

Unsupervised Abstractive Summarization of Bengali Text Documents

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Abstract

Abstractive summarization systems generally rely on large collections of document-summary pairs. However, the performance of abstractive systems remains a challenge due to the unavailability of the parallel data for low-resource languages like Bengali. To overcome this problem, we propose a graph-based unsupervised abstractive summarization system in the single-document setting for Bengali text documents, which requires only a Part-Of-Speech (POS) tagger and a pre-trained language model trained on Bengali texts. We also provide a human-annotated dataset with document-summary pairs to evaluate our abstractive model and to support the comparison of future abstractive summarization systems of the Bengali Language. We conduct experiments on this dataset and compare our system with several well-established unsupervised extractive summarization systems. Our unsupervised abstractive summarization model outperforms the baselines without being exposed to any human-annotated reference summaries.¹

1 Introduction

The process of shortening a large text document with the most relevant information of the source is known as automatic text summarization. A good summary should be coherent, non-redundant, and grammatically readable while retaining the original document's most important contents (Nenkova and McKeown, 2012; Nayeem et al., 2018). There are

two types of summarizations: extractive and abstractive. Extractive summarization is about ranking important sentences from the original text. The abstractive method generates human-like sentences using natural language generation techniques. Traditionally used abstractive techniques are sentence compression, syntactic reorganization, sentence fusion, and lexical paraphrasing (Lin and Ng, 2019). Compared to extractive, abstractive summary generation is indeed a challenging task.

A cluster of sentences uses multi-sentence compression (MSC) to summarize into one single sentence originally called sentence fusion (Barzilay and McKeown, 2005; Nayeem and Chali, 2017b). The success of neural sequence-to-sequence (seq2seq) models with attention (Bahdanau et al., 2015; Luong et al., 2015) provides an effective way for text generation which has been extensively applied in the case of abstractive summarization of English language documents (Rush et al., 2015; Chopra et al., 2016; Nallapati et al., 2016; Miao and Blunsom, 2016; Paulus et al., 2018; Nayeem et al., 2019). These models are usually trained with lots of gold summaries, but there is no large-scale human-annotated abstractive summaries available for low-resource language like Bengali. In contrast, the unsupervised approach reduces the human effort and cost for collecting and annotating large amount of paired training data. Therefore, we choose to create an effective Bengali Text Summarizer with an unsupervised approach. The summary of our contributions:

- To the best of our knowledge, our **Bengali Text Summarization model (BenSumm)** is

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¹We make our code & dataset publicly available at <https://github.com/tafseer-nayeem/BengaliSummarization> for reproducibility.

the very first unsupervised model to generate abstractive summary from Bengali text documents while being simple yet robust.

- We also introduce a highly abstractive dataset with document-summary pairs to evaluate our model, which is written by professional summary writers of National Curriculum and Textbook Board (NCTB).²
- We design an unsupervised abstractive sentence generation model that performs sentence fusion on Bengali texts. Our model requires only POS tagger and a pre-trained language model, which is easily reproducible.

2 Related works

Many researchers have worked on text summarization and introduced different extractive and abstractive methods. Nevertheless, very few attempts have been made for Bengali Text summarization despite Bangla being the 7th most spoken language.³ Das and Bandyopadhyay (2010) developed Bengali opinion based text summarizer using given topic which can determine the information on sentiments of the original texts. Haque et al. (2017, 2015) worked on extractive Bengali text summarization using pronoun replacement, sentence ranking with term frequency, numerical figures, and overlapping of title words with the document sentences. Unfortunately, the methods are limited to extractive summarization, which ranks some important sentences from the document instead of generating new sentences which is challenging for an extremely low resource language like Bengali. Moreover, there is no human-annotated dataset to compare abstractive summarization methods of this language.

Jing and McKeown (2000) worked on Sentence Compression (SC) which has received considerable attention in the NLP community. Potential utility for extractive text summarization made SC very popular for single or multi-document summarization (Nenkova and McKeown, 2012). TextRank (Mihalcea and Tarau, 2004) and LexRank (Erkan and Radev, 2004) are graph-based methods for extracting important sentences from a document. Clarke and Lapata (2008); Filippova (2010) showed a first intermediate step towards abstractive summarization, which compresses original sentences for a summary generation. The Word-Graph

based approaches were first proposed by (Filippova, 2010), which require only a POS tagger and a list of stopwords. Boudin and Morin (2013) improved Filippova’s approach by re-ranking the compression paths according to keyphrases, which resulted in more informative sentences. Nayeem et al. (2018) developed an unsupervised abstractive summarization system that jointly performs sentence fusion and paraphrasing.

3 BenSumm Model

We here describe each of the steps involved in our Bengali Unsupervised Abstractive Text Summarization model (BenSumm) for single document setting. Our preprocessing step includes tokenization, removal of stopwords, Part-Of-Speech (POS) tagging, and filtering of punctuation marks. We use the NLTK⁴ and BNL⁵ to preprocess each sentence and obtain a more accurate representation of the information.

3.1 Sentence Clustering

The clustering step allows us to group similar sentences from a given document. This step is critical to ensure good coverage of the whole document and avoid redundancy by selecting at most one sentence from each cluster (Nayeem and Chali, 2017a). The Term Frequency-Inverse Document Frequency (TF-IDF) measure does not work well (Aggarwal and Zhai, 2012). Therefore, we calculate the cosine similarity between the sentence vectors obtained from ULMfit pre-trained language model (Howard and Ruder, 2018). We use hierarchical agglomerative clustering with the ward’s method (Murtagh and Legendre, 2014). There will be a minimum of 2 and a maximum of $n - 1$ clusters. Here, n denotes the number of sentences in the document. We measure the number of clusters for a given document using the silhouette value. The clusters are highly coherent as it has to contain sentences similar to every other sentence in the same cluster even if the clusters are small. The following formula can measure silhouette Score:

$$\text{Silhouette Score} = \frac{(x - y)}{\max(x, y)} \quad (1)$$

where y denotes mean distance to the other instances of intra-cluster and x is the mean distance to the instances of the next closest cluster.

⁴<https://www.nltk.org>

⁵<https://bnlp.readthedocs.io/en/latest/>

²<http://www.nctb.gov.bd/>

³<https://w.wiki/57>

3.2 Word Graph (WG) Construction

Textual graphs to generate abstractive summaries provide effective results (Ganesan et al., 2010). We chose to build an abstractive summarizer with a sentence fusion technique by generating word graphs (Filippova, 2010; Boudin and Morin, 2013) for the Bengali Language. This method is entirely unsupervised and needs only a POS tagger, which is highly suitable for the low-resource setting. Given a cluster of related sentences, we construct a word-graph following (Filippova, 2010; Boudin and Morin, 2013). Let, a set of related sentences $S = \{s_1, s_2, \dots, s_n\}$, we construct a graph $G = (V, E)$ by iteratively adding sentences to it. The words are represented as vertices along with the parts-of-speech (POS) tags. Directed edges are formed by connecting the adjacent words from the sentences. After the first sentence is added to the graph as word nodes (punctuation included), words from the other related sentences are mapped onto a node in the graph with the same POS tag. Each sentence of the cluster is connected to a dummy start and end node to mark the beginning and ending sentences. After constructing the word-graph, we can generate M -shortest paths from the dummy start node to the end node in the word graph (see Figure 1).

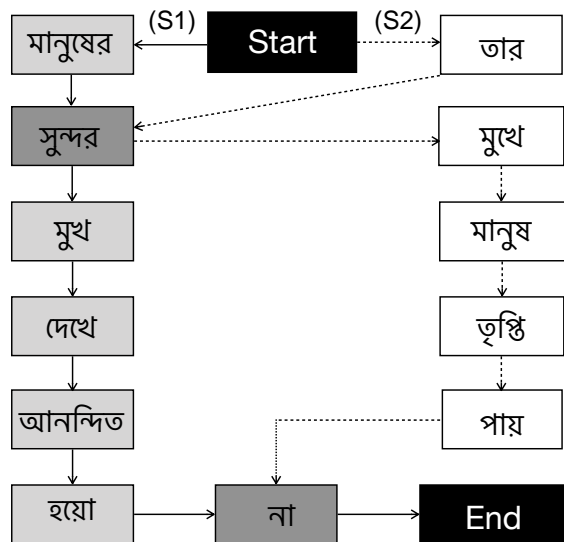


Figure 1: Sample WG of two related sentences.

Figure 2 presents two sentences, which is one of the source document clusters, and the possible paths with their weighted values are generated using the word-graph approach. Figure 1 illustrates an example WG for these two sentences.

After constructing clusters given a document, a

Sentences from Cluster n

- S1: মানুষের সুন্দর মুখ দেখে আনন্দিত হয়ো না
[Don't be happy to see the beautiful faces of people]
 S2: তার সুন্দর মুখে মানুষ তৃপ্তি পায় না
[People are not satisfied with beautiful faces]

Generated Paths with their scores

- 0.783 মানুষের সুন্দর মুখে মানুষ তৃপ্তি পায় না
[People are not satisfied with the beautiful faces of people]
 0.812 তার সুন্দর মুখে মানুষ তৃপ্তি পায় না
[People are not satisfied with the beautiful face]
 1.512 মানুষের সুন্দর মুখ দেখে আনন্দিত হয়ো না
[Don't be happy to see the beautiful faces of people]
 1.625 তার সুন্দর মুখ দেখে আনন্দিত হয়ো না
[Don't be happy to see the beautiful faces]

Figure 2: Output of WG given two related sentences. The underlined sentence is the top-ranked sentence to be included in the final summary.

word-graph is created for each cluster to get abstractive fusions from these related sentences. We get multiple weighted sentences (see Figure 2) from the clusters using the ranking strategy (Boudin and Morin, 2013). We take the top-ranked sentence from each cluster to present the summary. We generate the final summary by merging all the top-ranked sentences. The overall process is presented in Figure 3. We also present a detailed illustration of our framework with an example source document in the Appendix.

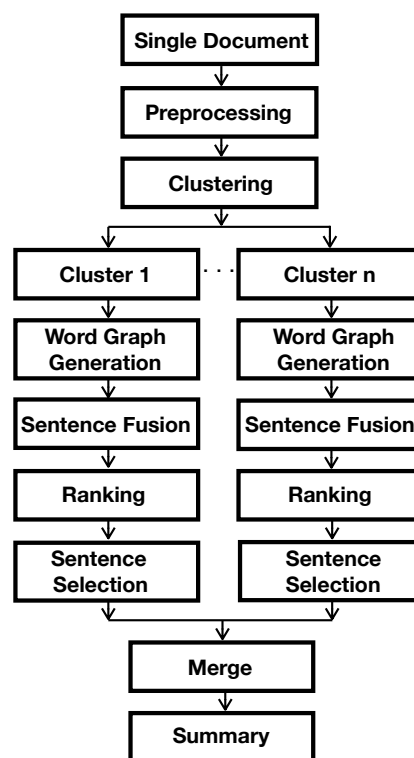


Figure 3: Overview of our BenSumm model.

System Summary

দুঃস্বভাবের মানুষ মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে। যার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। স্বভাব গঠনে কঠিন পরিশ্রম ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়। তার সুন্দর মুখ দেখে আনন্দিত হয়ো না।

[Evil people are fascinated by human form and enjoy its fruits. People hate his nature, his touch, his customs. We need hard work and pursuit to form the nature, otherwise it is not possible to defeat the devil. Don't be happy to see the beautiful faces.]

Human Reference

বাহ্যিক সৌন্দর্য নয়, স্বভাবের সৌন্দর্যই মানুষকে বিচারের মাপকাঠি। খারাপ স্বভাবের মানুষও বাহ্যিক সৌন্দর্যের অধিকারী হতে পারে। আর যারা খারাপ স্বভাবের তারাও সুন্দর স্বভাবের মানুষকে পছন্দ করে। তাই কঠোর পরিশ্রম ও সাধনার মাধ্যমে সুন্দর স্বভাবের অধিকারী হতে হবে।

[The beauty of nature, not external beauty, is the measure of human judgment. People with bad tempers can also have external beauty. And those who are bad in nature also like people who are good in nature. So you have to have a beautiful nature through hard work and pursuit.]

Figure 4: Example output of our **BenSumm** model with English translations.

4 Experiments

This section presents our experimental details for assessing the performance of the proposed **BenSumm** model.

Dataset We conduct experiments on our dataset which consists of 139 samples of human-written abstractive document-summary pairs written by professional summary writers of the National Curriculum and Textbook Board (NCTB). The NCTB is responsible for the development of the curriculum and distribution of textbooks. The majority of Bangladeshi schools follow these books.⁶ We collected the human written document-summary pairs from the several printed copy of NCTB books. The overall statistics of the datasets are presented in Table 1. From the dataset, we measure the *copy rate* between the source document and the human summaries. It's clearly visible from the table that our dataset is highly abstractive and will serve as a robust benchmark for this task's future works. Moreover, to provide our proposed framework's effectiveness, we also experiment with an extractive dataset **BNLPC**⁷ (Haque et al., 2015). We remove the abstractive sentence fusion part to compare with the baselines for the extractive evaluation.

⁶<https://w.wiki/ZwJ>

⁷<http://www.bnlpc.org/research.php>

	NCTB [Abstractive]	BNLPC [Extractive]
Total #Samples	139	200
Source Document Length	91.33	150.75
Human Reference Length	36.23	67.06
Summary Copy Rate	27%	99%

Table 1: Statistics of the datasets used for our experiment. Length is expressed as Avg. #tokens.

NCTB [Abstractive]	R-1	R-2	R-L
Random Baseline	9.43	1.45	9.08
GreedyKL	10.01	1.84	9.46
LexRank	10.65	1.78	10.04
TextRank	10.69	1.62	9.98
SumBasic	10.57	1.85	10.09
BenSumm [Abs] (ours)	12.17	1.92	11.35
BNLPC [Extractive]	R-1	R-2	R-L
Random Baseline	35.57	28.56	35.04
GreedyKL	48.85	43.80	48.55
LexRank	45.73	39.37	45.17
TextRank	60.81	56.46	60.58
SumBasic	35.51	26.58	34.72
BenSumm [Ext] (ours)	61.62	55.97	61.09

Table 2: Results on our NCTB Dataset and BNLPC.

Automatic Evaluation We evaluate our system (**BenSumm**) using an automatic evaluation metric ROUGE F1 (Lin, 2004) without any limit of words.⁸ We extract 3-best sentences from our system and the systems we compare as baselines. We report unigram and bigram overlap (ROUGE-1 and ROUGE-2) to measure informativeness and the longest common subsequence (ROUGE-L) to measure the summaries' fluency. Since ROUGE computes scores based on the lexical overlap at the surface level, there is no difference in implementation for summary evaluation of the Bengali language.

Baseline Systems We compare our system with various well established baseline systems like **LexRank** (Erkan and Radev, 2004), **TextRank** (Mihalcea and Tarau, 2004), **GreedyKL** (Haghighi and Vanderwende, 2009), and **SumBasic** (Nenkova and Vanderwende, 2005). We use an open source implementation⁹ of these summarizers and adapted it for Bengali language. It is important to note that these summarizers are completely extractive and

⁸<https://git.io/JUhq6>

⁹<https://git.io/JUhq1>

Bengali Text Documents Summarizer

Bengali Text:

মানুষের সুন্দর মুখ দেখে আনন্দিত হওয়া না। স্বভাবে সে সুন্দর নয়, দেখতে সুন্দর হলেও তার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। দুঃস্বভাবের মানুষ মানুষের হৃদয়ে জ্বালা ও বেদনা দেয়। তার সুন্দর মুখে মানুষ ভক্তি পায় না। অরোধ লোকেরা মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে। যার স্বভাব মন্দ, সে নিজেও দুঃস্থায়শীল, মিথ্যাবাদী, দুর্ভাজিক ঘৃণা করে। মানুষ নিজে স্বভাবে সুন্দর না হলেও সে স্বভাবের সৌন্দর্যকে ভালোবাসে। স্বভাব গঠনে কঠিন পরিচয় ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়।

Extractive Summary:

স্বভাবে সে সুন্দর নয়, দেখতে সুন্দর হলেও তার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। দুঃস্বভাবের মানুষ মানুষের হৃদয়ে জ্বালা ও বেদনা দেয়। অরোধ লোকেরা মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে।

Abstractive Summary:

দুঃস্বভাবের মানুষ মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে। যার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। স্বভাব গঠনে কঠিন পরিচয় ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়। তার সুন্দর মুখ দেখে আনন্দিত হওয়া না।

Again!

Figure 5: Interface of our Bengali Document Summarization tool. For an input document D with N sentences, our tool can provide both extractive and abstractive summary for the given document. The translations of both the document and summary are provided in the Appendix (see Figure 6).

designed for English language. On the other hand, our model is unsupervised and abstractive.

Results We report our model’s performance compared with the baselines in terms of F1 scores of R-1, R-2, and R-L in Table 2. According to Table 2, our abstractive summarization model outperforms all the extractive baselines in terms of all the ROUGE metrics even though the dataset itself is highly abstractive (reference summary contains almost 73% new words). Moreover, we compare our extractive version of our model **BenSumm** without the sentence fusion component. We get better scores in terms of R1 and RL compared to the baselines. Finally, we present an example of our model output in Figure 4. Moreover, We design a Bengali Document Summarization tool (see Figure 5) capable of providing both extractive and abstractive summary for an input document.¹⁰

Human Evaluation Though ROUGE (Lin, 2004) has been shown to correlate well with human judgments, it is biased towards surface level lexical similarities, and this makes it inappropriate for the evaluation of abstractive summaries. Therefore, we assign three different evaluators to rate each summary generated from our abstractive system (*BenSumm [Abs]*) considering three different aspects, i.e., Content, Readability, and Overall Quality. They have evaluated each system generated

¹⁰Video demonstration of our tool can be accessed from <https://youtu.be/LrnskktiXcg>

summary with scores ranges from 1 to 5, where 1 represents very poor performance, and 5 represents very good performance. Here, content means how well the summary can convey the original input document’s meaning, and readability represents the grammatical correction and the overall summary sentence coherence. We get an average score of **4.41**, **3.95**, and **4.2** in content, readability, and overall quality respectively.

5 Conclusion and Future Work

In this paper, we have developed an unsupervised abstractive text summarization system for Bengali text documents. We have implemented a graph-based model to fuse multiple related sentences, requiring only a **POS** tagger and a pre-trained language model. Experimental results on our proposed dataset demonstrate the superiority of our approach against strong extractive baselines. We design a Bengali Document Summarization tool to provide both extractive and abstractive summary of a given document. One of the limitations of our model is that it cannot generate new words. In the future, we would like to jointly model multi-sentence compression and paraphrasing in our system.

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A Appendix

A detailed illustration of our **BenSumm** model with outputs from each step for a sample input document is presented in Figure 6.

Input Document
<p>মানুষের সুন্দর মুখ দেখে আনন্দিত হওয়া না। স্বভাবে সে সুন্দর নয়, দেখতে সুন্দর হলেও তার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। দুঃস্বভাবের মানুষ মানুষের হৃদয়ে জ্বালা ও বেদনা দেয়। তার সুন্দর মুখে মানুষ তৃপ্তি পায় না। অবোধ লোকেরা মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে। যার স্বভাব মন্দ, সে নিজেও দুষ্ক্রিয়শীল, মিথ্যাবাদী, দুর্মতিকে ঘৃণা করে। মানুষ নিজে স্বভাবে সুন্দর না হলেও সে স্বভাবের সৌন্দর্যকে ভালোবাসে। স্বভাব গঠনে কঠিন পরিশ্রম ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়।</p> <p>[Do not be happy to see the beautiful faces of people. He/She is not beautiful by nature, although he/she is beautiful to look at, people hate his/her nature, touch, and manners. People with bad temper irritate and hurt people's hearts. People are not satisfied with the beautiful face. Ignorant people are fascinated by the human form and suffer in the long run. The one whose nature is evil, he is mischievous, a liar, and evil. Man himself is not beautiful by nature, but he loves the beauty of people's nature. We need hard work and pursuit to form nature; otherwise, it is impossible to defeat the devil.]</p>
Sentence Clustering
<p>Cluster #1: Sentence #1: দুঃস্বভাবের মানুষ মানুষের হৃদয়ে জ্বালা ও বেদনা দেয়। Sentence #2: অবোধ লোকেরা মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে।</p> <p>Cluster #2: Sentence #1: স্বভাবে সে সুন্দর নয়, দেখতে সুন্দর হলেও তার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। Sentence #2: যার স্বভাব মন্দ, সে নিজেও দুষ্ক্রিয়শীল, মিথ্যাবাদী, দুর্মতিকে ঘৃণা করে। Sentence #3: মানুষ নিজে স্বভাবে সুন্দর না হলেও সে স্বভাবের সৌন্দর্যকে ভালোবাসে।</p> <p>Cluster #3: Sentence #1: স্বভাব গঠনে কঠিন পরিশ্রম ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়।</p> <p>Cluster #4: Sentence #1: মানুষের সুন্দর মুখ দেখে আনন্দিত হওয়া না। Sentence #2: তার সুন্দর মুখে মানুষ তৃপ্তি পায় না।</p>
Sentence Fusion & Ranking
<p>Cluster #1: দুঃস্বভাবের মানুষ মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে।</p> <p>Cluster #2: যার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে।</p> <p>Cluster #3: স্বভাব গঠনে কঠিন পরিশ্রম ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়।</p> <p>Cluster #4: তার সুন্দর মুখ দেখে আনন্দিত হওয়া না।</p>
Final Summary
<p>দুঃস্বভাবের মানুষ মানুষের রূপ দেখে মুগ্ধ হয় এবং তার ফল ভোগ করে। যার স্বভাব, তার স্পর্শ, তার রীতিনীতিকে মানুষ ঘৃণা করে। স্বভাব গঠনে কঠিন পরিশ্রম ও সাধনা চাই, নইলে শয়তানকে পরাজিত করা সম্ভব নয়। তার সুন্দর মুখ দেখে আনন্দিত হওয়া না।</p> <p>[Evil people are fascinated by human form and enjoy its fruits. People hate his nature, his touch, and his customs. We need hard work and pursuit to form the nature, otherwise it is not possible to defeat the devil. Don't be happy to see the beautiful faces.]</p>

Figure 6: A detailed illustration with outputs from each step of our Bengali Abstractive Summarization model for a sample input document.