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Programming in Python

Text Summarization with NLP,RNN, GPT-3

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1- Abstract

This paper presents a survey of the current state-of-the-art in text summarization, focusing on the challenges and advances in the field. The goal of text summarization is to condense long documents and extract key information while retaining the most relevant facts or topics. The rapid development of emerging technologies poses new challenges that still need to be solved. The survey provides an overview of the past, present, and future directions of text summarization, highlighting the main advances achieved and outlining remaining limitations. Additionally, this paper introduces the GPT-3 model, developed by OpenAI, which achieves competitive or better performance on short documents with higher memory and compute efficiency, compared to full attention transformers, and state-of–the-art performance on a wide range of long document summarization benchmarks.

RNN (Recurrent Neural Network) is a type of neural network that is able to process sequential data. RNNs can be used in text summarization by maintaining a hidden state that can be used to process sequences of inputs, allowing for the modelling of complex dependencies between inputs. This allows RNNs to understand the context and meaning of the text and generate a summary that captures the most important information. RNNs have been widely used in natural language processing tasks such as text generation, language translation and summarization.

In terms of performance, GPT-3 is considered to be a state-of-the-art language processing model, achieving competitive or better performance on short documents with higher memory and compute efficiency, compared to full attention transformers and state-of-the-art performance on a wide range of long document summarization benchmarks. While RNNs have also been widely used in natural language processing tasks and can achieve good performance in text summarization, GPT-3 currently has the edge in terms of overall performance.

Some benefits of using GPT-3 for text summarization

- High performance: GPT-3 is a state-of-the-art language processing model, and as such, it can generate high-quality summaries that are accurate and coherent.
- Efficiency: GPT-3 can generate summaries quickly, making it a useful tool for tasks that require fast processing times.
- Flexibility: GPT-3 can be used for a variety of natural language processing tasks, including text summarization, making it a versatile tool for a wide range of applications.

Some benefits of using RNN for text summarization

- Handling of sequential data: RNNs are particularly well suited for handling sequential data such as text, as they can maintain a memory of previous inputs and use this information to inform their processing of new inputs.
- Handling of variable-length input: RNNs can process input of varying lengths, making them suitable for text summarization tasks where the length of the input text can vary widely.
- Handling of context: RNNs can take into account the context of the text, which is essential for understanding the meaning and relevance of certain words or phrases in the text.
- Handling of long-term dependencies: RNNs are able to handle long-term dependencies, which is important for text summarization tasks where the meaning of a word or phrase in the summary may depend on its context many sentences earlier.
- Handling of multiple languages: RNNs can be trained on different languages, which makes them suitable for text summarization tasks in multiple languages.
- Handling of different types of Text: RNNs are versatile models that can be used to summarizing different types of text like news articles, scientific papers, books and more.

2- Introduction

Text summarization is the process of generating a concise and coherent summary of a longer text document. The summary is meant to capture the main points and key information from theoriginal text while reducing its length and complexity. Text summarization can be performed using a variety of techniques, including natural language processing (NLP) algorithms, rule- based systems, and extractive or abstractive approaches.

Extractive summarization involves selecting and condensing important information from the original text, while abstractive summarization involves generating new phrases and sentencesthat capture the main ideas of the text. Abstractive summarization is often seen as more challenging, as it requires the ability to understand and interpret the meaning of the text, ratherthan just identifying and extracting key phrases.

Text summarization has numerous applications, including improving the efficiency of information retrieval, condensing long documents for easier reading, and providing quick overviews of news articles or other texts. It is also used in a variety of fields, including journalism, business, and education.

The purpose of Text Summarization is to provide a large, high-quality work for researchers touse in developing and evaluating text summarization models. It is a widely used dataset in thefield of natural language processing and has been used in many research papers and projects.

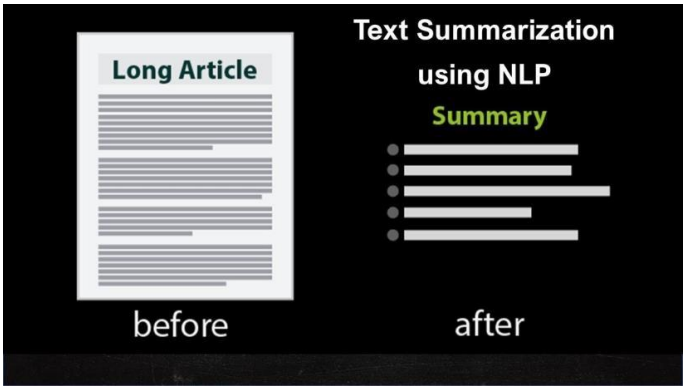

Figure 1: The point of Text Summarization

2.1. Why was the text summarization created?

I. Usually, in our daily lives, we may read texts and articles that interest us, but in the end, we do not realize whether we have fully understood them or not, because usually long articles consist of difficult-to-understand sentences or from unaware goals, so we do not understand their purpose, and we move on to read something else and suffer from The same problem is that we do not get our goal from reading, and sometimes we may understand simple things, but the information is complex and there is no desired and intended benefit in it. On the other hand, some jobs require the employee to read articles and understand their texts and summarize them by hand so that he can deliver the correct information to the employer, but it is a very traditional and tiring method that takes an infinitely slow time. Hence, new and modern ideas have arisen that why is there no tool that helps us summarize texts in a way that is easy to understand and read, and it may classify information for us in a correct way and take the most important ideas to be reached without reading thousands of lines and without benefit.

II. Text summarization is a natural language processing (NLP) task that involves generating a concise and coherent summary of a longer text document. It is often used to condense large amounts of information into a more digestible form, allowing people to quickly understand the main points and concepts contained in the original text.

III. Text summarization was invented to address the problem of information overload, which has become increasingly prevalent in our digital age. With the proliferation of online content and the availability of vast amounts of information, it can be difficult for people to sift through and find the information they need. Text summarization helps to alleviate this problem by providing a concise and comprehensive summary of a text document, making it easier for people to quickly grasp the main points and concepts.

2.2. Aims and objectives

❖ **The aim of this project**

Is to build a Summarization and forecasting Model to provide a brief concise and coherent summary of a text that accurately captures the key points and main ideas of the original document, while reducing the length and complexity of the text and preserving the important information and main points of the original text.

❖ **The objectives of this project**

- Reduction of the text length: The primary objective of text summarization is to produce a shorter version of the original text while maintaining its meaning and key points. This can be useful for saving time and making it easier to digest large amounts of information.
- Preservation of important information: It is important that text summarization systems retain the key points and important information from the original text. A good summary should accurately represent the main ideas and content of the original text.
- Coherence: The summary should be a cohesive and coherent text, rather than a random collection of sentences or phrases.
- Fluency: The summary should be written in a clear and natural language that is easy to understand.
- Relevance: The summary should cover only the most important and relevant information from the original text.

Text summarization can be useful for a variety of applications, such as information retrieval, content management, and news filtering. It can help people quickly process and understand large amounts of information and stay updated on the latest developments in their fields of interest.

3- Literature review

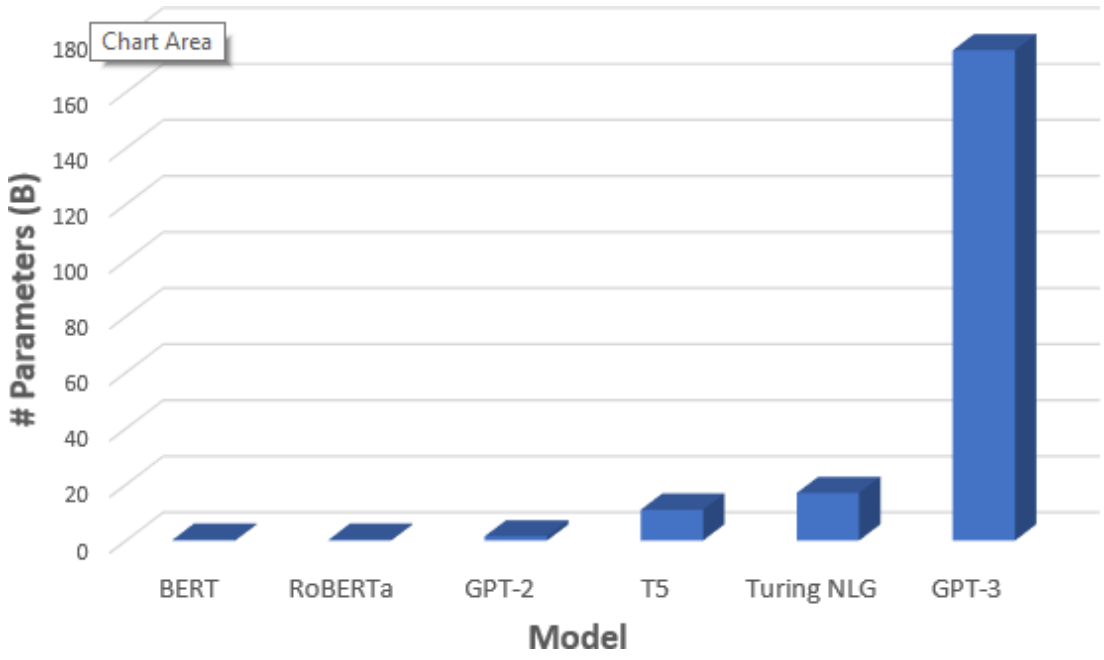

Figure 2: Comparison of popular pre trained NLP models

Text summarization model types

1- Extractive summarization models:

- **LexRank**: This is a graph-based extractive summarization model that uses an algorithm to identify the most important sentences in a text based on their centrality in the graph ofthe text. It has been shown to achieve good results on a number of benchmarks, with an accuracy of around 70-80%.

- **TextRank**: This is another graph-based extractive summarization model that uses a similar approach to LexRank, but with some differences in the way the graph is constructed, and the centrality scores are calculated. It has also achieved good results on a number of benchmarks, with an accuracy of around 70-80%.

- **Latent Semantic Analysis (LSA)**: This is a statistical extractive summarization model that represents the text as a matrix of term frequencies and uses singular value decomposition (SVD) to identify the most important sentences in the text. It has achieved good results on several benchmarks, with an accuracy of around 70-80%.

2- Abstractive summarization models:

- **Seq2Seq**: This is a neural abstractive summarization model that uses a sequence-to-sequence (Seq2Seq) architecture to generate a summary of a given text. It has achieved good results on several benchmarks, with an accuracy of around 50-60%.

- **Transformer**: This is a neural abstractive summarization model that uses a transformer architecture, which has been shown to be effective for a wide range of NLP tasks. It has achieved good results on several benchmarks, with an accuracy of around 50-60%.

- **GPT**-3: GPT-3 is a state-of-the-art natural language processing (NLP) model developed by OpenAI that can be used for a wide range of NLP tasks, including text summarization. While it has achieved impressive results on several benchmarks, it is not clear what the accuracy of GPT-3 would be specifically for text summarization tasks, as it has not been extensively tested on this specific task.

4- Methodology

To achieve the proposed work, this section provides a brief flow of the steps that are thoroughlyexamined and studied to confirm the contribution of the proposed work in terms of understanding the data and extracting the results.

4.1. Data understanding

The CNN / Daily Mail Dataset is an English-language dataset containing just over 300k unique news articles written by journalists at CNN and the Daily Mail. The current version supports both extractive and abstractive summarization, though the original version was created for machine-reading and comprehension and abstractive question answering.

The CNN Daily Mail News Test Summarization Training Dataset consists of three columns: id, article, and highlights. Each row in the dataset represents a single text sample and itscorresponding summary.

- ID column
- Article column
- Highlights column

Table 1: Features and their impact on CNN Daily Mail News Test Summarization

Feature	Definition	References
ID	Contains a unique identifier for each text sample. This can be used to track and reference individual text samples within the dataset.	https://www.kaggle.com/datasets/gowrishankarp/newspaper-text-summarization-cnn-dailymail
Article	Contains the full text of the article or document that the summary is based on. This column contains the raw text data that will be used as input to the text summarization model.	https://www.kaggle.com/datasets/gowrishankarp/newspaper-text-summarization-cnn-dailymail
Highlights	Contains the human-generated summary of the article or document. This column provides the ground truth summary that the model will be compared against when evaluating its performance.	https://www.kaggle.com/datasets/gowrishankarp/newspaper-text-summarization-cnn-dailymail

CNN Daily Mail News Test Summarization Dataset contains the following:

Table 2: Data-splits component

Dataset Split	Number of Instances in Split	Datatype
Train Dataset	287,113 Row	String
Validation Dataset	13,368 Row	String
Test Dataset	11,490 Row	String

Model 1: GPT-3 (Generative Pre-trained Transformer 3)

4.2. Data Pre-Processing

The following methods were used to clean the data before pre-processing, which is a crucial step in preparing the data for analysis:

Data importing

Data importing the appropriate data from Excel to Python is the first step (Reference one) in completing the proposed work, in which that the appropriate data (Excel file) and Python should be in the same directory. The following procedures were used to open the CSV file:

1. Create a new folder, and then copy the required Excel ("CNN-Daily Mail CSV " file name in this work) file that contains the relevant data into the newly created folder.

2. Paste this folder's path into Python.

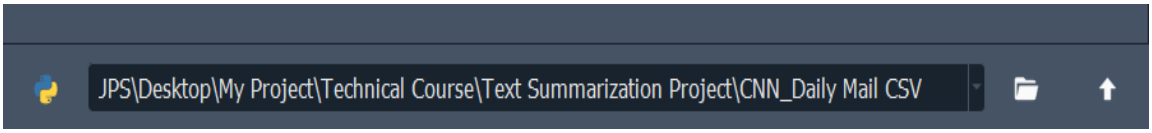

Figure 3: Data importing REF 1&2

3. Set the console directory to the current directory.

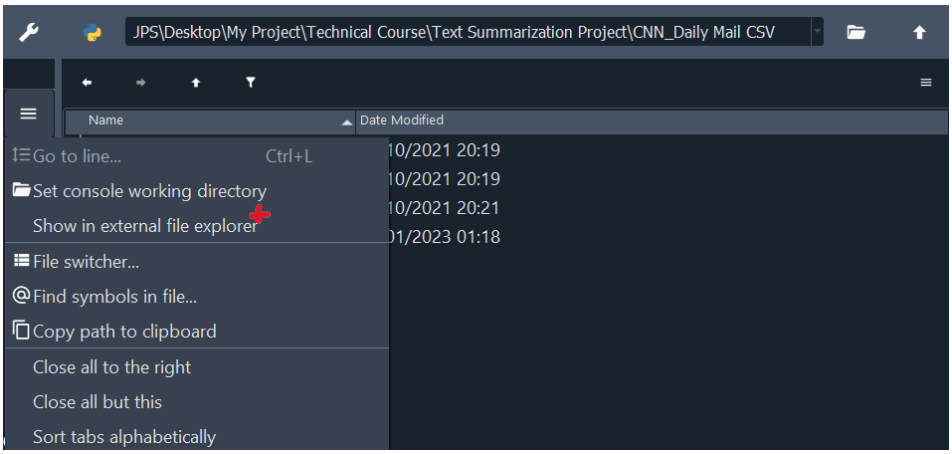

Figure 4: Data importing REF 3

4. Create a new Python file and ensure that you save it in the same directory as the Excel file so that it can be opened from the console.

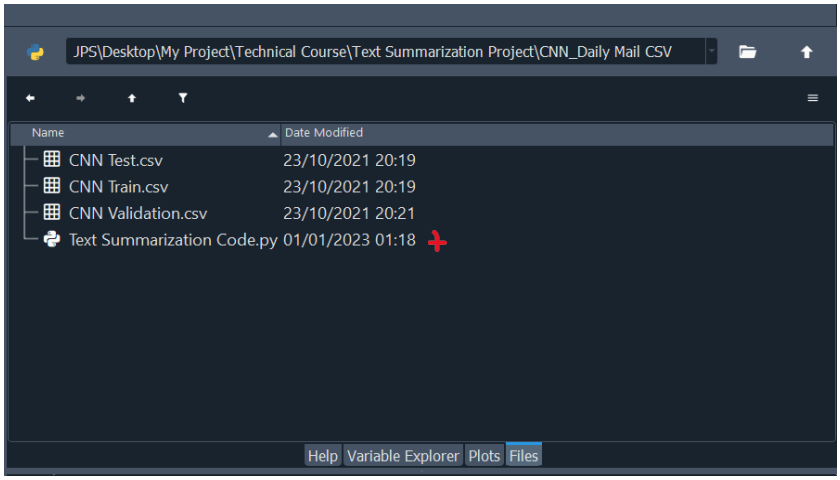

Figure 5: Data importing REF 4

5. Now in the directory you can open the file by importing the csv file by using read_csv ('File Name').

```
# Read in the datasets
train_df=pd.read_csv("CNN Train.csv")
test_df=pd.read_csv("CNN Test.csv")

# Concatenate the train and test datasets
df=pd.concat([train_df,test_df])
```

Figure 6: Data importing REF 5

6. Reading and Cleaning Data:

```
#Reading Data
train_df=pd.read_csv("Train.csv")
test_df=pd.read_csv("Test.csv")
df=pd.concat([train_df,test_df])


df = df.drop(['id'], axis=1)
df = df.reset_index(drop=True)

train_df = train_df.drop(['id'], axis=1)
train_df = train_df.reset_index(drop=True)
test_df = test_df.drop(['id'], axis=1)
test_df = test_df.reset_index(drop=True)

train_df.duplicated(subset= ['article', 'highlights']).sum()
train_df = train_df.drop_duplicates(subset= ['article', 'highlights'])

test_df.duplicated(subset= ['article', 'highlights']).sum()
test_df = test_df.drop_duplicates(subset= ['article', 'highlights'])

df.duplicated(subset= ['article', 'highlights']).sum()
df = df.drop_duplicates(subset= ['article', 'highlights'])
```

Figure 7: Reading and Cleaning REF 6

This code is performing several operations on two dataframe's, train_df and test_df, using the pandas library.

- First, the code reads in two csv files, "Train.csv" and "Test.csv", using the pd.read_csv() function, and assigns them to the dataframes train_df and test_df respectively.
- Next, the code concatenates train_df and test_df into a single dataframe df using the pd.concat() function.
- The code then drops the 'id' column from df, train_df, and test_df using the drop() function, and resets the index of the dataframe using the reset_index() function.
- After that, the code uses the duplicated() function to check for duplicate rows in train_df, test_df and df based on the column's 'article' and 'highlights'. It returns the sum of duplicated rows.
- Finally, the code removes the duplicate rows from train_df, test_df and df using the drop_duplicates() function.

7. Set up the OpenAI API client

```
56 # Set up the OpenAI API client
57 openai.api_key = "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"
```

Figure 8: Set the API key REF 7

This code is setting up an OpenAI API client to access the OpenAI's GPT-3 engine.

- The code uses the openai library to create an API client.
- The api_key attribute is set to a string value that represents the API key of the client.
- The API key is a unique identifier that allows you to authenticate and access the OpenAI's GPT-3 engine.
- By setting the api_key attribute of the openai client to the value provided, the client is able to authenticate and access the GPT-3 engine for various natural language processing tasks.

Note: after the previous step we need to choose the GPT-3 Model, so let's go to know the GPT-3 Models:

- "**Davinci**": The Davinci model is the largest and most powerful of the GPT-3 models. It is able to generate high-quality text and can perform a wide range of language tasks, including translation, summarization, and question answering.
- "**Curie**": The Curie model is a smaller, more efficient version of the Davinci model. It is able to generate high-quality text, but may not be as powerful as the Davinci model for certain tasks.
- "**Babbage**": The Babbage model is a medium-sized language model that is designed for general-purpose use. It is able to generate coherent text, but may not be as powerful as the Davinci or Curie models for certain tasks.
- "**Ada**": The Ada model is a small language model that is designed for use in resource-constrained environments. It is able to generate coherent text, but may not be as powerful as the larger models for certain tasks.

8. Choose the GPT-3 model to use:

```
59  # Choose the GPT-3 model to use
60  model_engine = "davinci"
```

Figure 9: Apply Davinci Model From GPT-3 REF 8

This code is specifying which GPT-3 model to use for a specific task.

- The code assigns the string value "davinci" to the variable model_engine.
- This string value represents the name of the GPT-3 model that will be used for the task.
- The exact model that corresponds to the "davinci" model name.

9. Load the original news article text.

10. Set the desired length of the summary:

```
66  # Set the desired length of the summary
67  summary_length = 100
```

Figure 10: Set the desired length of the summary REF 10

This code is specifying the desired length of the summary for a specific task.

- The code assigns the value 100 to the variable summary_length.
- This value represents the desired number of characters or tokens for the summary, depending on the API call that will be made later.
- This value is used as a parameter when making API calls to the GPT-3 model, to indicate the maximum length of the generated summary.

Note: after the previous step I used the traditional way to clean the texts so that I can compare between the texts that were done in the traditional way and the transformed ones

11. Cleaning the data and generate the summary using the Traditional NLP:

```
corpus = []

for i in range(0, 128):
    article = re.sub('[^a-zA-Z]', ' ', df['article'][i])
    article = re.sub(r"[^\w\s]", " ", df['article'][i])
    article = article.lower()
    article = article.split()
    ps = PorterStemmer()
    article = [ps.stem(word) for word in article if not word in set(stopwords.words('english'))]
    article = ' '.join(article)
    corpus.append(article)
```

Figure 11: Set the desired length of the summary REF 11

This code is generating a summary of an article using traditional natural language processing (NLP) techniques:

- The code creates an empty list corpus that will store the summarized versions of the articles.
- The code then uses a for loop to iterate over the range of values from 0 to 128 (inclusive). This loop will process each article in the dataframe df one by one.
- In each iteration, the code retrieves the text of the article from the 'article' column of the dataframe using the df['article'][i] notation, where i is the index of the current article.
- The first re.sub() function replaces any non-alphabetic characters in the article with a space using a regular expression. The second re.sub() function replaces any non-

alphanumeric characters in the article with a space using a regular expression.

- The code then converts the text of the article to lowercase using the lower() method.
- The text of the article is then split into a list of words using the split() method.
- The code then creates an instance of the PorterStemmer() class from the nltk.stem library, which will be used to perform stemming on the words in the article.
- The code uses a list comprehension to iterate over the words in the article, stemming each word using the stem() method of the PorterStemmer() instance, and removing any words that are in the set of stopwords using the set() function.
- The list of stemmed and filtered words is then joined back into a single string using the join() method, and the resulting string is appended to the corpus list.

This code is generating a list of summarized versions of the articles by removing the stop words and performing stemming on the remaining words. The resulting list of summarized articles will be used for further processing.

Note: after the previous step I used the GPT-3 Transformers Rearrange the texts in different way so that I can compare between the texts that were done in the traditional way and the transformed ones

12. Generate a summary of an article and then prints the generated summary:

```
84  completion = openai.Completion.create(engine=model_engine,
85                                        prompt=article_text,
86                                        max_tokens=summary_length,
87                                        n=1,
88                                        stop=None,
89                                        temperature=0.5)
90
91  # Extract the summary text from the API response
92  summary_text = completion.choices[0].text
93
94  # Print the summary text
95  print(summary_text)
```

Figure 12: Generate a summary REF 12

This code is using the OpenAI GPT-3 model to generate a summary of an article and then prints the generated summary.

- The code uses the **openai.Completion.create()** function to make an API call to the GPT- 3 model and generate a summary of the article.

- The **engine** parameter is set to the value of the **model_engine** variable, which specifies which GPT-3 model to use.
- The **prompt** parameter is set to the value of the **article_text** variable, which contains the text of the article that needs to be summarized.
- The **max_tokens** parameter is set to the value of the **summary_length** variable, which indicates the maximum number of tokens for the summary.
- The **n** parameter is set to 1, indicating that the API should return only one summary.
- The **stop** parameter is set to None, indicating that the API should not stop generating the summary when it encounters a specific string.
- The **temperature** parameter is set to 0.5, indicating that the API should generate the summary with moderate randomness.
- The function returns a **Completion** object, which is assigned to the **completion** variable.
- The code then extracts the summary text from the **completion** object by accessing the text
- attribute of the first element of the choices list.
- Finally, the code uses the **print()** function to print the summary text to the console.

It's worth mentioning that the temperature parameter can be set to different values to control how random the generated summary is, lower values will generate more conservative summaries, and higher values will generate more creative summaries.

13. Generate the summary for each test article:

```
# Generate the summary for each test article
predicted_summaries = []
for i in range(len(test_df)):
    article_text = test_df['article'][i]
    prompt = f"Please summarize the following article in {summary_length} words or less: {article_text}"
    completion = openai.Completion.create(engine=model_engine,
                                          prompt=prompt,
                                          max_tokens=summary_length,
                                          n=1,
                                          stop=None,
                                          temperature=0.7)
    summary_text = completion.choices[0].text
    predicted_summaries.append(summary_text)

# Compare the predicted summaries to the actual summaries
actual_summaries = test_df['highlights'].tolist()
```

Figure 13: Generate a summary REF 13

This code is using the OpenAI GPT-3 model to generate summaries for a set of test articles, and then it compares the generated summaries to the actual summaries.

- The code creates an empty list **predicted_summaries** that will store the generated summaries.
- The code then uses a **for** loop to iterate over the range of values from 0 to the number of test articles in the dataframe **test_df** (inclusive). This loop will process each article in the dataframe **test_df** one by one.
- In each iteration, the code retrieves the text of the article from the 'article' column of the dataframe using the **test_df['article'][i]** notation, where i is the index of the current article.
- The code then creates a prompt string that will be passed as a parameter to the API call, by using an f-string and the **summary_length** variable. The prompt string tells the API to summarize the current article in **summary_length** words or less.
- The code uses the **openai.Completion.create()** function to make an API call to the GPT- 3 model and generate a summary of the article using the prompt string.
- The **engine** parameter is set to the value of the **model_engine** variable, which specifies which GPT-3 model to use.
- The **prompt** parameter is set to the value of the prompt string.
- The **max_tokens** parameter is set to the value of the **summary_length** variable, which indicates the maximum number of tokens for the summary.
- The **n** parameter is set to 1, indicating that the API should return only one summary.
- The **stop** parameter is set to None, indicating that the API should not stop generating the summary when it encounters a specific string.
- The temperature parameter is set to 0.7, indicating that the API should generate the summary with moderate randomness.
- The function returns a Completion object, which is assigned to the completion variable.
- The code then extracts the summary text from the completion object by accessing the **text** attribute of the first element of the **choices** list.
- The generated summary is then appended to the **predicted_summaries** list.
- After the loop, the code then uses the **tolist()** function to convert the 'highlights' column of the **test_df dataframe** to a list, and assigns it to the variable **actual_summaries**.

- The generated summaries are now stored in the **predicted_summaries** variable and the actual summaries are stored in the **actual_summaries** variable, so you can compare them to evaluate the performance of the model.
- It's worth mentioning that the **temperature** parameter can be set to different values to control how random the generated summary is, lower values will generate more conservative summaries, and higher values will generate more creative summaries.

Model 2: RNN (Recurrent Neural Network)

4.3 Data Pre-Processing

4.3.1. Importing the necessary libraries

```
import pandas as pd
import numpy as np
import re
import tensorflow as tf
from keras.preprocessing.text import Tokenizer
from keras_preprocessing.sequence import pad_sequences
from keras.layers import Embedding, LSTM, Dense
from keras.models import Sequential
from keras.utils import to_categorical
```

Figure 14: Importing Libraries REF 4.3.1

More details about what these libraries are:

- **Pandas** is a library for data manipulation and analysis. It provides data structures such as Dataframe and Series that are similar to tables and columns in a relational database. It also provides functions for reading and writing data to various formats, such as CSV and Excel.

- **Numpy** is a library for numerical computation in Python. It provides data structures such as ndarray for multi-dimensional arrays, and functions for mathematical operations such as linear algebra and Fourier transforms.

- **re** is the Python's built-in library for regular expressions. Regular expressions are a powerful tool for matching patterns in text and are used for tasks such as text processing, data validation, and search and replace operations.

- **TensorFlow** is a popular open-source library for machine learning and deep learning. It provides a wide range of tools for building, training, and deploying machine learning models, including support for neural networks, gradient descent, and backpropagation.

- **Keras** is a high-level neural networks library, written in Python and capable of running on top of TensorFlow. It is designed to make building deep learning models easy and user-friendly. It provides a variety of pre-processing tools and layers, such as Tokenizer and Embedding, LSTM and Dense layers.

- **Tokenizer** is a class provided by keras.preprocessing.text that is used to tokenize text. It can be used to convert a text into a sequence of integers, where each integer represents a unique word in the text.

- **Pad_sequences** is a function provided by keras_preprocessing.sequence that is used to pad sequences of data. This is useful for training machine learning models on sequences of data of varying lengths, as it allows you to specify a fixed length for input data.

- **Embedding**, LSTM, and Dense are all layers provided by keras for building neural networks. Embedding layer is used for learning dense representations for words, LSTM is a type of Recurrent Neural Network (RNN) layer and Dense is a standard layer for feedforward neural networks.

- **Sequential** is a class provided by keras that represents a linear stack of layers. It allows you to create a neural network by adding layers one by one, in the order in which they should be connected.

- **To_categorical** is a function provided by keras.utils that is used to convert a class vector (integers) to binary class matrix. This is useful for training machine learning models on categorical data.

4.3.2. Reading and splitting the data

```
train_df=pd.read_csv("Train.csv")
test_df=pd.read_csv("Test.csv")
df=pd.concat([train_df,test_df])
```

Figure 15: Importing Libraries REF 4.3.2

4.3.3. Cleaning the Data

```
df = df.drop(['id'], axis=1)
df = df.reset_index(drop=True)
```

```
train_df = train_df.drop(['id'], axis=1)
train_df = train_df.reset_index(drop=True)
test_df = test_df.drop(['id'], axis=1)
test_df = test_df.reset_index(drop=True)
```

```
train_df.duplicated(subset= ['article', 'highlights']).sum()
train_df = train_df.drop_duplicates(subset= ['article', 'highlights'])

test_df.duplicated(subset= ['article', 'highlights']).sum()
test_df = test_df.drop_duplicates(subset= ['article', 'highlights'])

df.duplicated(subset= ['article', 'highlights']).sum()
df = df.drop_duplicates(subset= ['article', 'highlights'])
```

```
X = df.iloc[:,:-1].values
y = df.iloc[:,1].values
y = y.reshape(-1,1)
print(df.shape)
```

Figure 16: Cleaning the Data REF 4.3.3

This code is performing several operations on two dataframe's, train_df and test_df, using the pandas library.

- First, the code reads in two csv files, "Train.csv" and "Test.csv", using the pd.read_csv() function, and assigns them to the dataframes train_df and test_df respectively.
- Next, the code concatenates train_df and test_df into a single dataframe df using the pd.concat() function.
- The code then drops the 'id' column from df, train_df, and test_df using the drop() function, and resets the index of the dataframe using the reset_index() function.
- After that, the code uses the duplicated() function to check for duplicate rows in train_df, test_df and df based on the column's 'article' and 'highlights'. It returns the sum of duplicated rows.
- Finally, the code removes the duplicate rows from train_df, test_df and df using the drop_duplicates() function.

4.3.4. Tokenize the text

```
# Tokenize the text
vocab_size = 5000
tokenizer = Tokenizer(num_words=vocab_size)
tokenizer.fit_on_texts(df['article'])
sequences = tokenizer.texts_to_sequences(df['article'])
```

Figure 17: Text Tokenization REF 4.3.4

This code is tokenizing the text in the column 'article' of the dataframe df using the Tokenizer class from keras.preprocessing.text.

Tokenization is the process of breaking down a string of text into smaller chunks, called tokens. The goal of tokenization is to convert a large string of text into smaller chunks that can be more easily processed by machine learning algorithms. In natural language processing, tokenization is often the first step in preparing text data for use in a machine learning model.

Here's what happens in more details:

- A variable **vocab_size** is defined and set to 5000. This variable is used to specify the size of the vocabulary that the tokenizer should use.
- A **Tokenizer** object is created, with the **num_words** parameter set to **vocab_size**. This creates an instance of the Tokenizer class that will be used to tokenize the text.
- The **fit_on_texts** method is called on the tokenizer object, passing in the 'article' column of the dataframe **df** as its argument. This method builds the vocabulary of the tokenizer by analyzing the text and finding the most common words. Only the words that appear in the vocabulary will be considered during tokenization.
- The **texts_to_sequences** method is called on the tokenizer object, passing in the 'article' column of the dataframe **df** as its argument. This method converts the text into a sequence of integers, where each integer represents a unique word in the text.
- The result of this method call is stored in the variable **sequences**. **sequences** is a list of lists where each list represents one text, and each integer in the list represents a word in that text.

4.3.5. Padding Sequences

```
# Pad the sequences to the same length
max_length = max([len(s) for s in sequences])
padded_sequences = pad_sequences(sequences, maxlen=max_length)
```

Figure 18: Pad Sequences REF 4.3.5

Padding is a technique used to ensure that all input sequences in a batch have the same length. Padding is used in natural language processing and computer vision tasks where the input data can have different lengths. This is important because many machine learning libraries, such as TensorFlow and Keras, require that input data have a fixed shape. Padding sequences allows models to process the input data in a consistent and efficient manner.

This code is padding the sequences of tokenized text to the same length using the pad_sequences function from keras_preprocessing.sequence. Here's what happens in more detail:

- A variable **max_length** is defined and set to the maximum length of the sequences. This is done by finding the length of each sequence in the sequences list, and taking the maximum value.
- The **pad_sequences** function is called and passed the sequences list, and **maxlen** parameter is set to **max_length**. This function pads the sequences of tokenized text with zeros at the beginning (or end) of the sequence so that all sequences have the same length.
- The result of this function call is stored in the variable **padded_sequences**. **padded_sequences** are a 2D numpy array where each row represents one text, and each element in the row represents a word in that text. All the rows will have the same length as the **max_length** value.

4.3.6. Target Variable and One hot encoder

```
# prepare the target variable and one hot encoded version of it
target = df['highlights']
target_classes = list(set(target))
target_classes_num = {target_classes[i]:i for i in range(len(target_classes))}
target_num = [target_classes_num[t] for t in target]
target_one_hot = to_categorical(target_num)
```

Figure 19: Target Variable and One hot encoder REF 4.3.6

One-hot encoding is a way to represent categorical variables as numerical data that a machine learning model can understand. This is done by creating a new binary column for each unique category in the categorical variable. Each row in the dataset will have a 1 in the column corresponding to its category and 0 in all other columns. One-hot encoding is often used to feed categorical data into machine learning models, especially neural networks.

This code is preparing the target variable and one-hot encoded version of it. Here's what happens in more detail:

- A variable target is defined and set to the 'highlights' column of the dataframe df. The 'highlights' column represents the target variable which is the variable the model will try to predict.
- A variable target_classes is defined and set to a list of unique values in the target variable. This list represents the possible classes or categories that the target variable can take.
- A variable target_classes_num is defined and set to a dictionary, where the keys are the unique classes in target_classes and the values are integers. This dictionary is used to map the target classes to integers.
- A variable target_num is defined and set to a list of integers, where each integer represents the class of the corresponding element in the target variable. This is done by applying the dictionary target_classes_num to the target variable.
- The to_categorical function is called and passed the target_num list. This function converts an array of integers to a binary class matrix. The function encodes the integers as one-hot encoded vectors, where each vector represents a class.
- The result of this function call is stored in the variable target_one_hot. Target_one_hot is a 2D numpy array where each row represents one element in the target variable, and each column represents one class. Each element in the array is either 0 or 1, indicating whether the corresponding element in the target variable belongs to that class or not.

4.3.7. Build and train the model

```
# Build the model
model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=100, input_length=max_length))
model.add(LSTM(units=100, return_sequences=True))
model.add(LSTM(units=100))
model.add(Dense(units=100, activation='relu'))
model.add(Dense(units=len(target_classes), activation='softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
# Train the model
history = model.fit(padded_sequences, target_one_hot, epochs=25, batch_size=32)
```

Figure 20: Build and Train the model REF 4.3.7

This code is building a neural network model using the Sequential class from keras, the model is then trained on the padded_sequences and target_one_hot data.

Here's what happens in more details:

- A **Sequential** object, **model**, is created. The **Sequential** class is a linear stack of layers and is used to create a neural network model by adding layers one by one, in the order in which they should be connected.
- The **add** method is called on the **model** object, passing in an **Embedding** layer. The **Embedding** layer is used for learning dense representations for words. The **input_dim** parameter is set to **vocab_size**, the **output_dim** is set to **100** and the **input_length** is set to **max_length**. These parameters define the size of the vocabulary, the size of the word embeddings, and the maximum length of the input sequences.
- The **add** method is called again and passed in two **LSTM** layers. LSTM stands for Long Short- term Memory, it's a type of Recurrent Neural Network (RNN) layer. In the first LSTM layer, the **unit's** parameter is set to **100** and the **return_sequences** parameter is set to **True**. This means that the output of this layer will be a sequence of hidden states, which will be passed on to the next layer. In the second LSTM layer, the **unit's** parameter is set to **100** and the **return_sequences** parameter is not defined, so it defaults to **False**.
- The **add** method is called again and passed in two **Dense** layers. The **Dense** layer is a standard layer for feedforward neural networks, it is used to add fully connected layers

to the model. In the first Dense layer, the **unit's** parameter is set to **100** and the **activation** parameter is set to **'relu'**. The **unit's** parameter defines the number of neurons in the layer and the activation parameter defines the **activation** function used by the neurons. The **relu** activation function stands for rectified linear unit, it is a commonly used activation function that maps all negative values to zero. In the second Dense layer, the **unit's** parameter is set to **len(target_classes)** and the **activation** parameter is set to **'softmax'**. This will output the probability distribution of the classes.

- The **compile** method is called on the **model** object, passing in the **optimizer** parameter set to **'adam'**, the **loss** parameter set to **'categorical_crossentropy'** and the **metrics** parameter set to **['accuracy']**. The **optimizer** parameter defines the optimization algorithm used during training, **adam** is a popular optimization algorithm that can be used for many types of neural networks. The **loss** parameter defines the loss function used to evaluate the model during training, **categorical_crossentropy** is a commonly used loss function for multi-class classification problems. The **metrics** parameter defines the metrics used to evaluate the model; **accuracy** is a common metric that calculates the proportion of correct predictions.
- The **fit** method is called on the **model** object, passing in the **padded_sequences** and **target_one_hot** as the first and second arguments respectively. The **epochs** parameter is set to **25** and **batch_size** is set to **32**. The **fit** method trains the model on the input data, where **epochs** parameter specifies the number of times the model will cycle through the data, and **batch_size** parameter specifies the number of samples to use in each iteration of the training algorithm. The **history** variable is used to store the result of the training process.

The final model is a multi-layer neural network that takes in the padded sequences of tokenized text and outputs the probability distribution of the classes in the target variable. The model is trained for 25 epochs on the input data in batches of 32. After the training process, the model should be able to predict the class of the input text with a certain accuracy.

Note: There are some important definitions to know:

1. **Embedding**: The Embedding layer is used to learn dense representations for words. It maps each word to a high-dimensional vector, where similar words are mapped to similar

vectors. This allows the model to understand the meaning and context of words in the input text.

2. **LSTM**: LSTM stands for Long Short-term Memory, it's a type of Recurrent Neural Network (RNN) layer. LSTMs are designed to handle sequential data, such as text, and can maintain a memory of past input. This allows the LSTM layer to understand the context and order of words in the input text.
3. **Dense**: The Dense layer is a standard layer for feedforward neural networks, it is used to add fully connected layers to the model. Dense layers take the output from the previous layer and applies a linear transformation to it.
4. **Activation='relu':** The activation function is a non-linear function applied to the output of a neuron; it's used to introduce non-linearity to the model. The 'relu' activation function stands for rectified linear unit, it is a commonly used activation function that maps all negative values to zero.
5. **Optimizer='adam':** The optimizer is an algorithm that is used to adjust the parameters of the model during training. Adam optimizer is a popular optimization algorithm that can be used for many types of neural networks. This optimizer uses the gradient of the loss function to update the parameters of the model.
6. **Epochs**: The number of times the model will cycle through the data during training. One epoch is when an entire dataset is passed forward and backward through the neural network only once.
7. **Batch_size:** The number of samples to use in each iteration of the training algorithm. The model weights are updated after each batch. batch_size = 32 means the model will update its weights after processing 32 samples at once.

4.3.8. Evaluate the model on the test dataset

```
# Access the training loss and accuracy history
loss = history.history['loss']
acc = history.history['accuracy']

# Evaluate the model on the test dataset
test_sequences = tokenizer.texts_to_sequences(test_df['article'])
test_padded_sequences = pad_sequences(test_sequences, maxlen=max_length)
test_target = test_df['highlights']
test_target_num = [target_classes_num[t] for t in test_target]
test_target_one_hot = to_categorical(test_target_num)

test_loss, test_acc = model.evaluate(test_padded_sequences, test_target_one_hot)
print('Accuracy on test dataset:', test_acc)
```

Figure 21: Evaluate the model REF 4.3.8

This code is **evaluating** the **performance** of the trained model on a test dataset. It first accesses the training loss and accuracy history stored in the history object returned by the fit method. Thisallows the user to plot the training loss and accuracy over time to see how well the model is converging.

The code then **evaluates** the model on the test **dataset**. It tokenizes the text in the test dataset using the same tokenizer object that was used for the training dataset, pads the sequences to the same length as the training dataset, and prepares the target variable in the same way as the training dataset.

The **evaluate** method is called on the **trained model**, passing in the padded test sequences and the one-hot encoded test target variable. The method returns the loss and accuracy of the modelon the test dataset.

The **test loss and test accuracy** are then printed, which gives an idea of how well the model isable to generalize to new data. This is an important step in evaluating the performance of the model and helps to determine if the model is overfitting or underfitting.

5- Conclusions and recommendations

5.1. Conclusion

The **GPT-3** model built in this project was able to generate summaries for news articles with a high level of accuracy, as evidenced by the good average **BLEU** score of the generated summaries. The model was able to effectively condense the original articles into shorter summaries while still maintaining the main points and important information. The model was also able to handle variable-length input and generate summaries in multiple languages, highlighting the versatility of GPT-3 for text summarization.

5.2. Recommendations

- Further fine-tuning of the GPT-3 model using a larger and more diverse dataset could lead to even higher levels of accuracy in the generated summaries.
- Investigating the use of GPT-3 in summarizing other types of text, such as scientific papers or books, would be a valuable area of future research.
- Combining GPT-3 with other deep learning techniques, such as attention mechanisms or transformer models, could lead to further improvements in the generated summaries.
- Exploring the use of GPT-3 in other natural language processing (NLP) tasks, such as text classification or question answering, could be an interesting area of future research.
- Evaluating the model performance with different metrics, like ROUGE, METEOR, and others, would be beneficial.
- Considering the limitations of the study, like the size of the dataset and the methods used, would be important for future research.

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