Bengali Extractive Text Summarization Using Word Similarity Based Spectral Clustering

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Abstract

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1 Introduction

Automatic Text Summarization (ATS) is a major area of natural language processing (NLP) that aims to automatically shorten a document or a set of documents into a shorter version, while keeping all the key information [26]. This task has become more and more important in the current digital age, where the amount of textual data grows exponentially in many fields, such as news, legal documents, health reports, research papers, and social media content. ATS techniques allow users to quickly get the essential information without needing to read through large amounts of text [7].

There are two main types of text summarization: extractive and abstractive [24]. Extractive summarization, which is the focus of this paper, works by selecting best sentences or phrases directly from the source document, maintaining the original wording and sentence structure [17]. This is in contrast to abstractive summarization, which involves generating new sentences to capture the meaning of the text, similar we may summarize [16]. Extractive summarization is widely used because of its simplicity and effectiveness, especially for languages with limited NLP resources [10].

Text summarization is used in many fields, from automatic news summarization, content filtering, and recommendation systems to assisting legal professionals in going through long documents and researchers in reviewing academic papers. It can also play a critical role in personal assistants and chatbots, providing condensed information to users quickly and efficiently [24].

A commonly used method for extractive text summarization is graph-based summarization. This method represents the sentences of a document as nodes of a graph, and the edges between them are weighted by the similarity between the sentences [7]. Popular algorithms like LexRank [8] and TextRank [14] build graphs based on cosine similarity between sentence embeddings and apply ranking algorithms such as PageRank [18] in case of LexRank [8] or Random

Walk in case of TextRank [14] to determine which sentences are the most important. These sentences are then selected to make the summary. Graph-based methods offer a more robust way to capture sentence importance and relationship, ensuring that the extracted summary covers the key information while minimizing redundancy [7].

A subset of graph-based approach to extractive summarization is clustering-based summarization. Here, sentences are grouped into clusters based on their semantic similarity, and one representative sentence from each cluster is chosen to form the summary [15]. Clustering reduces redundancy by ensuring that similar sentences are grouped together and that only the most representative sentence is selected. This method is effective in documents that cover multiple topics or subtopics, as it allows the summary to touch on each area without being repetitive.

For Bengali, a low-resource language, early attempts at text summarization relied on traditional methods like TF-IDF (Term Frequency-Inverse Document Frequency) scoring [4, 23]. These approaches, while simple, faced challenges in capturing the true meaning of sentences, as they treated words as isolated terms [24]. Graph-based methods introduced improvements by incorporating sentence similarity, but they were still limited by the quality of the embeddings used for the Bengali language. With the advent of word embedding models like FastText [9], which supports over 157 languages, including Bengali, it became possible to represent words in a Vector Space Model, thus enabling more accurate sentence similarity calculations.

However, existing models that use word embeddings, such as Roychowdhury et al.'s [20] Sentence Average Similarity-based Spectral Clustering (SASbSC) method, encountered issues when averaging word vectors to represent sentence meaning. This method failed in most cases because words in a sentence are often complementary rather than being similar, leading to inaccurate sentence representations when averaging their vectors. As a result, important word-to-word relationships between sentences were lost, reducing the effectiveness of the method.

In this paper, we propose a new approach to address these challenges. Our method improves upon previous attempts by focusing on the individual similarity between words in sentences rather than averaging word vectors. Here the gaussian similarities between each word and the Most Similar Word from the other sentence for that word are used to get the similarity between the two sentence. This method captures the true semantic relationships between sentences more effectively. By applying Gaussian similarity to the Most Similar Word Distance (D_{msw}) values, we build an affinity matrix that better reflects sentence closeness. We then apply spectral clustering on this matrix to group similar sentences together and use TF-IDF to select the most representative sentences from each cluster. This approach reduces redundancy and improves the quality of the summary by selecting sentences that are not only relevant but also diverse. This method works really well for Bengali on four different diverse datasets consistently. It consistently outperforms other graph based methods like BenSumm [3], SASbSC [20], LexRank [8]. It also performs similarly well on every other low resource languages we tried it on. These languages are Hindi, Marathi and Turkish. These are the languages where reliable evaluation datasets could be found to test the effectiveness.

In summary, this paper contributes a novel methodology for extractive text summarization for the Bengali language by improving sentence similarity calculations and enhancing clustering techniques. It addresses the limitations of previous models, such as misleading word vector averages [20], and offers a better solution for creating less redundant and information rich summaries. Through this work, we aim to improve the performance of Bengali text summarization systems and contribute to the growing field of NLP for low-resource languages.

2 Literature Review

Automatic Text Summarization have been a problem people are trying to solve for a long time. Attempts at automatic text summarization started with indexing based methods [1]. In this attempt Baxendale [1] attempted to summarize by using a sentence scoring system where if sentences had some certain words, they would be scored higher. But methods like this failed to capture the topic and essence of the input text. To solve this, Text Summarization with statistical methods like TF-IDF became very popular. Edmundson [6] proposed their method which is also called Topic-based approach because it can focus on the central topic of a document. It uses two metric, Term Frequency (how many times a term appear in the input) and Inverse Document Frequency (inverse of how many documents the term appears in a corpus) to calculate the importance of a term in a document. This method identifies the words that are common in the input text but not as common in the language and identifying them as the central topic. But it was too prone to error due to it thinking every word as a unique isolated term and not having any semantic relation with other words. Some words may be a central topic of a document but not identified as such because they got divided into too many synonyms.

Modern breakthroughs into the extractive text summarization began with the usage of Graph-based Extractive Text Summarization methods [8, 14]. LexRank [8] calculates the similarity between two sentences using cosine similarity and builds a graph of all the similarity of every pair of sentence in the input. The most important sentences are then identified using the PageRank [18] algorithm on the graph. This algorithm ranked the sentences, who are most similar with other high ranked sentences, higher. TextRank [14] also uses a similar approach. But for every sentence, the method distributed its scores to its neighbours using random walk. The process was done over and over until the scores converge. Although these models are very novel compared to their time, they still lacked fundamental understanding of the words involved in a sentence.

Word Vector Embedding have been a novel concept for document abstraction for some time now. The seminal work of Salton et al. [22] have been pivotal in conceptualising Word Vector Space where the closer two word are in the vector space, the closer they are semantically. Using word vector for summarization have only been attempted recently [12].

Text Summarization attempts in Bengali is a more recent development than in other high resource languages. Earlier Extractive methods have been focused on some derivative of TF-IDF based text summarization [3, 4, 23]. Sarkar [23] used simple TF-IDF score of each sentence to rank them and pick the best sentences. Dash et al. [4] used weighted TF-IDF along with some other feature like sentence position to rank the sentences. Chowdhury et al. [3] however used TF-IDF matrix of a document to build a graph and perform Hierarchical Clustering to group sentences together and pick one sentence from each group. However, this model faced the problem of TF-IDF matrix not being semantically equivalent to the actual sentences. So it didn't perfectly represent the sentences' semantic closeness in the graph. Using Word Vector Embedding for Bengali solved this problem after The FastText [9] dataset came out that had word vector embedding for 157 languages including Bengali. Using this dataset, Roychowdhury et al. [20] proposed a model where they replaced all the words with their respective vector, then averaged the vectors in a sentence to get the vector for a sentence. The Gaussian Similarity between the vectors are used to build the graph. On the graph, spectral clustering was used to group them together and pick one sentence from each cluster using cosine similarity to get the summary.

But this model also had a critical weakness. Words in a sentence are not semantically related

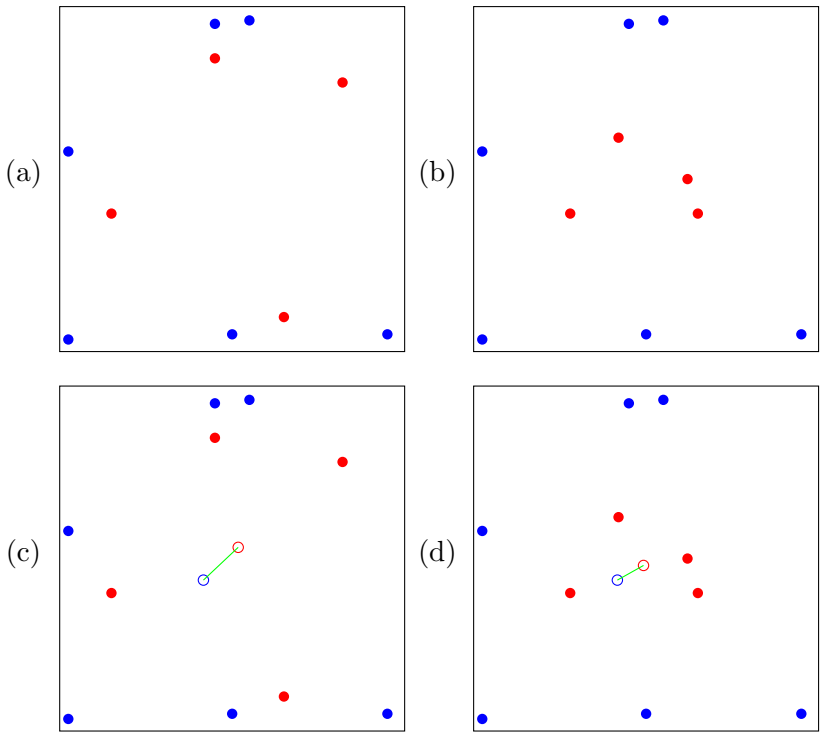


Figure 1: Scenarios where averaging method fails.

instead they are complementary. So word averages always tend to be in the center and doesn't represent the semantic similarity anymore because the word vectors get scattered throughout the vector space. An example is shown in Figure 1 where the distance between the average word vectors is being misleading. In the figure, each point represents a word vector. The words from the same sentence are grouped together by being colored the same. In Figure 1(a), a scenario is shown in which the words of the two sentences are closer together. The average distance between these two sentences can be seen in the Figure 1(c). In Figure 1(b), a different scenario is shown where the word vectors are farther apart. The Figure 1(d) shows the average vector for these two sentences. Although the words in the latter scenario are farther apart, their average is shown to be closer than in the first scenario, thus making this metric misleading.

3 Methodology

The summarization process followed here can be boiled down as, grouping together all the close sentences together based on their meaning and then picking one sentence from each group to minimize redundancy and maximize sentence coverage. Often most widely used extractive summarization methods involve scoring the sentences based on some metric and then picking the best scoring sentences to generate the summaries [4, 23]. But in a single topic text document it often picks similar sentences creating redundancy due to all of them having the central topic terms. To mitigate this, firstly grouped the sentences with similar meaning together and then finally picked one sentence from each group to generate a summary. This will ensure maximum coverage of topics while also reducing redundancy. This method has also been tried before by Roychowdhury et al. [20]. But the main challenge to reducing the redundancy is to develop a method that can accurately predict how close the meaning of the two sentences are. In this paper, we propose a method that can do it. The summarization process followed here involves total 4 steps. These are, in order of their use, Pre-processing, Sentence similarity calculation, Clustering and Summary generation. These steps are further discussed in the following subsections.

3.1 Pre-processing

Pre-processing is a standard step in Natural Language Processing that transforms the raw human language inputs into a format that can be used by a computer algorithm. Here the input document is transformed into a list of sets of vectors where each word is represented with a vector, each sentence as a set of vectors and the whole document as a list of said sets. The Pre-processing involves 3 steps. These are Tokenization, Stop Word Removal, Word Embedding. A very common step in Pre-processing, Word Stemming, isn't used in here as the word embedding dataset works best for the whole word instead of the stemmed word. These steps are further discussed bellow.

3.1.1 Tokenization

Tokenization is the step of dividing an input document into sentences and words in a usable format. Here the input document was firstly divided into sentences by using the NLTK library [2] of python by using regex matching. These sentences are then further divided into words using the same library. The words from the same sentence are put together in a list of strings representing a sentence. Then these lists are further compiled into a list of list for the whole input document. An example of performing this step is given bellow.

Before Tokenization:
রাশিয়া-ইউক্রেন যুদ্ধ শুরু হওয়ার পর মার্কিন ডলারের বিনিময় হার বেড়েছে। এতে অমদানিনির্ভর দেশগুল বিপাকে পড়েছে। বৈদেশিক মুদ্রার রিজার্ভ বা মজুত কমে যাওয়ায় বাংলাদেশকেও অমদানি সীমিত করতে হয়েছে।

After Tokenization:
((রাশিয়া, ইউক্রেন, যুদ্ধ, শুরু, হওয়ার, পর, মার্কিন, ডলারের, বিনিময়, হার, বেড়েছে), (এতে, অমদানিনির্ভর, দেশগুল, বিপাকে, পড়েছে), (বৈদেশিক, মুদ্রার, রিজার্ভ, বা, মজুত, কমে, যাওয়ায়, বাংলাদেশকেও, অমদানি, সীমিত, করতে, হয়েছে))

3.1.2 Stop Word Removal

Stop words are words used in a given language that does not add any significant meaning to the sentence but is necessary for sentence fluidity like prepositions, articles, conjunctions etc. For Bengali, a commonly used dataset[1] of 363 Bengali stop words used to remove the stop words on a matching basis. Some example of Bengali stop words are ওনেক, অবার, করে, হবে, চায়, টি etc. After completing this step the input document would look like this:
((রাশিয়া, ইউক্রেন, যুদ্ধ, শুরু, মার্কিন, ডলারের, বিনিময়, হার, বেড়েছে), (অমদানিনির্ভর, দেশগুল, বিপাকে, পড়েছে), (বৈদেশিক, মুদ্রার, রিজার্ভ, মজুত, কমে, যাওয়ায়, বাংলাদেশকেও, অমদানি, সীমিত))
Here the removed stop words are হওয়ার, পর, এতে, বা, করতে, হয়েছে

3.1.3 Word Embedding

Word Embedding is a step that replaces the words in a sentence with a corresponding vector in a vector space such that the closer two words are in terms of meaning to one another the smaller the distance of those vectors would be. To achieve this step, we used a dataset with 1.47 million Bengali words produced by Grave et al. [9] crawling Wikipedia and other online resources to make the word embedding vectors. Finally, each word that is present in the tokenized and filtered list is replaced with their corresponding vectors and the words that isn't found is ignored and considered to be too rare to be relevant.

[1] *https://www.ranks.nl/stopwords/bengali*

3.2 Sentence Similarity Calculation

To perform clustering in a graph, an affinity matrix is needed. A similarity calculation technique using individual word distance and Gaussian similarity have been proposed here. A previous similar method by Roychowdhury et al. [20] had averaged all the vectors present in a sentence to get a vector for the sentence. But this is not rally a sound strategy as words in a sentence are generally complementary instead of being similar. So the word vectors tend to scatter around in the vector space rather than being grouped closed together. This leads to the average word vector having a tendency towards the center of the vector space. This would lead to the affinity between these vectors not being representative of the actual meaning.

To mitigate this, in this study, similarity between individual words in a pair of sentences have been considered. For this, firstly, the Most Similar Word Distance (D_{msw}) have to be calculated as shown in Equation 1. The D_{msw} denotes the distance between a word vector and the word vector that is closest to its meaning from the other sentence.

$$D_{msw}(x, Y) = min(\{d(x, y_i) : y_i \in Y\}) \tag{1}$$

All the D_{msw} for each word in each sentence are then put together in a list like shown in Equation 2.

$$D_{msw} = \{D_{msw}(x, Y) : x \in X\} \cup \{D_{msw}(y, X) : y \in Y\} \tag{2}$$

Here, for every word vector x in a sentence X, the closest vector, in terms of Euclidean distance denoted by $d(x, y)$, is identified from all the word vectors y in the sentence Y. Secondly, the word similarity is calculated using Gaussian similarity for each of these D_{msw}. The equation involved is shown in Equation 3.

$$WSim_i = e^{\frac{-D^2_{msw_i}}{2\sigma^2}} \tag{3}$$

The Sentence similarity between the two sentence or $Sim(X, Y)$ is calculated as the Geometric mean of all the word similarities from both sentence so that the similarity between two sentence is symmetric. This is explained in the Equation 4

$$\begin{aligned} Sim(X, Y) &= \left(\prod_{i=1}^{n} WSim_i \right)^{\frac{1}{n}} \\ &= \left(e^{\frac{-D^2_{msw_1}}{2\sigma^2}} \cdot e^{\frac{-D^2_{msw_2}}{2\sigma^2}} \cdot \ldots \cdot e^{\frac{-D^2_{msw_n}}{2\sigma^2}} \right)^{\frac{1}{n}} \\ &= exp\left(-\frac{D^2_{msw_1} + D^2_{msw_2} + \ldots + D^2_{msw_n}}{2n\sigma^2} \right) \\ &= exp\left(-\frac{\sum_{i=1}^{n} D^2_{msw_i}}{2n\sigma^2} \right) \end{aligned} \tag{4}$$

Here, by taking geometric mean of the similarity between the closest words together in two sentence, an effective word to word comparison has been created between those sentences. This reduces any misleading distance that would have come from the word averaging method due to the tendency towards center. An example of this can be seen at Figure 2. Here, a more representative word association can be seen for both scenarios from Figure 1. Red and Blue dots in the figure represent two set of word vectors in a sentence pair. Black dashed lines show the Most Similar Distance ($D_{msw}(x, Y)$) for a word vector x and the other sentence Y. The

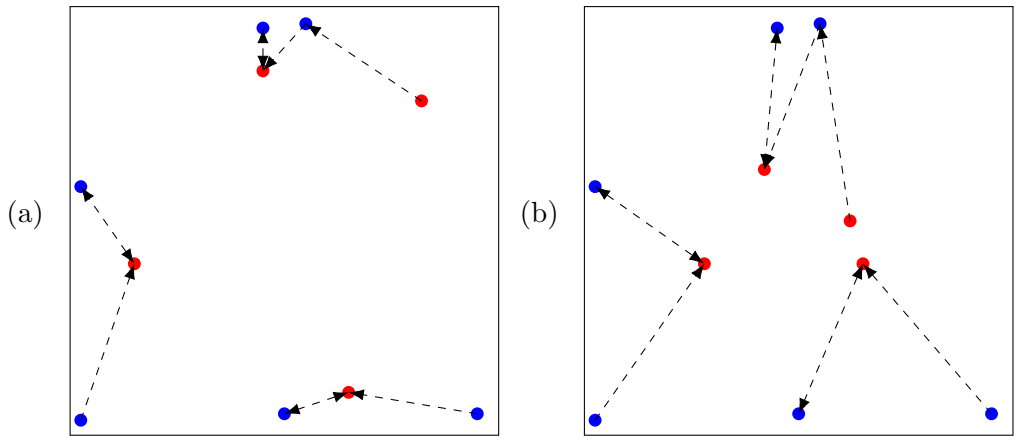


Figure 2: Process of obtaining D_{msw}

arrowheads point from x. The Figure 2(a) shows the D_{msw} for Scenario A in Figure 1(a). The Figure 2(b) Shows the D_{msw} for Scenario B in Figure 1(b). We can see that problem caused by the averaging method have been mitigated here.

The similarity equation (equation-4) has a standard deviation σ which works as a control variable and was fine-tuned to be 5×10^{-11} where it gave the best results.

3.2.1 Viability of this strategy

To get the similarity between two sentence, we needed a strategy that can match two sets of vectors. Other popular methods for the same functionality are also available. For example, Earth Mover's Distance (EMD) [21], Hausdorff distance, Procrustes Analysis etc. EMD tries to find the lowest amount of "work" needed to transform one set into the other one. This is very computationally expensive. And also it focuses on scaling and rotating which are not relevant in word vector space. Hausdorff distance takes the worst case scenario and is easily influenced by outliers. So, it was avoided. Procrustes Analysis tries to find the lowest amount of misalignment after scaling and rotating. Both of them are irrelevant in word vector space.

On the other hand, our method focuses on Local Point Correspondence between two sets which is more important for words. The Gaussian similarity function captures the proximity of points smoothly, providing continuous feedback on how similar two points are in a normalized way. It is also robust against small perturbations because of the use of a soft similarity measure (Gaussian) and geometric mean which helps smooth over small differences in point locations.

3.3 Clustering

The clustering is the most integral part of this summarization technique, aiming to group all the sentences with similar meanings together. Here, spectral clustering is used to cluster the sentences using sentence similarity calculated in the step above. Spectral clustering was chosen here because Roychowdhury et al. [20] found it to be better performing than DBSCAN method. The spectral clustering steps were followed according to the tutorial given by [25].

To perform spectral clustering on a data, firstly, an affinity matrix is required that shows the weight of edges between the vertexes in the graph. Here the affinity A is prepared using the following Equation 5.

$$A_{ij} = A_{ji} = Sim(S_i, S_j) \tag{5}$$

Here, S_i, S_j are sentences from the input document. The affinity matrix, A, is used in the spectral clustering implementation in the SciKit-learn tool [19] in python. Here, to use the function, we also need to provide the number of clusters to achieve. The number of clusters are fixed at $k = ceiling\left(\frac{N}{5}\right)$ due to it being a reasonable size to contain all necessary sentences as well as being short enough to be an effective summary.

3.4 Summary Generation

After clustering, we pick one sentence from each cluster. The sentences inside a cluster are ranked among themselves using TF-IDF . The best ranked sentence of the clusters by their order of TF-IDF score is selected from each cluster. We then rearranged these picked sentences are in their order of appearance to retain the normal flow of information in the input. These sentences are then concatenated together to produce the final output summary.

4 Result

The text summarization performance of the proposed model is compared against the BenSumm [3], LexRank [8] and Sentence Average Similarity-based Spectral Clustering(SASbSC)-based summarization method [20] methods. These methods are the recently published state of the art model for Bengali Extractive Text Summarization. A classic extractive text summarizing method LexRank [8] was also used as a benchmark for comparison.

4.1 Evaluation Datasets

To examine our proposed model, we compared our model along with the 3 benchmark models on 4 different diverse datasets. We did this so that the results doesn't become biased due to any problem with the dataset.

4.1.1 Dataset-1 (Self-curated)

To evaluate the performance of implemented text summarization methods [3, 8, 20], a curated Bengali extractive text summarization dataset was produced by an expert linguistic team. 250 news documents of various sizes were summarized for this purpose. Each document was summarized twice by two different person to minimize human bias. In total, there is 500 different document-summary pair in this dataset. This dataset is made publicly available[2] for other researchers to use for evaluation purpose in their research.

4.1.2 Dataset-2 (Towhid Ahmed Foysal)

This dataset is a collection of summary article pair from The Daily Prothom Alo. It was published by Towhid Ahmed Foysal in Kaggle[3]. The original dataset was filtered so that all the articles smaller than 50 characters and all the summaries that contains something not in the original articles were discarded. After filtering, total 10,204 articles remained, each with 2 summaries.

4.1.3 Dataset-3 (BNLPC)

This dataset is a collection of news article summaries published by Haque et al. [11]. The dataset was collected from GitHub[4]. The dataset contains 100 article with 3 different summaries for each article.

[2] *dataset link*
[3] *https://www.kaggle.com/datasets/towhidahmedfoysal/bangla-summarization-datasetprothom-alo*
[4] *https://github.com/tafseer-nayeem/BengaliSummarization/tree/main/Dataset/BNLPC/Dataset2*

4.1.4 Dataset-4 (Abid Mahdi)

This dataset was published by Abid Mahdi on GitHub[5]. The dataset contains 200 documents each with 2 summaries.

4.2 Text Summarization Models

Four different Bengali extractive text summarization models were implemented to evaluate them by comparing the machine generated summaries against the human generated summaries from the datasets described above.

Model-1: Model-1 is the proposed model for this paper. The model uses word vector based Gaussian similarity to perform spectral clustering to group similar sentences together and extract one sentence from each group. This is described as Word Similarity based Spectral Clustering (WSbSC)

Model-2: Model-2 (SASbSC) is the method proposed by Roychowdhury et al. [20]. This extractive text summarization method is similar to the proposed method. SCSbSC method uses the same word embedding dataset as ours to get word vectors. It uses a sentence center similarity based graph to perform spectral clustering inside the method. Then use cosine similarity to extract sentences from the input. To get sentence similarity, SCSbSC averages all the word vectors of a particular sentence to get the Sentence center. This method was implemented in python as described in their article.

Model-3: BenSumm describes two different summarization method in the study [3]. Here only the extractive method is implemented and compared because the proposed method is also extractive in nature. BenSumm implements a TF-IDF based cosine similarity graph between the sentences and then clusters the sentences using Agglomerative Clustering. The implementation codes are publicly available in GitHub[6].

Model-4: LexRank [8] uses a TF-IDF based Matrix and Googles PageRank algorithm [18] to rank sentences. The top ranked sentences are selected and arranged into summary after that. An implemented version of this method is available as a python package in PyPI as LexRank[7]. LexRank is applied using a large Bengali Wikipedia corpus[8].

4.3 Evaluation Metrics

To evaluate the correctness of the machine generated summaries compared to the human generated summaries, we used the ROUGE method [13]. It compares a human produced reference summary with a machine generated summary. The ROUGE method uses N-gram based overlapping to find a recall, precision and F-1 score. The ROUGE implementation that were used is available as a python package in PyPI[9]. There are three different metrics in the package for comparison of the summaries. These are:

1. **ROUGE-1:** It uses unigram matching to find how much similar two summaries are. It is a good first impression for performance but can be misleading too as many large enough texts will share very high proportion of uni-grams between them.

[5] *https://github.com/Abid-Mahadi/Bangla-Text-summarization-Dataset*
[6] *https://github.com/tafseer-nayeem/BengaliSummarization*
[7] *https://pypi.org/project/lexrank/*
[8] *https://www.kaggle.com/datasets/shazol/bangla-wikipedia-corpus*
[9] *https://pypi.org/project/rouge/*

Dataset-1 (SC)			
Model	Rouge-1	Rouge-2	Rouge-LCS
Model-1 (WSbSC)(Proposed)	**0.47**	**0.36**	**0.43**
Model-2 (BenSumm) [3]	0.41	0.29	0.36
Model-3 (SASbSC) [20]	0.42	0.29	0.37
Model-4 (LexRank) [8]	0.22	0.14	0.20
Dataset-2 (TAF)			
Model-1 (WSbSC)(Proposed)	**0.49**	**0.43**	**0.48**
Model-2 (BenSumm) [3]	0.29	0.22	0.26
Model-3 (SASbSC) [20]	0.23	0.12	0.18
Model-4 (LexRank) [8]	0.24	0.16	0.22
Dataset-3 (BNLPC)			
Model-1 (WSbSC)(Proposed)	**0.41**	**0.34**	**0.40**
Model-2 (BenSumm) [3]	0.36	0.28	0.34
Model-3 (SASbSC) [20]	**0.41**	0.33	0.39
Model-4 (LexRank) [8]	0.26	0.19	0.24
Dataset-4 (AM)			
Model-1 (WSbSC)(Proposed)	**0.49**	**0.41**	**0.47**
Model-2 (BenSumm) [3]	0.31	0.22	0.28
Model-3 (SASbSC) [20]	0.30	0.18	0.24
Model-4 (LexRank) [8]	0.22	0.14	0.20

Table 1: Comparison of average Rouge scores between graph based extractive summarization models on 4 different datasets

2. **ROUGE-2:** It uses bi-gram matching to find how much similar the two summaries are in a word level. Shared bigrams lead to a deeper analysis of syntactic similarities between the two summaries.

3. **ROUGE-LCS:** It finds the longest common sub-sequence between the summaries to calculate the rouge scores. It can calculate the similarity in flow of the sentences between two summaries.

In this study, we compared the F-1 scores from each of these metrics for the 4 models.

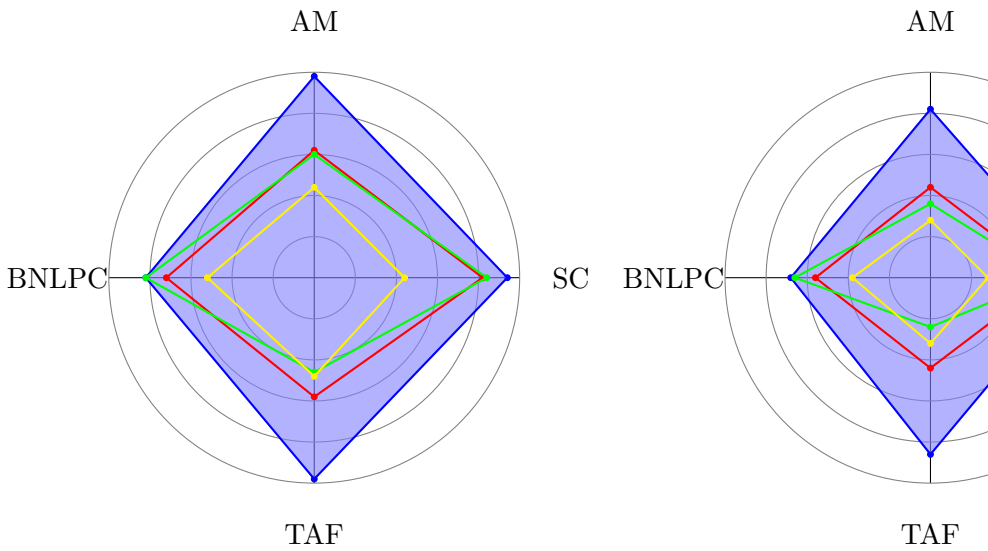
4.4 Comparison

Average F-1 scores for the three Rouge metrics (Rouge-1, Rouge-2, Rouge-LCS) of the four models(Proposed, SASbSC, BenSumm, LexRank) on the 4 datasets are shown in the table-1.

These results are further summarized into 3 radar charts so that the performance of each model on each metric for the datasets can be visualized.
These charts (Figure 3) shows us that the proposed method is much more dataset independent and performs uniformly on every metric across the datasets. Other models although performs good on certain datasets, fails to show consistency.

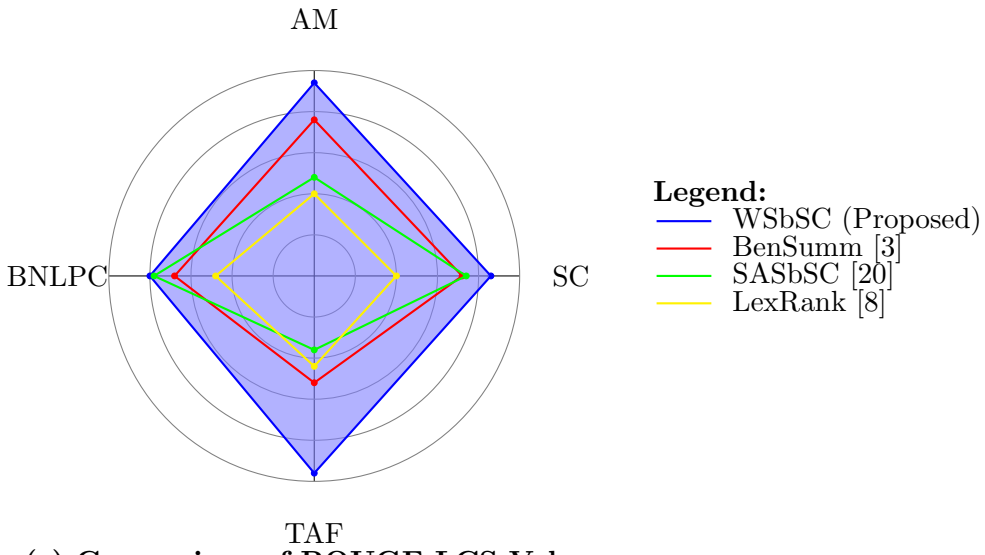
4.5 Different Ranking Techniques Inside Clusters

We implemented two ranking methods to pick the best sentence from each clusters. First one is the First Rank method where we just pick the sentence that is first in terms of their order of appearance inside the input document. The second one is the TF-IDF ranking, where we ranked the sentences by their TF-IDF scores and pick the best one. We can see in the table 4.5 that the TF-IDF scores better on a high quality dataset like our Self-curated one.



(a) Comparison of ROUGE-1 Values

(b) Comparison of ROUGE-2 Values



(c) Comparison of ROUGE-LCS Values

Figure 3: Radar chart of the models being compared on 3 different metrics and 4 datasets.

Method	Rouge-1	Rouge-2	Rouge-LCS
FirstRank	0.47	0.36	0.43
TF-IDF	**0.50**	**0.40**	**0.46**

Table 2: Comparison of Result of different ranking techniques

Language	Rouge-1	Rouge-2	Rouge-LCS
Bengali (Dataset - 1)	0.47	0.36	0.43
Bengali (Dataset - 2)	0.49	0.43	0.48
Bengali (Dataset - 3)	0.41	0.34	0.40
Bengali (Dataset - 4)	0.49	0.41	0.47
Bengali (Average)	0.47	0.38	0.44
Hindi	0.40	0.26	0.36
Marathi	0.50	0.42	0.50
Turkish	0.48	0.39	0.47

Table 3: Comparison of Result of proposed summarization method in other low-resource languages

4.6 Implementation Into Other Languages

The model discussed here is not language dependent. So the model can be easily extended into other languages. To perform this method into a language, we only need a language specific tokenizer, a list of stop-words and a word vector embedding dataset. We tried to find quality extractive text summarization dataset for evaluating the method, but could only find relevant datasets on 3 other languages. These are Hindi, Marathi and Turkish. We adopted this Model into these 3 low resource languages to check this hypothesis.

The Table-3 shows the result of the proposed word similarity based spectral clustering method for extractive summarization in other low resource languages. For the Hindi language, we used a Kaggle dataset[10] produced by Gaurav Arora. For the Marathi language we used another Kaggle dataset[11] produced by Ketki Nirantar. For the Turkish language we used a Github dataset[12] produced by the XTINGE [5] team. We can see that the results remain very close despite the change in language.

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