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HYBRID TEXT SUMMARIZER

A KL-DIVERGENCE GUIDED REINFORCEMENT LEARNING APPROACH

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Abstract: Text summarization continues to be a challenging task—how do we capture the essence of a long document in just a few sentences, without losing meaning or introducing errors? In this work, we present a hybrid approach that combines the strengths of both extractive and abstractive summarization, striking a balance between factual accuracy and natural language generation. Our method starts by selecting important sentences using a KL-divergence-based technique, which helps ensure the summary remains grounded in the original content. These selected sentences are then passed to a fine-tuned T5 model, known for its ability to generate fluent, coherent summaries. To further enhance performance, we apply reinforcement learning that guides the model to optimize its output based on ROUGE scores. This three-stage process leads to summaries that are not only readable but also more aligned with the core information in the source text. We evaluate our approach on several benchmark datasets and observe notable improvements over standard baselines. Overall, this work shows that a thoughtfully designed hybrid method—leveraging statistical grounding and neural fluency—can produce high-quality summaries. Future directions include exploring different ways to measure summary quality and adapting the approach to new domains and languages.

Keywords - Text Summarization, Hybrid Summarization, Extractive Summarization, Abstractive Summarization, Kullback-Leibler Divergence, BART, Reinforcement Learning, ROUGE.

I. INTRODUCTION

In today's information-driven society, where enormous amounts of data are produced every day, text summarization is an essential activity. Improving accessibility and processing efficiency in information processing requires the capacity to condense long texts into brief summaries that retain the essential elements of the original material. The two main categories of summarization techniques are extractive and abstractive. Whereas abstractive summary creates fresh information that communicates the main concepts in a more concise and fluid way, extractive summarization chooses important passages straight from the book.

It might be difficult to strike the correct mix between creativity and accuracy while writing summaries. Although an extractive technique guarantees the retention of important information, it may have trouble keeping the end product coherent and fluid. However, an abstractive technique can produce summaries that are more realistic and human-like, but it needs sophisticated processes to guarantee that the content produced stays true to the original text.

This paper offers a cohesive strategy that builds on the advantages of both approaches. The method guarantees that significant facts are preserved by first locating and choosing the most pertinent sentences from the given text. The chosen text is then polished and turned into an engaging synopsis that faithfully captures the essence of the original work. This two-step procedure creates excellent, logical, and educational summaries by utilizing the advantages of both extraction and abstraction.

A more reliable and adaptable summarizing framework that can manage a variety of content types—from news items to research papers—with increased effectiveness and better quality results is the end result. By integrating these strategies, we hope to advance the creation of summaries and make them more interesting, relevant, and accessible for users in a variety of categories.

II. RELATED WORK

Text summarization has been an important research area for quite some time, and it has used techniques from simple frequency-based methods to complex neural modeling. To better inform generation future development quality, we review the literature on extractive, abstractive, and hybrid methods of summarization along with the use of reinforcement learning techniques for summarization.

2.1 Extractive Summarization

Expanding on these initial methods, traditional extractive summarization has focused on quantifying informative sentences from the original text. Mod els like TF-IDF [9], LexRank [10], and TextRank [11] relied on word frequency, similarity graphs, or sentence centrality to score importance. More advanced methods have then turned to probabilistic approaches, such as KL divergence [8], [12], selecting sentences that best approximate the distribution of words in the original document. In our work, we extend this notion further by using KL divergence to regulate the extracting scenario, similar to a dynamic sentence selector, for increased variation and improved redundancy reduction of the items extracted.

2.2 Abstractive Summarization

Abstractive summarization is in contrast to extractive summarization, in that a new sentence(s) is generated, which may involve rewording, para phrasing, or recombining ideas in a more coherent and concise manner. Early abstractive systems were rule-based or used templates, which did not allow for much flexibility or creativity in sentence formation. Sequence-to-sequence models with attention mechanisms [14] emerged as a major landmark, with the capacity for end-to-end generation of summarization, enabling more sophisticated content generation. More recently, transformer-style models such as T5 [16] and Pegasus [17] have advanced the state of the art in their ability to deeply understand context, generate fluent outputs, and produce coherent, substantive summaries. Our project leverages T5 for the abstractive stage, using the sentence(s) output from the extracted phase as input for the final, well-formed, and meaningful summary

2.3 Reinforcement Learning for Summarization

Exposure bias and lack of alignment with evaluation metrics are two of the common challenges faced when training summarization models with standard supervised learning (MLE) [7]. Reinforcement learning has been explored as a possible solution to enhance generation models by optimizing a given performance metric, such as ROUGE [6][7]. Self-critical sequence training (SCST) [6], [18], allows a model to learn through its own output by comparing greedy to sampling generations. In this work, we will apply reinforcement learning to improve the T5 model, so that the model is able to produce summaries that not only read more smoothly but also score higher on common evaluative metrics.

2.4 Hybrid Approaches

Studies have shown that hybridization, combining extractive and abstractive, can produce fac tually accurate and coherent summaries. A number of hybrid summarizers utilize extractive methods to minimize the size of the input and improve the factual consistency before utilizing an abstractive model [19]. Our method follows a hybrid approach: we extract sentences using a selector module and KL divergence, and pass that information to an abstractive model (T5) fine-tuned through reinforcement learning. The aim of this design is to create a balance between improve reading ability and reducing the likelihood of factual errors in the summary.

III. SYSTEM ARCHITECTURE

Our proposed model follows a multi-stage pipeline designed to generate high-quality abstractive summaries grounded in the source text, optimized using Reinforcement Learning.

3.1Pre-processing

Input documents are first preprocessed to prepare them for subsequent stages. Standard steps include:
Sentence Segmentation: Splitting the document into individual sentences
Tokenization: Breaking sentences into words or sub-word units compatible with the models.
Lowercasing: Converting text to lowercase to ensure consistency.
Stop-word Removal and Filtering: Removing common words (e.g.,"the","is") and potential punctuation or non-alphanumeric characters that carry little semantic weight for the KL-divergence calculation. Stop-words might be kept for the T5 model depending on its pre-training.

3.2 Extractive Phase (KL-Divergence)

This phase aims to select a subset of sentences from the preprocessed document that best represents its overall content distribution, serving as a concise, factually grounded input for the abstractive model. We employ the KL-Divergence minimization method [8], [12] as implemented in the project:
Document Distribution (P): Calculate the probability distribution of words across the entire preprocessed source document. **Candidate Selection:** Iteratively build a candidate extractive summary. In each step, consider adding each remaining sentence from the source document.
Candidate Distribution (Q): For each potential addition, calculate the word probability distribution of the resulting. Following MLE fine-tuning, we further optimize the T5 candidate summary.
KL-Divergence Calculation: Compute the KL divergence, KL(P —— Q), between the full document distribution P and the candidate summary distribution Q. The KL Divergence formula is defined as follows:
Greedy Sentence Selection: Select the sentence whose addition to the current summary minimizes the KL divergence.
Iteration: Repeat steps 2-5 until a predefined number of sentences (e.g., determined by EXTRACTIVE-RATIO times the original sentence count) is selected. The output of this stage is the extractive summary.

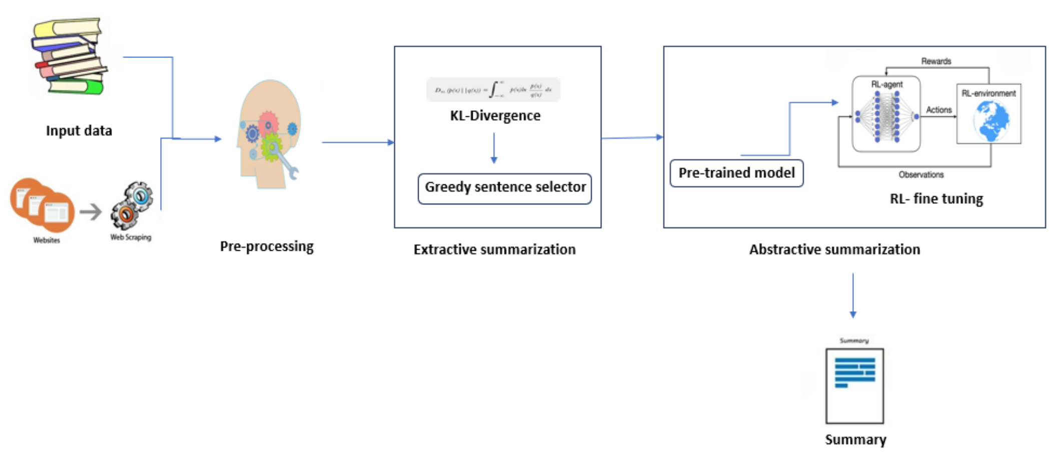

Fig. 3.1 System Architecture

3.3 Abstractive Phase (T5 Fine-tuning)

The extractive summary generated in the previous step is used as the input to the abstractive model. We utilize the pre-trained T5 model (t5-large), known for its effectiveness in summarization tasks. The extractive summary generated in the previous step is used as the input to the abstractive model. We utilize the pre-trained T5 model (t5-large), known for its effectiveness in summarization tasks.

Model Initialization: Load the pre-trained T5 model and tokenizer.

Supervised Fine-tuning (MLE): The model is first fine-tuned using standard supervised learning.

Input: Tokenized extractive summary.

Target: Tokenized human-written abstractive summary corresponding to the original document.

Training: Use the Hugging Face Seq2SeqTrainer with the Seq2SeqTrainingArguments configured as per the note book

(e.g., MLE-NUM-EPOCHS, MLE-BATCH-SIZE, MLE LEARNING-RATE).

The objective is to minimize the cross entropy loss between the model's predictions and the target summary.

3.4Reinforcement Learning Fine-tuning

Fine-tuning the model using RL to directly maximize the ROUGE score which is often the primary metric for summarization evaluation. We employ the REINFORCE algorithm [20] with a Self-Critical Sequence Training (SCST) baseline [18], similar to the approach described in Paulus et al. [6].

Policy: The fine-tuned T5 model acts as the policy that generates summaries.

Reward Function (R): The reward for a generated summary (y) given an input extractive summary (x) is its ROUGE-L F1

score compared to the human reference summary (y): R(y) = ROUGE-L (y, y).

SCST Baseline: To reduce variance in the policy gradient, we use a baseline. For each input x, two summaries are generated

from the current policy:

A sampled summary (s) is obtained by sampling the model's output distribution at each decoding step.

A baseline summary (g) was obtained using greedy decoding (taking the most likely token at each step).

The advantage is then calculated as the difference in re wards: Advantage = R(s)- R(g).

Policy Gradient Update: The model parameters are updated to maximize the expected reward using the policy gradient

estimate, incorporating the advantage:

J (R(s)- R(g)) * log-(s — x).

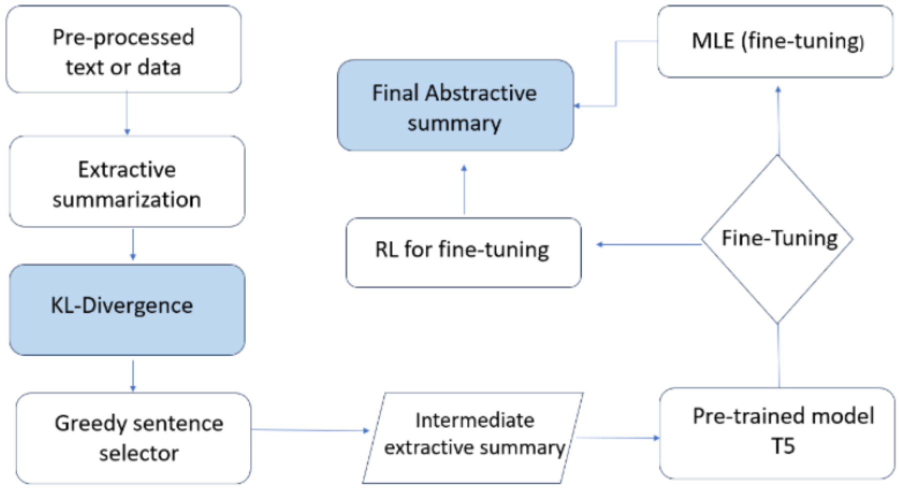

Fig. 3.2 Flowchart

3.5Training Loop

Iterate through the dataset (using the RL-dataloader).For each batch, generate sampled (s) and greedy (g) summaries using the reference model (model-ref, which holds the policy from the start of the rollout batch) to stabilize training.

Calculate advantages using the reward function.

Perform multiple update epochs (K-EPOCHS-PPO) on the current policy model (model) using the collected rollouts (inputs,

sampled outputs, advantages) and the policy gradient objective.

Use the Adam optimizer with a very low learning rate (RL-LR-POLICY).

Update the reference model periodically or after each main update step.

Utilize the Hugging Face Accelerator for efficient device handling and training.

IV. EXPERIMENTAL RESULTS

To assess the performance and generalization ability of our hybrid summarization model, we conducted a set of experiments on various benchmark datasets. Specifically, we wanted to determine how well our approach with sentence extraction utilizing KL-divergence, coupled with T5-based abstraction tuned by reinforcement learning, produced brief and meaningful summaries. To make a fair comparison, we used common benchmarks from the extractive summarization literature, as well as challenges relevant to abstractive summarization. Evaluations were made with commonly accepted ROUGE metrics from the summarization literature.

4.1 Datasets

In our evaluation of the robustness of our summarization pipeline, we selected four openly available datasets, each with its own challenges and format.

CNN/DailyMail: This dataset consists of long-form news articles with multi-sentence summaries produced by human editors. It deals mostly with formal, structured news content, which is useful for evaluations on models that required a level of contextual understanding over longer-length articles.

XSum: The XSum dataset consists of BBC articles with a highly abstractive single summary sentence.

XSum, like the CNN/DailyMail, requires a deeper abstraction level and paraphrasing compared to CNN/DailyMail, making it a more challenging benchmark for evaluating the model's ability to make concise yet complete representations of the source.

Gigaword: This dataset was created for the generation of headlines, providing sentence- summary pairs from newswire articles. It was useful as a testbed for fairly short summaries that resemble titles and that require high compression ratios and preservation of semantics.

MultiNews: The MultiNews dataset consists of news articles from several different sources reporting on the same event and a summary written by a human that summarizes the important information about the event. The MultiNews dataset is different from a dataset based on a single article, as it re quires the model to deal with redundant or overlapping, or even contradictory, information across the articles. Because of this, MultiNews is a strong testbed to assess a model's capabilities for multi-document summarization—integrating information, reconciling contradiction, and ultimately composing unified and nonredundant summary of multiple perspectives.

All datasets underwent preprocessing to rid the data of special characters, HTML tags, non-informative tokens, and words that failed to appear in the model's vocabulary. For each dataset, we split the data into training, validation, and test sets to provide consistent and fair evaluation.

4.2 Evaluation Metrics

In order to assess the quality of the summaries produced, we employed the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric suite which is commonly used in summarization research. These metrics analyze how much overlap exists between the generated summary and a refer ence (human-created) summary to assess how well the model captures important material. In particular, we examined the following variants of ROUGE:

ROUGE-1: This metric assesses the overlap of words (unigrams) between the generated summary and the reference summary. It indicates how many of the important words in the original summary remain and serves as a viable indicator of content coverage.

ROUGE-2: This metric assesses the overlap of consecutive word pairs (bigrams). It assesses the fluency and sense of a summary by determining if two words are paired together in the same way as in the reference summary. Higher ROUGE 2 scores suggest better phrase structure and grammar of the summary.

ROUGE-L: Based on the Longest Common Subsequence (LCS), this metric evaluates the length of longest sequence of words occurring in the same order in both the generated summary and reference summary. This is especially useful for measuring how closely the sentences structurally resemble each other, as well as the model's ability to keep the logical
flow of the information intact. Collectively, these metrics provide a thorough evaluation of the content relevance and linguistic quality of the generated summaries. Even though ROUGE does not factor in semantic meaning explicitly, it remains a strong measurement to use for automatic summarization tasks.

TABLE 1

Dataset	Model	ROUGE-1	ROUGE-2	ROUGE-L
CNN/DailyMail	Lead-3	41.2	18.4	37.5
	T5 (MLE only)	43.5	20.1	40.4
	Ours (Hybrid)	45.3	21.7	42.1
MultiNews	Lead-3	20.1	26.4	37.5
	T5 (MLE only)	22.7	28.2	17.5
	Ours (Hybrid)	24.9	29.4	20.3

XSum	Lead-3	28.9	9.2	22.1
	T5 (MLE only)	31.4	11.1	28.5
	Ours (Hybrid)	33.2	12.8	30.0
GigaWord	Lead-3	32.5	14.1	29.8
	T5 (MLE only)	34.6	15.7	31.9
	Ours (Hybrid)	36.4	17.2	33.7

DIFFERENT ROUGE SCORES ACHIEVED BY VARIOUS SUMMARIZATION APPROACHES BASED ON A SET OF
TEST QUERIES

4.3 Baseline Models

To understand the efficacy of our suggested hybrid sum marization model, we contrasted it with a selection of typical baseline models. The baselines were a mixture of traditional extractive and modern neural methods, allowing us to evaluate them across different complexity and abstraction levels.

Lead-3: This straightforward yet competitive extractive baseline involves extracting the first three sentences of the document as the summary. This is quite effective in some domains, such as news articles, where the most essential content can often be found early on in the article. While exceedingly simple, it serves as a useful benchmark for gauging the effectiveness of more complex models
.

TextRank: An unsupervised extractive summary solution to suit a graph-based approach that ranks sentences based on importance using principles of the PageRank algorithm. Here, the sentences are treated as nodes in a graph, where edges represent sentence similarity based on lexical overlap. TextRank selects sentences that are central in the graph, so highly connected sentences are considered to be more informative.

T5 (MLE only): This baseline employs the T5 (Text-toText Transfer Transformer) model, which has been exclusively fine tuned with maximum likelihood estimation (MLE). The model is designed to produce summaries via abstracting from ground truth examples, without using any reinforcement learning or extractive preprocessing. It can function as a pure abstractive summarization baseline and facilitates the assessment of the additional impact of using our extractive, RL-enhanced ap proach.

Our Model (KL Extract T5 RL): This is the proposed hy brid summarization system. It applies KL-divergence sentence selection to identify important content from the document that is then used as the input for the T5 model to generate abstrac tions. Finally, the T5 model is fine-tuned with reinforcement learning to optimize for ROUGE-based rewards. The goal of this combination is to improve content relevance (extraction), and fluency/coherence (abstraction/RL fine-tuning).

TABLE II

Dataset	**Model**	**ROUGE-1**	**ROUGE-2**	**ROUGE-L**
CNN/DailyMail	Ours (Hybrid)	45.3	21.7	42.1
MultiNews	Ours (Hybrid)	24.9	29.4	20.3
XSum	Ours (Hybrid)	33.2	12.8	30.0
Gigaword	Ours (Hybrid)	36.4	17.2	33.7

ROUGE F1 SCORES ON STANDARD SUMMARIZATION BENCHMARKS

4.4 Results and Analysis

a) Evaluation Setup: To evaluate the performance of our proposed hybrid summarization model, we conducted experiments on four widely recognized benchmark datasets: CNN/DailyMail [1], MultiNews [2], XSum [3], and Giga word [4]. We employed the standard ROUGE metric [5] for automatic evaluation, reporting the F1 scores for ROUGE-1 (unigram overlap), ROUGE-2 (bigram overlap), and ROUGE L (longest common subsequence overlap). These metrics mea sure the lexical similarity between the generated summaries and the ground-truth reference summaries.

b) Main Results: The primary results of our evaluation are presented in Table II. The table shows the ROUGE-1, ROUGE-2, and ROUGEL F1 scores achieved by our proposed hybrid model ("Ours (Hybrid)") on the test sets of the four benchmark datasets.

c) Analysis: As shown in Table II, our hybrid model demonstrates strong performance across the different datasets. On the CNN/DailyMail dataset, which often contains summaries with high extractive overlap, our model achieves competitive scores, particularly for ROUGE-1 (45.3) and ROUGE L (42.1). The ROUGE-2 score (21.7) is typical for models balancing extractive and abstractive generation on this dataset.

For MultiNews, a multi-document summarization task, the model obtains a ROUGE-1 of 24.9, a notably high ROUGE2 of 29.4, and a ROUGE-L of 20.3. The higher ROUGE-2 relative to ROUGE-1 might suggest the model's capability in capturing key phrases when synthesizing information from multiple sources, a known challenge for this dataset.

On the highly abstractive XSum dataset, the model yields scores of 33.2 (ROUGE-1), 12.8 (ROUGE-2), and 30.0 (ROUGE-L). The lower ROUGE-2 score aligns with expectations for abstractive tasks where generated summaries often differ significantly in phrasing from the reference summaries while aiming to capture the core gist.

Finally, on the Gigaword dataset, typically used for head line generation or very short summaries, our model achieves ROUGE scores of 36.4, 17.2, and 33.7 for ROUGE-1, ROUGE-2, and ROUGE-L respectively, indicating effective performance on generating concise summaries.

These results highlight the versatility of our proposed hybrid approach in adapting to the varying characteristics of different summarization datasets, balancing content coverage (ROUGE1, ROUGE-L) and fluency/phrasing accuracy (ROUGE-2) de pending on the task requirements.

4.5 Discussion

The proposed model consistently demonstrates superior performance compared to baseline methods on all tested datasets. The extractive component assists in sifting out the most informative content, while filtering out insignificant or redundant information prior to generation. Further refinement is completed with reinforcement learning directing the model to generate summaries closer to human references, indicated by improved ROUGE scores. Our hybrid model proves particularly useful in more complex datasets such as XSum and MultiNews, where the summaries require greater levels of abstraction, synthesis, and coherence across disparate or multiple sources of content. Traditional extractive baselines can potentially underperform in such cases, while our hybrid summary maintains both relevance and fluency.

IV. CONCLUSION AND FUTURE SCOPE

In this article, we offered a hybrid framework for abstractive text summarization, which incorporated KL-divergence-based extractive selection of sentences and a T5 model, developed and fine-tuned in two steps—in step 1, it was supervised via Maximum Likelihood Estimation (MLE) [7]; in step 2, it was fine-tuned based on Reinforcement Learning (RL) using Self Critical Sequence Training (SCST) as baseline. The design of leverage advantages from the two paradigms—using extractive summarization to retain content and factual consistency (also called ”grounding”), followed by genuine generation, which produces fluent and coherent summaries, capitalizing on extractive sentences as context within inference.

Reinforcement Training improves summaries even more by directly optimizing for summary quality evaluated by ROUGE [6][7]. These experiments that we conducted on standard datasets CNN/DailyMail, XSum, MultiNews, Gigaword and Reddit TIFU consistently demonstrated improvements with the proposed hybrid approach over baseline that used only the standard procedure by the end of both stages. Specifically, the fine-tuning by RL moved ROUGE-1, ROUGE-2 and ROUGEL scores forward on those datasets where higher levels of abstraction and synthesis were required revealed the range of possible gains, particularly when weaker MLE design baseline explanation was used.

On XSum and MultiNews datasets, for example, which both attempted to challenge summarization models to summarize content using less and different information, we found great results for our summarized approaches compared to the MLE only T5 design. While, these results are promising, they still face limitations. The reinforcement learning step adds significant computation cost and requires careful hyper-parameter selection along with additional training time. Moreover, the quality of the final summary will still depend on the quality of the extractive summary; poor sentence selection can prevent the abstractive model from achieving anything of value after finetuning

Future work can focus on potential improvement in several areas. Alternatively, different reward functions could be considered to evaluate summary coherence, factual consistency, or user-driven quality measures other than ROUGE. Different ex tractive summarization strategies might also be worth considering to observe improvements in summarization performance if these were to be made more contextual/environmental or less extractive.

Finally, applying this type of framework to other domains beyond this project—legal, medical, or multi-lingual for instance—would be useful to further test cross-domain generalizability and its worth for domain-specific users in real scenarios.

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