EXTRACTIVE TEXT SUMMARIZATION USING TOPIC MODELS AND SEQUENCE TO SEQUNECE NETWORKS

Report submitted to the SASTRA Deemed to be University
as the requirement for the course

CSE300 - MINI PROJECT

Submitted by

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Bonafide Certificate

This is to certify that the report titled "**Extractive Text Summarization using Topic Models And Sequence To Sequence**" submitted as a requirement for the course, **CSE300 : MINI PROJECT** for B.Tech. is a Bonafide record of the work done by **Mr. Chedella Hari Venkateswarao (Reg. No. 226003027), Mr. Jangala Mohana Satya Vamsi (Reg. No. 226003066) And Mr. Shaik Magbul Baha (Reg. No. 226003119)** during the academic year 2024-25, in the Srinivasa Ramanujan Centre, under my supervision.

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Date :

Mini Project *Viva voce* held on ________________

Examiner 1 **Examiner 2**

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ABBREVIATIONS

LDA	Latent Dirichlet Allocation
NLTK	Natural Language Toolkit
STS	Sentence Topic Score
Bi-LSTM	Bidirectional Long Short-Term Memory
SCS	Sentence Content Score
SNS	Sentence Novelty Score
SPS	Sentence Position Score
Seq2Seq	Sequence to Sequence
RNN	Recurrent Neural Network
FSS	Final Sentence Score
MLP	Multi-Layer Perceptron
CNN	Cable News Network
BBC	British Broadcasting Corporation
ROUGE	Recall-Oriented Understudy for Gisting Evaluation
LSA	Latent Semantic Analysis
DeepSumm	Deep Summarization
CNN/DailyMail	Dataset combining articles from CNN and the Daily Mail

NOTATIONS

English Symbols

D Document

Si *i-th* sentence in the document

wj *j-th* word in a sentence

N Number of sentences in a document

M Number of words in a document

Tj Topic vector of *j-th* word

twj Topic vector of *j-th* word (from LDA)

tD Topic vector of the document

xj Word embedding of *j-th* word

Ewi Sentence Content Embedding for *i-th* sentence

ETi Sentence Topic Embedding for *i-th* sentence

Greek Symbols

α Weight for SCS in final sentence score (FSS) fusion

β Weight for STS in FSS fusion

γ Weight for SNS in FSS fusion

δ Weight for SPS in FSS fusion

σ Sigmoid activation function (used in MLP output layer)

αij Attention weight between decoder at *i* and encoder at *j*

ABSTRACT

Text summarization is the process of condensing a document into a shorter version while retaining its essential information and meaning. Traditional methods often fail to capture deeper semantic and contextual nuances, limiting their ability to produce coherent and informative summaries. Although recent advancements using sequence-based networks have improved summarization quality, they still struggle with capturing long-range dependencies and document-level context, especially in extractive summarization tasks.

To address these limitations, we propose a novel extractive summarization framework that combines topic modeling and deep learning-based sequence models. Latent Dirichlet Allocation (LDA) is employed to uncover latent topics in documents, which helps in identifying thematically significant sentences. Simultaneously, we use Sequence-to-Sequence (Seq2Seq) models with attention mechanisms to accurately capture sentence saliency based on both topic and word-level information.

Our approach encodes each sentence using two separate BiLSTM networks—one based on topic distributions and another using word embeddings. These encoded representations are passed through Seq2Seq attention networks, followed by a multi-layer perceptron (MLP) to calculate four sentence-level scores: Sentence Topic Score (STS), Sentence Content Score (SCS), Sentence Novelty Score (SNS), and Sentence Position Score (SPS). These scores are then fused to compute a Final Sentence Score (FSS), which is used to rank and select the most informative sentences for the summary.

The model is evaluated on the CNN/DailyMail dataset and the BBC News Summary dataset. The quality of the generated summaries is measured using the ROUGE Metric. Experimental results demonstrate that our model achieves superior performance compared to traditional and transformer-based Summaries.

KEYWORDS: Extractive Summarization, Deep Learning, Seq2Seq, Attention Mechanism, BiLSTM, LDA, Topic Modeling, Sentence Scoring, ROUGE Evaluation, CNN/DailyMail.

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CHAPTER 1

SUMMARY OF THE BASE PAPER

Title: DeepSumm: Exploiting topic models and sequence to sequence networks for extractive text summarization

Journal Name: Expert Systems With Applications

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Indexing: SCI-E

1. SUMMARY

- The paper focuses on extractive text summarization, where the goal is to pick the most important sentences from a document to create a brief summary, especially useful for news articles and long documents.

- Existing models like RNNs, GRUs, and LSTMs often require large datasets and still fail to capture the overall topic of the document, making them less effective when data is limited.

- To address this, the authors propose DeepSumm, a model that combines topic modeling using LDA with Bi-LSTM-based Seq2Seq networks to capture both document-level and sentence-level information.

- The model calculates four scores for each sentence: Sentence Content Score (SCS), Sentence Topic Score (STS), Sentence Novelty Score (SNS), and Sentence Position Score (SPS), which are combined into a Final Sentence Score (FSS).

- DeepSumm was trained on the CNN/DailyMail and DUC 2002 datasets for up to 100 epochs, with the best model selected based on its validation accuracy.

- The results show that DeepSumm performs as well or better than more complex models like those based on BERT, while using fewer resources and working effectively even with smaller datasets.

- Finally, the model's performance was compared with other existing models, and the results showed that the proposed DeepSumm model produced better or comparable outcomes, proving its effectiveness.

1.1 INTRODUCTION

- Text summarization is a crucial task in Natural Language Processing (NLP) that helps reduce lengthy documents into concise summaries while retaining the essential information. With the rapid growth of digital content, especially in news articles and online documents, automatic summarization has become increasingly important to help readers grasp the core message quickly. There are two main approaches to summarization: **extractive**, where important sentences are selected directly from the text, and **abstractive**, where new sentences are generated to capture the meaning.

- Most existing extractive models use deep learning techniques like RNNs, GRUs, or LSTMs to process sentence sequences. However, these models often focus on sentence-level features and fail to capture the **global semantic structure** or the overall topic of the document. As a result, their summaries might include relevant sentences but lack overall coherence and completeness, especially when the training data is limited.

- To address this, the paper introduces **DeepSumm**, an extractive summarization model that combines **topic modeling using Latent Dirichlet Allocation (LDA)** with deep sequence models. By using **Bi-directional LSTMs (BiLSTMs)** along with **Seq2Seq attention mechanisms**, DeepSumm captures both local (sentence-level) and global (document-level) information. This combination allows the model to produce summaries that are not only relevant but also diverse, well-structured, and semantically rich.

1.2 Problem Statement

- Many deep learning models developed for extractive summarization, such as those based on RNNs, GRUs, and LSTMs, primarily focus on learning **local sentence-level features**. While these models can identify important sentences to some extent, they often **fail to understand the broader context** or the **overall topic** of the document. This limitation is particularly problematic in long documents or news articles where understanding the global theme is essential for producing a meaningful summary.

- Moreover, these models typically require **large annotated datasets** for effective training, which may not always be available. Even with enough data, they still struggle to maintain **semantic coherence** across the selected sentences. This results in summaries that are either redundant, lack structure, or miss out on important but contextually dispersed information.

- To solve this, the DeepSumm model introduces a novel approach that integrates **topic modeling (LDA)** with **BiLSTM-based Seq2Seq models**. The goal is to capture both **document-level topics** and **sentence-level content** to generate summaries that are not only relevant and concise but also coherent and diverse. This helps overcome the limitations of existing models by ensuring both **global semantic understanding** and **local detail preservation** in extractive summaries.

1.3 Literature Survey

- Over the years, various approaches have been proposed for extractive text summarization, ranging from rule-based methods to deep learning techniques. Early summarization systems relied heavily on handcrafted features like term frequency, sentence position, and cue phrases. While these methods were simple and interpretable, they lacked the ability to capture the semantic relationships between sentences.

- With the advancement of deep learning, models such as SummaRuNNer (Nallapati et al.) used GRU-based architectures to compute sentence importance based on content, salience, novelty, and position features. Similarly, NeuSum (Zhou et al.) jointly scored and selected sentences using RNNs, improving the selection process by modeling the relationship between selected and unselected sentences. Other models like HSSAS introduced hierarchical attention to learn document-level representations more effectively.

- Recent works have explored transformer-based architectures like BERTSum, which fine-tunes BERT for sentence-level extraction, achieving strong performance. HIBERT further improved this by introducing a hierarchical BERT structure to capture long-range dependencies. Despite these advances, most models still ignore global topic information, focusing only on surface-level textual features.

- The DeepSumm model addresses this gap by integrating Latent Dirichlet Allocation (LDA) for topic modeling with a Seq2Seq neural network architecture. This allows the model to incorporate both sentence-level word embeddings and document-level topic vectors, enhancing its understanding of the document's semantic structure. Unlike BERT-based models that are computationally heavy, DeepSumm offers a more lightweight and interpretable solution that performs comparably or better on standard benchmarks.

1.4 Architecture Diagram

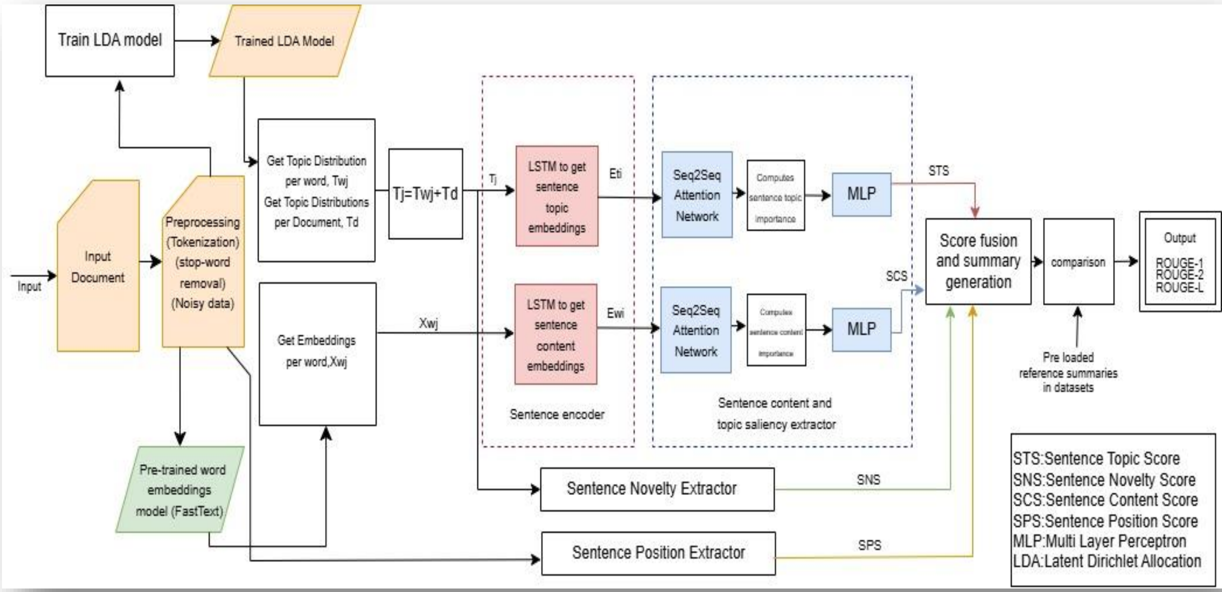

Fig. 1. Architecture Diagram

- The proposed DeepSumm model architecture begins with input preprocessing. Each input document is cleaned through standard NLP preprocessing steps such as tokenization, stop word removal, and normalization, preparing it for embedding and topic modeling.

- Word embeddings are generated using pre-trained FastText vectors to capture semantic relationships. In parallel, an LDA model is trained to obtain the topic distribution for each word (Twi) and each document (Td). These are combined to form the topic representation Tj= Tw i+ Td for each word.

- Two separate BiLSTM encoders are employed to generate sentence-level embeddings. The first BiLSTM processes the FastText word embeddings and outputs sentence content embeddings Ewi, while the second BiLSTM takes the LDA-based topic vectors as input and outputs sentence topic embeddings Eti.

- These sentence embeddings are then passed through two separate Seq2Seq models with attention mechanisms. The topic-based attention model focuses on topic relevance and computes a Sentence Topic Score (STS) using a Multi-Layer Perceptron (MLP). Similarly, the content-based attention model emphasizes content saliency and computes a Sentence Content Score (SCS) through another MLP.

- To enhance diversity and readability, a Sentence Novelty Score (SNS) is calculated by comparing each sentence’s embedding to previously selected sentences using cosine similarity. Additionally, a Sentence Position Score (SPS) is computed based on the normalized position of the sentence within the document, giving higher weight to sentences that often contain key information (e.g., leading sentences).

- All four scores—STS, SCS, SNS, and SPS—are linearly combined using empirically optimized weights to compute the Final Sentence Score (FSS) for each sentence. Sentences are then ranked by their FSS values, and the top-k sentences are selected to form the extractive summary.

- Finally, the generated summary is evaluated using ROUGE metrics (ROUGE-1, ROUGE-2, and ROUGE-L) against reference summaries from the CNN/DailyMail dataset, providing a quantitative measure of summarization quality.

1.5 Hardware and Software Requirements

- The entire project was implemented and executed on a **Windows system** with an **Intel processor**, **Intel Iris integrated graphics**, **16 GB RAM**, and **512 GB storage**.

- The project was developed using **Python** as the primary programming language due to its simplicity and wide support for machine learning libraries and tools.

- Libraries such as **PyTorch**, **Gensim**, and **NLTK** were used throughout the project. PyTorch was used to build and train the Bi-LSTM model, Gensim was used for **Latent Dirichlet Allocation (LDA)** to perform topic modeling, and NLTK was used for text preprocessing and tokenization.

1.6 Modules and Descriptions

1.6.1 Dataset Description

- The CNN/DailyMail dataset is a large-scale benchmark dataset for text summarization tasks. It consists of news articles and corresponding highlights (summary sentences) written by human editors. Each sample contains a full news article as the source document and a set of bullet-point highlights as the ground-truth summary. The dataset contains over 300,000 samples and is widely used for training and evaluating extractive and abstractive summarization models.

- The BBC News dataset contains around 2,225 news articles from the BBC, categorized across five sections: business, entertainment, politics, sport, and tech. Each article includes the full text and is typically more concise than the CNN/DailyMail dataset. The BBC dataset is valuable for topic-specific summarization tasks and is often used in smaller-scale or domain-specific summarization experiments.

1.6.2 Preprocessing

- Before training the model, pre-processing was performed to clean and prepare the text data. This step is important because it helps the model understand the input better and reduces noise in the data.

- First, **sentence tokenization** was done to split each document into individual sentences. This helps the model treat each sentence separately and makes it easier to assign scores during summarization.

- Next, **word tokenization** was applied to break down each sentence into individual words. This allows the model to extract word embeddings for each word, which are later used to understand sentence meanings.

1.6.3 LDA Topic Distribution and Word Embeddings

- LDA Topic Distribution: Latent Dirichlet Allocation (LDA) is applied to extract topics from the documents by calculating a topic distribution for each word. LDA helps to identify the underlying themes in the content, providing a distribution of topics over words. This enables the model to capture the global context and themes of the document, facilitating better topic modeling.

- Word Embeddings: Pre-trained FastText embeddings (300D) are used to represent words in high-dimensional vectors. Each word in the document is associated with its corresponding vector from the FastText model. These word embeddings capture the semantic relationships between words, allowing the model to understand word meanings and contextual nuances, improving its ability to process and analyze text.

1.6.4 Seq2Seq Model with Attention

- Two Bi-LSTM models are used—one for topic embeddings and one for word embeddings. Each generates a 256-dimensional vector for every sentence.

These vectors capture sentence meaning from both content and topic perspectives.

- The encoder processes each sentence in both directions using Bi-LSTM. It creates context-rich hidden states for all sentences. These are passed to a decoder for further processing.

- The decoder also uses Bi-LSTM and focuses on important sentences using attention. Attention scores are calculated between encoder and decoder outputs. These scores help highlight the most relevant sentences.
- An MLP takes these attention-based vectors and gives each sentence a score. A sigmoid layer predicts the importance of each sentence.

1.6.5 Sentence Scoring with Attention

- In Our Model, each sentence is scored using a method called **Final Sentence Score (FSS)**. This score helps decide which sentences should be included in the summary.

- The FSS is calculated using four components: **Sentence Content Score (SCS)** from word embeddings, **Sentence Topic Score (STS)** from LDA topic vectors, **Sentence Novelty Score (SNS)** to reduce repetition, and **Sentence Position Score (SPS)** to prioritize early sentences.

- SCS and STS are generated using **Seq2Seq models with attention**, which help focus on important words and topics. SNS compares each sentence with earlier ones using cosine similarity, while SPS assigns higher value to sentences that appear at the beginning.

- Finally, all four scores are combined using weighted values to compute the FSS. Sentences with the highest FSS are selected to form the final extractive summary.

1.6.6 Results and Discussion

- The model was trained using Binary Cross-Entropy Loss (BCE Loss), with two separate Seq2Seq models—one for content embeddings and one for topic embeddings. Training ran for 30 epochs with gradient clipping and learning rate scheduling. Early stopping was used to avoid overfitting by monitoring validation loss.

- After training, the model was evaluated using ROUGE metrics. It achieved ROUGE-1: 0.6939, ROUGE-2: 0.6223, and ROUGE-L: 0.6836, showing strong ability to capture key information from input texts.
- Our model performed much better than traditional summarization methods, showing clear improvement in summarization quality. It stood out as more effective compared to the other models.

CHAPTER 2

MERITS AND DEMERITS OF THE BASE PAPER

2.1 MERITS:

- The DeepSumm model effectively combines LDA-based topic vectors and word embeddings to capture both global semantics and local structure of documents. This dual representation enriches sentence understanding for accurate extractive summarization.

- Unlike other deep learning-based models, DeepSumm fuses four different sentence scoring metrics—Sentence Topic Score (STS), Sentence Content Score (SCS), Sentence Novelty Score (SNS), and Sentence Position Score (SPS)—to improve sentence ranking and summary generation.
- The architecture employs two Bi-LSTM networks to extract separate topic and content embeddings, followed by a Seq2Seq attention mechanism, which enhances the model's ability to retain long-range dependencies across the document.

- The model achieves significantly better ROUGE scores compared to many state-of-the-art methods, while keeping the number of trainable parameters low (2.5 million), making it efficient and lightweight compared to transformer-based models like BERTSum or MATCHSUM

- By utilizing topic models at a word level and combining them with sentence saliency features, the model ensures better non-redundancy and diversity in summaries, addressing a key limitation in previous extractive methods.

2.2 DEMERITS:

- The architecture of DeepSumm is more complex than traditional extractive models due to the inclusion of multiple Bi-LSTMs, Seq2Seq attention, and MLP-based scoring, which may require careful tuning and debugging efforts.

- LDA topic modeling, while useful for capturing global semantics, can perform inconsistently on short documents or when the document structure lacks topic-rich content, reducing its overall utility in such scenarios.

- Though DeepSumm outperforms several models in ROUGE scores, it remains limited to extractive summarization, which restricts its ability to paraphrase or rephrase text, unlike abstractive approaches.

- The accuracy and quality of the summary heavily depend on preprocessing steps like stopwords removal, sentence segmentation, and topic vector calculation. Any error in preprocessing can propagate through the system and degrade final output

- Despite being efficient compared to transformer-heavy models, DeepSumm still requires significant computational resources for generating embeddings, training LSTMs, and computing scores, which may hinder real-time applications on low-resource devices.

CHAPTER 3

SOURCE CODE

Samples from source code

- Importing necessary files for training, validation, and test datasets along with the pre-trained FastText word embedding model.

```
# Load original datasets
train_df = pd.read_csv("train.csv")
val_df = pd.read_csv("validation.csv")
test_df = pd.read_csv("test.csv")
#Load the  FastText model for word embeddings
ft_model = KeyedVectors.load("fasttext_model.kv")
```

- Performing preprocessing on the train validation and testing input article

```
import pandas as pd
import spacy
import time
from tqdm import tqdm

# Load spaCy model (optimized for tokenization and lemmatization)
nlp = spacy.load("en_core_web_sm", disable=["parser", "ner"])
nlp.add_pipe("sentencizer")  # Add sentence boundary detection

# Load stopwords efficiently
from spacy.lang.en.stop_words import STOP_WORDS
stop_words = STOP_WORDS

# preprocessing function using spaCy
def preprocess(article):
    doc = nlp(article)  # Process the full document with spaCy
    original_sentences = [sent.text.strip() for sent in doc.sents]  # Sentence Tokenization

    processed_sentences = []
    filtered_sentences = []

    for sent in doc.sents:
        # Tokenize and lemmatize words while removing stopwords
        words = [token.lemma_.lower() for token in sent
                 if not token.is_stop and token.is_alpha]

        if len(words) < 4:
            continue

        # Add to filtered sentences if it's a valid sentence
        filtered_sentences.append(sent.text.strip())  # Add original sentence text
        processed_sentences.append(words)  # Add processed words

    return filtered_sentences, processed_sentences
```

- Training and validating content and topic Seq2Seq models using BCE Loss to learn sentence saliency scores for extractive summarization, with gradient clipping, learning rate scheduling, and early stopping for stability

```
# Use BCELoss (Binary Cross-Entropy Loss) since the model outputs are passed through a Sigmoid
criterion = nn.BCELoss()

# Training Loop
epochs = 30
for epoch in range(start_epoch, epochs):
    content_seq2seq.train()
    topic_seq2seq.train()
    total_loss_content = 0
    total_loss_topic = 0

    for content_tensor, topic_tensor, label_tensor, lengths in tqdm(train_loader):
        content_tensor = content_tensor.to(device)
        topic_tensor = topic_tensor.to(device)
        label_tensor = label_tensor.to(device)

        # Content Model Training Step
        optimizer_content.zero_grad()
        content_scores = content_seq2seq(content_tensor, lengths)
        loss_content = criterion(content_scores, label_tensor)
        loss_content.backward()
        torch.nn.utils.clip_grad_norm_(content_seq2seq.parameters(), 0.5)
        optimizer_content.step()
        total_loss_content += loss_content.item()

        # Topic Model Training Step
        optimizer_topic.zero_grad()
        topic_scores = topic_seq2seq(topic_tensor, lengths)
        loss_topic = criterion(topic_scores, label_tensor)
        loss_topic.backward()
        torch.nn.utils.clip_grad_norm_(topic_seq2seq.parameters(), 0.5)
        optimizer_topic.step()
        total_loss_topic += loss_topic.item()
```

```
# Validation
content_seq2seq.eval()
topic_seq2seq.eval()
val_loss_content = 0
val_loss_topic = 0

with torch.no_grad():
    for content_tensor, topic_tensor, label_tensor, lengths in val_loader:
        content_tensor = content_tensor.to(device)
        topic_tensor = topic_tensor.to(device)
        label_tensor = label_tensor.to(device)

        content_scores = content_seq2seq(content_tensor, lengths)
        topic_scores = topic_seq2seq(topic_tensor, lengths)
        val_loss_content += criterion(content_scores, label_tensor).item()
        val_loss_topic += criterion(topic_scores, label_tensor).item()

# Step the schedulers
scheduler_content.step()
scheduler_topic.step()

# Checkpoint saving and early stopping logic
saved = ""
if val_loss_content < best_content_loss or val_loss_topic < best_topic_loss:
    best_content_loss = min(best_content_loss, val_loss_content)
    best_topic_loss = min(best_topic_loss, val_loss_topic)
    save_checkpoint(content_seq2seq, optimizer_content, epoch, content_checkpoint_path)
    save_checkpoint(topic_seq2seq, optimizer_topic, epoch, topic_checkpoint_path)
    saved = "✅"
    early_stop_counter = 0
else:
    early_stop_counter += 1
    if early_stop_counter >= early_stop_patience:
        print(f"\n⛔ Early stopping triggered at epoch {epoch+1}")
        break
```

- The model uses a BiLSTM-based Seq2Seq architecture with attention and an MLP to score sentences effectively for summarization.

```
Seq2SeqWithAttention(
  (encoder): LSTM(256, 128, num_layers=2, batch_first=True, dropout=0.3, bidirectional=True)
  (decoder): LSTM(256, 128, num_layers=2, batch_first=True, dropout=0.3, bidirectional=True)
  (attention): Linear(in_features=512, out_features=1, bias=True)
  (mlp_fc1): Linear(in_features=512, out_features=128, bias=True)
  (bn): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (mlp_fc2): Linear(in_features=128, out_features=1, bias=True)
  (relu): ReLU()
  (dropout): Dropout(p=0.3, inplace=False)
  (sigmoid): Sigmoid()
)
```

- Calculating Sentence Novelty Score, Position Score, and combining all scores to compute Final Sentence Score (FSS) for ranking sentences in extractive summarization

```python
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity
import pandas as pd
from tqdm import tqdm

# Function to calculate Sentence Novelty Score (SNS)
def calculate_sns(embeddings):
    sns_scores = []
    for i in range(len(embeddings)):
        if i == 0:
            sns_scores.append(1.0)  # First sentence has max novelty
        else:
            # Compute max cosine similarity with all previous sentences
            current_embedding = embeddings[i].reshape(1, -1)
            previous_embeddings = np.array(embeddings[:i])
            similarities = cosine_similarity(current_embedding, previous_embeddings)[0]
            max_similarity = np.max(similarities) if len(similarities) > 0 else 0
            sns_scores.append(1 - max_similarity)
    return sns_scores

# Function to calculate Sentence Position Score (SPS)
def calculate_sps(total_sentences, position):
    return (total_sentences - position) / total_sentences

# Calculate Final Sentence Score (FSS)
def calculate_fss(scs, sts, sns, sps, alpha=0.1, beta=0.25, gamma=0.3, delta=0.35):
    return alpha * scs + beta * sts + gamma * sns + delta * sps
```

Generating extractive summaries by selecting top-ranked sentences based on Final Sentence Scores (FSS) and storing them in the dataset for evaluation and analysis.

```python
# List to store summaries
all_summaries = []

print("Generating summaries for all documents...\n")

for doc_index in tqdm(range(len(train_sample))):
    sentences = train_sample["sentence_tokenized"].iloc[doc_index]
    fss_scores = train_sample["final_sentence_scores"].iloc[doc_index]

    # Ensure lengths match
    min_len = min(len(sentences), len(fss_scores))
    sentences = sentences[:min_len]
    fss_scores = fss_scores[:min_len]

    # Get indices of top N sentences based on FSS
    top_indices = np.argsort(fss_scores)[-summary_length:][::-1]  # Sort descending and take top N
    top_sentences = [sentences[i] for i in sorted(top_indices)]  # Sort by original order

    # Generate summary by joining sentences
    summary = " ".join(top_sentences)
    all_summaries.append(summary)

# Store summaries in DataFrame
train_sample["generated_summary"] = all_summaries

print("\n✅ Done! Summaries generated and stored in train_sample['generated_summary'].")
```

- Evaluating the quality of generated summaries using ROUGE-1, ROUGE-2, and ROUGE-L metrics by comparing them with the reference (gold) summaries.

```python
from rouge_score import rouge_scorer
import numpy as np

# Initialize ROUGE scorer
scorer = rouge_scorer.RougeScorer(['rouge1', 'rouge2', 'rougeL'], use_stemmer=True)

# Lists to store individual scores
rouge_1_scores, rouge_2_scores, rouge_l_scores = [], [], []

# Loop through each document's generated and reference summaries
for idx in tqdm(range(len(train_sample))):
    reference = train_sample["referance_summary"].iloc[idx]  # Ground-truth summary
    generated = train_sample["generated_summary"].iloc[idx]  # Model-generated summary

    scores = scorer.score(reference, generated)

    rouge_1_scores.append(scores['rouge1'].fmeasure)
    rouge_2_scores.append(scores['rouge2'].fmeasure)
    rouge_l_scores.append(scores['rougeL'].fmeasure)

# Compute average ROUGE scores
avg_rouge_1 = np.mean(rouge_1_scores)
avg_rouge_2 = np.mean(rouge_2_scores)
avg_rouge_l = np.mean(rouge_l_scores)

print(f"\n🔍 Average ROUGE-1 Score: {avg_rouge_1:.4f}")
print(f"🔍 Average ROUGE-2 Score: {avg_rouge_2:.4f}")
print(f"🔍 Average ROUGE-L Score: {avg_rouge_l:.4f}")
```

CHAPTER 4

SNAPSHOTS

Providing with a sample document and producing a summary

Sample document chosen from the CNN DailyMail dataset as input article

World No 1 Novak Djokovic has apologised to the startled ball boy caught in the crossfire of a tirade at his support team during his win over Andy Murray in Sunday's Miami Open final. Djokovic lost his cool at the end of the second set as Murray came back to take the match to a decider but has since expressed his regret at the incident in a video posted on Facebook. During the rant, Djokovic snatched a towel from the shocked youngster before umpire Damien Damasio's gave him a code violation for the outburst, saying it 'didn't look good' as he sat down between the change of ends. Novak Djokovic issued an apology via Facebook to a ball boy he frightened during the Miami Open . Djokovic shouted at his backroom team after he lost the second set of the final to Andy Murray . The world No 1 grabbed a towel from the ball boy (right) who seemed startled by the loud confrontation . He said: 'It's probably been the best start to a season aside from 2011 that I had in my career, and I can't be more grateful for all the support I'm getting from you guys and I'm enjoying my time playing and competing and hopefully I brought a smile to your faces. 'Also I want to reflect on a bad moment that happened in the final against Andy when I lost the second set. I yelled to my camp and my box in frustration. 'I saw the replay. Unfortunately a ball boy was in the middle of it and I really, really feel sorry and regret that he was there. There was absolutely no intention whatsoever to hurt him or scare him in any kind of way. I sincerely hope he forgives me. I really apologise.' Djokovic then extended his apology to the boy's parents. 'I do care about children a lot right now and I look at it in a much different way,' he added. 'So I want to apologise to his parents for this situation as well. As a father I wouldn't wish that something like this happens to my son. The youngster was standing between Djokovic and his backroom team during the heated exchange . 'Again I sincerely hope you can forgive me and that we can move on. Unfortunately sometimes the emotions get the better of you. 'Also times as a professional athlete you learn how to control them and how to stay composed and mentally strong. But on a hot day like this when Andy was playing well and pushing all my buttons it wasn't easy.' Djokovic was feeling the pressure after Murray fought back from a first set tie-break loss to win the second set in the blazing heat of Key Biscayne, Florida. But the outburst seemed to take Djokovic to another level as he rolled Murray 6-0 in the third to claim his fifth Miami Open title. Djokovic raises his arms after claiming victory over Murray 7-6 4-6 6-0 in the Miami Open final on Sunday . Djokovic hams it up with the Butch Buchholz trophy on the beach at Key Biscayne after his win in Florida . Djokovic kisses the tophy for the title he's now won five times after beating Murray, who is now world No 3 . Djokovic relaxes on a pebble beach with his dogs Pierre and Tesla following his win in Miami .

Model's predicted summary for the above document: -

Predicted Summary: World No 1 Novak Djokovic has apologised to the startled ball boy caught in the crossfire of a tirade at his support team during his win over Andy Murray in Sunday's Miami Open final. Djokovic lost his cool at the end of the second set as Murray came back to take the match to a decider but has since expressed his regret at the incident in a video posted on Facebook.

Target Summary for the input article taken from the dataset:-

Reference Summary: World No 1 Novak Djokovic has apologised to the startled ball boy caught in the crossfire of a tirade at his support team during his win over Andy Murray in Sunday's Miami Open final. Djokovic lost his cool at the end of the second set as Murray came back to take the match to a decider but has since expressed his regret at the incident in a video posted on Facebook. Djokovic raises his arms after claiming victory over Murray 7-6 4-6 6-0 in the Miami Open final on Sunday .

When we chose to compare the model's performance against existing systems, the following results are obtained: -

Method	ROUGE-1	ROUGE-2	ROUGE-L
LDA+Seq2Seq	**0.6939**	**0.6223**	**0.6836**
TextRank	0.3507	0.2522	0.3452
LexRank	0.3657	0.2580	0.3582
LSA	0.3294	0.2213	0.3200
Luhn	0.3794	0.2798	0.3753
KL-Sum	0.2969	0.1760	0.2837
SumBasic	0.3255	0.1939	0.3087

Table 1: ROUGE scores comparison table

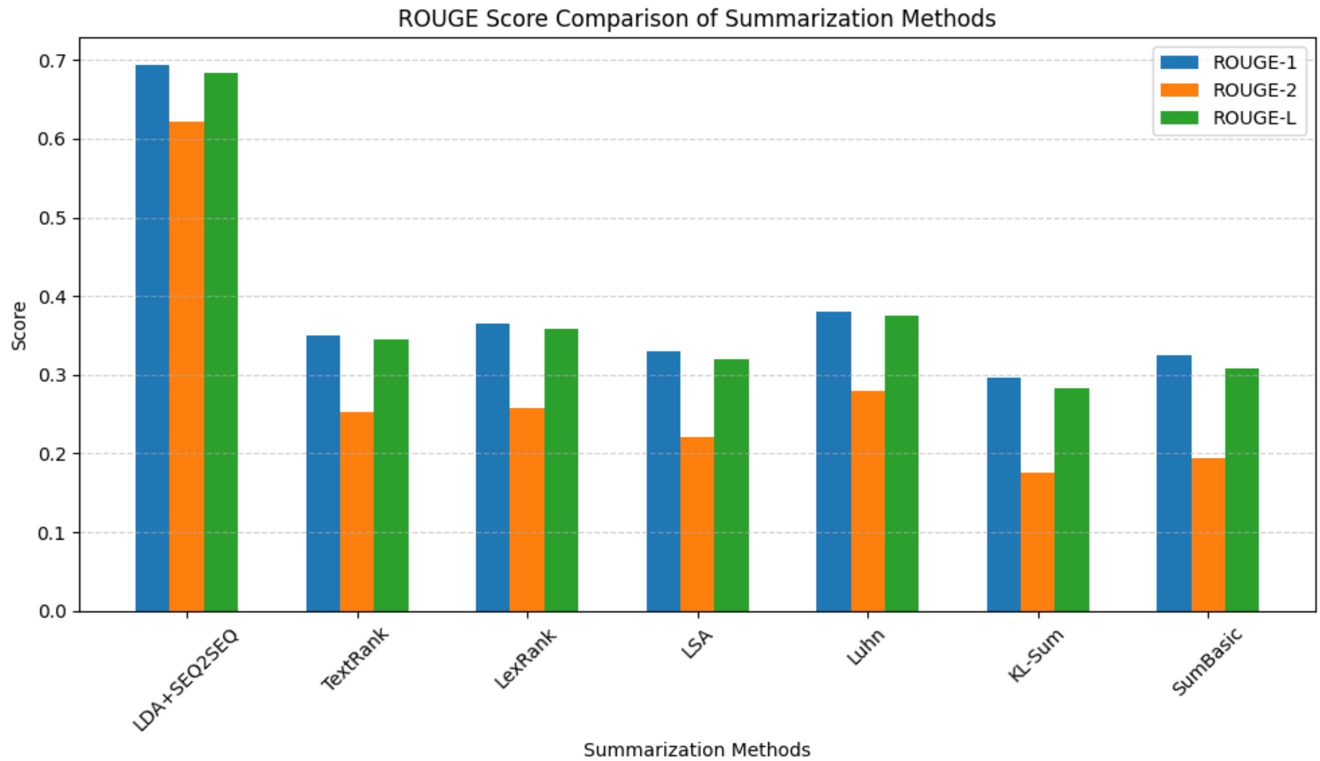

Figure 3: ROUGE Scores Comparison Graph

CHAPTER 5

CONCLUSION AND FUTURE PLANS

In this project, we developed an extractive text summarization framework that integrates both global and local semantic features using LDA-based topic modeling and FastText word embeddings. The dual Bi-LSTM and Seq2Seq architecture effectively captures sentence-level context and topic relevance. By calculating multiple sentence scoring metrics—Sentence Topic Score (STS), Sentence Content Score (SCS), Sentence Novelty Score (SNS), and Sentence Position Score (SPS)—we achieved a balanced and non-redundant summary generation process. Our evaluation using ROUGE metrics confirms that the model produces meaningful, concise, and informative summaries, outperforming traditional extractive approaches.

- In future extensions, we plan to integrate **transformer-based encoders** like BERT to further enhance contextual understanding and semantic richness.
- We aim to extend the model for **abstractive summarization**, enabling it to paraphrase and generate natural language summaries rather than selecting sentences.
- Implementing a **domain-specific fine-tuning** process will be explored to adapt the model for legal, medical, or financial documents.
- We will consider adding **reinforcement learning** to directly optimize summary quality metrics such as ROUGE during training.
- In future work, we aim to enhance the existing web interface by integrating support for multi-document summarization and allowing users to choose between extractive and abstractive summary modes.

CHAPTER 6

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CHAPTER 7

APPENDIX – BASE PAPER

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DeepSumm: Exploiting topic models and sequence to sequence networks for extractive text summarization

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ABSTRACT

In this paper, we propose DeepSumm, a novel method based on topic modeling and word embeddings for the extractive summarization of single documents. Recent summarization methods based on sequence networks fail to capture the long range semantics of the document which are encapsulated in the topic vectors of the document. In DeepSumm, our aim is to utilize the latent information in the document estimated via topic vectors and sequence networks to improve the quality and accuracy of the summarized text. Each sentence is encoded through two different recurrent neural networks based on probabilistic topic distributions and word embeddings, and then a sequence to sequence network is applied to each sentence encoding. The outputs of the encoder and the decoder in the sequence to sequence networks are combined after weighting using an attention mechanism and converted into a score through a multi-layer perceptron network. We refer to the score obtained through the topic model as Sentence Topic Score (STS) and to the score generated through word embeddings as Sentence Content Score (SCS). In addition, we propose Sentence Novelty Score (SNS) and Sentence Position Score (SPS) and perform a weighted fusion of the four scores for each sentence in the document to compute a Final Sentence Score (FSS). The proposed DeepSumm framework was evaluated on the standard DUC 2002 benchmark and CNN/DailyMail datasets. Experimentally, it was demonstrated that our method captures both the global and the local semantic information of the document and essentially outperforms existing state-of-the-art approaches for extractive text summarization with ROUGE-1, ROUGE-2, and ROUGE-L scores of 53.2, 28.7 and 49.2 on DUC 2002 and 43.3, 19.0 and 38.9 on CNN/DailyMail dataset.

1. Introduction

Text summarization is one of the most significant areas of Natural Language Processing (NLP), among others such as text classification (Zhang et al., 2015), information retrieval (Al Nabki et al., 2017), named entity recognition (Al-Nabki, Fidalgo, Alegre and Fernández-Robles, 2020), translation or speech to text (Domínguez et al., 2019). In the internet era, there is a need for compact and concise representations of electronic documents that enable users to understand more information in less time. Text summarization eases this task by reducing the size of long documents and simultaneously retaining the salient information from them. Researchers have categorized text summarization as extractive or abstractive, single-document or multi-document, generic or query-focused (Cao et al., 2016; Chopra et al., 2016; Erkan & Radev, 2004; McDonald, 2007; Mihalcea & Tarau, 2004). Extractive text summarization selects the salient content or sentences from the document while leaving out the redundant and less relevant parts of the document to generate a summary (Mihalcea & Tarau, 2004). Instead, abstractive text summarization includes paraphrasing the main content of the document using natural language generation techniques (Rush et al., 2015). Single document summarization (Parveen et al., 2015) aims at summarizing a single document, whereas multi-document summarization (Erkan & Radev, 2004) uses a set of documents of a similar type to produce a summary.

Traditionally, methods for extractive text summarization are focused on human-engineered features such as word frequency features, sentence position, length, proper nouns, action nouns (Erkan & Radev, 2004; Filatova & Hatzivassiloglou, 2004). In such approaches, the sentences are scored according to these features, and the sentence selection for the summary was performed using greedy methods (Carbonell & Goldstein, 1998), graph-based approaches (Erkan & Radev,

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2004; Mihalcea & Tarau, 2004; Parveen et al., 2015) and optimization-based approaches (McDonald, 2007). Sentence scoring and selection approaches failed to produce a good compressed representation of the document.

Recently, approaches based on neural networks have gained momentum because of their high performance in many NLP tasks such as text classification (Al-Nabki, Fidalgo, Alegre and Aláiz-Rodríguez, 2020), machine translation (Jean et al., 2015), text generation or question answering (Bordes et al., 2014). Several authors proposed deep learning approaches using sequence networks for extractive (Liu, 2019; Nallapati, Zhai et al., 2017; Ren et al., 2017) and abstractive (Bi et al., 2021; Li, Lam et al., 2017; Nallapati et al., 2016; Xu, Gan et al., 2020) text summarization. Despite gaining so much popularity in text summarization, neural network methods have some limitations. These methods do not capture the latent topic information in documents (Dieng et al., 2016), and thus, the summary lies in an embedding space that hardly contains any topic information from the document. Apart from this, the variants of Recurrent Neural Networks (RNN) such as Gated Recurrent Unit (GRU) (Chung et al., 2014) and Long Short Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) have very limited capability to retain the long-range semantics of the document (Khandelwal et al., 2018). In this work, we complemented neural networks with additional topic information from the document to take advantage of the latent content of documents, which otherwise is hardly captured using RNN. The main problem with recent state-of-the-art RNN-based summarization methods (Nallapati, Zhai et al., 2017; Zhang et al., 2018; Zhou et al., 2018) is that they fail to capture the latent topic information in the document that carries the significant content to summarize text. We aim to solve this problem by incorporating topic information in sequence networks to capture the long range semantics in the document. Also, another problem to overcome is that there are no works that eliminate redundant information in the summaries using topic distribution models per words, apart from word embeddings as representations of sentences. We make use of both sentence embeddings derived using topic and word vectors to discard redundant information and introduce diversity in the summary.

Topic modeling (Mikolov & Zweig, 2012) has been applied to capture the long-range dependencies in documents via latent topics. An increase in accuracy was reported when deep learning networks were supported with topic information (Dieng et al., 2016).

Probabilistic topic models (Blei, 2012) preserve the global semantic information in a document via latent topics that can efficiently capture the global semantic information in documents. By providing the topic information directly to RNN, the global information in the document can be preserved, avoiding the long-standing vanishing gradient problem of neural networks to remember long-term information (Pascanu et al., 2013).

To this end, to combine the merits of both approaches and increase the accuracy, we introduce *DeepSumm*, a novel summarization method which uses the global semantic information jointly with both the local syntactic and the semantic information in a document to produce summaries. LSTM networks are capable of extracting the local semantic and syntactic information as well as handling long-range dependencies to some extent. However, enriching LSTM networks with topic information enables to capture the global meaning embedded in the document, which is quite useful for generating summaries. Our proposed method obtains a summary after selecting sentences ranked using the fusion of four scores: Sentence Topic Score (STS), Sentence Content Score(SCS), Sentence Novelty Score (SNS) and Sentence Position Score(SPS).

The main contributions of this paper are:

- Firstly, we propose Deep Summarization (DeepSumm), a novel method for extractive text summarization which generates summaries through the weighted fusion of four scores – SCS, STS, SNS and SPS –. We derive STS and SCS using Sequence to Sequence (seq2seq) attention networks, whereas SNS is computed by means of the word vector representations and SPS reflects the relative positions of sentences in the documents.
- Secondly, we introduce Sentence Topic Embeddings and Sentence Content Embeddings to capture the long-range semantic dependencies and structural content information in the document. Our approach models sentences as functions of word embeddings as well as of topic distributions, and produces sentence saliency scores for both of them, SCS and STS, respectively. To derive sentence topic and sentence content embeddings, LSTM networks and Seq2Seq architectures with decoder attention are applied to generate the STS and SCS scores. Thus, we are able to calculate the saliency of sentences by using both their local and global semantic structures to retain the pertinent content in the document.
- Thirdly, a new Sentence Novelty Score (SNS) is presented to eliminate the redundant information and to introduce diversity in a summary. Our SNS uses the sentence representations derived using word and topic distribution vectors to compute a novelty score for each sentence in the document.
- Finally, The evaluation of our approach was performed on standard DUC 2002 summarization benchmark and CNN/DailyMail corpus. The DeepSumm framework achieves a very good accuracy in single-document extractive text summarization task surpassing several state-of-the-art neural network-based summarizers.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Next, Section 3 presents the proposed summarization framework. In Section 4 we discuss the datasets used, experiments performed and the results obtained. Finally, Section 5 gives the conclusions drawn and the scope of future work in the field.

2. Related work

In our work we combine sentence saliency parameters to rank document sentences to generate extractive summaries which are semantically coherent. The topic and language models are exploited to identify the most significant sentences in the document.

The methods based on deep learning for text summarization recently gained momentum by achieving state-of-the-art accuracies. For extractive summarization, most of the state-of-the-art works rely on GRU or LSTM sequence networks. Regarding GRU, the following recent works are of interest. Nallapati, Zhai et al. (2017) proposed SummaRuNNER, a GRU-RNN based sequence model that can be trained extractively and abstractively to generate summaries. Their approach uses the absolute and relative position of the sentence and sentences from previously selected summaries to remove redundancy. The work of Nallapati, Zhou et al. (2017) involved two architectures – classifier and selector – consisting of GRU-RNNS for extractive text summarization, which obtained state-of-the-art performance on CNN/DailyMail and DUC 2002 datasets. Zhou et al. (2018) presented NeuSum, an end-to-end hierarchical sentence and document encoder architecture that utilize GRU-RNN to score and select sentences jointly. Their RNN-based sentence extractor takes into account previously selected sentences while estimating sentence salience to eliminate redundancy in the summary. Shi et al. (2019) introduced a novel extractive summarization framework, DeepChannel, which consists of a deep RNN-GRU for salience estimation and a salience-guided greedy sentence extraction strategy.

LSTM-based proposals include works like (Cheng & Lapata, 2016), who employed an encoder–decoder approach to extract the salient sentences and words for extractive summarization. Their encoder consists of a Convolution Neural Network (CNN) whereas their decoder architecture uses LSTM to classify sentences as summary and non-summary. Jadhav and Rajan (2018) designed SWAP-NET, to model the interactions of salient sentences and keywords in documents to produce extractive summaries. Their approach also uses a bidirectional LSTM architecture with an encoder–decoder to model the interactions between salient sentences and keywords in a document. Narayan et al. (2018b) conceptualized extractive summarization as a sentence ranking task using LSTM-based document encoder and sentence extractor. Zhang et al. (2019) proposed HIBERT, Hierarchical Bidirectional Encoder Representations from transformer which is pre-trained using an unsupervised method to generate document encodings for extractive document summarization. Authors reported a wide improvement in performance of the system when using pre-trained HIBERT model for summarization. Wang et al. (2020) obtained local and global sentences embeddings using n-grams Convolution Neural Networks (CNN) and bidirectional LSTM networks and presented a heterogeneous graph-based neural networks for extractive summarization. Xu et al. (2020a) exploited sentence level attention in hierarchical transformer to rank sentences for unsupervised extractive summarization which in turn boosted the summarization accuracy.

Narayan et al. (2017) designed a hierarchical LSTM document encoder and an attention-based extractor with attention over side information. The side information that authors considered significant in an article is its title and image captions, along with the main body of the document. They proposed a novel training algorithm which globally optimizes the Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metric through a reinforcement learning objective. Zhang et al. (2018) built a latent extractive model based on a LSTM network, which instead of maximizing the likelihood of gold standard labels, directly maximizes the likelihood of human summaries given selected sentences. Tarnpradab et al. (2017) utilized hierarchical attention networks based on LSTM for extractive summarization of forum threads. Liu (2019) fine-tuned Bidirectional Encoder Representations from Transformers (BERT), a pre-trained encoder–decoder based transformer architecture to boost the accuracies for extractive summarization.

A wide variety of other approaches, including Reinforcement Learning (RL), have been applied for extractive text summarization. Feng et al. (2018) presented an Attentive Encoder Summarization (AES) which consists of an attention-based document encoder and an attention-based sentence extractor. Wu and Hu (2018) focused on introducing coherence into the neural extractive model via reinforcement learning. Their neural coherence model is composed of a word-level CNN encoder and a bidirectional GRU sentence level encoder, allowing to capture the cross-sentence local entity transitions. Yao et al. (2018) applied deep reinforcement learning for extractive text summarization in which they used Deep Q-Network (DQN). Their sentence encoder consisted of CNN and document encoder modeled using bidirectional GRU. It can model salience and redundancy of sentences in the Q-value approximation and learn a policy that maximizes the ROUGE score with respect to gold summaries. Zhong et al. (2019) explored combination of several networks for extractive summarization and found that BERT-based LSTM-pointer networks further optimized by RL gives the best accuracy.

Zhong et al. (2020) formulated the extractive summarization task as a semantic text matching problem and propose a novel summary-level framework utilizing BERT to match the source document and candidate summaries in the semantic space. Bi et al. (2021) introduced AREDSUM-SEQ redundancy-based conditional sentence order generator network to score and select sentences by jointly considering their salience and diversity within the selected summary sentences. Their second model, AREDSUM-CTX, used an additional sentence selection model to learn to balance the salience and redundancy of constructed summaries. To capture long-range dependencies throughout a documents, Xu, Gan et al. (2020) presented a DISCOBERT, a discourse-aware neural summarization model to extract sub-sentential discourse units as candidates for extractive selection on a finer granularity and structural discourse graphs are constructed based on RST trees. Some unsupervised approaches have also been introduced by Joshi et al. (2019), Li, Lam et al. (2017), Li, Wang et al. (2017), Liu et al. (2021) and Xu et al. (2020b) for extractive summarization.

Though RNN-based models can remember long context, such large-scale networks are unable to capture the global information present in long documents (Pascanu et al., 2013; Sutskever et al., 2013) which can otherwise be encapsulated through topic models. Topic models have been used earlier for improving the sequence networks (Dieng et al., 2016; Lau et al., 2017; Le & Mikolov, 2014; Mikolov & Zweig, 2012; Wang, Orton et al., 2018) but these models fail to capture the structural content of text. Ghosh et al. (2016) presented contextual LSTM models, which incorporate the topic information of the text in LSTM networks. Ji et al. (2016) explored multi-level recurrent architectures by efficiently leveraging document context information in language models. Tang et al. (2019) tried to combine a sequence modeling component with topic modeling component to contain the semantics and sequential structure of the texts for text generation (Tang et al., 2019).

However, none of the approaches based on deep neural network for text summarization made use of topic information to encode the documents and sentences in them. The approaches indicated above utilized word embeddings to represent the documents but missed on the global information content which can be captured using topic vectors. In our encoder–decoder framework, we fuse the information obtained from both word embeddings and topic vectors. Our encoder–decoder framework is also different from previous works, as we encode our sentences using LSTM networks and produce sentence content and sentence topic embeddings. Then, sequence to sequence LSTM network is applied to generate score for sentences. We use the scores from the LSTM network and finally fused them with other sentence scores to classify sentences as summary/non-summary. Moreover, to the best of our knowledge, there are no works that eliminate redundant information in the summaries using topic distribution models per words, apart from word embeddings as representations of sentences. In our work, we utilized both sentence content and sentence topic embeddings in the Sentence Novelty Parameter to produce non-redundant and diverse summaries.

Wu et al. (2017) presented an importance evaluation function using topics to generate single document summaries. Issam et al. (2021) utilized topic clusters in the document to generate sub-documents based on topics and then applied TextRank to produce final summaries from sub-documents. Authors (Zheng et al., 2020) presented a method to embed topic model component into seq2seq model, by using the last hidden state from the encoder to infer topic information and incorporate the topic-level features for abstractive summarization. Our framework differs from them as we embed the topic information obtained using Latent Dirichlet Allocation (LDA) in the sequence networks rather obtaining any topic information directly from sequence models. Wang, Yao et al. (2018) used topic level and word level attention in Convolutional Sequence to Sequence networks for abstractive summarization. Their approach is distinct from ours as they only incorporated topic information as attention weights whereas we generated sentence topic embeddings to attend to topic information in document apart from word level information. Xiao and Carenini (2019) focused on extracting local and global content from the document leveraging topic information but the extracted topic from LSTM minus network.

Narayan et al. (2018b) proposed topic-conditioned convolution Seq2Seq networks for extreme summarization – one line summaries – of news articles. They experimentally demonstrated that convolution layers capture long-range dependencies in document better than RNNs, which is useful to perform document level abstraction and inference. Though they utilized topic information in their framework, their approach is different from ours because they used topic information with CNN networks to generate one line abstractive summaries of documents. However, our framework is focused on extractive summarization using sequence networks rather than convolution networks. Mehta et al. (2018) proposed LSTM based sequence encoders that jointly use topic models to learn attention weights across sentence words to produce abstracts of scientific articles. Their approach is quite different

Table 1
Framework parameters.

S.no	Acronym	Parameters
1	T_j	Topic vector of jth word
2	x_j	Word embedding of jth *word*
3	E_{wi}	Sentence Content Embeddings of ith sentence
4	E_{Ti}	Sentence Topic Embeddings of ith sentence
5	SCS	Sentence Content Score
6	SPS	Sentence Position Score
7	SNS	Sentence Novelty Score
8	FSS	Final Sentence Score
9	Seq2seq	Sequence to Sequence
10	MLP	Multi-Layer Perceptron

from ours as they used modified Latent Dirichlet Allocation (LDA) to generate document context embeddings, whereas we make use of both LDA and sequence networks to generate sentence and document vectors based on topic and word information. This gives an edge over the document context encapsulated using LDA model only.

3. Proposed DeepSumm method

3.1. Problem formulation

We formulate the problem of extractive text summarization as a combination of a sentence scoring and a selection problem. Each sentence in the document is ranked based on its relevance according to the assigned score, and then, a given number of the top-ranked sentences are selected to form the summary. Given a document D made up by a sequence of N sentences $S_1, S_2, \ldots, S_N$ and sequence of M words as $w_1, w_2, \ldots, w_M$, the summary is generated by a subset of N that contains the most relevant sentences in the document. The relevance of the sentences are determined based on their structural content, topic information, relative position and novelty of that sentence in the document.

In this work, the self-attention sequence networks (Vaswani et al., 2017) are employed to encode the information in the document. They are appropriate for identifying local structural context because of their sequential nature. The overall pipeline of the proposed DeepSumm framework is illustrated in Fig. 1. The parameters used in the DeepSumm framework are given in Table 1. In the subsequent sections, we describe the key components of the proposed deep learning framework for the generation of an extractive single-document summary.

3.1.1. Probabilistic topic distribution per word

Probabilistic topic models were proposed by Blei (2012) to capture the global semantic structure of the documents. The main objective of topic modeling methods is to model documents as collections of multiple latent topics. Each topic can be seen as a distribution of semantically coherent terms and each document exhibits these topics with different probabilities or proportions. One of the probabilistic topic models is LDA (Blei et al., 2003), whose main goal is to find the K latent topics $T = \{T_1, T_2, \ldots, T_k\}$ in a collection of documents where each topic is a collection of words that tend to co-occur together. LDA is better than other topic models—Latent Semantic Analysis (LSA) (Landauer et al., 1998) and Probabilistic Latent Semantic Analysis (pLSA) (Hofmann, 1999) as LDA generalizes well for new documents and has less risk of over-fitting. We use LDA to generate topic vectors T_D for each document present in the distribution, and topic vectors for each word, as t_{w_j} for the jth word, w_j, in a document. In this work, we consider topic vectors for each word T_j as point-wise addition of the word topic vector t_{w_j} generated by LDA, plus the document topic vector t_D, as: $T_j = t_{w_j} + t_D$.

3.1.2. Word embeddings

The word embeddings for each word are computed in the document to capture the structural content information. The pre-trained word vectors (Pennington et al., 2014) are used to represent each word as x_j in d-dimensional embedding space, $R^{M \times d}$.

3.1.3. Sentence encoder

We encode topic vectors per word, T_j and word vectors, x_j computed using pre-trained embeddings, as sentence vectors by means of two bi-directional LSTMs. On the one hand, a bidirectional LSTM takes the topic vectors of each word, T_j, in a sentence as input to extract the sentence embedding, termed as E_{Ti}, which relates to the topic information of ith sentence. The forward LSTM reads the sentence S_i from T_{i1} to T_{im} and the backward LSTM from T_{im} to T_{i1}. E_{Ti} is produced by concatenating the final hidden output states, $\overrightarrow{h_{Ti}}$ and $\overleftarrow{h_{Ti}}$ of the forward and backward LSTMs as stated in Eqs. (1), (2) and (3).

$$\overrightarrow{h_{Tt}} = \text{LSTM}(T_t, \overrightarrow{h_{T(t-1)}}) \tag{1}$$

$$\overleftarrow{h_{Tt}} = \text{LSTM}(T_t, \overleftarrow{h_{T(t+1)}}) \tag{2}$$

$$E_{Ti} = [\overrightarrow{h_{Ti}}, \overleftarrow{h_{Ti}}] \tag{3}$$

On the other hand but similarly, word embeddings, x_{im}, of a sentence i, are inputted to another bidirectional LSTM to extract the sentence embedding, E_{wi}. The forward LSTM for producing E_{wi} reads the sentence S_i from x_{i1} to x_{im} and the backward LSTM from x_{im} to x_{i1}. Eqs. (4)–(6) indicate the calculation of sentence embeddings E_{wi}.

$$\overrightarrow{h_{xt}} = \text{LSTM}(x_t, \overrightarrow{h_{x(t-1)}}) \tag{4}$$

$$\overleftarrow{h_{xt}} = \text{LSTM}(x_t, \overleftarrow{h_{x(t+1)}}) \tag{5}$$

$$E_{wi} = [\overrightarrow{h_{xi}}, \overleftarrow{h_{xi}}] \tag{6}$$

3.1.4. Sentence content and topic saliency extractor

As in the previous Section 3.1.3, two similar pipelines are designed for computing sentence salience and scores from sentence vectors; one for sentence topic embeddings, E_{Ti}, and the other one for sentence embeddings, E_{wi} based on word vectors. The Sequence to Sequence (seq2seq) attention networks are employed to obtain the sentence saliency based on topic and word vectors. The proposed Seq2Seq architecture consists of a LSTM encoder that reads the sentences one by one and a LSTM decoder that tries to generate the target sequence through an attention mechanism (Bahdanau et al., 2015). The objective of the encoder is to derive a document representation based on the sentences and words present in it.

In the following, we formulate the pipeline that inputs sentence embeddings, E_{wi} obtained using word vectors in the previous section. The encoder consists of a bidirectional LSTM that takes sentence embeddings E_{wi} as input to generate an encoded document representation as described in Eqs. (7) and (8).

$$\overrightarrow{h_{E_w i}} = \text{LSTM}_{\text{encoder}}(E_{wi}, \overrightarrow{h_{E_w(i-1)}}) \tag{7}$$

$$\overleftarrow{h_{E_w i}} = \text{LSTM}_{\text{encoder}}(E_{wi}, \overleftarrow{h_{E_w(i+1)}}) \tag{8}$$

The decoder is also composed by a bi-directional LSTM that takes the sentence embeddings and attention weighted encoder outputs into consideration to produce decoder hidden states, $\overrightarrow{h_{D_w i}}$ and $\overleftarrow{h_{D_w i}}$ as given in Eqs. (9) and (10).

$$\overrightarrow{h_{D_w i}} = \text{LSTM}_{\text{decoder}}(E_{wi}, \overrightarrow{h_{D_w(i-1)}}) \tag{9}$$

$$\overleftarrow{h_{D_w i}} = \text{LSTM}_{\text{decoder}}(E_{wi}, \overleftarrow{h_{D_w(i+1)}}) \tag{10}$$

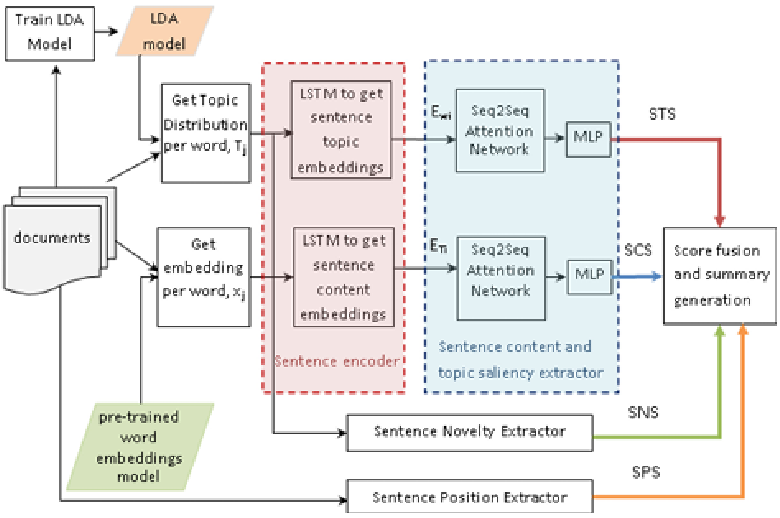


Fig. 1. Schema of the DeepSumm architecture.

The encoder and decoder outputs e_i, d_i of our pipeline consist of the following hidden states as given in Eqs. (11) and (12), respectively.

$$e_i = (\overline{\overrightarrow{h}_{E_{w}i}}, \overline{\overleftarrow{h}_{E_{w}i}}) \tag{11}$$

$$d_i = (\overline{\overrightarrow{h}_{D_{w}i}}, \overline{\overleftarrow{h}_{D_{w}i}}) \tag{12}$$

Then, an attention mechanism is applied to find the global sentence saliency for each sentence using the following Eqs. (13) and (14).

$$\alpha_{ij} = \frac{\exp(d_i, e_j)}{\sum_{j=1}^{N} \exp(d_i \cdot e_j)} \tag{13}$$

$$\overline{e_i} = \sum_{j=1}^{N} \alpha_{ij} \cdot e_j \tag{14}$$

where α_{ij} is a scalar value indicating the importance of ith sentence and $\overline{e_i}$ is the weighted sum of sentence vectors.

The decoder and attention weighted encoder outputs are finally fed into a MLP network to generate scores for each sentence in the document as in Eqs. (15) and (16).

$$a_i = \mathrm{ReLU}(U \cdot [\overline{e_j}; d_i] + u) \tag{15}$$

$$P(y_i = 1 | E_{wi}) = \sigma(V \cdot a_i + v) \tag{16}$$

where, U, V are the learned weights of the encoder and decoder, respectively, and u, v are the bias parameters of the encoder and decoder, respectively. ReLU is a Rectified Linear Activation function that output the input directly if the input is positive otherwise, 0.

Thus, Sentence Content Score (SCS) is computed using Eq. (17)– by inputting the sentence embeddings E_{wi} to the pipeline described in this section. The Sentence Topic Score (STS) is obtained as given in – Eq. (18)– by inputting the topic distribution sentence encodings E_{Ti} to another seq2seq network designed for encoding sentence topic vectors. STS is able to capture the global semantics in the document whereas, using SCS, we are able to apprehend the local syntactic information in the document.

$$\mathrm{SCS}_i = P(y_i = 1 | E_{wi}) \tag{17}$$

$$\mathrm{STS}_i = P(y_i = 1 | E_{Ti}) \tag{18}$$

3.1.5. Sentence novelty extractor

We propose a new Sentence Novelty Score (SNS) that progressively scans the document one sentence at a time and assigns a score to each sentence depending on the novelty of the sentence with respect to all the previous ones. The novelty of each sentence is calculated based on the sentence embeddings E_{wi} and the topic distribution sentence encodings E_{Ti} as given in Eq. (19).

$$\mathrm{SNS}_i = \begin{cases} 1 & \text{if } i = 1 \\ \frac{1}{i-1} \sum_{j=1}^{i-1} \frac{(1-(\mathrm{Sim}(E_{wi}, E_{wj})+\mathrm{Sim}(E_{Ti}, E_{Tj})))}{2} & \text{otherwise} \end{cases} \tag{19}$$

where, $\mathrm{Sim}(x, y)$ is the cosine similarity between vectors x and y. SNS_1 is set to 1 considering the first sentence of the article as the most significant and novel to be included in the summary. To obtain the sentence novelty, both sentence content and topic representations as generated in Section 3.1.3 are used. Through sentence content embeddings, we can find the sentences which are semantically similar to each other and thus can eliminate redundancy in summary. Enriching the novelty calculation with sentence topic embeddings, those sentences in summary can be discarded which discuss about similar topics and sometimes, may not be captured with sentence content embeddings only. Experimentally on small test dataset, it was found that average of both scores work better in computing novelty score for each sentence. The SNS is low for redundant sentences in the document, and it is robust enough to introduce diversity in the summary by producing a high score for sentences which are not covered in the previous text of the document.

3.1.6. Sentence position extractor

In news documents, the sentences which occur earlier in the document are deemed more significant in comparison to other sentences in the document (Edmundson, 1969; Luhn, 1958). Therefore, our Sentence Position Score (SPS) assigns to each sentence a relative score based on its relative position on the document and computed as given in Eq. (20).

$$\mathrm{SPS}_i = \frac{N - P_i}{N} \tag{20}$$

where, P_i is the absolute position of sentence, i in the document. The SPS will assign higher scores to the sentences which are in the

Table 2
Databases information. # stands for 'number of'.

Dataset	Type	Usage	# Documents	# Categories
CNN/DailyMail	News	Training	287,227	–
		Validation	13,368	–
		Testing	11,490	–
DUC 2002	News	Testing	567	59

beginning of the document compared to those which occur in later part of the document.

3.1.7. Scores fusion and summary generation

We finally fused SCS, STS, SNS and SPS to obtain a final sentence score (FSS) for a sentence i, as given in Eq. (21).

$$FSS_i = \alpha \cdot SCS_i + \beta \cdot STS_i + \gamma \cdot SNS_i + \delta \cdot SPS_i \tag{21}$$

In FSS_i, the sentence with highest score is considered as the most significant to be included in the summary. The values of α, β, γ, and δ are determined empirically. Finally, the sentences of a document are arranged in descending order with respect to their FSS and the top k sentences or words of the list are picked to form the extractive text summary of the document.

It should be noted that the time complexity for the computation of SCS, STS, and SPS scores is O(N), assuming that we are given a document with N sentences to be summarized. In the case of SNS calculation, we compute the cosine similarity of each sentence with all the sentences preceding it in the document. The cosine similarity is calculated based on the sentence embeddings, E_{ai}, and the topic distribution sentence encodings E_{T_i} as given in Eq. (19). Hence, the time complexity of sentence novelty calculation using sentence embeddings becomes O(N(N-1)/2) and, similarly, the complexity using topic distribution sentence encodings is O(N(N-1)/2). Since both of them can be computed in the same loop/pass, the overall complexity of SNS calculation can be given as O(N(N-1)/2).

4. Experimental analysis and results

4.1. Datasets

For the supervised – training – of our method, we need a large annotated dataset for text summarization. CNN/DailyMail (Hermann et al., 2015) is the biggest dataset that contains news articles and is frequently used in question-answering research. CNN and DailyMail comprise 197,000 and 90,000 stories, respectively. As extractive summaries of news documents are not available, we utilize the highlights, which are actually abstractive summaries, given along with the news articles to produce their extractive summaries. Those sentences are greedily added from the document to the gold summary that maximizes the ROUGE-1 and ROUGE-2 scores when matching them with the highlights. A similar approach was followed by Cheng and Lapata (2016) to obtain summaries from CNN/DailyMail datasets to train their extractive summarization methods. The standard train, test and validation split for the dataset as given in Table 2 are used in this work. For validating our approach on a different dataset, we also make use of the standard summarization benchmark dataset DUC2002. DUC 2002[1] was created by the National Institute of Standards and Technology (NIST) for Document Understanding Conferences (DUC) to evaluate and analyze the advances in the field of text summarization. The DUC 2002 dataset consists of 567 news articles from 59 news categories. There are two or more human summaries given for each of the news articles.

[1] https://duc.nist.gov/data.html.

4.2. Experimental set up

We first split the document into sentences and tokenized them into words. For this purpose, we used the sentence and word tokenizer functionality from the freely available Natural Language Processing Toolkit (NLTK).[2] The words were represented by means of 100-dimensional GloVe embeddings (Pennington et al., 2014). The length of topic vectors for each word and document extracted using LDA is 432. For LDA, different dimensions were tried on CNN/DailyMail validation set and best accuracy is reported at 432 dimensions. The size of the hidden layer of LSTM was set to 256 and of MLP to 128. We used a 0.0001 learning rate and employed gradient clipping of ± 0.5. The learning rate was initially set to 0.01 and reduced by a factor of 10 first after 50th iteration and then after 75th iteration. The batch size was kept 64 and we trained our network using stochastic gradient descent and Adam optimization algorithm (Kingma & Ba, 2014). The dropout probability of 0.5 have been applied in the encoder and 0.25 in the decoder. Our network was trained for a maximum of 100 epochs and the best model was selected based on validation accuracy metric. We set values of α, β, γ and δ in Eq. (21) to 0.45, 0.45, 0.05 and 0.05 respectively. The values of these parameters were determined empirically on a set of 5000 news documents randomly selected from the CNN/DailyMail validation data. To determine the optimal parameters, a grid search is performed over the values of α, β, γ and $\delta \in [0, .05, \ldots, 0.95, 1]$ with $\alpha + \beta + \gamma + \delta = 1$, which outputs the feasible combinations. The parameter values which yielded the highest values of average over Recall-Oriented Understudy for Gisting Evaluation scores (ROUGE) (Lin, 2004) were selected as final values for α, β, γ and δ as given in Eq. (22)

$$\{\alpha, \beta, \gamma, \delta\} = \mathrm{argmax}_{\{\alpha,\beta,\gamma,\delta \in [0,0.05,\ldots,1]\}} \frac{\text{ROUGE-1} + \text{ROUGE-2}}{2} \tag{22}$$

where, ROUGE-1 and ROUGE-2 are the evaluation metrics used for evaluating summaries (Lin, 2004). The experiments have been carried out in a machine with 2 T K40M GPUs with 12 GB memory each, Intel Xeon processor with 3.00 GHz frequency, and 64 GB RAM.

4.3. Evaluation

The ROUGE-1, ROUGE-2 and ROUGE-L metrics (Lin, 2004) have been used to evaluate and compare our approach with other state-of-the-art methods. ROUGE metrics are computed by matching unigrams, bigrams and the longest common subsequences between the system and gold summaries. For DUC 2002 dataset, we kept the summary length to 100 words, and for CNN/DailyMail dataset full-length ROUGE metric is used to ease the comparison of our results with other approaches.

We selected the following state-of-the-art methods to carry out a comparative analysis of the results achieved with our method. For both datasets, we considered the following methods:

NN-SE (Cheng & Lapata, 2016) consists of a hierarchical document encoder and attention-based content extractor that jointly scores and select sentences to generate extractive summaries.

SummaRuNNer (Nallapati, Zhai et al., 2017) is a simple RNN-based sequence classifier for extractive summarization. It employed a novel training mechanism to train the network using abstractive summaries.

HSSAS (Al-Sabahi et al., 2018), is a general neural network-based approach that extracts sentences from a document by treating summarization problem as a classification task. Their network follows a hierarchical structure to reflect the hierarchical nature of documents and used two levels of self-attention mechanism to attend more important content for summarization.

LEAD baseline selects the first three leading sentences from the document to produce a summary for comparison.

[2] https://www.nltk.org/.

DeepSumm-content is our deep summarization framework where only sentence content embeddings have been used for evaluating the summarization framework.

DeepSumm-topic is our deep summarization framework where we utilized only topic information and embeddings in the document to perform a comparative evaluation of our system with DeepSumm where both sentence content and topic embeddings have been exploited for summary generation.

Specifically for CNN/DailyMail dataset, the results are also reported on following methods:

REFRESH (Narayan et al., 2018a), that globally optimize the ROUGE evaluation metric rather cross entropy objective and produces extractive summaries using learning to rank sentences via a reinforcement learning algorithm.

Bi-AES (Feng et al., 2018) is an attentive bi-directional encoder based extractive summarization technique to generate summaries. Bi-AES can generate a rich document representation by considering both the global information of a document and the relationships of sentences in the document

RNES (Wu & Hu, 2018) is a neural coherence model to capture the cross-sentence semantic and syntactic coherence patterns. The model obviates the need for feature engineering and can be trained in an end-to-end fashion using unlabeled data. The RNES model learns to optimize coherence and informative importance of the summary simultaneously using reinforcement learning.

NeuSum (Zhou et al., 2020) is a neural network framework for extractive summarization that jointly scores and select the summary sentences. It uses document encoder to encode each sentence of the document and then RNN-based sentence extractor to score sentences with their representations while remembering the partial output summary.

BERTSum (Liu, 2019) is an extractive summarization technique that fine-tuned BERT architecture for extractive summarization. Authors tried several summarization layers over BERT architecture and found BERTSum with inter-sentence transformer layers achieve the best performance.

PACSUM(BERT) (Zheng & Lapata, 2019) is an unsupervised summarization algorithm that employed BERT to capture sentence similarity and built graphs with directed edges arguing the contribution of any two nodes to their respective centrality is influenced by their relative position in document.

DASG (Liu et al., 2021) presented a graph-based single-document unsupervised extractive method that creates a distance-augmented sentence graph (DASG) from a document that enables fine-grained modeling of sentences and characterize the original document structures.

JECS (Xu & Durrett, 2019) consists of a sentence extraction model joined with a compression classifier that decides whether or not to delete syntax-derived compression for each sentence.

HIBERT (Zhang et al., 2019) is an unsupervised approach that used Hierarchical Bidirectional Encoder Representations from Transformers for document modeling and then pre-trained HIBERT model is exploited for achieving document summarization.

PNBERT+RL (Zhong et al., 2019) is a supervised extractive summarization technique based on the combination of several networks such as LSTM Pointer networks, pre-trained with BERT and further optimized by Reinforcement Learning to improve the accuracy.

STAS + PACSUM (Xu et al., 2020a) is a Sentence Level Transformer based Attentive Summarization that combines the ranking of sentences with the ones obtained from PACSUM network to improve the summarization performance.

AREDSUM (Bi et al., 2021) are redundancy-aware iterative ranking methods for extractive summarization extending BERTSUMEXT (Liu, 2019).

HSG (Wang et al., 2020) is a heterogeneous graph-based neural network for extractive text summarization.

DISCOBERT is a discourse-aware extractive summarization system that leverages two types of discourse graphs as inductive bias to capture long-range dependencies among discourse units.

MATCHSUM (Zhong et al., 2020) is a novel summary-level framework to match the source document and candidate summaries in the semantic space.

Whereas for DUC 2002 dataset, we took into consideration:

Integer linear programming (ILP) is a phrase-based summarization system proposed by Woodsend and Lapata (2012) that attempts to cover multiple aspects of summarization such as content selection, surface realization, paraphrasing, and stylish conventions. These features are learned separately using specific "expert" predictors but are optimized jointly using ILP model to generate summaries.

Egraph (Parveen & Strube, 2015) is an entity graph-based method for extractive single-document summarization that considers importance, non-redundancy and local coherence simultaneously. The input documents are represented by bipartite graph, and sentences are ranked based on importance by applying a graph-based ranking algorithm.

Tgraph (Parveen et al., 2015) is another unsupervised entity graph-based system, wherein the nodes are represented using topics rather entities, and the graph is weighted and dense as compared to Egraph method (Parveen & Strube, 2015).

URANK (Wan, 2010) is a unified rank methodology that simultaneously performs single and multi-document summarization. The mutual influences between the two tasks are incorporated into a graph model and the ranking scores of a sentence for the two tasks can be obtained in a unified ranking process.

CoRank (Fang et al., 2017) is an unsupervised summary extraction method that combines word–sentence relationship into the graph-based ranking model, such that the mutual influence is able to convey the intrinsic status of words and sentences accurately.

SummCoder (Joshi et al., 2019) is an auto-encoder based unsupervised extractive summarization method. Authors did a weighted fusion of sentence scores based on its saliency derived using auto-encoders, sentence position and novelty parameter to get the final scores for ranking sentences for generating extractive summaries.

4.4. Results

As shown in Table 3, DeepSumm achieved very good accuracy for the task of single-document extractive summarization on DUC 2002 dataset. The ROUGE-1, ROUGE-2 and ROUGE-L scores of 53.2, 28.7 and 49.2 yielded by DeepSumm outperformed all the considered state-of-the-art approaches. None of the state-of-the-art RNN-based summarization approaches such as NN-SE, SummaRuNNer, SummCoder, HSSAS utilizes latent topic information in the document which makes our proposed method superior to them. This supports the efficacy of our proposed framework that utilizes both topic distribution vectors and language models to derive extractive summaries of the document. A comparative evaluation on our DeepSumm-topic and DeepSumm-content also shows that both topic and word embeddings carry complementary information. The combination of the two increases the accuracy of the summarization system.

A comparative analysis of the performance of different sentence scores, SCS, STS and FSS, from 20 randomly selected documents on DUC 2002 dataset is illustrated in Fig. 2. ROUGE-1, ROUGE-2 and ROUGE-L metrics were computed when raking and extracting the sentences of the documents to generate the extractive summaries using SCS and STS, besides the default score FSS. It can be seen that STS, which is computed using topic distribution sentence encodings, achieved as good ROUGE scores on the documents as SCS, which is based on word embeddings. Even in some documents, STS yielded higher ROUGE scores than SCS. It depicts that probabilistic topic distribution encodings are capable of extracting the latent topic information of the document, which is complementary to the information captured using word embeddings. The global semantic information encapsulated using topic distribution encodings is quite relevant for generating good summaries and can contribute towards better summarization systems. The final sentence score – FSS – generated using the fusion of SCS, STS, SNS and SPS scores

Table 3
Comparative analysis of DeepSumm with state-of-the-art algorithms on DUC 2002.

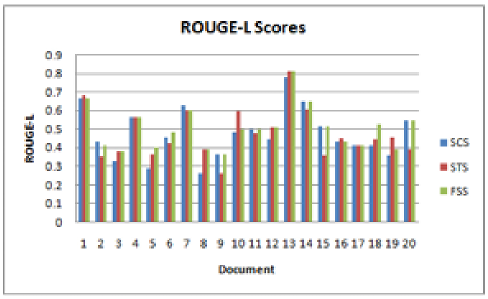
Method	ROUGE-1	ROUGE-2	ROUGE-L
LEAD	43.6	21.0	40.2
ILP	45.4	21.3	42.8
NN-SE	47.4	23.0	–
SummaRuNNer	47.4	24.0	14.7
Egraph + coh	47.9	23.8	–
Tgraph + coh	48.1	24.3	
URANK	48.5	21.5	–
SummCoder	51.7	27.5	44.6
HSSAS	52.1	24.5	48.8
CoRank	52.6	25.8	
DeepSumm-content	52.1	27.7	48.3
DeepSumm-topic	52.7	28.5	48.8
DeepSumm	**53.2**	**28.7**	**49.2**

Table 4
Gold summary and DeepSumm generated summary for a document from DUC 2002 dataset.

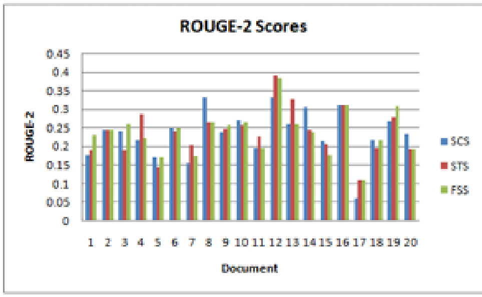
Gold summary
President Bush named career diplomat Deane Hinton as ambassador to Panama as a recess appointment since Congress is not in session. Hinton, currently ambassador to Costa Rica, replaces Arthur Davis who had been recalled in protest of what the administration\considered the stealing of the Panamanian elections by General Manuel Noriega. Davis was later returned to Panama after US forces invaded Panama and Guillermo Endara was installed as president. Hinton has also been ambassador to El Salvador and Pakistan. Senate Majority Leader George Mitchell called Hinton highly qualified because of his "wide-ranging experience and expertise in Central America".
DeepSumm summary
President Bush has named career diplomat Deane Hinton as ambassador to Panama, the White House announced Tuesday. Hinton, currently ambassador to Costa Rica, replaces Ambassador Arthur H. Davis, who was recalled by Bush in protest of what the administration considered the stealing of the Panamanian elections last May by Gen. Manuel Antonio Noriega. Bush sent Davis back to Panama City after the Dec. 20 invasion of Panama by U.S. forces and installation of Guillermo Endara as president. Independent observers mostly concluded Endara had won the elections by a hefty margin.

is able to accomplish a good overall accuracy on all the documents. Table 4 presents an example of the summary generated by our proposed method for a DUC 2002 document.

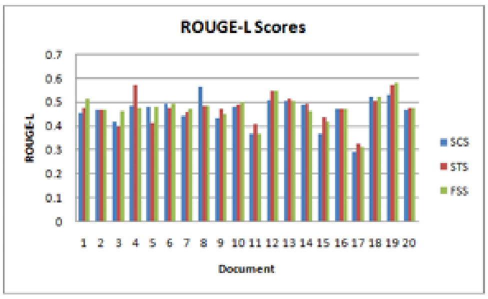
On CNN/DailyMail dataset, our method obtained the highest ROUGE-1 score and ROUGE-2 and ROUGE-L scores comparable to the best extractive summarization approaches of the literature as it can be seen in Table 6. Our algorithm achieved comparable or better ROUGE-1 score of 43.3, ROUGE-2 score of 19.0 and ROUGE-L score of 38.9. The DeepSumm method surpassed NN-SE, SummaRuNNer, Bi-AES with a very high margin of 4, 3.3, 3.4 for ROUGE-1, ROUGE-2 and ROUGE-L scores. Other state-of-the-art methods such as REFERESH and RNES that used reinforcement learning also lag in performance in comparison to our summarization proposal. We also got better ROUGE scores than those of NeuSum and HSSAS, which are based on sequence networks. DeepSumm only fall behind AREDSUM, DISCOBERT, and MATCHSUM for ROUGE-1, ROUGE-2 and ROUGE-L scores and HSG and BertSum for ROUGE-2 and ROUGE-L scores. AREDSUM, DISCOBERT, BERTSum, and MATCHSUM are intensive in terms of memory and resources. Their architectures are complex and use more number of layers as compared to our proposed architecture. As illustrated in Table 5, AREDSUM, DISCOBERT, BERTSum, and MATCHSUM utilized BERT (Devlin et al., 2019) as the base architecture of their system which has 110 Million trainable parameters with 12 GRU layers and 768 neurons in each hidden layer. Instead, our architecture consists of two bi-directional LSTM layers (one encoder and one decoder) accounting for a total of 2.5 Million trainable parameters. This states that our architecture consists of fewer parameters compared to other state-of-the-art architectures with comparatively better accuracies.



(a) ROUGE-1 graph



(b) ROUGE-2 graph



(c) ROUGE-L graph

Fig. 2. Illustration of ROUGE-1, ROUGE-2 and ROUGE-L metrics considering SCS, STS and FSS scores for the ranking of sentences on 20 randomly selected documents of DUC 2002.

We also evaluated our DeepSumm-content and DeepSumm-topic approach, which alone uses word and topic embeddings. As depicted in Table 6, DeepSumm-topic and DeepSumm-content are better than most approaches. Still, they cannot provide better ROUGE scores than when their scores are fused to capture the pertinent content in the document. The notable increase in accuracy compared to most recent approaches proved that our method is quite robust towards producing good summaries. DeepSumm can condense the salient information from the document, which is otherwise not captured alone using language models and thus, it boosts the overall accuracy of extractive summarization.

Table 5
Comparison of DeepSumm Network with other state-of-the-art Architectures.

Method	Network architecture	Neurons in hidden layer	No. of layers	Parameters (Million)
BERT	–	768	12	110
BERTSum	BERT base + 2 transformer layers	768	6	55+
MATCHSUM	2 BERTs	768	–	–
DISCOBERT	BERT as Encoder	768	–	–
AREDSUM	BERT	768	–	–
DeepSumm	**Encoder–Decoder**	**256**	**2**	**2.5**

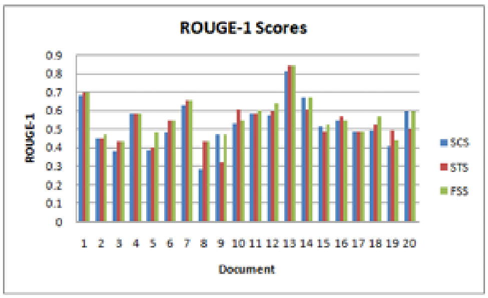
Table 6
Comparative analysis of DeepSumm with state-of-the-art algorithms on CNN/DailyMail.

Methods	ROUGE-1	ROUGE-2	ROUGE-L
NN-SE	35.5	14.7	32.2
Bi-AES	38.8	12.6	33.85
LEAD	39.2	15.7	35.5
SummaRuNNer	39.6	16.2	35.3
REFRESH	40.0	18.2	36.6
PACSUM(BERT)	40.7	17.8	36.9
RNES	41.2	18.8	37.7
STAS + PACSUM	41.26	18.18	37.48
NeuSum	41.5	19.0	37.9
DASG	41.6	18.5	37.8
JECS	41.7	18.5	37.9
HSSAS	42.3	17.8	37.6
HIBERT	42.3	19.9	38.83
PNBERT + RL	42.6	19.6	38.8
HSG + Tri-Blocking	42.9	19.7	39.2
BertSum	43.2	20.2	39.6
DeepSumm-content	41.8	18.3	37.5
DeepSumm-topic	42.9	18.8	38.3
DeepSumm	43.3	19.0	38.9
AREDSUM-CTX	43.4	20.4	39.8
DISCOBERT	43.77	20.85	40.67
MATCHSUM(RoBERTa-base)	**44.41**	**20.86**	**40.55**

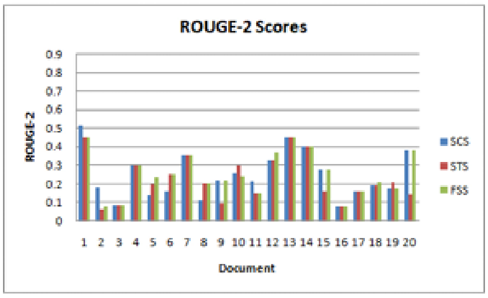
We also illustrated in Fig. 3 a comparative analysis of the performance obtained with sentence scores SCS, STS and FSS for the ranking and extraction summary sentences of documents on CNN/DailyMail dataset. Similarly to DUC 2002 dataset, it can be seen that STS yielded as good ROUGE scores on the documents as SCS did. Therefore, topic distribution sentence encodings are quite relevant for finding the pertinent content in the document to obtain semantically coherent and meaningful summaries. An exemplary summary of a CNN/DailyMail document produced by DeepSumm method is shown in Table 7.

5. Conclusions

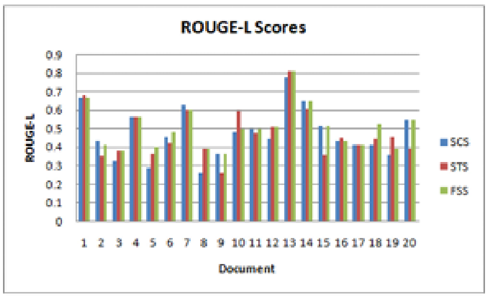
In this paper, we have presented DeepSumm, a novel method for extractive summarization which produces compact single-document representations. DeepSumm captures structural and semantic features of the document by utilizing a combination of topic and language vector encodings. We encoded the document sentences using word embeddings and word probabilistic topic distributions, creating their corresponding sentence representations. The inclusion of probabilistic topic distributions in our method makes it possible to consider the latent semantic structure of the document, which is otherwise not captured in the word embedding space. Sequence to Sequence attention networks were applied over the sentence embeddings and encodings to extract the salient sentences based on their content and topic scores, respectively. We also introduced a new novelty computation measure, SNS, to generate a non-redundant and diversified summary of the document. Last, the position of the sentence in the document was also taken into consideration using Sentence Position Score. A weighted fusion of the Sentence Content, Topic, Novelty and Position scores was used to determine the salient sentences in the document.



(a) ROUGE-1 graph



(b) ROUGE-2 graph



(c) ROUGE-L graph

Fig. 3. Illustration of ROUGE-1, ROUGE-2 and ROUGE-L metrics considering SCS, STS and FSS scores for the ranking of sentences on 20 randomly selected documents of CNN/DailyMail dataset.

The experimental results demonstrated that DeepSumm outperformed all the state-of-the-art baselines evaluated on DUC 2002 dataset,

Table 7
Gold summary and DeepSumm generated summary for a document from CNN/DailyMail dataset.

Gold summary
And this week its lyrics, hand-written in 1971 by a young folk singer called Don McLean, were sold at auction in New York for more than $ 1 million. Don McLean (pictured) is responsible American Pie, the lyrics of which have been puzzled over for decades. Argued over by generations of geeky fans, deciphered and re-deciphered by code-breaking rock nerds and considered to be poetic reflections on mid-20_{th} century U.S. social history by even groovier academics, it 's called American Pie. For more than 40 years, its lyrics have been an enigma wrapped in an eight-and-a-half minute long rock 'n' roll puzzle.
DeepSumm summary
Don Mclean pictured is responsible American pie the lyrics of which have been puzzled over for decades. Argued over by generations of geeky fans deciphered and re-deciphered by code breaking rock nerds and considered to be poetic reflections on century us social history by even groovier academics its called American pie and this week its lyrics handwritten in by a young folk singer called don mclean were sold at auction in new York for more than million. Its also a paean to education mclean loves words he says almost as much as life that may be a slight overstatement but it shows of course like all poets mclean did not give us a key to the riddle of what his song was about when he released his multi million selling single that would have spoiled it.

and achieved a competitive performance on CNN/DailyMail dataset. It has also been illustrated that high-level document features extracted using probabilistic topic distribution models are quite relevant towards generating informative summaries. There are many possibilities which can be explored in the future to extend the presented work. One possibility would be to derive other abstract features that can be combined in the existing network to increase the accuracy of the system. Secondly, we could make use of probabilistic topic distributions and sequence networks for abstractive text summarization. The third direction to investigate would be to utilize topic information in unsupervised methods for the task of extractive text summarization, which will eliminate the need for labeled summarization data for training the networks.

CRediT authorship contribution statement

Akanksha Joshi: Investigation, Conceptualization, Methodology, Software, Validation, Writing – original draft, Data curation. **Eduardo Fidalgo:** Investigation, Conceptualization, Supervision, Project administration, Resources, Writing – reviewing and editing. **Enrique Alegre:** Investigation, Conceptualization, Supervision, Writing – reviewing and editing, Funding acquisition. **Laura Fernández-Robles:** Investigation, Writing – reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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