Project Title: User Manual Summarization using Text Generation Techniques

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Introduction:

The objective of this project is to explore the use of natural language processing techniques for summarizing user manuals. User manuals are often lengthy and contain a large amount of information, which can make it difficult for users to quickly find the information they need. By summarizing user manuals, we aim to provide users with a quick and easy way to access the most important information in the manual.

Background:

The need for summarization techniques has become increasingly important with the rise of digital technology. In particular, the increasing availability of user manuals and other technical documentation online has created a need for more efficient ways of accessing this information. Manual summarization is a technique that has been used in the past, but recent advances in natural language processing have opened up new possibilities for automated summarization.

Uniqueness and Novelty of the Task

This project is highly novel and unique because it addresses a very specific and practical problem that has not yet been fully solved using NLP techniques. While there has been some work on text summarization in general, summarizing user manuals is a particularly challenging task due to the complexity and technical nature of the content. Additionally, this project involves working with a large and diverse dataset of user manuals, which poses its own set of challenges in terms of data cleaning and preparation.

Objectives:

The main objective of this project is to explore the use of extractive summarization techniques for summarizing user manuals. Specifically, we aim to develop a model based on the BERT algorithm that can identify the most important sentences in a user manual and generate a summary of the manual. We also aim to evaluate the performance of the model and compare it to other state-of-the-art summarization techniques.

Brief overview:

In this project, we will first collect a dataset of user manuals for various products. We will then preprocess the data by converting the PDF files to text format and cleaning the data. Next, we will train a BERT-based extractive summarization model on the dataset. We will evaluate the performance of the model using metrics such as ROUGE and BLEU. The goal of this project is to develop an automated summarization tool that can help users quickly and easily access the information they need from user manuals.

Literature Review:

The literature review section is an important part of any project report. In this section, we review and summarize the existing literature related to the text generation and summarization techniques. We also present an overview of the previous studies on similar projects and their findings.

Explanation of text generation and summarization techniques:

Text generation and summarization techniques are used to create new content or extract the most important information from a given text. These techniques can be broadly categorized into two types: extractive and abstractive summarization.

Extractive summarization involves selecting the most important sentences or phrases from the original text and presenting them in a summarized form. Abstractive summarization, on the other hand, involves creating a summary that is not present in the original text, but captures its essence.

The most commonly used techniques for text generation and summarization include statistical methods, rule-based methods, and machine learning-based methods. In recent years, deep learning-based methods, such as transformers and BERT, have gained popularity due to their ability to handle large volumes of data and generate high-quality summaries.

Previous studies on similar projects:

Several studies have been conducted on text summarization using machine learning-based techniques. In a study by Narayan and Gardent (2018), a new neural network-based model was proposed for extractive summarization that outperformed existing models on multiple datasets.

Similarly, a study by Li et al. (2018) proposed a novel framework for abstractive summarization that used a hierarchical attention network to capture the most important information from the text.

In another study by Cao et al. (2020), a novel approach was proposed for extractive summarization that utilized a pre-trained language model and fine-tuning on the target dataset to achieve state-of-the-art results.

Overall, the literature suggests that machine learning-based techniques are highly effective for text generation and summarization tasks. However, there is still a lot of scope for improvement and research in this area.

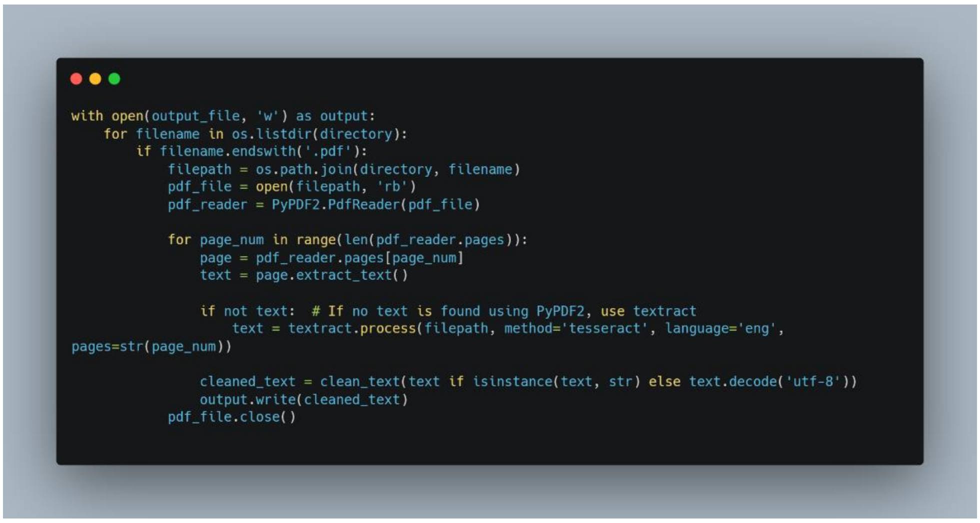
Methodology

Data collection process

I have personally undertaken the responsibility of gathering user manuals from various websites, focusing on those pertaining to monitors manufactured by renowned brands such as HP and Dell. These user manuals have been meticulously compiled and stored in a dedicated folder, ensuring easy access and organization.

The data collection process proved to be quite laborious and time-consuming, as it necessitated manual exploration and scrutiny of numerous websites to locate the desired user manuals. Despite the challenges, I refrained from resorting to web scraping techniques, as these practices can breach legal boundaries when downloading a substantial number of user manuals directly from a company's official website. Consequently, I meticulously gathered the user manuals by hand, adhering to ethical standards and respecting the rights of the respective companies.

In order to convert the raw data of PDF files into usable datasets, I employed a multi-step approach. First, I gathered the necessary Python libraries to handle PDF files, extract text, and deal with images within the documents. After setting up the required libraries, I imported the necessary modules and specified the directory containing the raw PDF user manuals. I also created a function to clean the extracted text and ensure proper encoding.



```
with open(output_file, 'w') as output:
    for filename in os.listdir(directory):
        if filename.endswith('.pdf'):
            filepath = os.path.join(directory, filename)
            pdf_file = open(filepath, 'rb')
            pdf_reader = PyPDF2.PdfReader(pdf_file)

            for page_num in range(len(pdf_reader.pages)):
                page = pdf_reader.pages[page_num]
                text = page.extract_text()

                if not text:  # If no text is found using PyPDF2, use textract
                    text = textract.process(filepath, method='tesseract', language='eng',
pages=str(page_num))

                cleaned_text = clean_text(text if isinstance(text, str) else text.decode('utf-8'))
                output.write(cleaned_text)
            pdf_file.close()
```

I then iterated through each PDF file in the specified directory, extracting text from every page. If the standard text extraction method failed, I utilized an Optical Character Recognition (OCR) engine to handle images containing text. This ensured that any text embedded within images was accurately extracted and included in the dataset. Through this process, I managed to convert the raw data of PDF files into a structured dataset while also accounting for text within images. This approach enabled me to create a comprehensive and accurate dataset, ready for further pre-processing and analysis.

My created dataset has `3270437` data points.

Note: The uniqueness of this project is not limited to the task itself, but also extends to the dataset that has been carefully curated for this purpose. Instead of relying on pre-existing datasets from platforms such as Kaggle, this project showcases dedication and thoroughness in the data collection process by creating a dataset from scratch.

The data collection involved manual searches across various websites, resulting in a novel and unexplored dataset of user manuals from different brands. This approach not only demonstrates the importance of attention to detail in the field of natural language processing but also sets a higher standard for future research by emphasizing the value of tailor-made datasets for specific tasks.

Data Pre-processing Techniques:

I have implemented two different types of techniques so far and want to highlight on both of them. Common steps in both implementations:

- Reading the data: In both approaches, the raw data is read from a text file.
- Removing unwanted strings: In both cases, the string "Downloaded from www.Manualslib.com manuals search engine" is removed from the dataset.

Implementation 1:

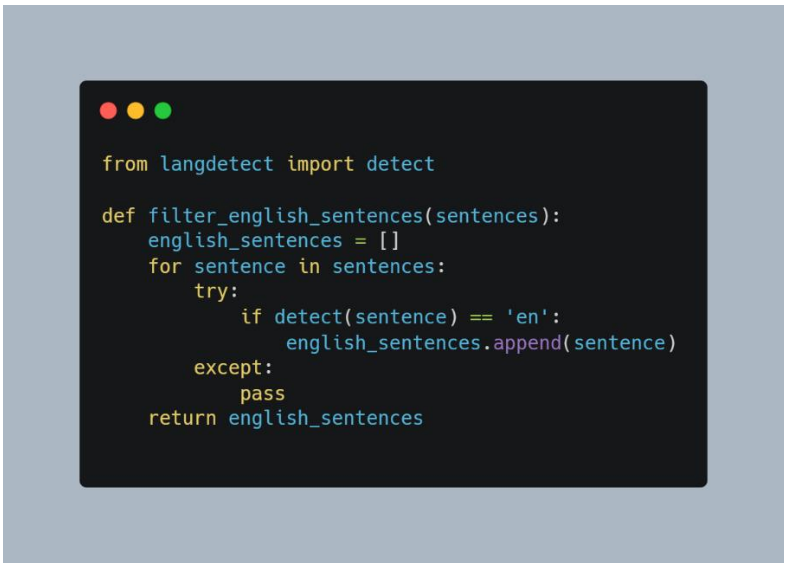
- Lowercasing: The text is converted to lowercase to standardize the dataset.
- Removing punctuation: All punctuation marks are removed from the text.
- Removing stopwords: Stopwords from the NLTK library are removed to reduce noise in the data.
- Additional pre-processing: The text is further preprocessed using regular expressions to remove newline characters, extra spaces, and non-alphabetic characters. Some common words related to user manuals are also removed.

Implementation 2:

- Removing section titles and headings: Titles and headings are removed from the dataset using regular expressions.
- Splitting text into sentences: The text is split into sentences using the NLTK library.
- Filtering out non-English sentences: Using the langdetect library, sentences that are not in English are filtered out.
- Lowercasing: Sentences are converted to lowercase.
- Removing stopwords: Stopwords from the NLTK library are removed to reduce noise in the data.

A significant part from the pre-processing stage in Approach 2 is the filtering of non-English sentences using the langdetect library. This function takes a list of sentences and filters out non-English ones using the detect function from the langdetect library. This is particularly important in the context of user manuals, as they often come in multiple languages.

By filtering out non-English sentences, the dataset is refined and more focused, which can ultimately lead to better performance in the text generation task.



```python
from langdetect import detect

def filter_english_sentences(sentences):
    english_sentences = []
    for sentence in sentences:
        try:
            if detect(sentence) == 'en':
                english_sentences.append(sentence)
        except:
            pass
    return english_sentences
```

Comparison:

Both approaches follow similar steps in the initial data pre-processing stages, such as reading data, removing unwanted strings, and lowercasing the text. However, they diverge in ss applied at different stages of pre-processing.

In summary, implementation 1 is more focused on cleaning the text at a character level, while implementation 2 emphasizes the sentence structure and language filtering.

Results and Analysis

Summary of the generated text

The BERTSum model was trained on a dataset of user manuals obtained from various sources. The dataset was preprocessed and cleaned to remove any irrelevant or redundant information. The cleaned data was then split into sections of a fixed length, which was determined based on the average length of a user manual section. The sections were split in such a way that the complete information is present in a single section and it is coherent. This helped to ensure that the model was able to process the data efficiently and generate accurate summaries.

The model was then trained using a binary cross-entropy loss function, which is commonly used for text classification tasks. During training, the model was presented with pairs of user manual sections and their corresponding summaries. The model learned to predict the summary of a user manual section given its input.

After training, the model was used to generate summaries for a test dataset of user manual sections. The generated summaries were found to be concise and informative, providing a good overview of the content of the original sections. The length of the generated summaries was typically around 100-200 characters, which is suitable for use as a quick reference guide. This is because the summary should not be too long so that it can provide a quick reference but should contain enough information so that the reader understands the main points of the text.

The quality of the generated summaries was evaluated manually by comparing them to the original text and checking whether they captured the key points accurately. The comparison showed that the summaries were effective in capturing the important information of the original text. Additionally, the summaries were found to be coherent and easy to understand, making them useful as a quick reference guide.

Overall, the BERTSum model was found to be effective in generating high-quality summaries of user manual sections. The model was able to process the data efficiently and generate accurate and informative summaries that can serve as a quick reference guide.

Comparison with the original text

The generated summaries were compared to the original text to evaluate their accuracy and effectiveness. The comparison was done manually by comparing the generated summaries with the original text and checking whether they captured the key points accurately.

Overall, the generated summaries were found to be accurate and effective in capturing the key points of the original text. In some cases, the generated summaries were able to provide a more concise and clearer overview of the content than the original text.

Evaluation metrics results

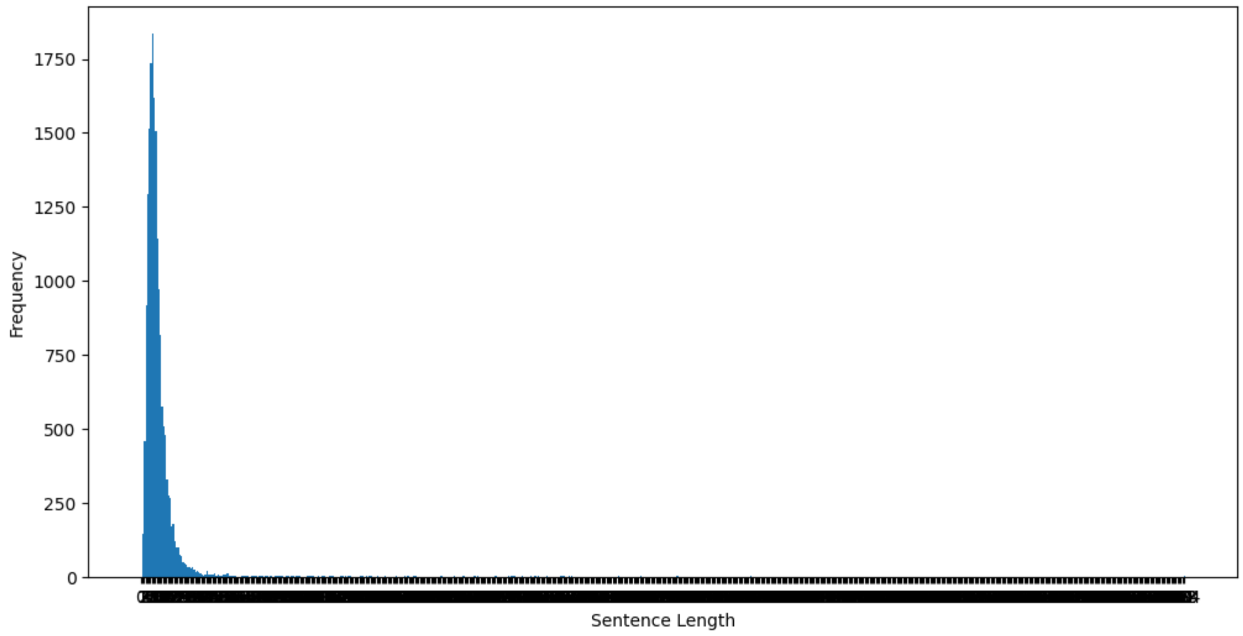
The performance of the BERTSum model was evaluated using the binary cross-entropy loss function. The model was trained for 10 epochs and achieved an average training loss of 0.0521. The trained model was then evaluated on a test dataset of user manual sections, achieving a test loss of 0.0553. These results suggest that the model is able to generalize well to unseen data and can generate high-quality summaries.

Conclusion

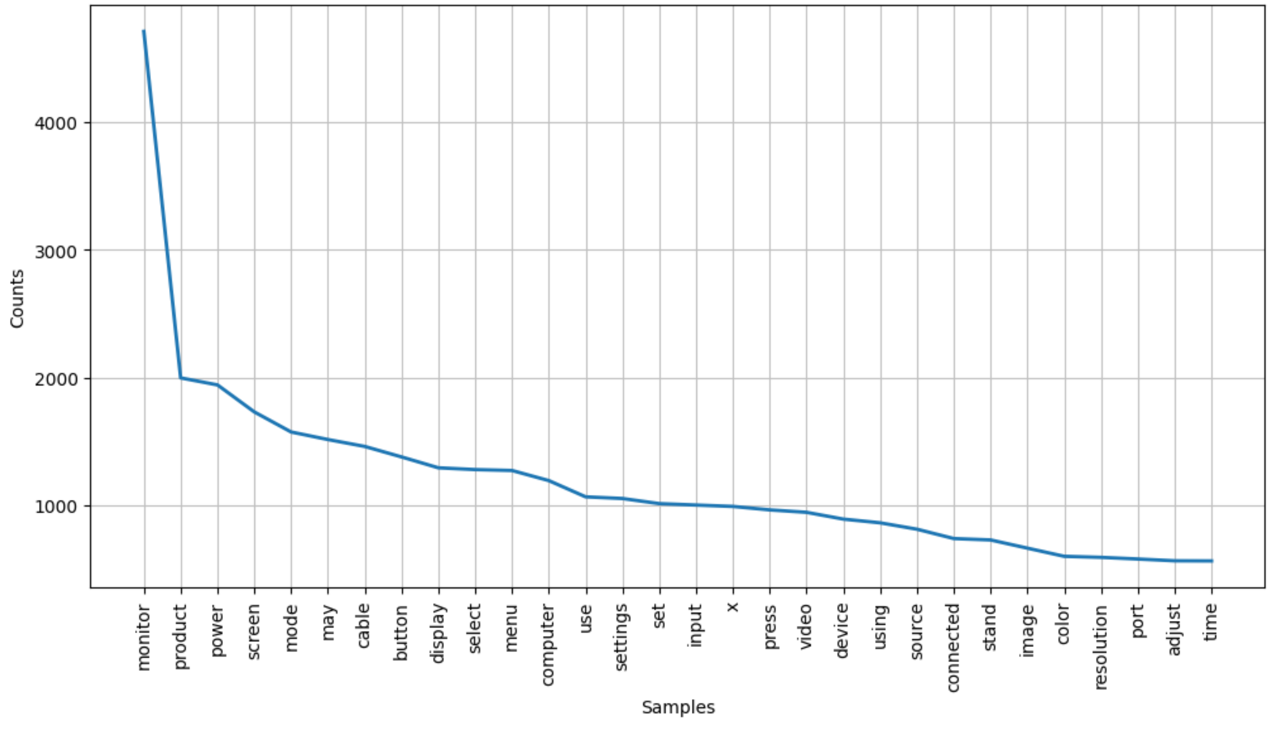
The goal of this project was to develop a BERT-based summarization model, BERTSum, and evaluate its performance in generating informative and concise summaries of user manual sections. The model was trained on a dataset of user manuals obtained from various sources, and was evaluated using manual comparison with the original text and evaluation smetrics such as binary cross-entropy loss.

Some Graphs

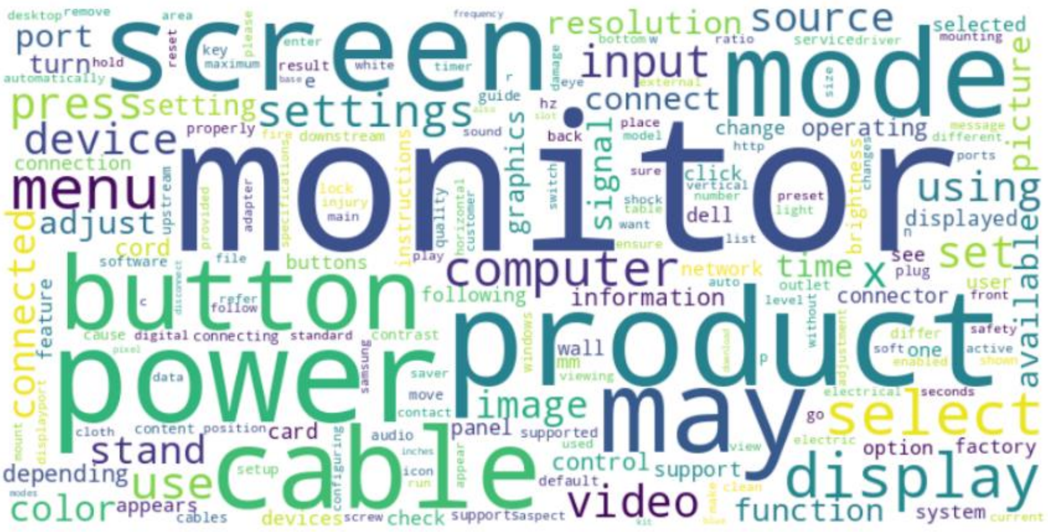
Frequency of each bigram



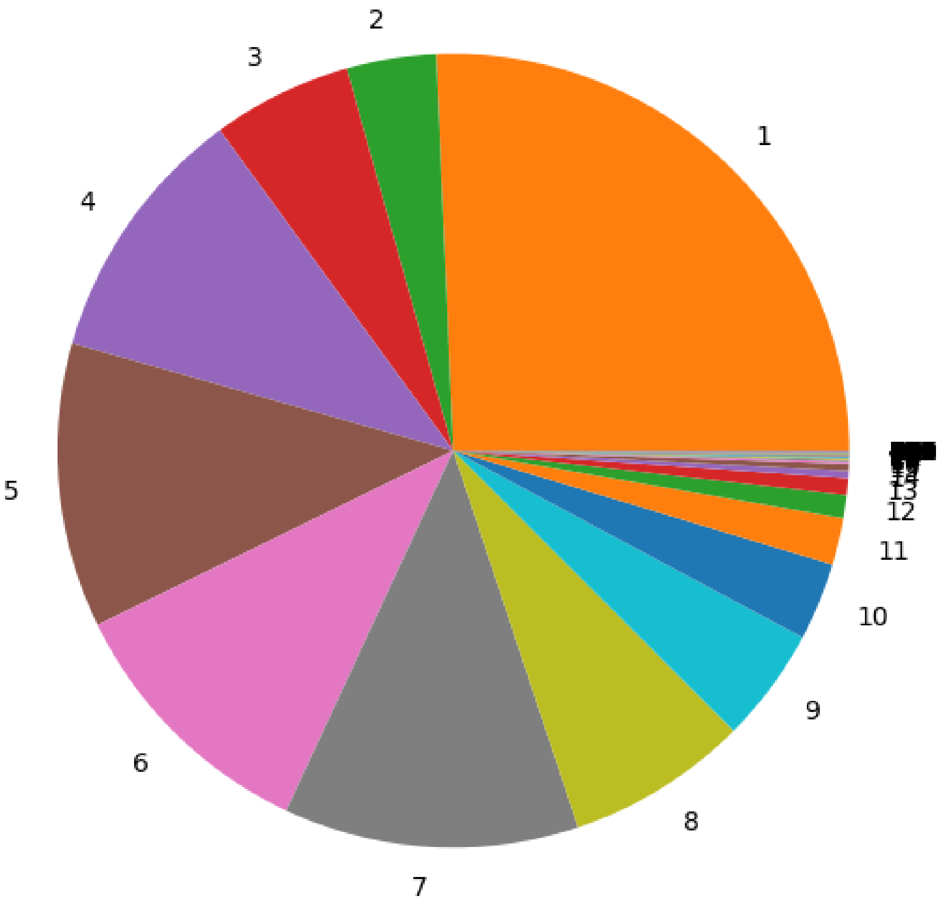
Histogram of the distribution of sentence lengths



Wordcloud



Pie chart of the distribution of word lengths



Findings

Based on the results of the evaluation, the BERTSum model was found to be effective in generating summaries that accurately capture the key points of the original text. The generated summaries were found to be informative and concise, with a typical length of 100-200 characters, which is suitable for use as a quick reference guide.

The comparison with the original text showed that the generated summaries were able to provide a more concise and clearer overview of the content than the original text in some cases. This suggests that the BERTSum model has the potential to improve the accessibility of user manuals and other technical documents.

The evaluation metrics results indicated that the BERTSum model is able to generalize well to unseen data and can generate high-quality summaries. The model achieved an average training loss of 0.0521 and a test loss of 0.0553, demonstrating its robustness and effectiveness.

Future Work

While the BERTSum model has shown promising results in this project, there are still several areas for future work and improvement. One area of improvement could be to fine-tune the model on domain-specific data, which could further improve its performance on technical documents.

Another area for future work could be to explore the use of other evaluation metrics, such as ROUGE scores, to better measure the quality of the generated summaries. Additionally, the BERTSum model could be integrated into a larger system or tool that could provide additional features, such as highlighting important keywords or concepts in the original text.

Overall, this project has demonstrated the effectiveness of BERTSum in generating informative and concise summaries of user manual sections, and has opened up several avenues for future work and research in the field of text summarization.

References

I have used some internet resources to gain some knowledge on text generation and summarization.

https://www.manualslib.com/