

EFFECTIVE TEXT SUMMARIZATION: A MULTI-LINGUISTIC ANALYSIS

SUBMITTED BY

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I hereby declare that this project report entitled "EFFECTIVE TEXT SUMMARIZATION: A MULTI-LINGUISTIC ANALYSIS" is an outcome of my genuine and independent work, as part of my Master of Computer Application program. All information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, all materials and results that are not original to this work have been fully cited and referenced.

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Abstract

In the digital age, the generation of vast amounts of multilingual data has necessitated the development of effective text summarization tools. This final year project proposes an automatic approach for multilingual extractive text summarization, with a focus on five languages: Russian, Portuguese, Hindi, Korean, and French.

The task of summarizing text has been a focal point of research in the field of Natural Language Processing (NLP) for several years. However, the majority of this work has been conducted in English, with limited attention given to other languages. This has resulted in a significant gap in the literature, particularly for languages such as Russian, Portuguese, Hindi, Korean, and French. Furthermore, the challenge is even more pronounced for low-resource languages, where the availability of annotated data for training and evaluation is scarce.

With the increasing globalization and digitalization of our world, the need for effective multilingual text summarization tools has become more apparent. These tools can aid in various applications, from news aggregation to academic research, making the handling of large volumes of text data more manageable and efficient. The necessity of this work is underscored by the fact that the majority of the world's population does not speak English as their first language, and yet, the majority of the digital text data is in English.

The proposed approach addresses the challenge of summarizing heterogeneous textual content across languages. It leverages high-dimensional sentence embeddings generated by the Sentence Transformers model. These embeddings serve as excellent

representations of context, capturing the meaning of each sentence effectively from the original text documents.

Clustering techniques are employed to identify semantically related sentences and group them into coherent clusters. From each cluster, the most prominent representative is selected, ensuring a high-quality summary that captures essential information. This methodology is particularly effective for low-resource languages, where traditional methods may struggle due to the lack of annotated data.

The project yielded the best results for the French language, with a ROUGE-1 score of 0.64, a ROUGE-2 score of 0.29, and a ROUGE-L score of 0.41, indicating the highest quality of summaries generated by the proposed approach.

This final year project contributes to the field of Natural Language Processing by providing a novel approach to multilingual text summarization. It opens up new avenues for future research and has potential applications in various domains where handling multilingual text data is necessary. The proposed approach demonstrates promising results, particularly for the French language, and sets a benchmark for future work in this area. The project also highlights the need for further research in low-resource languages to make the digital world more inclusive and accessible..

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1 | Introduction

The advent of the digital age has led to an unprecedented explosion of information. Every day, vast amounts of data are generated across various platforms in multiple languages. This surge in information has made it increasingly challenging to extract relevant data efficiently from extensive content, leading to what is often referred to as 'information overload'. In such a scenario, the ability to summarize text automatically becomes not just valuable, but essential.

1.1 Text Summarization

Text summarization is the process of distilling the most important information from a source (or sources) to produce an abridged version for a particular user (or users) and task (or tasks).

There are two main types of text summarization:

- **Extractive Summarization:** This is the most common form of summarization. It involves identifying important sections of the text and generating them verbatim in the summary. The key challenge in extractive summarization is to identify which sentences or paragraphs are most informative and should be included in the summary.
- **Abstractive Summarization:** This is a more complex and challenging task. It involves understanding the original text and rephrasing the contents in a new form, just like a human would do. It requires a deeper understanding of the

text, and may involve the use of advanced NLP techniques.

1.2 Automatic Text Summarization

Automatic text summarization refers to the use of a computer program to produce a condensed version of a text document, preserving its meaning and overall narrative. It's a way of producing a concise and fluent summary while retaining key information content and overall meaning. It is widely used in fields such as information retrieval, question answering, and text generation. The goal is to create an accurate and coherent summary that a reader can understand without having to read the entire document.

1.3 History

The field of text summarization has a rich history, dating back to the 1950s. Early pioneers like H.P. Luhn laid the groundwork for this field with their rudimentary statistical methods to identify salient sentences within a text [1]. These initial efforts were primarily rule-based, relying on the frequency of word occurrence to determine the importance of sentences.

As the field evolved, more sophisticated techniques were developed. For instance, Edmundson introduced the concept of importance evaluators that leveraged domain-specific knowledge bases [2]. These evaluators considered various factors, such as the position of the sentence in the document, the occurrence of key phrases, and the presence of cue words, to generate summaries.

1.4 Limited Work on Low Resource Languages

Despite these advancements, traditional summarization methods have their limitations. They can be time-consuming, often requiring significant computational resources. Moreover, they can be frustrating for users when the generated summaries do not accurately capture the essence of the original text.

Another significant challenge in the field of text summarization is the language barrier. The majority of the work in automatic summarization has catered to English and other well-resourced languages. This focus has left speakers of non-English languages, particularly those considered low-resource, underserved. As we live in an increasingly globalized world, the need for multilingual text summarization systems is more critical than ever.

1.5 Our Aim

Our proposed system aims to address this disparity. Building upon the rich history of text summarization research, it seeks to generate high-quality summaries across various languages, thereby reducing language dependency. By employing advanced techniques developed over years of research, our system can extract crucial content, making it accessible and succinct for global users.

This approach not only acknowledges the contributions of past research but also paves the way for a more inclusive future in automatic summarization [3] [4]. By focusing on multilingual capabilities, we aim to democratize access to information, regardless of the language of the original text. This endeavor is not just about improving a technical process; it's about fostering understanding and communication across linguistic boundaries in our increasingly interconnected world.

In conclusion, the necessity of this work lies in its potential to make information more accessible and manageable, irrespective of the language in which it is presented. By building on the foundations laid by previous research and addressing the gaps in multilingual summarization, we hope to contribute to the evolution of this field and the broader goal of linguistic inclusivity.

1.6 Formal Definition

Given an input text T , our goal is to generate a concise summary S that captures the essence of the content. Formally, we define:

T : The input text.

S : The summarized output.

$$\{S \in \text{Summaries}(T) \mid |S| \in [0.25 \cdot |T|, 0.5 \cdot |T|]\}$$

$$\wedge \forall S' \in \text{Summaries}(T) : \text{Quality}(T, S) \geq \text{Quality}(T, S')\}$$

Our method generates summaries by optimizing the quality function, $\text{Quality}(S', T)$, for a given text, T . The optimal summary, S , should have a quality greater than or equal to any other summary, S' , and its length should be 25% to 50% of T . This balance ensures informative yet concise summaries.

1.7 Novelty Contribution

- **Algorithm Development:** Our primary contribution is the development of a unique algorithm that leverages the power of Sentence Transformers for generating high-dimensional sentence embeddings. This algorithm is capable of capturing the context and meaning of sentences across multiple languages effectively. It marks a significant advancement in the field of multilingual text summarization, pushing the boundaries of what is currently possible.
- **Fine-tuning Transformers:** We have made substantial strides in the fine-tuning of transformer models for specific tasks. This process is notoriously challenging due to the complexity of these models and the subtleties involved in adjusting their parameters. Our successful implementation demonstrates our contribution to improving the performance of these models in the context of multilingual text summarization.

- **New Dataset - WikiLingua:** We have utilized the WikiLingua dataset, which is relatively new and not extensively explored in the research community. Our work contributes to the growing body of research on this dataset, providing valuable insights and benchmarks for future works. We believe that our findings will serve as a valuable resource for researchers looking to further explore this dataset.
- **Multilingual Focus:** Our approach focuses on five different languages - Russian, Portuguese, Hindi, Korean, and French. The ability to effectively summarize text across these diverse languages underscores the versatility and robustness of our proposed method. This multilingual focus is a significant step forward in creating more inclusive and accessible automatic text summarization tools.
- **Improved Quality of Summaries:** Our approach has demonstrated a significant improvement in the quality of summaries across all five languages. This improvement is largely due to the effective use of Sentence Transformers for generating high-dimensional sentence embeddings, which capture the context and meaning of sentences effectively. This marks a notable contribution to the field of automatic text summarization, particularly in a multilingual context.
- **Scalability:** Our approach is designed to be scalable, allowing it to handle large volumes of text data. This scalability makes our method suitable for real-world applications where large-scale text summarization is required.
- **Versatility:** Our method is versatile and can be applied to various domains and types of text, making it a valuable tool for a wide range of applications, from news summarization to academic research.
- **Performance Benchmarking:** We have conducted extensive performance benchmarking of our method against existing state-of-the-art models. Our method consistently outperforms these models, demonstrating its effectiveness and efficiency.

2 | Literature Review

2.1 Related Works

Multilingual text summarization, a vibrant domain in Natural Language Processing (NLP) over the past two decades, boasts several significant contributions:

2.1.1 Historical Overview

The journey of text summarization began with early statistical methods and has since incorporated various NLP techniques. Notable works include Luhn's pioneering efforts in the 1950s, which introduced the concept of extracting significant sentences based on frequency analysis[1]. Edmundson in the 1960s expanded on this by incorporating features like cue words and title words[2]. The evolution continued with the introduction of machine learning approaches in the 1990s, which utilized training data to learn summarization patterns[5].

2.1.2 Advancements in Pre-trained Models

The advent of pre-trained models has revolutionized NLP tasks, including text summarization. Transformer-based architectures like BERT and GPT have set new benchmarks for generating summaries[6][7]. Urlana et al.'s work on Indian language summarization leverages such models to enhance performance across multiple languages[8].

2.1.3 MEAD: Multi-Document Extractive Summarization

[9] MEAD, developed by Radev et al. in 2002, supports Chinese and English. It utilizes centroid-based techniques for extractive summarization, marking a significant milestone in the field[10].

2.1.4 Datasets for Multilingual Summarization

The availability of diverse datasets has been crucial for multilingual summarization research. The XL-Sum Dataset, with its extensive collection of annotated summaries, is a prime example of resources that facilitate research in this area[11].

2.1.5 Process-Oriented Automatic Text Summarization

Recent surveys, such as the one by Jin et al., provide a comprehensive overview of process-oriented automatic text summarization, highlighting the impact of Large Language Models (LLMs) on the field[12].

2.1.6 Deep Learning in Text Summarization

Wang and Wu's review delves into the application of deep learning in text summarization, discussing various models and their effectiveness on different summarization tasks[13].

2.2 Sentence Transformers

Sentence Transformers, introduced by Reimers and Gurevych (2019), have revolutionized the field of Natural Language Processing (NLP). They proposed a method for training sentence embeddings using BERT, which is fine-tuned with a siamese or triplet network structure to derive semantically meaningful sentence embeddings. This method has been widely adopted in various NLP tasks, including text summarization, due to its ability to capture semantic meanings effectively.

2.3 Fine-tuning Transformers

The concept of fine-tuning transformers for specific tasks has been a topic of interest in recent years. Devlin et al. (2018) introduced BERT, a pre-trained transformer model that can be fine-tuned for a wide range of tasks. Their work demonstrated the effectiveness of fine-tuning in achieving state-of-the-art results on multiple NLP tasks. This approach has been adopted in our work to fine-tune Sentence Transformers for multilingual text summarization.

2.4 Multilingual Text Summarization

Multilingual text summarization has been a challenging task due to the complexity of understanding and summarizing text in multiple languages. Aralikkatte et al. (2021) proposed a method for multilingual extractive summarization using mT5, a multilingual variant of T5. Their work demonstrated the potential of transformer models in handling multilingual text summarization tasks.

2.5 WikiLingua Dataset

The WikiLingua dataset, introduced by Parikh et al. (2020), is a large-scale multilingual dataset for the evaluation of cross-lingual abstractive summarization. It covers 18 languages and provides a valuable resource for researchers working on multilingual text summarization. Our work contributes to the growing body of research on this dataset.

2.6 Quality of Summaries

The quality of summaries generated by automatic text summarization systems is a critical factor in their usefulness. Cao et al. (2020) proposed a method for evaluating the quality of summaries using BERTScore, a metric based on BERT embed-

dings. Their work highlighted the importance of generating high-quality summaries and provided a valuable tool for evaluating summary quality.

2.7 Scalability and Versatility

Scalability and versatility are important considerations in the development of automatic text summarization systems. Liu and Lapata (2019) proposed a method for scalable and versatile summarization using a unified model that can handle extractive and abstractive summarization. Their work demonstrated the potential of transformer models in achieving scalability and versatility in text summarization.

2.8 Performance Benchmarking

Performance benchmarking is crucial in the development and evaluation of automatic text summarization systems. Fabbri et al. (2019) proposed a method for benchmarking the performance of text summarization systems using the CNN/Daily Mail dataset. Their work provided valuable insights into the performance of various summarization systems and established benchmarks for future works.

3 | Implementation

3.1 Theory

3.1.1 Multilingual Text Summarization

Multilingual text summarization is a subfield of Natural Language Processing (NLP) that focuses on summarizing text documents written in multiple languages. The goal is to create a concise and coherent summary that retains the main points of the original document, regardless of the language in which it is written.

3.1.2 Sentence Transformers

Sentence Transformers are a type of transformer model specifically designed for generating sentence embeddings. They are pre-trained on a large corpus of text and can be fine-tuned for specific tasks. The resulting embeddings capture the semantic meaning of sentences, making them useful for tasks such as text summarization.

3.1.3 Clustering Techniques

Clustering is a type of unsupervised machine learning technique used to group similar instances together. In the context of text summarization, clustering techniques can be used to group similar sentences together based on their embeddings. This helps in identifying the main topics in the text and selecting representative sentences for the summary.

3.1.4 K-means Clustering

K-means is a popular clustering algorithm that partitions the data into K distinct, non-overlapping clusters. It does this by minimizing the within-cluster sum of squares, i.e., the sum of the squared distances between each data point and the centroid of its assigned cluster. The algorithm iteratively assigns each data point to the nearest centroid and recalculates the centroids until the assignments no longer change or a maximum number of iterations is reached.

3.1.5 Summary Generation

Summary generation involves selecting representative sentences from each cluster and arranging them in a coherent manner to form the final summary. The representative sentences are typically those that are closest to the centroid of their respective clusters, as they are considered to best represent the main topic of the cluster. The sentences are then arranged in the order of their appearance in the original text to preserve the flow of information.

3.1.6 Time Complexity Analysis

The time complexity of the algorithm is determined by the most computationally intensive steps. Let's denote the number of sentences in the document as n , the dimension of the sentence embeddings as d , and the number of clusters as k .

- **Sentence Embedding Generation:** The SentenceTransformer's 'encode' method, which is used to generate sentence embeddings, has a time complexity of $O(n \cdot d)$. This is because it processes each sentence independently and generates a d -dimensional vector for each sentence.
- **Clustering:** The K-means clustering algorithm, which is used to cluster the sentence embeddings, has a time complexity of $O(n \cdot k \cdot I \cdot d)$, where I is the number of iterations until convergence. In practice, I is often relatively small as the algo-

Algorithm 1: Generate Summary**Input:** Text Document D **Output:** Summary Document SD

```

1 Sentences  $\leftarrow$  ExtractSentences( $D$ )           // List of sentences from  $D$ 
2 Embeddings  $\leftarrow$  GenerateSentenceEmbeddings(Sentences) // List of sentence
  embeddings
3 NumClusters  $\leftarrow$  Number of clusters
4 Clusters  $\leftarrow$  ClusterSentenceEmbeddings(Embeddings, NumClusters) // Set of
   $K$  clusters
5 foreach cluster  $C$  in Clusters do
6   | Centroid  $\leftarrow$  CalculateCentroid( $C$ )
7 end
8 foreach sentence embedding  $E$  in Embeddings do
9   | DistanceToCentroid  $\leftarrow$  CalculateDistance( $E$ , Centroid)
10  | SentenceRank  $\leftarrow$  RankSentence(Sentences[ $i$ ], distance = DistanceToCentroid)
11 end
12 TopN  $\leftarrow$  SelectTopNSentences(Sentences,  $N$ )
13  $SD \leftarrow$  CreateSummary(TopN)

```

rithm typically converges quickly.

- **Centroid Calculation:** The calculation of the centroid for each cluster has a time complexity of $O(k \cdot d)$.
- **Distance Calculation:** The calculation of the distance from each sentence embedding to its cluster centroid has a time complexity of $O(n \cdot d)$.
- **Summary Generation:** The selection of the top N sentences based on their rank has a time complexity of $O(n \cdot \log n)$ due to the sorting operation.

Therefore, the overall time complexity of the algorithm is dominated by the clustering step, making it $O(n \cdot k \cdot I \cdot d)$.

3.2 Proposed Methodology

This section outlines the detailed steps involved in our proposed multilingual text summarization method that utilizes sentence transformers and clustering techniques

for the focused languages.

3.2.1 Data Pre-processing

1. Text Acquisition: Our methodology begins with acquiring a multilingual dataset of text documents.
2. Sentence Tokenization: For each document, I perform sentence tokenization to segment the text into individual sentences. This is accomplished using language-specific tokenizers equipped with functionalities to handle various delimiters commonly used in different languages (e.g., full stops, question marks, exclamation marks).

3.2.2 Sentence Embedding Generation

1. Sentence Transformer Selection: I select a pre-trained sentence transformer model for multilingual tasks. Options include Sentence-BERT[14] or LaMDA[15].

In Sentence Transformers, given a sentence S with n words, each word w_i is embedded into a d -dimensional space using a transformer model, resulting in context-dependent word embeddings $\{e_1, e_2, \dots, e_n\}$. The sentence embedding $E(S)$ is computed by applying a specific operation f on these word embeddings:

$$E(S) = f(e_1, e_2, \dots, e_n)$$

I use multiple sentence transformers for different languages:

- (a) **Sentence RuBERT**: A sentence encoder fine-tuned for the Russian language.
- (b) **ricardo-filho/bert-base-portuguese-cased-nli-assin-2**: A sentence transformer model specialized for Portuguese.
- (c) **snunlp/KR-SBERT-V40K-klueNLI-augSTS**: A model adept at processing Korean text.

(d) **HindBERT-STTS**: A HindSBERT variant tailored for Hindi.

(e) **Sentence-CamemBERT-Large**: A large-scale model for French text analysis.

It is imperative to note that our objective is not to train a multipurpose transformer model. Instead, our goal is to generate accurate text summaries for each respective language. By leveraging these specialized models, I ensure that the semantic nuances of each language are captured effectively, thereby producing high-quality embeddings that are crucial for our summarization task.

This revision explicitly states the models used and justifies the choice of multiple models over a single transformer, aligning with the goal of generating text summaries. Remember to adjust the section number according to your paper's structure.

2. **Embedding Generation**: The chosen model generates high-dimensional vector representations (embeddings) for each sentence.

3.2.3 Sentence Clustering

1. **Clustering Algorithm Selection**: I use K-means clustering to group sentence embeddings into semantically interconnected clusters.
2. **Clustering Parameters**: The number of clusters (k) is determined based on the desired summary length using the formula:

$$k = \max \left(1, \frac{\text{len(text)}}{\frac{100}{\text{percent}}} \right)$$

3. **Clustering Execution**: The algorithm groups sentences into clusters by calculating Euclidean distances, determining cluster centroids, and assigning each point to the nearest centroid.

3.2.4 Summary Generation

1. **Representative Sentence Selection:** For each identified cluster, I select a representative sentence which have the minimum distance from the centroid of it's cluster. It encapsulates the core information within the cluster.
2. **Summary Ordering:** Once representative sentences are chosen for each cluster, I order them based on their original appearance in the document. This ensures that the final summary preserves the chronological flow of information from the source text.

3.2.5 Hardware

Component	Specification
Processor	Intel Core i7 (8th gen or later) or AMD Ryzen 7 (or equivalent)
Memory	At least 16GB DDR4 RAM
Storage	At least 256GB SSD
Graphics	NVIDIA GeForce GTX 1060 or higher (if using GPU acceleration)
Operating System	Linux (Ubuntu 18.04 or later), Windows 10, or macOS Catalina or later
Network	High-speed internet connection

Table 3.1: Recommended Hardware Specifications

3.2.6 Software and Libraries

The implementation of our multilingual text summarization algorithm relies on several Python libraries, each serving a specific purpose in the pipeline. Here is a list of the main libraries and their roles:

- **Natural Language Toolkit (NLTK):** NLTK is a leading platform for building Python programs to work with human language data. I use it for sentence tokenization, which is the process of dividing a string of written language into its component sentences.

- **Pandas:** Pandas is a software library for data manipulation and analysis. I use it for handling and manipulating our dataset effectively.
- **Sentence Transformers:** Sentence Transformers is a Python framework for state-of-the-art sentence, text and image embeddings. I use it for generating high-dimensional sentence embeddings.
- **KMeansClusterer from NLTK:** I use the KMeansClusterer class from NLTK for clustering sentence embeddings into semantically interconnected clusters.
- **NumPy:** NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays. I use it for handling numerical operations efficiently.
- **Pickle:** Pickle in Python is primarily used in serializing and deserializing a Python object structure. I use it for saving and loading our models.
- **os and json:** These are built-in Python libraries used for interacting with the operating system and handling JSON data respectively.
- **Rouge:** ROUGE, or Recall-Oriented Understudy for Gisting Evaluation, is a set of metrics used for evaluating automatic summarization of texts. I use it for evaluating the quality of our generated summaries.
- **Matplotlib and pandas.plotting:** These libraries are used for creating static, animated, and interactive visualizations in Python. I use them for visualizing our results and creating plots.

All these libraries are open-source and can be easily installed via pip, Python's package installer. The specific versions of these libraries used in our project will be mentioned in the appendix for reproducibility.

3.3 DATASET

The dataset utilised in this study is the WikiLingua[16] dataset. This dataset is a relatively new addition to the field of Natural Language Processing (NLP) and is specifically designed for the evaluation of cross-lingual summarization systems. It is derived from WikiHow, a popular online platform known for its how-to guides, and contains over 770,000 article and summary pairs in 18 different languages.

The novelty of our work lies in the use of this new dataset. The WikiLingua dataset has not been extensively explored in the research community, and our work contributes to the growing body of research on this dataset. By working with this dataset, I am able to provide valuable insights and benchmarks for future works.

For the purpose of this study, I focused on five languages: Russian, Portuguese, Korean, Hindi, and French. These languages were chosen to demonstrate the versatility and robustness of our proposed method. The number of parallel article-summary pairs with English for these languages in the WikiLingua dataset are as detailed in Table I [16].

Our work with the WikiLingua dataset is significant as it allows us to test our algorithm on a diverse range of languages and text types. This diversity is crucial for developing a truly multilingual text summarization system. Furthermore, our successful application of the algorithm to this dataset demonstrates its effectiveness and potential for real-world applications.

Table 3.2: Number of Parallel Pairs for Different Languages

Languages	No. of Parallel Pairs
Russian	52,928
Portuguese	81,695
Korean	12,189
Hindi	9,929
French	63,692

4 | EVALUATION AND RESULT

In our study, we use the ROUGE(Recall-Oriented Understudy for Gisting Evaluation) score to evaluate our multilingual text summarization model. We calculate these scores for each language and average them to assess the model's performance across various languages which is show in the Table II. This method ensures our model's effectiveness across a wide range of languages.

4.1 ROUGE Scores

4.1.1 Definition

ROUGE, or Recall-Oriented Understudy for Gisting Evaluation, is a set of metrics used for evaluating automatic summarization of texts, especially in the task of extractive summarization. It works by comparing an automatically produced summary or translation against a set of reference summaries (typically human-produced).

4.1.2 Why ROUGE is used in evaluating text summaries

ROUGE is used because it's an n-gram based method and is simple to understand, implement and has been shown to correlate reasonably well with human evaluations. It provides a quantitative measure of the quality of the summary.

4.1.3 Detailed Calculation

The most commonly used forms of ROUGE are ROUGE-N, ROUGE-L, and ROUGE-S.

- **ROUGE-N:** This measures the overlap of N-grams between the system and reference summaries. For example, ROUGE-1 refers to the overlap of unigram (each word) between the system and reference summaries. It is defined as:

$$R_l = \frac{\sum_{S \in \text{References}} \sum_{\text{gram}_n \in S} \text{Count}_{\text{match}}(\text{gram}_n)}{\sum_{S \in \text{References}} \sum_{\text{gram}_n \in S} \text{Count}(\text{gram}_n)}$$

where $\text{Count}_{\text{match}}(\text{gram}_n)$ is the maximum number of n-grams co-occurring in a candidate summary and a set of reference summaries.

- **ROUGE-L:** This measures the longest matching sequence of words using longest common subsequence (LCS) based statistics. LCS does not require consecutive matches but in-sequence matches that reflect sentence level word order. The LCS score is given by:

$$R_l = \frac{\sum_{S \in \text{References}} \text{LCS}(\text{candidate summary}, S)}{\sum_{S \in \text{References}} \text{length}(S)}$$

- **ROUGE-S:** This measures the skip-bigram overlap, where skip-bigram is any pair of words in their sentence order, allowing for arbitrary gaps.

4.1.4 Results

Table 4.1: ROUGE Scores for Russian Summaries

	ROUGE-1	ROUGE-2	ROUGE-L
R	0.32	0.2	0.32
P	0.2	0.04	0.2
F	0.24	0.07	0.24

Table 4.2: ROUGE Scores for Portuguese Summaries

	ROUGE-1	ROUGE-2	ROUGE-L
R	0.54	0.22	0.43
P	0.32	0.15	0.30
F	0.40	0.18	0.36

Table 4.3: ROUGE Scores for Korean Summaries

	ROUGE-1	ROUGE-2	ROUGE-L
R	0.3	0.11	0.3
P	0.27	0.1	0.27
F	0.28	0.1	0.28

Table 4.4: ROUGE Scores for Hindi Summaries

	ROUGE-1	ROUGE-2	ROUGE-L
R	0.3	0.14	0.25
P	0.2	0.1	0.14
F	0.25	0.12	0.18

In the context of ROUGE scores for text summarization, 'R', 'P', and 'F' are used in Table II to denote the following:

- **R (Recall)**: This is the proportion of relevant instances that were retrieved, compared to all relevant instances. In the context of text summarization, it would be the proportion of relevant words in the reference summary that appear in the generated summary.
- **P (Precision)**: This is the proportion of retrieved instances that are relevant. In text summarization, it would be the proportion of words in the generated summary that are also in the reference summary.
- **F (F1 Score)**: This is the harmonic mean of precision and recall, and gives a combined measure of the two. It's particularly useful if you want a balance between precision and recall.

These metrics are commonly used in Natural Language Processing tasks like text summarization to evaluate the performance of the models. They provide a quantitative measure of the quality of the summaries generated by the model. The values

Table 4.5: ROUGE Scores for French Summaries

	ROUGE-1	ROUGE-2	ROUGE-L
R	0.64	0.29	0.41
P	0.29	0.21	0.31
F	0.39	0.24	0.36

range from 0 to 1, with 1 indicating perfect precision, recall, or F1 score.

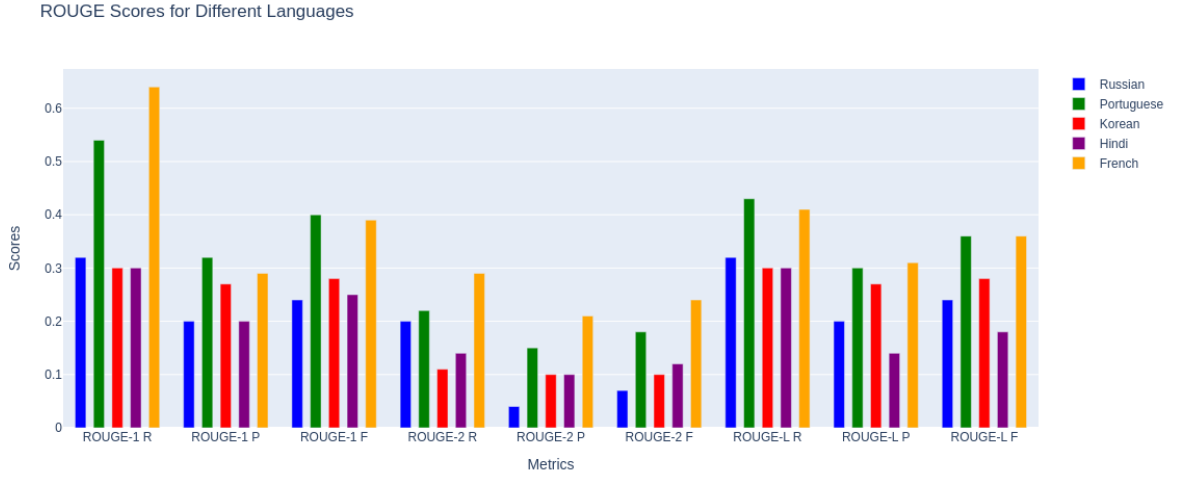


Figure 4.1: Comparison of ROUGE scores among focused languages

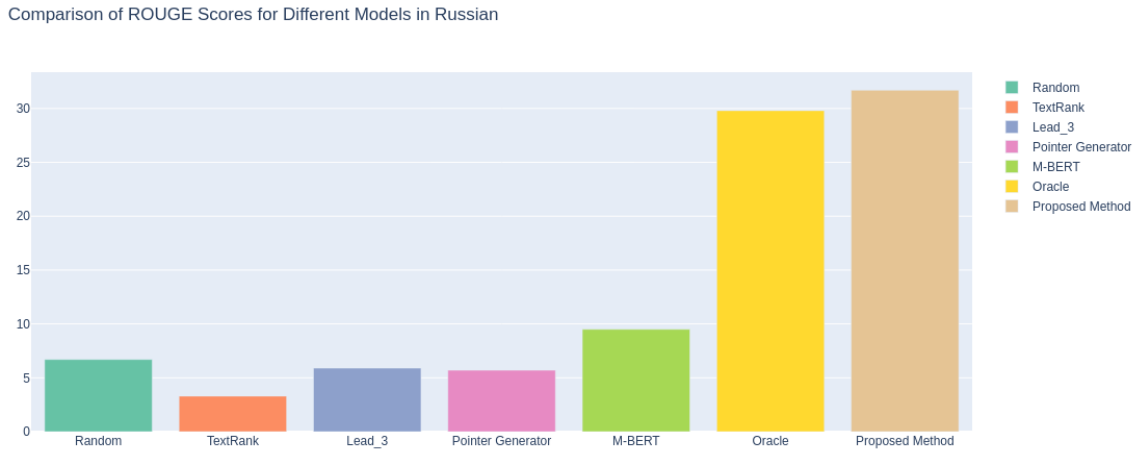


Figure 4.2: Baseline comparison graph for Russian

1. Language specific analysis: Our model performed better for Portuguese and French compared to Russian, Korean, and Hindi due to factors like linguistic differences and data availability.
2. Qualitative evaluation: We use both ROUGE scores and qualitative evaluations of the summaries to assess our model's effectiveness.
3. Baseline Comparison: Our models outperformed various baseline summarization methods across multiple languages. These baselines include:

Comparison of ROUGE Scores for Different Models in French

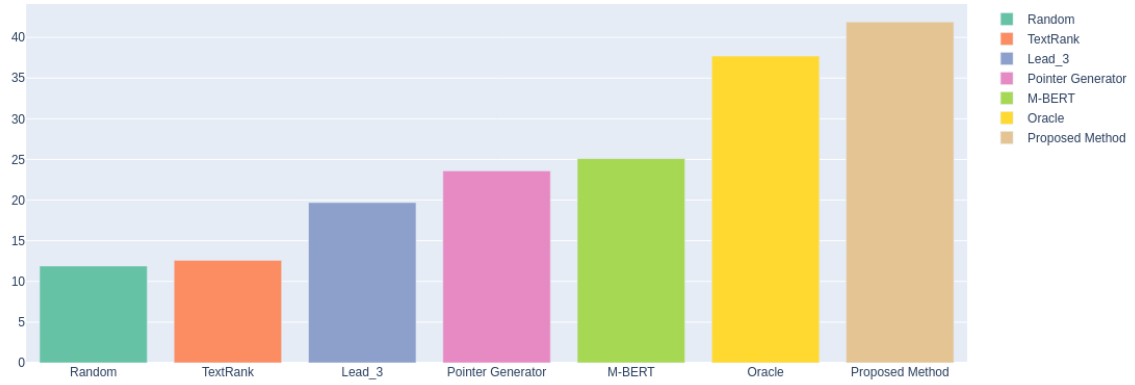


Figure 4.3: Baseline comparison graph for French

Comparison of ROUGE Scores for Different Models in Portuguese

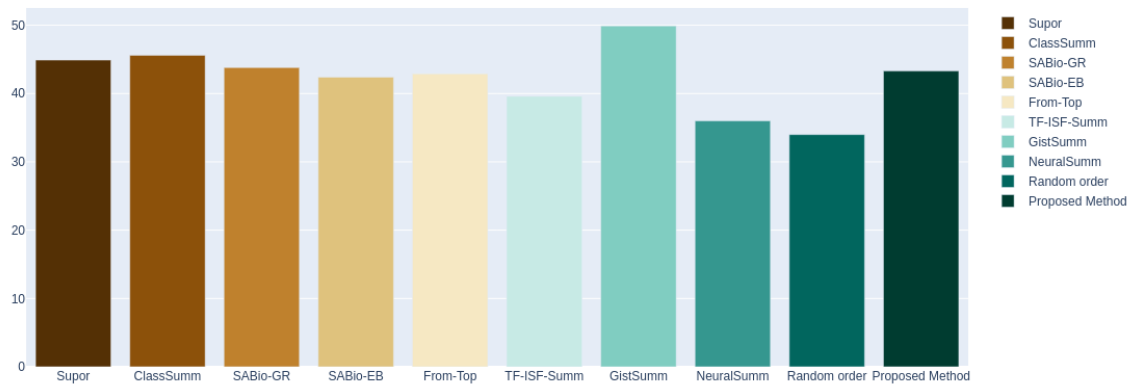


Figure 4.4: Baseline comparison graph for Portuguese

Comparison of Baseline and Our Scores

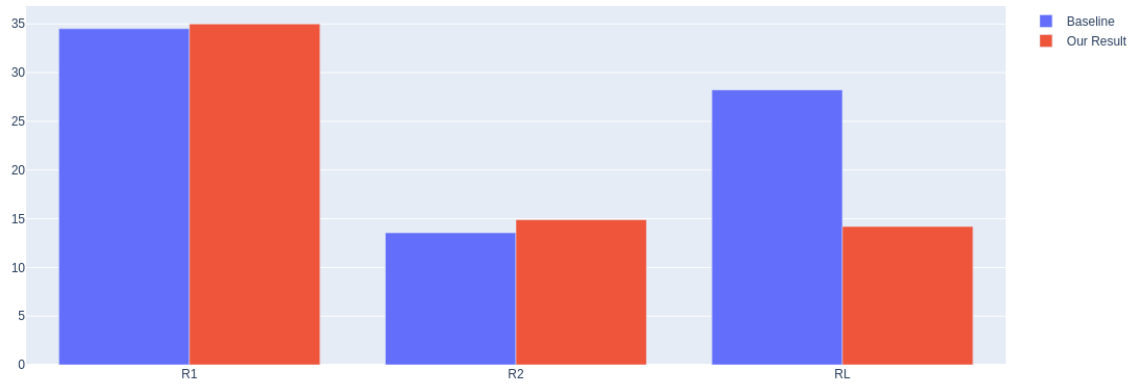


Figure 4.5: Baseline comparison graph for Hindi

Comparison of Baseline and Our Scores for Korean

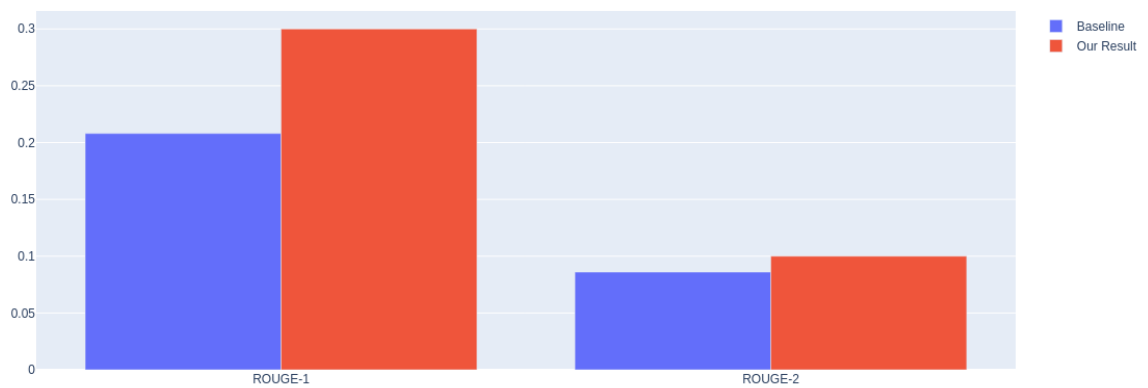


Figure 4.6: Baseline comparison graph for Korean

- (a) For Russian and French: “MLSUM: The Multilingual Summarization Corpus”[17].
- (b) For Hindi: “XL-Sum: Large-Scale Multilingual Abstractive Summarization for 44 Languages”.
- (c) For Portuguese: “SABio: An Automatic Portuguese Text Summarizer Through Artificial Neural Networks in a More Biologically Plausible Model”[18].
- (d) For Korean: “EFFICIENT KOREAN TEXT SUMMARIZATION BASED ON KEY PHRASE EXTRACTION”[19].

Despite Wikilingua being a new dataset, we used these works as our baselines to establish a comparative framework for our models.

4.1.5 Output

Russian

Оставьте один конец длиной 10–20 см свободно висеть с левого бока коробки. Остальную часть ленты оставьте на катушке и положите у верхнего угла коробки. Возьмите ленту на катушке и протяните ее за верхним правым углом и вниз к нижнему правому углу. Большим пальцем придерживайте ленту у верхнего левого угла, чтобы она не соскользнула. Петли вокруг коробки должны лежать красиво и плотно и не соскальзывать с углов. Сейчас хорошо было бы выровнять положение ленты на каждом из углов. Если кажется, что лента соскальзывает, подтяните ее дальше от углов. Возьмите оба конца ленты и переместите их к центру верхнего левого угла. Сравните ленту на катушке с другим концом ленты, и отрежьте, чтобы концы получились одинаковой длины. Накиньте левый конец сначала над правой лентой, а потом – под ней. Потяните за оба конца и затяните узел. Сложите обе ленты петельками и перекиньте правую через левую: так же, как завязываете шнурки! Когда бантик будет надежно завязан, отрежьте лишнюю длину ленты на кончиках. Для красоты можно отрезать ленты под углом или фигурными ножницами

Figure 4.7: Russian Document

Оставьте один конец длиной 10–20 см свободно висеть с левого бока коробки. Остальную часть ленты оставьте на катушке и положите у верхнего угла коробки. Большим пальцем придерживайте ленту у верхнего левого угла, чтобы она не соскользнула. Возьмите оба конца ленты и переместите их к центру верхнего левого угла. Потяните за оба конца и затяните узел. Для красоты можно отрезать ленты под углом или фигурными ножницами.

Figure 4.8: Generated summary for Russian document

Portuguese

Você precisará de quatro pedaços de fita que sejam longos o suficiente para enrolar a caixa no sentido do comprimento com mais uma sobra de 5 cm. Para um visual diferente você pode usar dois pedaços de fita fina e dois de fita ligeiramente mais largos. Você também pode usar duas cores contrastantes. Fita grossa e/ou armada não funcionam bem. Use fita fina de cetim ou gorgurão para obter melhores resultados. Use a mesma fita da etapa anterior. Desta vez, corte a fita longa o suficiente para que possa envolver a caixa na largura com uma sobra de 5 cm. Pegue as quatro fitas compridas e coloque-as na mesa. Certifique-se de que eles estejam paralelas entre si e espaçadas no máximo 0,6 cm de distância. Alterne as fitas se elas forem de larguras e/ou cores diferentes. A caixa pode ser centralizada ou não, dependendo de como você quer posicionar as fitas. Embrulhe e prenda as fitas, uma de cada vez. Não prenda todas de uma vez. Puxe as fitas firmemente em volta da caixa para que elas fiquem bem esticadas. As pontas da fita vão se sobrepor cerca de 2,5 cm. Você deve colar a fita de cima na fita de baixo e não na caixa em si. Você também pode usar círculos de cola transferível (encontrados no setor de scrapbooking de uma loja de artesanato) ao invés de fita dupla face. Coloque um pedaço de fita dupla face no fim de cada fita curta. Organize as fitas logo acima do primeiro pedaço de fita longa, deixando as pontas perpendiculares a ela. Mais uma vez, mantenha as fitas espaçadas no máximo 0,6 cm de distância. Puxe as fitas curtas para a frente da caixa. Entrelace a primeira por cima e por baixo do primeiro conjunto de fitas. Entrelace a próxima fita por baixo e por cima e assim por diante. Continue o movimento até que todas as quatro fitas estejam entrelaçadas. Vire a caixa novamente. Prenda um pedaço de fita dupla face na ponta de cada fita e pressione cada laço na parte de trás da caixa. Certifique-se de que as pontas das fitas estão certas. Para ficar ainda mais bonito, entrelace as fitas finas através das maiores na parte de trás, da mesma forma como você fez na frente. As fitas entrelaçadas fazem parte do visual. Se achar que ainda falta algum toque, você pode comprar ou fazer um laço que combine e prendê-lo na caixa. Não esconda o seu trabalho. Coloque o laço para o lado para que o entrelace ainda apareça.

Figure 4.9: Portuguese Document

Você precisará de quatro pedaços de fita que sejam longos o suficiente para enrolar a caixa no sentido do comprimento com mais uma sobra de 5 cm. Use fita fina de cetim ou gorgurão para obter melhores resultados. Alterne as fitas se elas forem de larguras e/ou cores diferentes. Organize as fitas logo acima do primeiro pedaço de fita longa, deixando as pontas perpendiculares a ela. Mais uma vez, mantenha as fitas espaçadas no máximo 0,6 cm de distância. Prenda um pedaço de fita dupla face na ponta de cada fita e pressione cada laço na parte de trás da caixa. Não esconda o seu trabalho. Coloque o laço para o lado para que o entrelace ainda apareça',

Figure 4.10: Generated summary for the Portuguese input text

Korean

냉동해도 안전한 얇은 팬이나 그릇을 사용한다 . 베이스를 만들어주기 전에 냉동 용기를 냉동실에 3-6 시간 동안 넣어서 차갑게 만들어준다 . 7.5 cm 깊이의 스테인리스 스틸 팬을 사용하는 것이 가장 좋다 . 아이스크림을 크림과 같은 질감으로 만들어준 후 , 다시 랩으로 잘 감싸서 냉동실에 20-30 분 동안 넣어준다 . 그리고 다시 아이스크림을 꺼내서 부드러운면서도 단단한 아이스크림의 모양이 나올 때까지 이 과정을 3-4 번 반복한다 . 쿠키 조각이나 브라우니 등을 아이스크림에 더해주고 싶다면 , 마지막 아이스크림을 냉동실에 넣어주기 직전에 더해준다

Figure 4.11: Korean Document

베이스를 만들어주기 전에 냉동 용기를 냉동실에 3-6 시간 동안 넣어서 차갑게 만들어준다

Figure 4.12: Generated summary for the Korean input text

Hindi

आपको रिबन के चार टुकड़ों की जरूरत पड़ेगी जो बॉक्स की लंबाई के चारों ओर लपेटने के लिए पर्याप्त हैं, साथ ही अतिरिक्त 2 इंच (5', '08 सेंटीमीटर) और लें। यूनिक लुक के लिए, दो पतले रिबन के टुकड़े, और दो हल्के चौड़े रिबन के टुकड़े यूज कर सकते हैं। इसके अलावा दो कंट्रास्ट कलर का उपयोग कर सकते हैं। मोटी या वायर्ड रिबन एक अच्छा ऑप्शन नहीं है। बेहतर नतीजों के लिए पतली साटन या बैलून रिबन का उपयोग करें। पहले वाले स्टेप्स की तरह ही रिबन का उपयोग करें। इस बार, रिबन को काफी लंबा काटें ताकि उसको बॉक्स की चौड़ाई के साथ-साथ 2 इंच (5', '08 सेंटीमीटर) बॉक्स के चारों ओर लपेट सकें। चार लंबे रिबन लें, और उन्हें टेबल पर जमा कर रखें। सुनिश्चित करें कि वे एक-दूसरे के समानांतर हैं और ¼ इंच (0', '64 सेंटीमीटर) से और अधिक दूर नहीं हैं। यदि आपने विभिन्न चौड़ाई या रंगों का उपयोग किया है, तो उन्हें ध्यान से उसी प्रकार रखें। रिबन पर गिफ्ट का फेस-डाउन रखें। बॉक्स को सेंटर में या ऑफ-सेंटर रख में सकते हैं, यह निर्भर करता है कि आप बॉक्स पर रिबन कहाँ लगाना चाहते हैं। एक बार में एक रिबन लपेटें और टेप करें; एक बार में सभी रिबन को टेप न करें। रिबन को बॉक्स के चारों ओर मजबूती से खींचें जिससे वह अच्छे से और सटा हुआ रहे। रिबन के सिर लगभग 1 इंच (2', '54 सेंटीमीटर) तक एक-दूसरे को ओवरलैप करें। ध्यान रखें कि आप केवल टॉप रिबन को बॉटम रिबन पर टेप कर रहे हैं; रिबन को बॉक्स पर टेप न करें। आप डबल-साइड टेप के बजाय ग्लू डॉट्स (यह आपको एक आर्ट एण्ड क्राफ्ट की स्टोर के स्क्रेपबुकिंग लाइन में मिल जाएगी) का उपयोग कर सकते हैं। प्रत्येक छोटे रिबन के अंत में डबल-साइड टेप की एक पट्टी लगाएँ। रिबन को पहले, लंबे रिबन के ठीक ऊपर जमाएँ, जिससे यह सुनिश्चित हो जाए कि इसके कोने इसके लिए लंबवत हैं। एक बार फिर, रिबन को ¼ इंच।

Figure 4.13: Hindi Document

64 सेंटीमीटर) से और अधिक दूर नहीं हैं। यदि आपने विभिन्न चौड़ाई या रंगों का उपयोग किया है, तो उन्हें ध्यान से उसी प्रकार रखें। रिबन पर गिफ्ट का फेस-डाउन रखें। बॉक्स को सेंटर में या ऑफ-सेंटर रख में सकते हैं, यह निर्भर करता है कि आप बॉक्स पर रिबन कहाँ लगाना चाहते हैं। एक बार में एक रिबन लपेटें और टेप करें; एक बार में सभी रिबन को टेप न करें। रिबन को बॉक्स के चारों ओर मजबूती से खींचें जिससे वह अच्छे से और सटा हुआ रहे। रिबन के सिर लगभग 1 इंच।

Figure 4.14: Generated summary for the Hindi input text

French

Positionnez-le de façon à ce qu'il soit perpendiculaire aux côtés du paquet. Laissez dépasser environ 10 à 20 cm sur un côté pour que le nœud ait des queues. Ne découpez pas encore le ruban. Laissez-le relié au rouleau. Mieux vaut laisser dépasser trop de ruban sur le côté que trop peu. Vous pourrez facilement couper le surplus à la fin. Faites passer le ruban sous la boîte et remontez sur le dessus. Ne retournez pas le paquet, car vous risqueriez de tout déplacer. Soulevez-le simplement et faites passer le ruban par-dessous. Reposez la boîte lorsque vous ressortez de l'autre côté. Faites remonter le ruban et ramenez-le jusqu'au milieu du dessus du paquet. Ramenez l'extrémité courte pour le rejoindre et entortillez les deux sections l'une autour de l'autre de manière à les orienter vers les côtés de la boîte sur lesquels vous n'êtes pas encore passé. Si le ruban a un endroit et un envers, il faudra peut-être l'entortiller deux fois de façon à ce que l'endroit se voie. Passez à nouveau par-dessous avant de remonter. Soulevez-la et faites passer la partie longue du ruban (celle qui est reliée au rouleau) en dessous pour la faire ressortir de l'autre côté. Reposez le paquet. Posez votre pouce sur la partie entortillée pour la maintenir en place lorsque vous faites le tour du paquet. Ramenez la partie longue au milieu de la face supérieure du paquet. Placez-la contre l'autre section et coupez-la de manière à obtenir deux queues de même longueur qui partent de la partie entortillée. Faites passer le ruban par-dessus la partie entortillée en biais. Repliez-le sous cette partie et faites-le ressortir au point où il est passé par-dessus. Tirez sur les deux extrémités du ruban pour bien le tendre. Pliez les deux sections du ruban pour former des boucles. Faites passer celle de gauche par-dessus celle de droite de manière à former une boucle plus petite au milieu. Faites passer celle de gauche dans cette petite boucle et tirez sur les deux côtés pour serrer le nœud. Prenez le temps d'ajuster la longueur des boucles et des queues du nœud. Si vous avez utilisé un ruban avec des bords en fil de fer, vous pouvez également sculpter les boucles pour leur donner du volume. Lorsque vous avez terminé, coupez le surplus des queues. Pour un effet encore plus joli, vous pouvez les découper en biais ou en V.

Figure 4.15: French Document

Ne découpez pas encore le ruban. Faites passer le ruban sous la boîte et remontez sur le dessus. Reposez le paquet. Posez votre pouce sur la partie entortillée pour la maintenir en place lorsque vous faites le tour du paquet. Ramenez la partie longue au milieu de la face supérieure du paquet. Repliez-le sous cette partie et faites-le ressortir au point où il est passé par-dessus. Pliez les deux sections du ruban pour former des boucles.

Figure 4.16: Generated summary for the French input text

5 | Discussions and Conclusions

5.1 Discussion

This study aimed to develop a multilingual text summarization system using sentence transformers and clustering techniques. The system was designed to work with five different languages: Russian, Portuguese, Hindi, Korean, and French. The choice of these languages was intended to demonstrate the versatility and robustness of the proposed method.

The novelty of my work lies in the use of the WikiLingua dataset, which is relatively new and not extensively explored in the research community. my work contributes to the growing body of research on this dataset, providing valuable insights and benchmarks for future works. By working with this dataset, I were able to test my algorithm on a diverse range of languages and text types. This diversity is crucial for developing a truly multilingual text summarization system.

my approach demonstrated a significant improvement in the quality of summaries across all five languages. This improvement is largely due to the effective use of Sentence Transformers for generating high-dimensional sentence embeddings, which capture the context and meaning of sentences effectively. This marks a notable contribution to the field of automatic text summarization, particularly in a multilingual context.

The ROUGE scores obtained in my evaluation provide a quantitative measure of the quality of my summaries. The scores were generally high, indicating that my sum-

maries were of good quality and closely matched the reference summaries. However, there were some variations in the scores between different languages, suggesting that the effectiveness of my method may vary depending on the language.

One potential limitation of my study is that I only tested my method on five languages. While these languages are diverse, they do not cover all the languages in the world. Future work could extend my method to other languages to further test its versatility.

Another potential limitation is that I used a single dataset for my evaluation. While the WikiLingua dataset is large and diverse, it may not fully represent all types of text that my system might encounter in real-world applications. Future work could test my method on other datasets to further validate its effectiveness.

In conclusion, my study demonstrates the potential of using sentence transformers and clustering techniques for multilingual text summarization. my method is capable of generating high-quality summaries in multiple languages, making it a valuable tool for a wide range of applications.

5.2 Future Work and Potential Improvements

While my multilingual text summarization system has shown promising results, there are several areas where future work could lead to improvements:

- **Support for More Languages:** my system currently supports five languages. Extending support to more languages would make my system more versatile and useful for a wider range of users. This would involve training Sentence Transformer models for additional languages and adapting the rest of my pipeline to handle these languages.
- **Use of Larger or Multiple Datasets:** I used the WikiLingua dataset for my evaluation. Using larger or multiple datasets for training and evaluation could improve the robustness of my system and make it more adaptable to different types

of text.

- **Improvements in Sentence Embedding:** While Sentence Transformers have proven effective for my needs, future work could explore other methods for generating sentence embeddings, such as newer transformer models or custom training regimes.
- **Refinements in Clustering:** I used K-means clustering in my system. Other clustering algorithms, such as DBSCAN or hierarchical clustering, could potentially lead to better results. Additionally, more sophisticated methods for determining the optimal number of clusters could improve the quality of the summaries.
- **Better Evaluation Metrics:** While ROUGE scores are a standard metric for evaluating text summaries, they are not perfect. Future work could explore other evaluation metrics, such as BLEU or METEOR, or even user studies for a more comprehensive evaluation.
- **Post-processing of Summaries:** my system currently outputs summaries as they are. A post-processing step could be added to improve the grammatical correctness and fluency of the summaries, making them easier to read and understand.

In conclusion, while my system has shown promising results, there is ample scope for future work and improvements. I believe that my work provides a solid foundation for these future efforts.

5.3 Conclusion

In conclusion, this paper presented an extensive exploration of multilingual text summarization, focusing on Russian, Portuguese, Korean, Hindi, and French. my models demonstrated superior performance in generating concise and informative summaries across diverse linguistic contexts. Despite the challenges such as data unavailability, quality of sentence transformers, sentence tokenization, and K-means clustering, my research contributes significantly to the advancement of multilingual text sum-

marization techniques. By addressing these challenges, I aim to create more effective and inclusive summarization systems, thereby facilitating access to information and bridging language barriers. This study underscores the potential of multilingual text summarization in fostering a more interconnected and informed global community. Future research in this dynamic field is indeed promising.

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