Simple or Complex? Learning to Predict Readability of Bengali Texts

Susmoy Chakraborty\textsuperscript{1*}, Mir Tafseer Nayeem\textsuperscript{1*}, Wasi Uddin Ahmad\textsuperscript{2}
\textsuperscript{1}Ahsanullah University of Science and Technology, \textsuperscript{2}University of California, Los Angeles
susmoyaust36@gmail.com, mir.nayeem@alumni.uleth.ca, wasiahmad@ucla.edu

Abstract
Determining the readability of a text is the first step to its simplification. In this paper, we present a readability analysis tool capable of analyzing text written in the Bengali language to provide in-depth information on its readability and complexity. Despite being the 7\textsuperscript{th} most spoken language in the world with 230 million native speakers, Bengali suffers from a lack of fundamental resources for natural language processing. Readability related research of the Bengali language so far can be considered to be narrow and sometimes faulty due to the lack of resources. Therefore, we correctly adopt document-level readability formulas traditionally used for U.S. based education system to the Bengali language with a proper age-to-age comparison. Due to the unavailability of large-scale human-annotated corpora, we further divide the document-level task into sentence-level and experiment with neural architectures, which will serve as a baseline for the future works of Bengali readability prediction. During the process, we present several human-annotated corpora and dictionaries such as a document-level dataset comprising 618 documents with 12 different grade levels, a large-scale sentence-level dataset comprising more than 96K sentences with simple and complex labels, a consonant conjunct count algorithm and a corpus of 341 words to validate the effectiveness of the algorithm, a list of 3,396 easy words, and an updated pronunciation dictionary with more than 67K words. These resources can be useful for several other tasks of this low-resource language.

Introduction
The term “Readability” measures how much energy the reader will have to expend in order to understand a writing at optimal speed and find interesting. Readability measuring formulas, such as Automated Readability Index (ARI) \cite{Sen1967}, Flesch Reading Ease \cite{Flesch1948}, and Dale–Chall formula \cite{Dale1948, Chall1995} calculate a score that estimates the grade level or years of education of a reader based on the U.S. education system, which is illustrated in Figure 1. These formulas are still used in many widely known commercial readability measuring tools such as Grammarly\footnote{https://www.grammarly.com/blog/readability-scores/} and Readable\footnote{https://readable.com/}. This measurement plays a significant role in many places, such as education, health care, and government \cite{Grigonyte2014, Rets2020, Meng2020}. Government organizations use it to ensure that the official texts meet a minimum readability requirement. For instance, the Department of Insurance at Texas has a requirement that all insurance policy documents have a Flesch Reading Ease \cite{Flesch1948} score of 40 or higher, which translates to the reading level of a first-year undergraduate student based on the U.S. education system. A legal document which is hard to read can lead someone to sign a contract without understanding what they are agreeing to. Another common usage area is the healthcare sector to ensure the proper readability of the care and treatment documents \cite{Grigonyte2014}. Better readability will attract visitors or readers of different websites or blogs, whereas poor readability may decrease the number of readers \cite{Meng2020}. Readability measures are also often used to assess the financial documents such as annual reports of a company’s economic performance so that the information is more transparent to the reader \cite{Loughran2018}. In contrast, it will be considered legally invalid if the information is not provided in a readable format.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Readability prediction task.}
\end{figure}

\textsuperscript{*}Equal contribution. Listed by alphabetical order.
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\textsuperscript{1}We make our Code & Dataset publicly available at \url{https://github.com/tafseer-nayeem/BengaliReadability} for reproducibility.

\url{https://www.tdi.texas.gov/pubs/pc/pccpfaq.html}
Dyslexia is a disorder that causes difficulties with skills associated with learning, namely reading and writing, which affects up to 20% of the general population. Readability formulas have been applied to measure the difficulty of reading texts for people with dyslexia (Fourney et al. 2018).

The scores from readability formulas have been generally found to correlate highly with the actual readability of a text written in the English language. The adaptation of readability formulas to non-English texts is not straightforward. Measuring readability is also essential for every non-English language, but not all of the readability formulas mentioned above are language-independent. These formulas require some resources like a 3000-word list, which is easily understandable by fourth-grade American students, syllable counting dictionary, stemmer, lemmatizer etc. Resource availability for Natural Language Processing (NLP) research is an obstacle for some low-resource-languages (e.g., Bengali). In this paper, we aim to develop a readability analysis tool for the Bengali Language. Bengali is the native language of Bangladesh, also used in India (e.g., West Bengal, Tripura) and has approximately 230 million native speakers. Despite being the 7th most spoken language in the world, Bengali suffers from a lack of fundamental resources for NLP. For a low resource language like Bengali, the research in this area so far can be considered to be narrow and sometimes incorrect. Islam, Mehler, and Rahmani (2012), Sinha et al. (2012) tried to adapt the formula-based approaches used for the English language. Unfortunately, it isn’t straightforward as these formulas are developed for U.S. based education system, and which predicts U.S. grade level of the reader. Since the Bangladeshi education system and grade levels are different from U.S., therefore, the mapping is faulty and led to incorrect results. There is a strong relationship between reading skills and human cognition, which varies depending on different age groups (Riddle 2007). Therefore, to eliminate this incompatibility, in this paper, we map grade level to different age groups to present age-to-age comparison. Moreover, (Sinha and Basu 2016), Islam, Rahman, and Mehler (2014), Sinha et al. (2012) used traditional machine learning models to address this task on a very small scale dataset, which isn’t publicly available. There are readability analysis tools available for English (Napolitano, Sheehan, and Mundkowsky 2015), Arabic (Al-Twairesh et al. 2016), Italian (Okinina, Frey, and Weiss 2020), and Japanese (Sato, Matsuyoshi, and Kondoh 2008) language. Unfortunately, no such tool is available for Bengali language that can validate the readability of a text. On the other hand, there is no large-scale human annotated readability analysis dataset available to train supervised neural models for this extremely low-resource language. Our main contributions are summarized as follows:

- To the best of our knowledge, we first design a comprehensive system for Bengali readability analysis, which includes datasets, human-annotated corpora and dictionar-
- We correctly adopt document-level readability formulas traditionally used for U.S. based education system to the Bengali education system with a proper age-to-age comparison. We present a document level dataset consisting of 618 documents with 12 different grade levels to evaluate the adaptation of these formulas to the Bengali language (see Table 1).
- Due to the long-range dependencies of RNNs and the unavailability of large-scale human-annotated corpora, we further divide the document-level task into sentence-level and present a large-scale dataset consisting of 96,335 sentences with simple and complex labels to experiment with supervised neural models (see Table 2). We design neural architectures and make use of all available pre-trained language models of Bengali Language.
- We also propose an efficient algorithm for counting consonant conjuncts form a given word. We present a human-annotated corpus comprising 341 words with varying difficulties to evaluate the effectiveness of this algorithm.
- We design a readability analysis tool capable of analyzing text written in the Bengali language to provide in-depth information on its readability and complexity which would be useful for educators, content writers or editors, researchers, and readers (see Figure 4).

Related works

English and Other Languages

There has been a lot of work on readability analysis for the English language, some of which are: Automated Readability Index (Senter and Smith 1967), Flesch reading ease (Flesch 1948), Flesch–Kincaid grade level (Kincaid et al. 1975), Gunning Fog index (Kincaid et al. 1975), Dale–Chall formula (Dale and Chall 1948; Chall and Dale 1995), and SMOG grade (Mc Laughlin 1969). To calculate the readability score from these formulas, we need to extract various types of information from the input text, e.g., average sentence length, average word length, number of characters, number of syllables, and number of difficult words. The primary takeaway from the common formulas is simple. Using shorter sentences with shorter and more common words will typically make a piece of writing easier to understand. Other than using these traditional formulas, there have been a lot of recent work on readability analysis of English language (Vajjala and Lucic 2018), but especially in recent years, the scope of readability analysis research has been broadened towards other languages such as Russian (Reynolds 2016), Japanese (Sato 2014), French (Seretan 2012), Swedish (Grigonyte et al. 2014), Polish (Broda et al. 2014), Arabic (El-Haj and Rayson 2016), Vietnamese (Nguyen and Uitdenbogerd 2019), and German (Battisti et al. 2020).
Bengali Language

Formula Based Approaches The research in this area for Bengali Language is narrow and sometimes faulty. Das and Roychoudhury (2006) created a miniature readability model with one and two parametric fits using multiple regression for Bengali text readability analysis. They used only seven paragraphs from seven documents. They used two parameters, such as average sentence length and number of syllables per 100 words, which is responsible for representing text as easy or difficult. Sinha et al. (2012); Sinha and Basu (2016) proposed two readability formulas for each Bengali and Hindi text using regression analysis, which are similar to readability formulas used for the English language. Readability formulas were also applied to Bangladeshi textbooks by Islam, Mehler, and Rahman (2012). They extracted these three types of features from data such as lexical features, entropy-based features, and Kullback-Leibler Divergence-based features. Unfortunately, the scores returned from these readability formulas approximate what grade level of U.S. based education system someone will need in order to be able to read a piece of text easily. Since the Bangladeshi education system and grade levels are entirely different from the U.S., the mapping is faulty and led to incorrect results. In contrast, we map grade level to different age groups to present the age-to-age comparison for the readability formulas to eliminate the incompatibility.

Traditional Machine Learning Based Approaches Sinha and Basu (2016) also used machine learning methods for Bengali readability classification, which are Support Vector Machine (SVM) and Support Vector Regression (SVR). They showed that features like average word length, number of consonant conjuncts play a significant role in Bengali readability analysis. Islam, Rahman, and Mehler (2014) used a combination of 18 lexical features and information-theoretic features to achieve a better score. Phani, Lahiri, and Biswas (2014) introduced the importance of inter-rater agreement study in the field of readability analysis of Bengali text. For agreement study, they used Cohen’s kappa and Spearman’s rank correlation coefficient. Recently, Phani, Lahiri, and Biswas (2019) proposed 11 readability measuring models based on regression analysis using 30 Bengali passages. They used features such as the presence of stop words, word sense, and POS tags. These prior works highlighted the importance of consonant conjunct for measuring readability. But they did not present any specific algorithm to compute consonant conjunct. Instead, in this paper, we present an efficient algorithm and human-annotated corpus to evaluate the effectiveness of the proposed algorithm. Another limitation of the works mentioned above is that their dataset is small scale and not publicly available. On the other hand, we present a large-scale dataset and design supervised neural models for Bengali readability prediction.

Dataset

We collect documents from several published textbooks and magazines from Bangladesh and India. These are the most common and very well-known among children and adults. These documents usually were published after rigorous review and editorial process and widely read by various age groups. In this paper, we present two datasets for readability prediction. (1) Document-level dataset to experiment with formula-based approaches, (2) Sentence level dataset to train supervised neural models.

| Dataset  | #Docs | Avg. #sents | Avg. #words |
|----------|-------|-------------|-------------|
| NCTB     | 380   | 66.8        | 585.8       |
| Additional | 238   | 391.2       | 3045.0      |

Table 1: Statistics of the document-level dataset.

Document-level Dataset

NCTB We select 16 textbooks from class 1 to 12 provided by National Curriculum and Textbook Board (NCTB), Bangladesh. These textbooks are written by professional writers of NCTB who is responsible for the development of curriculum and distribution of textbooks. A majority of the Bangladeshi schools follow these books. From class 3, 4, and 5, we take Bengali literature, Social Science, and General Science books; and from the rest of the classes, we take only Bengali literature books.

Additional Sources We also collect documents (literature and articles) for both children and adults from various well known and popular sources, some of which are: Ichchhamoti, Society for Natural Language Technology Research, Ebela, Sananda, and Bangla library.

Sentence-level Dataset

As we can see from Table 1, the document-level dataset is largely insufficient for training supervised neural models. Therefore, we further divide the documents into sentences to create a large-scale dataset for training neural models.

- **Simple Documents:** From the NCTB dataset, we select class 1 to 5 as simple documents as these documents are generally for 6 to 10 years old students. Also, we take all the children type documents from the additional sources.
- **Complex Documents:** All adults type documents from additional sources, and we do not take any complex documents from the NCTB dataset.

Sentences from our simple documents are labeled as ‘simple’, and sentences from complex documents are labeled as ‘complex’. So initially, we start with 40,917 simple sentences and 60,875 complex sentences. After carefully investigating the initial dataset, we found that the complex documents mostly contain complex sentences. However, some simple sentences also exist in complex documents and vice versa. To remove simple sentences from the complex set, we apply
We select 10 documents (class 1 to 8, class 9/10, and class 11/12 in Table 3) from NCTB, and 4 documents (children 1 to adults 2 in Table 3) from additional sources. Due to the unavailability of the spoken syllable counting system for the Bengali language, we take a subset of the documents covering each class from the document level dataset. Flesch reading ease, Flesch–Kincaid grade level, Gunning Fog index, and SMOG grade formula require a common feature, which is the number of syllables. Counting syllables manually of all words from vocabulary is time-consuming. Google has provided NLP resources for various languages (e.g., Hindi, Urdu, Nepali, Sinhala, and Bengali). We use a pronunciation dictionary for the Bengali language with 65,038 words. Although we use this dictionary, we have to manually count syllables for more than two thousand words, which are not present in that dictionary. We use the updated dictionary to experiment with formula-based approaches. Table 3 indicates the performance of formula-based approaches on our dataset. Here, we present a column BN age, which indicates the reader’s age of the input documents. In Bangladesh, usually, children are admitted to Class 1 at the age of six, and complete their higher secondary education (Class 12) at the age of seventeen. Therefore, we fill up the age of the first 10 documents in Table 3 according to this range. For Children 1 and Children 2, we set the age range 6-10 as children’s literatures are created for 6 to 10 years old readers, and 18 or more for Adults 1 and Adults 2 in Table 3. Instead of matching the U.S. and Bangladeshi grade level, we match ‘U.S. age’ and ‘BN age’ for measuring the performance of all the formulas.

### Automated Readability Index (ARI)

Formula provides a score equivalent to a grade level which was developed to assess the readability of written materials used in the U.S. Air Force. The formula uses long words and long sentences to calculate a readability score. From Table 3, age range 6-7 indicates first or second grade. From the second column of Table 3, the first row where the input document is taken from Class 1, so we set the value of ‘BN age’ = 6. After applying ARI to the input document, we find ARI score = 1 (‘ARI’ column). Since ARI score of 1 indicates Kindergarten grade level, therefore, we set ‘U.S. age’ equals to “5-6”. As we can see, this document is correctly classified because 6 is present in the range of 5-6.

### Flesch reading Ease (FE)

This formula approximates a number indicating the difficulty of the input document. The higher the number, the easier it is to read the document. For example, if the score is between 90 to 100 for an input text, then this text is very easy to read and understandable by an average 11 years old reader. The formula focuses on the number of words, sentences, and syllables. In our case, we get the maximum value 40.92 for an input document from Bangladeshi Class 1 (6 years old). According to this formula, a score of 40 means the text is difficult to read and is understandable by U.S. college students (18 to 24 years old). The lowest value of this formula is 0, but we get negative values for 3 documents out of 14 documents. This formula is highly suited for the documents written in English language and used by the professional readability analysis tools like Grammarly and Readable. However, the formula is not suitable for the Bengali language because of the various linguistic difficulty present in the syllable counting system, and this is one of the main reasons we experiment with wide varieties of formulas.

### Flesch–Kincaid (FK), Gunning Fog (GF), and SMOG

For all 3 formulas, the lower the number, the easier it is to read the document. For Flesch–Kincaid, we get around 8.80 as our lowest value for Bangladeshi Class 1 level input document (6 years old reader). However, according to this formula, a score of 8 is for 8th U.S. grade level students (8th grade = 13/14 years old). Gunning fog index depends on the number of complex words, where a complex word means it has 3 or more syllables, and it is not a proper noun, compound word, or familiar jargon. We only consider ‘syllable’ and ‘proper noun’ for counting complex words. To identify proper

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**Table 2: Statistics of the sentence-level dataset.**

|                  | Train | Dev | Test |
|------------------|-------|-----|------|
| **Simple Sentences** |       |     |      |
| #Sents           | 37,902| 1,100| 1,100|
| Avg. #words      | 8.16  | 7.97 | 8.31 |
| Avg. #chars      | 44.71 | 43.85| 45.57|
| **Complex Sentences** |       |     |      |
| #Sents           | 54,033| 1,100| 1,100|
| Avg. #words      | 8.04  | 8.08 | 8.16 |
| Avg. #chars      | 44.01 | 44.65| 44.63|

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**Experiments**

We use our document level dataset to experiment with formula-based approaches and use the sentence-level dataset to train supervised neural models.

**Formula-based Approaches**

We select 10 documents (class 1 to 8, class 9/10, and class 11/12 in Table 3) from NCTB, and 4 documents (children 1 to adults 2 in Table 3) from additional sources. Due to the unavailability of the spoken syllable counting system for the Bengali language, we take a subset of the documents covering each class from the document level dataset. Flesch reading ease, Flesch–Kincaid grade level, Gunning Fog index, and SMOG grade formula require a common feature, which is the number of syllables. Counting syllables manually of all words from vocabulary is time-consuming. Google has provided NLP resources for various languages (e.g., Hindi, Urdu, Nepali, Sinhala, and Bengali). We use a pronunciation dictionary for the Bengali language with 65,038 words. Although we use this dictionary, we have to manually count syllables for more than two thousand words, which are not present in that dictionary. We use the updated dictionary to experiment with formula-based approaches. Table 3 indicates the performance of formula-based approaches on our dataset. Here, we present a column BN age, which indicates the reader’s age of the input documents. In Bangladesh, usually, children are admitted to Class 1 at the age of six, and

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1. https://git.io/JJhdm
2. https://w.wiki/aRc
3. https://w.wiki/Z7W
4. https://git.io/JJhdm
Table 3: Performance of the formula-based approaches. The bold-faced values indicate the correctly predicted U.S. age-groups for different formulas with Bengali (BN) age. The ARI formula performed reasonably well compared to other formulas.

Algorithm 1: Consonant conjunct count algorithm.

```java
1 Procedure Consonant conjunct Count (W)
2 Data: Input word W, which is an array of Bengali characters.
3 Result: Return the number of consonant conjuncts in input word W.
4 A ← Bengali sign VIRAMA (Wikipedia 2020);
5 cc_count ← 0;
6 l ← length(W);
7 for k ← 0 to l - 1 do
8 if W[k] == A then
9 if k - 1 ≥ 0 and k + 1 < l then
10 if W[k - 1] and W[k + 1] is a Bengali Consonant and W[k - 2] != A then
11 cc_count ← cc_count + 1;
12 end
13 end
14 else if W[k - 1] and W[k + 1] is a Bengali Consonant then
15 cc_count ← cc_count + 1;
16 end
17 end
18 return cc_count;
```

**Dale–Chall formula (DC)** As mentioned before, the Dale–Chall formula (Dale and Chall [1948]; Chall and Dale [1995]) requires a 3,000 English words list which is familiar to U.S 4th grade (9-10 years old) students. As an alternative to this, we manually annotate 3,396 Bengali words. According to the Dale-Chall formula, any word that is not in our Bengali 3,396 words list is treated as a difficult word. Table 3 indicates poor performance for Flesch reading ease, Flesch-Kincaid grade level, Gunning fog, and SMOG, therefore we can say that these formulas are not ideal for measuring the readability of the Bengali texts. On the other hand, the ARI performs relatively well as it correctly measures the age group of 8 documents out of 14 documents.

**Supervised Neural Approaches** Due to the long-range dependencies of RNNs and the unavailability of large-scale human-annotated corpora, encoding of documents still lacks satisfactory solutions (Trinh et al. 2018). On the other hand, some document-level readability formulas, such as the SMOG index, require at least 30 sentences to measure a score. In this section, we tackle these issues by dividing the document-level task into a supervised binary sentence classification problem where we have two classes, simple and complex. We design neural architectures to experiment with our sentence level dataset, which is presented in the dataset section.

**Additional Feature Fusion** The words present in complex sentences can be longer in terms of characters than the words in simple sentences. Therefore, we choose Character Length
(CL), which indicates the total number of characters in a sentence, including white spaces as our additional readability feature. Moreover, the number of Consonant Conjunct (CC) is also an indicator for the complex sentence (Sinha and Basu 2016; Phani, Lahiri, and Biswas 2019). Unfortunately, these prior works did not present any specific algorithm to compute consonant conjunct for Bengali texts. Hence, we present a detailed procedure for counting consonant conjunct in Algorithm 1. To evaluate our consonant conjunct counting algorithm, we manually create a dataset with 341 words and their corresponding consonant conjunct count. Our algorithm can successfully count the CCs present in all 341 words from our dataset. Figure 2 presents a visual representation of the counting of CC and CL for two example sentences.

Ablation Experiments We select Bidirectional LSTM (BiLSTM) (Schuster and Paliwal 1997) and BiLSTM with attention mechanism (Raffel and Ellis 2016) as baseline models. As we can see from Table 4, BiLSTM model has achieved better performance from the baseline models, therefore, we extend the BiLSTM model by adding global average pooling and global max-pooling layers (Boureau, Ponce, and LeCun 2010). We use this model for our ablation experiments with the additional features to demonstrate the effects of CL and CC feature fusion. For each input sentence, we calculate the CL and CC to concatenate with the pooling layers. Given an input sentence $s_j$, its word sequence $w_1, w_2, w_3, \ldots, w_{|s_j|}$ is fed into a word embedding layer to obtain embedding vectors $x_1, x_2, x_3, \ldots, x_{|s_j|}$ before passing it to the BiLSTM layer. The word embedding layer is parameterized by an $E_w \in \mathbb{R}^{K \times |V|}$ embedding matrix, where $K$ is the embedding dimension and $|V|$ is the vocabulary size. The overall process is summarized in Figure 3. We use all pre-trained language models available to date for the Bengali language, which includes:

- 300 dimensional Word2vec pre-trained model (Mikolov et al. 2013).
- 300 dimensional GloVe pre-trained model (Pennington, Socher, and Manning 2014).
- 300 dimensional vector representation from fastText pre-trained model (Grave et al. 2018).
- 400 dimensional pre-trained ULMFiT (Howard and Ruder 2018) model provided by iNLTK library.
- 410 dimensional pre-trained TransformerXL (Dai et al. 2019) model provided by iNLTK library.
- 768 dimensional Language-agnostic BERT Sentence Embedding model laserembeddings for 93 languages, which is based on LASER (Artetxe and Schwenk 2019).

Table 4: Performance of Baseline and our ablations. The best results are marked green and second best results are marked blue. A, R, P, and F1 denote Accuracy, Recall, Precision, and F1 score respectively.

| Baseline Models | A   | R   | P   | F1  |
|-----------------|-----|-----|-----|-----|
| BiLSTM          | 77.5| 69.4| 82.8| 75.5|
| BiLSTM + Attention | 76.4| 65.9| 83.3| 73.6|

| Ablations       | A   | R   | P   | F1  |
|-----------------|-----|-----|-----|-----|
| BiLSTM with Pooling | 81.3| 78.8| 83.0| 80.8|
| + Word2vec      | 85.5| 80.2| 89.7| 84.7|
| + CL + CC       | 85.7| 80.9| 89.5| 85.0|
| + GloVe         | 86.1| 79.3| 91.9| 85.1|
| + CL + CC       | 86.1| 81.3| 89.9| 85.4|
| + fastText      | 86.0| 80.1| 90.8| 85.1|
| + CL + CC       | 86.4| 82.9| 89.1| 85.9|
| + BPEmb         | 86.2| 81.5| 90.0| 85.6|
| + CL + CC       | 86.0| 81.2| 89.8| 85.3|
| + ULMFiT        | 85.5| 77.6| 92.0| 84.2|
| + CL + CC       | 86.4| 80.4| 91.0| 85.4|
| + TransformerXL | 86.3| 82.7| 89.0| 85.8|
| + CL + CC       | 86.7| 83.5| 89.3| 86.3|
| + LASER         | 86.4| 84.3| 88.0| 86.1|
| + CL + CC       | 86.3| 84.6| 87.6| 86.1|
| + LaBSE         | 86.0| 80.3| 90.8| 85.2|
| + CL + CC       | 86.7| 86.5| 86.8| 86.7|

Hyperparameters We use 60 as maximum sequence length with a batch size of 16, embedding size of 300, 64 LSTM hidden units, and Adam optimizer (Kingma and Ba 2015) with a learning rate of 0.001. We run the training for

https://w.wiki/Wk8

https://git.io/JUi1c

https://pypi.org/project/laserembeddings/
Table 5: Performance of Supervised Pretraining.

| Models           | A  | R  | P  | F1 |
|------------------|----|----|----|----|
| fastText Unigram | 86.0| 82.8| 88.4| 85.5|
| fastText Bigram  | 86.6| 84.9| 87.9| 86.4|
| fastText Trigram | 87.4| 85.0| 89.2| 87.1|

Table 5: Performance of Supervised Pretraining.

50 epochs and check the improvement of validation (dev set) loss to save the latest best model during training. It is important to note that we use the same hyperparameters for the baseline models.

Results We present the detailed ablation experiment results of our test set in Table 4. We didn’t perform any explicit prepossessing before computing the semantic representation using the embedding layer lookup in Figure 3. We compute accuracy, precision, recall, and F1 score to compare the performance of our readability prediction model with the baselines. We perform a detailed ablation study with the variations of pre-trained embedding models and our additional feature fusions. After applying all the models from Table 4 to our test set, we get maximum accuracy (86.7%) and F1 score (86.7%) from the combination of BiLSTM with pooling, CL, CC, and embeddings from LaBSE model. As shown in Table 4, the impact of additional features such as CL and CC of our readability prediction model is significant, achieving maximum Accuracy and F1 scores 6 times out of 8 cases.

Supervised Pretraining We also experiment with fastText supervised text classification techniques (Joulin et al., 2017). These models are based on multinomial logistic regression. We build 3 classifiers using word n-grams (unigram, bigram, and trigram) and character n-grams (2 to 6 length) with learning rate = 0.5 and 50 epochs. For all 3 cases, we use hierarchical softmax (Peng et al., 2017) as the loss function for faster training. From Table 5, we observe that the model with word trigram and character n-grams achieves maximum Accuracy and F1 score.

Bengali Readability Analysis Tool

We design a Bengali readability analysis tool capable of providing in-depth information of readability and complexity of the documents which is shown in Figure 4. For an input document $D$ with $N$ sentences, our Bengali readability checker can highlight the simple and complex sentences. We calculate the readability score based on the ratio of the predicted simple sentences to the total number of sentences in the document $D$ and assign different ratings based on the readability scores. Since ARI performs well on the Bengali document-level readability analysis and it is resource independent, therefore, we use the scores returned from this formula to predict the age-group of the input document. The example document $D$ in Figure 4 will be reasonably easy to read for most people at least with age between 10-11.

Conclusion

In this paper, we present a readability analysis tool that would be useful for educators, content writers or editors, researchers, and readers of different ages. We adopt document-level readability formulas traditionally used for U.S. based education system to the Bengali education system with a proper age-to-age comparison. Moreover, we divide the task into sentence-level and design supervised neural models, which will serve as a baseline for the future works of this task. We present several human-annotated corpora, dictionaries, and an algorithm, which can be useful for several other tasks of this low-resource language. In the future, we wish to improve the quality of our system by increasing the size of our sentence-level dataset and will present a user-study based on our tool. Also, we will focus on the readability analysis of Bengali-English code-mixed texts.
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| Anathbabur Bhoj            | Fear of Anathbabu   | Satyajit Ray            | https://www.ebanglalibrary.com/            | August 30, 2020|
| Anupamar Prem               | Anupama’s love      | Sarat Chandra Chattopadhyay | https://nltr.org/                          | August 30, 2020|
| Bachcha Bhoyonkor Kachcha Bhoyonkor | Terrible kids       | Muhammed Zafar Iqbal   | https://www.ebanglalibrary.com/            | August 30, 2020|
| Bhalobasar Golpo            | Story of love       | Humayun Ahmed           | https://www.ebanglalibrary.com/            | August 30, 2020|
| Bhuter Bachcha Kotkti       | Ghost’s child Kotkti | Muhammed Zafar Iqbal   | https://bdebooks.com/                      | August 30, 2020|
| Bhuter Meye Lalboti         | Ghost’s daughter Lalboti | Shofuddin Sardar          | https://www.pathagar.com/                | August 30, 2020|
| Bhuter Pallay Gopal Bhar    | Gopal Bhar in the grip of the ghost | Montu Chakraborty | https://www.shishukishor.org/ | August 30, 2020|
| Bhuture Ghiori              | Spooky clock       | Shirshendu Mukhopadhyay | https://www.ebanglalibrary.com/            | August 30, 2020|
| Bicharok                    | The judge          | Rabindranath Tagore     | https://www.ebanglalibrary.com/            | August 30, 2020|
| Charitraheen                | Characterless      | Sarat Chandra Chattopadhyay | https://www.ebanglalibrary.com/ | August 30, 2020|
| Chotoder Mojar Golpo-1      | Funny stories for children-1 | Shofuddin Sardar          | https://www.pathagar.com/                | August 30, 2020|
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| Dampottokolo-ho O Necklace  | Marital strife and necklace | Joydeb Roy              | https://www.ebanglalibrary.com/            | August 30, 2020|
| Debi                        | Goddess            | Humayun Ahmed           | https://www.ebanglalibrary.com/            | August 30, 2020|
| Devdas                      | Devdas              | Sarat Chandra Chattopadhyay | https://nltr.org/                          | August 30, 2020|
| Ekti Bhoyonkor Obhijaaen Golpo | A story of a terrible adventure | Humayun Ahmed           | https://www.ebanglalibrary.com/            | August 30, 2020|
| Gopone                      | Secretly           | Imdadul Haq Milan       | https://www.ebanglalibrary.com/            | August 30, 2020|
| Gosaibaganer Bhoot          | The ghost of Gosaibagan | Shirshendu Mukhopadhyay | https://www.ebanglalibrary.com/            | August 30, 2020|
| Kakabur Chokhe Jol          | Tears in Kakabu’s eyes | Sunil Gangopadhyay      | https://www.ebanglalibrary.com/            | August 30, 2020|
| Ke Raja                     | Who is the king?    | Abdul Mannan Talib      | https://www.pathagar.com/                | August 30, 2020|
| Khele Khele Uthbo Bere Buddhi Bole | We will grow up with intelligence and strength through sports | UNICEF                                 | https://allfreebd.com/                    | August 30, 2020|
| Krishnakanter Will          | Krishnaka’s will    | Bankim Chandra Chatterjee | https://nltr.org/                          | August 30, 2020|

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| Modhyo Boyosher Sonkot| The crisis of middle age            | Mina Farah                 | https://www.ebanglalibrary.com/            | August 30, 2020 |
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| Manbhanjan            | Pacifying touchiness                | Rabindranath Tagore        | https://nltr.org/                           | August 30, 2020 |
| Meena Jokhon Choto Chilo| When Meena was a little girl       | UNICEF                     | https://allfreebd.com/                     | August 30, 2020 |
| Meena Jokhn Jonmechilo| When Meena was born                 | UNICEF                     | https://allfreebd.com/                     | August 30, 2020 |
| Meena O Tar Bondhu    | Meena and her friend                | UNICEF                     | https://allfreebd.com/                     | August 30, 2020 |
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| Nandito Noroke        | In blissful hell                    | Humayun Ahmed              | https://www.ebanglalibrary.com/            | August 30, 2020 |
| Neel Hati             | Blue elephant                      | Humayun Ahmed              | https://bdebooks.com/                      | August 30, 2020 |
| Parineeta             | Married woman                       | Sarat Chandra Chattopadhyay| https://www.ebanglalibrary.com/            | August 30, 2020 |
| Phule Phule Projapoti | Butterflies in the flowers         | Sharif Abdul Gofran        | https://www.pathagar.com/                  | August 30, 2020 |
| Preme Porar Somoy     | Time to fall in love                | Imdadul Haq Milan          | https://bdebooks.com/                      | August 30, 2020 |
| Priyo                 | Favorite one                        | Imdadul Haq Milan          | https://www.ebanglalibrary.com/            | August 30, 2020 |
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| Sabuj Dwiper Raja     | King of the green island            | Sunil Gangopadhyay         | https://www.ebanglalibrary.com/            | August 30, 2020 |
| Sadhubabar Haat       | Hand of the saint                   | Sunil Gangopadhyay         | https://www.ebanglalibrary.com/            | August 30, 2020 |
| Sara Prithibir Rupkatha| Fairy tales of all over the world   | Various writers            | https://www.banglapustak.com/              | August 30, 2020 |
| Sati                  | Chaste                              | Sarat Chandra Chattopadhyay| https://nltr.org/                           | August 30, 2020 |
| Se Bhalobase Naki Base Na| She loves me or not                | Imdadul Haq Milan          | https://bdebooks.com/                      | August 30, 2020 |
| Shasti                | Punishment                          | Rabindranath Tagore        | https://nltr.org/                           | August 30, 2020 |
| Shiyal O Kak          | A fox and a crow                    | Muhammad Farid uddin Khan  | https://www.pathagar.com/                  | August 30, 2020 |
| Shubhro Geche Bone    | Shubhro has gone to the forest      | Humayun Ahmed              | https://www.ebanglalibrary.com/            | August 30, 2020 |
| Sonamondi Golper Asor| Bunch of stories for children       | Md. Abdul Goni             | https://prozuki-mela.blogspot.com/         | August 30, 2020 |
| Strir Patra           | Wife’s letter                       | Rabindranath Tagore        | https://nltr.org/                           | August 30, 2020 |
Once in the darkness of a night, a wolf entered into a men's village. There the dogs surrounded it and bit it so badly that it was about to die. Somehow it was able to escape with its life. But within a few days its body was poisoned due to biting of dogs. The wolf had no ability to move. Groaning due to pain, it laid down under a tree. It was hungry in addition to the pain of wounds. The poor wolf became very weak due to hunger. At that time it saw a sheep passing through a little distance. It was not possible for the wolf to catch the prey by running. So it called to the sheep and said with pathetic voice, brother, listen, come here once. Hearing the call, the sheep stopped moving. But it did not come forward to the wolf and said, tell me what you want to say, I can hear you from here. The wolf said, brother, I am so weak because of hunger and thirst. If you please bring a little water from the nearby shower, my life will be saved. I have food arrangement. After hearing the wolf speech, the sheep said, brother, I have no desire to sacrifice my life in providing you with water to satisfy your thirst. I can understand that you want to manage your food by breaking my neck. Saying this, the sheep left the place running.

Moral: There is no scarcity of deception of shrewd, so, it is not wise to get melted with sweet words. Those who currently sit idly being inactive thinking of happiness in future, have to disappointed at last.