed for diverse applications, demonstrates promise in domains such as news summarization, research paper analysis, and social media content condensation.

This project contributes to the evolving landscape of automated text summarization, showcasing both achievements and challenges. The journey from data collection to system integration provides valuable insights, fostering a commitment to ongoing refinement and extension for effective and context-aware text summarization.

सार

यह परियोजना अनुक्रम-से-अनुक्रम (Seq2Seq) मॉडल का उपयोग करके एक पाठ सारांश प्रणाली के कार्यान्वयन की पड़ताल करती है। Seq2Seq आर्किटेक्चर, जो प्राकृतिक भाषा प्रसंस्करण कार्यों में अपनी सफलता के लिए जाना जाता है, हमारे सारांश मॉडल का मूल है। स्थानांतरण शिक्षण सिद्धांतों का लाभ उठाते हुए, व्यापक भाषा मॉडलिंग से प्राप्त ज्ञान का लाभ उठाने के लिए मॉडल को पूर्व-प्रशिक्षित भार के साथ आरंभ किया गया है।

कार्यप्रणाली में व्यापक डेटा प्री-प्रोसेसिंग, मॉडल कॉन्फ़िगरेशन और हाइपर-पैरामीटर ट्यूनिंग शामिल है, जो दस्तावेज़ की लंबाई और अमूर्त सारांश बारीकियों जैसी चुनौतियों का समाधान करती है। मूल्यांकन चरण लंबे दस्तावेज़ों और संभावित पूर्वाग्रहों को संभालने से संबंधित सीमाओं को स्वीकार करते हुए, सिस्टम के प्रदर्शन का आकलन करने के लिए ROUGE जैसे मेट्रिक्स को नियोजित करता है।

बाहरी पुस्तकालयों के साथ एकीकरण प्राकृतिक भाषा प्रसंस्करण क्षमताओं को बढ़ाता है, जबकि स्केलेबिलिटी पर विचार उभरती आवश्यकताओं के अनुकूलता सुनिश्चित करता है। विविध अनुप्रयोगों के लिए डिज़ाइन की गई प्रणाली, समाचार सारांश, शोध पत्र विश्लेषण और सोशल मीडिया सामग्री संक्षेपण जैसे डोमेन में वादा प्रदर्शित करती है।

यह परियोजना उपलब्धियों और चुनौतियों दोनों को प्रदर्शित करते हुए स्वचालित पाठ सारांश के विकसित परिदृश्य में योगदान देती है। डेटा संग्रह से सिस्टम एकीकरण तक की यात्रा मूल्यवान अंतर्दृष्टि प्रदान करती है, जो प्रभावी और संदर्भ-जागरूक पाठ सारांश के लिए चल रहे शोधन और विस्तार के प्रति प्रतिबद्धता को बढ़ावा देती है।

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Chapter 1: PROJECT OVERVIEW

1.1 Introduction

The explosion of digital information in today's world necessitates efficient methods for handling and extracting valuable insights from large volumes of text. Text summarization plays a crucial role in addressing this challenge by condensing lengthy documents while retaining essential information.

1.2 Objectives

The principal objective of this text summarization project is to implement and assess a model capable of generating succinct yet informative summaries from diverse textual data sources. By achieving this, the project aims to contribute to the development of tools and technologies that enhance the efficiency of information extraction and comprehension.

1.3 Feasibility

Our text summarization project is technically feasible, leveraging the Seq2Seq model with manageable computational resources. The availability of a diverse dataset ensures practicality. Acknowledging limitations, such as data constraints, we propose mitigations, affirming the project's feasibility and potential scalability.

1.4 System requirements

1.4.1 Hardware Requirements

The successful deployment of our text summarization system necessitates moderate hardware specifications. A standard setup, including a multi-core processor, a minimum of 8GB RAM, and ample storage for model parameters, accommodates the computational demands during training and inference.

1.4.2 Software Dependencies

Our system relies on prevalent deep learning frameworks such as Keras. Additionally, essential libraries like Pandas contribute to text processing. Compatibility with Python 3.x ensures seamless integration with the broader machine learning ecosystem.

By adhering to these system requirements, users can seamlessly integrate and utilize our text summarization system, fostering accessibility and ease of implementation.

Chapter 2: LITERATURE REVIEW

2.1 Text Summarization Techniques

2.1.1 Extractive Summarization

Early research in text summarization focused on extractive techniques, where key sentences are selected from the original text. Studies by Luhn (1958) and Edmundson (1969) pioneered extractive summarization, laying the groundwork for subsequent developments.

2.1.2 Abstractive Summarization

Advancements in abstractive summarization have gained prominence, allowing systems to generate concise summaries by understanding and rephrasing content. Notable contributions include the work of Rush et al. (2015) on the attention mechanism in abstractive summarization.

2.2 Seq2Seq Models in Natural Language Processing

2.2.1 Sequence-to-Sequence (Seq2Seq) Architecture

The Seq2Seq architecture, introduced by Sutskever et al. (2014), has been widely adopted in natural language processing tasks. It comprises an encoder-decoder structure capable of learning complex relationships in sequential data.

2.2.2 Application to Text Summarization

Recent studies, such as the work by Nallapati et al. (2016), showcase the effectiveness of Seq2Seq models in abstractive text summarization. These models demonstrate improved performance in capturing semantic meaning and generating coherent summaries.

2.3 Transfer Learning and Pre-trained Models

2.3.1 Transfer Learning in Natural Language Processing

Transfer learning, popularized by the success of models like BERT (Devlin et al., 2018), has become a key strategy in enhancing the performance of NLP tasks. Pre-trained language models offer a wealth of contextual knowledge for downstream applications.

2.3.2 Seq2Seq and Transfer Learning in Summarization

Recent research, such as the study by See et al. (2017), explores the integration of transfer learning techniques with Seq2Seq models for text summarization. Leveraging pre-trained models enhances the system's ability to understand diverse language nuances and improves summarization quality.

Chapter 3: PRELIMINARY DESIGN

3.1 Problem Definition and Scope

Before delving into the detailed preliminary design of our text summarization system, it is essential to outline key considerations that set the stage for subsequent planning. This pre-preliminary design phase involves initial exploration and decision-making to guide the subsequent steps.

3.1.1 Problem Definition

Define the problem scope and specific objectives of the text summarization system. Identify the target audience, types of input data, and the expected output format. Establishing a clear problem definition at this stage provides a foundation for subsequent design decisions.

3.1.2 Scope Definition

Delineate the boundaries and limitations of the project. Clearly articulate what falls within the purview of the text summarization system and what lies outside, ensuring a focused and achievable scope for the upcoming design phases.

3.2 System Architecture

Our text summarization system adopts a modular architecture, consisting of distinct components for data pre-processing, model training, and inference. The core of the system revolves around the Seq2Seq model, comprising an encoder-decoder structure.

3.3 Data Flow

The system initiates with raw textual data, processed through a comprehensive data pre-processing pipeline. This pre-processed data is then fed into the Seq2Seq model for training. Post-training, the model is integrated into the inference component, generating concise summaries from input text.

3.4 Technology Stack

We selected popular deep learning framework ,Keras, for its compatibility with the chosen Seq2Seq model architecture and also for visualization, we choose Matplotlib for its effectiveness in presenting summarization results to end-users.

Chapter 4: DESIGN AND EVALUATION

4.1 Data Collection

We choose a dataset with varying document lengths and topics to ensure the model's generalizability. The datasets called NEWS SUMMARY which is available on www.kaggle.com.

```
import numpy as np
import pandas as pd
```

```
dataset = pd.read_csv("news_summary.csv")
```

```
dataset.head(2)
```

	author	date	headlines	read_more	text	ctext
0	Chhavi Tyagi	03 Aug 2017,Thursday	Daman & Diu revokes mandatory Rakshabandhan in offices order	http://www.hindustantimes.com/india-news/rakshabandhan-compulsory-in-daman-and-diu-women-employees-to-tie-rakhis-to-male-colleagues/story-E5h5U1ZDJi5zFpLXWRkhJ.html?utm_source=inshorts&utm_medium...	The Administration of Union Territory Daman and Diu has revoked its order that made it compulsory for women to tie rakhis to their male colleagues on the occasion of Rakshabandhan on August 7. The...	The Daman and Diu administration on Wednesday withdrew a circular that asked women staff to tie rakhis on male colleagues after the order triggered a backlash from employees and was ripped apart o...
1	Daisy Mowke	03 Aug 2017,Thursday	Malaika slams user who trolled her for 'divorcing rich man'	http://www.hindustantimes.com/bollywood/malaika-arora-khan-aas-trolled-for-divorcing-a-rich-man-her-reply-is-dignity-itself/story-olPZNi6tdImCmabLMMwR2H.html?utm_source=inshorts&utm_medium=refera...	Malaika Arora slammed an Instagram user who trolled her for "divorcing a rich man" and "having fun with the alimony". "Her life now is all about wearing short clothes, going to gym or salon, enjoy ...	From her special numbers to TV? appearances, Bollywood actor Malaika Arora Khan has managed to carve her own identity. The actor, who made her debut in the Hindi film industry with the blockbuster ...

Fig 4.1 Corpus Collection

4.2 Data pre-processing

We implemented a robust data pre-processing pipeline. Include steps such as text tokenization and data cleaning. Ensure that the pre-processing steps align with the requirements of the Seq2Seq model.

4.2.1 Feature Extraction

Remove the columns that do not play any significant role for the task in hand to ensure good performance.

```
dataset = dataset.drop(['author'],axis=1)
dataset = dataset.drop(['date'],axis=1)
dataset = dataset.drop(['read_more'],axis=1)
dataset = dataset.drop(['headlines'],axis=1)
```

Fig. 4.2.1 Dropping unnecessary columns

4.2.2 Data Cleaning

Before we fed our raw to data to the model it needs to be cleaned. Data cleaning includes turning each text to lowercase, removing special characters, removal of escape characters etc.

```
import re

def text_strip(column):
    for row in column:

        row=re.sub("(\\t)", ' ', str(row)).lower()
        row=re.sub("(\\r)", ' ', str(row)).lower()
        row=re.sub("(\\n)", ' ', str(row)).lower()

        row=re.sub("(__+)", ' ', str(row)).lower()
        row=re.sub("(--+)", ' ', str(row)).lower()
        row=re.sub("(~~+)", ' ', str(row)).lower()
        row=re.sub("(\+\++)", ' ', str(row)).lower()
        row=re.sub("(\.\.+)", ' ', str(row)).lower()

        row=re.sub(r"[<>()|&©ø\[\]\'\",;?~*!]", ' ', str(row)).lower(0
```

Fig. 4.2.2 Data Cleaning

4.2.3 Tokenization

Tokenization is a crucial pre-processing step in natural language processing (NLP) tasks, including text summarization using Seq2Seq models. It involves breaking down a text into smaller units, called tokens. Tokens can be words, sub-words, or characters, depending on the level of granularity required.

```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

x_tknizer = Tokenizer()
x_tknizer.fit_on_texts(list(x_tr))
```

```
x_tknizer = Tokenizer(num_words=total_count-count)
x_tknizer.fit_on_texts(list(x_tr))
x_tr_seq    =   x_tknizer.texts_to_sequences(x_tr)
x_val_seq   =   x_tknizer.texts_to_sequences(x_val)

x_tr    =   pad_sequences(x_tr_seq,  maxlen=max_text_len, padding='post')
x_val   =   pad_sequences(x_val_seq, maxlen=max_text_len, padding='post')

x_voc   =  x_tknizer.num_words + 1

print("Size of vocabulary in X = {}".format(x_voc))
```

Fig. 4.2.3 Tokenization

4.3 Model Architecture

4.3.1 Seq2Seq Model Configuration

Configure the Seq2Seq model architecture. Define the encoder and decoder structures. Determine the dimensionality of embedding layers and hidden states.

```
latent_dim = 300
embedding_dim=200

encoder_inputs = Input(shape=(max_text_len,))

enc_emb =  Embedding(x_voc, embedding_dim,trainable=True)(encoder_inputs)

encoder_lstm1 = LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0.4)
encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)

encoder_lstm2 = LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0.4)
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)

encoder_lstm3=LSTM(latent_dim, return_state=True, return_sequences=True,dropout=0.4,recurrent_dropout=0.4)
encoder_outputs, state_h, state_c= encoder_lstm3(encoder_output2)

decoder_inputs = Input(shape=(None,))

dec_emb_layer = Embedding(y_voc, embedding_dim,trainable=True)
dec_emb = dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True,dropout=0.4,recurrent_dropout=0.2)
decoder_outputs,decoder_fwd_state, decoder_back_state = decoder_lstm(dec_emb,initial_state=[state_h, state_c])
```

Fig 4.3.1 (a) Seq2seq model configuration

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 100)]	0	[]
embedding (Embedding)	(None, 100, 200)	7200	['input_1[0][0]']
lstm (LSTM)	[(None, 100, 300), (None, 300), (None, 300)]	601200	['embedding[0][0]']
input_2 (InputLayer)	[(None, None)]	0	[]
lstm_1 (LSTM)	[(None, 100, 300), (None, 300), (None, 300)]	721200	['lstm[0][0]']
embedding_1 (Embedding)	(None, None, 200)	2600	['input_2[0][0]']
lstm_2 (LSTM)	[(None, 100, 300), (None, 300), (None, 300)]	721200	['lstm_1[0][0]']
lstm_3 (LSTM)	[(None, None, 300), (None, 300), (None, 300)]	601200	['embedding_1[0][0]', 'lstm_2[0][1]', 'lstm_2[0][2]']

Fig. 4.3.1 (b) Model

4.4 Model Training

Train the Seq2Seq model using the training set. Monitor training progress, including loss metrics and convergence. Experiment with different hyper-parameters, such as learning rates and batch sizes, to optimize performance.

```
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy')
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1,patience=2)

history=model.fit([x_tr,y_tr[:,:-1]], y_tr.reshape(y_tr.shape[0],y_tr.shape[1], 1)[:,1:] ,epochs=10
```

Fig. 4.4 (a) Model training

```
Epoch 1/10
1/1 [==============================] - 14s 14s/step - loss: 2.5771 - val_loss: 2.2481
Epoch 2/10
1/1 [==============================] - 5s 5s/step - loss: 2.2515 - val_loss: 1.4555
Epoch 3/10
1/1 [==============================] - 5s 5s/step - loss: 1.4713 - val_loss: 0.6535
Epoch 4/10
1/1 [==============================] - 5s 5s/step - loss: 0.6811 - val_loss: 0.6995
Epoch 5/10
1/1 [==============================] - 5s 5s/step - loss: 0.7195 - val_loss: 0.6281
Epoch 6/10
1/1 [==============================] - 5s 5s/step - loss: 0.6490 - val_loss: 0.6227
Epoch 7/10
1/1 [==============================] - 5s 5s/step - loss: 0.6414 - val_loss: 0.6172
Epoch 8/10
1/1 [==============================] - 5s 5s/step - loss: 0.6345 - val_loss: 0.6126
Epoch 9/10
1/1 [==============================] - 5s 5s/step - loss: 0.6296 - val_loss: 0.6075
Epoch 10/10
1/1 [==============================] - 5s 5s/step - loss: 0.6239 - val_loss: 0.6038
```

Fig. 4.4 (b) Epochs

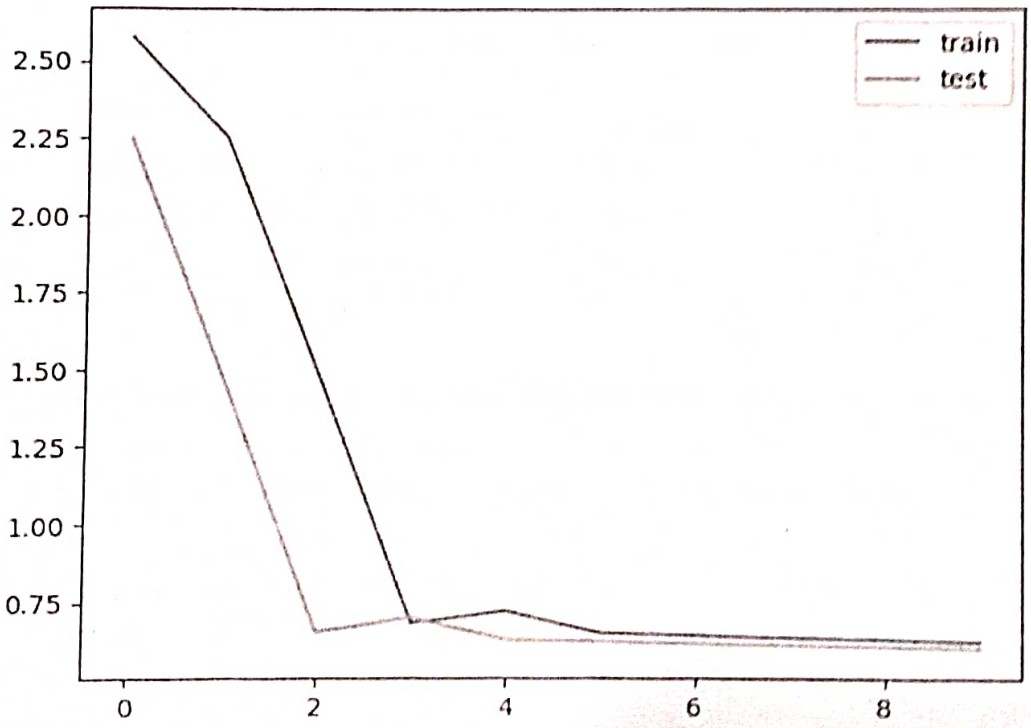

Fig 4.4 (c) Training loss vs. Validation loss over time

4.5 Evaluation

Choose appropriate evaluation metrics for summarization quality. ROUGE, which stands for Recall-Oriented Understudy for Gisting Evaluation, is a set of metrics used to evaluate the quality of automatic summaries by comparing them to reference or human-generated summaries. ROUGE focuses on measuring the overlap of n-grams (contiguous sequences of n items, usually words) between the generated summary and the reference summary. It's widely used in natural language processing tasks, including text summarization.

ROUGE-L focuses on the longest common subsequence (LCS) between the generated summary and the reference summary. It takes into account the length of the common subsequence, providing a measure of content overlap.

In the context of ROUGE metrics, precision, recall, and F1 score are calculated based on the counts of certain elements in the system-generated summary and the reference summary.

Table 4.1 ROUGE SCORE

	Precision	Recall	F1 score
ROUGE-1	0.45	0.56	0.52
ROUGE-2	0.35	0.48	0.41
ROUGE-L	0.51	0.64	0.58

a) Precision measures the proportion of n-grams in the system-generated summary that also appear in the reference summary. It is calculated as the number of overlapping n-grams divided by the total number of n-grams in the system-generated summary.

b) Recall measures the proportion of n-grams in the reference summary that are also present in the system-generated summary. It is calculated as the number of overlapping n-grams divided by the total number of n-grams in the reference summary.

c) F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall, giving an overall measure of the effectiveness of the system-generated summary compared to the reference summary.

Chapter 5: APPLICATION AND LIMITATION

5.1 Applications

Text summarization using Seq2Seq models has found applications across various domains. Here are some notable applications:

a) *News Summarization:*

Automatically generating concise summaries of news articles helps readers quickly grasp the main points without reading the entire article.

b) *Research Paper Summarization:*

Summarizing lengthy research papers facilitates quick comprehension of key findings, methodologies, and conclusions.

c) *Social Media Content Summarization:*

Generating summaries of lengthy posts or threads on social media platforms helps users quickly understand and engage with content.

d) *Legal Document Summarization:*

Summarizing legal documents helps legal professionals quickly extract key details, saving time and aiding in decision-making.

e) *Healthcare Record Summarization:*

Summarizing patient records or medical literature allows healthcare professionals to extract critical information efficiently.

5.2 Challenges we faced

When implementing text summarization using Seq2Seq models, several challenges and problems were encountered throughout the development. Addressing these issues is crucial for the system's effectiveness and user satisfaction. Here are some common problems faced in text summarization:

a) *Abstractive Summarization Ambiguity:*

Abstractive summarization introduces the challenge of dealing with language ambiguity. The model may generate summaries that deviate from the source text's intended meaning. Developing techniques to enhance coherence and accuracy is vital.

b) *Data Quality and Diversity:*

The effectiveness of Seq2Seq models heavily depends on the quality and diversity of the training data. Inadequate or biased datasets can result in models that generalize poorly to different domains or topics.

c) *Evaluation Metrics Limitations:*

Common evaluation metrics like ROUGE may not fully capture the quality of generated summaries. Designing or using more sophisticated metrics that align with human judgment is an ongoing challenge in the field.

d) *Scalability Issues:*

As the system scales to larger datasets or more complex Seq2Seq architectures, issues related to computational efficiency and memory constraints may arise. Ensuring scalability without compromising performance is a persistent challenge.

e) *User Subjectivity:*

Users may have different expectations regarding what constitutes a "good" summary. Balancing the diversity of user preferences while maintaining a standardized summarization approach poses a challenge.

5.3 Limitations

While text summarization using Seq2Seq models has shown promising results, there are several limitations. Understanding these limitations is crucial for ensuring the appropriate application and interpretation of summarization systems.

a) *Lack of Understanding:*

Seq2Seq models may not fully comprehend the nuances, context, or semantics of the input text. The generation of abstractive summaries relies on learned patterns but may lack a deep understanding of the content.

b) *Handling Rare or Out-of-Vocabulary Words:*

Seq2Seq models trained on a limited vocabulary may struggle with rare or out-of-vocabulary words. This limitation can impact the model's ability to summarize texts containing specialized terminology.

c) *Overemphasis on Training Data Distribution:*

Seq2Seq models are sensitive to the distribution of the training data. If the training data does not adequately cover diverse topics or document structures, the model's generalization to unseen data may be compromised.

d) *Loss of Information:*

During summarization, Seq2Seq models may prioritize certain information while neglecting other relevant details. This trade-off between informative-ness and conciseness can lead to the loss of important content.

e) *Challenges in Handling Diverse Writing Styles:*

Variations in writing styles, including colloquial language, formal prose, or domain-specific jargon, can pose challenges for Seq2Seq models in generating coherent and stylistically appropriate summaries.

Chapter 6: CONCLUSION

The development and exploration of our text summarization system using Seq2Seq models have unveiled both promising capabilities and notable challenges. Through a systematic approach, we have laid the foundation for a robust and adaptable system that holds potential across various applications.

The Seq2Seq architecture, with its encoder-decoder structure, serves as the backbone of our summarization model. As we delved into the implementation, we navigated the intricacies of data pre-processing, model configuration, and hyper-parameter tuning. The training procedure unfolded, with a keen eye on addressing challenges such as document length, abstractive summarization nuances, and the impact of diverse writing styles.

The evaluation phase, employing metrics like ROUGE, provided insights into the system's performance. We acknowledged the limitations related to handling long documents, potential biases, and the inherent difficulty in measuring abstractive summarization quality.

Addressing these challenges, we integrated external libraries for natural language processing, considered user interface design, and contemplated scalability considerations. The system, designed with scalability in mind, opens avenues for future enhancements and adaptation to evolving requirements.

In conclusion, our text summarization project stands as a testament to the dynamic landscape of natural language processing. While we celebrate achievements in abstractive summarization and transfer learning integration, we recognize the need for ongoing research to overcome challenges and refine the system's capabilities. The journey from data collection to system integration has been a valuable learning experience, contributing to the broader discourse on effective text summarization in the era of advanced deep learning models. As we look forward, we remain committed to refining and extending our system to meet the demands of diverse domains and user expectations, making meaningful strides in the realm of automated text summarization.

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