

# Web Extension for Lexical Simplification

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**Abstract**—Lexical simplification means the process of providing alternatives to the complex words in the sentence with texts that are much more simpler to understand, while also preserving the context and grammar of the original text to make the whole sentence more easier to understand. Unsupervised machine learning is used to learn simpler alternatives of complex words. But the drawback of most of the time has been the fact that they provide simpler words without taking the context of the complex word in the sentence in account. In this paper, we are proposing a lexical simplifier which is based on contextual learnings from the sentence. We have applied the pre-trained representation model from GOOGLE called BERT. It is a very powerful tool which can make use of the wider context of the sentence in both forward and backward direction. We have also taken the word frequency indicator from the Subtlex list, to produce results that will be more correct both semantically and grammatically. We have also added a web extension for the simplification of the text on the webpage, which takes the input from the user, processes the text on the server end, and gives the result in return after computation is over.

**Index Terms**—Lexical simplification, Unsupervised, BERT, Pretrained Representation Model

## I. INTRODUCTION

With respect to Natural Language Processing (NLP), the process of Lexical Simplification (LS) tries to outperform earlier known task, Text Simplification (TS) by aiming the structure of the model on lexical information available in the sentence. This can also be described as the process of replacing complex words in the sentence provided to make it more simpler, without changing the structure of the sentence or making any additional modifications. LS is a whole pipeline which mainly consists of identifying harder words in a sentence, and searching for its best alternative. The best substitution has to be simple, while also maintaining the grammar of the sentence and upholding the original meaning of the sentence as much as possible. This itself could prove to be very difficult to do, since different subjects can have different understanding of an alternative provided by the model, i.e Users from different languages might not

understand the synonym of the target word. LS can help all kinds of people, like children, not native speakers, etc, to deduce the sentence more efficiently. LS can be a very helpful way to simplify the sentence and some works [16] also reflect on the fact that people who have an understanding of one vocabulary can understand the sentence and its meaning, despite the fact that the sentence may be grammatically or syntactically incoherent.

We propose to create a Lexical Simplification Model which will allow simplification of a given segment without changing the definition of the segment by identifying complex words and replacing them with alternatives which retain the same meaning as the

original word which then will be deployed with the help of a web-extension using FastAPI to help users with difficulties in understand complex articles and resources online and simply them for their benefit.

The LS framework is usually divided into three subtasks: Complex Word Identification (CWI), Substitute Generation (SG), and Substitute Ranking (SR). The task for complex word identification can also be recognized as an independent task since it is usually solved with unsupervised learning methods to produce synonyms. Most simplification systems currently existing make use of a set of already defined rules to substitute the target words with their simpler counterparts from structured databases, like WordNet [3]. Some methods also make use of word embedding models for searching their synonyms by finding the most similar vectors to the target word vector.

Our LS model has the advantage of making use of the contextual meanings of the sentence in all three steps while generating a substitute for the target word and replacing it in the sentence. Let's take the example of the sentence "How a photograph of a young man cradling his dying friend sent me on a journey across India". Here, the words "cradling", "photograph" and "journey" are identified as complex words and can contain different meanings based on the context of the sentence. Some online websites which offer to simplify the text have given different results. e.g. Rewordify.com

gives the result as “How a photograph of a young man cradling his dying friend sent me on a trip across India”. Here, only the text “journey” is replaced with its simplified counterpart “tour”. Other websites such as Simplish.org gives the result as “How a photograph of a young man resting his coming near to death friend sent me on a journey across India”. The words “cradling” and “dying” are considered as complex and are replaced with “resting” and “coming near to death” as complex counterparts. Both the grammatical and contextual meaning of the sentence changes here. Our model gives the result as “How a shot of a young man and his dead friend sent me on a tour across India”. The words “cradling”, “photograph” and “journey” are replaced along with preserving the contextual meaning of the sentence and making it simpler to understand as well.

In this paper, we have explained the pipeline of our model and how it is to be implemented as a web-browser extension. The identification part depends on what the context of the text is by exploiting the features of a Bi-LSTM algorithm and making use of the transfer learning features from the Global Vectors embeddings [12]. To get the suitable substitutes, we make use of the self-supervised pre-trained model BERT [13]. We replace the complex word by the symbol ‘[MASK]’, making a new sequence of words whose context does not change with respect to the complex word. We use these sequences and choose new substitutes with suitable probability distribution from BERT [13]. For the filtering of the substitutes, we have employed the Zipf frequency and chosen a threshold to filter out the simpler substitutes for replacing the word. Then, we use this trained model and employ it as a web-extension for the users to simplify the text on their web pages if they feel the need to do so.

The rest of this paper is organized as follows. Section 2 contains the literature reviews of the research papers studied for this project. Section 3 contains the methodology of the project. It explains the process and the pipeline of the model. Section 4 has a brief summarization of Results and Discussions of the model. We have discussed the results of our model in that section. Finally we draw our Conclusion in the last section. We have summarized a brief conclusion along with what more is left to be done in our project. At the end of this paper are all the references that have been cited in this paper.

#### A. Objectives

- 1) The complexity of a word can depend upon the context of the sentence in which it is used. Some research would be done on determining a Machine Learning Model which takes the context of a sentence into account while determining the complexity of the word.
- 2) Out of all the candidates generated for the complex word, one must be selected which has the same meaning as the complex word and the complexity of the word should be low. Work could be done to derive an algo-

rithm which can rank candidates by taking into account the meaning and complexity of the word.

- 3) As a result of the above two objectives, creation of a text simplification system for overall simplification of the textual information
- 4) Creation of Web-based extension which will take selected content from web pages, communicate with text simplification system, relay the simplified content back to the web-pages.

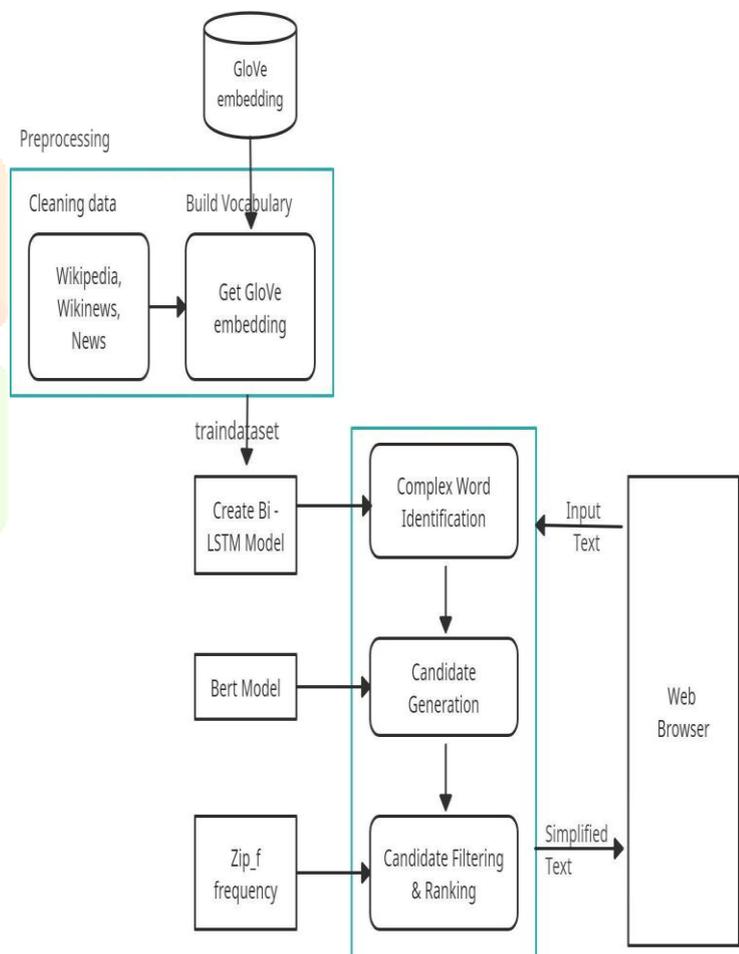


Fig. 1. An architecture of Bi-LSTM

We are looking to create a lexical simplification model which can then be implemented in a web browser extension to simplify the text on the web pages which the user can then use to make the text simple to understand and preserve the semantic meaning of the text. The complete method can be divided into 2 tasks - making the simplification model using BERT [13] and creating the extension.

#### A. Simplification Model

The pipeline of simplification of the text can be divided into 3 sub-tasks, namely complex word identification, substitute generation, and substitute filtering and ranking. In this section, we briefly explain each step and the method used in the simplification process. Refer to Fig. 1 for the architecture of our whole simplification model and the whole flow diagram of the model is shown in fig. 4.

1) *Complex Word Identification (CWI)*: The main goal of this task is to identify all the complex words in the text which may need to be simplified by the model. Complex word identification from here on out would be represented by CWI in this paper.

The dataset used for the training and testing purpose of the CWI model is taken from [11]. This dataset is divided into a training set and a test set. We have used the pre-trained GloVe Vectors (GloVe) embeddings [12] to create an embedding matrix for all the words in the training dataset. The GloVe Embeddings [12] are an unsupervised learning algorithm developed by researchers at Stanford University. This algorithm aims at generating word embeddings with the help of co-occurrence matrix. The co-occurrence matrices are aggregated from the given corpus. We have made use of the 300-dimensional GloVe embeddings [12] as word representations, where dimensions represent the features of the words that have been pre-defined by the researchers, like the length, morphology of the word, ambiguity of the word, etc. This algorithm is then used to predict whether the target word is complex or not and saves the result in a binary matrix.

The CWI task uses a bidirectional long short term memory (bi-LSTM) algorithm [10] which is trained and tested on the dataset prepared by Yimam et al. (2017). With the help of the bidirectional LSTM [10] will run the inputs in both forward and backward directions. This will help the model to understand the context of the text in both directions. It preserves the information from the future as well as the past using the two hidden states combined. As it is clear

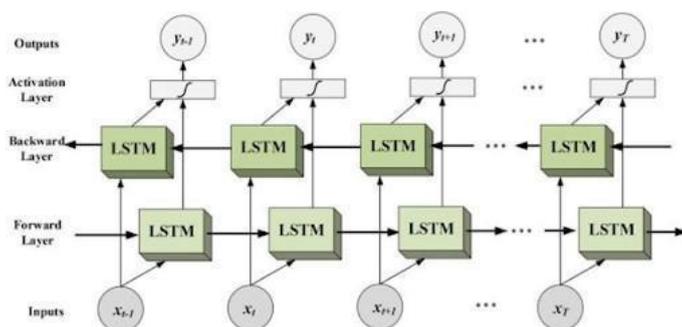


Fig. 2. An architecture of Bi-LSTM

from the fig. 2, the flow of data is in both the directions. Bi-LSTM is employed for sequence to sequence learning tasks. It makes use of the hidden states to pass the data and process it. The forget gate is the first activation in one LSTM [10] cell. It makes use of the previous hidden state

$h_{t-1}$  and the input  $x_t$ . The input gate makes use of the next activations, sigmoid and the tanh function. Finally, the output gate makes use of the last activation and the tanh function above it. This algorithm is implemented on both sides. The mathematical equations corresponding to the inner working of a bi-LSTM algorithm are mentioned from equations (1) to (5).

$$\text{ForgetGate} : f = (W_f[h_{t-1}, x] + b_f) \quad (1)$$

$$\text{InputGate} : i = (W_i[h_{t-1}, x] + b_i) \quad (2)$$

$$\text{Gategate} : g = \tanh(W_g[h_{t-1}, x] + b_g) \quad (3)$$

$$\text{CellState} : c_t = f \cdot c_{t-1} + i \cdot g \quad (4)$$

$$\text{OutputGate} : o = (W_o[h_{t-1}, x] + b_o) \quad (5)$$

Where the sigmoid function is defined as

$$\frac{1}{1 + e^{-x}}$$

This model provides advantages as compared to other existing models since it takes the context of the text in account in both directions and requires less features to be taken into account while determining the complex words from the sentence.

2) *substitute Generation*: This task is performed to produce the substitute candidates for the complex word  $w$  identified by the CWI task. We have used the pre-trained language model BERT [13] which produces the substitute candidates for complex words  $w$ . In this section, we will briefly summarize what BERT [13] is and how it works.

BERT [13] stands for Bidirectional Encoder Representation from Transformers. Transformers are based on attention and don't require any sequential computation per layer, only a single step is needed. Additionally, the gradient steps that need to be taken from the last output to the first input are only one. For RNNs, it increases with how much longer the sequence is. BERT [13] is a self-supervised model and makes use of transfer learning and pre-training. These are the two steps in the BERT [13] framework. During the pre-training phase, the model is run on unlabelled data. BERT [13] is also optimized for better performance on the data. It uses Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). MLM helps in predicting the missing token in the given sequence, provided its right and left context. The next optimization is of the NSP task. It processes the new sequence of text with masked tokens and prepends every sentence with the delimiter as the specialized token [CLS] and the delimiter of the appen- dations of the sentences as separator token [SEP]. As shown

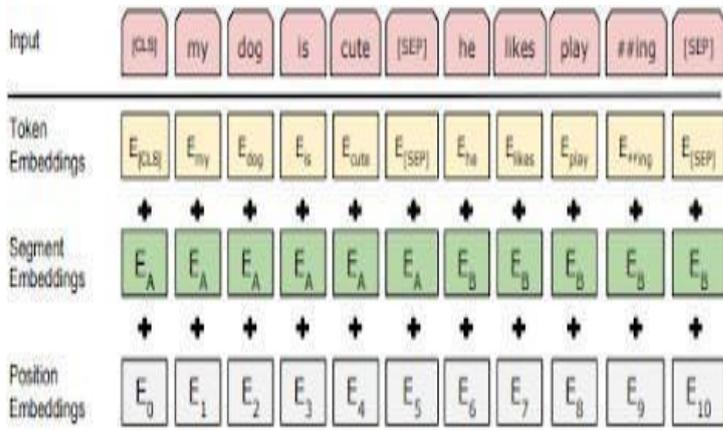


Fig. 3. BERT Objective

in fig. 3, BERT [13] has a predefined set of rules to represent the input text of the model. The Position Embeddings are used to express the position of words in the sentence  $S$ . Segment Embeddings breaks the input into pairs and takes them as input for performing different tasks like Question Answering. The Token Embeddings are the embeddings learned for the specific token from the WordPiece Token vocabulary. For a given token, its given input is constructed by summing the corresponding token, position and segment embeddings.

The BERT [13] pre-trained model takes the sentence as input, replaces the complex word with the special token "[MASK]" making a new sequence of letters. Then it concatenates both the original and the new sequence of the words with the token "[SEP]". This is how BERT [13] uses the making language model and gives new substitutes to the [MASK] token. Each new substitute generated is used to compute the probability distribution of the sequence and best of these substitutes are selected for the next step, filtering and ranking.

3) *Filtering and Ranking*: After Substitute Generation, the next task in simplification of the text is to filter them and replace the substitutes with the best option. Threshold based filtering is performed to remove some of the complex substitutes. For this purpose, Zipf frequencies are considered and their value is set to a specific frequency. The Zipf frequencies are extracted from the SUBTLEX list [14]. This list has been chosen because some experiments [15] have shown that the word frequencies from this corpus correlate on human judgements on simplicity. The Zipf frequency of a word is the base-10 logarithm of the occurrence of a word per billion words.

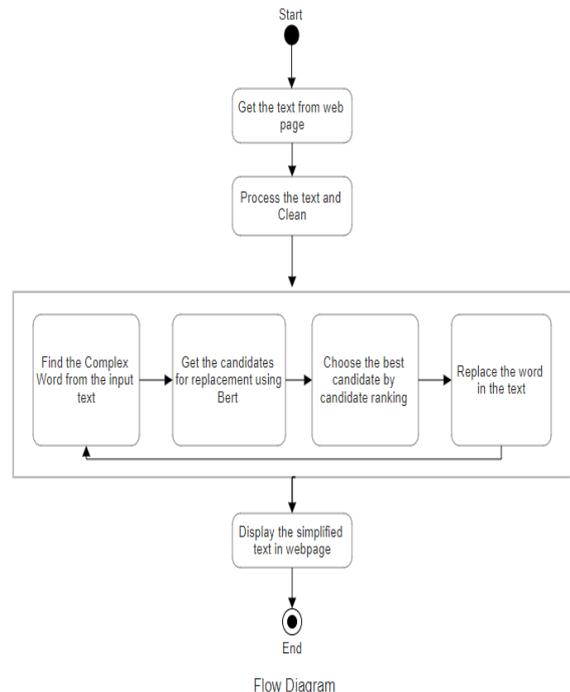
Fig. 4. Flow Diagram of our model

*B. Web-Browser Extension*

The next step of this project would be to implement this model as a web-extension for Chrome Browser. The users would be able to select the text that they want to be simplified, then use the extension. The extension will be supported in only one language, i.e. English.

To use this extension, navigate to the web page and select the text that needs to be simplified, then right click on it. The Chrome dialog box appears. Select the Lexical Simplification Extension.

Lexical Simplification Extension gets the selected text from the webpage and then calls the server using FastAPI. We have used FastAPI over other alternatives because of its more



modern framework, better speed, robustness, easy to implementation, short and intuitive.. The development of FastAPI was done keeping the speed of operation, experience of developers and open standards in mind. It supports asynchronous tasks, which results in better speed than other alternatives. The architecture of FastAPI has a built-in system for validation of data types so that it can detect invalid initializations during the processing phase and returns the errors in JSON format. For data validation it uses Pydantic, i.e. a tool that allows system datatypes to be defined.

For our project, we have used our local machine as a server for performing all the computational processes. The Lexical Simplification Model is stored on the server, and takes the

selected text from the webpage as input and runs the model and generates the simplified text, which then it sends back to the browser page through FastAPI. Fig. 5 shows the flow diagram of how the web extension interacts with the FastAPI to perform the simplification task on the webpage. The Lexical Simplification Extension then scans the webpage

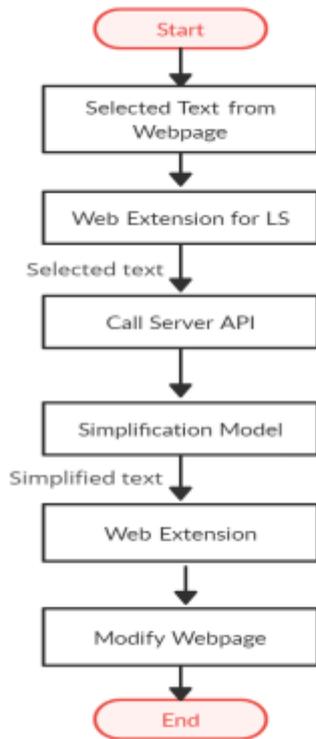


Fig. 5. Flow Diagram of Web Extension

and replaces the selected text by simplified text sent by Lexical Simplification Model from the server. The web extension has been deployed on the Chrome web store under the name of Lexical Simplification. Anyone interested can download the extension from the store on their local device.

II. RESULTS AND DISCUSSION

In this section, we will discuss the results of our CWI model and provide further discussions on what more we are going to implement in the project.

A. Results

We report the results on the CWI Shared Dataset prepared by Yimam et al. (2017) [11] on Wikipedia, Wikinews and News Datasets. We have used both the Wikinews and News datasets since the text in News are written by professionals while those written by Wikinews are written by common people so it is bound to contain more grammatical mistakes. After running the model for 5 epochs with 199 iterations in each epoch, we have plotted the graphs for the quantitative analysis of how our model behaves and gives results. We have employed regular metrics like Accuracy, Recall, Precision, F1 Score for measuring the metrics of the CWI algorithm. These are used to measure how the model performs with our dataset. We observe that the total loss of

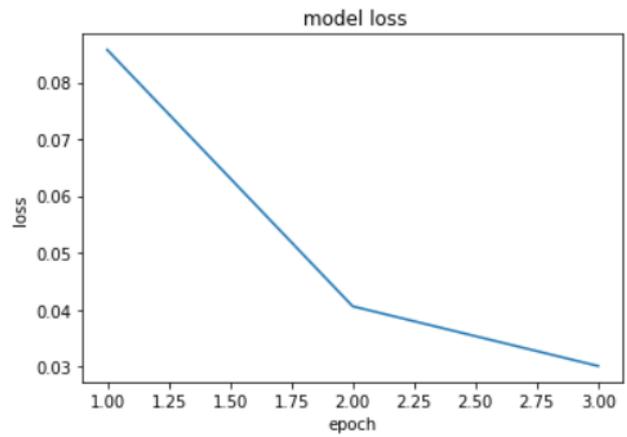
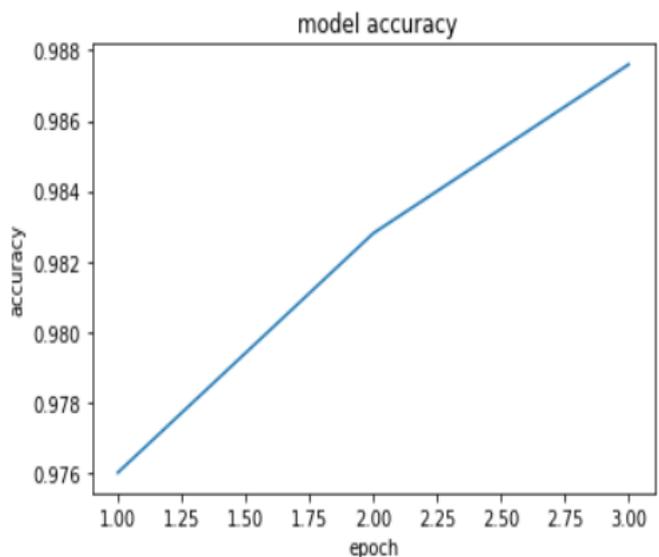


Fig. 6. Graph between Model Loss and Epochs

the model keeps on decreasing after every epoch. This means that with every iteration the model learns. The dataset contains a total of 2041 sentences out of which 1988 are split into training data and remaining 53 sentences are reserved for the validation of the model for CWI task. The training loss and the validation loss of the model after running for 3 epochs with 199 iterations each remains almost constant with 0.02 loss for training the model and 0.05 loss while validating the model at the end of epochs.



BEFORE:

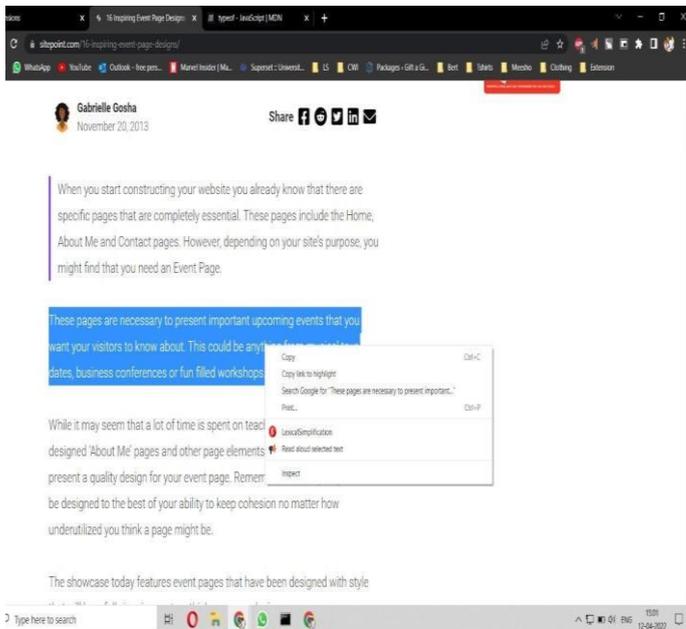


Fig. 8. Highlighted text on the webpage before using the extension

AFTER :

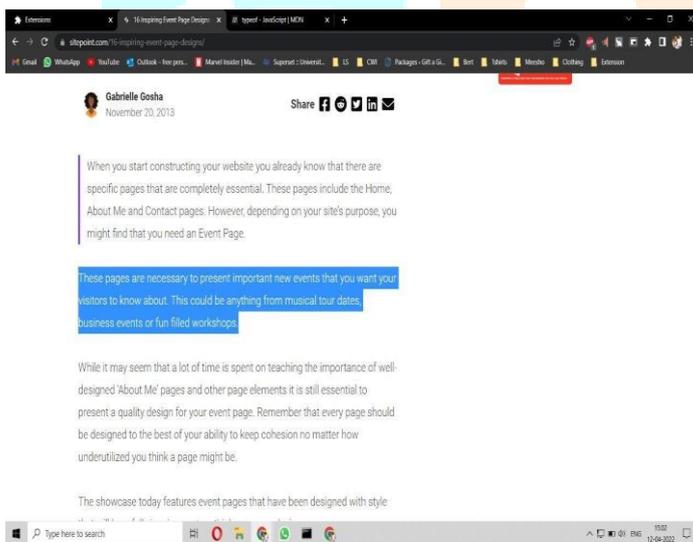


Fig. 9. After the use of the extension

For running the extension, simply highlight the text that needs to be simplified by the user and right click so that the chrome dialog box appears. Select the Lexical Simplification option. It sends the selected sequence of texts to the server, which returns the simplified version on the webpage. This can be illustrated with the following two figures given below (fig. 8 and fig. 9). The text that is highlighted to be simplified is "These pages are necessary to present important upcoming events that you want your visitors to know about. This could be anything from musical tour dates, business conferences or fun- filled workshops." The words "upcoming" and "conferences" were identified as

complex and were replaced by "new" and "events" respectively.

### B. Discussion

We have till now done the CWI model which has a model loss of around 0.03 after 5 epochs and F1 Score of 0.68. The complex words identified are expressed in a numpy array of 0s and 1s making this a binary classification array. These words have substitutes generated from BERT [13] pre-trained model, which leverages on the masking language model and next sentence prediction model of BERT [13]. It focuses on the context of the complex word. The ranking of these substitute is done with Zipf frequencies with the threshold of 3.1. For the future, we are looking to add more metrics into the ranking and filtering task of the pipeline to select the substitutes with better contextual coherence in the sentence.

## III. CONCLUSION AND FUTURE SCOPE

We propose a simple Framework based on BERT [13] for lexical simplification. Existing lexical simplification models only consider the context into consideration on the last stage only (Substitute Ranking), but by using BERT [13] for substitute generation and Bi-LSTM algorithm [10] for complex word generation our system considers the context in all three stages of lexical simplification. The complex word identification model is completed and has a high accuracy. The substitute generation uses pre-trained BERT's [13] masked language modeling (MLM). The substitute ranking is based on Zipf Frequency of the word. We have created a Browser Extension which simplifies the text on the webpage with the help of our lexical simplification model on one-click.

To further improve the system we can fine tune BERT for the process of Substitute Generation of target word. In the substitute ranking phase more matrices such as co-sine similarity taken into consideration to improve the ranking system. The current system only works with single words system can be improve to include phrases as well. Also some machine learning libraries can be added to take lexical simplification to another level.

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